

MINISTERUL EDUCAȚIEI NAȚIONALE
ROMÂNIA
UNIVERSITATEA DE MEDICINĂ,
FARMACIE, ȘTIINȚE ȘI TEHNOLOGIE
„GEORGE EMIL PALADE"
DIN TÂRGU MUREȘ



"GEORGE EMIL PALADE" UNIVERSITY OF MEDICINE, PHARMACY, SCIENCE, AND TECHNOLOGY OF TÂRGU MUREȘ

DOCTORAL SCHOOL OF LETTERS, HUMANITIES AND APPLIED SCIENCES

SCIENTIFIC FIELD: INFORMATICS

UNIVERSITY OF MALAGA

PROGRAMA DE DOCTORADO EN CIENCIAS DE LA SALUD

SCIENTIFIC FIELD: HEALTH SCIENCES

JOINT PHD THESIS

ADVANCED DISTANT DIAGNOSTICS TECHNIQUES AND SENSORS IN SPORTS SAFETY AND HEALTH CONDITION PREDICTION

PhD Candidate:
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Scientific Co-Supervisor:
Prof. Dr. Jaime MARTIN-MARTIN, University of Malaga



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"To bring about change,
you must not be afraid to take the first step.
We will fail when we fail to try."

Rosa Parks

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Resumen

El auge de los deportes de competición ha supuesto un desarrollo en el uso de sistemas complementarios para el desarrollo de una práctica deportiva segura, siendo un tema en constante evolución. La integración de sensores, wearebles y procesamientos avanzados junto a métodos innovadores de recuperación, ha supuesto un nuevo impulso en la investigación sobre seguridad deportiva, monitoirzación de entrenamiento y recuperación de lesiones y enfermedades. El avance de la inteligencia artificial (IA) y los métodos de detección rápida pueden ayudar a reducir los casos de infradiagnóstico. En este sentido, los ecosistemas actuales permiten prever los datos, estableciendo relaciones entre las lesiones, los metadatos vinculados con estas y los datos sobre la salud de los jugadores para generar modelos de análisis de datos personalizados relacionados con los hábitos.

La investigación multidisciplinar se centra en encontrar tecnologías emergentes basadas en IA para mejorar los diagnósticos a distancia y la seguridad deportiva para prevenir lesiones o acelerar los periodos de recuperación. Además incorpora nuevas tecnologías para proporcionar consultas y diganósticos a distancia, tanto a tiempo real, como colaborativas en el deporte y la rehabilitación.Este proyecto presenta una conceptualización para gestionar un futuro ecosistema deportivo más rápido y seguro, minimizando los factores de riesgo, controlándolos y haciendo hincapié en las mejores prácticas. Los enfoques relacionados con la telemedicina en este contexto también destacan en la investigación, junto con la adaptación de algoritmos de aprendizaje automático y aprendizaje profundo para que los médicos deportivos tomen sus decisiones. Los tres componentes principales de la investigación en este ámbito son: (1) La IA utilizada en la consulta a distancia para proporcionar servicios eficaces de dominio cruzado; (2) investigación de la relación entre los algoritmos de IA y la predicción de la fatiga, la prevención de lesiones en deportes de alto rendimiento y la detección precoz de enfermedades o anomalías; (3) investigación sobre indicadores de seguridad deportiva como MET, sRPE, ACWR, utilizando algoritmos avanzados e IA para mejorar el rendimiento deportivo y la seguridad deportiva.

Los nuevos modelos y metodologías de Machine Learning (ML) demuestran la amplitud y el cambio de este paradigma. Incluye la recopilación e integración de datos, el preprocesamiento y la extracción de características, el desarrollo y entrenamiento de modelos, su validación y mejora, su despliegue y seguimiento en tiempo real, la realización de sugerencias e intervenciones personalizadas, y la evaluación y automejora de los procesos. Este campo de estudio puede mejorar la seguridad, el rendimiento y el acondicionamiento deportivos analizando comportamientos y actividades con IA y análisis predictivos.

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Abstract

The rise of competitive sports has made sports safety a prominent topic. Integrating distance and wearable sensors with innovative recovery or rehabilitation methods has revolutionized training cycles, accelerated progress, and altered fatigue and recovery trends in performance sports. Advances in artificial intelligence (AI) and rapid detection methods can help reduce cases of underdiagnosis. Sports ecosystems or platforms can forecast injury-related data by merging daily metadata with vital and players' health data to generate customized habit-related data analytics.

The multilayered and multidisciplinary thesis is focused on finding/adopting emerging technologies with artificial intelligence to enhance distant diagnostics and methods in performance sports and sports safety to prevent injuries or speed recovery periods. In addition, it applies technology-enabled pipelines, techniques, and models to provide collaborative, real-time, remote consultancies, and diagnosis in sports. The thesis presents a conceptualization to manage a safer and faster future sports ecosystem, minimize risk factors, control them, and emphasize best practices. Telemedicine-related approaches, as part of burnout or neurodegenerative diseases or anomaly detection from voices and text combined with sentiment analysis, will also be highlighted in the research, along with the adaptation of machine learning (ML) and deep learning (DL) algorithms. Providing real-time injury predictions with data analysis reports is a practical and innovative tool for sports physicians to assess injury risks in a preventive way. The three main pillars of the thesis are (1) AI used in remote consulting to provide adequate cross-domain services, which studies collaborative tools that facilitate direct contact between individuals using AI-enhanced, nearly real-time technological pipelines; (2) research the relationship between AI algorithms and fatigue prediction, injury prevention in high-performance sports, and early detection of diseases or abnormalities; (3) research on Sports Safety indicators such as Metabolic Equivalent of Task (MET), Session Rating of Perceived Exertion (sRPE), Acute: Chronic work load ratio (ACWR), injury, fatigue, regeneration cycles, aggregation of health conditions and forecasts using advanced algorithms and AI to enhance performance sports and sports safety. The results prove the scientific value of the thesis. They comprise data collection and integration, pre-processing and feature extraction, model development and training, validation and improvement, deployment and real-time monitoring, tailored suggestions and interventions, and process evaluation and self-improvement. By analyzing behaviors and activities with AI and predictive analytics, this field of study can improve sports safety, performance, and conditioning.

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List of publications

The evaluation of the author's publications[1] is in accordance with the standards set by CNATDCU in Romania (National Council for the Accreditation of University Degrees, Diplomas and Certificates), applicable to doctoral students enrolled after October 1, 2018. The rankings are presented based on the classification of conferences[2] and journals[3] in the field of computer science.

1. **A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi, "*SRPE and ACWR to control fatigue levels and minimize injuries in performance sports*", IEEE International Conference on Systems, Man, and Cybernetics (SMC), Special Section Cyber, p.2808–2813, Honolulu, Oahu, HI, USA, **2023**, *IEEE Xplore*, DOI: 10.1109/SMC53992.2023.10394349.
   Conference Paper, Rank[2]: B.

2. **A. Biró**, A.I. Cuesta-Vargas, S.M. Szilágyi, "*Real-time disease and COVID-19 detection pipeline from voice for performance sports*", IEEE International Conference on Systems, Man, and Cybernetics (SMC), Special Section Cyber, p.2309–2314, Honolulu, Oahu, HI, USA, **2023**, *IEEE Xplore*,
   DOI: 10.1109/SMC53992.2023.10394396.
   Conference Paper, Rank[2]: B.

3. A.I. Cuesta-Vargas, **A. Biró**, A. Escriche-Escuder, et al. "*Effectiveness of a gamified digital intervention based on lifestyle modification (iGame) in secondary prevention: a protocol for a randomised controlled trial*", *BMJ Open*, 13, **2023**, DOI: 10.1136/bmjopen-2022-066669.
   Journal Paper, Rank AIS[3]: Q2 (A)[4], Impact Factor (IF)[5]: 3.007.

[1]Publications: with DOI, where the PhD candidate is listed as the 1st or 2nd author
[2]Source CORE Conference Ranking Portal: http://portal.core.edu.au/conf-ranks
[3]Source UEFISCDI: https://uefiscdi.gov.ro/premierea-rezultatelor-cercetarii-articole (October, 2022)
[4]BMJ Open placed 6th; according to policy, it be considered and calculated as a higher (A) Rank
[5]Source 2022 Journal Impact Factors, Journal Citation Reports TM (Clarivate, 2023)

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4. **A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi, "*AI-assisted fatigue and stamina control for performance sports on IMU-generated multivariate times series datasets*", MDPI, *Sensors*, 24(1): 132, **2024**, DOI: 10.3390/s24010132.
   Journal Paper, Rank AIS[3]: Q2 (B), Impact Factor (IF)[4]: 3.9.

5. **A. Biró**, S.M. Szilágyi, L. Szilágyi, J. Martin-Martin, A.I. Cuesta-Vargas, "*Machine learning on prediction of relative physical activity intensity using medical radar sensor and 3D accelerometer*", MDPI, *Sensors*, 23(3595), **2023**, DOI: 10.3390/s23073595.
   Journal Paper, Rank AIS[3]: Q2 (B), Impact Factor (IF)[4]: 3.9.

6. **A. Biró**, S.M. Szilágyi, L. Szilágyi, "*Optimal training dataset preparation for AI-supported multi-language real-time OCRs using visual methods*", MDPI, *Applied Sciences*, 13(24): 13107, **2023**, DOI: 10.3390/app132413107.
   Journal Paper, Rank AIS[3]: Q3 (C), Impact Factor (IF)[4]: 2.7.

7. **A. Biró**, A.I. Cuesta-Vargas, J. Martin-Martin, L. Szilágyi, S.M. Szilágyi "*Synthetized multilanguage OCR using CRNN and SVTR models for realtime collaborative tools*", MDPI, *Applied Sciences*, 13(4419), **2023**, DOI: 10.3390/app13074419.
   Journal Paper, Rank AIS[3]: Q3 (C), Impact Factor (IF)[4]: 2.7.

8. **A. Biró**, K.T. Jánosi-Rancz, L. Szilágyi, A.I. Cuesta-Vargas, J. Martin-Martin, S.M. Szilágyi, "*Visual object detection with DETR to support video-diagnosis using conference tools*", MDPI, *Appl. Sciences*, 12(5977), **2022**, DOI: 10.3390/app12125977.
   Journal Paper, Rank AIS[3]: Q3 (C), Impact Factor (IF)[4]: 2.7.

9. **A. Biró**, "*Gamification, GenAI and reinforcement learning as motivational assets in performance sports*", IEEE 18th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, **2024**, p.315–320, *IEEE Xplore*, DOI: 10.1109/SACI60582.2024.10619802.
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Glossary

ACWR	Acute:Chronic Workload Ratio
AI	Artificial Intelligence
ALS	Amyotrophic Lateral Sclerosis
ANN	Artificial Neural Network
CCPA	California Consumer Privacy Act
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CRNN	Convolutional recurrent neural network
CT	Computed Tomography
CSF	Cerebrospinal Fluid
DAG	Directed Acyclic Graph
DC	Doubly Constraint
DCT	Discrete Cosine Transformation
DETR	DEtection TRansformer
DL	Deep Learning
DNN	Deep Neural Network
DSM	Diagnostic and Statistical Manual of Mental Disorders
DTW	Dynamic Time Warping
DX	Digital Transformation
EDA	Exploratory Data Analysis
FFT	Fast Fourier Transformation
GAN	Generative Adversarial Networks
GDPR	General Data Protection Regulation
GENAI	Generative Artificial Intelligence
GPU	Graphics Processing Unit
GRU	Gated Recurrent Unit
HGG	High-Grade Glioma
HNR	Harmonics-to-Noise Ratio
HPC	High Performance Computing
HR	Heart Rate
ICD	International Classification of Diseases

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IMU	Inertial Measurement Unit
IQR	InterQuartile Range
kNN	k-Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LGG	Low-grade Glioma
LSTM	Long Short-Term Memory
mAP	Mean Average Precision
MET	Metabolic Equivalent of Task
MFCC	Mel-frequency cepstral coefficient
MHA	Multi-head attention
MHSA	Multi-head self-attention
ML	Machine Learning
MLP	Multi-layer Perceptron
MMR	Mixed Method Research
MPC	Model Predictive Control
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
MTS	Multivariate Time Series
MVP	Minimum Viable Product
NAS	Neural Architecture Search
NDD	NeuroDegenerative Disorders
NLP	Natural Language Processing
NMS	Non-Maximum suppression
NN	Neural Network
OCR	Optical Character Recognition
OLS	Ordinary Least Squares
PET	Positron Emission Tomography
PoC	Proof-of-Concept
PoT	Proof-of-Technology
PSD	Power Spectral Density
PWA	Progressive WebApp
QDA	Quadratic Discriminant Analysis
R-CNN	Region-based Convolutional Neural Network
ReLU	Rectified Linear Unit
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RPAI	Relative Physical Activity Intensity
RPE	Rating of Perceived Exertion

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RPS	Radar-based Physiological Sensing
RQ	Research Question
SCD	Sudden Cardiac Death
SGD	Stochastic Gradient Descent
SMA	Signal Magnitude Area
sRPE	Session Rating of Perceived Exertion
SVM	Support Vector Machine
SVTR	Single Visual (scene) Text Recognition
TVOD	Textual and Visual Object Detection
VAE	Variational AutoEncoders
VOD	Visual Object Detection
VOTT	Visual Object Tagging Tool
YOLO-NAS	You Only Look Once Neural Architecture Search
YOLO	You Only Look Once

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1 Introduction

Digital Transformation (DX), Machine Learning (ML), and Deep Learning (DL) models are all becoming existing technologies in Remote Diagnosis, as illustrated by Benis *et al* [8] – we live in the "age of data"! Data science is already providing new perspectives for all sectors, as introduced by Zhong *et al* [9]. As a positive side effect of the COVID-19 pandemic, the DX process has been increasing and new collaborative technologies have already been introduced, such as *remote work* and *social distancing*, catalyzing the rise of *new types of mindset* around the world. Artificial intelligence (AI) is used in remote diagnosis, particularly video analysis, to help prevent injuries and detect fatigue. It also helps to detect potential diseases and risk factors early and alerts medical personnel to diseases before their intervention is required, as described by Feng *et al* [10]. AI solutions already assist healthcare professionals once athletes or patients are under their supervision, as mentioned by Fischer-Suárez *et al* [11]. The healthcare system generates high volumes of data that would go unused without the support of Data Science. Not only is AI used to develop innovative drug therapies and personalized medicine, but robots are also increasingly being used to support different fields (e.g., precision surgery, diagnostic precision through quantitative imaging, and personalization with intelligent image acquisition). The COVID-19 pandemic has increased the potential for sports safety, as described by Deshpande *et al* [12].

Sports safety [13] has become a central topic with the explosive growth of competitive sports. The use of distance sensors (such as medical radar [14]) and wearable sensors [15] (such as 3-axial accelerometers) in conjunction with new recovery or rehabilitation techniques has completely changed the type and style of training cycles, accelerating evolution, and modifying fatigue and recovery patterns. The rise of AI and quick and easy detection can help mitigate underdiagnoses. By combining injury-related day-to-day metadata with vital data, sports ecosystems and / or platforms can predict injury-related data and analysis and create personalized habit-related data analytics with player health data. Multilayered and multidisciplinary thesis experiments (see Table 1.1) were conducted to find and adopt emerging technologies with artificial intelligence to improve distant diagnostics and methods in sports performance and sports safety to prevent injuries or speed recovery periods. In addition, it applies technology-enabled pipelines, techniques,

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and models to provide collaborative, real-time, remote consultancies, and diagnosis in sports. The thesis also presents a conceptualization for managing a faster and safer future sports ecosystem, minimizing risk factors, controlling them, and emphasizing best practices. Parts of the thesis focus on highlighting COVID-19-related methods [16] to detect diseases or abnormalities of the voice, as identified by Deshpande *et al* [17]. In addition, I explored the application of ML and DL techniques in this context. Providing real-time injury predictions with data analysis reports is a practical and innovative tool for sports physicians to assess injury risks in a preventive way.

- *Justifications*: the techniques and methods used by the thesis can potentially revolutionize sports safety and performance. AI can utilize personalized data-driven real-time insights to prevent injuries, improve performance, and promote the general health and well-being of athletes. In addition, it can help prevent or predict sudden cardiac death (SCD), burnout [18], and neurodegenerative diseases [19], as described by Mahesh and Donati [20]. The thesis experiments highlight the most essential fields as well, like injury prevention, fatigue control [21], performance optimization [22], real-time monitoring and feedback, personalized recommendations, early detection of health issues, rehabilitation and recovery control, data-driven decision making, multilingual remote diagnosis, cost-effectiveness models with AI-supported remote diagnosis as identified by Yen *et al* [23],

- *Necessity*: adopting the thesis topics can profoundly affect society and individuals interested in sports safety and performance. These technologies can improve public health, democratize access to sports performance resources, promote informed decision making, drive economic growth, and increase education and awareness of the best sports safety [13] and health practices. The need factors are multilayered but are centered on improving public health, sports safety, improving the quality of life of athletes, promoting healthier lifestyles, generating economic benefits, enabling informed decision making for staff members /coaches /health professionals, increasing equity and accessibility in sports, and fostering education and awareness. These factors highlight the importance of these technologies for both society and individuals interested in sports safety and performance,

- *Future-tech insights and new research lines*: future-tech insights (e.g., biomechanics [24] and AI-driven movement analysis, AI-powered mental health and well-being diagnostics, genomics and personalized sports medicine, predictive analytics, telemedicine and remote coaching, AI-enhanced rehabilitation [22]) demonstrate the potential to drive innovation and open new research lines, ultimately transforming the landscape of sports safety, performance, and medicine, as identified by Gouttebarge *et al* [25],

- *Remote sensing*: continuous remote monitoring of vital signs using various sensors,

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along with specific questionnaires such as those for COVID-19 and Session Rating of Perceived Exertion (sRPE), is essential for early detection and prediction of factors that could impact the well-being or performance of athletes. This monitoring also provides information on the Acute Chronic Workload Ratio (ACWR) [26]. This technology will be crucial to sports safety, as it can quickly and accurately predict changes in health conditions, regeneration cycles, and various diseases using artificial intelligence. This will enable the creation of a secure sports environment experiencing a rapidly expanding pace. Non-contact remote sensing (such as medical radar sensors [27]) and the integration of wearable sensors with mobile technologies will generate a new field of remote monitoring and diagnosis [23] as their precision level becomes acceptable in the medical field [28]. I tested the correlations between acceleration and fatigue, (post) COVID-19 and fatigue, fatigue, and injuries, and COVID-19 and ACWR/sRPE because they could provide preventive pipelines and processes in the field of performance sports, as illustrated by Bowen *et al* [29].

The thesis highlights and creates synergies in research in advanced distant diagnostic techniques, artificial intelligence (AI), and sensors in the prediction of sports safety and health conditions and encompasses a variety of interdisciplinary fields and technological advancements. The identified key areas and their targeted activities include: (1) new models help understanding – through the sports safety and sport medicine digitalization – the next-generation development of remote diagnostics techniques [30] using multilingual collaborative tools and algorithms, which will be capable of accurately assessing athletes' health and performance; (2) study of condition, sRPE, METs, ACWR [26] supported with AI solutions, provides insights into injury prevention, performance optimization [22], and the development of appropriate training programs or in case of injured athletes, about the regeneration process; (3) the emergence of telemedicine and remote diagnostics technologies (such as medical radar sensors [15]) has enabled real-time monitoring and assessment of athletes' health conditions, regardless of their geographical location; (4) techniques for processing and filtering raw data from sensors (e.g, radar sensors [31], 3-axial accelerometers, IMUs [32, 33]), such as noise reduction and normalization, are essential for obtaining accurate and reliable information for further analysis; (5) the proliferation of large-scale data and data analytics in the field of sports enables us to discern patterns, trends, and connections that may be leveraged to enhance the well-being and performance of athletes [34]; and (6) the development of applied AI algorithms, including supervised, unsupervised, and RL models, has been pivotal in analyzing complex datasets and generating actionable insights for sports safety and performance to predict the fatigue and forecast and prevent the injuries.

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1.1 Overview

The integration of various disciplines has led to the development of sophisticated diagnostic tools, such as real-time lesion and tumor detection [28] after severe head injuries [35] and measurement of energy expenditure [19]. These tools are crucial for early detection and prevention strategies. The application of AI in predictive analytics, as seen in predictions of health conditions such as lesions and tumor detection and relative intensity of physical activity (RPAI) [36], demonstrates the ability of ML to predict threats to health and improve training programs. Research spans not only physical health, but also mental well-being, as evidenced by studies on mental health and neurodegenerative disorders (NDD) [19, 26] and burnout syndrome [18]. The multidisciplinary nature of this program also requires a focus on ethical and legal aspects, particularly in the use of AI and the handling of sensitive data, ensuring that the welfare of the athlete remains at the forefront. In conclusion, the multidisciplinary approach of the thesis has successfully bridged the gap between various academic disciplines (e.g., sport, health, psychology, IT) leading to innovative solutions in sports safety and prediction of health conditions.

The multidisciplinary nature of this thesis is academically enriching and practically vital. By bridging these diverse fields, the results of the thesis foster a holistic understanding of the athlete as a biological, psychological, and social entity operating within a complex and dynamic environment of global performance sports. The use of AI as a future-uniting technology approach in sports amplifies the potential of this article, enabling the integration and analysis of vast and varied datasets (per use case), leading to more accurate predictions and personalized interventions.

The thesis presents a quintessential model of multidisciplinary integration (focusing primarily on team, group habits, and psychology). This integrative and synergistic approach is novel and essential to address the complex and multifaceted challenges associated with predicting sports safety [37] and health. Given the extensive research already published on the results, the publications prove that the interdisciplinary approach has produced significant contributions in various domains. The research results demonstrate the successful integration of humanities, natural and applied sciences, and social sciences, each playing a critical role in advancing sports safety, disease prevention, and prediction of health conditions.

The thesis part in collaborative video diagnosis [33], [32], [28], text and sentiment analysis [18], as well as voice and sentiment analysis [38] exemplifies the integration of language processing with technical domains. The application of multilingual synthesized optical character recognition (OCR) [39] and advanced sentiment analysis techniques reflects the importance of linguistic diversity and the humanistic aspect of language in understanding the behavior and responses of athletes. These technologies, using natural language processing (NLP), improve the communication and interpretation of complex datasets, making them accessible and actionable across linguistic and cultural barriers.

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The thesis experiments with different types of sensors [36], [19], [40], [41], including medical radar sensors [27], accelerometers, inertial measurement units (IMUs [32, 33]), and the application of Doppler techniques [36], represent a significant advancement in monitoring, analyzing, and understanding the physical conditions of athletes in real time, remotely, and invisibly. The integration of AI-assisted fatigue and stamina control [41] and the development of AI-controlled training methods [22] and predictive sports strategies [16] indicate a deep understanding of physical sciences applied to sports [15].

Research on the efficacy of digital intervention through gamification [35, 42], the novel approach to activity-based lie detection [15], and the non-invasive exploration of mental health and NDD [26] highlight the influence of social sciences. Understanding athlete psychology and social behavior is critical to effectively implementing these technologies. The thesis study on burnout syndrome [18] and the impact of COVID-19 [16] on athletes [38] further underscores the importance of considering psychological and sociological aspects in sports health research.

1.1.1 Context

In the contemporary academic landscape, the field of this thesis represents a cutting-edge confluence of interdisciplinary research. The topic is multifaceted and includes various disciplines ranging from engineering and computer science to physiology, psychology, and beyond. The overarching objective of this field is to improve the safety of athletes and optimize health outcomes using sophisticated diagnostic tools and predictive models. This is achieved by taking advantage of advances in sensor (including medical radars and 3D accelerometeres, IMU sensors) technology, artificial intelligence (AI), and data analysis within the broader context of sports science. The continual evolution of this field reflects the ever-changing landscape of technology and the growing understanding of the complex interplay between physical, mental, and social factors in sports performance and health.

The core of this research domain lies in the application of next-generation advanced sensor technologies [43] and diagnostic tools. These include wearable devices equipped with accelerometers, medical radar sensors [31], and IMUs [32, 33], which collectively collect a large amount of data on the physical state of an athlete in real time [15]. The data captured by these devices, ranging from heart rate variability (HR) through pulse to movement patterns [44] connected to speed and acceleration, are intricate and require sophisticated analytical approaches to extract meaningful insights. The scope extends beyond technology and science, incorporating elements of psychology, sociology, and even linguistics. For example, analyzing sentiment and language provides insight into an athlete's mental state, contributing to a holistic understanding of their overall health. This integration underscores the importance of a multidisciplinary approach in addressing the multifaceted nature of sports safety and health. Ethical and legal considerations are paramount in any field that deals with sensitive personal data, mainly health-related in-

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formation. The responsible use of AI, the adherence to privacy laws, and the ethical implications of predictive diagnostics are critical components of this research domain. Ensuring that the welfare and consent of athletes are at the forefront is essential to develop and apply these advanced technologies. The field also recognizes the importance of global and cultural considerations in sports science. Athletes come from diverse cultural backgrounds, and diagnostic tools and predictive models must be adaptable to various cultural and linguistic contexts. This diversity requires a global perspective to ensure that the technologies and methodologies developed are universally applicable and sensitive to cultural nuances.

Distant diagnostics in health and sports

Nowadays, the importance of multilingual translation has increased exponentially due to the impact of the COVID-19 pandemic. Visual Object Detection (VOD) (moreover, Textual Object Detection), as a central topic of remote diagnosis and consultation based on video conferences, has intensified DX in the medical field [36]. The issue generates a new "real-time multilingual data processing" market to catalyze the elimination of existing communication barriers to multilingual video conferences. Adopting VOD in the healthcare domain will increase the efficacy of remote diagnosis processes, reducing the reaction time in remote consultations [36]. Furthermore, OCR is becoming more popular because it is considered a central pillar of many advanced technologies, particularly related to real-time object detection. The Textual and Visual Object Detection (TVOD) method analyzed popular algorithms and models in object detection (e.g., Fast R-CNN, Faster R-CNN, Region-Based Convolutional Neural Networks (CNNs), Region-Based Fully Convolutional Networks, as well as real-time object detectors such as YOLO, DETECTRON, and DETR) to synthesize the results and provide reliable outcomes for a new type of collaborative working model. The results of the thesis can be easily adapted to the field of sports safety using video conference tools or platforms [36].

1.1.2 Research motivation

Motivation is multifaceted and reflects scientific curiosity, technological advancement, and commitment to the welfare of the athlete. It is rooted in the desire to improve athlete safety, improve performance [22], leverage technological advancements, encourage interdisciplinary research, capitalize on economic opportunities, respond to global health trends and maintain ethical standards in sports. This convergence of factors makes it a highly relevant and rapidly evolving area of scientific inquiry and technological development. This field is driven by several key objectives and considerations:

(1) *Enhancing athlete safety and health of athletes*: at its core, this field is motivated [35] by the imperative to improve the safety and health of athletes. Sports, while beneficial for physical fitness and mental well-being, carry inherent risks of injury and

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health problems. Advanced diagnostic techniques and sensors provide a means of monitoring athletes' health indicators in real time; (2) *Optimizing stamina and performance*: beyond safety, there is significant interest in using these technologies to improve athletic performance [22]. Through data analysis on the physical state and performance of the athlete, coaches and trainers can customize training regimens to suit the specific requirements of each athlete. This approach improves performance while reducing the likelihood of excessive training and injury; (3) *Adoption of technological innovations*: rapid advancement of technology in areas such as AI, ML, sensor development, and data analytics is a strong motivator. The sports sector presents a unique and challenging application for these technologies, driving innovation and testing the limits of what is technologically feasible; (4) *Interdisciplinary research and collaboration*: this field stands at the intersection of various disciplines, from engineering and computer science to physiology and psychology. This interdisciplinary nature fosters collaboration and intellectual cross-pollination, making it an exciting and dynamic area for research and development; (5) *Understanding the economic potential*: the development of advanced diagnostics and sensor technologies has significant commercial potential. The sports industry, including professional sports teams, leagues, and individual athletes, represents a lucrative market for these innovations; (6) *Localization of global health trends and public interest*: there is a growing public interest in health and fitness, accompanied by a surge in participation in both amateur and professional sports. This trend increases the demand for technologies to help monitor and prevent sports injuries, aligning with larger public health goals. (7) *Understanding the ethical and legal considerations of applied AI*: the ethical imperative to protect athletes from harm and the legal implications of sports-related injuries drive innovation in this field. Ensuring that athletes are not exposed to unnecessary risks and that their health and well-being are prioritized is a crucial motivator for stakeholders in sports science.

1.1.3 Significance

The multidisciplinary approach not only fosters innovation by combining diverse expertise (navigating the ethical, legal, and societal dimensions inherent in modern sports science and technology), but also ensures that technological advancements are ethically sound, culturally sensitive, economically viable and beneficial for both individual athletes and the broader community. This comprehensive approach is crucial to address the complex challenges in sports safety and health, which ultimately lead to safer sporting environments and better care for athletes. The significance of the thesis lies in its comprehensive approach to addressing the complex challenges of sports safety, taking into consideration the performance optimizations of individual athletes or groups/teams, offering a holistic and thorough understanding of athlete health (by identifying risks and possible upcoming anomalies or disease) and performance indexes. This field is at the intersection of various academic disciplines, including engineering, computer science, medicine, physiology,

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psychology, and data science, each of which uniquely contributes to improving athlete health and performance. This approach is paramount in addressing the various aspects of sports safety and health, from physical injuries to psychological well-being and individual athlete care, to the broad implications for public health.

1.1.4 Ethics

The multidisciplinary thesis exemplifies a well-structured and ethically robust research approach characterized by a solid adherence to scientific rigor, participant rights, and ethical standards. The following synthesis highlights key considerations and their implementation in the thesis.

1. *Validity of the research*: each research experiment of the thesis – connected to the objectives - was conducted to answer a particular RQ, and the conclusions match these requirements. This approach not only strengthens the reliability of the research outcomes but also ensures that the research contributes meaningfully to the field of study;

2. *Research method*: the research methods selected completely fit the research, with all the relevant risks investigated and declared before adopting the specific methods. Before their implementation, a comprehensive risk assessment was performed to ensure that all potential risks were identified and mitigated. This thoroughness in method selection and risk assessment not only enhances the credibility of the research findings but also reflects a commitment to ethical research practices;

3. *Consent of participants*: when human participants were included in the research, such as measuring the MET in humans, they were provided with detailed information about all the activities involved in the studies. Before beginning the research activity, they were required to give their informed consent in accordance with the seventh version of the Declaration of Helsinki (2013);

4. *Confidentiality*: participants' identifying information was guaranteed to be excluded from the research reports and any other published documents. The participants were always identified as anonymous in the research papers connected to thesis;

5. *Risks*: the participants were provided with information regarding the nature of the studies and the related risks. They were given the option to withdraw from the studies or research at any time;

6. *Anonymity and data privacy*: the preservation of participants' anonymity was a crucial element in the study procedures, and I took into account the worldwide regulations on data privacy, such as the General Data Protection Regulation (GDPR)

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and the California Consumer Privacy Act (CCPA). This attention to legal and ethical standards in data privacy further underscores the commitment to protecting participant rights and personal data;

7. *Sampling*: the sampling of the participants was discussed with directors and tutors, ensuring that the sampling strategy was appropriate for the research objectives and methodologies;

8. *Accessibility*: only relevant information was collected, demonstrating a controlled method on data collection procedures. This practice not only streamlines the research process but also aligns with ethical considerations regarding the collection and use of data;

9. *Integrity and transparency*: all potential conflicts of interest that could affect the research activities were revealed.

The meticulous evaluation of the validity of the thesis, the suitability of the methodology, the consent of the participants, confidentiality, risk management, data privacy, sampling tactics, the usefulness of the information and the integrity and transparency establish a rigorous benchmark for future postdoctoral research efforts on the subject.

1.1.5 Limitations

Although the approach offers considerable advantages, it is not without limitations. Acknowledging these limitations is crucial for a balanced understanding and further advance in this field. These constraints are inherent in the complexity and scope of integrating multiple disciplines, each with its methodologies, theories, and paradigms. These include integration complexity, data management issues, ethical and privacy concerns, economic disparities, cultural acceptance, generalizability issues, educational gaps, and regulatory challenges. Addressing these limitations requires concerted efforts from researchers, practitioners, policymakers, and educators alike. Specific limitations are highlighted in Section 5.

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1.2 Research questions

The central research questions (RQs) revolve around effective leveraging emerging technologies and AI to improve athlete safety, optimize performance, and prevent injuries by predicting anomalies and / or diseases related to performance sports and sports safety. Addressing these questions requires an integrated approach that incorporates the expertise of various disciplines to create innovative, ethical, and practical solutions in sports science.

- **RQ1**: How can cross-disciplinary collaboration be enhanced to foster innovation and comprehensive understanding in sports diagnostics and prediction?
- **RQ2**: How can advanced diagnostic techniques and sensor technologies be effectively integrated into sports practice to enhance real-time monitoring and prediction of athletes' health and performance?
- **RQ3**: How can these advanced diagnostics and sensor technologies be integrated into existing sports training and healthcare infrastructures?
- **RQ4**: How can advanced sensor technologies be optimized for real-time monitoring of athletes' physiological and biomechanical data?
- **RQ5**: What are the optimal algorithms and AI models to interpret data from sports-related sensors to predict health risks and performance outcomes?
- **RQ6**: How can these technologies be tailored to accommodate the various physiological, psychological, and biomechanical profiles of individual athletes?
- **RQ7**: What are the ethical implications and privacy considerations in using advanced diagnostic technologies (sensors, radars) and artificial intelligence in sports, particularly with respect to data privacy and athlete consent?
- **RQ8**: How can these diagnostic techniques be used to develop injury prevention strategies and improve overall athlete well-being?
- **RQ9**: What are the most effective AI and ML algorithms to predict injuries and health conditions in athletes?
- **RQ10**: How can these technologies be tailored to individual athletes, considering their unique physiological and psychological profiles?
- **RQ11**: What are the long term effects of using these technologies on the physical and mental health of athletes?

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These RQs collectively define, in general, the problems of the experiments behind the thesis to harness technological advances to improve the health, safety, and performance of athletes while considering factors of individual, economic, and ethical variability. They address technological development, data analysis, personalized medicine, ethical considerations, practical implementation, long-term impacts, and cultural and economic influences. Answering these questions requires a multidisciplinary approach that integrates insights from engineering, computer science, sports medicine, ethics, psychology, and sociology.

1.3 Research objectives

To address the various interdisciplinary focal points, three main pillars were established for the thesis.

1. **Thesis Group I (S1)**: Advanced Distance Diagnostics Techniques and Sensors;
2. **Thesis Group II (S2)**: Sports safety and injury prevention;
3. **Thesis Group III (S3)**: Prediction of health conditions.

Based on the research questions defined in Chapter 1.2 and the thesis pillars, specific research objectives (RO) have been established to address these pillars, which are the research directions. These research objectives aim to harness the power of AI, machine learning (ML) and advanced data analytics to improve diagnostics, training, rehabilitation, and mental health support for athletes, ultimately enhancing performance, safety, and well-being in sports.

- **RO1** - *Enhancement of real-time diagnostics and monitoring*: develop and refine near real-time diagnostic and monitoring systems using advanced AI models and sensor-based pipelines to support athletes' health, performance, and safety across various sports disciplines,
- **RO2** - *AI-based health and performance prediction*: investigate and create AI-driven prediction models for assessing and enhancing athletes' health conditions, stamina, and performance, incorporating comprehensive data sources such as physiological markers or psychological factors,
- **RO3** - *Development of multilingual and multimodal collaboration tools*: investigate the AI-assisted tools (realtime OCR solutions) for visual and textual data recognition and translation in multilingual, multiuser collaborative environments, thereby boosting the efficacy of distance diagnosis and communication in sports and other fields,

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- **RO4** - *Optimization of training and rehabilitation processes*: formulate and implement AI-controlled technological pipelines, frameworks and methodologies for optimizing training regimens, rehabilitation processes, and performance hardening, ensuring personalized, adaptive, and effective approaches to athlete development and recovery,

- **RO5** - *Integration of AI in strategic sports analysis*: develop method using AI technologies such as YOLO and YOLO-NAS, or openCV for real-time player and object tracking, strategy extraction, and performance analysis, facilitating data-driven decision-making and strategic development in sports,

- **RO6** - *Innovative approaches to disease detection and prevention*: investigate and develop non-invasive, AI-supported pipelines for early detection and monitoring of diseases and health anomalies using advanced feature extraction methods, with an emphasis on voice-based detection and prevention of cross-contamination in sports events,

- **RO7** - *Psychological and mental health monitoring*: formulate and develop AI and NLP techniques for early identification and intervention of psychological and mental health disorders, including burnout and neurogenerative disorders, ensuring comprehensive support for athletes' mental well-being,

- **RO8** - *Gamification and adaptive training enhancements*: investigate and formulate method combining gamification, generative AI, and reinforcement learning to create engaging and adaptive training environments, enhancing athlete motivation, performance, and psychological involvement,

- **RO9** - *Comprehensive data analysis for performance improvement*: develop AI-supported retrospective learning methods with historical data analysis to identify performance trends, evaluate strategies, and set realistic goals, thus enhancing the effectiveness of training programs and overall development of the athlete.

1.4 Research methodology

Taking into account the multidisciplinary type of the thesis, Mixed Method Research (MMR), integrating both qualitative and quantitative techniques with the help of the universities involved (UMA[1], UMFST[2], SAPIENTIA[3], OBUDA[4]) and performance sports professionals (e.g., coaches, trainers, physiotherapists) from Hungary and Japan (Toyo University), was used with sports strategy developers as follows:

[1]UMA - University of Malaga
[2]UMFST - G.E. Palade University of Medicine, Pharmacy, Science, and Technology of Targu Mures
[3]SAPIENTIA - Sapientia Hungarian University of Transylvania, Targu Mures
[4]OBUDA - Physiological Controls Research Center, Óbuda University, Budapest

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1.4.1 Qualitative techniques

- *Focus groups* - involved the Ice Hockey team of Toyo University from Tokyo in further research connected to RPE/sRPE, ACWR, FATIGUE, BURNOUT, DISEASE (focusing on the neurodegenerative ones), LESION DETECTION, VOICE, and VIDEO analysis developments. The composition of the focus group and the age range remained similar. However, it was expanded to include university teams (and sports) to provide a more comprehensive coverage of results related to predictive health conditions, regeneration cycle forecasting, and alerting algorithms. For the validation of the algorithms, I used freely available validated datasets,

- *Observations* - a qualitative approach was used for both on-site and in-concept options, bringing the whole ecosystem to the sports safety field to analyze the proposed architectures, algorithms, ML models, and remote sensing solutions combined with other system elements. Based on the initial research, the software solution implemented in the Cloud Campus (SBCC) Ecosystem was expanded with new elements involving on-field specialists like coaches, strength and condition trainers, mental coaches, and strategy coaches,

- *Document analysis* - this technique included interrogating (sports activity, health activity, sRPE/ACWR, burnout, mood, and COVID-19 data) reports as an input source for future Systematic Reviews with/and/or Meta-Analysis. This was done with the help of a Progressive WebApp (PWA) connected to the Cloud Campus Ecosystem. The results of the analysis were published as articles or conferences.

1.4.2 Quantitative techniques

- *Surveys and questionnaires* - the current solution designs' future use of remote sensors (wearable and protector-based) because the attached ones are inconvenient for most sports. Currently, sRPE/ACWR is calculated using dedicated questionnaires that use ice hockey players as field participants. The survey results will transform Likert scales into accurate numerical data, which will potentially help sensor manufacturers enforce their research and build more reliable sensor solutions. Experiments were conducted in connection with 3-axial accelerometers, inertial measurements units (IMUs [32, 33]) and disseminated the novel approaches and results,

- *Observations* - were applied during different phases of investigations. I continuously improved the diagnostic algorithms and used methods based on specific use cases and focus group-based observations. This resulted in being able to transcode the sport-field observational data into numbers and specific phenomenon occurrences, improving the assisted learning algorithms,

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- *Thesis experiments* - During the research activites in connection with the thesis, Proof-of-Technologies (PoT), ML Proofs-of-Concept (PoCs), and Minimum Viable Products (MVPs) were built to test the hypotheses not only in laboratory conditions and with generated data (see the released publications) but also on-site, in natural conditions, testing cause and effect relationships, through on-field experiments, or via quasi- or real-life experiments with fast sports like (ice hockey, running, futsal, soccer). The results will be adopted as the next steps for other sports such as basketball, rugby, and American football.

1.5 Structure of the thesis

1.5.1 Disclaimer

This thesis is a compilation of previously published papers, each serving as a chapter element. The material was also standardized to provide consistency in writing style throughout the thesis.

1.5.2 Contributions summary

This chapter presents (see Tables 1.1, 1.2, 1.3) a structured and quantified summary of published scholarly contributions, offering transparency and insight into the distribution of my work and the impact of each article on the scientific community. The "stages" section indicates the phases of the investigation, providing a snapshot of the research progress and methodology. "Methods" section specifies the approach taken in each study, including requirement analysis, experiments, and use case studies. "Type" section delineates the distinctions between conceptual and empirical research. Impact factors (IF) and the h-index – related to journals – provide a metric of the influence of the research and the overall impact of the citation of the author in the scientific community. The journals in which the research has been published are listed, suggesting acceptance of the research within the academic community and contributing to the academic discourse. The Contribution section breaks down the percentage contributions of the listed author, in some cases detailing their participation in concept development, methodology, writing, visualization, and supervision. Each chapter concludes with a section-level summary (see Sections 2.6, 3.6, 4.2, 5.6, 6.6, 7.5, 8.6 and 9.6) of notable scientific contributions.

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Table 1.1: Scientific contribution 1/4.

Category	Article 1 [P1]	Article 2 [P2]	Article 3 [P3]	Article 4 [P4]	Article 5 [P5]
Title	Visual Object Detection with DETR to Support Video-Diagnosis Using Conference Tools	Synthetized Multilanguage OCR Using CRNN and SVTR Models for Realtime Collaborative Tools	Optimal Training Dataset Preparation for AI-Supported Multilanguage Real-Time OCRs Using Visual Methods	Machine Learning on Prediction of Relative Physical Activity Intensity Using Medical Radar Sensor and 3D Accelerometer	AI-Assisted Fatigue and Stamina Control for Performance Sports on IMU-generated Multivariate Times Series Datasets
Authors	**A. Biró**, K.T. Jánosi-Rancz, L. Szilágyi, A.I. Cuesta-Vargas, J. Martin-Martin, S.M. Szilágyi	**A. Biró**, A.I. Cuesta-Vargas, J. Martin-Martin, L. Szilágyi, S.M. Szilágyi	**A. Biró**, S.M. Szilágyi, L. Szilágyi	**A. Biró**, S.M. Szilágyi, L. Szilágyi, J. Martin-Martin, A.I. Cuesta-Vargas	**A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi
Stages	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation
Methods	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies
Future line	–	–	Highlighted	–	Highlighted
Type	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Applied research**: -Prototype development; -Methods definition **Empirical research:** -Prototype development; -Methods definitions; -Empirical findings Methods	**Analytical research**: -Methods definition **Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Analytical research**: -Methods definition **Empirical research:** -Prototype development; -Methods definitions; -Empirical findings
Impact	**IF[4]: 2.7** h-Index: 75	**IF[4]: 2.7** h-Index: 75	**IF[4]: 2.7** h-Index: 75	**IF[4]: 3.9** h-Index: 196	**IF[4]: 3.9** h-Index: 196
Publication	*Journal* Applied Sciences, MDPI, **2022**	*Journal* Applied Sciences, MDPI, **2023**	*Journal* Applied Sciences, MDPI, **2023**	*Journal* Sensors, MDPI, **2023**	*Journal* Sensors, MDPI, **2024**
Status	*Published*	*Published*	*Published*	*Published*	*Published*
Contributions	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%

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Table 1.2: Scientific contribution 2/4.

Category	Article 6 [P6]	Article 7 [P7]	Article 8 [P8]	Article 9 [P9]	Article 10 [P10]
Title	AI-controlled training method for performance hardening or injury recovery in sports	Applied AI for Real-Time Detection of Lesions and Tumors Following Severe Head Injuries	Predictive Sports Strategy Approach Using YOLO and YOLO-NAS in Performance Sports	Effectiveness of a gamified digital intervention based on lifestyle modification (igame) in secondary prevention: a protocol for a randomised controlled trial	sRPE and ACWR to Control Fatigue Levels and Minimize Injuries in Performance Sports
Authors	**A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi	**A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi	**A. Biró**, A.I. Cuesta-Vargas, S.M. Szilágyi	A.I. Cuesta-Vargas, **A. Biró**, A. Escriche-Escuder, and et al.	**A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi
Stages	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation
Methods	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Trials; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies
Future line	Highlighted	–	Highlighted	Highlighted	Highlighted
Type	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings Methods	**Applied research**: -Prototype development; -Methods definition **Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings
Impact	**RANK National**[1] **(D)**	**RANK National**[1] **(D)**	**RANK National**[1] **(D)**	**IF**[4]**: 3.007** h-Index: 121	**RANK**[1] **B**
Publication	*Conference Proceedings* IEEE Xplore, IEEE, **2024**	*Conference Proceedings* IEEE Xplore, IEEE, **2023**	*Conference Proceedings* IEEE Xplore, IEEE, **2023**	*Journal* BMJ Open, BMJ Journals, **2023**	*Conference Proceedings* IEEE Xplore, IEEE, **2023**
Status	*Published*	*Published*	*Published*	*Published*	*Published*
Contributions	Own contribution: 98% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 95%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualisation: 95% Supervision: 90%	Own contribution: 21% Concept: 20% Methodology: 20% Writing: 5% Visualization: 30% Supervision: 30%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualization: 95% Supervision: 90%

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Table 1.3: Scientific contribution 3/4.

Category	Article 11 [P11]	Article 12 [P12]	Article 13 [P13]	Article 14 [P14]
Title	Real-time Artificial Intelligence Text Analysis for Identifying Burnout Syndromes in High-Performance Athletes	Precognition of mental health and neurogenerative disorders using AI-parsed text and sentiment analysis	Real-Time Disease and COVID-19 Detection Pipeline from Voice for Performance Sports	Gamification, GenAI and Reinforcement Learning as Motivational AI-Assets in Performance Sports
Authors	**A. Biró**, K. T. Jánosi-Rancz, L. Szilágyi	**A. Biró**, A.I. Cuesta-Vargas, L. Szilágyi	**A. Biró**, A.I. Cuesta-Vargas, S.M. Szilágyi	**A. Biró**
Stages	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Precognition of mental health and neurogenerative disorders using AI-parsed text and sentiment analysis	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation	Problem Identification; Theoretical Model; Artefact Implementation; Result Validation
Methods	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies	Requirements Analysis; Experiments; Use Case Studies
Future line	Highlighted	Highlighted	Highlighted	Highlighted
Type	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings Methods	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings	**Empirical research:** -Prototype development; -Methods definitions; -Empirical findings
Impact	**RANK National[1] (D)**	**IF[4]: 0.3**	**RANK[1] B**	**RANK National[1] (D)**
Publication	*Conference Proceedings* IEEE Xplore, IEEE, **2024**	*Journal* Informatica, Acta Universitatis Sapientiae, **2023**	*Conference Proceedings* IEEE Xplore, IEEE, **2024**	*Conference Proceedings* IEEE Xplore, IEEE, **2024**
Status	*Published*	*Published*	*Published*	*Published*
Contributions	Own contribution: 98% Concept: 100% Methodology: 100% Writing: 100% Visualization: 95% Supervision: 95%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualization: 95% Supervision: 90%	Own contribution: 97% Concept: 100% Methodology: 100% Writing: 100% Visualization: 95% Supervision: 90%	Own contribution: 100% Concept: 100% Methodology: 100% Writing: 100% Visualization: 100% Supervision: 100%

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2 Related work

This chapter provides a comprehensive overview of existing solutions, methods, and models at various levels, focusing on remote diagnostic instruments and sensors that improve sports safety and predict health anomalies. It thoroughly reviews the critical findings related to a spectrum of technologies associated with several key areas: remote consultation, radar and sensor technology [27, 31], health monitoring, disease identification and injury prevention, and forecasting and gamification of sports strategies. This analysis aims to synthesize the disparate viewpoints and integrate them into a coherent understanding of the current state of the art in these fields.

2.1 Related work in Remote consultancy and diagnosis services

2.1.1 Multilingual remote consultancy

Real-time multilingual phrase detection is necessary for fast remote diagnostics during online video presentations. This involves the ability to recognize and preprocess visual objects (textual) in near-real time so that they may be further analyzed. The most efficient way to connect remote professionals and exchange specialized ideas is using their native language. The difficulty of this subject is related to the multitude of languages and dialects spoken by the specialists involved, which often requires the use of human translators [45]. However, these intermediaries can potentially be replaced by AI-enabled technical pipelines. The precision in identifying visual textual elements is directly correlated with the complexity, excellence, and diversity of the training datasets gathered [36]. VOD as a topic of remote diagnosis and consulting based on central video conferences has intensified DX in the medical field [36]. The multilingual collaborative real-time conversation translation issue generates a new "real-time multilingual data processing market" to catalyze the elimination of existing communication barriers for multilingual video conferences. Adopting VOD in the healthcare domain will increase the effectiveness of remote diagnosis processes, reducing reaction time in remote consultations. Further-

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more, OCR [39] is becoming more popular, as it is considered a central pillar of many advanced technologies, particularly related to the detection of objects in real time [36]. The TVOD method analyzed popular algorithms and models in object detection (e.g., Fast R-CNN [46], Faster R-CNN, Region-based CNNs, Region-based Fully Convolutional Networks, as well as real-time object detectors such as YOLO [47], DETECTRON [48] and DETR [1]) to synthesize the results and provide reliable results for a new type of collaborative working model. [36]. Unlike traditional computer vision techniques, DETR approaches object detection as a direct set prediction problem. It relies on a set-based global loss, which forces unique predictions through bipartite matching, and a "Transformer Encoder-Decoder" architecture [49].

2.1.2 Real-time synthesized and multilanguage OCR

Remote diagnosis using collaborative tools has led to multilingual joint working sessions in various domains, including comprehensive health care, resulting in more inclusive health care services [38]. One of the main challenges is providing a real-time solution for shared documents and presentations on display to improve the efficacy of non-invasive, safe, and far-reaching collaborative models. Classic OCR solutions fail when there is a mixture of languages or dialects or when there is participation of different technical levels and skills. Due to the risk of miscommunications caused by mistranslations or lack of domain knowledge of the interpreters involved, the technological pipeline also needs AI-supported improvements on the OCR side [38]. In recent years, due to remote diagnosis using collaborative tools [50], multilingual joint working sessions have begun to take place in several domains, including health care. One of the challenges in establishing non-invasive, safe, and distant cooperation models is to provide a solution that allows the sharing of documents and presentations on the screen in real time to increase the effectiveness of these non-invasive, safe, and distant cooperation models. Traditionally, OCR solutions [51, 52] have not been successful when a combination of languages, dialects, technical linguistic layers, or different levels or skills of technicians are involved in the process [38]. There are also risks of misinterpretations caused by incorrect translations or the interpreters' lack of domain knowledge. Therefore, AI must also improve [53] the OCR part of this technological pipeline to avoid misunderstandings [54]. Real-time translation pipelines now include OCR [55, 56] as one of their central pillars, helping to solve all translation and interpretation problems [38].

2.1.3 Flexible dataset preparation in visual object detection

The area of remote diagnosis has undergone a transformational change due to the power of cutting-edge collaboration tools, ushered in a new era of cooperative multilingual working sessions that span many sectors, most especially healthcare. The quest to establish remote, secure, and non-invasive cooperation models is gaining momentum, the apex of

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which is to find a solution that facilitates the real-time sharing of documents and presentations, thus amplifying the efficacy of these cooperative models [8]. Previously, the application of OCR solutions posed a substantial challenge when mixed code, multiple languages, or synthesized languages (a mixture of context-sensitive languages combined with Anglo-Saxon and Latin language families), dialects, or varying degrees of technical linguistic proficiency were involved. Furthermore, the risks associated with misinterpretations induced by incorrect translations and deficiencies in the domain knowledge of interpreters cannot be underestimated. PaddleOCR [40,57] provides promising results for languages in the Far East (such as Japanese and Chinese) and handles the multilingual approach with flexible and adaptable AI models [40, 51].

2.2 Related work in radars and 3D accelerometers in sports

2.2.1 RPA intensity with radars and 3D accelerometers

Borg implemented a scale called the RPE scale to measure the intensity of physical activity. Perceived exertion is a concept that describes how much effort a person believes their body is exerting on their behalf. It is based on physiological sensations (e.g., increased HR, respiration, breathing rate, perspiration, and muscle tension) that an individual experiences while exercising. These sensations are felt during physical activity.

Despite these limitations, HR and RPE are legitimate and reliable markers of exercise intensity [58] and are often used to prescribe and evaluate exercise. HR can be used as an objective indicator of activity intensity. In contrast, RPE is a subjective indicator of how difficult an individual thinks the activity is. RPE is also associated with various physiological markers such as blood lactate, ventilatory threshold, and blood pressure, among others, and could be a valuable tool to match the intensity of exercise with the correct intensity zone, which can optimize training and prevent overreaching or overtraining.

There is a strong correlation between the RPE [59] multiplied by ten and the actual HR of a person during physical activity; therefore, a person's effort rating may provide a reasonable estimate of their actual HR when participating in physical activity. In other words, if an individual has a perceived effort of 12, then 10 times 12 equals 120 beats per minute. If the HR is at its maximum; there should be around 120 beats per minute, as the HR should be as high as possible [59].

One of the most critical topics in sports safety today is reducing injury risks through controlled fatigue [21] using non-invasive athlete monitoring [15]. Due to the risk of injury, the use of accelerometer-based smart trackers, activity measurement bracelets, and smartwatches to record health parameters during performance sports activities is prohibited. The use of body sensors in sports (such as wearable body sensors, head impact sensors, mouth guards, heart rate (HR), and motion sensors) to measure human performance and

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behavior in activity and eHealth / mHealth applications became not a future plan, but reality [60,61]. Furthermore, several novel sensing approaches, such as textile-based wearable sensors, microneedles, microfluidic sensor platforms, and flexible sensor form factors, have recently been introduced to accurately measure human performance in sports (and other contexts) [43]. These technologies can adequately monitor and measure the physical performance of an athlete. Consequently, they can be used to continuously collect biomechanical and physiological performance data to prevent significant adverse effects (sometimes even death) and increase the team's efficiency by maintaining the players in a virtually optimal physical condition. In indoor sports [62] games such as ice hockey, handball, and basketball, the players may be more or less tired, exhausted, losing water (causing dehydration [63, 64], which is also a cause of hypernatremia) depending on the game velocity and intensity level, as well as the surrounding ecosystem, including humidity/temperature conditions. Furthermore, the performance of players fluctuates from game to game based on time, location, and field position.

2.2.2 Fatigue and stamina control on multivariate time series datasets

Optimal sports performance requires a balance between hard training and rest. IMUs [32, 33] provide objective quantifiable data to analyze performance dynamics [22] despite the difficulties in quantifying training loads for athletes. AI's ability to analyze complicated datasets brings innovation to athlete training cycle monitoring and optimization. Traditional techniques use subjective evaluations to prevent overtraining, which can cause injury and underperformance. IMUs provide objective, quantitative data on the physical status of athletes during action. AI and ML can turn these data into useful insights that enable data-driven athlete performance management.

The interdependencies between various physiological and biomechanical factors [24] are central to sports science [65]. For example, an athlete's performance depends not solely on individual metrics like HR or speed, but also on how these metrics interact. Multivariate time series analysis [66] allows sports scientists to simultaneously assess factors such as muscle fatigue, hydration levels, and biomechanical efficiency [67]. For example, simultaneously analyzing joint stress, muscle activation, and impact forces can help identify patterns that precede common injuries. By understanding how these factors merge over time, interventions can be designed to reinforce the safety of the athlete. The complexity of an athlete's adaptation to training on various time scales [68] also requires multivariate analysis [69,70]. Univariate time series may overlook patterns of overtraining or subtle signs of imminent injury that only become evident when multiple variables are considered together. In sports medicine, the monitoring of a variety of health indicators can provide a holistic view of the recovery progress of an athlete or the readiness to compete, thus facilitating personalized healthcare interventions [71]. In high-performance

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sports, the ability to detect and respond quickly to such anomalies can be the difference between winning and sustaining an injury.

2.2.3 Microsleep analysis for fatigue control

Identification of microsleep episodes has become a focal point in sleep research, particularly given its implications for safety-critical applications and fatigues control (in case of performance sports). State-of-the-art models for detecting microsleep primarily leverage ML techniques, incorporating a wide array of physiological signals, notably electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) data. Deep learning architectures, such as convolutional neural networks (CNN) and recurrent neural networks (RNNs), have shown promising results in capturing the complex temporal patterns associated with microsleep episodes. Hybrid approaches that combine traditional signal processing techniques with ML have also been explored, with the aim of enhancing detection accuracy by preprocessing the input signals to extract meaningful features. The Voronoi tessellation [72] and coverage control algorithms [73] have been widely used in various applications, ranging from mobile sensor networks to robotics for efficient area coverage and spatial partitioning. The Kalman filter [74] is an effective technique for determining the state of a linear dynamical system based on a sequence of noisy data. When evaluating the use of these algorithms in the staging of microsleep and real-time sleep, it is crucial to understand their potential contributions to this field.

2.3 Related work in health condition control in sports

2.3.1 Injury prevention with fatigue control

sRPE and ACWR are effective sport-health-related techniques to manage fatigue levels [21] and reduce the risk of injury in high-performance sports [26]. Their ability to offer personalized evaluation, incorporate subjective and objective metrics, and facilitate data-based decision making makes them indispensable elements of a comprehensive sports safety and performance monitoring system. Today, the hot topics in performance sports are related to sports safety through fatigue control [75], as well as injury prevention training and recovery models. Both sRPE [76], [77], and ACWR [29, 78] offer individualized training load metrics, allowing coaches and sports health specialists to monitor and adjust training programs [79, 80] according to each athlete's unique response to exercise. sRPE considers the athlete's RPE, which can provide valuable information beyond objective measures such as HR and power output. Research has shown that higher ACWR values (typically greater than 1.5) are associated with an increased risk of injury. Monitoring ACWR (with injury risk assessment) can help coaches and sports health specialists identify periods of increased injury risk, allowing them to make informed decisions about the adjustment of training loads [81].

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2.3.2 Personalized recovery

In contemporary sports science, artificial intelligence has emerged as a key tool, driving breakthroughs in training and rehabilitation of athletes [22]. In the realm of sports training, artificial intelligence is a pioneering innovation that is transforming athletic management and performance optimization [82].

2.4 Related work in disease detection and injury prevention in sports

2.4.1 Disease detection from voice

Early detection of health problems in sports can prevent injuries, maintain peak performance, and prolong the career of an athlete. Voice-based AI can potentially identify subtle changes in speech patterns and acoustic characteristics that may indicate the onset of health problems or fatigue, allowing for early intervention. Voice-based AI [83] offers a non-invasive, convenient, and time-efficient alternative that can be easily integrated into an athlete's routine. Furthermore, AI-driven voice analysis [84] can help develop personalized training and recovery programs for athletes considering their unique physiological and psychological needs, which ultimately leads to better performance and reduced risk of injury [22]. The most critical acoustic and prosodic features extracted from speech signals that can play a significant role in differentiating between healthy and affected individuals are the following: (1) *Harmony-to-noise ratio (HNR)* [85]: HNR is the ratio between the harmonic (periodic) components and the noise (aperiodic) elements of a speech signal. A decrease in HNR may indicate a deterioration in voice quality due to various health issues; (2) *Mel-frequency cepstral coefficients (MFCCs)*: MFCCs represent the short-term power spectrum of a speech signal and are widely used in speech processing to capture spectral characteristics, which can be indicative of different diseases; (3) *pitch (Fundamental Frequency, F0)* [86]: The pitch of a voice is related to the vibration of the vocal cords and can be affected by various diseases. Changes in pitch can help identify certain voice disorders or even neurological conditions; (3) *Jitter and Shimmer* [87]: The jitter is the variability in the pitch period and is used to measure the instability of the voice. An increase in jitter can be indicative of voice disorders or neurological diseases. Shimmer is the variability in amplitude and is another measure of voice instability. Similarly to jitter, shimmer can help identify voice disorders or other health problems that affect vocal production.

Other well-known feature extraction methods include (a) formants, which are the resonant frequencies of the vocal tract during speech production. Changes in formant frequencies can be related to anatomical or physiological changes in the vocal tract, which can indicate diseases; (b) Voice onset time (VOT) is the time difference between the

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release of a stop consonant and the onset of voicing. Changes in VOT can indicate speech disorders or neurological conditions; (c) the spoken rate is the number of syllables or words spoken per unit of time. Fig. 2.1 shows the segmentation most commonly applied to voice samples.

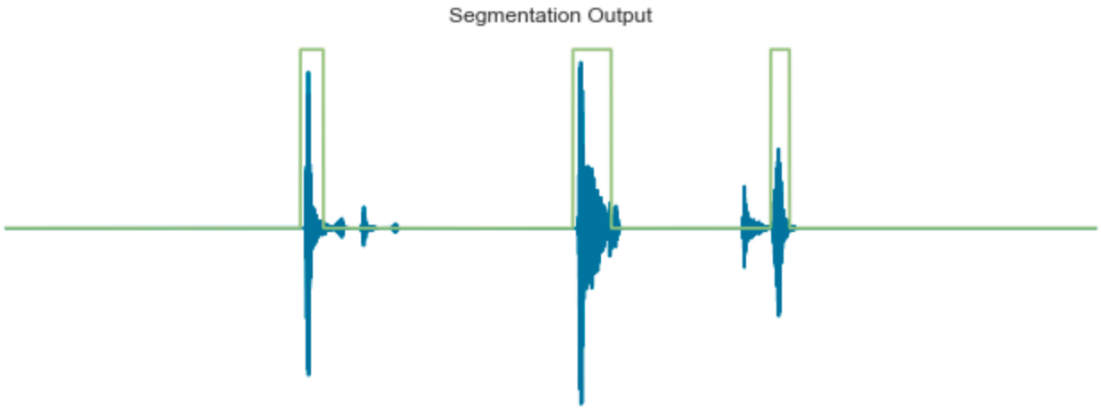


Figure 2.1: Segmentation on voice sample

Alterations in speaking rate can be a sign of speech disorders, cognitive decline, or other neurological issues; (d) the duration and frequency of speech pauses can provide information on cognitive processing, fluency, and speech motor control. Changes in pause patterns can indicate mental or neurological disorders, and (e) intonation and stress patterns can reveal information about emotional state, cognitive function, and neurological health. A combination of these features is usually used to build robust and accurate models for voice-based disease detection in disease or anomaly detection. The relevant research experiments connected to the thesis examined these combinations to provide a feasible model that can be applied to sports to support field specialists.

2.4.2 Pneumonia diagnosis using AI

Diagnostic imaging, particularly the convergence of artificial intelligence (AI) and health care, has recently advanced [88]. In sports medicine, AI can quickly identify conditions such as pneumonia [89], improving the care and performance of athletes. Athletes who suffer from pneumonia must be diagnosed quickly to avoid complications and speedy recovery. Traditional diagnostic methods are useful, but they often do not meet the needs of sports that require rapid decision making. The thesis study uses a novel approach to fill this gap. This study examines chest radiographs in real time using YOLOv9 [90], a sophisticated object identification technology, to allow rapid treatment. This introduction sets the stage for AI research in sports medicine. It highlights how this technology can improve athlete management by improving diagnostic accuracy and operational efficiency. To improve deep neural networks (NNs), YOLOv9 provides technical innovations [7,90,91] to solve information bottlenecks and network processing inefficiencies. PGI dynamically

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adjusts the gradient flow throughout the layers of the neural network – it preserves and enhances object identification characteristics during training, hence enhancing model acquisition. GELAN minimizes layer interactions and aggregation to optimize latency and enhance performance. This results in faster and more accurate object detection while minimizing information loss.

Comparison of the YOLO models

Table 2.1 shows the major differences between the YOLO models, where "*PARAMS*" represents the number of parameters in millions, "*FLOPS*" the number of floating-point operations in gigaflops, and "*AP*" the average precision across IOU thresholds from 0.5 to 0.95.

Table 2.1: YOLO v7/v8/v9 models comparison [7]

Model	PARAMS (M)	FLOPS (G)	AP[50:95]%
YOLOv7-X	71.3	189.9	52.9
YOLOv8-X	68.2 (↓4.3%)	257.8 (↑36%)	53.9 (↑1.0%)
YOLOv9-E	58.1 (↓19%)	192.5 (↓1.4%)	55.6 (↑2.7%)

2.4.3 Burnout in performance sport

Forecasting athlete burnout [92] by using artificial intelligence and text analysis is a breakthrough in sports science, psychology, and technology [18]. It helps sports specialists understand athletes' well-being and create better training and recovery programs. Physiotherapists can accelerate and improve athlete recovery by adapting rehabilitation programs [22] to their physical and mental states [93]. With a nuanced understanding, physicians can detect early burnout, stress, and mental health disorders that routine consultations overlook. Burnout is experienced by 34.7% of male athletes and 39.2% of female athletes [94]. Burnout is the reason 45% young athletes stop competing [95]. According to the Changing the Game Project, 70% of young athletes stop competing at 13 years of age due to fatigue. Burnout is seen in more than 60% of adolescent athletes. 87% of athletes endure extreme stress that could lead to burnout. Journal of Athletic Training reports that adolescents who experience sports burnout have twice as high a risk of injury [96]. Burnout was cited as a significant motivator of early retirement by almost 80% professional athletes. According to a consensus declaration of the International Olympic Committee, 20–30% of elite athletes experience burnout. It is mental exhaustion that leads to 50% of elite young swimmers quitting. According to a study published in the British Journal of Sports Medicine, burnout poses a serious risk to 87.5% of Olympic athletes. Burnout was cited as a serious psychological problem in college athletics by 46. 8% of the respondents [97].

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2.4.4 Disease detection from written communication

The early detection of mental health (such as depression, anxiety, psychotic disorders, Alzheimer's disease, and dementia) and NDD (such as Parkinson's disease) remains a critical challenge in clinical practice. Traditional diagnostic methods rely on clinical evaluations that may be subjective and episodic. Recent advances in AI and NLP have opened new avenues for precognitive health assessments, suggesting that variations in language and expressed sentiments in written text can serve as potential biomarkers for these conditions. Research using social media posts and other digital footprints as potential sources of health-related information has started to become a serious topic nowadays, considering that any tool developed to identify disease from text [98] would need to be highly accurate and widely validated to be used in a clinical setting.

Identification of diseases through text messages [99] can be challenging but feasible in specific contexts. The approach relies on analyzing language patterns that can indicate cognitive, psychological, or even physical health conditions. Here is how it might work for various conditions, like: (1) *Mental health disorders* [25,100]: (a) changes in the frequency of communication, use of negative words, and shifts in the complexity of language may suggest *depression or anxiety* [101]; (b) disorganized thought patterns that manifest in how a person composes messages could be a warning sign of *psychotic disorders* [102]; or (c) repeated questions, more superficial sentence structures, or a notable decline in the complexity of language could indicate cognitive decline, like *Alzheimer's disease* and *dementia* [103]; (2) *Neurodegenerative diseases* [19,104,105]: while not directly identifiable through text, subtle changes in typing speed and fine motor skills required for typing might provide early clues of *Parkinson's disease* [106–109]; (3) *Sleep disorders* [110, 111]: late-night time stamps and content that indicates restlessness or consistent complaints about lack of sleep may be suggestive of *insomnia*; (4) *Infectious diseases* [112–115]: it is less likely to identify infectious diseases from text messages unless the content explicitly describes symptoms or experiences related to the *infectious disease* [112]; (5) *Chronic diseases* [116–118]: if someone frequently discusses feelings of tiredness, changes in weight, or other symptomatic experiences, this could indirectly hint at chronic conditions like *diabetes or thyroid issues* [119].

2.4.5 Lesions and tumor detection on severe head injuries

Early detection and intervention of brain injuries, lesions, or abnormalities can significantly improve the recovery process of athletes, reducing the long-term impact and unexpected health side effects [28]. AI-supported health anomaly detection systems provide high accuracy and consistency in real-time image analysis, outperforming human counterparts, especially in high-throughput situations. Furthermore, the scalability of AI allows for rapid processing of large amounts of data, making a comprehensive selection of athletes feasible. Motivation-wise, AI's ability to integrate multiple data sources, like game statis-

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tics and wearable sensor data, offers a holistic approach to understanding, managing, or even preventing head injury risks in time. The novelty in this field lies in applying neural architecture search (NAS) to optimize model architectures, transfer learning to enhance the model, multimodal learning to provide comprehensive analysis, and explainable AI to provide intelligible insights, thus building confidence in applied AI ecosystems.

2.5 Related work in sport strategy predictions and gamification

The use of the YOLO (You Only Look Once) [36,120] and YOLO-NAS (YOLO-NAS) [121] models in the extraction of sports performance strategies [122] brings a novel approach to analyzing and understanding the dynamics of sports drills, as shown in Fig. 5.7. By applying these models to video footage, coaches and analysts can efficiently detect and track players, extract valuable information on player movement patterns and interactions, and identify strategic elements to enhance team performance. The use of advanced technologies to improve both training and performance in competitive sports is growing [15]. Training programs mostly use traditional approaches. Technology is being used for performance analysis [42] rather than instruction. Sports are adopting gamification, which involves real-time feedback and rewards. These components have been shown to improve educational and commercial participation. The full potential of its sporting use has not been realized.

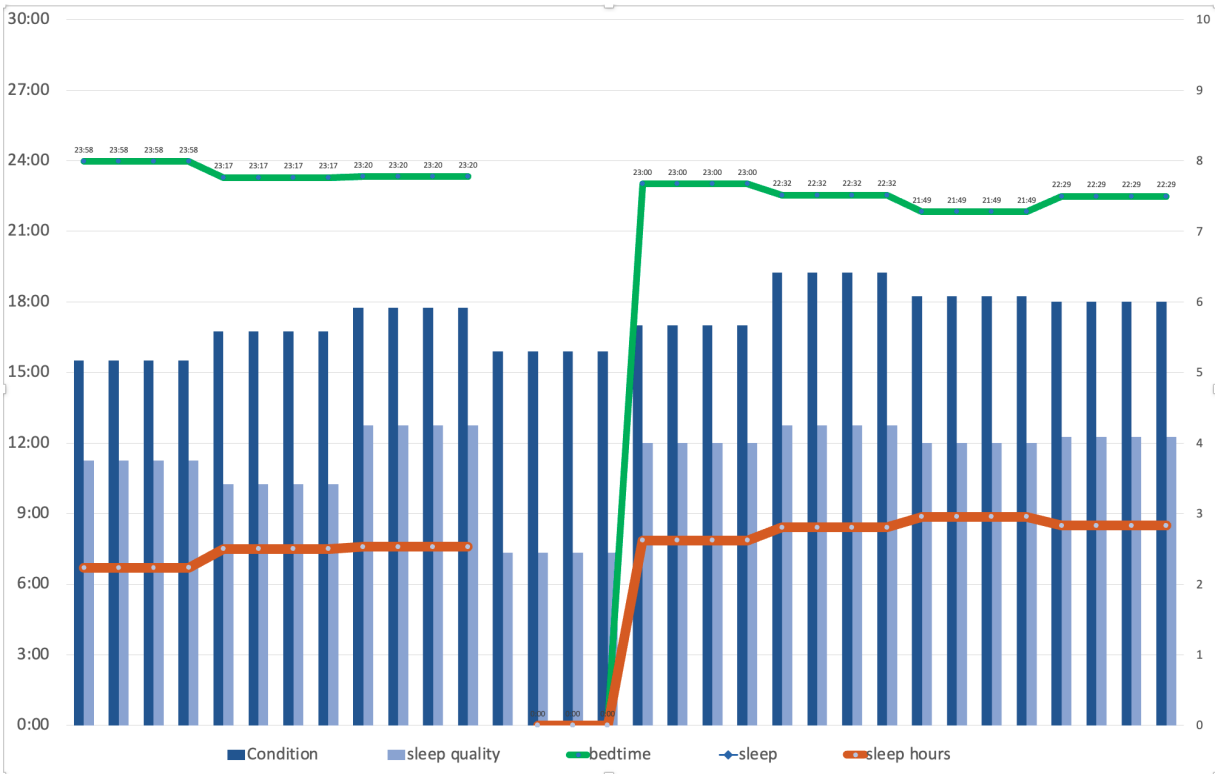


Figure 2.2: Basketball - condition and sleep corelation monitoring

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Generative AI [123] (GenAI) is revolutionizing entertainment and customer service. Its sporting potential is just being explored. This technology may produce personalized training scenarios and mimic competitive situations, which is beneficial for team sports, which require flexibility and strategic preparation. Athletes want effective and inspiring training that aligns with their personal and professional goals [124]. Motivation, engagement, and mental fortitude (see Fig. 2.2) are becoming as important as physical proficiency in training [125]. This makes gamification and GenAI in performance sports crucial. It helps to understand how these technologies can improve players' physical [15,26,42], mental [125] and strategic preparation [26]. It also encourages the reevaluation of the training model, leading to more participatory, customizable, and data-driven methodologies. This conversation is essential for sports training innovation that improves athlete performance and satisfaction.

Traditional methods on training programs

Traditional methods that dominate training programs in performance sports typically include a mix of physical conditioning, skill development, tactical training, and psychological coaching [126]. Here are some key traditional training methods commonly used: (1) *Physical conditioning*: includes strength training, cardiovascular exercises, flexibility routines, and other forms of physical workout designed to enhance overall fitness and endurance; (2) *Skills development*: involves specific drills and practices focused on improving unique technical skills of the sport [127]; (3) *Tactical training*: team strategies and game play tactics are taught through playbook sessions [127], video analysis of past games, and simulated scenarios. This method helps athletes and teams develop better decision-making skills and understanding of the game;

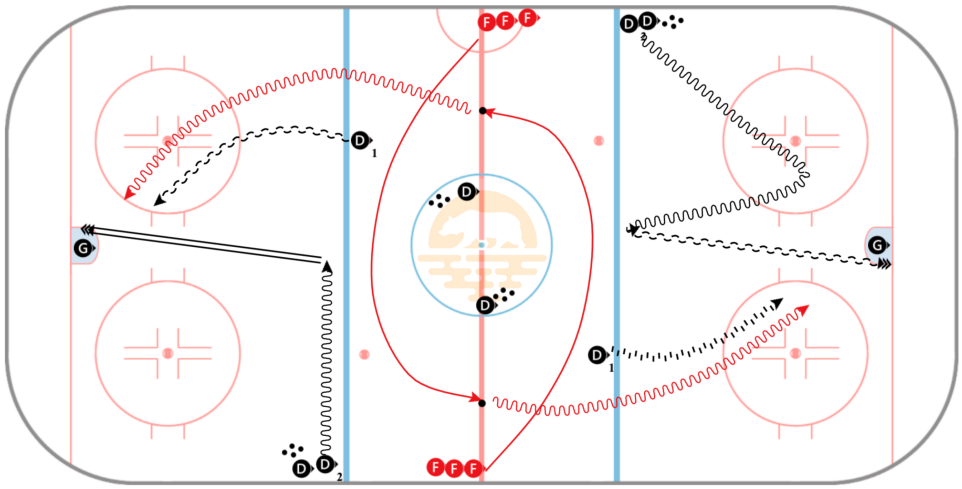


Figure 2.3: Icehockey: "1 vs 1 screen the net" drill from Sunbears Cloud Campus

(4) *Repetition and drills (see Fig. 2.3)*: repetitive practice of specific actions or strategies to build muscle memory and proficiency; (5) *One-on-One coaching*: personalized

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coaching sessions where coaches provide individualized feedback and guidance to improve an athlete's performance and address specific weaknesses; (6) *Video analysis*: review of training session and competition recordings to analyze techniques, strategies, and opponent behaviors; (7) *Psychological coaching*: techniques such as visualization, concentration exercises, stress management, and mental toughness [128] training are used to mentally prepare athletes for competition; (8) *Group dynamics and team building activities*: exercises and activities designed to enhance teamwork, communication, and trust among team members, which are crucial for team sports.

2.5.1 Digital intervention efficacy with gamification

The efficacy of digital interventions using gamification [35] in everyday life and sports performance represents a paradigm change in the way people or athletes train, learn and participate in their activity or sport. This approach promises better physical performance and cultivates a more holistic and sustainable athlete development model that encompasses physical, cognitive, and psychological growth. In performance sports, the implementation of digital interventions that utilize gamification is a sign of a new era of advances and results, enriching training methodologies, and overall athlete experience. One of the most significant outcomes is the higher level of motivation and participation among athletes. Gamification [35] uses the intrinsic motivation that games naturally evoke, encouraging athletes to engage more deeply and consistently with their training programs. This is particularly effective in repetitive and routine training scenarios, where gamification can inject an element of fun and competition. Digitally transformed sports interventions can involve the acquisition and examination of large amounts of data. The conclusion of the chapter provides a concise overview of the scientific contributions.

2.6 Summary of scientific contributions

The primary scientific contribution of this chapter is a comprehensive study of modern distant diagnostic techniques and sensors in the prediction of sports safety and health conditions. The focus is on conducting a thorough examination of the scientific literature in order to provide a multidisciplinary perspective. The services offered include remote consultation and diagnosis, the use of sensors such as medical radar sensors and 3D accelerometers, the monitoring of health conditions, and the detection of diseases and the prevention of injuries.

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3 Detailed scientific objectives

This chapter will offer a in-depth exploration of research questions (RQ), research objectives (RO), challenges and particular limitations, emphasizing the key scientific goals of the three main areas of the thesis group: (1) advanced remote diagnostic techniques and sensors; (2) sports safety and injury prevention; (3) prediction of health conditions. will discuss the multidisciplinary, multilayered aims of sophisticated distant diagnostic techniques and sensors in sports safety and prediction of health conditions, focusing on the most important outcomes from the following perspectives: (1) remote consultation, (2) radars [31] and other sensors, (3) monitoring of health status, (4) diagnosis and prevention of health diseases of sports injuries, and (5) prediction and gamification of sports strategies. The proposed future development lines and proposals – validated by the publications and conference papers – will also be presented.

3.1 Objectives in remote consultancy and collaborative diagnosis

3.1.1 Multilingual remote consultancy

The main goal of this part of the thesis [36] is to look at DETR models, architectures, hyperparameters and specific procedures with more straightforward methods to obtain good accuracy for finding textual objects in real time so that they can be further analyzed, to show that it is possible to find and label textual and other visual elements accurately, even with small training datasets, by using screenshots from collaborative tools. The purpose of the experiments was to perform limited validation-type experiments in each candidate group and to summarize their results simultaneously to measure, compare, and analyze the results, as well as to provide specific requirements regarding the efficacy of the input data and the preparation process. Furthermore, using AI models already established in other sectors can achieve high-precision results by detecting textual bounding boxes for videoconference tools. These models might be part of a further cooperative communication layer between video diagnostic attendees [36].

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3.1.2 Real-time synthesized and multilanguage OCR

The thesis [38, 40] examines the feasibility of ML-supported OCR in a multilingual environment. The goals for the Synthetic and Multilanguage OCR system employing CRNN and SVTR models within real-time collaborative tools, as related to this thesis, are outlined as follows: (1) customize hyperparameters of the PaddleOCR system to accurately recognize text in multiple languages by using CRNN and SVTR models; (2) compare the performance of CRNN and SVTR models for multilanguage OCR to identify which model is more effective for this task; (3) evaluate the performance and limitations of the PaddleOCR on a large dataset of multilingual images; (4) investigate the impact of different multi/synthetic language models and parameters on the PaddleOCR system to identify which languages and vocabulary sets are more challenging for the system to recognize. (5) investigate the impact of different levels of text blurriness, distortion, and noise on the performance of the OCR system, identify which image conditions are more challenging for the system to recognize; (6) investigate the scalability of the OCR system to handle large volumes of images, to ensure that it can handle collaborative tasks in real time efficiently; (7) investigate the robustness of the OCR system to handle different font types and sizes, to ensure that it can handle real-world scenarios efficiently; (8) investigate customized vocabulary on synthesized multilingual models [40].

3.1.3 Optimal dataset preparation in visual object detection

The thesis introduces a comprehensive methodology that synergistically integrates cutting-edge approaches, culminating in a significant time-efficient tool for OCR developers. This approach paves the way for the development of high-precision models by facilitating the construction of optimal, purpose-specific datasets. The primary objectives of this thesis research can be formulated as follows.

1. Developing an optimal vocabulary-based training dataset for multilingual, "artificial intelligence"-powered, real-time OCR systems, fostering technical excellence and pushing the boundaries of the research field. Several modern text recognizers are presented in papers [38, 40] connected to the thesis, and all of them both have high accuracy and represent fast interference speeds: (a) CNN-RNN-based models [129], (b) Encoder-Decoder models [130] involving multi-head self-attention (MHSA) [131] and multi-head attention (MHA) mechanisms [132], (c) Vision-Language models [133]; and finally, (d) SVTR [134], which recognizes scene text using a single visual model and has been built with cross-lingual capability [135].

2. To ensure comprehensive language representation [40] in existing (like PaddleOCR) and future custom OCR systems, with an initial focus on English, Hungarian, and Japanese as representative languages, but with the flexibility to extend the methodology to any existing or synthesized languages.

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3. To secure and control the requirements of high-quality and diverse data samples, a balanced dataset is maintained, which can effectively support the development of accurate, efficient, and versatile OCR systems.

4. To enhance contextual understanding and facilitate domain-specific adaptation in OCR systems (e.g., healthcare, IT, industry, or cross-domain topics), enabling them to adapt to many real-world scenarios.

5. To enable scalability and extensibility in the OCR systems, demonstrating the potential of AI to grow and adapt to evolving societal needs (e.g., real-time, multilingual, cross-domain interpreter systems).

6. Using methods such as CNN, RNN, CRNN, and SVTR, it is possible to find a visually controlled solution [40] that simplifies the creation of training datasets and vocabulary for real-time OCR projects (such as PaddleOCR).

3.2 Objectives of radars & 3D accelerometers

3.2.1 RPA intensity with radars and 3D accelerometers

With the rise of mHealth applications in the leisure sports sector, connected smart wearables (from wristbands to t-shirts that manage movement) record steps and provide vital and valuable data [15]. During this transition, the unimaginable has become a reality, altering the lifestyle, the sport practiced, and the and sport itself (e.g., how to practice more effective fitness). Many who participate in sports or controlled training sessions have already incorporated IoT fitness devices or various activity trackers into their lives, primarily to help athletes in their practice.

Performance sports, especially indoor ones, have limitations due to injury prevention. Combining radar sensors [136] and accelerometers, performing an invisible data acquisition pipeline, during sports activities, will allow a safer sports ecosystem to be maintained. The main conclusion of this state-of-the-art study is as follows. Today, no vital systems aimed primarily at athletes have yet been integrated to collect data using radar sensors [31] or in an invisible way, that is, in a contactless form. The raw health data, without further modification, could give us more reliable information on perceived exertion or fatigue. These will help coaches prepare complex models using artificial intelligence to maximize their capabilities.

The thesis [15] first examines the viability and limits of integrating ML algorithms with medical radar sensors [14] and then combines the synergy of the data from the three-dimensional acceleration sensor to assess the relative intensity of physical activity of elite athletes. The objectives of this research [15] are to: (1) confirm the feasibility of adapting medical radar sensor technology [31] to sports, highlighting at the same time the limitations of the technology; (2) take advantage of the latest advances in wearable

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and radar sensor technology [27], combined with mobile computing platforms, to provide an athlete monitoring solution to critical stakeholders interested in maximizing athlete safety and performance; (3) add objective alternatives to the measure of perceived exertion rating (RPE) [137] on the Borg RPE scale as a control option for sports safety; (4) research the adaptability of ML models into sports safety, by implementing RPE or the session rating of perceived exertion (sRPE) [138], HR MET prediction prototypes and information on three axial acceleration, using the latest relevant to MET sports, collecting critical data and insights for future research with big data. The efficacy of ML models such as random forest, Extreme Gradient Boosting, and Decision Tree, as well as regressions such as Ordinary Least Squares (OLS), Least Absolute Shrinkage and Selection Operator (LASSO) and methods with premade feature sets were used to predict the relative level of physical activity and energy expenditure.

3.2.2 Fatigue and stamina control on multivariate time series datasets

The objectives of this research [42] are to use the AI and IMU-generated datasets [32, 33] to initiate a paradigm change (see Table 5.2) to understand and manage fatigue and stamina of athletes, leading to more effective and personalized approaches to improve sports performance [37]. The thesis focused on AI-assisted fatigue and stamina control for performance sports [139] using multivariate IMU-generated time series datasets, with the objective of improving athlete performance and well-being through innovative AI applications. These met objectives, broadly classified as the development, validation, and implementation of a predictive model informed by large and temporally rich datasets [42].

1. *Methodological contributions*: This research seeks to contribute methodologically to the fields of sports science, sports safety [13], and AI (see Table 5.3). The aim of the thesis is to demonstrate the application of cutting-edge AI techniques in the interpretation of high-dimensional physiological data, potentially setting new standards for research and practice in sports performance analytics.

2. *Development of predictive models*: the thesis aims to develop advanced predictive models that integrate ML algorithms capable of processing and interpreting complex multivariate time series data. The goal is to identify and quantify the latent variables and intricate patterns that signal the onset of fatigue and changes in stamina, which are often invisible to human observation.

3. *Real-time monitoring and analysis*: one of the central objectives is to enable real-time monitoring and analysis of athlete performance using IMUs, which continuously collect data across multiple axes. The research seeks to harness these data to provide immediate feedback on an athlete's biomechanical and physiological state,

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facilitating timely interventions to manage fatigue [21] and stamina during training and competitive events.

4. *Personalization of training regimens*: the research endeavors to personalize training regimens utilizing predictive models to tailor training and recovery programs to individual athletes' needs. Taking into account the unique physiological responses of each athlete, the aim is to optimize training loads and recovery periods, thus maximizing performance results while minimizing the risk of injury and overtraining.

5. *Enhancement of recovery strategies*: Enhancing recovery strategies through precise predictions of fatigue levels is another key objective. By accurately forecasting recovery timelines, the model would inform the development of individualized recovery protocols, integrating modalities such as nutrition, physical therapy, and rest.

6. *Strategic athletic planning*: Strategic planning for athletic training and competition schedules is another objective. The research aims to provide coaches and athletes with strategic tools to plan training cycles, transition phases, and competitive pace strategies based on predictive insights into fatigue and stamina.

In summary, prospective research [42] on AI-assisted fatigue and stamina control, using the power of IMU-generated multivariate time series datasets, is on the cusp of fostering transformative outcomes for athletic training. The convergence of AI, sensor technology, and personalized medicine holds the promise of revolutionizing performance sports, with implications that extend to the health and wellness industries, personalized healthcare, and beyond.

3.3 Objectives in health condition control

3.3.1 sRPE and ACWR on fatigue and injury control

The objective of the thesis [22, 26] was to analyze the existing methods of ACWR calculation used in the field of sports performance, to automate or / and improve the calculation processes, as well as to find a feasible way to replace them with ML models to provide predictions or/and forecasts to coaches based on the trained dataset of the respective teams to localize the risks of injury and plan training sessions in the most effective way possible. The purpose of the thesis is to validate whether AI-assisted models and pipelines (such as personalized and adaptive models, real-time monitoring, and predictions) can be applied to performance sports and whether there is flexibility for (3) integration with multiple data sources.

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3.3.2 Personalized recovery

The use of AI in athletic training aims to optimize performance by tailoring regimens based on individual biomechanical data [24]. These advanced methods prioritize injury prevention by proactively identifying potential stress points during exercises. When it comes to recovery from injury [22], AI ensures precise adherence to therapeutic protocols, fostering faster and safer rehabilitation [140]. The objective of the methodology revolves around a dynamic feedback system in which real-time metrics influence continuous training adjustments. In general, the goal is to combine improved athletic outcomes with a data-driven approach to safety [13] and recovery. The primary objectives of this thesis layer were to (1) verify the feasibility and effectiveness of the AI-driven training method in improving athletic performance compared to conventional training methods; (2) determine whether an AI-controlled method or pipeline can accelerate or control the rehabilitation process [22] after injury and if they improve the quality of recovery; (3) assess the ability of AI to tailor training and recovery plans to the unique physiology and biomechanics of individual athletes; (4) examine the precision and effectiveness of near real-time feedback mechanisms, ensuring that athletes can adjust their techniques immediately. As secondary objectives of this thesis pillar, the project investigated the feasibility and benefits of integrating AI with wearable devices (e.g., a 3-axial accelerometer) to continuously monitor data collection and cross-validate calculations.

3.4 Objectives of disease and injury prevention

3.4.1 Disease detection from voice

The objective of the thesis pillar presented in [16] is to confirm the feasibility of voice-based disease detection to identify or predict diseases, including COVID-19 [141], prematurely or in time from voice samples. With the help of models, it is analyzed whether the proposed technological pipeline can protect athletes and sports teams from cross-contamination. Through COVID-19 research [12,17,141–143] it was investigated whether the concept can be expanded to a wider range of disease detection while identifying anomalies in voice samples to identify players “healthy”, “risky” and “ill”.

This research [16] combines complex voice analysis algorithms with classification on different existing datasets (e.g., Coswara, Cough-Against-Covid data, ESC-50 dataset, and FluSense dataset). After performing the necessary optimizations on metainformation, a comparison methodology was applied to the samples to evaluate the results and provide feedback with predictions for each patient, helping to keep risky people safe, extract potential sick people, or check / isolate them with high risk factors until further medical check (see Fig. 3.1). These thesis experiments plan to provide a near-real-time technological pipeline in performance sports for coaches to provide a preventive and effi-

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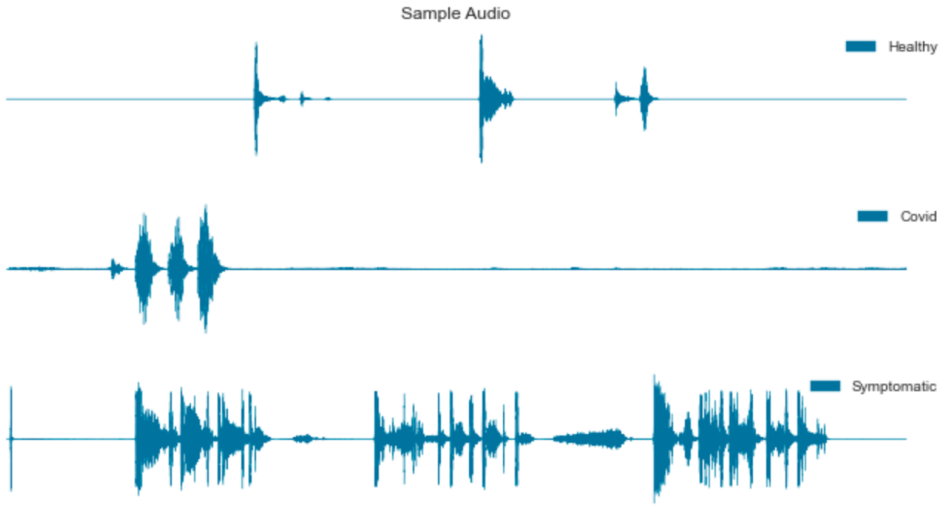


Figure 3.1: Healthy, COVID-19 and symptomatic voice samples

cient recovery program for sick players, keep team velocity at the same level, and protect them from well-known or suspicious diseases.

3.4.2 Early detection of pneumonia

The thesis research conducted uses YOLOv9, an advanced object detection system, to provide a novel and effective method for the early detection of athlete pneumonia. This thesis project [28] aims to integrate YOLOv9 into an accurate and real-time chest radiograph diagnostic framework to enable quick medical treatment. I aim to alter YOLOv9 to accurately detect and understand athletes' lungs, which differ from the general population due to their particular training and conditioning. Another goal is to seamlessly integrate this AI-supported system with sports health infrastructures to ensure its efficient functioning throughout training and tournaments without disrupting workflows. The conducted experiments also seek high diagnostic precision and low false positives and negatives (see Fig. 3.2 and 3.3). This is crucial for the early detection of pneumonia.

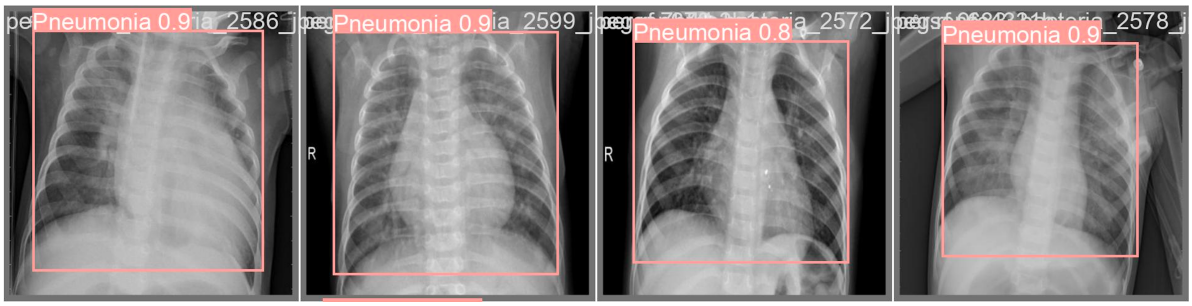


Figure 3.2: Pneumonia prediction

This involves rigorous training of the YOLOv9 model using a large dataset of athlete-specific annotated chest X-rays to improve its learning and prediction abilities. Another

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goal was to reduce healthcare costs for athlete respiratory infection by improving early identification and possibly reducing the intensity and duration of pneumonia treatment [28].

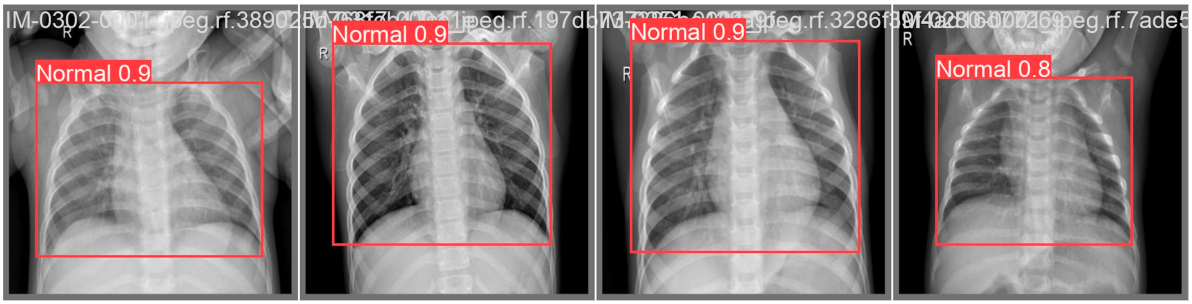


Figure 3.3: Normal health state prediction

The research also examined the ethical and privacy implications of instantaneous analysis of health data [144] while adhering to all laws and norms. Finally, the initiative will provide data on the efficacy of AI-assisted diagnostic tools in high-performance sports to improve sports medicine. This will require publishing extensive assessments of the system's impact on athlete health and its potential for development to other medical imaging and diagnostic applications.

3.4.3 Burnout in performance sport

This pillar of the thesis elaborated in the paper [18] first investigates whether a real-time AI-based pipeline can predict the burnout from textual information. Then it extends this system to detect and predict burnout syndromes in high-performance athletes by analyzing patterns and trends in their textual communication. This thesis study aims to provide a standardized technique to assess athlete mental health that reduces self-reporting [145] and third-party bias. Another secondary but essential goal is to incorporate this AI system into the athletic training and health management ecosystem to improve athlete safety and performance. The thesis also aims to personalize the diagnosis and prediction of burnout by learning from each athlete's unique communication patterns to tailor therapies to their specific situations. This AI program aims to advance sports science by demonstrating the viability of applying advanced techniques such as NLP and ML to the management of mental health in high-performance sports [18].

3.4.4 Disease detection from written communication

The [18,19] examines the efficacy of an AI-driven pipeline in accurately predicting different mental health and neurodegenerative problems [146] based on textual data. The purpose of the thesis is to contribute to the expanding field of sports science by showcasing the potential effectiveness of using sophisticated methodologies, such as NLP and ML, to manage mental health in high-performance sports.

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3.4.5 Lesions and tumor detection on severe head injuries

As a primary objective, this part of the thesis [28] aims to determine whether a real-time AI-based pipeline is feasible to predict severe brain injuries, lesions, and tumors in performance sports such as American football, rugby, and ice hockey. As secondary objectives, the following aspects were analyzed: (1) *Near real-time detection* – rapid and accurate detection of brain abnormalities after injury allows immediate medical intervention, reducing long term neurological damage and facilitating quicker recovery [147]; (2) *Injury prevention* [148] – By identifying patterns (HGG or LGG) in injury occurrence, AI can help formulating treatment strategies for patients with brain tumors [149], or in less drastic cases proposing targeted preventative measures, mitigating risks, and fostering a safer sporting environment; (3) *Augmented medical decision-making* [150] – if the AI pipeline can support physicians in decision-making, providing an additional layer of data-driven insight that complements their expertise, and ensures comprehensive care for athletes. (4) *Monitoring of health condition and treatment monitoring* [151] – if it is possible to provide a consistent and unbiased assessment of potential brain injuries to contribute to the optimal treatment or /and rehabilitation process [152] of all athletes, ensuring that the health and safety of the athletes are always prioritized.

3.5 Objectives in sport strategy prediction and gamification

The thesis objectives related to the validation of YOLO and YOLO-NAS in digital tracking [153] and the extraction of strategies [122] from videos are multifold. These models are crucial for accurately detecting and tracking players and objects in real time [38], which provides extensive data on movement patterns and interactions [154]. This capability allows for the extraction of strategic elements and patterns from the data, facilitating enhanced performance analysis and strategic planning. I have also investigated whether the incorporation of elements of game design into athlete training routines can increase engagement and motivation [155], thus resulting in better performance outcomes. By transforming potentially monotonous training tasks into stimulating and rewarding experiences, it is hypothesized that athletes will develop a more enthusiastic and committed approach, which is crucial for sustained high performance. In terms of retrospective type learning methods [156], athletes and coaches can use historical video data to identify trends, analyze past performance, and develop targeted training programs or adaptive strategies for future competitions. These methods facilitate [35] a data-driven approach to athlete and team development, improving performance, and strategic decision making in sports [41]. Furthermore, the thesis research seeks to harness the capabilities of generative AI (GenAI) [155] to develop adaptive training models that dynamically adjust to individual skill levels and progression of each athlete. This personalized approach is

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expected to optimize the learning curves of athletes, ensuring that they are consistently challenged and effectively supported in their developmental trajectories.

3.6 Summary of scientific contributions

The primary scientific contribution of this chapter is the comprehensive formulation of multidisciplinary scope elements that establish a connection between Computer Science and Health Sciences in various ways. This scope encompasses domains such as performance sports, sports safety, medical radars and sports sensors, control of health conditions (including mental health, detection of disease and health anomalies, inury prevention methods), sport psychology, athlete behavior analysis, sport strategy analysis, athlete performance analysis, physiotherapy and rehabilitation control, communication, sentiment analysis, retrospective learning, ethical implications, and artificial intelligence.

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4 Foundations, data and datasets

In this section, I will provide an overview of the datasets used in my thesis and explain the key concepts and approaches necessary to comprehend and assess the algorithms discussed in published publications. The conclusion of the chapter provides a concise overview of the scientific contributions.

4.1 Data, datasets and data generation

4.1.1 Data generator and synthesized data for vizual object detection

It was a curated dataset from real-life scenarios for VOD [36, 38, 40] tests, including data from actual video conferences and applications. Using pre-existing annotated datasets [38] was impossible because suitable options were not available. A specialized Python image extractor now facilitates data collection by generating images from textual metadata information. It has also been used for manual data collection. Thousands of raw photos were collected, filtered and classified. Finally, the dataset is organized into several independent study periods. The initial article had 248 train dataset records and 55 validation data instances in seven application categories and three object categories, meeting the minimum threshold required for a particular data science project [38]. The second phase [38] of the first investigation [36] included 512 training data records and 110 validation data instances for ten application categories and three object categories [36]. Human experts have labeled the data using a specialized annotation and data processing strategy. The input data have been modified for various models (YOLO4, DETR, Detectron2) through Python scripts. Human specialists used the Visual Object Tagging Tool (VOTT) [157] application for Windows10 and MacOS computers, together with the Label Image Tagging Tool (LabelImg) [158] on Linux or Mac for the annotation process. The studies were carried out using Python on the Google Colab Pro platform [36]. The second study of the thesis of this pillar [38] used a specialized image generation tool, developed in Python (Generator), to create training data. This tool generated single- and/or multiline images

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based on a customizable language corpus that included English, Japanese, and Hungarian layers. The generator can determine the specific text sources to be used and the proportions of these sources to be incorporated into the training data. Templates can be customized for each application to meet specific needs. The generator may customize fonts by accessing the operating system's font database, with the possibility to extend using external and local sources to meet the robustness criteria of the objectives. The commonly used fonts were incorporated into collaborative programs to address practical situations in the real world [38]. Like in the initial study [38], the preset annotated datasets were not used due to the lack of suitable alternatives. This method was also used for manual data collection. The validation dataset consisted of several raw photos collected, refined, and categorized using collaborative technologies. Multiple thesis experiments were conducted on the Linux (Ubuntu) operating system using Python, with or without visualization.

Synthetized and optimal training dataset

The training data [38] was created by a dedicated image generation tool, specifically a Python-based tool, which generates "collaborative tool template"-based single and/or multiline images from a fully customizable language corpus. The generator can specify which text sources will be used and the ratios of these sources to be included in the resulting training data. Templates can also be customized per application to meet real-life requirements. The generator was able to customize the fonts, using the font database of the operating system, having an additional external and local source expandability option to cover the robustness criteria of the objectives [38]. The most used fonts were included in collaborative applications to cover real-world scenarios.

For the research trials conducted [36, 38, 40] with video conference and application data, datasets representing real-world use situations were developed. Consequently, it was decided not to use predefined annotated datasets in absence of appropriate options. A dedicated Python picture extractor was developed to extract relevant video pictures. Manual data collection was also conducted by using this method. The validation dataset consisted of hundreds of raw images collected, filtered, and classified through collaborative tools. Several thesis experiments were conducted on the Linux (Ubuntu) platform utilizing Python, either with or without visualization. Table 4.1 shows the dataset and the evaluation size details for the research studies conducted in Phase 1 [36], Phase 2 [38], and Phase 3 [40]. Several datasets were also examined during the trials [38]. It was decided to stop these investigations because the predicted running times were not feasible to fit into the investigation time slots. The studies in later phases [40] were conducted in a high performance computing (HPC) environment.

Three different project categories were examined in the thesis experiments [36, 38, 40] and the results were confirmed using various datasets, as shown in [36,38,40]. The training category was divided into the following subcategories: (1) English, (2) Hungarian, and (3) multilingual training for datasets containing Japanese, English, and Hungarian languages.

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Table 4.1: Volume information about dataset and evaluation

Project	Name	Data	Training Size	Evaluation Size
OCR_hun	155k_hu_v2_2	hun_train	77 k	15 k
OCR_hun	155k_hu_v2_1	hun_train	77 k	15 k
OCR_enhu	SVTR	training1	66 k	33 k
OCR_enhu	CRNN	training1	66 k	33 k
OCR_multilang	5M_enhujp_v2_8	training10-200	5 M	101 k
OCR_multilang	5M_enhujp_v2_6	training9-200	5 M	101 k
OCR_multilang	5M_enhujp_v2_5	training10-200	5 M	101 k
OCR_multilang	5M_enhujp_v2_4	training9-200	5 M	101 k
OCR_multilang	5M_enhujp_v2_3	training8-200	8.5 M	170 k
OCR_multilang	5M_enhujp_v2_2	training8-200	8.5 M	170 k
OCR_multilang	5M_enhujp_v2_1	training7-100	5 M	100 k
OCR_multilang	10M_enhujp_v3_1	training8-200	8.5 M	170 k
OCR_multilang	5M_enhujp_v3_4	training7-100	5 M	100 k
OCR_multilang	5M_enhujp_v3_3	training7-100	5 M	100 k
OCR_multilang	5M_enhujp_v3_2	training7-100	5 M	100 k
OCR_multilang	4M_enhujp_pre_v3_1	training6	4.4 M	88 k
OCR_multilang	4M_enhujp_pre_v3_1	training6	4.4 M	88 k
OCR_multilang	4M_enhujp_v3_5	training6	4.4 M	88 k
OCR_multilang	4M_enhujp_v3_4	training6	4.4 M	88 k
OCR_multilang	2M_enhujp_v2_2	training3	2 M	220 k
OCR_hun	186k_hu_v2_1	training2	186 k	34 k

Large-scale datasets were also analyzed during the thesis experiments. However, because of the anticipated long running times, the studies were halted after the initial results and resumed in a high-performance computing (HPC) setup in later phases. Based on the training data, a vocabulary can be created using a unified dictionary or generating it from the training data. However, the size of the group will influence the training process. Table 4.2 highlights the different vocabularies (used in research experiments related to this part of the thesis) and their sizes and types.

For the thesis experiments, both the generated and the unified vocabulary types [36,38, 40] were used. Table 4.3 shows the Adaptive Vocabulary Selection used in the experiments for the research feasibility study, while Table 4.4 represents the validation phase with a wide variety of datasets and dictionaries.

Detailed steps for the generation of training datasets were presented in the publication [40]. Creating synthetic images that mimic real-world settings is essential for generating training data for a multilingual OCR system. This can be achieved by adjusting different attributes of the image, including font type, size, color, background texture, and noise levels. The images must accurately depict the various languages and writing systems that

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Table 4.2: Vocabulary sizes (expressed in characters) and types

Character dictionary	Dictionary size	Vocabulary type
606k_hun_vocab.txt	112	Generated
extended_vocab.txt	201	Unified
training9-200_vocab_min9500.txt	803	Generated
training9-200_vocab_min200.txt	2,737	Generated
jpn_latin_dict.txt	4,444	Unified
4M_vocab.txt	4,721	Generated
4M_min20_vocab.txt	3,980	Generated
2M_min2k_vocab.txt	968	Generated
186k_extended_vocab.txt	112	Unified

Table 4.3: Vocabularies on testing the approach

Name	Vocabulary name	Size	Type
15M_enhujp_v2_1	training9-200_vocab_min200.txt	2,737	Generated
30M_enhujp_v2_4	dashboard_vocab.txt	1,441	Generated
50M_enhujp_v2_2	training_min250_nQA.txt	3,964	Generated
3M_dashboard_eng_V1	training9-200_vocab_min9500.txt	803	Generated
3M_dashboard_hun_v1	186k_extended_vocab.txt	112	Unified
3M_dashboard_enhujp_v2_1	jpn_latin_dict.txt	4,444	Unified
10M_enhujp_v2_1	jpn_latin_dict.txt	4,444	Unified
30M_enhujp_v2_1	dashboard_vocab.txt	1,441	Generated

the OCR system is designed to identify. Below are listed the most common approaches and mathematical strategies that are used to create synthetic training datasets for a multi-language OCR:

1. *Text generation process*: The initial phase involves creating the text to be utilized in the artificial visuals. This can be achieved by applying NLP techniques, such as language models, or by assembling and organizing text datasets for each language.

2. *Font generation process*: Use fonts that accurately depict languages and writing systems is crucial to creating authentic synthetic visuals. Various techniques for developing fonts include generative adversarial networks (GANs) [159,160], variational autoencoders (VAEs) [161], or selecting fonts from preexisting libraries.

3. *Image generation process*: After generating the text and selecting the typeface, synthetic images can be produced. This can be achieved by picture editing techniques such as rotation, scaling, translation, and the addition of noise types such as blur, salt and pepper noise [162–165], or Gaussian noise.

4. *Augmentation process*: Improve the quality of the generated pictures by implementing various techniques to increase the diversity of the training dataset. These

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Table 4.4: Vocabulary for validation

Project	Name	Vocabulary name	Size	Vocabulary type
OCR_hun	155k_hu_v2_2	606k_hun_vocab.txt	112	Generated
OCR_hun	155k_hu_v2_1	606k_hun_vocab.txt	112	Generated
OCR_enhu	SVTR	extended_vocab.txt	201	Unified
OCR_enhu	CRNN	extended_vocab.txt	201	Unified
OCR_multilang	5M_enhujp_v2_8	training9200_vocab_min9500.txt	803	Generated
OCR_multilang	5M_enhujp_v2_6	training9200_vocab_min200.txt0	2,737	Generated
OCR_multilang	5M_enhujp_v2_5	training9200_vocab_min9500.txt	803	Generated
OCR_multilang	5M_enhujp_v2_4	training9200_vocab_min200.txt	2,737	Generated
OCR_multilang	5M_enhujp_v2_3	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	5M_enhujp_v2_2	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	5M_enhujp_v2_1	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	10M_enhujp_v3_ 1	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	5M_enhujp_v3_4	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	5M_enhujp_v3_3	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	5M_enhujp_v3_2	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	4M_enhujp_pre_v3_1	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	4M_enhujp_pre_v3_1	jpn_latin_dict.txt	4,444	Unified
OCR_multilang	4M_enhujp_v3_5	4M_vocab.txt	4,721	Generated
OCR_multilang	4M_enhujp_v3_4	4M_min20_vocab.txt	3,980	Generated
OCR_multilang	2M_enhujp_v2_2	2M_min2k_vocab.txt	968	Generated
OCR_hun	186k_hu_v2_1	186k_extended_vocab.txt	112	Unified

techniques involve random cropping, flipping, and color jittering.

5. *Labeling process*: Synthetic images must be accurately labeled with the corresponding character or text sequence they depict. This can be done by manually labeling the photos or using OCR techniques to extract text from the images.

Mathematical methods, including probability distributions, random number generation, and matrix transformations, are widely utilized to create synthetic images with realistic noise and other properties customized to specific use cases. An image can have random Gaussian noise added to it using a Gaussian distribution and can be rotated, scaled, or translated using affine transformations. Creating synthetic training datasets for a multilanguage OCR system requires a mix of text and font creation, image editing, image enhancement, and tagging methods. Mathematical techniques are utilized to change the properties of images and create authentic noise to aid in training the OCR system to identify characters and text sequences in real-world situations. In the publication [40], a novel convergence approach was presented to optimally prepare the dataset. Interpreting the results of the model from the experiments requires the use of a specific pivot table based on metadata. The pivot table offers insight into the error ratio linked to several types of feature set, highlighting the relative importance of these sets. It also pinpoints the areas that need further data injection to enhance the model's accuracy. The pivot includes important elements such as "Formatting," "Fonts," "Word count," and "Bad recognitions", as well as the ability to perform a human examination. Meta-data-based

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evaluation involves importing the predictions into a Jupyter notebook. Subsequently, the notebook uses a filtering process to detect any absent predictions. The forecasts are ultimately combined with the metadata table. The existing pivot table is filled with the data, creating an updated table with the latest information. This comprises the original data, along with the associated information and prediction. The model and its associated period are added to the table for a detailed description [40]. The PaddleOCR and Jaccard scores of the selected model were calculated and displayed on a graph. The Jaccard index assessed various text formatting options such as alignment, background color, text color, Blur, Noise, Italic, Bold, etc., categorized. If the valid field is indicated in green, the model earns a Jaccard score above 85% in many cases (see details in [40]).

4.1.2 RPAI dataset

During the first phase of research [15], the usability and applicability of medical radar sensors to the sports sector were validated using a real-time remote data acquisition process. The initial feasibility validation of the thesis experiments was conducted on its basis. During the validation phase, the research participants were professional athletes, with a minimum of 30 activities per participant sample per player. During the thesis experiments, a fixed installation was used by attaching the radar sensors to the benches, resulting in an optimal measurement range of 30–50 cm between the athletes and the sensor devices. These samples were used to validate the usability of medical radar sensors in the sports domain. For a more in-depth analysis, it is suggested to perform a more in-depth analysis per sport, per sector, and per location running dedicated trials.

To measure "RPAI Using a medical radar sensor and a 3D accelerator" [15], in the evaluation phase [15], a synthetic data set generated by medical radar sensors available during the research and inertial sensors [166] was used to validate the algorithms. The research has direct connectivity with two other published research papers: on the inertial sensor validity side with [32], and on the energy expenditure algorithm validation analysis side [32, 33] with [33]. After evaluating the results, the research was shifted to the second phase, where it used an already validated dataset with combined information about HR and 3-axial acceleration to determine the feasibility of ML algorithms using the PAMAP2 DATASET. The dataset "PAMAP2 Physical Activity Monitoring" (PAMAP2) contains around 18 activities (e.g., walking, running, cycling, Nordic walking, football, rope jumping, etc.).

PAMAP2's most important attributes are the following: (a) has multivariable time series data characteristics, (b) 3,850,505 instances, (c) 52 attributes, which are the following: the manual data have been prepared according to the General Data Protection Regulation (GDPR) using an anonymized dataset. Table 4.5 shows anonymized information on PAMAP2 users, providing information on sex, age, height, weight, resting HR, maximum HR (calculated value), and dominant hand. The ML algorithm feasibility test

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Table 4.5: PAMAP2 dataset

Subject ID	Sex	Age	Height	Weight	Resting HR	Max HR	Dominant hand
Player1	Male	27	182	83	75	193	right
Player2	Female	25	169	78	74	195	right
Player3	Male	31	187	92	68	189	right
Player4	Male	24	194	95	58	196	right
Player5	Male	26	180	73	70	194	right
Player6	Male	26	183	69	60	194	right
Player7	Male	23	173	86	60	197	right
Player8	Male	32	179	87	66	188	left
Player9	Male	31	168	65	54	189	right

used synthetically generated datasets and anonymized sample datasets. It collected the minimum data threshold for a specific data science project. Data adjustments were made with dedicated Python scripts. For analysis, the Google Colab platform was used.

4.1.3 IMU-generated multivariate time series dataset

The "AI-Assisted fatigue and stamina control for performance sports on IMU-generated multivariate times series datasets" research [42] of fully adaptive real-time systems that can adjust training prescription instantaneously based on continuous data streams represents a significant future direction. These systems would operate as intelligent digital coaches, offering moment-to-moment guidance. Customized models that adapt to the individual characteristics of athletes, taking into account genetic factors, personal health history, and psychological state, could provide personalized training at an unprecedented level. The thesis used an openly accessible and validated multivariate time series dataset [166, 167], derived from IMU to monitor the kinematic patterns of 19 habitual, injury-free runners under conditions of fatigue and non-fatigue. The study protocol connected to the dataset used [167] was reviewed and approved by the Human Research Ethics Committee of the University College Dublin, Ireland. Data acquisition of the dataset was segmented into three distinct phases. Initially, subjects participated in a 400 m run, which was carried out at a self-determined comfortable pace. After this, a standardized fatigue-inducing protocol was administered, known as the beep test, which requires incremental running between two points 20 m apart in synchrony with audio cues that decrease in intervals over time. This protocol escalates in intensity until the participant cannot maintain the required pace. The final phase involved replicating the initial 400 m run, although under fatigue. Throughout these trials, the IMUs recorded triaxial measurements of acceleration, angular velocity, and electromagnetic orientation at a frequency of 256 samples per second. The protocol (also called the fatiguing protocol) ends when the

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runner can no longer match the escalating speed.

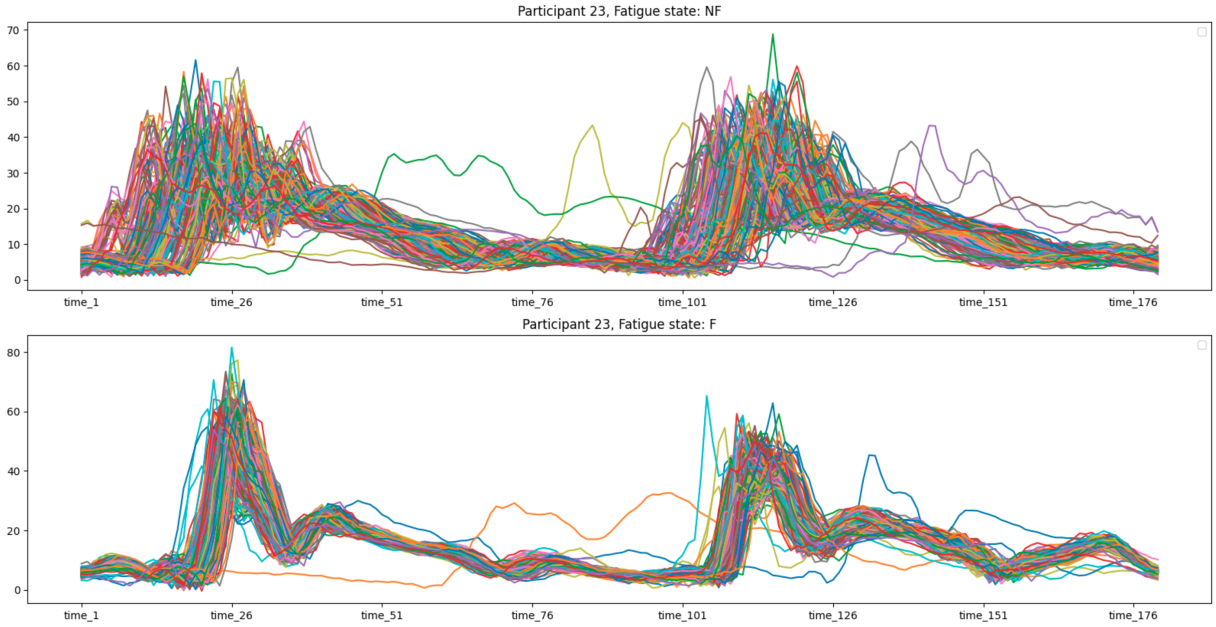


Figure 4.1: Participant 23—non-fatigue (NF) and fatigue (N) states. Details of more participants: See data availability statement.

All runs were carried out on an open field [166]. The compiled dataset encompasses segmented steps from 400-m runs across the entire cohort. Each data point is annotated with an identifier for the participant and a binary label indicating the presence ('F') or absence ('NF') of fatigue. An example of participation multivariate time series visualization is visible in Figure 4.1. The data set also includes measurements of triaxial accelerometers and gyroscopes, where the orientation of each axis is defined in relation to the positional coordinates of the sensor. In addition, composite signals representing the total acceleration and magnitude of the gyroscope were calculated from the primary measurements and incorporated into the subsequent analysis [167].

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4.1.4 Mental health and NDD dataset

For "Precognition of mental health and neurogenerative disorders using AI-parsed text and sentiment analysis" [19] at the data annotation process, human experts and already validated datasets [168, 169] were used. A collaborative AI-supported solution for more comprehensive annotation of data sets will be used in the future postdoctoral phase (see chapter 12.1).

4.1.5 Pneumonia detection dataset

For pneumonia detection thesis project [28], a data set [170] was used that comprises a large number of chest and OCT images that have been verified and studied in the publication titled "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning". The photos are divided into a training set and a testing set consisting of separate patients. The images are categorized according to the disease, the randomized patient ID, and the picture number. In addition, a secondary validation dataset [171], freely available for research purposes, was used.

4.1.6 Burnout datasets

Two datasets were used for "real-time AI text analysis to identify burnout syndromes in high-performance athletes" [18] research [18] to form the test group for data classification. The first dataset consisted of 1,590 manually collected posts, which are burnout confessions gathered from various webpages spanning different categories such as athlete, work, parent, friend, relationship, school, hospital, gifted kid, and others. These posts describe user experiences with burnout. For the second dataset, 30,000 tweets were extracted from Twitter using the keyword "burnout" and its variations. User identity information was not collected in either of these datasets.

Table 4.6: Burnout research - sample data extractions from the dataset

Line	Text	BL	Length
773	i got a new boss that doesn't perform his job ...	3	54
642	i am taking 18 credits this semester.	3	37
879	i have been home the whole time	1	31
4354	Well, fer starters getting my shit straitened ...	2	85
7012	I don't think I realised how stressful it was ...	4	169
4781	Some things honestly are not worth your energy...	2	97
7484	From mid January my girlfriend broke up with m...	5	298
2481	The amount of work due to remote learning is t...	4	65
6939	As a software developer, yeah right! In 20 min...	5	439
4939	I have exams tomorrow, and I haven't reviewed ...	2	50

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The posting time of the tweets was also captured [18], as it could reveal valuable information. Functional words were examined, such as personal pronouns and conjunctions, in tweets and their relationship with human emotions (see Table 4.6). Compared to non-burnout users, individuals experiencing burnout use personal pronouns much more frequently, possibly reflecting their heightened self-awareness. In some cases, rather than focusing on negative sentiment in the text, a 5% increase in the usage of the word "I" can be a strong indicator of internal mental distress. If something occurs more than once, it reinforces the assumption: among these 30,000 tweets, 1,444 users posted tweets containing references to burnout more than twice. The information collected is freely available on request for future projects.

4.1.7 COVID-19 dataset

"Real-time disease and COVID-19 detection pipeline of voice for performance sports" [16] used several well-known validated datasets freely available for research purposes, such as *Coswara* [172], *Cough-Against-Covid-data*, *ESC-50 Dataset*, *FluSense Dataset*. After a preliminary data quality check, the Coswara dataset with 47 parameters was chosen. The dataset comprises 12,474 healthy, 2,586 symptomatic, and 1,153 COVID-19 samples.

4.1.8 Tumor, LGG, HGG dataset

For "Applied AI for real-time detection of lesions and tumors after severe head injuries" [28], two datasets were used, "Br35H" [167] dataset of 3,060 brain magnetic resonance images. This dataset used a simple annotation type "object" (tumor). To cross-validate and expand the possibilities of YOLO and YOLO-NAS, the "Flair-Train Dataset" [173] of 1,280 images was chosen, with annotations layered as "LGG" and "HGG". Both datasets are open-source for computer vision projects. For data annotation and quick labeling, the Roboflow platform was used, popularizing the AI-assisted labeling solution with features such as bounding boxes, polygons, and instance segmentation. The collaborative layer is planned to be used in the next phases.

4.1.9 Condition dataset

The "sRPE and ACWR to control fatigue levels and minimize injuries in performance sports" [26] used [26] – at the Proof-of-Technology (PoT) experiment level – a manually collected dataset from Toyo University. Parameters: ice hockey sport, team formation, team sessions, male athletes, age between 22-24 years, activity durations of 40-60 minutes. In the feasibility study phase, the "PMData: a sports logging database" [174] was used, which contains a dataset of 16-person activities for 5 months. Parameters: age between 48-60, male and female athletes, sports activities: running, strength, and soccer on the team, with activity durations between 20 and 80 minutes.

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4.1.10 Microsleep experiments dataset

For the research, both a synthetic generated data set and a validated one were used, such as the expanded "Sleep-EDF database" [175]. A total of 197 PolySomnoGraphic sleep recordings have been incorporated into the sleep-edf database, which include EEG, EOG, chin EMG and event markers. Composition: 7 men (20-60 years), 15 women (18-79 years). Respiration and body temperature are also included in certain recordings. Each of the EOG and EEG signals was sampled at a frequency of 100 Hz. Subsequent to the application of electrical high-pass filtering, rectification, and low-pass filtering to the submental EMG signal, the resultant EMG envelope was captured at a frequency of 1 Hz and quantified in microvolts rms (root mean square). Measurements of oro-nasal airflow, rectal body temperature, and event markers were performed similarly at a frequency of 1 Hz.

4.1.11 Strategy prediction dataset

For "the predictive sports strategy approach using YOLO and YOLO-NAS in performance sports" [41], the videos used in the thesis experiments were collected with smartphones with the help of and Tokyo University [127]. A manually collected dataset from Toyo University was used for the Proof-of-Technology (PoT) experiments [41]. Human experts manually prepared the annotation of the data. The drills and systems used were collected and prepared in the Ecosystem [127] under the guidance of professional ice hockey coaches. Video parameters: ice hockey training, team formation, team sessions, male athletes, age between 22-24 years, activity durations of 40-60 minutes. The efficacy of a gamified digital intervention, centered on lifestyle change [35], was examined in the Horizon H2020 project. The thesis study aimed to explore the use of various activity-based techniques for different types of activities and intensity levels.

4.1.12 Recovery dataset

For the "AI-controlled training method to improve performance or recover from sports injuries" [22], the dataset was manually prepared and processed by human experts [22]. Coaches and sports professionals validated the exercises. The dataset and results will be freely available for future projects upon request.

4.2 Summary of scientific contributions

The chapter encapsulates scientific contributions related to dataset preparation and dataset maintenance as follows: (1) conceptualization and design of synthetic, complex dataset generator for VOD and OCR projects, based on analyzed, curated, real-life scenarios; (2) definitions and recommendations on data collection processes on multiple types of projects

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(e.g., multilingual OCR, burnout /disease /anomaly detection, stategy prediction), domains (e.g., IT, health, sport), metadata-based image generations and annotation process and techniques; (3) extensive benchmark on synthetic training dataset preparation for multilingual OCR topics; (4) applicability of medical radar sensors in the sports domain from the perspective of data acquisition and dataset preparation; (5) freely available dataset for further burnout analysis and condition analysis projects.

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5 Scientific challenges

This chapter comprehensively analyzes the challenges, barriers and specific restrictions and limits related to current remote diagnostic instruments and sensors to predict sports safety and health concerns. It will emphasize key findings involving numerous viewpoints like (1) remote consulting; (2) radar and sensor technology [15]; (3) health monitoring; (4) disease identification and injury prevention; and (5) forecasting and gamification of sports strategies [35]. The chapter will also make proposals on how to tackle the challenges described.

5.1 Challenges of remote consultancy and diagnosis services

5.1.1 Multilingual remote consultancy

To validate the feasibility of DETR, additional experiments were carried out with three of the most promising real-time object detector models, YOLO4, Detectron2 and DETR, each with different model variations. Given a fixed small set of learned object queries, DETR reasons about the relations of the objects and the global image context to directly output the final set of predictions in parallel. Due to this parallel nature, DETR is very fast and efficient, so it was proposed to employ End-to-End TVOD with Transformers [49].

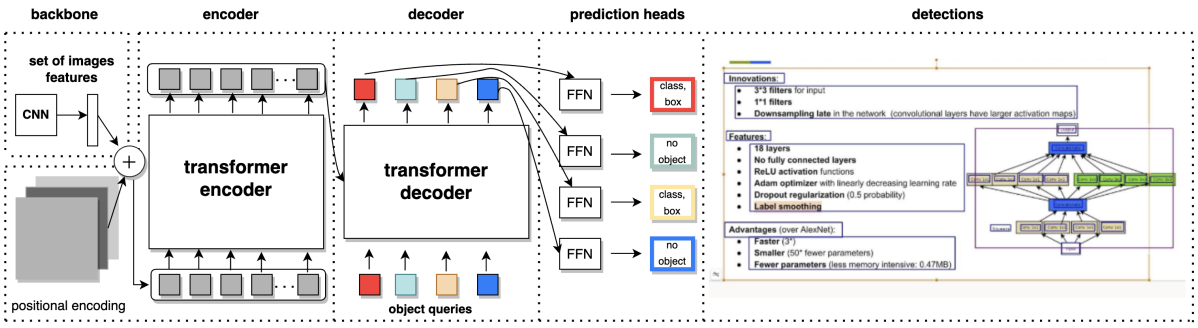


Figure 5.1: DETR architecture in TVOD based on Carion, Massa, Synnaeve *et al* [1].

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This research validates the feasibility of VOD topics, using several "real-time object detection AI" models and architectures "to detect objects in real time" to support non-supervised communication in video diagnosis, using conference tools [36] (e.g., zoom, teams, webex, skype). Unfortunately, such systems, ready for multilingual interpretation support, are not available to the best of my knowledge, and such attempts are not visible in the literature. The findings of the thesis constitute an important contribution, as they propose a practical method for establishing a communication link between health experts utilizing an imperceptible technology layer known as the "multilingual real-time translator engine". In some specific languages, it is not enough to identify just the phrases on the screen because, based on the context, they might have different meanings. In the case of languages such as the 22 Indian languages, Chinese, or Japanese, the topic/issue of contextualization will arise. When translating a specific word, phrase, or sentence, the system considers additional broader information that clarifies the text in question. However, it is not clear what could and should be considered context when combined with visual and beneficial context information [36].

These topics generate a central issue for human translators. To obtain an adequate interpretation while attending a dedicated technical health-based conference call, attendees must submit their presentation with all relevant information a few days before the live session. In the case of multilingual (ad hoc) video consultancies, where every minute matters, there is no place for such preparation. There are models and methods for bidirectional translation. Still, in the case of multilingual and multi-user conferences, when the parties involved speak in languages that do not come from the same language families, the complexity of translation becomes high, increasing the latency time of translation and decreasing the translation quality.

Challenging topics are currently solved with human interpreters, but this set-up is expensive and requires additional arrangements. To replace the human factor with a highly reliable solution, several research works have been carried out [54], providing various approaches for different setups. This pillar of the thesis proposes a "DEtection TRansformer" DETR-based solution design (Figure 5.1 shows the concept of DETR [36]) and the procedure to detect textual objects (visual) and find the threshold where feasible accuracy can be achieved that can support remote multilingual video diagnostics [36]. For this research on the validity and feasibility check side, DL-based model structures were applied, such as YOLO4 ("You Only Look Once"), DETR and Detectron2 [46, 176]. For this pillar of the thesis, experiments were conducted in two phases: the first round contained the technical minimum training dataset for reasonable statistical learning models and analyses of different model architectures' hyperparameters. Furthermore, the data collection and annotation protocol based on these experiments was updated. Finally, the initial training and validation datasets were doubled to improve the experiments according to the lessons learned from the first phase [36].

Other approaches on the market were analyzed and thesis experiments were performed

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on COCO 2,017 detections with 118 k training images and 5 k validation images. The objective was to find a feasible solution with minimal training data required and an accessible environment for the healthcare sector. The thesis provides solutions in which the model requires a minimum training dataset [177]. The thesis goal of both phases was to conduct limited validation-type experiment rounds in each candidate group and to summarize their results simultaneously to measure, compare, and analyze the findings, as well as to bring about specific requirements regarding input data and the efficacy of the preparation process. The main scope of the experiments was to prove that detection and localization of textual and other visual element types is possible with high accuracy (even in limited training datasets) by applying screenshot images [36].

Disadvantages of DETR from the textual object detection perspective

According to the DETR research paper [36] related to the thesis, one of the main disadvantages of DETR from the "perspective of detection of textual objects" is that the detection efficacy on small targets is generally poor [36]. To solve this problem, the model needs significant improvements [178]. In the case of videoconferencing tools, this deficiency is not present. In this research, the following outcomes were highlighted: (a) it requires heavy computational power (minimum 8 GB of GPU memory required for the model), (b) the Transformer is a black box for interactive interoperability, and (c) the Transformer network requires the most considerable amount of training data [36].

5.1.2 Real-time synthesized and multilanguage OCR

It was investigated whether a near-real-time environment (see Figure 5.2) – which supports collaborative videoconferencing tools and platforms – can be applied to healthcare and sports safety.

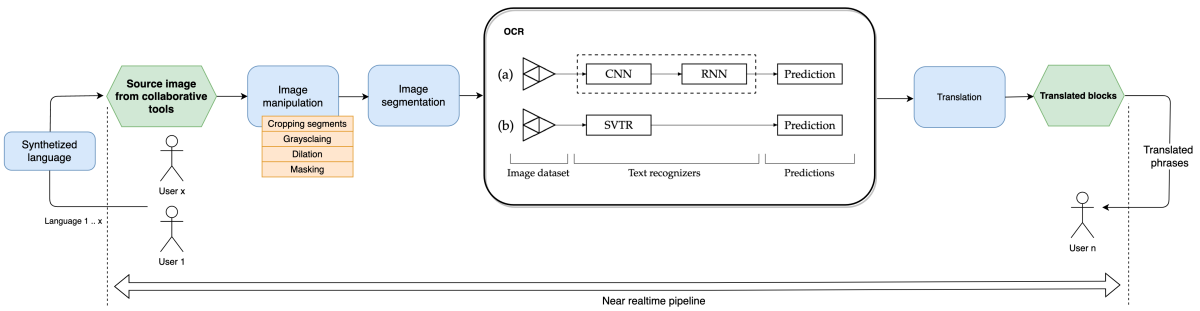


Figure 5.2: Near real-time synthesized language translation pipeline, using modern text recognizers as illustrated in Figure 6.2

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5.1.3 Flexible dataset preparation in visual object detection

In the realm of multilingual OCR systems powered by AI in real time, this research explores the creation of an optimal [38] vocabulary-based training dataset. This comprehensive endeavor seeks to include a range of criteria: comprehensive language representation, high-quality and diverse data, balanced datasets, contextual understanding, domain-specific adaptation, robustness and noise tolerance, as well as scalability and extensibility [38]. According to the research conducted, not even PaddleOCR could handle accurate phrase recognition in multilingual or synthetic languages used in the IT or sports sector for on-screen simulations [38, 40]. The research experiment connected to the thesis analyzed existing solutions available on the market, and one important outcome is that currently there is no magic formula that can be applied to prepare an optimal training dataset that covers all of the requirements of the on-screen collaboration tools. Every use case is different, so it is suggested to handle the topics as standalone projects. The use case that involves languages and specific vocabulary will define the volume of the training dataset. The existing annotated datasets are not golden sets, but can be used to prepare the method that covers all aspects of the requested OCR system [51]. Formulating an optimal vocabulary-based training dataset for multilingual real-time OCR systems requires a strategic approach to various key elements. These include carefully selecting adaptive vocabulary, implementing cross-lingual pre-training [179], implementing dynamic dataset augmentation strategies, ensuring domain-specific adaptation, addressing data imbalance issues, applying multimodal learning, and establishing appropriate evaluation metrics and benchmarks. [40, 180].

Challenges and mitigation strategies

Various challenges, such as time-consuming procedures, unforeseen issues, and inconsistencies in observed behaviors, characterized the experimental phase [38, 40]. The challenges and constraints faced throughout the execution of PaddleOCR are highlighted below.

1. *Single-line and/or multi-line approach*: one of the essential technical questions [40] was the capacity of PaddleOCR to handle multiple lines of text. During the experimental phase of the thesis, it was seen that the system exhibited restricted multi-line capabilities under certain conditions. Specifically, this limitation became apparent when the vocabulary size was sufficiently short (ranging from 100 to 200 characters), and the training examples were chosen meticulously. During the multilingual experimentation of the thesis, providing sufficient time for manual review of training data that involved character-based multiline analysis was beyond the scope. This difficulty was addressed by chosing the single-line solution offered by PaddleOCR [40].

2. *Vocabulary generation*: PaddleOCR currently lacks an in-process vocabulary gen-

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erating tool [40]. The process of forming vocabulary requires manual management. There are two methods by which a lexicon or dictionary can be generated for training: (1) a potential approach is the development of a cohesive and standardized lexicon, commonly referred to as a "golden" vocabulary, which is meticulously monitored and curated by knowledgeable human specialists; (2) an alternative approach involves the generation of a language based on the training data. With this approach, it can be guaranteed that the vocabulary includes only characters found in the training sample, eliminating extraneous characters.

3. *SVTR vs. CRNN*: During the investigation [40], PaddleOCR introduced a new iteration of its software that incorporates the SVTR paradigm. According to PaddleOCR, the newly proposed model architecture exhibits superior performance compared to its predecessor, CRNN. Numerous experiments were conducted on the novel model architecture, consistently revealing its inferior performance compared to the capabilities demonstrated by the prior architecture. A detailed analysis of the results obtained from the SVTR determined that reverting to the use of CRNN models is the most appropriate course of action. In the post doctoral phase, as a future research direction I intend to examine both methodologies comprehensively in the high-performance computing (HPC) environment (see chapter 12.1).

4. *Word spacing and segmentation issues*: Japanese texts had an improper word spacing during experiments [40]. Using a tiny-segmenter Japanese text tokenizer improved the answer. Setting up tiny segments and tokenizing/segmenting Japanese or Chinese requires expertise. Japanese vs. Unicode character coding is another issue. The model looks at each character to identify it, which may lead to errors. Imagine identical characters with different character codes. In this example, the model will recognize the character as one of two options during training. If this character belongs to another character code, the model returns the information that it made a mistake because it is not that character. This causes mistakes in training and inferences for the model. The solution proposed by the thesis is to identify and change these homoglyphs to the selected one. For Latin characters, dictionaries solve the problem, but homoglyphs require further study and depend on the domain of Japanese or Chinese literature. The "normalizeHomoglyps" attribute works with a pre-defined homoglyph table to handle characters/symbols that seem similar but have various character encodings for text sources. Using the NFKC method, the latest version provides automatic Unicode normalization for each text source.

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Localized limitations

While the research endeavors to address significant challenges in multilingual OCR and synthesized languages [40] for collaborative OCR solutions on screen (especially in healthcare and remote diagnosis), there were localized limitations that underscore the complexity

of the task. Specific constraints that require a thorough examination are as follows.

1. *Synthesized languages*: investigating synthesized languages (like health language, legal language, and IT language), which may not have well-established linguistic resources or standardized writing systems, introduces an additional layer of complexity. The availability of reliable linguistic references and textual corpora for such languages can be limited, potentially hampering the completeness and authenticity of synthetic training data.

2. *Computational resources*: the research involves computationally intensive tasks, including the generation of synthetic data and the training of DL models. Substantial computational resources or high performance computing (HPC) environment are required, depending on the scale of the dataset and the complexity of the models. Access to such resources can pose limitations, particularly for researchers with limited access to HPC environments.

3. *Generalization*: while the research seeks to optimize training datasets and models for multilingual OCR, the degree to which the findings can be generalized to various applications and domains of OCR may be limited.

4. *Evaluation challenges*: The establishment of robust metadata-driven evaluation methodologies and benchmarks for multilingual OCR systems, which take into account the intricacies of synthesized languages, represents a formidable challenge. Creating evaluation frameworks that adequately reflect real-world scenarios (such as cross-domain or field cooperation) and effectively assess system performance across multiple languages is an ongoing challenge.

5. *Data annotation*: Generating high-quality, linguistically accurate annotations for synthetic training datasets is resource intensive and time-consuming. The practicality of creating comprehensive annotations that encompass diverse linguistic features across multiple languages and/or domains (law, IT, healthcare, sports, and industry), especially for context-sensitive and synthesized languages, may present significant logistical challenges, even in HPC environments.

6. *Language diversity coverage*: Developing a single universally applicable methodology for training dataset preparation may be challenging. The need for language-specific considerations can introduce complexity and complicate the generalization of findings between languages. Involving the Japanese language in synthesized language alongside some Latin and Anglo-Saxon languages can limit the vocabulary to 5,000 - 6,500 characters if it is limited to the IT domain. However, in the case of the health domain, the vocabulary will have more than 10,000 characters.

Recognizing these limitations is essential to provide a balanced perspective and guide future research efforts in this demanding and dynamic field of OCR technology [38].

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Generating synthetic training datasets for training a mixed natural (e.g., Japanese, English, Hungarian) or synthesized multilanguage [38, 40] (e.g., industry, health, law, IT languages) OCR system presents various challenges and problems, both in a "classic AI infrastructure" and in an HPC (High-Performance Computing) cluster environment. Table 5.1 shows a comparison of the challenges and considerations in both scenarios and the reasons why the thesis proposes to introduce multilingual OCR approaches in HPC environments. In conclusion, while classic AI infrastructures and HPC clusters can be used to generate synthetic training datasets for multilingual OCR, HPC environments offer significant advantages in terms of computational power, scalability, and resource management. However, data quality, labeling, variability, and resource availability challenges remain shared in both scenarios and require careful consideration in the dataset generation process.

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Open challenges and HPC approach

Table 5.1: Open challenges comparison - Classic AI infrastructure vs HPC environment

Topic	Classic AI infrastructure	HPC cluster environment
Computational power/resources	In a classic AI infrastructure, users are limited by the computational resources available on a single machine or a small cluster. Generating synthetic training data for multiple languages with a large dataset can be *computationally intensive and time-consuming*	HPC clusters offer significantly more computational power, allowing to generate larger and more complex synthetic datasets for multilanguage OCR efficiently.
Scalability	Classic AI infrastructures may lack the scalability required to efficiently generate synthetic datasets for multiple languages simultaneously. Users may need to create separate workflows for each language, which can be inefficient.	HPC clusters are designed for parallel processing, which means users can distribute the workload across multiple nodes, enabling simultaneous dataset generation for multiple languages. This enhances efficiency and reduces time.
Data handling/volume	Managing and storing large volumes of synthetic data for multiple languages can be challenging in a traditional setup. Users might encounter storage limitations and data management issues.	HPC environments provide advanced data storage and management capabilities. Handling and storing large volumes of synthetic data is more streamlined
Parallelism /distributed computing	Implementing parallelism for data generation is more complex in a classic infrastructure, making it harder to exploit multi-core CPUs or GPUs efficiently.	HPC clusters are well-suited for distributed computing, enabling users to distribute the dataset generation tasks across multiple nodes, which is especially beneficial for generating synthetic datasets for multiple languages
Resource management	–	HPC environments offer sophisticated resource management tools and job schedulers, allowing users to optimize resource allocation and utilization for dataset generation tasks.

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5.2 Challenges of using radars and 3D accelerometers in sports

5.2.1 RPA intensity with radars and 3D accelerometers

The most challenging aspect of indoor performance sports is how to achieve data collection in an invisible but protective way from athletes using well-known devices and sensing networks (e.g., medical health sensors, smart watches, or various types of activity sensors) to provide timely updates to key stakeholders (including managers, trainers, doctors, and coaches) regarding athlete performance [22] and the possibility of them entering dangerous health states (such as excessive hydration or dehydration). The hidden patterns of the data [127] will be identified using real-time predictive algorithms based on the incoming sensor data streams. The initial stage is to identify the least harmful device and communication route and set up the data collection pipeline.

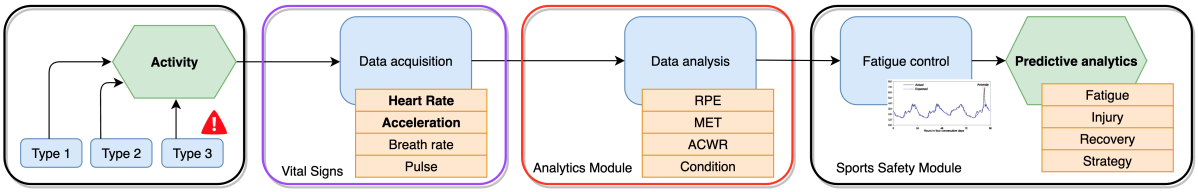


Figure 5.3: Next-generation sports safety approach.

Recent advances in next-generation technologies enable intelligent "health" sensors, dedicated radar sensing devices, three-axial accelerometer sensors, and various health activity and health-state tracking pathways to achieve these objectives [15]. Figure 5.3 shows the next-generation (expected) approach of sports safety, as a novelty concept, where Type 1 activities are sports that allow any sensors during game sessions, Type 2 are the injury-based regulated and limited ones, and Type 3 which do not allow any attached or wearable sensors, only remote sensing. The novelty consists not only in the early adoption of a wearable with remote sensing solutions, such as medical radar sensors, but also in the introduction of AI as the main data analytics asset and sports safety [15].

Controlling fatigue through non-invasive athlete monitoring is one of the most relevant topics in sports safety today. The goal is to improve injury prevention by decreasing the risk of injury due to fatigue control. There is a risk of contact-related harm when accelerometer-based smart trackers, activity measurement wristbands, or smart watches are used to measure health parameters during high-performance sports activities; therefore, these devices should not be utilized. Unlike other approaches, radar sensors use a 24-GHz Doppler radar sensor [27] to detect vital signs, such as HR and respiration. This is achieved without touching or approaching the subject [15]. Therefore, it can predict the degree of activity that will be performed. Three-axial (3D) accelerometer sensors are

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used as dedicated devices attached to protectors (with potential adaptability to ice hockey and American football) or as wrist devices, such as smartwatches.

Limitatons of medical radar sensor technology

Medical radar sensors represent a relatively new technology that has the potential to revolutionize the way vital signs are measured and monitored.

1. The precision of medical radar sensors is one of their main limitations. Although they can accurately monitor vital indicators such as HR, breathing rate level, and blood flow, their measurements can be affected by factors such as body posture, motion, and other objects within the field of view. Furthermore, the accuracy of the measurements can be influenced by the type and configuration of the radar sensor used.

2. Another issue is their ability to penetrate various materials and electronic gadgets. The signal of medical radar sensors, which typically operate at a few gigahertz, is absorbed or dispersed by elements such as water, metal, or clothing worn by the patient.

3. Medical radar sensors are also sensitive to other electronic devices operating at the same or similar frequencies, so the presence of cell phones, WiFi routers, or other medical equipment can interfere with their findings.

The thesis substantiated that, despite these limitations, medical radar sensors are a reliable and valuable tool for monitoring vital signs in various medical applications, such as telemedicine, remote patient or player monitoring, and postoperative care [15].

5.2.2 Fatigue and stamina control on multivariate time series datasets

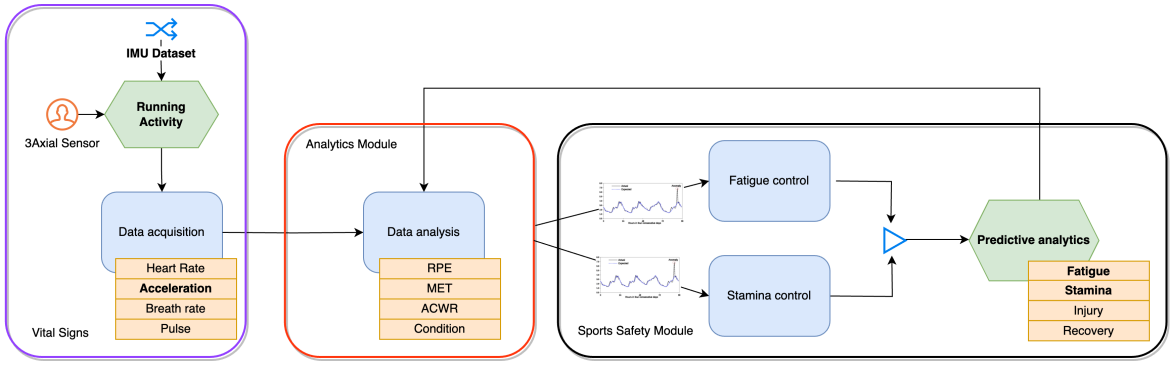


Figure 5.4: Sports safety approach on specific use case to manage multivariate time series datasets

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In sports and sports safety, the application of multivariate time series datasets is particularly pertinent due to the dynamic and multifactorial nature of athletic performance and stamina [13]. These datasets consolidate multiple variables recorded sequentially over time, offering an integrative view that is instrumental in understanding and improving athletic performance while ensuring the safety of athletes (see Figure 5.3). By analyzing historical data on multiple dimensions of an athlete's training load and physiological responses [181], predictive models can provide insights that guide training periodization, competition strategies, and injury prevention plans. Furthermore, nuanced anomaly detection within these datasets can preemptively alert coaches and medical personnel to deviations from the typical performance profile of an athlete [22], which can indicate emerging health concerns or the onset of fatigue [21]. Predictive modeling, powered by multivariate time series data, is invaluable for forecasting future performance and potential injury risks.

Table 5.2: Contrasting the challenges in sports health with the solutions provided by classic methods and those provided by the novelties of the AI-assisted approaches

Challenges / Issues	**Existing solutions [69, 70]**	**Novelties of the AI-assisted approach**
Fatigue detection	Reliant on subjective measures, such as athlete self-reports and coach observations.	AI models predict fatigue objectively before physical symptoms manifest, using physiological data.
Personalization	Generic training programs, one-size-fits-all approach with limited personalization.	Tailored training regimens adapted to the individual physiological responses and recovery profiles.
Real-time feedback	Delayed feedback post-training sessions, based on manual data review.	Instantaneous feedback during training via wearable tech integration, enabling immediate adjustments.
Injury prevention	Reactive approaches that respond to injuries post-occurrence.	Proactive injury risk assessments and preventative suggestions based on predictive analytics.
Training load optimization	Empirical methods for deciding on training loads, often leading to over- or undertraining.	Data-driven load optimization that continuously adapts to an athlete's current state and needs.
Long term monitoring	Fragmented data collection with sporadic athletes testing, lacking continuity.	Continuous monitoring and longitudinal performance tracking, with detailed historical data analysis.

Table 5.3: Comparison between existing solutions and AI-assisted approaches for fatigue and stamina control in performance sports.

Aspect	**Existing solutions [69, 70]**	**Novelties of the AI-Assisted approach**
Simplicity and accessibility	Rely on easily interpretable metrics like HR; less technical expertise required.	May require specialized knowledge to interpret complex AI model outputs.
Proven frameworks	Backed by empirical research and traditional sports science principles.	Emerging, potentially backed by data science and ML principles.
Ease of implementation	Can be implemented without complex infrastructure.	Requires significant investment in data collection and processing infrastructure.
Data utilization	Limited to simple and fewer data points; may miss multifaceted fatigue indicators.	Utilizes large, multivariate datasets from IMUs for a comprehensive analysis.
Predictive capabilities	Generally reactive, identifying issues after they occur.	Predictive, with the potential to preemptively adjust training to prevent fatigue.
Personalization	Often generic, leading to one-size-fits-all training programs.	Highly personalized, with tailored training and recovery recommendations.
Continuous learning	Static models with limited adaptability to new data.	Models improve over time with continuous learning and data input.
Infrastructure requirements	Minimal technical requirements for data collection and analysis.	Requires advanced systems for real-time data collection and ML analysis.

In terms of how they are used, multivariate time series datasets [182] help to improve complex AI models, such as DL networks, which need many different kinds of data to find

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hidden patterns [183]. These models are increasingly used to simulate complex athletic scenarios and develop real-time decision-making tools for in-game strategy and training adjustments [184]. The introduction of big data technologies has enabled the sports industry to use large-scale multivariate datasets for real-time analytics, giving it a competitive advantage and strengthening the safety standards that protect athletes. In conclusion, multivariate time series datasets are important in sports and sports safety because they provide as a solid platform for developing advanced analytical tools that increase athletic performance and protect athlete health. Their comprehensive nature allows for a more in-depth understanding of the many facets of sports dynamics, making them a useful asset in data-driven improvement of athletic training and care.

Limitations of the approach

Although AI-assisted fatigue and stamina control in performance sports has progressed, some issues and limitations must still be carefully considered when using multivariate time series datasets generated by IMU [42]. First, the quality and granularity of the data collected by the IMUs are crucial. IMUs [32, 33] can be susceptible to noise and errors in data capture, which can lead to inaccuracies in AI analysis (see Table 5.3) and subsequent recommendations. The precision of the sensors, where they are placed in the body of the athlete, and the algorithms used to clean and process the data [185] can make the method less useful. Furthermore, the interpretation of AI-generated insights requires domain expertise. Coaches and sports scientists must understand the context and limitations of the data. Dependence excessively on AI without a thorough grasp of an athlete's physical and psychological state may result in poor or even harmful training decisions. Another issue is that athletes vary greatly. AI models frequently need a big quantity of data to effectively forecast fatigue and stamina thresholds. There is also the risk of overfitting, in which an AI model performs extraordinarily well on past data but fails to generalize to new or unexplored data. This might happen when the model learns about the noise in the dataset rather than the underlying pattern it is supposed to predict.

Furthermore, due to the dynamic nature of human physiology, psychological stress, sleep quality, nutrition, and other lifestyle factors can all affect an athlete's level of fatigue and stamina. The exclusion of these factors can limit the completeness of AI assessments. Ethical considerations also come into play. Pervasive surveillance of athletes raises privacy concerns and data must be handled with strict confidentiality and consent protocols. Coaches and sports professionals may hesitate to adopt AI-driven methods, preferring traditional training and recovery methodologies. This resistance can slow down the integration of AI technologies into athletic training and management. In general, AI-assisted fatigue and stamina control using IMU-generated [42] data [32, 33] has a lot of potential to improve athletic performance [22]. However, it is limited by technological, methodological and ethical issues that must be solved by technologists, sports scientists, coaches, and athletes working together.

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5.3 Challenges of health condition control in sports

5.3.1 Injury prevention with fatigue control

ACWR helps identify imbalances between acute (short-term) and chronic (long-term) workloads [26]. Maintaining an optimal balance between these two components is crucial to maximize performance gains [22] while minimizing the risk of injury. Integrating subjective and objective metrics with sRPE and ACWR allows a more comprehensive understanding of the training load [81] and the level of fatigue of an athlete. The main challenge of the thesis was to validate whether sRPE and ACWR [29] can be used in conjunction with other monitoring tools, such as GPS tracking [186], HR variability, and condition level questionnaires, to provide a complete understanding of the physiological state of an athlete [187] and readiness for training, making them highly compatible with other sports safety monitoring tools. The thesis substantiated that, by tracking sRPE and ACWR, coaches and sports health professionals can identify early signs of excessive fatigue, overtraining, or increased risk of injury and act accordingly to prevent adverse outcomes [26].

5.3.2 Microsleep analysis for fatigue control

CNNs are at the forefront, effectively processing spatial-temporal data from EEG signals to identify patterns indicative of microsleep. RNNs, specifically LSTM networks, are highly effective in capturing time-dependent changes in physiological signals. This makes them well-suited for identifying the sequential patterns that are typical of microsleep episodes. Large annotated data sets [175] let these DL models learn complex microsleep state representations. Pre-trained models can adapt to tasks or physiological signal variations using transfer learning and fine-tuning, enhancing detection accuracy. Real-time monitoring systems with DL models (see Fig.5.5) could alter safety measures for microsleep-prone scenarios such as driving or operating heavy machinery. Researchers can identify microsleep episodes using pre-processing, feature extraction, and classification to study sleep patterns and design safety-critical applications.

To effectively utilize Voronoi and coverage control algorithms, a comprehensive understanding of the intricacies of sleep physiology and the distinct brain activity patterns related to various stages of sleep [188] is requested. The models need to be tailored to capture the complexities of sleep dynamics. The effectiveness of these algorithms in microsleep detection and real-time sleep staging heavily depends on the advancements in sensor technology (e.g., sensitivity, specificity, and form factor) and data processing capabilities (e.g., real-time analysis, ML algorithms for pattern recognition).

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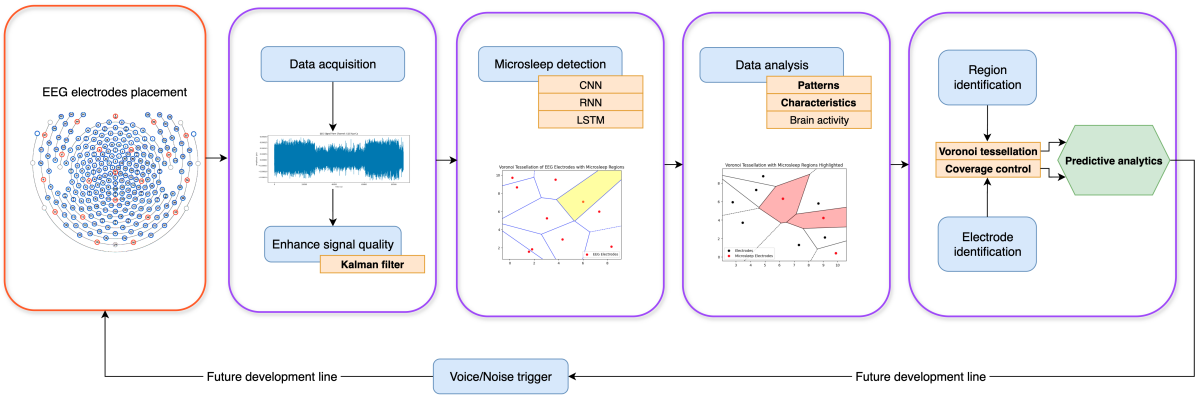


Figure 5.5: Proposed technological pipeline

5.3.3 Personalized recovery

Personalized training schedules, sculpted using AI algorithms, promise optimized performance [22] and reduced risk of injury. Cognitive training tools develop athlete decision making and reflexes, which are crucial in competitive situations [22]. The psychological well-being of athletes is also taken into account, with AI discerning early indicators of emotional stress. One of the most significant improvements is AI's capacity to build personalized training routines tailored to individual athletes, ensuring optimal performance while reducing the risk of injury. This is reinforced by the rapid emergence of wearable technology, which gives real-time metrics that can lead immediate changes in training approaches. It facilitates proactive modifications in training routines, ensuring that athletes maintain physical integrity.

5.4 Challenges of disease detection and injury prevention in sports

5.4.1 Disease detection from voice

Developing voice-based, non-invasive disease detection systems requires collaboration between multiple fields, including data science, linguistics, ML, and medical research. Voice-based disease detection [189] with AI [190] is gaining attention as a novel and disruptive topic in various sectors, including sports. Traditional health monitoring techniques [191] may require invasive tests, specialized equipment, or time-consuming procedures, while the AI-based detection system described in the thesis removes all these disadvantages.

5.4.2 Burnout in performance sport

Predicting burnout from texts by using AI requires an interdisciplinary approach that combines sports science, psychology, and ML. AI-driven insights [18] can assist players in self-regulation, balancing stamina, and fatigue. Simultaneous analysis of stamina and

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fatigue will result in a burnout analysis from the point of view of physical, emotional, and psychic exhaustion. Burnout can be due to overtraining and exhaustion [192]. Text analysis can reveal a player's mental condition [193] and small emotional changes, revealing their burnout. This technique promotes mental well-being, breaks stigma in the demanding sports sector, and benefits society. Holistic athlete welfare leads to longer and healthier sports careers and establishes a model for mental health in other high-pressure industries.

5.4.3 Disease detection from written communication

Text message analysis can provide signals indicative of a health problem [194, 195], this method is far from diagnostic, so it can be just a preventive support tool for specialists (see Figure 5.6). Identifying diseases requires a thorough clinical evaluation and should not be performed solely on the basis of text message analysis. Furthermore, ethical considerations around privacy and consent are paramount when analyzing personal communications for health-related insights. From a data science and AI perspective, the process would involve (1) data collection and /or preparation, (2) NLP, (3) ML and (4) validation. What is of paramount importance is to obtain a large, reproducible, valid dataset of text messages with appropriate permissions. This process is followed by employing techniques to analyze semantic content, sentiment [196], and changes in language patterns over time. The next step is to develop predictive models that could correlate certain characteristics of the text with disease markers, followed by a rigorous testing and validation process with clinical data to ensure that the predictions have real-world applicability and do not result in false positives or negatives.

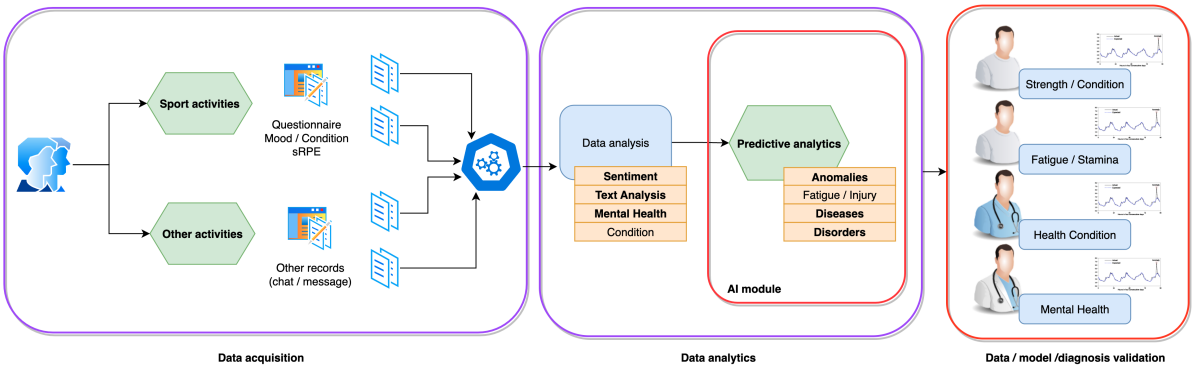


Figure 5.6: Text to diagnosis with AI: conceptual approach

In the quest to understand and improve the diagnosis of mental health and neurodegenerative disorders [19], it is imperative to *thoroughly examine current diagnostic methodologies* (Section 5.4.3), *acknowledge their inherent limitations* (Section 5.4.3), and emphasize the *importance of ongoing research in sports and sports safety*, which offers a unique perspective on cognitive and psychological well-being.

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Existing methods of mental health and NDD diagnosis

The diagnosis of mental health and NDD is an intricate and multifaceted process that traditionally involves a combination of clinical evaluation, neuropsychological testing, biomarker analysis, and neuroimaging techniques. Clinicians rely on structured interviews and standardized questionnaires [197] to determine the presence of symptomatology consistent with diagnostic criteria, such as those described in the Diagnostic and Statistical Manual of Mental Disorders (DSM) or the International Classification of Diseases (ICD). Neuropsychological evaluations [198] provide a quantitative measure of cognitive functions, including memory, attention, language, and executive function, which can indicate specific neurocognitive disorders. In the realm of neurodegenerative diseases [19], the use of biomarkers obtained from cerebrospinal fluid (CSF) and blood tests [199, 200] can offer biochemical evidence of the underlying pathophysiology, such as the presence of amyloid beta or tau proteins in Alzheimer's disease [200]. Neuroimaging techniques, including magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT), help visualize structural and functional changes in the brain [201–203]. These traditional methods, while robust, are complemented by emerging technologies such as digital phenotyping and ML algorithms that analyze patterns in speech, typing, and daily activity data to improve early detection and personalized care approaches. However, the integration of these novel methods into clinical practice remains a subject of ongoing research and ethical scrutiny. Ethical scrutiny and ongoing research, to which this thesis also contributes.

Limitations of mental health and NDD diagnosis methods

The diagnostic paradigms for mental health and NDD [204] have several limitations that can hinder their efficacy. Clinically, reliance on self-reported symptoms and observable behavior during patient interviews is subject to bias [145] and the variable ability of patients to accurately communicate their experiences. The heterogeneity of the presentation of symptoms and the overlap between different disorders can lead to diagnostic ambiguity. Neuropsychological tests, while invaluable, are time-consuming, require specialized personnel to administer, and can be influenced by an individual's educational background, cultural factors, and test-retest variability [205]. In the context of neurodegenerative diseases [20], the definitive diagnosis [206] is often only possible postmortem through histopathological examination, and current in vivo techniques provide mainly supporting evidence. Biomarkers, although a promising avenue for early detection, are not universally available and can lack specificity, as many are not exclusive to a single disorder. Neuroimaging [207], while providing detailed information on brain structure and function, is expensive, not always accessible, and can produce false negatives, especially in the early stages of neurodegenerative processes. These limitations underscore the need for the continuous refinement of diagnostic tools, and the thesis contributes to the

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development of more accessible, objective, and precise assessment methods.

Limitations of AI-parsed text analysis on prediagnosis

While innovative, precognition of mental health and NDD through AI-parsed text and sentiment analysis encounters specific constraints that limit its current clinical utility [19]. One significant limitation is the potential for algorithmic bias, where AI models may exhibit skewed performance due to imbalances or lack of diversity in training datasets. Such biases can result in differential accuracy between populations, leading to misclassification or underrepresentation of certain demographic groups [208]. Sentiment analysis algorithms can misclassify the emotional value of such nuanced communication, potentially resulting in false indicators of a disorder. The inherent ambiguity in language, especially when considering text out of context or in short snippets typical of digital communication, further exacerbates the risk of erroneous conclusions. Data privacy is a critical issue, as the use of personal text data for AI analysis [36] requires rigorous consent protocols and data protection measures to protect against confidentiality breaches. Ethical considerations also extend to the implications of false positives or negatives, which can profoundly affect individuals' lives, including unwarranted distress, stigmatization, or inappropriate medical intervention. The variability in individual communication styles and changes over time adds to the complexity of establishing consistent and reliable diagnostic criteria through text analysis. For neurodegenerative diseases [19], which progress over time, establishing a baseline for comparison can be challenging, and deviations from the baseline can be subtle and gradual, making them difficult to detect reliably. Lastly, current diagnostic standards for mental health and NDD involve a multifaceted clinical approach, including direct patient interviews, cognitive assessments, and medical examinations. While providing valuable additional information, AI-parsed text and sentiment analysis cannot yet replicate the depth and breadth of these traditional methods. Clinicians must interpret AI-generated data with caution, integrating them with a comprehensive clinical picture to make informed decisions about diagnosis and treatment.

5.4.4 Lesions and tumor detection on severe head injuries

Real-time detection of brain lesions [209,210] and tumors after severe head injuries [28,147] in sports of performance is a significant concern today in the field of sports safety and performance (especially in the case of ice hockey and American football). Applying AI, such as using object detection models, for example, YOLO, YOLO-NAS, to this problem can offer several justifications and novelties, as follows: (1) Early detection of a brain injury brings an earlier intervention with earlier treatment, which can significantly improve results, increasing the percentage of a quicker rehabilitation process [22] [36]. The AI pipeline proposed in the article [28] can analyze medical images in real time and alert medical personnel if it detects a potential lesion or tumor (which can be low-grade

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gliomas (LGG) and high-grade gliomas (HGG)) [28, 211], allowing immediate intervention; (2) YOLO and YOLO-NAS [212] have the potential to match or even exceed the performance of human experts in interpreting medical images. The accuracy depends on the training dataset. Dedicated models can be trained to identify subtle patterns that humans may miss and do not suffer from fatigue or cognitive biases; (3) ML models can provide consistent results, unlike human experts. They analyze every image in the same way, regardless of the time of day, how many images they have already analyzed, or other factors that could affect human performance; (4) An AI-supported brain / injury / anomaly detection system can analyze images much faster than a human expert can, and multiple images can be analyzed simultaneously if sufficient computational resources are available. This type of scalability makes it possible to screen a large number of athletes, even in sports where head injuries are common, such as American football [213] or rugby, as later proved by this thesis.

5.5 Challenges of sport strategy predictions and gamification

The usages of You Only Look Once (YOLO) and You Only Look Once Neural Architecture Search (YOLO-NAS) models in digital tracking and strategy extraction [41] from videos is multifold. First, these models aim to detect and track players and objects in real time accurately, providing comprehensive data on their movements and interactions [35]. Second, they seek to extract strategic elements and patterns from the tracked data to help with performance analysis and strategy development [41]. Additionally, YOLO-NAS explicitly aims to optimize the network architecture for better tracking and strategy extraction.

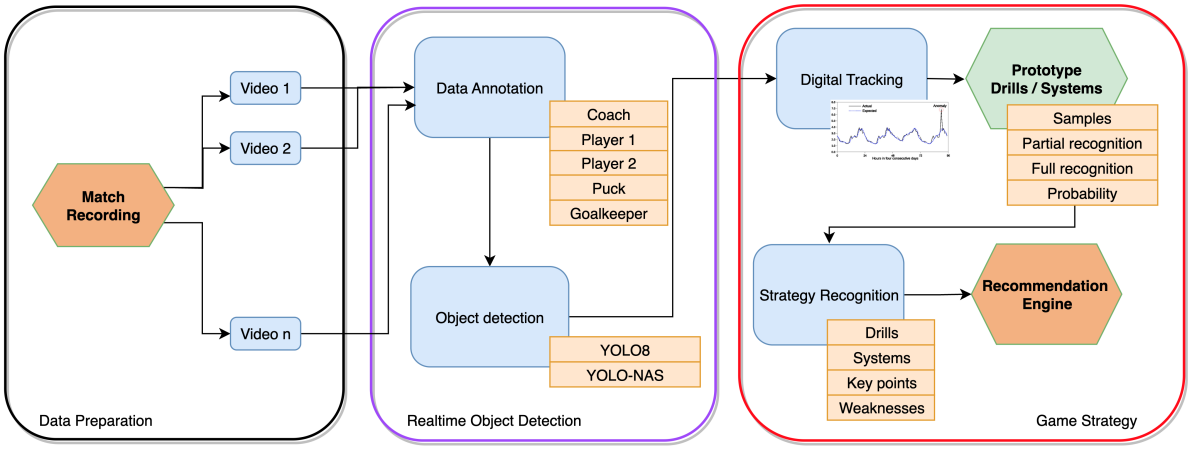


Figure 5.7: Predictive sports strategy technological approach

YOLO and YOLO-NAS applied in performance sports offer a data-driven solution [41]

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to optimize training, game strategies, and player development as follows: (1) the models can be applied to detect and track players and objects of interest in performance sports videos with high accuracy and near real-time. This enables the extraction of valuable data on player movement, puck / ball trajectory, and positional interactions, providing a detailed understanding of drill / strategy [214] or game dynamics; (2) By analyzing detected objects and their interactions, applied models can identify recurring patterns and strategic elements within sports drills or games. This information can be used to evaluate the effectiveness of specific strategies, evaluate player performance, and gain insight into team dynamics; (3) the extracted information can help recommend optimal strategies for performance sports. Coaches and analysts can take advantage of the insights obtained from these models to refine training routines, adapt game plans, and make data-driven decisions [215] to improve team performance and success. The real-time nature of the YOLO / YOLO-NAS models allows the analysis of live sports events on the fly, providing instantaneous feedback to coaches and players. This capability allows quick adjustments, tactical interventions, and immediate strategy recommendations [41] based on the analysis of current gameplay.

Using gamification, gernerative AI (GenAI) and reinforcement learning (RL) as motivational assets in performance sports [155] is unique in the sense that: it increases psychological engagement through gamified elements and physical training through customized dynamic scenarios, addressing both physical and mental aspects of sports performance in an integrated technology-driven framework. Integrating gamification and GenAI into performance team sports is innovative because it synergistically blends psychological motivation and adaptive technical innovation. RL [216] provides another level of motivation. Team sports training tends to focus on physical and tactical skills rather than using advanced digital technologies to motivate and engage athletes [217]. Game concepts such as points, levels, and achievement badges enhance training with gamification [218]. This fosters a culture of challenge and reward and capitalizes on the competitive spirit of sports, which can motivate athletes to train harder. RL-boosted GenAI systems can optimize real-time training settings (intensity, duration, structure, drills) by analyzing massive volumes of individual performance data (sRPE, MET, ACWR) [26]. To maximize training efficacy, this tailored approach matches training demands to each athlete's development stage and performance goals. AI can also mimic a number of competitive scenarios that athletes may not meet, preparing them for more potential competitiveness. Coaches and trainers can scale team dynamics management with these technologies. Coaches can identify individual and team needs more efficiently by automating data and sentiment analysis [18] and feedback, allowing more targeted human intervention. Furthermore, feedback loops between athletes' performance data and AI-driven training changes create an evolving data-driven training culture.

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5.5.1 Digital intervention efficacy with gamification

Gamification strategies are particularly effective in instigating behavioral change and informing new habits. The elements of the game in training can encourage consistent practice and adherence to prescribed routines, leading to long-term behavioral changes.

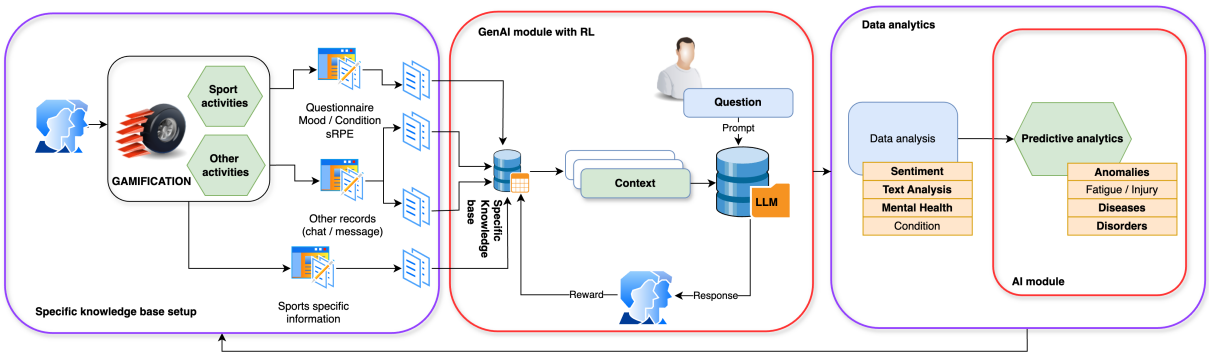


Figure 5.8: Motivational asset concept using gamification, GenAI and RL

The thesis investigates a more detailed and thorough understanding of an athlete's performance, which can be achieved by integrating gamification tactics with specialized training sets and digital technologies (see Fig. 5.8). This data-centric approach allows for a more individualized and efficient training program according to the abilities and limitations of each athlete. By turning training exercises into interactive and engaging games (providing more personalized training), athletes can learn new skills more quickly and effectively. This is due to the increased cognitive engagement and positive reinforcement mechanisms inherent in gamified systems [155]. Digital gamification in sport is challenging because it incorporates social elements, such as leaderboards [35], team challenges, and features of social sharing. Athletes are more likely to remain committed to their sport, group, team, or association when they find the training process enjoyable and rewarding (at the individual or team level). The prediction of tactics with specialized training sets and gamified digital technologies, as proposed by this thesis, contributes to the achievement of these benefits.

5.6 Summary of scientific contributions

The main scientific contributions of this chapter are summarized as follows: (1) extensive analysis of near real-time collaborative and videoconferencing tools with existing OCR implementations to handle context-sensitive languages, polysemy, ambiguity; (2) architecture analysis for End-to-End TVOD with Transformers using DETR (see Fig. 5.1) with limitations analysis; (3) design of a near real-time synthesized language translation pipeline, using modern text recognizers (see Fig. 5.2); (4) an in-depth analysis of existing solutions to prepare optimal training datasets for multilingual OCR projects and

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formulating the importance of vocabulary-based training datasets for multilingual real-time OCRs; (5) analysis of challenges, mitigation strategies and limitations of multilingual near real-time OCR solutions; (6) scalability analysis of multilingual OCR solutions and comparison analysis for HPC environment preparation; (7) conceptualization of a next-generation sports safety architecture approach concept (see Fig. 5.3); (7) conceptualization of a new sports safety architecture approach to manage multivariate time series datasets (see Fig. 5.4); (8) extensive benchmark analysis on existing solutions and the novelties of the AI-assisted approaches connected to fatigue and stamina control on multivariate time series datasets, higlighting the limitations as well; (9) conceptualization of a novel text to diagnosis technological pipeline with AI (see Fig. 5.6); (10) extensive benchmark on existing methods and limitations of existing mental health and NDD diagnosis methods, highlighting the limitations of AI-parsed text analysis on pre-diagnosis as well; (11) conceptualization of a novel predictive sports strategy technological pipeline (see Fig. 5.7); (12) conceptualization of a novel motivational asset method architecture concept using gamification, GenAI and RL (see Fig. 5.8).

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6 Methods

This chapter discusses validated, peer-reviewed, and published methods for advanced distant diagnostic techniques and sensors in sports safety and health condition predictions. It emphasizes key outcomes related to remote consultancy, radars and other sensors, health condition control, disease detection, injury prevention, and sports strategy prediction. The conclusion of the chapter provides a concise overview of the scientific contributions.

6.1 Methods in remote consultancy services

Instantaneous remote diagnostics during online video presentations require the prompt detection of multilingual phrases in real time, which in turn requires the rapid detection and pre-processing of visual objects for further analysis. Using the native language is the most efficient method to connect with remote experts and exchange specific ideas. This work seeks to investigate and provide models, architectures, hyperparameter suggestions, and particular techniques that use DETR to achieve precise real-time textual item detection for further analysis.

6.1.1 Multilingual remote consultancy

In this research [36,38,40], the DETR model was investigated with several variations. Research highlights the differences between the most prominent real-time object detectors, YOLO4, DETR, and Detectron2, and brings AI-based novelty to collaborative solutions combined with OCR. The TVOD method analyzed popular algorithms and models in object detection (e.g., Fast R-CNN, Faster R-CNN, Region-based CNNs, Region-based Fully Convolutional Networks, as well as real-time object detectors such as YOLO, DETECTRON and DETR) to synthesize the results and provide reliable results for a new type of collaborative working model [36]. The research results can be easily adapted to the field of sports safety using video conference tools or platforms. As mentioned by N. Carion et al., "DETR model directly predicts (in parallel) the final set of detections by combining a common CNN with a transformer architecture" [36].

Generically, the Transformer contains five major parts: (1) *input transformation for*

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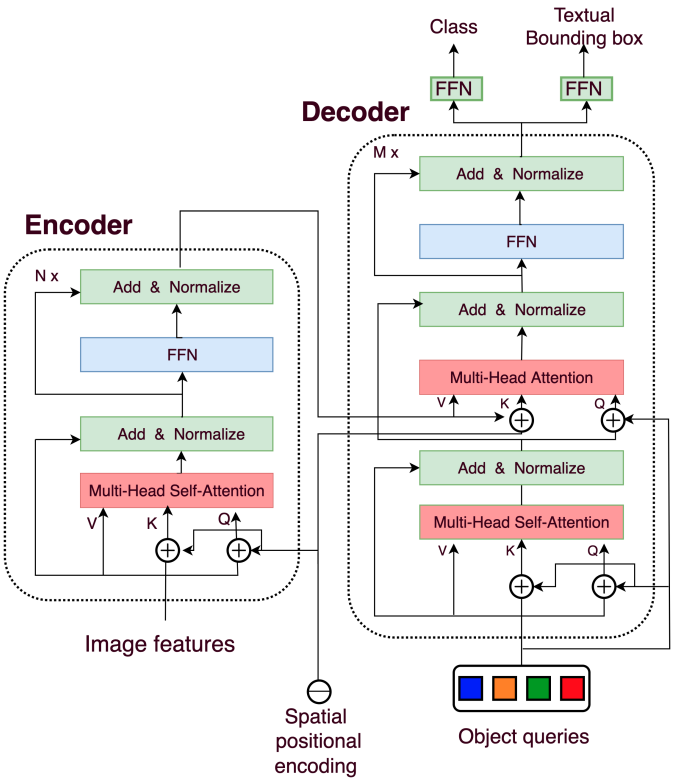


Figure 6.1: Detailed DETR transformer architecture according to Carion, Massa, Synnaeve *et al* [1].

Encoder, (2) *input transformation for Decoder*, (3) *encoder* – to extract the contextual features from the input sequence through the multi-head self-attention mechanism, (4) *decoder* – from encoder output to generate the next prediction, and (5) *Final layer* to map decoder output to the object probability space. As shown in Figure 5.1, the logic of the algorithm is structured as follows: (a) the ResNet50 backbone predicts the image characteristics, (b) the algorithm calculates the spatial positional encoding for each block of the predicted image resized to the size range of 800 to 1,333 pixels, (c) run the Transformer module on the blocks with the associated positional encoding, (d) each Transformer head predicts the bounding box and the object within it, and finally (e) the Transformer predicts the number of objects in the image.

There are two pillars of direct set predictions in the detection algorithm, as shown in Figure 5.1: (1) a set prediction loss, which allows for unique matching between the predicted and ground truth boxes, as well as (2) a dedicated architecture, which allows the prediction of a set of objects and models the relations in one step. The DETR transformer uses positional encodings in every attention layer, as shown in Figure 6.1. The image features are passed through the transformer encoder from the CNN backbone in parallel with the spatial positional encoding. These features are added to queries and keys within the "multi-head self-attention" layers. After that, the decoder gets the queries, outputs (i) positional encoding, and (ii) encoder memory. Finally, the final set of "predicted class labels" and "textual bounding boxes" are generated through the "multiple

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multi-head self-attention" and the "decoder-encoder attention" [36].

From a textual object detection perspective, DETR offers a simpler and more flexible pipeline architecture that requires fewer heuristics and casts the object detection task (in the case of text detection) as an image-to-set problem [36]. Traditional computer vision models use complex pipelines with custom layers to locate objects in an image and extract features. In contrast, DETR replaces this approach with a simpler neural network (NN), resulting in a deep end-to-end learning (DL) solution to the object detection problem. In TVOD research, the most important advantages are as follows: (a) Fast model–12 frames per second on GPU with the most accurate model configuration, (b) State-of-the-art accuracy as of 2020, and (c) it has a straightforward implementation thanks to the PyTorch wrapper. In the thesis experiments, a modest testing environment was used, accessible to anyone currently on the market [36].

6.1.2 Real-time synthesized and multilanguage OCR

ML-Based text recognizers

In this thesis study [38], the following types of modern text recognizer were used as shown in Figure 6.2: (a) CNN-RNN models and (b) the SVTR model – a single visual (scene) text recognition model explicitly designed for multilingual applications [2].

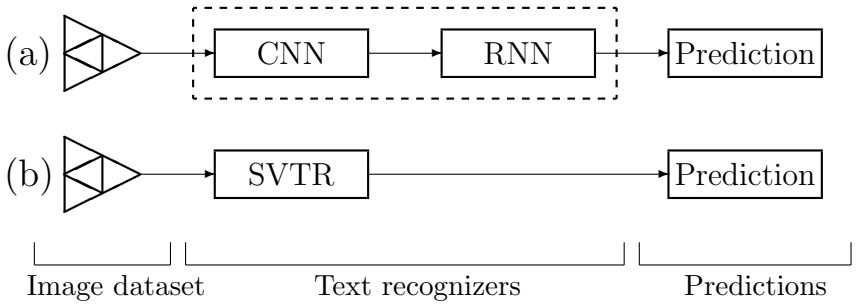


Figure 6.2: Modern text recognizers using (a) CRNN and (b) SVTR models, adapted from Du, Chen, Jia *et al* [2]

The thesis experiments carried out [40] were carried out using models (a) and (b). Through experiments [40], it was established that the accuracy and speed of inference play a critical role in decision making. The dataset and the model have been sufficiently trained to allow us to understand how to optimize the dataset and the model. Optimal input parameters and configurations for model training have been identified through some experiments. In addition to offering several configurable model training options, PaddleOCR has been configured to work with multiple model architectures [36, 38, 40]. The configuration of the most effective hyperparameters experimented with various model mutations, optimizing the parameters until the optimal ones were achieved. At the end of the investigations, a model was trained with 94% precision.

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CRNN model type

In case of CRNN, the convolutional layers extract characteristics from the input sequence, whereas the recurrent layers capture temporal dependencies. The output of the last convolutional layer is fed into a recurrent layer, either the Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) layer. The input to the network comprises the following sequence of "input vectors" $x_1, x_2, \ldots, x_T$, where T is considered the "length of the sequence." The output of this network is made up of the following 'output vector $y_1, y_2, \ldots, y_T$. The output of the i^{th} the "convolutional layer" can be defined as:

$$h_i = f(W_i * x + b_i), \tag{6.1}$$

where W_i is considered as the "weight matrix" for the ith "convolutional layer", where b_i is considered as the "bias vector" for the ith convolutional layer, $*$ shows the "convolution op", and f is an "activation function". The output of the recurrent layer is shown as $h_t = g(h_{t-1}, x_t)$, where h_t is considered as the "hidden state" of the recurrent layer at time t, g is the "recurrent function," and h_{t-1} is the "hidden state" of the recurrent layer defined at time $t-1$. The LSTM is a recurrent layer that is used in the CRNN algorithm to capture temporal dependencies in the input sequence. For an LSTM layer, the recurrent function g can be expressed as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \tag{6.2}$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \tag{6.3}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tag{6.4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c), \tag{6.5}$$

$$h_t = o_t \odot \tanh(c_t), \tag{6.6}$$

where i_t, f_t, o_t, and c_t are the vectors "InputGate", "ForgetGate", "OutputGate", and "Cell-State" vectors at time t, and W_i, W_f, W_o, W_c, U_i, U_f, U_o, U_c, b_i, b_f, b_o, and b_c is the "weight matrices" and "bias vectors" for LSTM [219]. GRU is a recurrent layer that is used in the CRNN to capture temporal dependencies in the input sequence. For a GRU layer, the recurrent function g can be expressed as

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \tag{6.7}$$

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$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z), \tag{6.8}$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h), \tag{6.9}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t, \tag{6.10}$$

where r_t, z_t, and $\tilde{h}_t$ are the "ResetGate", "UpdateGate", and "CandidateHiddenState" vectors at time t, while W_r, W_z, W_h, U_r, U_z, U_h, b_r, b_z, and b_h is the "weight matrices" and "bias vectors" for the GRU. As shown in the CRNN architecture in Figure 6.3, the extraction process of beneficial features is performed sequentially, applying convolutions and maximum grouping operations. When these are received, they are put into the recurrent unit, which stores information based on how it happened in time.

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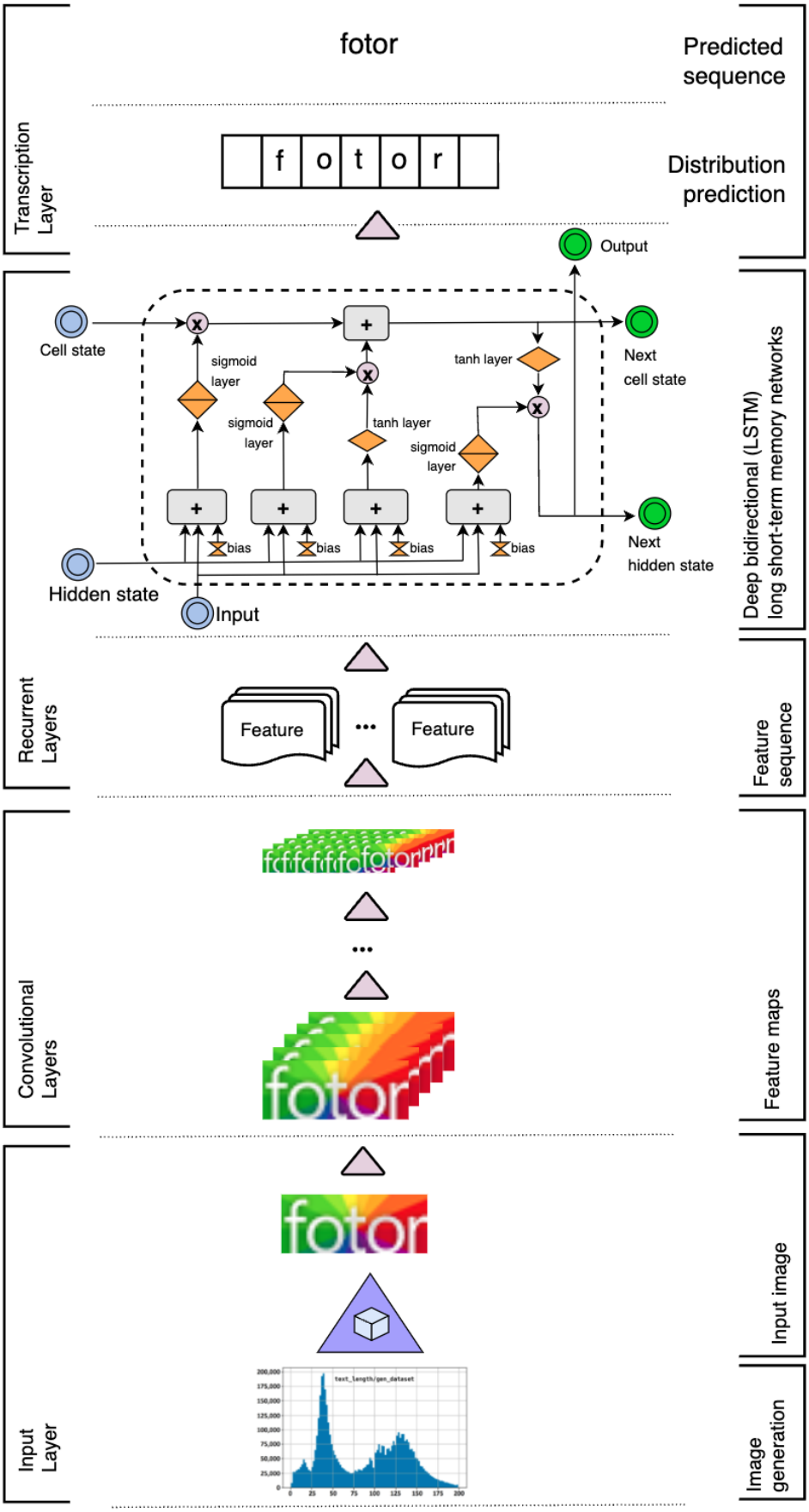


Figure 6.3: CRNN architecture with CRNN feature extraction, adapted from Keren, Schuller [3]

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SVTR model type

The SVTR [2,220] model, as presented in Figure 6.4, uses a patch-wise image tokenization framework [38], eliminating the need for sequential modeling [220].

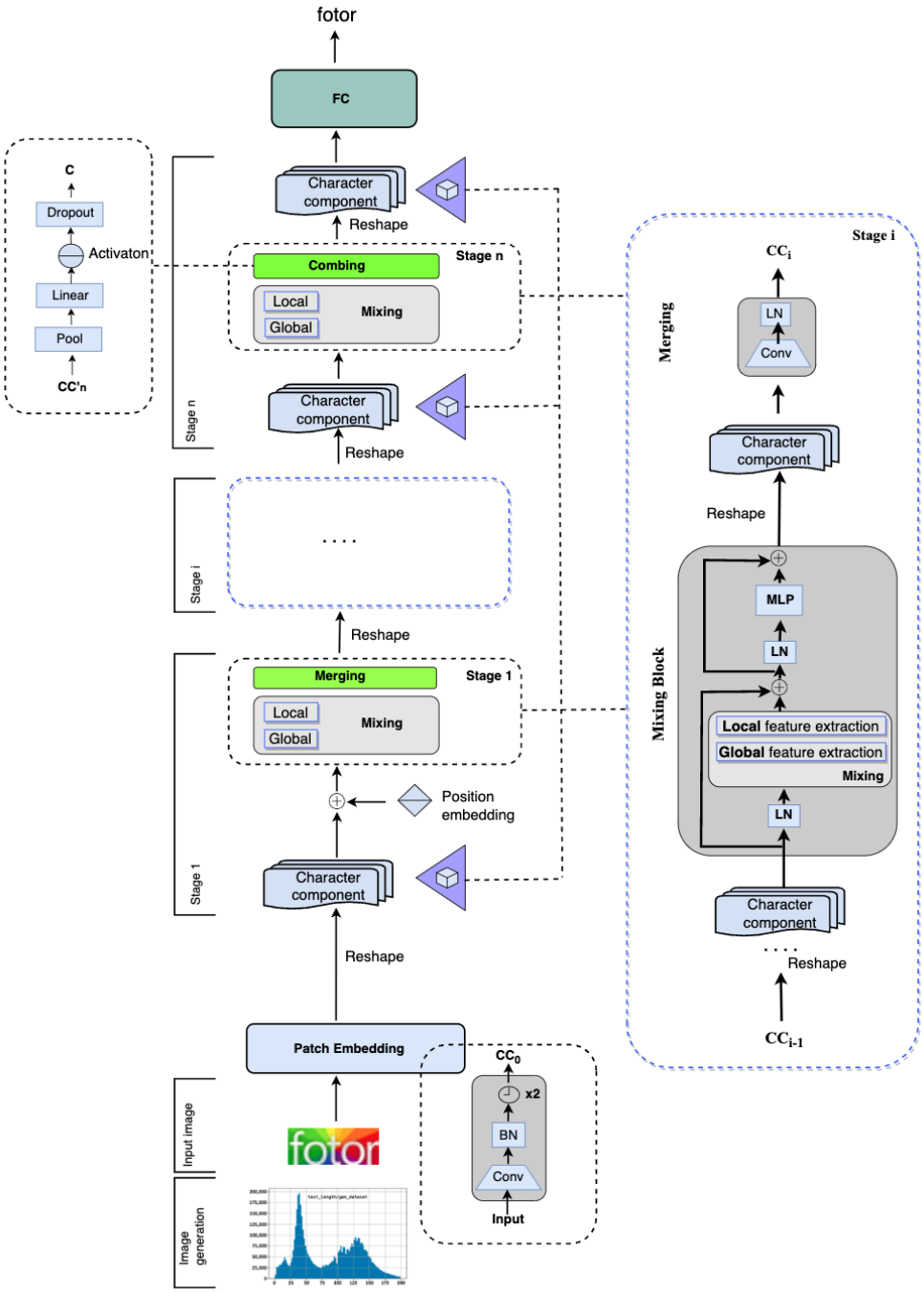


Figure 6.4: SVTR architecture adapted from Du, Chen, Jia *et al* [2].

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It uses a single visual model to recognize text in scenes. SVTR [38] can be defined as:

$$y(t) = f[t; z(t)] + e(t), \tag{6.11}$$

where $y(t)$ is the response variable at time t, $f[t; z(t)]$ is the piecewise linear function with varying thresholds, $z(t)$ are the threshold values, and $e(t)$ is the error term at time t. The piecewise linear function with varying thresholds can be written as:

$$f[t; z(t)] = \beta_0(t) + \beta_1(t)x(t) + \theta_i(t)[\beta_2(t) + \beta_3(t)x(t)], \tag{6.12}$$

where $\beta_0(t)$ and $\beta_1(t)$ are the "intercept param" and "slope param" for the linear segment, $\beta_2(t)$ and $\beta_3(t)$ are the intercept and slope parameters for the threshold segment, $\theta_i(t)$ is the indicator function that equals 1 when $z(t) > \tau_i$ and 0 otherwise, and τ_i is the threshold value i^{th}. The indicator function $\theta_i(t)$:

$$\theta_i(t) = \begin{cases} 1 & \text{if } z(t) > \tau_i \\ 0 & \text{otherwise} \end{cases}. \tag{6.13}$$

The threshold values $z(t)$ can be modeled using a threshold function $g(t; \theta)$ that varies with time t and a smoothing parameter λ:

$$z(t) = g(t; \theta) + \epsilon(t), \tag{6.14}$$

where $\epsilon(t)$ is the 'error term' for the threshold value at time t. A common choice of threshold function is the sigmoid function.

$$g(t; \theta) = \frac{c}{1 + e^{-(t-d)/a}}, \tag{6.15}$$

where c, a, d, and θ are the model parameters that determine the shape and location of the threshold function. The SVTR algorithm can be estimated by using the maximum likelihood estimation or Bayesian inference methods [38]. The model parameters can be estimated using iterative algorithms, such as the EM algorithm, or gradient descent methods, such as the stochastic gradient descent (SGD) algorithm. Following this, the hierarchy of stages is repeated for the mixing, merging, and combining of the components at the component level. To perceive inter- and intra-character patterns, global and local mixing blocks are combined, resulting in a multigrain perception of character components. Due to the use of this model by PaddleOCR3 [36,38,40], these model architectures were called version 3 (v3) during this thesis experiment [38]. Figure 6.4 illustrates the architecture of SVTR.

Differences between CRNN and SVTR models

Both CRNN and SVTR are ML-based OCR engine architectures proposed to increase the precision and efficiency of OCR systems [38]. Here are a few significant distinctions

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between the two models.

- *Inputs*: CRNNs are designed to operate with image inputs, but SVTRs can process pictures, videos, and live video streams. CRNNs use a combination of CNNs and RNNs to detect text in images, whereas SVTRs use a combination of DL and conventional image processing techniques,
- *Text recognition*: CRNNs are adept at recognizing texts of various font styles, sizes, and orientations, as well as multiple lines of text in an image, and can perform well in scene text recognition, while SVTRs are specifically designed to handle scene text in images, which can vary significantly in terms of lighting, orientation, and skew,
- *Attention mechanism*: CRNNs lack an attention mechanism, but SVTRs possess one. This attention mechanism enables the network to concentrate on an image's significant parts and increases the model's noise and distortion resistance. Due to the attention mechanism they employ, SVTRs are more resistant to noise and distortion. CRNNs are susceptible to noise and distortion,
- *Training and fine-tuning*: CRNN and SVTR architectures are adaptive and can be fine-tuned with more data to increase accuracy. However, CRNN models require substantial training data to produce accurate results. In contrast, SVTR models can also learn from fewer data.

CRNNs are faster than conventional OCR engines because they can run on parallel architectures such as GPUs. In contrast, SVTRs can run on various platforms, including smartphones and embedded systems [38].

Hyperparameter tuning

Several aspects of the training process and the model were adjusted and/or calibrated to achieve better results. You can find a list of configurable parameters and their meaning in the Results section [38].

6.1.3 Optimal dataset preparation in visual object detection

To improve the performance of AI-supported OCRs, it is essential to provide diverse and representative training data. One approach is to use multimodal data augmentation approaches, which entail creating fresh training samples by integrating text, graphics, and other media. This can involve modeling different text fonts, sizes, and orientations, adding noise and artifacts to simulate real-world situations, and using image context, such as background components or text within photos, to increase OCR accuracy.

Traditional training datasets are often static and may not evolve with changing requirements of the OCR system.

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Single-line / multi-line regularization

It is essential to handle single and multi-line pictures properly; this is the first point where it is possible to apply visual control to the data generation process. To optimize the dataset, the Sobel filter [221] was used on top of the generated dataset to identify, extract, and annotate multi-line pictures for further analysis. Figure 6.5 presents the application of the Sobel filter, where the horizontal axis represents the rows of the image and the vertical axis represents the number of bright pixels. When using this filter, the algorithms can determine whether the image contains multiple rows based on peaks on the chart if a large number of paler pixels are present in a given pixel row. Consequently, it includes characters. See the statistics of single-line and multi-line images with six text lines below.

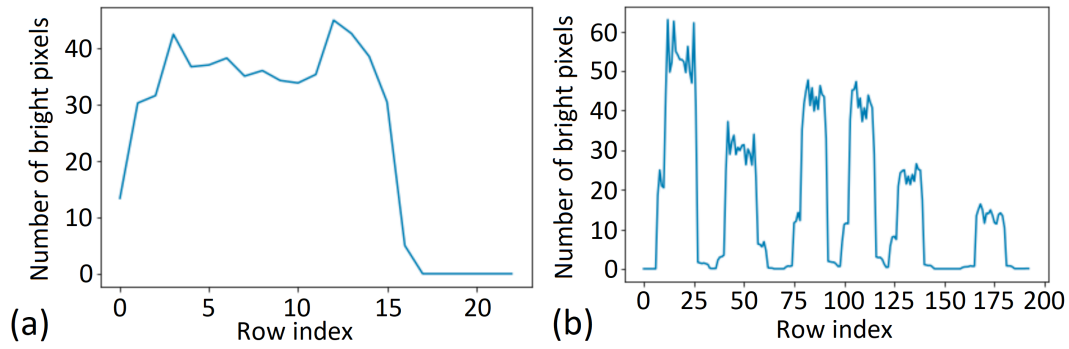


Figure 6.5: Sobel filter on data generation: (a) in case of single-line text; (b) in case of multi-line text

Active learning is a technique that helps to identify areas where the model is uncertain and prioritizes those areas for human annotation. Incorporating a human-in-the-loop approach [47] can continuously refine the training dataset based on model performance, focusing on the most difficult or ambiguous cases. This enables the OCR system to better adapt to real-time requirements, leading to a more accurate and robust model. Multi-language, real-time OCR systems in domain-specific use cases (e.g., collaborative work, remote diagnosis) must recognize and understand texts in various languages, often with limited or unbalanced training data for each language [36]. Cross-lingual and cross-domain transfer learning techniques can transfer the understanding of one language or field to another, improving the model's performance on low-resource or underrepresented domains. Pre-training the model on large, diverse, multilingual text corpora can fine-tune it to specific languages or domains with limited data, leading to a more efficient and accurate OCR system.

Optimal data distribution calculation

Data pre-processing: the prerequisites for OCR training include pre-processing of data and ensuring their cleanliness and correct formatting. The following formula represents

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the data pre-processing step:

$$x_{pre}^{(i)} = \text{Preprocess}(x^{(i)}), \tag{6.16}$$

where $x^{(i)}$ represents the i^{th} training sample and $x_{pre}^{(i)}$ represents the preprocessed version of the sample.

Feature extraction: After pre-processing the data, the next step is to extract the characteristics that can be used to train the OCR system. The following formula represents the feature extraction step:

$$f(x_{pre}^{(i)}) = \text{ExtractFeatures}(x_{pre}^{(i)}), \tag{6.17}$$

where $f(x_{pre}^{(i)})$ represents the features extracted for the training sample i^{th}.

Model training: once the features have been extracted, the OCR system can be trained using a suitable ML algorithm. The following formula represents the model training step:

$$\hat{y}^{(i)} = \text{Train}(f(x_{pre}^{(i)}), y^{(i)}), \tag{6.18}$$

where $\hat{y}^{(i)}$ represents the predicted output for the i^{th} training sample, $y^{(i)}$ represents the true label for the sample, and Train represents the training algorithm.

Data Distribution Calculation: the following formula can be used to calculate the optimal data distribution to train an OCR system for the English, Hungarian, and Japanese languages:

$$p_i = \frac{n_i}{\sum_{j=1}^{m} n_j}, \tag{6.19}$$

where p_i represents the probability of selecting a training sample from language i, n_i represents the number of training samples in language i, and m represents the total number of languages in the dataset [222, 223]. Combined with suitable ML algorithms and training techniques, these formulas can optimize the data distribution to train OCR systems for English, Hungarian, and Japanese.

Training dataset

The thesis experiments used training datasets of 15M, 30M and 50M of generated phrases with a character number generated between 0 and 200 characters in English, Hungarian, and Japanese. Python used realistic template-based picture generation [36] for data generation.

Exploratory data analysis

It is recommended that the data generation process be iterative and that the distribution of the training dataset be visualized according to templates or application categories, as

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represented in [36]. The visual representation of the text length is the most critical in the case of multilanguage OCR, especially when it combines European language families (e.g., Anglo-Saxon, Latin, Germanic) with Asian ones (e.g., Japanese, Chinese).

Vocabulary generation

The method used for both (Generated and Unified) types of vocabulary generation is presented in [36]. The thesis experiments suggest that the vocabulary generated from the training dataset gives more accurate results but needs expert supervision on dataset generation. This option is recommended because this method ensures that only the characters present in the training dataset will appear in the vocabulary and there will be no unnecessary characters. This will be an important factor when a Japanese or Chinese character set is included in the scope of OCR development.

6.2 Methods in the usage of radars and 3D accelerometers

6.2.1 RPA Intensity with radars and 3D accelerometers

HR targets for vigorous-intensity physical activity

Correlation algorithms [15] can assess the relationship between HR and RPE rating. Numerous strategies have been developed in the literature to calculate this correlation. An example is the algorithm that uses a modified version of Pearson's correlation coefficient to calculate the correlation between HR and RPE. This algorithm uses the following steps: (i) acquire HR and RPE data from a physical activity dataset; (ii) represent the data in a scatter plot diagram (HR on the axis x and RPE on the axis y; (iii) determine the correlation coefficient (r) between HR and RPE using the Equation (6.20) shown below:

$$r = \frac{n\sum xy - \sum x \sum y}{\sqrt{n\sum x^2 - (\sum x)^2}\sqrt{n\sum y^2 - (\sum y)^2}} \ , \tag{6.20}$$

where n is the number of data points, x is HR, y is RPE, $\sum x$ is the sum of all HR values, $\sum y$ is the sum of all RPE values, $\sum xy$ is the sum of all HR products and RPE values, $\sum x^2$ is the sum of the squares of the HR values, and $\sum y^2$ is the sum of the squares of the RPE values. The correlation coefficient r is defined as follows in the relation between HR and RPE: (a) if $r = 1$, then a perfect positive correlation; (b) if $r = -1$, then a perfect negative correlation is visible; (c) if $r = 0$, this is the case without correlation; (d) if $0 < r < 1$, then it is a positive correlation; lastly, (e) if $-1 < r < 0$, then that is an existing negative correlation. It is important to note that this is just one example of a correlation algorithm for HR and RPE. Depending on the specific context or RQ, different approaches or variations can be applied. Additionally, this algorithm provides

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the correlation between both variables, but another approach, such as regression or ML algorithms, could provide more insight and accurate predictions.

Physical activity intensity

It is often classified as light, moderate and vigorous exercise based on the absolute amount of energy expended during physical exercise. The multiples of MET express energy expenditure [224]. MET estimates the energy expended during a particular activity.

The root mean square (RMS) of the acceleration data in each axis may be calculated, which can provide an overall measure of the intensity of the movement. Once the data are processed, a regression model or equation is needed to convert the data into an estimate of MET. Several existing models and equations can be used for this purpose. The thesis experiments carried out reused the results of one of the existing previous research projects. However, they typically require calibration using data collected from a sample of people performing the activity while measuring energy expenditure [224] using more direct methods, such as indirect calorimetry.

Depending on the sport or activity in which we participate, the level of granularity or precision required, and the type of device and sensor used, a different method might be used. As explained in the previous paragraph, the absolute level of aerobic exercise intensity is measured in terms of metabolic equivalents (MET). A light intensity activity requires less than 3.0 metabolic equivalents per minute for its performance to be effective, i.e., it is a non-sedentary waking activity. The amount of energy expended walking at a speed of 2.0 miles per hour is 2.5 METs, so walking at 2.0 miles per hour is classified as low intensity exercise because the amount of energy expended is not greater than 2.5 METs. Exercise can take many forms, including running, jogging, lifting heavy objects, taking vigorous exercise classes, and even carrying heavy objects up and down the stairs.

To describe the amount of energy expended with a particular type of activity [32,33], METs or metabolic equivalents of tasks are valuable units of measurement. These units can be used to determine the amount of energy expended. A MET is defined as the ratio of an individual's energy expenditure during exercise to their energy expenditure when at rest. For example, the MET index can be used to measure how much energy a person consumes at rest. It is estimated that if an individual engages in an activity for 30 minutes and performs 4 METs of physical activity, they will have performed 120 MET minutes, equivalent to 2 MET hours. To reach 120 MET minutes, complete 15 minutes of activities needing 8 METs each at a speed of 2 MET per minute. This allows one to accumulate 120 MET minutes.

MET calculation algorithm

Several algorithms have been proposed to calculate the metabolic equivalent of a task (MET) based on physical activity data, such as 3D acceleration or HR data. Depending

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on the nature of the activity and the available data, the specifics of the algorithm will vary. Still, in general, it will include the following steps: (1) *data collection* from the activity of interest using accelerometry, HR sensors, or other devices; (2) *data pre-processing*: clean and preprocess the data to remove any noise or outliers. This step may also include filtering and extraction of characteristics to extract relevant information from the data; (3) *calibration*: establish a relationship between the data of physical activity and the energy expenditure [224] by using data collected from a sample of people performing the activity while also measuring the energy expenditure using more direct methods, such as indirect calorimetry; (4) *model development*: Develop a model that can estimate MET from the physical activity data with the calibration data. This can be performed using regression analysis or other statistical techniques; (5)*model validation*: test the developed model with a separate dataset to ensure that it is accurate and generalizable; (6) *MET calculation*: use the developed model to estimate MET from new data.

It is crucial to note that the precision and accuracy of the MET calculations will vary depending on, among other things, the activity, the device and sensors used, and the participant sample. Different algorithms have been developed for various situations and sports, as well as for variable levels of granularity. Therefore, these factors are also crucial when deciding which algorithm to employ. The technique provided by Trost et al., in 2003, in their article "A Non-Exercise Prediction of Functional Aerobic Capacity" [225], is one example of a specific approach for calculating MET using 3-axial acceleration data. The algorithm used the following steps: (1) *collect accelerometry* data from a sample of people performing different activities, such as walking, running, cycling, and resistance training; (2) *preprocess* the data by removing any noise or outliers and calculating relevant characteristics such as average acceleration, RMS, and variance of the acceleration data on each axis; (3) *Calibrate the data* by measuring energy expenditure in the same activities in a subset of the sample using indirect calorimetry; (4) *develop a regression model* that relates the relevant features of the accelerometry data to energy expenditure using the calibration dataset; (5) *test the model* on a validation dataset; (6) *use /apply the developed model* to estimate energy expenditure in other new datasets. The specific mathematical form of the regression model used in the algorithm is as follows.

$MET = \alpha + \beta_1(\text{average acceleration}) + \beta_2(\text{RMS}) + \beta_3(\text{variance of acceleration in x-axis}) + \beta_4(\text{variance of acceleration in y-axis}) + \beta_5(\text{variance of acceleration in z-axis})$, where $\alpha, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the coefficients of the regression model, which are calculated from the calibration dataset.

The importance of this fact should be highlighted since this is only one example of a MET calculation algorithm. In addition to the type of accelerometer used to measure a person's acceleration, the activity being performed and the characteristics of the sample of participants need to be considered. Before using the algorithm to estimate MET in practice, it is crucial to validate the algorithm by analyzing data from a representative sample of individuals and activities. This will ensure that the algorithm has been adequately

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developed.

Methods for estimation algorithm of energy expenditure

Several methods to estimate energy expenditure use medical radar sensors and 3-axial accelerometers [15]. One common approach is to use the data from these sensors to calculate the individual's metabolic rate, which measures the body's energy at a given moment. This can be carried out using several algorithms based on physiological models and assumptions.

1. **Non-parametric approach**: One popular algorithm used to estimate energy expenditure is the nonparametric approach to quantifying physical activity intensity (NPAI) algorithm. This algorithm takes raw data from the 3-axial accelerometer. The method applies a series of mathematical transformations to convert the data into an estimate of the individual's physical activity intensity (PAI) and energy expenditure. The NPAI algorithm integrates several data processing steps, including data cleaning, segmentation, feature extraction, and classification [32,33]. The NPAI algorithm makes no assumptions about the specific type of physical activity performed. Therefore, it can provide a comprehensive estimate of an individual's overall physical activity level. In the NPAI algorithm, data cleansing is a critical process. During data segmentation, accelerometer data is divided into segments that correspond to different activities, such as walking, running, and sitting, using the accelerometer data. The third stage is the feature extraction phase.

   This involves extracting valuable elements from the accelerometer data, such as the mean value and standard deviation of the acceleration data. In this way, different types of activity can be distinguished from each other. Based on the extracted characteristics, the segments are classified according to their intensity of physical activity. The segments are then classified according to the intensity of physical activity of the extracted features. To estimate energy consumption, data must first be separated and classified. The system calculates each action's energy expenditure based on its metabolic equivalent (MET). It is also essential to validate the algorithm with actual energy expenditure measurements to assess its performance.

2. **Doubly constrained energy expenditure algorithm**: Another approach is the Doubly Constraint Energy Expenditure (DC) algorithm, which estimates energy expenditure using the 3-axis accelerometer and HR data. This algorithm assumes that HR and oxygen consumption are linearly related and that the oxygen consumption rate can be used to estimate energy expenditure [32, 33]. The DC algorithm uses a mathematical model to estimate the oxygen consumption rate from HR data. The accelerometer readings are then used to estimate the percentage of oxygen consumption attributed to physical activity. The DC method calculates energy

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expenditure by combining data from 3-axial accelerometers and HR sensors. The algorithm presupposes that HR is precisely proportional to oxygen consumption and that oxygen consumption can be used to predict energy expenditure. Typically, the DC algorithm consists of the following steps: (a) *data cleaning*: artifacts or outliers are removed from the accelerometer and HR data at this stage. (b) *estimating oxygen consumption*: this phase involves applying a mathematical model to HR data to determine the oxygen consumption rate; this model can utilize the Fick equation or other comparable models. (c) *estimation of the energy expenditure of physical activity*: at this stage, the accelerometer data estimate the proportion of oxygen consumption attributable to physical activity; It is possible to link the accelerometer data with the energy expenditure of physical activity using a mathematical model to link the data. (d) *estimation of total energy expenditure*: the final phase estimates the individual's total energy expenditure by combining oxygen consumption and energy expenditure from physical activity.

In addition, the accuracy of the algorithm can be restricted by the quality of the HR and accelerometer data and the implementation of the algorithm. As with any energy expenditure estimation method, validating the DC algorithm using actual energy expenditure data to evaluate its performance is essential.

Both algorithms are based on assumptions and models that may not be entirely accurate for all individuals, so validating the algorithm with actual energy expenditure measurements is essential. Methods should also be validated for different populations, such as elite athletes or patients with chronic diseases. Another approach is to use ML techniques to develop models that predict energy expenditure from sensor data. They can be more robust and accurate than traditional algorithms, mainly when a good-quality dataset is used to train the model. However, similarly to conventional algorithms, these models also require validation.

6.2.2 Fatigue and stamina control on multivariate time series datasets

Fatigue detection on IMU-generated multivariate times series dataset

The specific algorithm to detect fatigue from IMU-generated multivariate time series datasets involves the following steps [42]: $\mathbf{X}(t)$ is introduced, which represents the multivariate time series data obtained from IMU, where t indicates the time step. This data could include, for instance, acceleration, angular velocity, and magnetometer data along three axes such that:

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$$\mathbf{X}(t) = \begin{bmatrix} a_x(t) & a_y(t) & a_z(t) \\ \omega_x(t) & \omega_y(t) & \omega_z(t) \\ m_x(t) & m_y(t) & m_z(t) \end{bmatrix} \tag{6.21}$$

where a represents acceleration, ω represents angular velocity, and m represents the orientation of the magnetic field, each along the x, y, and z axes, respectively. The normalization and IMU filter will follow it to remove noise and artifacts:

$$\mathbf{X}'(t) = f(\mathbf{X}(t)) \tag{6.22}$$

where f represents a series of pre-processing functions such as filtering and normalization. This is followed by feature extraction, where the relevant features $\mathbf{F}$ are data indicative of fatigue from the preprocessed data:

$$\mathbf{F}(t) = g(\mathbf{X}'(t)) \tag{6.23}$$

where g is a function that could include statistical measures, frequency domain analysis, or other feature extraction methods. After this, a predictive model M can be defined , which relates the characteristics $\mathbf{F}$ to a binary fatigue state $Y(t)$, where $Y(t) \in \{0, 1\}$ indicates the non-fatigued and fatigued states, respectively:

$$Y(t) = M(\mathbf{F}(t), \Theta) \tag{6.24}$$

where Θ represents the model parameters learned during training. In model training, it uses a labeled dataset $\mathbf{D} = \{(\mathbf{F}_i, Y_i)\}_{i=1}^{N}$, where N is the number of samples, to learn the model parameters Θ using a suitable learning algorithm L:

$$\Theta^* = L(\mathbf{D}) \tag{6.25}$$

The algorithm will then apply the trained model to the new IMU data to detect fatigue:

$$\hat{Y}(t) = M(\mathbf{F}(t), \Theta^*) \tag{6.26}$$

where $\hat{Y}(t)$ is the fatigue state predicted. Finally, a thresholding function h was implemented to determine fatigue:

$$\text{Fatigue}(t) = \begin{cases} 1 & \text{if } h(\hat{Y}(t)) \geq \tau \\ 0 & \text{otherwise} \end{cases} \tag{6.27}$$

where τ is a predefined threshold that discriminates between fatigued and non-fatigued states. The specific form of the functions f, g, M and L, as well as the threshold τ, were determined by the characteristics of the dataset, the nature of the sporting activity and

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the algorithm performance objectives. AI models like DNN encapsulate most of these steps within their architecture, automating feature extraction and prediction through end-to-end learning.

Stamina detection on IMU-generated multivariate times series dataset

To delineate a more specific algorithm [42] to detect stamina using multivariate time series datasets generated by IMU [226, 227], the processed data must be refined with additional mathematical constructs and data science terminologies that are adapted to this context. Here, stamina is quantified as a measure of an athlete's capacity to maintain optimal performance levels over time. Given a multivariate time series dataset $\mathbf{X}(t)$ from an IMU, the dataset is first defined more formally:

$$\mathbf{X}(t) = \{\mathbf{x}_1(t), \mathbf{x}_2(t), \ldots, \mathbf{x}_p(t)\} \tag{6.28}$$

where each $\mathbf{x}_i(t)$ is a vector containing the i^{th} sensor readings at time t, and p is the total number of sensors. The data pre-processing ($\mathcal{P}$) phase transforms the raw IMU data [32, 33] to reduce noise and correct for bias and drift:

$$\mathbf{X}'(t) = \mathcal{P}(\mathbf{X}(t)) \tag{6.29}$$

This may include techniques such as Butterworth filtering, detrending, and normalization procedures to standardize sensor readings [228, 229]. In feature extraction ($\mathcal{F}$), from preprocessed data, extraction of features that are believed to correlate with stamina potentially involves: (1) time domain features such as mean, median, variance, and root mean square of sensor signals; (2) frequency domain features obtained by fast Fourier transform (FFT) or power spectral density (PSD) analysis; as well as (3) entropy-based features that can indicate physiological complexity and resilience.

$$\mathbf{F}(t) = \mathcal{F}(\mathbf{X}'(t)) \tag{6.30}$$

DL architecture ($\mathcal{D}$ is used to model complex relationships and temporal dependencies:

$$\mathbf{H}(t) = \mathcal{D}(\mathbf{F}(t), \Phi) \tag{6.31}$$

where $\mathbf{H}(t)$ represents high-level features learned by the DL model (e.g., an LSTM network [230]), and Φ denotes the network parameters. It integrates a set of models ($\mathcal{E}$) that captures different aspects of the data and learns diverse representations:

$$\mathbf{Y}(t) = \mathcal{E}(\mathbf{H}(t), \Psi) \tag{6.32}$$

where $\mathbf{Y}(t)$ is the ensemble prediction for stamina, and Ψ represents the ensemble parameters. The ensemble may include models like Random Forests, Gradient Boosting

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Machines, or additional NNs. The model training and optimization ($\mathcal{O}$) phase will adjust the parameters of the DL model and the ensemble method by minimizing a loss function over a labeled dataset.

$$\Phi^*, \Psi^* = \underset{\Phi,\Psi}{\operatorname{argmin}} \mathcal{L}(\mathbf{Y}(t), Z_{\text{true}}(t)) \tag{6.33}$$

where $Z_{\text{true}}(t)$ represents the ground truth stamina levels, and $\mathcal{L}$ is a suitable loss function, such as cross-entropy for classification tasks or mean squared error (MSE) for regression tasks. Now, it can apply Dynamic Time Warping (DTW) [231], which helps us to compare time series of varying durations (as stamina exercises might vary in duration). The DTW for alignment is defined as follows:

$$\mathbf{F}_{\text{aligned}}(t) = \text{DTW}(\mathbf{F}(t)) \tag{6.34}$$

The stamina metric definition (Z) defines a continuous stamina metric based on physiological and performance thresholds normalized to a suitable scale:

$$Z(t) = \mathcal{Z}(\mathbf{F}_{\text{aligned}}(t)) \tag{6.35}$$

This function could be a linear combination or a more complex non-linear model calibrated through physiological studies. The model training and parameter estimation ($\mathcal{M}$, Θ) will train a predictive model $\mathcal{M}$ by using a suitable algorithm (e.g., regression, support vector machine (SVM), NNs) to relate the features $\mathbf{F}$ to the stamina metric Z:

$$\Theta^* = \text{argmin}_\Theta \mathcal{L}(\mathcal{M}(\mathbf{F}(t), \Theta), Z(t)) \tag{6.36}$$

where $\mathcal{L}$ is a loss function that quantifies the error in stamina estimation, and Θ^* represents the optimized model parameters. The stamina estimation ($\hat{Z}$) estimates the specific metric for new data by using the trained model:

$$\hat{Z}(t) = \mathcal{M}(\mathbf{F}(t), \Theta^*) \tag{6.37}$$

After this, stamina levels ($\mathcal{T}$) can be categorized using predefined physiological thresholds based on normalized stamina metrics:

$$\text{Stamina_Category}(t) = \mathcal{T}(\hat{Z}(t))$$

where $\mathcal{T}$ applies threshold values that segment the stamina metric into distinct categories, such as "low","medium" and "high" endurance. Lastly, the validation of the model predictions ($\mathcal{V}$) is performed with actual athlete performance data, using metrics such as

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correlation coefficients or Bland-Altman plots to assess agreement:

$$\mathcal{V}(\hat{Z}(t), Z_{\text{true}}(t)) \tag{6.38}$$

where $Z_{\text{true}}(t)$ are true stamina values obtained from performance tests or expert assessments. If Stamina_Category is not used, then the model validation ($\mathcal{V}$) for predictive power using appropriate validation techniques such as k-fold cross-validation or time series cross-validation will be as below:

$$\mathcal{V}(\mathbf{Y}(t), Z_{\text{true}}(t)) \tag{6.39}$$

Finally, the feedback loop for real-time adaptation ($\mathcal{FB}$) will adopt a feedback loop that allows the model to adapt based on real-time data, enhancing the model's predictive accuracy over time:

$$\Phi^{*'}, \Psi^{*'} = \mathcal{FB}(\Phi^*, \Psi^*, \text{new data}) \tag{6.40}$$

In this algorithm, $\mathcal{D}$ could use architectures such as CNN to extract spatial features from IMU data [232–234], followed by LSTMs or gated recurring units (GRUs) to capture temporal patterns. The ensemble $\mathcal{E}$ would harness the predictive capabilities of multiple models to improve generalizability and reduce the likelihood of overfitting the training data. Using a predictive model trained on labeled data allows for the continuous quantification of stamina, offering a detailed view of the athlete's endurance capabilities over time. The final validation step ensures that the model's reliable estimates reflect true stamina levels.

Stamina and fatigue control model

Creating an algorithm to control stamina and fatigue during training sessions with IMU-generated multivariate time series datasets [42] involves a complex interplay of *signal processing*, *feature extraction*, *statistical modeling* and *sports management*. The algorithm is expected to provide real-time feedback and adapt the training intensity based on the athlete's current stamina and fatigue levels. The $\mathbf{X}(t)$ matrix of sensor readings from the IMU at time t is used, encompassing acceleration (a), angular velocity (ω), and other measures such as magnetic orientation (m) across three axes x, y, z, as previously defined. In the data pre-processing ($\mathcal{P}$) phase it is applied the filtering and normalization to the raw IMU data:

$$\mathbf{X}'(t) = \mathcal{P}(\mathbf{X}(t)) \tag{6.41}$$

This may include detrending, smoothing, or other techniques for detecting sensor bias and noise. This is followed by the feature extraction ($\mathcal{F}$), which derives a feature set $\mathbf{F}(t)$ that captures aspects related to fatigue and stamina:

$$\mathbf{F}(t) = \mathcal{F}(\mathbf{X}'(t)) \tag{6.42}$$

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The features include mean and variance of acceleration, signal magnitude area (SMA) and entropy measures. The fatigue and stamina Indicators ($\mathcal{I}_{\text{fatigue}}, \mathcal{I}_{\text{stamina}}$) will develop indicators for fatigue and stamina based on the features:

$$I_{\text{fatigue}}(t) = \mathcal{I}_{\text{fatigue}}(\mathbf{F}(t)) \tag{6.43}$$

$$I_{\text{stamina}}(t) = \mathcal{I}_{\text{stamina}}(\mathbf{F}(t)) \tag{6.44}$$

These indicators reflect the current state of the athlete and are sensitive to changes over time. The training session control ($\mathcal{C}$) formulates the control mechanisms that adjust the intensity of the training based on fatigue and stamina levels.

$$\mathbf{T}(t) = \mathcal{C}(I_{\text{fatigue}}(t), I_{\text{stamina}}(t)) \tag{6.45}$$

where $\mathbf{T}(t)$ represents the training parameters to be adjusted, such as intensity, duration, or rest periods. Model training and parameter estimation ($\mathcal{M}$, Θ) use historical training data to train a model $\mathcal{M}$, which correlates fatigue and stamina indicators with optimal training results.

$$\Theta^* = \text{argmin}_\Theta \mathcal{L}(\mathcal{M}(\mathbf{F}(t), \Theta), \mathbf{O}(t)) \tag{6.46}$$

where $\mathcal{L}$ is the loss function, $\mathbf{O}(t)$ represents the desired training outcomes, and Θ^* represents the optimized parameters. The feedback loop ($\mathcal{F}_{\text{loop}}$) implements a feedback loop to provide real-time adjustments:

$$\mathbf{T}'(t+1) = \mathcal{F}_{\text{loop}}(\mathbf{T}(t), \Delta I_{\text{fatigue}}(t), \Delta I_{\text{stamina}}(t)) \tag{6.47}$$

where Δ denotes the change in fatigue and stamina indicators, providing the basis for adjusting $\mathbf{T}$ for the next time step. Finally, validation and adaptation ($\mathcal{V}$, $\mathcal{A}$) will continuously validate and adapt the control model:

$$\mathcal{V}(\mathbf{T}'(t), \mathbf{O}(t)) \tag{6.48}$$

$$\Theta^{*'} = \mathcal{A}(\Theta^*, \mathcal{V}) \tag{6.49}$$

where $\mathcal{V}$ assesses the effectiveness of the training adjustments, and $\mathcal{A}$ modifies the model parameters Θ as needed for improved control. A complex ML model could be added to this algorithm $\mathcal{M}$, which requires iterative updates as more data is collected. The control mechanism $\mathcal{C}$ is planned to ensure that training intensity does not exceed the athlete's recovery capacity, thus optimizing performance gains while minimizing the risk of overtraining.

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Bias localization and minimization

Incorporating a control function into the algorithm to localize and minimize biases in predicting stamina and fatigue from IMU-generated data [32, 33] requires an iterative process [42]. This process involves identifying the source of the bias within the predictive models and iteratively refining the model to reduce this bias. First, $\mathbf{X}(t)$ denotes the multivariate time series data from the IMU, where $\hat{S}(t)$ and $\hat{F}(t)$ represent the predictions of the models for stamina and fatigue at time t, respectively, with $S_{\text{true}}(t)$ and $F_{\text{true}}(t)$ being the valid values. The control function for bias localization and minimization can be described as follows. It can estimate the bias for stamina and fatigue predictions as:

$$B_{\text{stamina}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{S}(t) - S_{\text{true}}(t)) \tag{6.50}$$

$$B_{\text{fatigue}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{F}(t) - F_{\text{true}}(t)) \tag{6.51}$$

This will be followed by identifying patterns or features within $\mathbf{X}(t)$, which are consistently associated with bias in predictions, using a diagnostic analysis $\mathcal{D}$:

$$\mathbf{L}_{\text{stamina}} = \mathcal{D}(\mathbf{X}(t), B_{\text{stamina}}) \tag{6.52}$$

$$\mathbf{L}_{\text{fatigue}} = \mathcal{D}(\mathbf{X}(t), B_{\text{fatigue}}) \tag{6.53}$$

$\mathbf{L}_{\text{stamina}}$ and $\mathbf{L}_{\text{fatigue}}$ represent localized features that contribute to bias. The control function ($\mathcal{C}$) to adjust model parameters or features to minimize bias is defined as:

$$\Theta'_{\text{stamina}} = \mathcal{C}(\Theta_{\text{stamina}}, \mathbf{L}_{\text{stamina}}) \tag{6.54}$$

$$\Theta'_{\text{fatigue}} = \mathcal{C}(\Theta_{\text{fatigue}}, \mathbf{L}_{\text{fatigue}}) \tag{6.55}$$

where Θ'_{stamina} and Θ'_{fatigue} are the adjusted model parameters. The main scope of the model update and the bias minimization mechanism is to update the models with the new parameters:

$$\hat{S}'(t) = M_{\text{stamina}}(\mathbf{X}'(t), \Theta'_{\text{stamina}}) \tag{6.56}$$

$$\hat{F}'(t) = M_{\text{fatigue}}(\mathbf{X}'(t), \Theta'_{\text{fatigue}}) \tag{6.57}$$

After this step, the bias will be recalculated to assess the effectiveness of the control function:

$$B'_{\text{stamina}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{S}'(t) - S_{\text{true}}(t)) \tag{6.58}$$

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$$B'_{\text{fatigue}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{F}'(t) - F_{\text{true}}(t)) \tag{6.59}$$

Furthermore, an iterative refinement will be applied to the control function until the biases B'_{stamina} and B'_{fatigue} are minimized to below the predefined threshold ϵ:

$$\text{while } (|B'_{\text{stamina}}| > \epsilon) \text{ or } (|B'_{\text{fatigue}}| > \epsilon) : \tag{6.60}$$

$$\Theta'_{\text{stamina}}, \Theta'_{\text{fatigue}} = \mathcal{C}(\ldots) \tag{6.61}$$

$$\text{Recalculate biases (see formulas (6.58) and (6.59)} \tag{6.62}$$

Once the biases are minimized, finalize the updated models for stamina and fatigue predictions. This algorithm incorporates an advanced control theory approach to systematically reduce bias in predictive modeling. The control function $\mathcal{C}$ is designed to be adaptive, capable of responding to localized bias sources and iteratively tuning the model parameters to address these issues.

Training session duration and intensity optimization

The following presents an advanced algorithmic structure with an integrated control function for this purpose: $\mathbf{X}(t)$ represents the multivariate time series data from the IMU, with $\mathbf{P}(t)$ denoting the training parameters at time t, including duration $d(t)$ and intensity $i(t)$. The real-time stamina and fatigue levels of the athlete are estimated as $\hat{S}(t)$ and $\hat{F}(t)$, respectively, with biases B_{stamina} and B_{fatigue} calculated as previously described. The control function to optimize training parameters can be structured as follows. First, it will establish initial training parameters based on the athlete's baseline performance data.

$$\mathbf{P}(0) = \{d(0), i(0)\} \tag{6.63}$$

In the execution of the planned training session, the training session will be conducted with the given parameters, and the IMU data will be collected.

$$\text{ExecuteTraining}(\mathbf{P}(t)) \tag{6.64}$$

$$\mathbf{X}(t) = \text{CollectData}() \tag{6.65}$$

Stamina and fatigue were estimated for the real-time prediction and bias correction functionality while simultaneously applying the bias corrections of previous iterations.

$$\hat{S}_{\text{corrected}}(t), \hat{F}_{\text{corrected}}(t) = \text{PredictAndCorrect}(\mathbf{X}(t), \mathbf{B}) \tag{6.66}$$

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The control function for optimization ($\mathcal{C}_{\text{opt}}$) is defined based on the corrected stamina and fatigue estimates, adjusting the training parameters:

$$\mathbf{P}'(t+1) = \mathcal{C}_{\text{opt}}(\hat{S}_{\text{corrected}}(t), \hat{F}_{\text{corrected}}(t), \mathbf{P}(t)) \tag{6.67}$$

The step is followed by a recalculation of biases based on the outcomes of the optimized training session:

$$\mathbf{B}' = \text{RecalculateBiases}(\mathbf{X}(t), \mathbf{P}'(t+1)) \tag{6.68}$$

The next step is called the adaptive parameter update to facilitate the training parameters for the next session using the control function outputs and recalculated biases:

$$\mathbf{P}(t+1) = \text{UpdateParameters}(\mathbf{P}'(t+1), \mathbf{B}') \tag{6.69}$$

The iterative loop is applied to perform steps 2-6 for subsequent training sessions, continuously adjusting for biases and optimizing training parameters. The control function $\mathcal{C}_{\text{opt}}$ could use optimization techniques such as: (1) *model predictive control (MPC)*: A form of control that uses a model of the athlete's response to training to predict future states and make adjustments to optimize the training load; (2) *reinforcement learning*: An area of ML is concerned with how software agents should take actions in an environment to maximize the notion of cumulative reward, which could be the athlete's performance metrics. The algorithm should also incorporate a learning rate α that determines the magnitude of adjustments to the training parameters to avoid drastic changes that could harm the athlete.

Comparison against gold-standard methods

Within the domain of performance sports, the most reliable techniques to assess athlete fatigue and endurance have typically been based on physiological evaluations (see Table 6.1), including VO2 max tests, lactate threshold measures, EMG data, and subjective scales such as the Rate of Perceived Exertion (RPE). Although these methods have been verified and proven to be trustworthy, they generally involve intrusive procedures, require a significant amount of time, and strongly correlate with kinematic data. Physical therapists and sports trainers widely use kinematic measurements to quantify fatigue and injuries, and video-based optoelectronic systems are the gold standard; however, outside the laboratory, the IMU system has been shown to be a solid alternative.

The emergence of AI-assisted methodologies, specifically those that use IMU-generated multivariate time series data, offers a novel alternative to these conventional approaches [42]. AI models enable data collection in a non-invasive and real-time manner, allowing continuous monitoring of physiological and biomechanical indicators [235] without significantly disturbing the athlete's natural performance environment. AI-based models provide a constant and dynamic examination of an athlete's state, allowing for more

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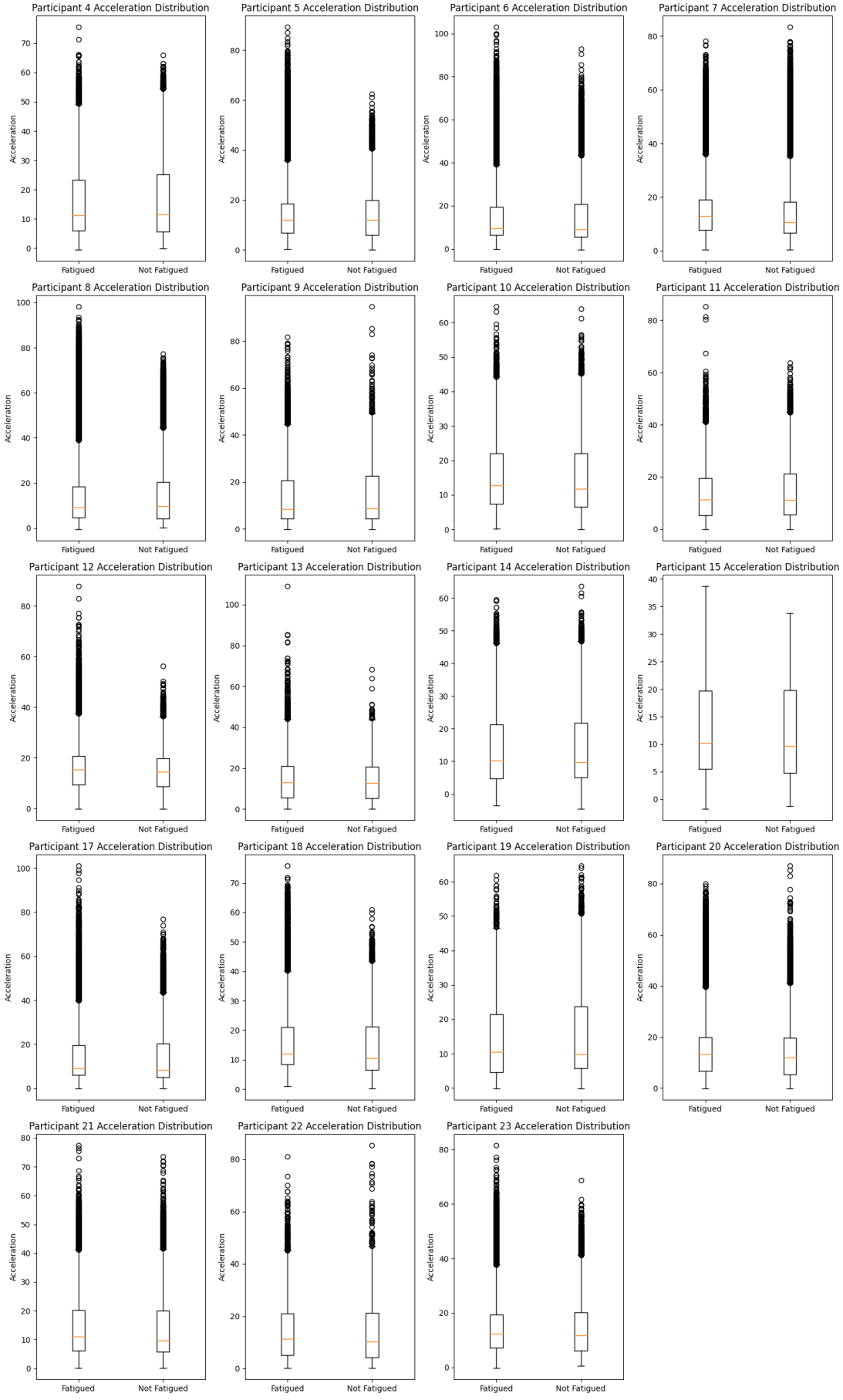


Figure 6.6: Acceleration distribution per participants

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Table 6.1: Comparison between physiological and AI-assisted methods for athlete fatigue and stamina assessment: physiological versus kinematic data comparison

Aspect	**Physiological methods**	**AI-assisted methods**
Data collection	Invasive and episodic	Non-invasive and continuous
Real-time analysis	Limited	Enabled
Cost	Often high	Potentially lower
Accessibility	Specialized facilities	Broad accessibility
Precision	High for single assessments	Developing for continuous monitoring
Frequency	Periodic testing	Continuous feedback
Invasiveness	Typically high	Low
User experience	Can be disruptive	Minimally disruptive
Validation	Established	Ongoing

accurate and timely detection of fatigue and changes in stamina compared to periodic evaluations using gold standard approaches [42].

Table 6.2: Comparison between video-based analysis and AI-assisted methods with IMUs for athlete fatigue and stamina assessment

Aspect	**Video-based analysis (Gold Standard)**	**AI-assisted methods with IMUs**
Data collection	Manual recording	Automated and continuous
Real-time analysis	Typically delayed	Enabled and instantaneous
Cost	Resource-intensive for analysis	Cost-effective in the long term
Accessibility	Requires presence and setup	Portable and accessible in various settings
Precision	High with expert analysis	High with advanced algorithms
Frequency	During specific sessions	Throughout training and competition
Invasiveness	Non-invasive but can be obtrusive	Non-invasive and unobtrusive
User experience	Potentially interruptive	Seamless integration into gear
Data richness	Limited to visual capture	Multidimensional kinematic data
Analytical depth	Subject to analyst's expertise	Deep, algorithm-driven insights
Validation	Well-established	Subject to ongoing research

Although AI-assisted techniques show promising results, such as refined Quadratic Discriminant Analysis (QDA) discernment or the high rates of correctly identifying relevant instances in SVMs, they now serve as supplementary tools rather than complete substitutes for conventional measurements. The dataset shows accuracy values that consistently hover around the 50% threshold, suggesting that these approaches are still in their early stages of development. Furthermore, it is crucial to thoroughly compare and evaluate the accuracy and effectiveness of AI techniques with established and highly reliable methodologies to determine their efficacy. Comparison of traditional video-based analysis as the gold standard against IMUs [32, 33] integrated with AI-assisted methods (see Table 6.2) will reflect the specific contrasts between video-based techniques, traditionally considered the gold standard, especially in technique analysis and movement studies, and emerging AI-driven approaches using IMUs for a detailed and continuous evaluation of athletic performance. In conclusion, the comparison with gold standard methods demonstrates that AI-assisted techniques can transform athlete monitoring by offering a consistent and

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comprehensive view of performance metrics. However, to match the effectiveness of established methods, it is crucial to further improve AI models to increase their ability to anticipate results accurately. This will ensure that these new approaches can be trusted as independent instruments in the high-pressure field of competitive sports.

Fatigue and stamina calculation algorithm

To include fatigue and stamina calculations in a complex algorithm that uses DL and ensemble methods, a combined method would be needed to tell the difference between the two states. First, it will represent the multivariate time series data from the IMUs. In algorithms, a deep neural network (DNN) [9, 236] can easily be integrated, including convolutional layers for the extraction of spatial features and recurrent layers, such as LSTM [237, 238] or GRU, for temporal dependencies. The ensemble method for stamina and fatigue consists of various ML models such as gradient boosting, bagging, or additional NNs [239], each trained to predict stamina and fatigue from the high-level features learned by the DL model. The ensemble methods capture different aspects of complex physiological data and also help improve the robustness and accuracy of the predictions for stamina and fatigue. The feedback mechanism ensures that the models remain dynamic and adaptive, refining the predictions as more data are collected.

Kalman filter and Voronoi tessellation in microsleep detection

Applying the Kalman filter in the context of detecting microsleep episodes from EEG signals in the Sleep-EDF dataset is beneficial to improving the precision and reliability of the detection process. In the case of EEG signal analysis for microsleep detection, the Kalman filter (see Fig. 6.7) can be utilized to improve signal quality by filtering out noise and artifacts, as well as to improve feature extraction and prediction accuracy through the estimation of signal parameters over time [74].

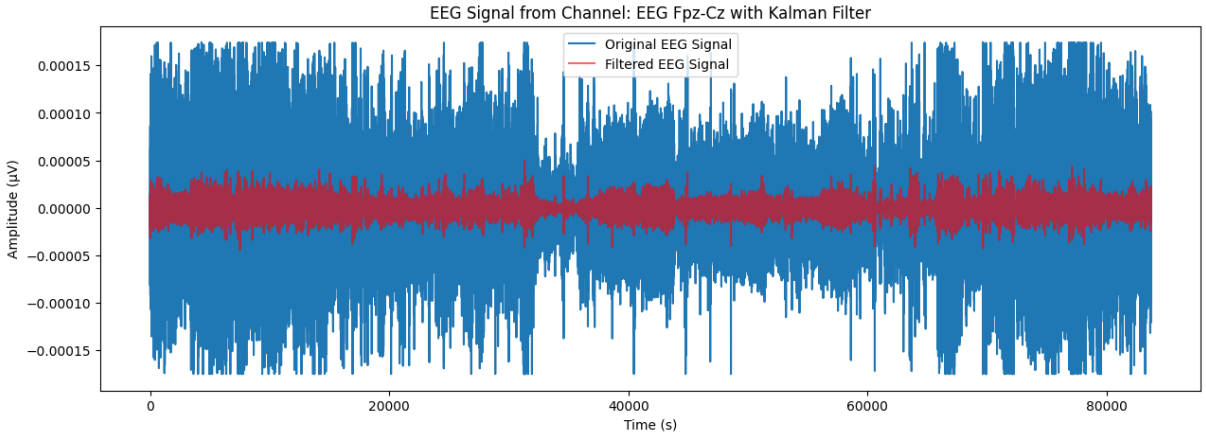


Figure 6.7: Kalman filter on EEG signal

First, in signal modeling, the EEG signal can be modeled as a state-space system. The state at time k, indicated as x_k, could represent the underlying brain activity, and

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the observed EEG signal, indicated as z_k, is a noisy measurement of this state. The state-space model can be represented as

$$x_k = F_k x_{k-1} + w_{k-1} \tag{6.70}$$

$$z_k = H_k x_k + v_k \tag{6.71}$$

where: F_k is the state transition matrix, H_k is the observation matrix, w_k is the process noise, and v_k is the observation noise. The Kalman filter estimates the state x_k from the noisy measurements z_k through two main steps: prediction (a), (b) and update (c), (d) and (e) as follows:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{6.72}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{6.73}$$

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \tag{6.74}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}) \tag{6.75}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{6.76}$$

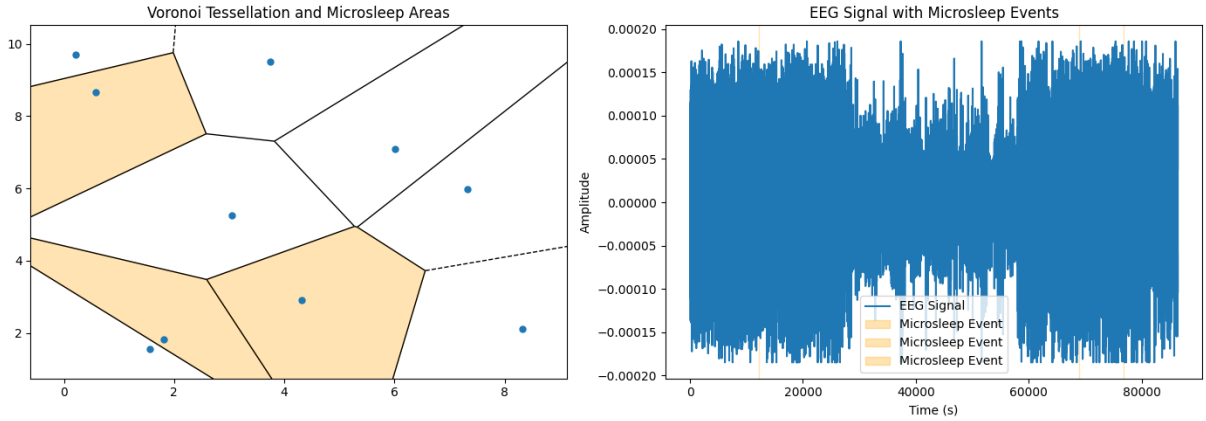


Figure 6.8: Voronoi tesselation and microsleep events

where: F_k denotes the state transition matrix, B_k represents the control input matrix, wherein u_k signifies any control input, Q_k is defined as the process noise covariance matrix, H_k refers to the observation matrix, R_k characterizes the measurement noise covariance matrix, z_k is the observed measurement at time k, K_k is identified as the *Kalman Gain*, and I represents the identity matrix. After applying the Kalman filter (see Fig. 6.7) to the EEG signal, extract features from the estimated state $\hat{x}_{k|k}$ rather than directly from the raw EEG signal. This step can help in reducing the impact of noise on the feature values, leading to more accurate detection of microsleep episodes (see Fig. 6.8). The Kalman filter [74] can improve microsleep detection in several ways: (1) by effectively filtering out noise and artifacts from EEG signals (noise reduction), leading to clearer signals for analysis; (2) by providing a mechanism to estimate and track changes in brain

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activity over time (as dynamic state estimation), which is essential for detecting brief and sudden microsleep episodes; (3) by ensuring that the features extracted for classification are based on less noisy and more accurate estimates of the underlying brain activity (called improved feature accuracy). Implementing the Kalman filter requires tuning parameters such as the state transition matrix F_k, observation matrix H_k, and noise covariances Q_k and R_k to match the characteristics of the EEG signals and the dynamics of microsleep episodes. This process often involves experimental adjustments and validation against known instances of microsleep in the dataset.

Voronoi tessellation in microsleep detection

The Voronoi tessellation is a mathematical concept used to partition a plane into regions based on distances to a specified set of objects, which are, in many cases, points [240]. For a given set of seed points $P = \{p_1, p_2, \ldots, p_n\}$ in the plane, the Voronoi tessellation divides the plane into regions $V(p_i)$ for each point p_i in such a way that every point in the region $V(p_i)$ is closer to p_i than to any other point p_j. The regions $V(p_i)$ are called Voronoi cells. The formal definition of a Voronoi cell for a point p_i in a set P of distinct points in the plane is as follows:

$$V(p_i) = \{q \in \mathbb{R}^2 : \forall p_j \in P, i \neq j, d(q, p_i) < d(q, p_j)\} \tag{6.77}$$

where $d(q, p_i)$ represents the distance between the point q and the seed point p_i. The most common metric used is the Euclidean distance, defined as:

$$d(q, p_i) = \sqrt{(q_x - p_{i_x})^2 + (q_y - p_{i_y})^2} \tag{6.78}$$

for points $q = (q_x, q_y)$ and $p_i = (p_{i_x}, p_{i_y})$. The boundaries of the Voronoi cells are made up of line segments and vertices where three or more cells meet. These lines and vertices are equidistant from the nearest seed points. Each Voronoi cell $V(p_i)$ constitutes a convex polygon. Two points p_i and p_j within the set P are designated as nearest neighbors only under the condition that their corresponding Voronoi cells $V(p_i)$ and $V(p_j)$ share a common boundary. The geographical distribution of Voronoi cells coupled to EEG electrodes helps researchers identify microsleep and other neurological activities. This type of analysis covers the scalp completely. The Voronoi tessellation is a powerful tool for analyzing spatial data such as sleep study EEG signals because it partitions space geometrically and mathematically (see Fig. 6.9). This phenomenon improves the identification of sleep stage or microsleep episodes, reducing the need for dense electrode arrays while retaining data integrity.

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6.2.3 Coverage control for real-time sleep staging

Integrating coverage control [73] with Voronoi tessellation for real-time microsleep detection [241] and staging involves dynamical allocation of monitoring resources based on Voronoi partitioning of the area of interest, such as the scalp in the case of EEG monitoring (see Fig. 6.9). This allows for optimized spatial analysis of brain activity, improving the detection and classification of microsleep episodes by focusing on the most relevant areas.

The set of points $P = \{p_1, p_2, ..., p_n\}$ represents the EEG electrodes on the scalp, the Voronoi tessellation divides the scalp into regions $V(p_i)$ so that all points in $V(p_i)$ are closer to p_i than any other point in P. This sets the stage for spatially aware coverage control. A coverage quality function $Q(V, S)$ can be defined for each Voronoi region V based on the current sensor configuration (electrode) S. This function assesses the effectiveness of the monitoring setup in capturing relevant data for microsleep detection within each region [242].

$$Q(V, S) = \sum_{i=1}^{n} f(V(p_i), S_i) \tag{6.79}$$

where $f(V(p_i), S_i)$ measures the coverage quality of region $V(p_i)$ under sensor configuration S_i, possibly considering factors like signal clarity, noise levels, and the likelihood of detecting microsleep episodes. Finally, a dynamic control law $\dot{S} = g(S, Y)$ is applied that adjusts the sensor configuration S over time based on observed data Y, aiming to optimize $Q(V, S)$. This might involve changing the sensitivity or focus of certain electrodes based on the evolving understanding of microsleep dynamics.The algorithmic approach is as follows: (1) collection of EEG data using an initial sensor configuration, applying preliminary microsleep detection algorithmss; (2) for each Voronoi region $V(p_i)$, evaluate the coverage quality $f(V(p_i), S_i)$, identifying regions where improvements are needed for better microsleep detections; (3) adjustment of the sensor configuration S dynamically, focusing more resources on regions with lower coverage quality or higher microsleep detection potential. This adjustment is guided by the control law $\dot{S} = g(S, Y)$, which might, for example, increase the sampling rate or sensitivity of electrodes in key areas; (4) continuously monitoring the effectiveness of the current configuration S and make further adjustments as necessary, based on real-time data analysis and the ongoing evaluation of coverage quality across the Voronoi partitions (see Fig. 6.9); and finally (5) utilizing of visual tools to map the dynamic adjustments and microsleep detections back onto the scalp model, offering insights into the spatial-temporal patterns of microsleep episodes and the effectiveness of the coverage control strategy [73].

In the context of wearable or implantable sensors monitoring sleep stages, coverage control algorithms will dynamically adjust the sensing strategy or focus based on the detected sleep stage, resulting in a dynamic sensor deployment approach. For example,

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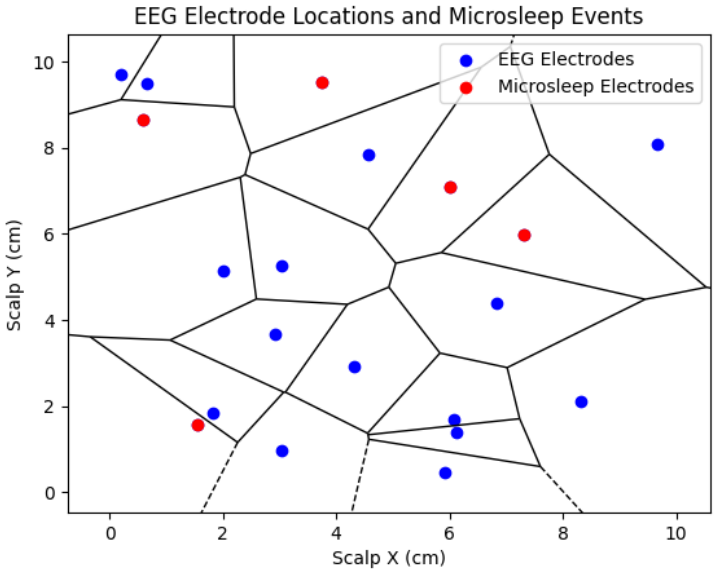


Figure 6.9: EEG electrode locations and microsleep events

certain brain regions might be more relevant during different sleep stages, and coverage control can optimize sensor resources toward these regions. Coverage control strategies can be used to adapt the density of data acquisition in real time, resulting in adaptive data acquisition. This means increasing the resolution of data collection during critical sleep transitions or microsleep episodes and reducing it during less critical times, thus optimizing power consumption and data processing workload.

Bias calculation

Calculating bias in the context of stamina and fatigue detection [193] algorithms involves adjusting the predictive models to account for systematic errors that could affect their precision. This requires understanding how the models' predictions deviate from the true values over a dataset. First, $\mathbf{X}(t)$ will represent the multivariate time series data from the IMUs, where t indices time. These data include readings of the IMU sensor such as *acceleration* (a), *angular velocity* (ω), and *magnetic field orientation* (m) in a three-dimensional space:

$$\mathbf{X}(t) = \begin{bmatrix} a_x(t) & a_y(t) & a_z(t) \\ \omega_x(t) & \omega_y(t) & \omega_z(t) \\ m_x(t) & m_y(t) & m_z(t) \end{bmatrix} \tag{6.80}$$

Assuming that there are defined predictive models for stamina and fatigue, the estimated values of stamina and fatigue at time t are now denoted as $\hat{S}(t)$ and $\hat{F}(t)$, respectively. The true values of stamina and fatigue are $S_{\text{true}}(t)$ and $F_{\text{true}}(t)$. The algorithm to calculate bias will be structured as follows: prediction generation for stamina and fatigue

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over a validation dataset D of size N:

$$\hat{S}(t) = M_{\text{stamina}}(\mathbf{X}'(t), \Theta_{\text{stamina}}) \tag{6.81}$$

$$\hat{F}(t) = M_{\text{fatigue}}(\mathbf{X}'(t), \Theta_{\text{fatigue}}) \tag{6.82}$$

where M_{stamina} and M_{fatigue} are the trained models, and Θ_{stamina} and Θ_{fatigue} are the model parameters. The bias for stamina (B_{stamina}) is the average difference between the predicted and true stamina values:

$$B_{\text{stamina}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{S}(t) - S_{\text{true}}(t)) \tag{6.83}$$

Similarly, the bias for fatigue (B_{fatigue}) is the average difference between the predicted and true fatigue values:

$$B_{\text{fatigue}} = \frac{1}{N}\sum_{t=1}^{N}(\hat{F}(t) - F_{\text{true}}(t)) \tag{6.84}$$

If the bias is significant, the models' predictions need to be updated to correct for the bias:

$$\hat{S}_{\text{corrected}}(t) = \hat{S}(t) - B_{\text{stamina}} \tag{6.85}$$

$$\hat{F}_{\text{corrected}}(t) = \hat{F}(t) - B_{\text{fatigue}} \tag{6.86}$$

After bias correction, the models need to be re-evaluated by using the corrected predictions to ensure the bias is minimized:

$$\text{Evaluate}(\hat{S}_{\text{corrected}}(t), S_{\text{true}}(t)) \tag{6.87}$$

$$\text{Evaluate}(\hat{F}_{\text{corrected}}(t), F_{\text{true}}(t)) \tag{6.88}$$

This algorithm quantifies the bias as the mean error in the dataset. If bias is detected, the model predictions are adjusted accordingly. This correction ensures that the models provide unbiased estimates of stamina and fatigue, which is critical to accurately monitoring and adjusting training regimens. Bias calculation and correction are essential in the implementation of predictive models to ensure that they perform well on new, unseen data and are robust across different populations and conditions.

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6.3 Methods in health condition control

6.3.1 sRPE and ACWR on fatigue and injury control

To estimate fatigue using RPE, sRPE, and ACWR, an algorithm can be initialized incorporating these three metrics to provide an overall fatigue score [26].

Rate of perceived exertion (RPE)

Rate of perceived exertion (RPE) is a subjective measure of an individual's level of exertion during exercise. The most common RPE scale is the Borg scale, ranging from 6 to 20:

$$RPE = 6(\text{no exertion}) \rightarrow 20(\text{maximal exertion}), \tag{6.89}$$

Session rate of perceived exertion (sRPE)

Session rate of perceived exertion (sRPE) is calculated by multiplying the RPE by the duration of the exercise session (in minutes).

$$sRPE = RPE \times duration, \tag{6.90}$$

The RPE and sRPE methods provide valuable information for athletes, coaches, and sports health specialists: (1) *subjective workload assessment* [243]: RPE and sRPE allow for an individualized assessment of an athlete's perceived effort during training, which can be used in conjunction with objective measures (e.g., HR) to understand the training load better [81]; (2) *monitoring fatigue and recovery* [244]: tracking RPE and sRPE can help identify fatigue and recovery patterns, allowing coaches and athletes to optimize training plans and prevent over-training; (3) *individualization*: RPE and sRPE enable coaches and athletes to tailor training programs based on individual responses, promote optimal performance, and reduce injury risk; (4) *communication*: RPE is an accessible method for athletes to communicate their perceived exertion to coaches and support staff, facilitating adjustments to the training load as needed.Acute workload (AW) is the total training load over a week (usually 7 days).

$$AW = \sum_{i=1}^{7} TL_i, \tag{6.91}$$

where TL_i is the daily training load on day i.
Chronic Workload (CW) is the average training load over a longer period, typically four weeks.

$$CW = \frac{1}{4} \sum_{j=1}^{4} \sum_{i=1}^{7} TL_{i,j}, \tag{6.92}$$

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where $TL_{i,j}$ is the daily training load on day i of week j.
Finally, the Acute: Chronic Workload Ratio (ACWR) is calculated by dividing acute workload (AW) [245] by chronic workload (CW).

$$ACWR = \frac{AW}{CW}, \tag{6.93}$$

The ACWR provides several valuable information for athletes, coaches, and sports health specialists: (1) *assessment of injury risk*: higher ACWR values (typically above 1.5) are associated with an increased risk of injury, while values in the range of 0.8 to 1.3 are considered optimal for reducing injury risk; (2) *training load monitoring* [75]: the ACWR allows coaches and athletes to monitor and adjust training loads, ensuring a balance between adequate training stimulus and sufficient recovery [26]; (3) *individualization*: by tracking the ACWR for each athlete, coaches can tailor training programs to individual needs, helping to optimize performance and minimize the risk of injury; (4) *periodization*: ACWR can be used to guide periodization strategies, ensuring that athletes are at peak at the right time for competitions.

Fatigue score calculation

The fatigue score (F) can be calculated by combining RPE, sRPE, and ACWR using a weighted sum method.

$$F = w_1 \times RPE + w_2 \times sRPE + w_3 \times ACWR, \tag{6.94}$$

where, w_1, w_2, and w_3 are the weights assigned to RPE, sRPE, and ACWR, respectively. These ranges are based on the assumption that the fatigue score (F) is calculated using the weighted sum method of RPE, sRPE and ACWR. The fatigue score ranges (Low, Moderate, High, Extreme) are based on the assumption that the fatigue score (F) is calculated using the weighted sum method of RPE, sRPE, and ACWR. To effectively apply these ranges, it is first necessary to determine the appropriate weights (w_1, w_2, w_3) for RPE, sRPE and ACWR based on the specific needs and demands of hockey players in this age group. These standardized ranges should be adjusted based on individual factors and monitoring per group or sport.

6.3.2 Personalized recovery

The architecture has a special section, called the *BlazePalm subcomponent* to manage the prediction of hand landmarks. It uses a similar two-step approach with a detector followed by a keypoint model. The primary technique utilized by MediaPipe Pose is DL with CNNs. Both the detector and the keypoint model are based on CNN architectures. Networks consist of (1) *convolutions*, or filters that slide over the input data to extract features. These are typically followed by nonlinear activation functions, such as the Rectified Linear

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Unit (ReLU); (2) *pooling layers* to down-sample the feature maps, reducing dimensions and computational needs while retaining important features; (3) *fully connected layers*, where neurons are densely connected to all activations in the previous layer.

They help in the final prediction tasks. The model is trained by using a loss function tailored for pose estimation, often a combination of a heatmap (usually a 2D Gaussian), centered where the ground-truth position is generated. The model predictions are then compared to these heatmaps to increase accuracy; the model also predicts offsets from the center of each heatmap cell to the exact landmark location.

Post-processing is managed by (1) *heatmap decoding*: the predicted heat maps are decoded to obtain landmark positions. This often involves finding the maximum value in each heatmap, and (2) *nonmaximum suppression* (NMS): When multiple ROIs detected overlap significantly, NMS is used to keep only the most confident prediction and eliminate others.

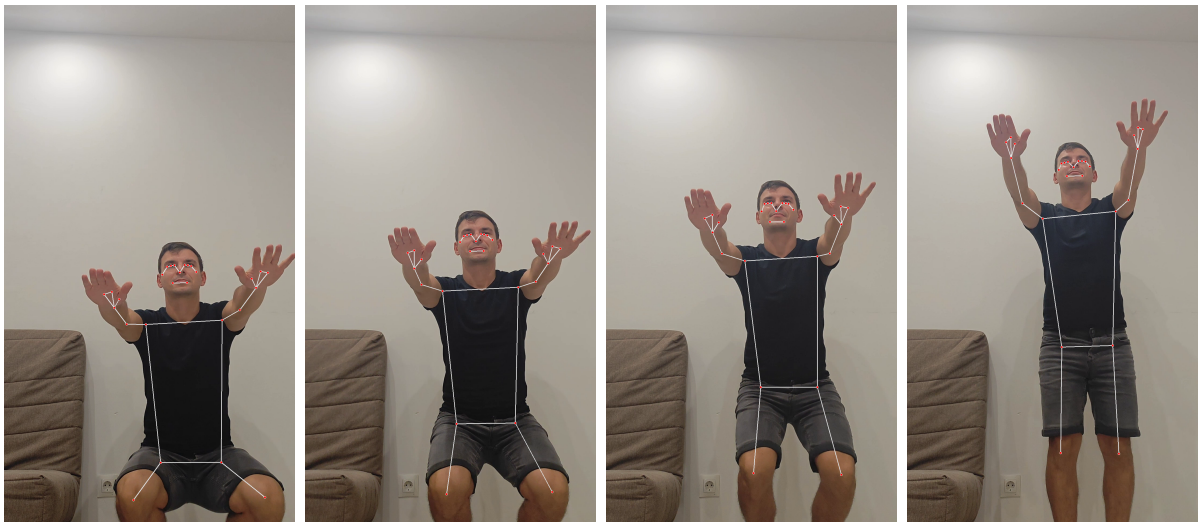


Figure 6.10: Exercise with "BlazePose landmark model"-based AI pipeline

It chose the MediaPipe Pose solution because it typically leverages the previous frame's results in video sequences to ensure temporal consistency and reduce jitter. For example, the ROI of the last frame can influence the search region of the current frame.

Extracting the acceleration data

Acceleration data for the skeleton can be obtained by obtaining the velocity of each landmark between frames and then finding the change in velocity in subsequent frames. Acceleration a can be approximated by:

$$a(t) = \frac{v(t) - v(t-1)}{\Delta t} \tag{6.95}$$

where: $v(t)$ is the velocity at time t, $v(t-1)$ is the velocity at time $t-1$, Δt is the time difference between two frames. The approximation of the velocity v between two points

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can be done with:

$$v(t) = \frac{d(t) - d(t-1)}{\Delta t} \tag{6.96}$$

where: $d(t)$ is the position of the landmark at time t, $d(t-1)$ is the position of the landmark at time $t-1$.

Skeleton extraction

The thesis introduced the term "landmark", which refers to a specific point on the body (for example, the nose or the left wrist), as identified by the pose estimation model. The set of all landmarks in a particular frame finally forms the "skeleton" for that frame. The skeleton extraction algorithm is made up of the following sublayers: Let V be the input video, where $V = \{f_1, f_2, \ldots, f_N\}$ and N is the total number of frames in the video. Now comes the landmark extraction. For each frame f_i in V, use the MediaPipe Pose estimation to extract the poses of P.

$$f_i \rightarrow \text{MediaPipe Pose} \rightarrow L_i \tag{6.97}$$

where $L_i = \{l_1^i, l_2^i, \ldots, l_P^i\}$ is the set of landmarks for frame f_i and each landmark l_j^i is represented as:

$$l_j^i = \{x_j^i, y_j^i, z_j^i\} \tag{6.98}$$

These landmarks form the skeleton of each frame. As a result, it will result in the list of landmarks for all frames $L = \{L_1, L_2, \ldots, L_N\}$. Then, the set can be connected to the acceleration calculation, where the first step is the *velocity calculation*. For each successive pair of frames (f_i, f_{i+1}), and calculation of the velocity v_j^i for each point of reference l_j^i:

$$v_j^i = l_j^{i+1} - l_j^i \tag{6.99}$$

The difference is element-wise for the landmark's x, y, and z coordinates. This is followed by the *acceleration calculation*. For each successive pair of velocities (v_j^i, v_j^{i+1}), the calculation of acceleration a_j^i for each landmark resulting in the list of accelerations for all frames:

$$a_j^i = v_j^{i+1} - v_j^i \tag{6.100}$$

MediaPipe Pose estimation algorithm

The MediaPipe Pose estimation is a real-time pose tracking solution developed by Google. It provides high-fidelity spatial localization points to track body parts, which offer a skeletal representation of the body's significant parts from the user's video input. The

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pose estimation algorithm aims to predict a set of landmarks L, which represent key points in the body, having as input parameters images or video frames I. MediaPipe Pose model architecture uses a multistage pipeline to predict real-time pose landmarks. ML leverages ML to infer 33, 2D landmarks of a body from a single frame. Given an image I of dimensions $H \times W$, where H is the height and W is the width of the image.

$$I \in \mathbb{R}^{H \times W \times 3} \tag{6.101}$$

It provides a region of interest in the image where the body is likely to be. First, it adopts a lightweight model, the BlazePose detector, to estimate the area in the image where a person is present. This stage generates a bounding box B that contains the observed person. After this process, it predicts the landmarks within the region of interest. The region within the bounding box B is then processed by a more complex model, the BlazePose landmark model, to predict the pose landmarks L. Upon detection, the entire image is first passed through the detector to find the region of interest (ROI).

$$I \rightarrow \text{BlazePose Detector} \rightarrow \text{ROI} \tag{6.102}$$

Within ROI, the keypoint model predicts the pose landmarks P:

$$\text{ROI} \rightarrow \text{BlazePose Keypoint Model} \rightarrow L \tag{6.103}$$

where the landmarks L are given by:

$$L = \{l_1, l_2, \ldots, l_{33}\} \tag{6.104}$$

where each landmark l_i has a 3D coordinate representation:

$$l_i = \{x_i, y_i, z_i\} \tag{6.105}$$

The MediaPipe Pose models are trained on a large-scale dataset containing diverse images of people in various poses. The ground truth landmarks for training are obtained manually or through other reliable pose estimation methods. During training, a typical loss function $\mathcal{L}$ is the MSE between predicted landmarks and ground-truth landmarks. Given n training examples:

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} ||L_i^{\text{predicted}} - L_i^{\text{ground truth}}||^2 \tag{6.106}$$

where $||.||$ denotes the L2 norm. The loss function $\mathcal{L}$ is minimized by using optimization techniques, commonly SGD or its variants, to update the model weights during training. Implementing the system involved various optimizations, tweaks, and heuristics to make it robust and efficient. The model outputs P landmarks, which provide key points in the body. These can be used to construct the pose skeleton for that frame. Heatmap decoding,

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NMS, and other techniques may be applied after prediction to refine and improve the quality of detected landmarks.

6.4 Methods in disease injury prevention

6.4.1 Disease detection from voice

Feature extraction with HNR

The HNR [85] is a characteristic commonly used in speech signal analysis to quantify the relationship between the harmonic (periodic) components and the noise (aperiodic) elements of a speech signal. A higher HNR indicates a more precise and periodic voice, while a lower HNR suggests a noisier and less periodic one. As an initial step, the speech signal was divided into overlapping frames:

$$x_i[n] = x[n + i \cdot L], \tag{6.107}$$

where x is the speech signal, i is the frame index, n is the sample index within the frame, and L is the frame shift (in samples). The next step is to compute the autocorrelation function for each frame:

$$R_i(\tau) = \sum_{n=0}^{N-\tau-1} x_i[n] \cdot x_i[n + \tau], \tag{6.108}$$

where $R_i(\tau)$ is the autocorrelation function for frame i with lag τ, and N is the frame length. The fundamental frequency ($F0$) was then determined for each frame by finding the maximum value of the autocorrelation function for the lags corresponding to the expected pitch range.

$$F0_i = \arg \max_{\tau_{\min} \leq \tau \leq \tau_{\max}} R_i(\tau), \tag{6.109}$$

where $\tau_{\min}$ and $\tau_{\max}$ are the minimum and maximum lags corresponding to the expected pitch range. The calculation of the HNR for each frame follows this.

$$\text{HNR}_i = 10 \cdot \log_{10} \frac{R_i(0) - R_i(F0_i)}{R_i(F0_i)}, \tag{6.110}$$

Finally, the overall HNR it is calculated by averaging the HNR values across all frames:

$$\text{HNR}_{\text{overall}} = \frac{1}{I} \sum_{i=0}^{I-1} \text{HNR}_i, \tag{6.111}$$

where I is the total number of frames.

The HNR feature is valuable in the detection of voice-based diseases for the following

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reasons: (1) *Quantifying voice quality* [246]: HNR provides a measure of voice quality, which can help detect voice disorders or monitor the progression of diseases that affect vocal production; (2) *Identifying pathology*: A decrease in HNR can indicate a deterioration in voice quality due to various health problems, such as vocal fold lesions, neurological disorders, or respiratory diseases; (3) *Objective evaluation*: HNR offers an objective and quantitative measure of voice quality, which can complement subjective evaluations made by clinicians; (4) *Non-invasive*: HNR can be extracted from voice recordings, providing a non-invasive method to evaluate vocal health and monitor disease progression.

Feature extraction with MFCCs

The MFCCs are widely used features in speech and audio processing to capture the spectral characteristics of the signal. MFCCs are particularly useful in various applications, including speaker identification, speech recognition, and voice-based disease detection. MFCC calculation involves the following steps: pre-emphasis:

$$y[n] = x[n] - \alpha x[n-1], \tag{6.112}$$

then it can be applied to the framing and windowing

$$w[n] = x[n] \cdot h[n], \tag{6.113}$$

then the calculation of the periodogram estimation of the power spectrum

$$P[k] = \frac{1}{N} \left| \sum_{n=0}^{N-1} w[n] \cdot e^{-j\frac{2\pi}{N}kn} \right|^2, \tag{6.114}$$

then the Mel filterbank can be applied and take the logarithm:

$$M[k] = \log \left(\sum_{i=0}^{N-1} P[i] \cdot H_m[i] \right) \tag{6.115}$$

and calculate the MFCCs by using the Discrete Cosine Transformation (DCT)

$$c_n = \sum_{m=0}^{M-1} M[m] \cdot \cos \left[\frac{\pi}{M} \left(m + \frac{1}{2} \right) n \right] \tag{6.116}$$

The MFCC feature is valuable in voice-based disease detection for the following reasons: (1) *spectral representation*: MFCCs provide a compact representation of the spectral characteristics of a speech signal (as presented in Fig. 6.11), which can help detect voice disorders or monitor the progression of diseases that affect vocal production;

(2) *robustness*: MFCCs are robust to background noise and variations in recording conditions, making them suitable for real-world applications; (3) *discriminative power*:

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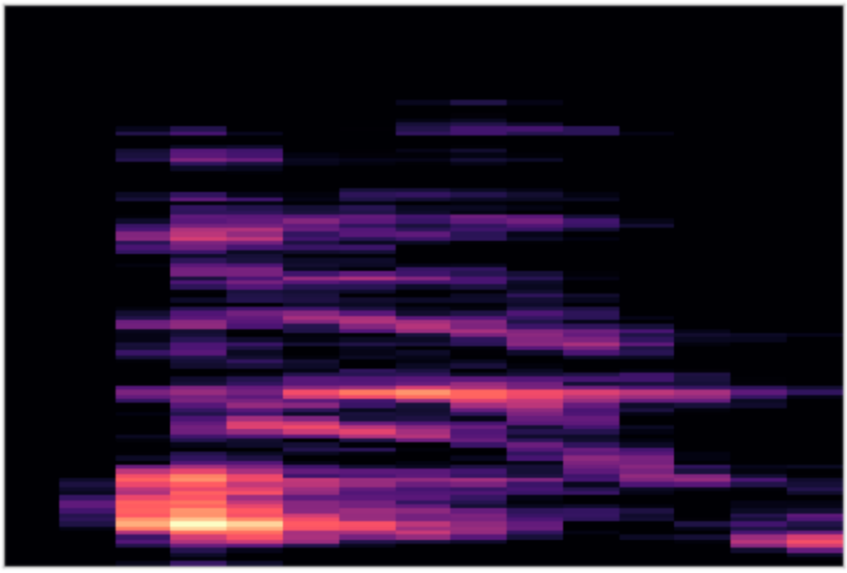


Figure 6.11: Spectogram of a voice sample

MFCCs have been shown to be effective in discriminating between different speakers, speech content, and even health conditions that affect voice; (4) *compatibility with ML algorithms*: MFCCs can be easily used as input features for various ML algorithms, such as NNs, SVMs, and decision trees, to build accurate and robust models for voice-based disease detection.

Feature extraction with pitch of a voice

The pitch of a voice is related to the vibration of the vocal cords, and it can be affected by various diseases. The pitch (fundamental frequency, F0) is an essential feature in speech processing and analysis, as it relates to the vibration of the vocal cords during speech production, as presented in Fig. 6.12. Changes in pitch can help identify certain voice disorders or neurological conditions. One standard method to estimate pitch is the autocorrelation method, which has the following steps: (1) Divide the speech signal into overlapping frames:

$$x_i[n] = x[n + i \cdot L], \tag{6.117}$$

autocorrelation function for each frame can be calculated with

$$R_i(\tau) = \sum_{n=0}^{N-\tau-1} x_i[n] \cdot x_i[n + \tau], \tag{6.118}$$

and finally it the fundamental frequency ($F0$) can be determined for each frame by finding the maximum value of the autocorrelation function for lags corresponding to the expected pitch range:

$$F0_i = \arg \max_{\tau_{\min} \leq \tau \leq \tau_{\max}} R_i(\tau), \tag{6.119}$$

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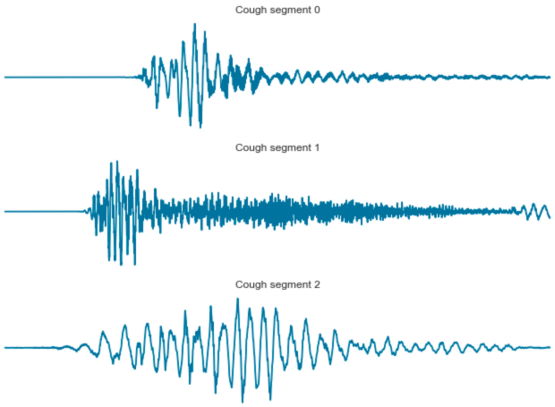


Figure 6.12: Cough segments from voice

where $\tau_{\min}$ and $\tau_{\max}$ are the minimum and maximum lags corresponding to the expected pitch range. The pitch feature (F0) is valuable in voice-based disease detection for the following reasons: (1) *sensitivity to vocal fold vibration*: F0 is directly related to the vibration of the vocal cords and can be affected by various diseases, such as paralysis of the vocal fold, nodules, or neurological conditions; (2) *detection of voice disorders*: changes in pitch, such as abnormal pitch variability or deviations from the typical pitch range, can help identify voice disorders; (3) *monitoring neurological diseases*: alterations in pitch can be indicative of neurological conditions such as Parkinson's disease [106], multiple sclerosis, or amyotrophic lateral sclerosis (ALS) [247]; (4) *non-invasive*: pitch can be extracted from voice recordings and providing a non-invasive method to evaluate vocal health and monitor disease progression.

Feature extraction with Jitter and Shimmer

Jitter is the variability in pitch period, and shimmer is the variability in amplitude. Both features measure the voice instability, which can indicate certain diseases. Jitter and shimmer are voice quality features that quantify the variability of pitch (fundamental frequency, F0) and amplitude, respectively. These features can help identify voice disorders and monitor the progression of diseases that affect the vocal folds.

Jitter algorithm: Input the sequences of pitch periods – the durations between consecutive vocal fold vibrations – extracted from the voice signal. The output is typically expressed as a percentage; this value represents the average absolute difference between consecutive pitch periods, divided by the average pitch period. High jitter values can suggest rough or unstable voice quality. Define the period (T_i) between successive pitch periods:

$$T_i = \frac{1}{F0_i}, \tag{6.120}$$

Calculate the absolute differences between consecutive periods:

$$\Delta T_i = |T_{i+1} - T_i|, \tag{6.121}$$

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Compute jitter as the mean absolute difference divided by the average period:

$$\text{Jitter} = \frac{\sum_{i=1}^{N-1} \Delta T_i}{\sum_{i=1}^{N-1} T_i}, \tag{6.122}$$

Shimmer algorithm: the input is the sequences of peak amplitudes measured over successive vocal fold vibrations. The output of this algorithm is typically expressed as a percentage, indicating the average absolute difference between the amplitudes of consecutive cycles relative to the average amplitude. Elevated shimmer values can be indicative of soft or weak voice quality. The absolute differences between consecutive amplitude values (A_i) of the speech signal:

$$\Delta A_i = |A_{i+1} - A_i|, \tag{6.123}$$

Compute shimmer as the mean absolute difference divided by the average amplitude:

$$\text{Shimmer} = \frac{\sum_{i=1}^{N-1} \Delta A_i}{\sum_{i=1}^{N-1} A_i}, \tag{6.124}$$

The jitter and shimmer characteristics are valuable in the detection of voice-based diseases for the following reasons: (1) *sensitivity to vocal fold vibration*: jitter and shimmer are sensitive to irregularities in the vibration of the vocal fold, which can be affected by various diseases, such as paralysis of the vocal fold, nodules, or neurological conditions; (2) *detection of voice disorders* [248]: changes in jitter and shimmer can help identify voice disorders by quantifying the variability in pitch and amplitude, respectively; (3) *monitoring neurological diseases* [23]: alterations in jitter and shimmer can be indicative of neurological conditions such as Parkinson's disease, multiple sclerosis, or ALS [247]; (4) *non-invasive*: jitter and shimmer can be extracted from voice recordings, providing a non-invasive method to assess vocal health and monitor disease progression.

6.4.2 Pneumonia detection in performance sports

In the YOLOv9 framework, the innovative approach aimed at optimizing object detection incorporates several advanced concepts, notably the Information Bottleneck Principle (IB) [249], Reversible Functions, PGI and the GELAN. These components work in concert to address common challenges in DL such as information loss and efficiency. The IB principle is expressed mathematically as follows:

$$\max_{p(t|x)} I(T;Y) - \beta I(T;X) \tag{6.125}$$

where T is the transformed representation of the input X aimed at retaining as much information as possible about the output Y, while ignoring irrelevant information contained in X. This principle guides the design of NNs to focus on the most informative features for

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decision-making, directly influencing how features are extracted and compressed within the network. Reversible functions are employed to mitigate the loss of information during the transformation process, as described by the reversible function equation.

$$X_{n+1} = f(X_n, \theta_n) \tag{6.126}$$

$$X_n = g(X_{n+1}, \theta_n) \tag{6.127}$$

In this setup, f and g are functions such that g is the inverse of f, ensuring no information is lost between the input X_n and the output X_{n+1}. This is directly related to the IB principle by facilitating a network design where each layer's transformation preserves mutual information optimally, enhancing the fidelity of the bottleneck representation T. PGI addresses the optimization of the training process.

$$\text{PGI} = \text{Optimize}(\nabla I(T;Y), \nabla I(T;X)) \tag{6.128}$$

PGI leverages programmable components within the network to dynamically adjust gradient flow, which ensures that during backpropagation, gradients are optimized to reduce information loss and improve learning efficiency [250]. This method improves the application of the IB principle [249] by providing a mechanism to fine-tune the way information is preserved or discarded through the network layers, based on relevance to the desired output Y. GELAN structures the NN to optimize data flow and computational efficiency.

$$\text{GELAN} = \text{EfficientLayer}(X_n, \theta_n) \tag{6.129}$$

GELAN uses a specialized architecture that aggregates layers in a way that balances computational efficiency with the need to process and preserve information effectively. This architectural method supports the PGI by ensuring that the network structure itself contributes to maintaining efficient gradient flow and information preservation, aligned with the goals set by the IB principle.

In case of YOLOv9 framework: (1) the *IB principle* sets the theoretical basis for what information should be preserved during learning; (2) the *reversible functions* provide a practical implementation strategy to ensure that this preservation is achieved without loss; (3) the *PGI* dynamically optimizes the network learning process to adhere to the IB principle efficiently; (4) the *GELAN* structures the network in a way that supports efficient information processing, complementing the dynamic adjustments made by PGI. This synergy ensures that the network is not only fast and accurate but also robust against common pitfalls in DL, such as overfitting and irrelevant feature retention.

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6.4.3 Burnout in performance sport

Burnout, using sentiment analysis

Sentiment analysis [251] can be used to estimate burnout levels by analyzing feelings and emotions expressed in text data [18]. The premise is that burnout can be reflected in an individual's sentiments and emotional expressions. In the research [18], the burnout detector framework was composed as follows:

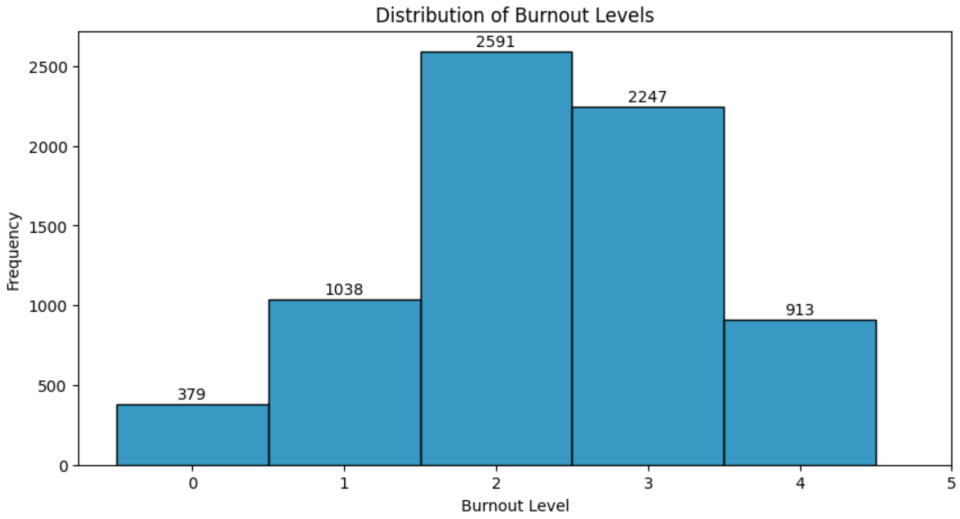


Figure 6.13: Distribution of Burnout Levels

1. *Sentiment scores*: The DistilBERT sentiment analysis mode was used to obtain sentiment scores for a piece of text. The score typically ranges from 0 (very negative) to 1 (very positive).

$$\text{sentiment_score} = f_{\text{sentiment}}(\text{text}) \tag{6.130}$$

where $f_{\text{sentiment}}$ is the sentiment analysis function.

2. *Thresholds and categories*: The thresholds to categorize the sentiment scores into different sentiment categories (sentiments) were set as follows.

$$\text{sentiments} = \begin{cases} \text{“Very Negative”} & \text{if } 0 \leq \text{score} < 0.2 \\ \text{“Negative”} & \text{if } 0.2 \leq \text{score} < 0.4 \\ \text{“Neutral”} & \text{if } 0.4 \leq \text{score} < 0.6 \\ \text{“Positive”} & \text{if } 0.6 \leq \text{score} < 0.8 \\ \text{“Very Positive”} & \text{if } 0.8 \leq \text{score} \leq 1 \end{cases} \tag{6.131}$$

3. *Mapping sentiment to burnout*: Burnout levels were established on the basis of sentiment categories. The rationale is that more negative sentiments might correlate with higher levels of burnout.

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$$\text{burnout_level} = \begin{cases} 0 & \text{if sentiment_category} = \text{“Very Positive”} \\ 1 & \text{if sentiment_category} = \text{“Positive”} \\ 2 & \text{if sentiment_category} = \text{“Neutral”} \\ 3 & \text{if sentiment_category} = \text{“Negative”} \\ 4 & \text{if sentiment_category} = \text{“Very Negative”} \end{cases} \tag{6.132}$$

The research [18] shows a simplistic mapping to conceptualize pipeline [36]. Fig. 6.13 shows the confusion matrix.

In reality, the relationship between sentiment and burnout is more complex. More granular sentiment analysis is required, such as detecting specific emotions (stress, frustration, exhaustion) or employing more sophisticated models that consider the context and sequence of sentiments over time.

A more sophisticated model could be conceptualized as follows:

$$\text{burnout_level} = f(\text{sentiment_score}, \text{other_features}) \tag{6.133}$$

where f is a complex function (potentially an ML model) that considers sentiment scores and other relevant characteristics to predict burnout levels (see Table 6.3).

Table 6.3: Sample from the dataset (The dataset will be shared on request)

Nr	Text	Burnout	Sentiment	Length	Score
...	...	...	...	...	...
1918	my husband is stressing me out. he lost his jo...	3	Very Negative	81	0.012483
2770	This issue about Covid-19 is very stressful to...	4	Very Positive	50	0.997141
2376	school have been stressing me out a bit. i hav...	3	Positive	72	0.658553
3013	work has been so stressful	2	Neutral	26	0.513116
3058	work is so ridiculously busy and we have littl...	2	Very Negative	58	0.000256
4493	it sucks because i'm pretty much busy all the ...	2	Very Negative	69	0.006867
...	...	...	...	...	...
6508	then school is stressful.	2	Negative	25	0.223963
...	...	...	...	...	...

Using sentiment scores alone might not provide a comprehensive understanding, but they can act as a valuable feature among others in predicting or estimating burnout levels.

Correlation between stamina and burnout

In a wider approach, athlete burnout and physical stamina (or lack thereof, often termed fatigue) can interact in several ways from different aspects:

1. *Physical aspect*: continuous and rigorous training without adequate rest can reduce an athlete's stamina, leading to physical fatigue. This chronic fatigue can contribute to burnout, as the athlete may feel overwhelmed, exhausted, and unable to perform at their best.

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2. *Mental aspect*: the mental strain of the pressure to perform, coupled with reduced stamina, can intensify feelings of burnout. As stamina decreases, performance can decrease, leading to frustration, self-doubt, and increased mental stress.

3. *Interrelationship aspect*: burnout can lead to reduced motivation, affecting stamina. An athlete feeling mentally burnt out may not train effectively, leading to a decline in physical stamina.

To quantify the correlation between stamina (or fatigue) and burnout, the Pearson correlation coefficient was used [252]. Given two variables X (representing stamina) and Y (representing burnout), the Pearson correlation coefficient r is given by:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{6.134}$$

where: n is the number of observations, X_i and Y_i are the individual data points, $\bar{X}$ and $\bar{Y}$ are the means of X and Y respectively. The coefficient r ranges from -1 to 1. A value close to 1 implies a strong positive correlation: as stamina increases, burnout decreases. A value close to -1 implies a strong negative correlation: As stamina decreases, burnout increases. A value close to 0 implies a minor to no linear correlation between stamina and burnout. In the context of athletes: (i) if r is close to -1, it indicates that as the athlete's stamina decreases, their burnout levels increase; (ii) if r is close to 1, it would be an unusual scenario indicating that as stamina increases, burnout also increases (this is not the typical expectation). To determine this correlation, data on athlete stamina (through fitness tests, time-to-exhaustion tests, or other stamina indicators) and burnout levels (through psychological surveys or assessments) would need to be collected and then the Pearson correlation coefficient would need to be calculated. It should be noted that, while the correlation can indicate the linear relationship between two variables, it does not imply causation. Furthermore, athletes are influenced by many factors, so although there can be a correlation between stamina and burnout [18], it is essential to consider the broader context and other variables that influence it.

6.4.4 Disease detection from written communication

Mental health disorder identification

Translating an algorithm to detect mental health disorders from text into mathematical language involves defining functions and representations for feature extraction, transformation, and classification processes. The mathematical formulation of the problem is as follows. First the variables and functions were introduced: (1) let D be a set of documents $\{d_1, d_2, ..., d_n\}$, where each document d_i represents a piece of text; (2) let L be a set of labels $\{l_1, l_2, ..., l_m\}$, where each label corresponds to a mental health disorder (e.g.,

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depression, psychosis, Alzheimer's); (3) Preprocess(d) is a function that takes a document d and returns a preprocessed document; (4) Tokenize(d) is a function that takes a preprocessed document d and returns a set of tokens T; (5) Vectorize(T) is a function that converts tokens T to a feature vector $\mathbf{x}$; (6) Classify($\mathbf{x}$) is a function that assigns a label l to a feature vector $\mathbf{x}$. For the frequency inverse document frequency term (TF-IDF), tfidf(t, d, D) can be defined , which computes the TF-IDF score for a term t in the document d within the set of documents D.

$$\text{tf}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{6.135}$$

$$\text{idf}(t, D) = \log \frac{|D|}{|\{d \in D | t \in d\}|} \tag{6.136}$$

$$\text{tfidf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D) \tag{6.137}$$

Sentiment analysis could use a predefined sentiment lexicon S, where each word w has an associated sentiment score $s(w)$ [93]. The sentiment score of a document d is a sum of the sentiment scores of its words:

$$\text{SentimentScore}(d) = \sum_{w \in d} s(w) \tag{6.138}$$

The complexity measures involve computing the diversity of words Diversity(d) or the readability Readability(d) of the document. A classifier can be represented by a function C that maps feature vectors to labels. If using an SVM, for instance, the decision function for a binary classification looks like this:

$$C(\mathbf{x}) = \text{sgn}(\mathbf{w}^T \mathbf{x} + b) \tag{6.139}$$

where $\mathbf{w}$ is the weight vector, b is the bias, and sgn is the sign function.

For a probabilistic output, such as from a logistic regression or NN with a softmax layer, the classifier could output a probability vector over labels:

$$C(\mathbf{x}) = \text{softmax}(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{6.140}$$

where $\mathbf{W}$ is a weight matrix and $\mathbf{b}$ is a bias vector. The mathematical representation of the algorithm is as follows:

1. Pre-processing:

$$\forall d_i \in D, \tilde{d}_i = \text{Preprocess}(d_i) \tag{6.141}$$

2. Tokenization and vectorization:

$$\forall \tilde{d}_i, T_i = \text{Tokenize}(\tilde{d}_i) \tag{6.142}$$

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$$\forall T_i, \mathbf{x_i} = \text{Vectorize}(T_i) \tag{6.143}$$

Let us include the sentiment and complexity features in $\mathbf{x_i}$.

3. Classification:

$$\forall \mathbf{x_i}, l_i = C(\mathbf{x_i}) \tag{6.144}$$

4. Model training (if not using a predefined model): find $\mathbf{W}$ and $\mathbf{b}$ that minimize a loss function

$$\mathcal{L}(C(\mathbf{x_i}), y_i) \tag{6.145}$$

over the training data, where y_i is the true label.

5. Inference: for a new document d, it will be calculated as

$$l = C(\text{Vectorize}(\text{Tokenize}(\text{Preprocess}(d)))) \tag{6.146}$$

Neurodegenerative diseases detection

Detecting neurodegenerative diseases such as Alzheimer's [253] from text [19] could involve strategies similar to those used for mental health disorders. However, the focus might shift to detecting cognitive impairment, which can manifest in language differently. The mathematical framework should be adapted to capture these nuances. First, the variables and functions for neurodegenerative diseases will be defined: (1) let C denote cognitive features extracted from text, such as coherence, vocabulary richness or syntactic complexity; (2) define CoherenceScore(d) as a function that measures the logical flow and clarity of ideas within the text; (3) define SyntacticComplexity(d) as a function that measures the complexity of sentence structures; (4) define VocabularyRichness(d) as a function that measures the diversity of vocabulary used in the document. In feature engineering, coherence can be measured through the consistency of topics or entities mentioned in a text. Let $\mathcal{T}$ be a topic model; then coherence can be quantified as

$$\text{CoherenceScore}(d) = \sum_{i=1}^{n-1} \text{similarity}(\mathcal{T}(s_i), \mathcal{T}(s_{i+1})) \tag{6.147}$$

where $\mathcal{T}(s)$ is the topic distribution of sentence s and similarity is a function that measures the similarity between the topic distributions (e.g., cosine similarity). *Syntactic complexity* might involve parsing trees and measuring their depth or branch factor:

$$\text{SyntacticComplexity}(d) = \frac{1}{|S|} \sum_{s \in S} \text{TreeDepth}(\text{ParseTree}(s)) \tag{6.148}$$

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where S is the set of sentences in d, and ParseTree(s) is the syntactic parsing tree of sentence s. The *vocabulary richness* might use metrics such as the type-token ratio (TTR) or unique words:

$$\text{VocabularyRichness}(d) = \frac{|\text{unique words in } d|}{|\text{tokens in } d|} \tag{6.149}$$

The Classification Model, which will be an ML model in this case, potentially an NN with architecture suited to capture temporal and cognitive features, could be represented as:

$$C(\mathbf{x}) = \text{softmax}(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1) + \mathbf{b}_2) \tag{6.150}$$

where $\mathbf{x}$ includes traditional NLP characteristics along with neurodegenerative-specific cognitive characteristics, $\mathbf{W}_1, \mathbf{W}_2$ are weight matrices, $\mathbf{b}_1, \mathbf{b}_2$ are bias vectors, and ReLU is the ReLU activation function. The mathematical representation will be as follows:

1. Pre-processing and feature engineering:

$$\forall d_i \in D, \tilde{d}_i = \text{Preprocess}(d_i) \tag{6.151}$$

$$\forall \tilde{d}_i, T_i = \text{Tokenize}(\tilde{d}_i), C_i = \text{CognitiveFeatures}(\tilde{d}_i) \tag{6.152}$$

$$\forall T_i, \mathbf{x}_i^{text} = \text{Vectorize}(T_i) \tag{6.153}$$

$$\mathbf{x}_i = [\mathbf{x}_i^{text}, C_i] \tag{6.154}$$

   where C_i includes coherence, complexity, and vocabulary richness.

2. Model training: $\mathbf{W}_1, \mathbf{W}_2, \mathbf{b}_1, \mathbf{b}_2$ can be optimized by minimizing the loss function $\mathcal{L}(C(\mathbf{x}_i), y_i)$.

3. Inference: for a new document d,

$$l = C(\text{Vectorize}(\text{Tokenize}(\text{Preprocess}(d))), \text{CognitiveFeatures}(d)) \tag{6.155}$$

Detecting neurodegenerative diseases from text [19] requires rigorous validation and should be supplemented with clinical assessments. The model presented in the thesis research [19] contains a concept with a minimal dataset, but needs to be expanded with a large and validated dataset. Cognitive features must be specifically tailored to the types of language deficits or changes associated with the particular neurodegenerative disease.

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Detecting chronic diseases

Detecting chronic diseases such as diabetes or thyroid disorders through text analysis can be pretty challenging because the symptoms and signs of these diseases are typically not as directly reflected in language as those of some mental disorder or NDD. However, if it is considered that people might express concerns, experiences, or symptoms related to their physical health in text messages, sentiment analysis and specific linguistic cues might provide indirect indicators. For this, the mathematical framework must incorporate sentiment analysis and pay attention to a specific lexicon related to physical symptoms, care management, and possibly lifestyle aspects that can be linked to chronic diseases. Identify SymptomLexicon(d) as a function that identifies the presence of words or phrases associated with symptoms or the management of chronic diseases; (2) let H represent healthcare management characteristics, such as mentions of medication, doctor visits or treatment-related activities; (3) let L represent lifestyle characteristics that can include dietary habits, physical activity levels or other behaviors relevant to chronic diseases; (4) SentimentAnalysis(d) remains a function that assigns a sentiment score to document d, but can also flag emotionally charged language that could be indicative of stress or frustration related to disease management; (4)

On the *feature engineering* side for chronic diseases, the *symptom mention* can be a binary or frequency-based feature indicating the presence of terms from a curated symptom lexicon:

$$\text{SymptomFeature}(d) = \sum_{t \in \text{SymptomLexicon}} \text{Ind}(t \in d) \tag{6.156}$$

where Ind is an indicator function that returns 1 if the term t is present in the document d and 0 otherwise. The *healthcare management features* can be quantified similarly by counting mentions of healthcare-related activities:

$$H(d) = \sum_{t \in \text{HealthcareLexicon}} \text{Ind}(t \in d) \tag{6.157}$$

The *lifestyle characteristics* can also be derived from the mentions of activities or habits:

$$L(d) = \sum_{t \in \text{LifestyleLexicon}} \text{Ind}(t \in d) \tag{6.158}$$

The *sentiment analysis* can be adapted to give more weight to the sentiments expressed in the context of health:

$$\text{HealthSentimentScore}(d) = \sum_{w \in d} s(w) \cdot \text{Ind}(w \in \text{HealthContext}) \tag{6.159}$$

where HealthContext is a set of contexts in which sentiment could be particularly relevant

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for chronic disease. As a classifier, the well-known models can be used, such as random forest or gradient boosting machine, which can handle sparse features effectively:

$$C(\mathbf{x}) = \text{softmax}(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{6.160}$$

where $\mathbf{x}$ includes traditional NLP characteristics, sentiment scores, symptoms characteristics, health management characteristics, and lifestyle characteristics. The complete mathematical model for chronic diseases can be formulated as follows: (1) *Feature Engineering*: for each document $d_i \in D$: (1) preprocess and extract text characteristics to form $\mathbf{x}_i^{text}$, (2) extract symptom, healthcare management and lifestyle characteristics to form $\mathbf{x}_i^{chronic}$ (3) perform sentiment analysis tailored to the health context and then (4) combine all characteristics:

$$\mathbf{x}_i = [\mathbf{x}_i^{text}, \mathbf{x}_i^{chronic}, \text{HealthSentimentScore}(d_i)] \tag{6.161}$$

(2) *Model training*: train the classifier C with characteristics $\mathbf{x}_i$ to predict labels y_i related to the likelihood of chronic disease-related discourse; (3) *Inference*: for a new document d, calculate the likelihood of chronic disease-related discourse: $l = C(\mathbf{x})$.

6.4.5 Lesions and tumor detection on severe head injuries

(1) Early detection of a brain injury brings an earlier intervention with an earlier treatment, which can significantly improve outcomes, increasing the percentage of faster rehabilitation process [28]. The AI pipeline proposed in the thesis (see Fig. 6.14) can analyze medical images in real time and alert medical personnel if it detects a potential lesion or tumor (which can be LGG and HGG [211], allowing immediate intervention; (2) YOLO and YOLO-NAS [212] have the potential to match, or even exceed, the performance of human experts in interpreting medical images. The accuracy depends on the training dataset. Dedicated models can be trained to identify subtle patterns that humans might miss and do not suffer from fatigue or cognitive biases; (3) Unlike human experts, ML models can provide consistent results. They analyze every image in the same way, regardless of the time of day, how many photos they have already analyzed, or other factors that might affect human performance; (4) An AI-supported brain injury and/or anomaly detection system can analyze images much faster than a human expert can, and multiple images can be analyzed simultaneously if sufficient computational resources are available. This type of scalability makes it possible to screen a large number of athletes, even in sports, where head injuries are common, such as American football [213] or rugby.

Feature extraction in CNN

Feature extraction is crucial for object detection algorithms, especially with medical images such as MRI or CT to detect brain lesions, anomalies, or tumors [28,36]. The features

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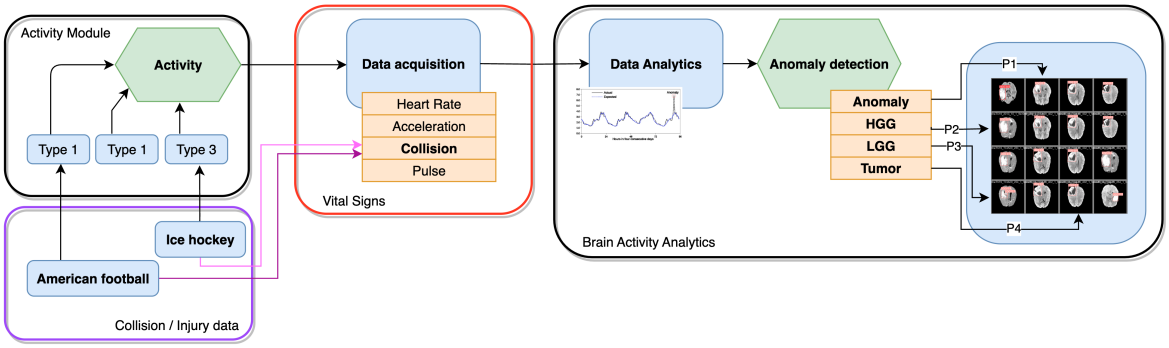


Figure 6.14: Brain injury detection pipeline in performance sports

can be extracted using a CNN: The initial layers perform a convolution operation. In this operation, a small matrix called a "filter" or "kernel" is applied to the image matrix. The formula for a convolution operation where I is the image matrix and K is the kernel can be formulated as follows:

$$(F * I)[i, j] = \sum_m \sum_n I[m, n] * K[i - m, j - n] \tag{6.162}$$

where $(F*I)[i, j]$ is considered the value of the pixel at location $[i, j]$ in the output feature map. These feature maps undergo operations such as ReLU to introduce nonlinearity and max-pooling to down-sample. In the final step, the final feature maps are flattened and input to a fully connected layer, which outputs the class probabilities after using softmax.

YOLO object detection

A widely used method for object detection is the YOLO (You Only Look Once) algorithm, which divides the image into grid cells and predicts bounding boxes and class probabilities for the cells in the grid [36]. MRI can detect lesions, anomalies, or tumors [254] in addition to general object detection [28, 36]. Each prediction of the bounding box can be defined as $(b_x, b_y, b_w, b_h, b_{conf})$, and the prediction of the class as c. Then, each grid cell gives us the following output in tensor T:

$$\begin{aligned} T[i, j, :] = (&b_{x_i,j}, b_{y_i,j}, b_{w_i,j}, b_{h_i,j}, b_{conf_i,j}, \\ &c_{1_i,j}, c_{2_i,j}, ..., c_{C_i,j}) \ , \end{aligned} \tag{6.163}$$

where i and j are the indices of the grid cells in the grid $S \times S$ and $c_{1_i,j}, c_{2_i,j}, ..., c_{C_i,j}$ are the probabilities of classes for each class in the grid cell (i, j). The model learns to adjust these predictions via a multipart loss function that considers classification error, localization error (error in predicting the box coordinates), and confidence error (the error between the predicted and actual IoU). The YOLO network structure uses convolutional layers for feature extraction and fully connected layers for output.

Assuming an input image of size 448×448, it goes through a series of convolutional

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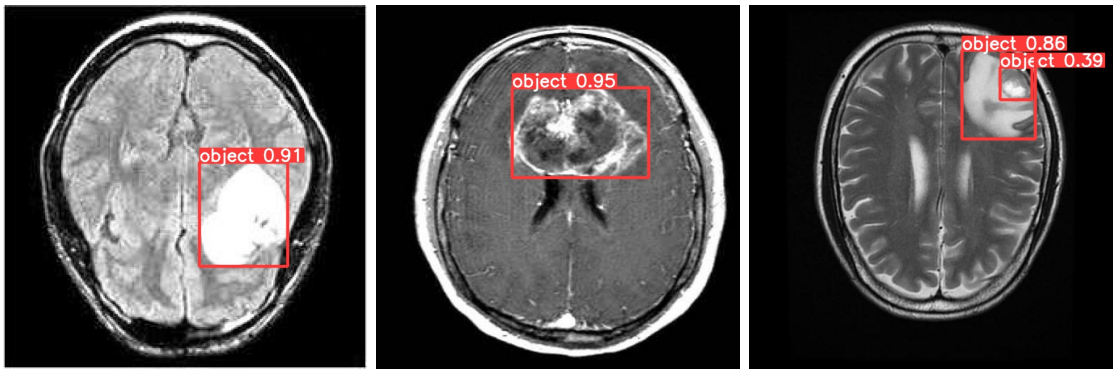


Figure 6.15: YOLO8-based tumor object detection

layers and max pooling layers, resulting in a $7 \times 7 \times 1024$ tensor output from the feature extraction part of the network. Given an image I with width W and height H, it was passed through a series of convolutional layers and pooling layers to extract features. This feature extraction process can be denoted as:

$$F = Conv(I) \tag{6.164}$$

where $Conv$ represents the series of convolutional and pooling operations, and F is the resulting feature map. This output is then reshaped into a $7 \times 7 \times (B \times 5 + C)$ tensor, where B - bounding box number. Each cell can predict (usually 2 from YOLOv1). C - the number of classes (for lesions, anomalies, or tumors, it would be 1). It has $S \times S$ grid cells and each grid cell has B bounding boxes and C class probabilities. Let $P_{i,j,k}$ be the probability that there is an object in cell (i, j), and the object belongs to class k.

The bounding boxes are denoted as $b_{i,j}^{(p)} = (x_{i,j}^{(p)}, y_{i,j}^{(p)}, w_{i,j}^{(p)}, h_{i,j}^{(p)})$, where p is the index of the bounding box in cell (i, j). Confidences are denoted as $Conf_{i,j}^{(p)}$, and class probabilities are denoted as $P_{i,j,k}$. The output tensor T of the network would be:

$$\begin{aligned} T[i, j, :] = (&P_{i,j,1}, b_{i,j}^{(1)}, C_{i,j}^{(1)}, ..., b_{i,j}^{(B)}, \\ &C_{i,j}^{(B)}, P_{i,j,2}, ..., P_{i,j,C}) \end{aligned} \tag{6.165}$$

This process of predicting bounding boxes, confidences, and class probabilities can be represented as

$$(b, Conf, P) = Regress(F) \tag{6.166}$$

where $Regress$ represents the regression operation. The final prediction for each cell is then the class with the highest probability and the bounding box with the highest confidence:

$$(c^*, b^*)_{i,j} = \arg\max_{k,p} P_{i,j,k} \times Conf_{i,j}^{(p)} \tag{6.167}$$

The network's final output would be a set of class probabilities and bounding-box

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coordinates for each cell in the grid. The loss function of the network would typically include three components: (1) classification loss, (2) localization loss (for the coordinates of the bounding box) [255], and (3) confidence loss. It is used to train the network to improve its ability to detect and classify objects. The advantages of YOLO include its ability to detect objects in real time and its approach to object detection as a single regression problem, which allows it to be highly efficient [36]. In the context of brain anomaly detection, the added values of YOLO include the following: (1) it processes images in a single forward pass through the network, making it much faster (assuring near real-time detection) than other methods that use selective search to identify regions of interest; (2) YOLO sees the entire image (using global context) during training and test time, allowing it to account for contextual information implicitly; (3) YOLO has fewer false positives in background areas.

YOLO-NAS expansion in object detection

A denotes the space of possible architectures, and let $a \in A$ be a specific architecture.

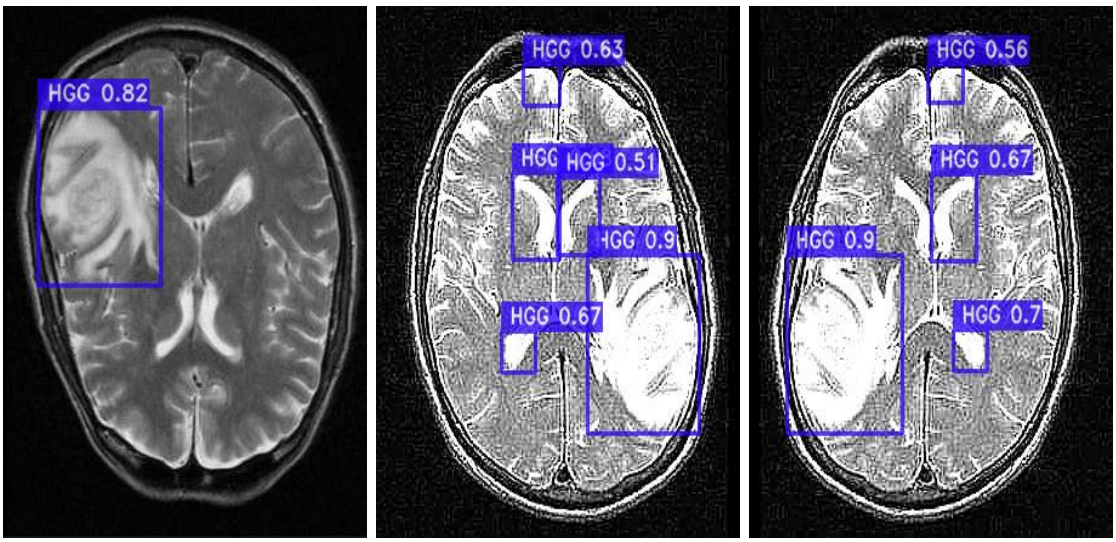


Figure 6.16: YOLO8-NAS-based HGG and LGG detection

Each architecture a can be trained as a YOLO model M_a using a brain scan dataset and evaluating its performance using a validation set. The NAS [256] algorithm searches the space of possible architectures to find the one that performs the best, according to some criteria (e.g., detection accuracy, Intersection over Union (IoU) score, etc.). Assuming that it has N architectures to explore, an optimization problem can be defined to find the best architecture:

$$a^* = \arg\max_{a \in A} P(M_a) \tag{6.168}$$

where $P(M_a)$ is the performance of the model M_a in the validation set. After finding the best architecture a^*, the final model can be trained using the entire dataset to detect

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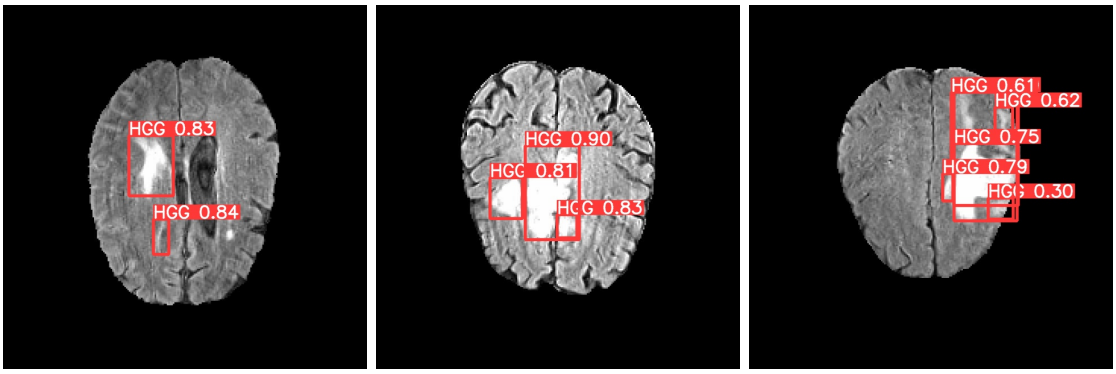


Figure 6.17: YOLO8-based HGG and LGG detection

lesions, anomalies, or tumors in new brain scans [28]. NAS involves more complexity, such as using surrogate models, exploration-exploitation strategies, and regularization techniques. It can be assumed that there is an initialized search space $\mathcal{A}$, which represents all possible architectures that the NAS algorithm can explore. Then, the NAS algorithm iteratively searches this space to find the optimal architecture $\mathcal{A}^*$ that performs best on a validation set:

$$\mathcal{A}^* = \arg\max_{\mathcal{A}\in\mathcal{S}} \mathbb{E}_{(x,y)\sim\text{Validation set}}[\text{IoU}(M_{\mathcal{A}}(x), y)] \tag{6.169}$$

$M_{\mathcal{A}}$ is YOLO architecture $\mathcal{A}$, IoU(.,.) is the "Intersection over Union" between the predicted and ground truth bounding boxes, and the expectation is over the validation set. After finding the optimal architecture $\mathcal{A}^*$, the final YOLO model $M_{\mathcal{A}^*}$ can be trained by using the entire dataset. The feature extraction and prediction process in the final YOLO model can be represented similarly to standard YOLO. Given an image I, it passed through the feature extraction part of the model, which consists of the optimal architecture $\mathcal{A}^*$ to obtain a feature map F:

$$F = M_{\mathcal{A}^*}(I) \tag{6.170}$$

The added value of YOLO-NAS for brain anomaly detection includes: (1) NAS could find a CNN architecture that is better at extracting features such as an "Optimized Architecture Approach" from brain scans than any manually designed architecture; (2) using the optimal architecture for feature extraction, YOLO-NAS provides higher detection accuracy; (3) maintaining the YOLO structure, YOLO-NAS retains the ability for real-time detection.

Manual data processing

Fig. 6.18 shows the YOLO8 confusion matrix, Fig. 6.19 shows the YOLO8 confusion matrix in HGG, LGG training and Fig. 6.20 shows the YOLO8-NAS confusion matrix in HGG, LGG training. The accuracy is lower than in the case of YOLO8, but this model

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needs more training data.

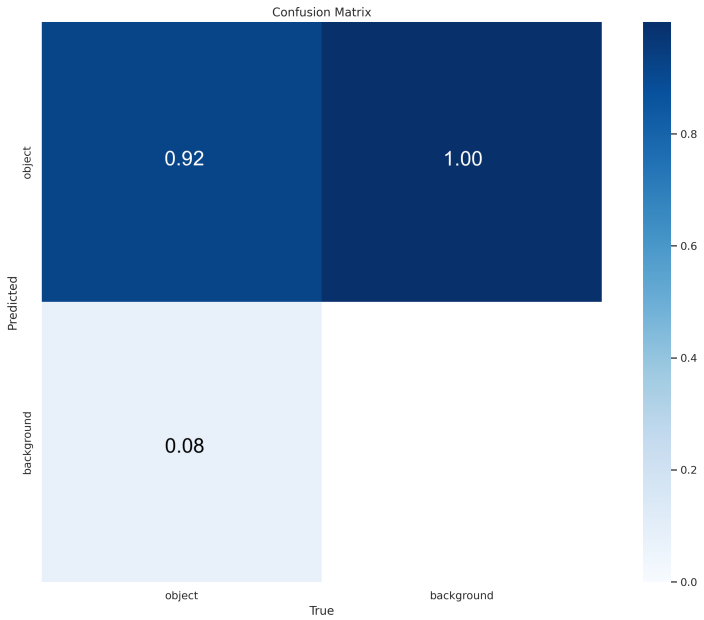


Figure 6.18: YOLO8 confusion matrix - object detection

6.5 Methods in strategy prediction & gamification

The use of You Only Look Once (YOLO) [36, 120] and YOLO-NAS (YOLO-NAS) [121] models in the extraction of performance sports strategies [122] brings a novel approach [41] to analyze and understand the dynamics of sports drills as shown in Fig. 6.21. By applying these models to video footage, coaches and analysts can efficiently detect and track players, extract valuable information on player movement patterns and interactions, and identify strategic elements to enhance team performance.

YOLO and YOLO-NAS applied in performance sports offer a data-driven solution [41] to optimize training, game strategies, and player development as follows: (1) the models can be applied to detect and track players and objects of interest in performance sports videos with high accuracy and near real-time. This enables the extraction of valuable data on player movement, puck/ball trajectory, and positional interactions, providing a detailed understanding of drill / strategy [214] or game dynamics; (2) by analyzing detected objects and their interactions, the applied models can identify recurring patterns and strategic elements within sports drills or games. This information can be used to evaluate the effectiveness of specific strategies, evaluate player performance, and gain insight into team dynamics; (3) the extracted data can help recommend optimal strategies for performance sports. Coaches and analysts can take advantage of the insights obtained from these models to refine training routines, adapt game plans, and make data-driven decisions [215] to improve team performance and success; the real-time nature of YOLO / YOLO-NAS

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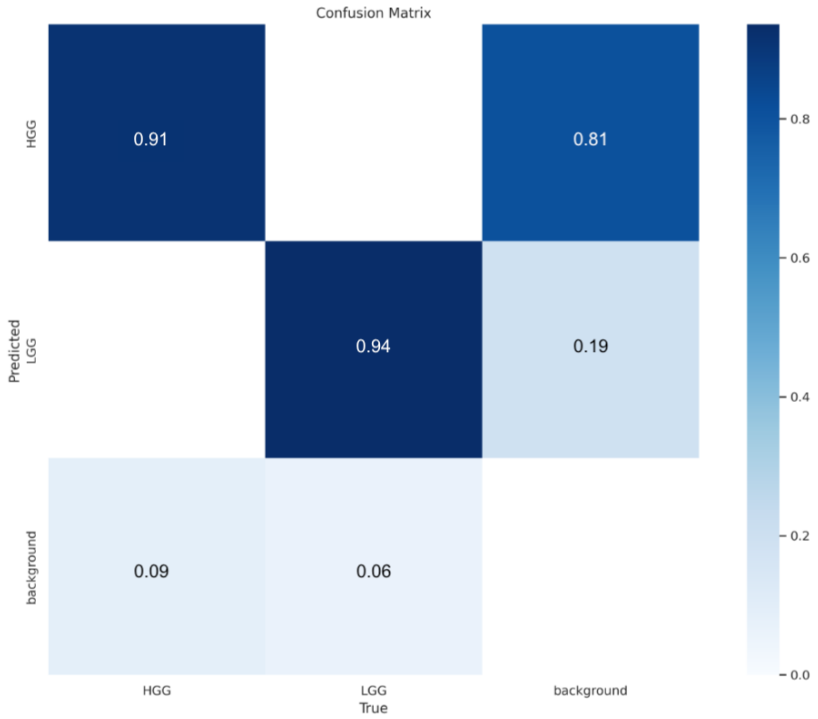


Figure 6.19: YOLO8 confusion matrix - HGG, LGG

models allows on-the-fly analysis of live sports events, providing instantaneous feedback to coaches and players. This capability allows quick adjustments, tactical interventions, and immediate strategy recommendations based on the analysis of current game play.

6.5.1 YOLO algorithm

YOLO [120] provides grid-based predictions using the following algorithm. Given an input image of size W × H, YOLO divides the image into an S × S grid, where each grid cell is responsible for predicting the bounding boxes and class probabilities. Each cell of the grid predicts the B bounding boxes, each characterized by 5 + C parameters, where 5 represents the coordinates (x, y, w, h, confidence) of the bounding box, and C represents the number of classes. Formally, the prediction tensor for each cell in the grid is of size B × (5 + C), denoted as YOLO predictions for each cell:

$$Y_{i,j} = [t^1_{i,j}, t^2_{i,j}, ..., t^B_{i,j}] \tag{6.171}$$

where (i, j) represents the coordinates of the grid cells.

Loss Function: YOL4O uses a combination of localization loss (L_{loc}), confidence loss (L_{conf}), and class probability loss (L_{class}) to train the model. The total loss is the sum of these individual losses, typically weighted by certain factors (λ_{loc}, λ_{conf}, and λ_{class}). The overall loss function can be represented as

$$L_{YOLO} = \lambda_{loc} * L_{loc} + \lambda_{conf} * L_{conf} + \lambda_{class} * L_{class} \tag{6.172}$$

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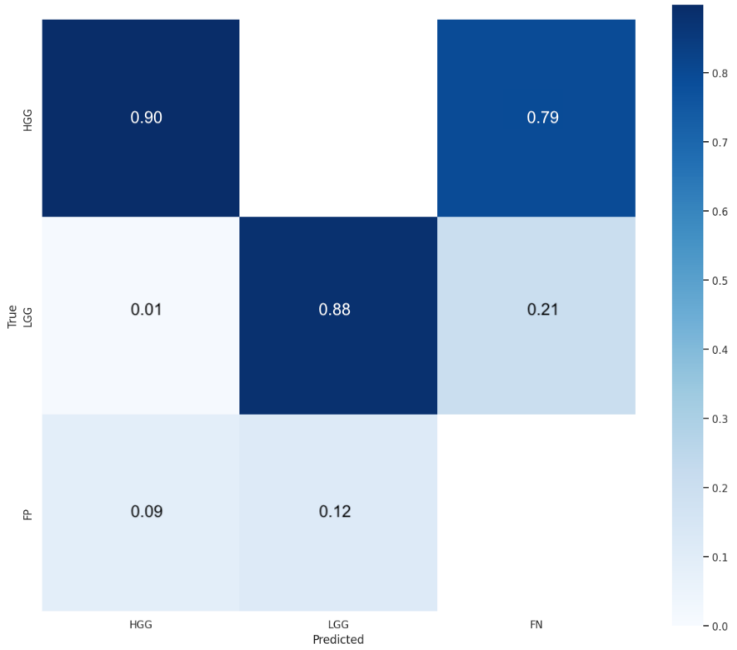


Figure 6.20: YOLO-NAS confusion matrix - HGG, LGG

6.5.2 YOLO-NAS algorithm

Neural Architecture Search: YOLO-NAS [121] incorporates NAS [257] techniques to find an optimal network architecture that maximizes performance on a given dataset; *Search Space and Architecture Representation*: The search space defines the possible architectural choices and configurations that can be explored during the NAS process. Architecture representation typically uses a directed acyclic graph (DAG) or a different type of encoding scheme to represent the network architecture; *Architecture Optimization*: YOLO-NAS optimizes the network architecture by training and evaluating multiple candidate architectures within the search space. The optimization process typically uses performance metrics (e.g., accuracy, mAP) as the objective to guide the search and techniques such as RL or evolutionary algorithms to update and evolve the architectures; *Flexible Architecture*: Unlike the fixed architecture of YOLO, YOLO-NAS allows greater flexibility in designing the network architecture by discovering new configurations, skip connections, or other architectural components through the NAS process.

6.5.3 Differences between YOLO and YOLO-NAS

(1) YOLO is a fixed architecture object detection model [258], while YOLO-NAS incorporates NAS to discover the optimal network architecture [36]; (2) YOLO divides the input image into a grid and predicts bounding boxes within each grid cell, whereas YOLO-NAS utilizes a similar grid-based approach, but focuses on searching for the best network architecture within the defined search space; (3) YOLO-NAS introduces a search space that defines the possible architectural choices and configurations, allowing for flexible

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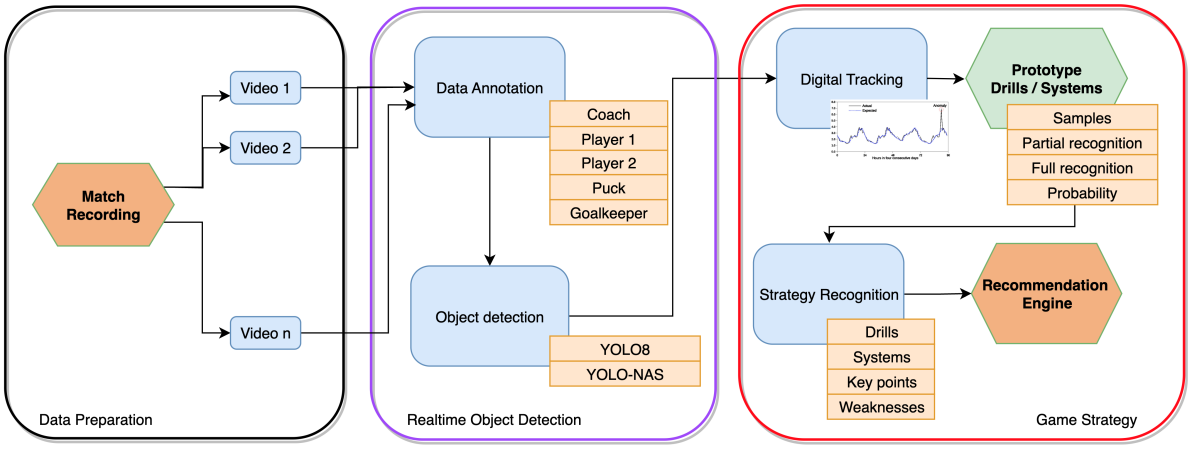


Figure 6.21: Predictive sports strategy

exploration of different convolutional layer configurations, skip connections, and feature fusion strategies. YOLO has a predetermined architecture with fixed anchor boxes; (4) YOLO-NAS performs a search process within the search space to find the best network architecture (such as RL or evolutionary algorithms). However, YOLO does not involve a search process and uses a single architecture throughout.

6.5.4 Limitations of YOLO and YOLO-NAS in digital tracking

(1) YOLO and YOLO-NAS may struggle with accurately tracking objects when occlusion or overlap occurs, making it challenging to capture precise positional information in such scenarios; (2) both models may face difficulty in detecting and tracking small objects, such as puck or distant players, as they can be easily missed or misclassified due to limited resolution or low visibility; (3) YOLO and YOLO-NAS may struggle in complex environments with cluttered backgrounds, varying lighting conditions, or unusual perspectives, leading to potential inaccuracies in tracking and strategy extraction [122]; (4) these models primarily focus on object detection and tracking, but may lack a comprehensive understanding of the game context, including player intentions, team strategies, or game dynamics, which can limit the depth of strategy extraction; (5) YOLO and YOLO-NAS can be computationally demanding, requiring powerful hardware and significant processing resources for real-time tracking and analysis, potentially limiting their accessibility.

6.6 Summary of scientific contributions

The main scientific contributions of this chapter are summarized as follows: (1) the design of real-time synthesized and multilanguage OCR for remote diagnosis, based on ML-based text recognizers using CRNN and SVTR models, and hyperparameter tuning; (2) the design of optimal dataset preparation in VOD; (3) the design of complex RPA

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intensity prediction architecture with radars and 3D accelerometers using HR, RPE and acceleration data; (4) the design of AI-based method of fatique and stamina control on multivariate time series datasets; (5) the design of the technological pipeline to estimate the overall fatigue score using RPE, sRPE, and ACWR; (6) the design of a personalized recovery model on to top of MediaPipe Pose estimation; (7) the design of a disease detection pipeline from voice adapted to peformance sports; (8) the design of a burnout detection method adapter to performance sports using sentiment analysis; (9) the design of a disease detection method focusing on mental health disorders and neurodegenerative and chronice diseases; (10) the design of a method for lesions and tumor detection on severe head injuries (see Fig. 6.14); (11) the design of the strategy prediction architecture using YOLO /YOLO-NAS (see Fig. 6.21).

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7 Novelties

This chapter presents validated, peer-reviewed novelties and proposed adjustments to existing models, methods, and technological pipelines for advanced distant diagnostics techniques and sensors in the prediction of sports safety and health conditions. The perspectives covered include remote consultation, radars and other sensors, health condition control, disease detection, injury prevention, prediction, and gamification of sports strategies. The conclusion of the chapter provides a concise overview of the scientific contributions.

7.1 Novelties in remote consultancy and collaborative diagnosis

7.1.1 Multilingual remote consultancy

The novelty and innovative content of this research is the adaptation of already known AI solutions and ML algorithms from other fields to healthcare to save time, save human resources, improve the efficacy of multilingual collaboration tools, break multilingual limits and save lives. In this way, the results can quickly cover other use cases with minimal effort [36].

7.1.2 Real-time synthesized and multilanguage OCR

In this pillar of the thesis [38], models of synthetic multilingual training convolutional recurrent neural networks (CRNN) and the patch-wise image tokenization framework (SVTR) were used for ML-based OCR engines [56] to (1) test the possibility of custom-generated multilanguage recognition and (2) increase the accuracy and efficiency of OCR. Mixing CNNs with Recurrent Neural Networks (RNNs) enables the CRNN kind of OCR engine to recognize image text. CNN retrieves features from the input image, while RNN models the sequential dependencies between characters in the text. CRNNs effectively recognize text in various contexts, including font sizes, font styles, and orientations. They can also handle many lines of text in an image and recognize the text of the scene

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accurately. SVTR is an advanced OCR engine that recognizes text in images using a combination of DL and traditional image processing techniques. The SVTR architectures can recognize scene text in photographs with changing lighting, orientation, and skew. In addition, it has an attention mechanism that allows the network to focus on the most important visual components, thus boosting the noise and distortion resistance of the model [38]. CRNN and SVTR offer innovative features compared to conventional OCR engines [38]. Advantages include the following: (i) CRNN can recognize texts of various font styles, sizes, and orientations, as well as several lines of text in an image, and is effective at scene text recognition, (ii) SVTR is resistant to noise and distortion due to the attention mechanism it employs to focus on critical portions of an image and can handle scene text in images, (iii) SVTR and CRNN are DL-based models that learn from complicated data correlations between the input image attributes and the output text, making them more effective than conventional algorithms, (iv) CRNN and SVTR are more efficient than conventional OCR engines since they can run on parallel systems, such as Graphic Processing Units (GPU), and (v) CRNN and SVTR architectures are adaptive and can be improved with additional training data [36, 38, 40]. It is crucial to note that OCR systems are complex and that the architecture we choose will depend on the particulars of the problem we are attempting to address. Each architecture [38] has benefits and drawbacks, and the ideal solution will depend on the nature of the problem, the amount and quality of the data, and other factors. In the thesis experiments [38], fine-tuned CRNN and SVTR models were used with a PaddleOCR framework.

7.1.3 Optimal dataset preparation in visual object detection

Alternative approaches and differences

1. *Focus on OCR training data preparation [38]*: the new approach primarily focuses on preparing synthetic training datasets for OCR tasks. It addresses the challenges of creating datasets that cover multiple languages, including context-sensitive languages and those from the Latin and Anglo-Saxon language families. The primary goal is to optimize the training of the OCR system, ensuring high accuracy in diverse languages and visual contexts.

2. *Visual methods*: the presented method emphasizes the incorporation of visual elements, such as fonts, writing styles, and document layouts, into the synthetic dataset generation process. This visual aspect is particularly relevant for OCR, where the recognition of characters and text from images is critical. Traditional NLP techniques, such as word embeddings and TF-IDF, do not address these visual considerations directly.

3. *Multimodal data considerations*: OCR involves the analysis of both textual and visual information. The suggested method considers both linguistic and visual fea-

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tures in the training dataset. This lets OCR systems handle documents that are written in more than one language or format.

4. *Language-specific challenges*: the new method recognizes linguistic and contextual differences between languages, especially when dealing with synthesized and context-sensitive languages. The purpose of the thesis is to tailor the dataset preparation process to address these language-specific challenges, ensuring that the OCR system performs optimally in diverse linguistic backgrounds.

5. *Application in near real-time collaborative "onScreenOCR"*: the proposed approach [38] targets real-time OCR applications within collaborative on-screen solutions.

Convergence method of optimal dataset preparation

Analysis of the results of the thesis experiment model [36, 38, 40] involves the use of a specialized pivot table based on metadata. If the Jaccard score is considered valid, the model shows a performance above 85%. Similarly, if the valid field is highlighted in green, the model achieves a Jaccard score greater than 85% in a significant proportion of the cases.

Novelty of distribution analysis and vocabulary management

The proposed visual controller method [40], which includes vocabulary, distribution and generation of single / multiline datasets, facilitates the precision tuning of the multilingual vocabulary set and the preparation of distribution. This precision, in turn, improves recognition accuracy in a wide range of languages and scripts. The OCR algorithm can recognize and assimilate certain visual aspects of each language by skillfully selecting different and representative examples for the training dataset. This leads to a marked increase in text recognition accuracy and fewer errors, which distinguishes it from conventional methods. The novelty lies in the system's adaptive capability. Through continuous monitoring of the performance of the OCR model and refinement of the set of multilingual vocabulary and distribution preparation, the system demonstrates a persistent improvement in performance. In addition, it shows remarkable flexibility in accommodating new languages, scripts, or domain-specific text, embodying a significant leap forward in OCR technology.

Rationale behind the new approach

Various multilingual OCR systems [36, 38, 40] are already available on the market with publicly accessible multilingual databases. These still focus on classic OCR use cases without bringing reliable on-screen, digital OCR solutions to real-time multilanguage, cross-sectorial collaborative, supportive works, workshops, and multigeolocation issues. In thesis experiments, one of the most reliable OCR solutions was chosen: PaddleOCR

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(Figure 7.1) – a practical ultra-lightweight OCR system that supports more than 80 languages.

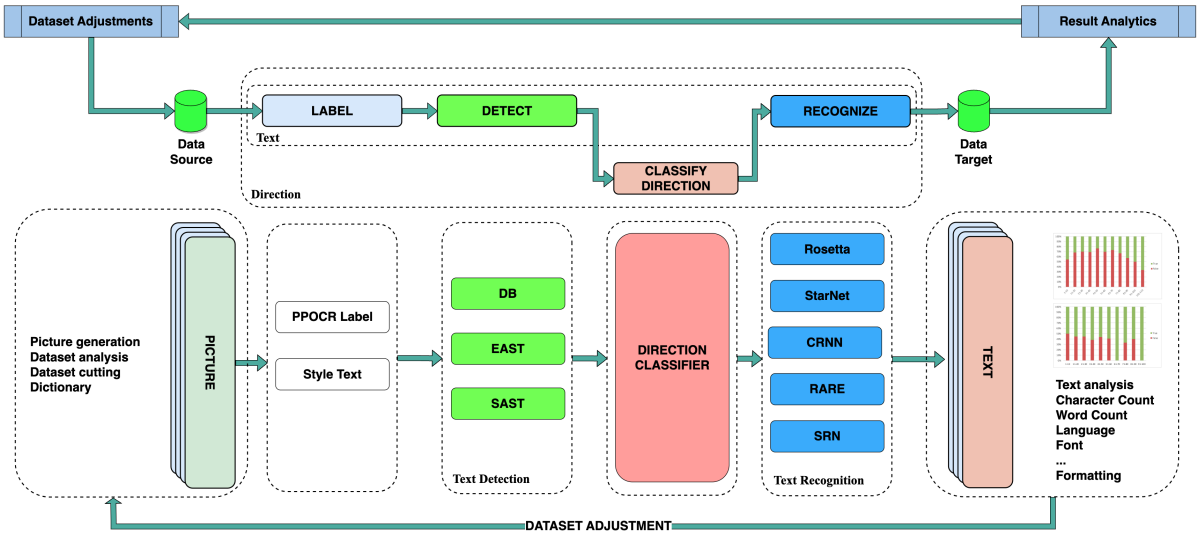


Figure 7.1: Adjusted PaddleOCR architecture, adapted from Tian, Wu *et al* [4]

PaddleOCR [57] provides promising results for languages in the Far East (such as Japanese and Chinese) and handles the multilingual approach with flexible and adaptable AI models [36, 38, 40]. Based on the research, not even PaddleOCR could manage the accurate phrase recognition in multilingual or synthetic languages used in the IT or sports sector for on-screen simulations. Research [36,38,40] analyzing existing solutions available on the market suggests that no magic formula can be applied to prepare an optimal training dataset that covers all of the onscreen collaboration tools requirements. It is suggested to handle the topics as standalone projects. The use case involving languages and specific vocabulary will define the volume of the training dataset. The existing annotated datasets are not golden sets, but can be used to prepare the method that covers all aspects of the requested OCR system [51].

Formulating an optimal vocabulary-based training dataset for multilingual real-time OCR systems [40] requires a strategic approach to various key elements. These include carefully selecting adaptive vocabulary, implementing cross-lingual pre-training [179], deploying dynamic dataset augmentation strategies, ensuring domain-specific adaptation, addressing data imbalance issues, applying multimodal learning, and establishing appropriate evaluation metrics and benchmarks. [180]. A data scientist who addresses these novel aspects can build OCR systems that are accurate, efficient, and capable of handling a wide range of languages and contexts.

Proposed improvements

To prepare an optimal distribution of vocabulary-based training datasets for multilingual OCR training, several aspects and approaches must be taken into account, as follows

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[36, 38, 40]:

1. *Dynamic dataset augmentation* [259,260]: the training dataset should be continually updated and expanded to include new text samples (using the Sobel filter [261]), variations in language, and emerging writing styles. This can be achieved through synthetic data generation, web scraping, and crowd-sourcing.

2. *Domain-specific adaptation* [262]: The training dataset should be enriched with domain-specific data to enhance the OCR system's performance in specific industries or use cases. For example, incorporating legal, medical, or technical jargon can help improve the system's performance in those fields.

3. *Cross-lingual pre-training* [263]: Using transfer learning from a pre-trained multilingual model [264] can aid in raising the efficiency of OCR systems for low-resource languages. Training on a large, diverse, high-quality dataset, the OCR model learns to identify common patterns and structures across different languages, leading to better generalization.

4. *Data imbalance mitigation* [265]: a balanced dataset (Figure 7.2) is essential to train a robust multilingual OCR system. This involves addressing class imbalances by oversampling underrepresented classes or undersampling overrepresented classes. Furthermore, the incorporation of data enhancement techniques [266], such as rotation, scaling, and noise addition, can help increase the variability of training data.

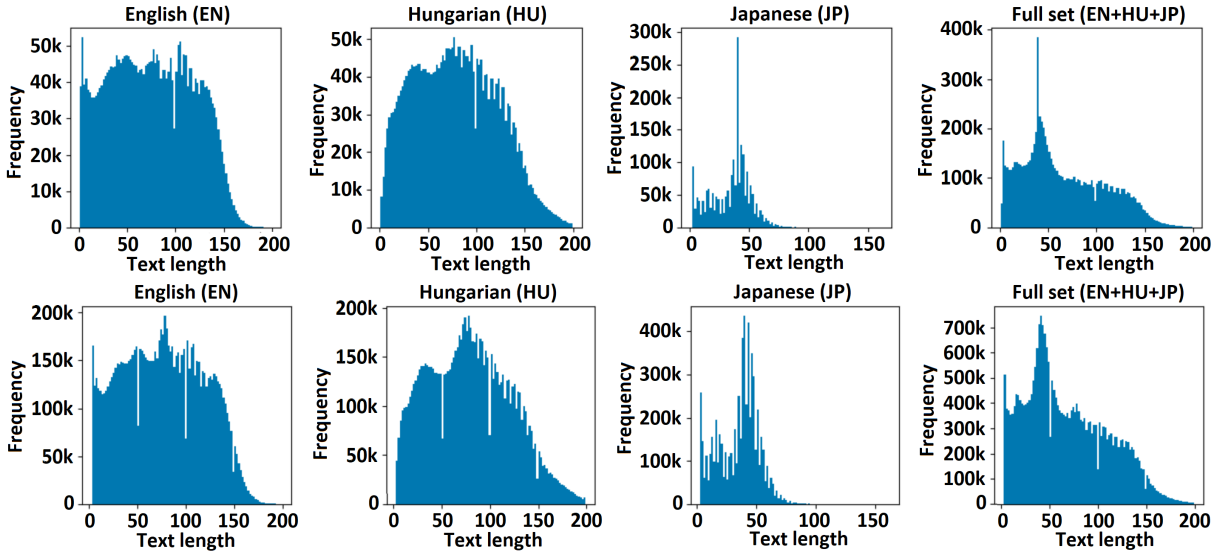


Figure 7.2: Result of the data imbalance mitigation

In the case of multilanguage training that simultaneously involves Japanese, English, and Hungarian, the frequency of character occurrence must be evaluated per domain, per target solution.

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5. *Evaluation metrics and benchmarks*: Establishing appropriate evaluation metrics and benchmarks for multilingual OCR systems [267] is vital to assess performance, identify areas for improvement, and facilitate model comparison. These metrics should include character- and word-level recognition rates, language identification accuracy, and domain-specific evaluation measures.

6. *Multimodal learning* [268]: incorporating additional contextual information such as domain-specific metadata can improve the ability of the OCR system to recognize text within different contexts. Multimodal learning enables the model to leverage multiple sources of information to improve its understanding of the text.

7.2 Novelties in the usage of radars and 3D accelerometers

7.2.1 RPA intensity with radars and 3D accelerometers

Why radar sensors?

Continuous remote monitoring of vital signs is essential to maintain patient well-being and early detection of conditions that may compromise patient well-being (such as monitoring breath level or HR). Medical Doppler radars are non-contact sensors [14] that use the Doppler shift principle to detect heartbeat and respiration rates by measuring the contraction and expansion of the chest wall. This technology can also be applied to the sports field. By incorporating AI into the sports industry, it can prevent or predict the onset of various diseases, making the sports field, which is a constantly fast-paced environment, much safer.

Most medical radar sensors currently on the market use Fujitsu's FWM7RAZ01-200002 radar module [269], which has 3 channels with dynamic selection and supports low-speed and high-speed object movements and varied but well-predefined data acquisition distances as well [15]. This sensor is suitable for various applications, including vital detection, machine monitoring, and other detection and analysis of moving objects. Figure 7.3 shows the three channels of the radar (Channel 1, Channel 2, Channel 3) without blocking objects between the sensing device and the athlete. The FWM7RAZ01 Doppler radar sensor consists of a 24 GHz transceiver, TX and RX array antennas, IF amplifier, MCU, DAC, E2PROM, and an LDO voltage regulator integrated into a single compact module measuring 30 mm × 44 mm × 9.5 mm [269]. Pin header terminals positioned on the back of the module simplify integration, even for designers unfamiliar with high-frequency circuits. Compared to other detection methods, such as infrared, ultrasound, and laser scans, 24 GHz radio waves are more stable and less affected by environmental conditions, such as weather, temperature, illuminance, sound, or dirt. Waves also easily penetrate clothing, curtains, glass, and most wooden structures. The calibration of the

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sensors needs to be conducted before starting every new type of sport or if there will be any change in the population per geolocation.

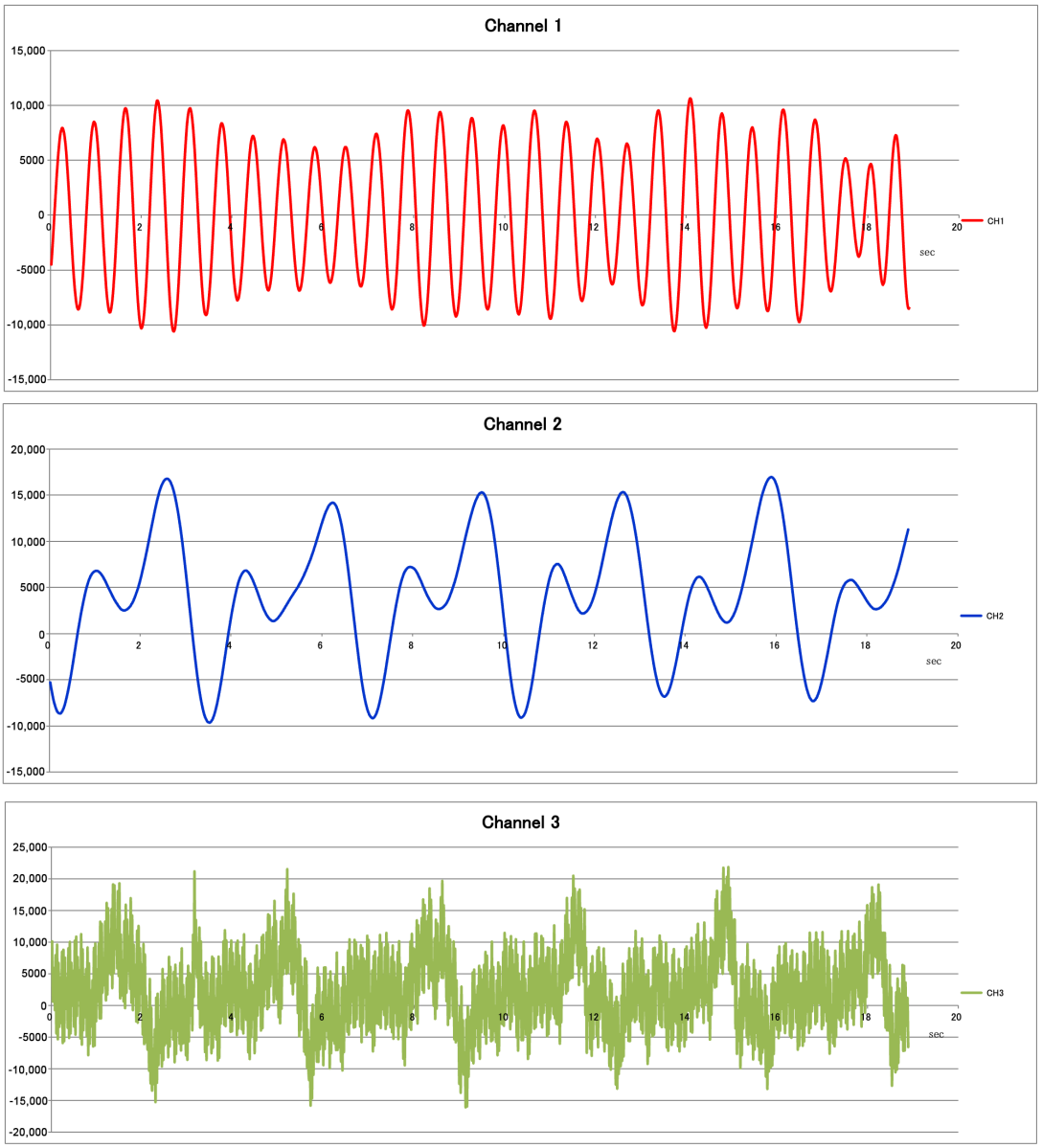


Figure 7.3: Channels of FWM7RAZ01 doppler radar sensor.

Heart rate and rating of perceived exertion

By measuring the effect of a sports activity on a person's HR and breathing rate, one can assess the intensity of the sports activity. There are two primary intensities of sports: moderate and vigorous intensity.

The thesis research [15] considered the relationship between RPE and HR using the Borg RPE scale of 6 to 20 with the regression equation: $HR = 8.88 \times RPE + 38.2$ (beats/minute). Consideration must be given to the deviation factor. HR will have a poorer connection with the perceived exertion rating when athletes perform dynamic

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(intense) and static exercises. The validation of the intensity of physical activity is derived from the pulse or HR level during physical activity by monitoring the target zone.

Radar sensors in sports

Medical radar sensors are related to the application of radar technology in the fields of medical, sports, and sport safety. This may involve using radars to measure physiological indicators, such as breathing and HR (see Figure 7.3). This technology can be used in hospitals, clinics, and even in the homes of patients. Still, based on the experiences, they need careful preparation to fit into the specific domain, considering the following: (1) The radar needs to avoid places with extreme weather conditions (e.g., intensive variations in humidity and temperature. (2) Before being used, it must be calibrated for specific sports and athletes. (3) It should be installed in places where they can make (trigger-based) measurements [35] of specific athletes. (4) If the athlete changes, a dedicated solution should be used to change users with predefined settings. (5) Data acquisition requires a protocol that covers data acquisitions per multiple radars and multiple users. (6) In the case of sports, it is proposed that the medical radar sensor be installed on chairs or benches.

Radar-based physiological detection (RPS) is an application of radar technology that measures physiological aspects of the human body, such as HR (see Figure 7.3), breathing rate, and movement [15]. One of the primary advantages of medical radar sensors [15] is that they can continuously monitor patients without the need for physical touch or cameras. The field of medical radars is a relatively young discipline and research is underway. However, several studies have already established the viability of using radars to measure physiological indicators, and several businesses have begun to develop commercial products based on this technique. The novelty of the RPS technology is that it is a non-contact method [14] that is more comfortable and convenient for patients, offers a new way of continuous monitoring, and can be used in various scenarios, such as remote monitoring, home care, and ambulatory monitoring. Furthermore, since technology is still in an early stage, there is significant potential for future advancements and applications.

Installing medical radar sensors on the benches and chairs used by athletes in the monitoring process will require that the datasets are free of transmitter factors or intentional interference [15]. Some technical challenges still need to be overcome to make radar-based physiological sensing more accurate and reliable, such as interference from other sources and the effects of a patient's movements on the radar signal. However, researchers are actively working on these issues and are making progress. Based on the empirical data collected through the thesis experiments, it has been observed that the fidelity of the measurements increases significantly when the athletes remain unaware of the ongoing monitoring process and use proximate installations, as previously delineated. Radar sensors can be used as a source of HR data acquisition. The examination as a clinical trial was not within the scope of this thesis. This thesis carried out experiments to measure

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and predict, using ML models, the RPE and sRPE (see Figure 9.4) and analyzed the context between MET and RPE (see Figure 9.5).

Radar sensors with three-axial accelerometers in sports

The combination of medical radar sensors with 3D accelerometers is a relatively new development in medical sensing [15]. Both sensors allow for the acquisition of more accurate and detailed information about the patient's physiological status and physical activity. The accelerometer data can be used to estimate the RPAI of a person (see Table 8.5) with METs, RPE, and sRPE, which can provide information on the level of activity that athletes perform at a given / expected moment (see sRPE in Figure 8.11). RPAI is a nonparametric approach to quantifying the physical activity intensity by using raw data from the accelerometer; it can be used to infer the body's energy expenditure and track the individual's physical activity.

When combined with medical radar sensors, accelerometer data can validate and enhance the information obtained from the radar [15]. For example, the radar can measure a patient's HR and respiration rate, while the accelerometer can measure their level of physical activity: (i) it allows more accurate predictions of RPAI. With data from the three-axial accelerometer, it is possible to classify different types of physical activity and estimate their energy expenditure as well as RPAI, which can be helpful in the promotion of health and in clinical and research settings. (ii) It is a novel and promising approach to monitoring physiological status and physical activity; it can open up new opportunities for remote patient monitoring, home care, and ambulatory monitoring. However, more research is needed to validate the effectiveness of these systems and address the technical challenges of specific targeted domains.

AI in precise detection and result generation

AI is capable of analyzing complex datasets (from multiple sources, such as wearable devices, training records, and physiological measurements) and identifying patterns, trends, and correlations that are difficult or impossible for humans to discern, learn and adapt as new data become available, allowing it to continuously refine its predictions and suggestions. Classic computations and models, in comparison, may require manual revisions and may not account for new information as efficiently. Furthermore, AI can represent complex, non-linear relationships between variables, which can be difficult to express by using conventional computations and models. With DL and RL, the sports safety system built on this concept will anticipate outcomes with greater precision than conventional models and deliver individualized recommendations based on the unique qualities of each athlete (e.g., level of conditioning, training history, and injury risk factors). These sophisticated strategies can more accurately account for the complexity and uncertainties inherent in sports performance and injury risk.

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There are additional future AI possibilities that can be adapted to improve conditioning/training performance [22] and injury detection, as well as to ensure better fatigue management, as it can connect additional sources of training or health data. Performance optimization can be strengthened with (a) linear regression models to deepen the modeling of the relationships between an athlete's performance, training load, recovery time, and nutrition; (b) a supervised learning algorithm (e.g., SVMs) to provide a classification or perform regression tasks, helping to identify factors that contribute to optimal performance; and (c) decision trees/random forests algorithms to identify key variables that impact performance, and support coaches to prepare data-driven decisions for training program adjustments. Injury prediction might be expanded with (a) logistic regression models to predict the likelihood of injury based on factors such as training load, previous injuries, and biomechanical variables [235]; (b) NNs to model complex relationships between input variables and injury risk, offering more accurate predictions compared to traditional models; and (c) Gradient Boosting Machines to improve the accuracy of injury predictions by combining multiple weak learners (e.g. decision trees) into a single, strong learner, by adapting an ensemble learning technique.

Fatigue control and management have the following improvement possibilities: (a) a time-series analysis (e.g., ARIMA and LSTM) to analyze and forecast trends in athlete fatigue level, allowing coaches to adjust training programs; (b) a k-Nearest Neighbors (kNN) analysis for comparison and analysis of similarity of athletes or / and training sessions based on factors such as RPE, sRPE, or HR variability, providing insights into appropriate recovery strategies; and (c) RL to provide the most SMART solution, a real-time pipeline aimed at maximizing performance indexes while minimizing fatigue and injury risk parameters. This model will require, of course, the most comprehensive input datasets.

7.2.2 Fatigue and stamina control on multivariate time series (MTS) datasets

The specificity of AI-assisted fatigue and stamina control in performance sports [44], utilizing IMU-generated multivariate time series datasets, lies in the precise and individualized insights it can provide, allowing a deeper understanding and more effective management of athlete performance. Several specific innovations are noteworthy:

1. *Granular biomechanical analysis* [24, 235]: AI can dissect the minute biomechanical changes that occur with fatigue, which are invisible to the human eye or traditional analysis (see Table 9.2). For example, slight alterations in stride length, gait symmetry, or joint angles during a run could indicate the onset of fatigue (see Figure 7.4). By detecting these subtle biomechanical changes, AI systems can signal the need for rest or adjustment of the technique to prevent injury.

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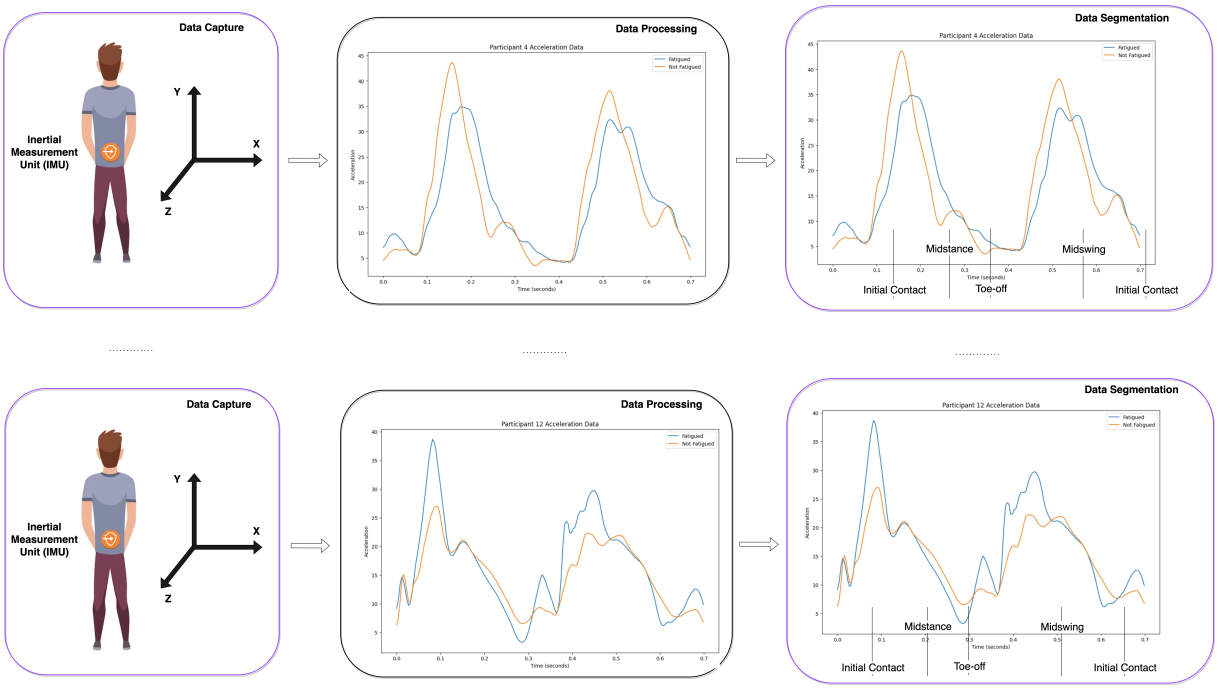


Figure 7.4: IMU data capturing, processing, and segmenting into strides.

2. *Fatigue profiling and benchmarking* [270]: ML models can be trained to establish a baseline profile of an athlete's performance when they are not fatigued. Subsequent performances can be continuously compared against this benchmark to detect deviations suggestive of fatigue. This approach allows each athlete to customize training loads and recovery times.

3. *Stamina capacity modeling* [271]: AI can model an athlete's stamina capacity across different conditions and over time through longitudinal tracking. This involves analyzing how long an athlete can maintain a certain intensity level before fatigue sets in and how this capacity changes with different training regimens, environmental conditions, or stages of the competitive season.

4. *Predictive fatigue onset detection* [272]: Using historical data, AI can predict when an athlete is likely to become fatigued in future training sessions or competitions. These predictions can inform the design of training sessions to avoid premature fatigue and can be used to optimize in-game strategies, such as player substitutions in team sports.

5. *Optimization of recovery protocols* [273,274]: AI can also monitor recovery, assessing whether an athlete's biomechanical signals have returned to their baseline post-exertion. This information can guide the type and duration of recovery methods, such as active recovery, massage, or specialized nutrition intake.

6. *Enhanced load management* [275]: by continuously analyzing an athlete's response to various training loads, AI can help design periodization programs that optimize

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performance while minimizing the risk of overtraining or undertraining. Innovative research may produce predictive mechanisms for injury prevention, identifying the precursors to common training injuries, and suggesting preventive measures.

7. *Customized tapering strategies* [276]: precompetition tapering is crucial for peak performance. AI systems can analyze how different durations and intensities of compression affect the performance of an athlete, allowing the creation of bespoke compression strategies that are precisely timed and scaled for maximum effect (see Table 5.3).

These innovations represent a move toward a personalized, data-driven approach to athletic training and competition. By leveraging AI's specific, actionable insights, sports professionals can make informed decisions that enhance performance, extend an athlete's career, and transform the landscape of competitive athletics.

Why multivariate times series datasets?

These datasets are made up of multiple variables or sequences recorded over time, which can provide a comprehensive view of the system being studied. Their utilization in AI projects brings several added values:

1. *Holistic approach*: multivariate time series data enable simultaneous analysis of multiple interconnected variables (see Figure 7.5). This approach facilitates a deeper understanding of complex systems, such as human physiology or financial markets, where the interaction between different factors is often as significant as the individual variables. In the context of recommendation systems, multivariate time series allow for the customization of user experiences by analyzing user interaction across various features, such as purchase history, browsing behavior, and search patterns.

2. *Improved prediction accuracy*: AI models trained on multivariate datasets can take advantage of the relationships between different variables to improve prediction accuracy. For example, temperature, humidity, and wind speed work together in weather forecasting to determine weather patterns, allowing for more accurate and reliable predictions.

3. *Advanced anomaly detection* [277]: AI systems can more effectively detect anomalies by monitoring several indicators over time. In healthcare, for example, the simultaneous analysis of multiple vital signs can help to detect critical conditions early, leading to timely interventions.

4. *Dynamic decision-making*: analyzing data across multiple time frames allows AI to understand short-term fluctuations versus long term trends, which is crucial for strategic planning in business and policy making.

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5. *Complex feature interactions* [30, 278]: AI models can discover non-linear interactions and dependencies between features that may not be apparent in univariate analysis. This capability is crucial in fields such as genomics, where the interaction between genes can influence the traits and health of an organism.

6. *Robustness to missing or partial data*: with multiple variables, AI techniques can better handle missing data by imputing missing values based on observed correlations in the dataset.

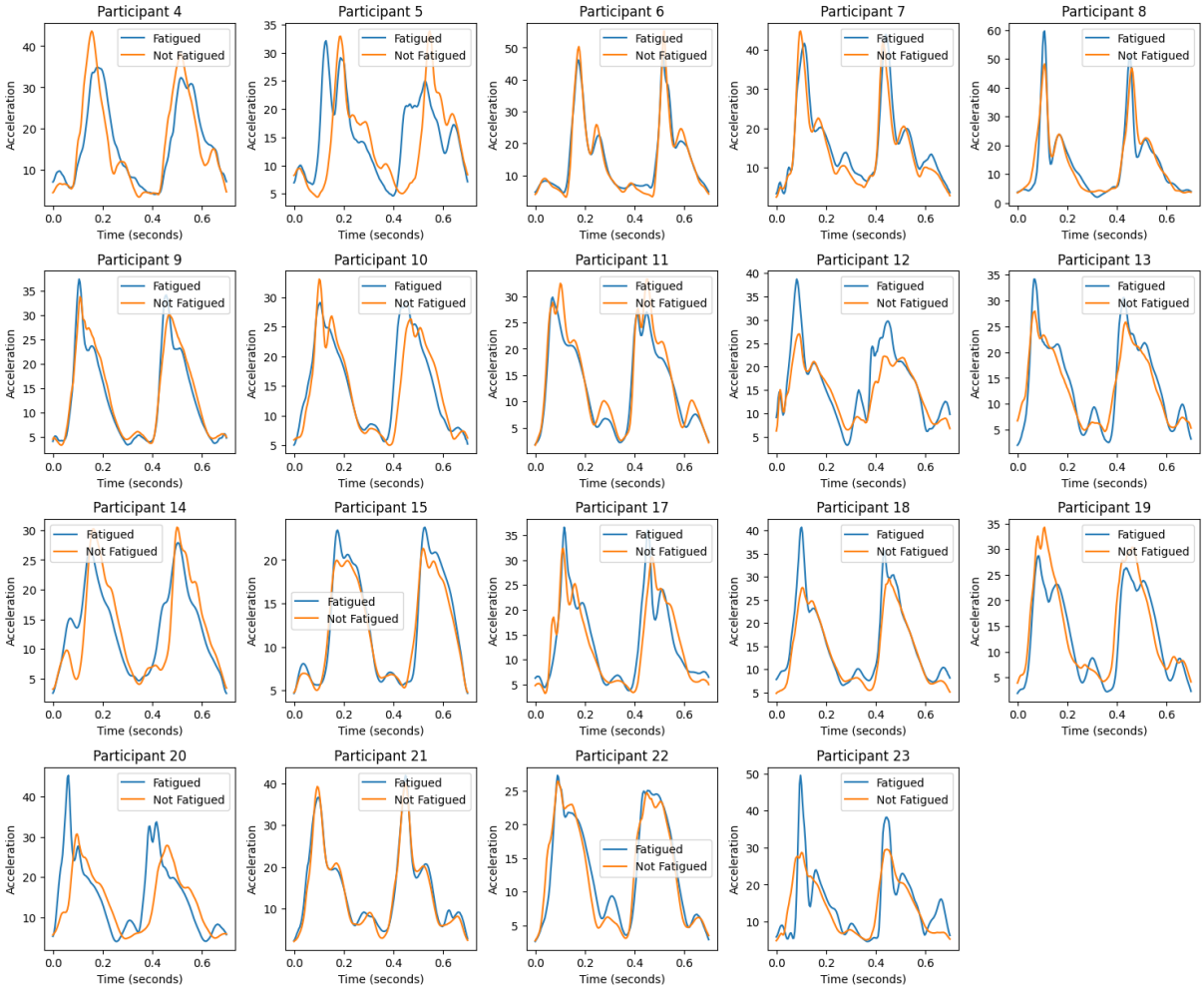


Figure 7.5: Acceleration data per specific segment for analysis

In conclusion, multivariate time series datasets are invaluable in enhancing the depth, accuracy, and operational efficiency of AI models across various disciplines. They provide a multidimensional perspective that captures the complexity of real-world phenomena.

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7.3 Novelties in health condition control

7.3.1 sRPE and ACWR on fatigue and injury control

Compared with existing approaches (for example, different types of manual calculation sheets per sport, activity, individual, group, team), AI-based ACWR and fatigue score calculation systems [26] will be able to adapt to individual athletes' data and, in later phases, physiological responses. Models can learn from the historical data of each athlete, identifying patterns, anti-patterns, anomalies, and trends that may not be apparent through manual calculations. This allows for a more personalized and accurate assessment of an athlete's fatigue levels and training load [81], helping to optimize performance and minimize the risk of injury [22]. AI-based models can process and analyze data in real time, providing immediate feedback on an athlete's ACWR and fatigue levels [26]. This will enable coaches, trainers, physiotherapists and physicians to make data-driven decisions about training adjustments, rest periods, and recovery strategies [279]. Manual calculations require more time and effort, potentially delaying critical decisions that could impact an athlete's performance or recovery. ML-based solutions can easily integrate data from various sources, such as wearable devices [280], GPS tracking devices, and HR monitors, to provide a comprehensive view of the training load and fatigue levels of an athlete. Combining multiple data streams, AI models can derive more accurate and nuanced insights into an athlete's ACWR and fatigue score, enabling better decision making in training and recovery plans. In contrast, manual calculations can only rely on a limited set of data points or are subject to human error and bias, potentially compromising the accuracy of fatigue assessment.

7.3.2 Microsleep detection for stamina control

To have a better understanding of stamina control, a novel microsleep detection thesis research was conducted. The Voronoi tessellation [72] and coverage control algorithms [73] have been widely used in various applications, ranging from mobile sensor networks to robotics for efficient area coverage and spatial partitioning. The Kalman filter [74] is an effective technique for determining the state of a linear dynamical system based on a sequence of noisy data. When evaluating the use of these algorithms in the staging of microsleep and real-time sleep, it is crucial to understand their potential contributions to this field.

7.3.3 Personalized recovery

AI has produced revolutionary improvements in sports science, namely in biomechanical analysis [281]. The BlazePose landmark model [22] allows for detailed investigation of velocities linked with human body features (see Fig. 6.10). This model [22] enables

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detailed inspection of an athlete's motions, capturing details that might otherwise go unnoticed. When an athlete's actions are caught and evaluated, it is possible to compare their performance to reference activities considered optimal or perfect. The ability to compare activities to established standards can serve as a system of alerts, indicating the possibility of injuries.

Using the BlazePose model, recovery exercises can be continuously monitored against reference exercises to ensure adherence to best practices, optimizing the healing process while minimizing the risks of injury recurrence. Furthermore, the analytical depth provided by such AI-driven models, particularly when analyzing landmark velocities, offers medical professionals and trainers a robust tool to tailor recovery or training regimens. By combining the richness of BlazePose landmark data with AI's analytical prowess, the sports domain is on the brink of a more informed, safer and performance-optimized future [22].

7.4 Novelties in disease detection and injury prevention

7.4.1 Disease detection from voice

Non-invasive and cost-effective diagnosis [16]: One of the most groundbreaking features of voice-based disease detection is its non-invasive nature, which allows for a quick, painless, and low-cost method of diagnosis. This is particularly important in resource-limited settings and remote areas with limited access to medical facilities. Early detection of diseases [282]: Voice-based AI systems can detect subtle changes in a person's voice that may indicate the onset of certain diseases. Early detection can lead to more effective treatment and better health outcomes.

7.4.2 Novelties of AI-based pneumonia detection in performance sports

A real-time AI pipeline [28] using YOLOv9 for pneumonia pre-diagnosis in performance sports increases sports medicine and respiratory care. YOLOv9, an improved edition of the series [7], provides fast and accurate object detection in this new method. The conducted thesis project is novel in many ways: (1) radiologists manually diagnose pneumonia on chest X-rays, which takes time and limits availability. Imaging data analysis can be accelerated, reducing symptoms from onset to diagnosis; (2) the AI system seamlessly integrates into the medical and training infrastructure, when it is implemented directly in sports facilities and during competitive events. This on-site deployment provides quick response to situations (like quick anomaly detection) that could harm an athlete's health and performance; (3) the pipeline uses YOLOv9 to detect pneumonia

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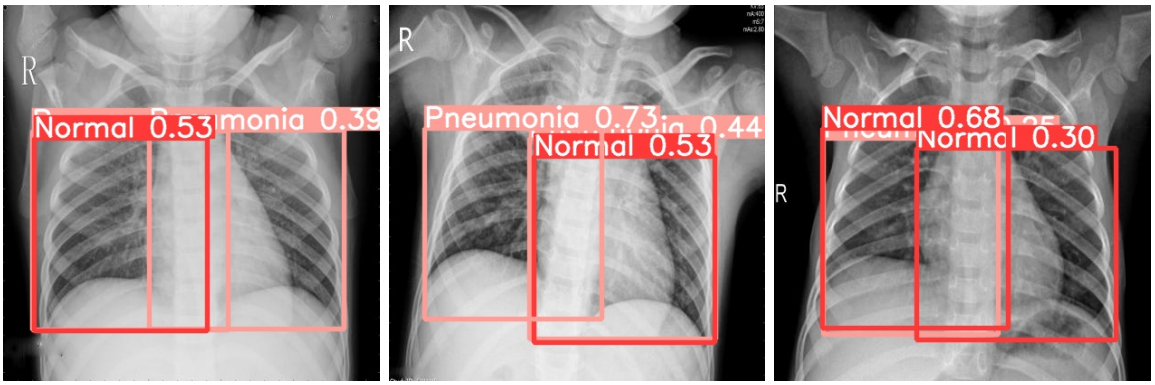


Figure 7.6: Supportive predictions: suspicious case detection to minimize the misdiagnosis

symptoms and subtle changes that pre-screening may overlook. YOLOv9's deep learning (DL) architecture increases imaging data interpretation for performance sports; (4) scalability and adaptability: the AI pipeline supports numerous sports and performance intensities. The pipeline proposed from [28] can be used in collegiate and amateur sports without expert medical diagnostics due to its adaptability; (5) predictive and preventive health management [41]: the pipeline shows risk factors for athletes and health patterns beyond pre-diagnosis. The suggested method can reduce the incidence of pneumonia and other respiratory diseases associated with sports. The proposed application of advanced AI in operational sports, the adaptability of the athlete, and the potential to improve interventions for sports medical performance make this thesis project significant.

This method uses YOLOv9, an advanced object recognition algorithm [7], to analyze chest X-rays for early symptoms of pneumonia, a common yet devastating infection that can seriously damage athletic performance and health. YOLOv9's processing speed and accuracy are excellent for real-time analysis, making its use in this context novel. The model's fast photo processing allows athletes to be evaluated and treated more quickly than before, reducing downtime and implications.

Second, training the model on a unique dataset of athlete-specific chest X-rays addresses athlete-specific difficulties including lung capacity and musculature. Customized to the physiological characteristics of the athlete, this specialization improves the diagnosis of the model. The real-time capabilities of the pipeline integrate seamlessly with the medical monitoring systems of sports facilities and events to provide instant diagnostic support without image analysis on site [283]. This integration improves on-site medical treatment, improving athlete safety, and performance continuity. The thesis project also raises the bar for preventive health management in sports by focusing on early identification and intervention to improve health and reduce healthcare costs. The proposed real-time AI pipeline revolutionizes the management of athlete pneumonia and respiratory diseases and shows how AI can be tailored to crucial sports performance needs. This scalable and efficient approach to the management of athlete health risk will transform sports health monitoring protocols.

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7.4.3 Burnout in performance sport

The innovative aspect of the thesis [18] is a paradigm shift from reactive to proactive, data-driven, and holistic approach to managing and preventing burnout in performance sports. Forecasting burnout in performance sports using a combination of texts, sentiment analysis [284], and potentially increased stamina (or fatigue) measurements powered by AI presents various novelties in sports science and athlete well-being: (1) holistic analysis; (2) real-time monitoring; (3) predictive modeling; (4) personalization; (5) enhanced sentiment analysis; (6) objective metrics for subjective states; (7) data-driven decisions; (8) enhanced recovery protocols; (9) educational insights.

Sentiment analysis, text messages and stamina

This correlation's precise nature and magnitude can vary depending on several variables, such as the sport, the athlete's training regimen, and individual differences. Integrating sentiment analysis from text messages into this analysis can provide a more comprehensive view of an athlete's physical state (via stamina/fatigue metrics) and emotional/psychological state (via sentiment scores). The following steps can be used to determine the relationship between endurance and burnout while also taking into account sentiment analysis.

1. *Quantifying stamina and fatigue*: this can be based on physical metrics such as HR variability, lactic acid levels, or performance benchmarks. Let S represent stamina levels, where higher values indicate better stamina and lower values indicate fatigue.

2. *Sentiment analysis on text messages*: the analysis of text messages to produce a sentiment score. Let T represent the sentiment score, where higher values indicate positive sentiment (e.g., happiness, motivation) and lower values indicate negative sentiment (e.g., stress, frustration).

3. *Measurement of burnout*: it can be a combination of self-reported scales, performance degradation, and other psychological assessments. Let B represent the burnout levels, where higher values indicate higher levels of burnout.

The correlation calculation will be defined as follows:

$$r = \frac{\sum_{i=1}^{n}(S_i - \bar{S})(B_i - \bar{B}) + (T_i - \bar{T})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2(B_i - \bar{B})^2} \times \sqrt{\sum_{i=1}^{n}(T_i - \bar{T})^2(B_i - \bar{B})^2}} \tag{7.1}$$

where: n is the number of observations, $\bar{S}$ is the mean level of stamina, $\bar{T}$ is the mean sentiment score and $\bar{B}$ is the mean level of burnout. This equation measures the combined correlation of stamina and sentiment analysis results with burnout. A positive value of

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r suggests a positive correlation (as stamina decreases or negative sentiment increases, burnout increases), while a negative value indicates a negative correlation. In practice, these correlations can be calculated separately and then combined in a multivariate analysis to see their combined effect on burnout. For this reason, this logic was also applied. Including sentiment analysis can help us understand the psychological aspect of burnout, while stamina provides insight into the physical facet.

Multivariate analysis

This is followed by a multivariate analysis of the correlation between stamina, text-based sentiment, and fatigue, as well as their combined effect.

Correlation between stamina and burnout:

$$r_{S,B} = \frac{\sum_{i=1}^{n}(S_i - \bar{S})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2 \sum_{i=1}^{n}(B_i - \bar{B})^2}} \tag{7.2}$$

Correlation between sentiment and burnout:

$$r_{T,B} = \frac{\sum_{i=1}^{n}(T_i - \bar{T})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^{n}(T_i - \bar{T})^2 \sum_{i=1}^{n}(B_i - \bar{B})^2}} \tag{7.3}$$

where: n is the number of observations, $\bar{S}$ is the mean level of stamina, $\bar{T}$ is the mean sentiment score, $\bar{B}$ is the mean level of burnout. *Multivariate model*: To combine these in a multivariate context, consider a multiple regression model in which both stamina and sentiment are predictor variables of burnout.

$$B_i = \beta_0 + \beta_1 S_i + \beta_2 T_i + \epsilon_i \tag{7.4}$$

where: B_i is the burnout level of the observation i^{th}, β_0 is the intercept, β_1 is the stamina coefficient, indicating how much burnout changes with a unit change in stamina, while sentiment remains constant, β_2 is the sentiment coefficient, indicating how much burnout changes with a unit change in sentiment while sentiment remains constant,ϵ_i is the error term. The significance and magnitude of β_1 and β_2 will tell us about the individual and combined effects of stamina and sentiment on burnout. If both are significant, it indicates that both stamina and sentiment are essential predictors of burnout. In addition, the adjusted R-squared value from this regression will indicate the proportion of variance in burnout, which can be explained by combined endurance and mood. By examining this multivariate model, researchers can deduce whether considering both stamina and sentiment together provides a better understanding of burnout than considering them separately.

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7.4.4 Disease detection from written communication

Connecting text analysis with sentiment analysis [285] can improve the ability to identify potential health problems [18]. Sentiment analysis is a form of NLP that assesses the affective state of the text, which could be related to the emotional state of the individual writing the message. In research settings, sentiment analysis is increasingly used to study large datasets from social media to identify public health trends and monitor specific individuals' well-being (with their consent). Sports psychology shows that athletes' mental health profiles differ from those of nonathletes. Many athletes, especially those in competitive and high-stakes contexts, learn resilience, stress management, discipline, and focus, which could affect their mental health differently than non-athletes. In addition, the type of sport done can affect mental health; Team sports encourage community and teamwork, while solo sports emphasize self-reliance and setting personal goals. Due to the cognitive demands of extreme sports, practitioners often have a higher tolerance to risk and better fear and anxiety management. These differences demonstrate the complex link between athletics and psychology. However, sentiment analysis should be part of a broader diagnostic and treatment framework which could be used effectively in a healthcare context under the supervision of healthcare professionals. Novel fields of interest [18] as follows:

1. *Mental health monitoring*: changes in sentiment could correlate with mental health issues such as depression, anxiety, or mood swings. For example, a person who typically expresses positive sentiments but suddenly shifts to predominantly negative sentiments might be experiencing emotional distress.

2. *Emotional well-being monitoring* [286]: A consistent decline in positive sentiments or an increase in language indicating stress or anger could sugess psychological distress or even social isolation, an important factor in overall health.

3. *Trend analysis* [287]: Analyzing sentiment over time might be able to identify trends indicative of a deteriorating or improving condition. For instance, the progression of a neurological disease like Alzheimer's disease might be subtly reflected in increasingly negative or confused sentiments in text messages.

4. *Treatment monitoring* [288]: For individuals undergoing treatment for conditions such as depression, changes in sentiment over time could indicate how well the treatment works.

5. *Predictive analysis*: Sentiment analysis could contribute to predictive models that attempt to predict health events, such as depressive episodes, by identifying warning signs in text communication.

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In psycholinguistics and clinical diagnostics, linguistic and paralinguistic elements are critical indicators that can reveal the underlying cognitive and emotional processes. Linguistically, alterations in syntax, such as simplified sentence structures or reduced complexity in clause embedding, may signal cognitive impairment. Lexical access difficulties often manifest in increased word search pauses, a reduced vocabulary range, and the reliance on nonspecific words such as "thing" or "stuff,", which can indicate neurodegenerative decline. Semantic anomalies, including tangentiality or the use of inappropriate words, and pragmatic failures, like the inability to adhere to conversational norms, also form part of the linguistic tapestry that may suggest pathology.

Paralinguistically, changes in speech prosody, such as a monotonous tone, reduced pitch variation, and altered speech rate, can indicate emotional distress or neurological disorders [289]. Further, detecting micro-expressions, or subtle facial movements, alongside analysis of gesture frequency and congruence with verbal output, can provide additional context to an individual's emotional state and cognitive functioning. When systematically analyzed, these deviations from normative patterns can yield significant insights into the presence and progression of mental health disorders and NDD, offering a rich substrate for AI-enhanced assessment tools. Through its nuanced parsing of affective language, sentiment analysis offers a granular perspective on the emotional state. It provides a continuous, unobtrusive proxy for mood and affect, which are the core components of many psychiatric evaluations [290]. In clinical applications, it extends beyond primary positive or negative classifications to encompass the intricate spectrum of human emotions relevant to psychiatric evaluations. Using computational linguistics, it can dissect the subtleties of affective language, offering insight into the intensity and fluctuations of emotional states.

For example, the evaluation of written or spoken discourse through sentiment analysis can identify linguistic markers of depression, such as an increase in the frequency of words associated with negative affect, an increase in the use of singular pronouns from the first person, or a decrease in the use of future tense, which can suggest hopelessness or lack of a forward-looking perspective. The system may detect anxiety-related speech patterns, which are defined as language that expresses excessive stress, anxiety, or ambiguity. In the context of NDD, sentiment analysis may reveal a decline in the complexity of emotional expression or a developing incongruence between the expressed feeling and the topic discussed, which is common in the early stages of such disorders. Sentiment analysis quantifies these linguistic aspects, providing a granular, continuous, and unobtrusive method of monitoring mood and affect, which is critical in identifying and managing mental health illnesses. It adds another dimension to standard psychiatric examinations, which are often based on intermittent and subjective self-reported measurements, allowing for better longitudinal tracking of mental health conditions.

In *individuals experiencing depression*, there may be a marked increase in the use of words that convey sadness, loneliness, and other negative emotions. Research suggests

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that a *high frequency of first-person singular pronoun*s can be a linguistic marker of *self-focused attention*, which can be related to depression or anxiety. It is crucial to have explicit consent from individuals to analyze their data with robust data protection measures; (3) the accuracy of sentiment analysis can vary, and false positives or negatives could have profound implications. Validation with clinical data is necessary; (4) There is an ethical dimension to consider regarding the surveillance of individuals' communications, which needs careful ethical oversight and regulation.

7.4.5 Lesions and tumor detection on severe head injuries

The novelties of this pillar of the thesis presented in [28] with respect to AI in the area of real-time detection of brain injuries [291] include: (1) implementation of neural architecture search (NAS) using AI to design better AI models. In the context of head injury detection, NAS could be used to optimize the CNN architecture used for feature extraction [292] in an object detection model such as YOLO; (2) it can be used in the multimodal learning approach, which involves the integration of multiple types of data into the learning process. (e.g., a model could integrate data from medical images, wearable sensors, and other sources to improve its performance); (3) AI can be used as a data scientist expert, which supports doctors with data and acts as an explainable AI. This could be particularly important not only for predictions, injury detection, and further analysis but also for giving doctors detailed explanations of why the model made a particular prediction.

7.5 Summary of scientific contributions

The main scientific contribution of this chapter is a detailed examination of the new elements introduced in the thesis. These include updates to the methodology, adjustments to parameters or components, analysis of alternative approaches and their variations, proposed fine-tuning of hyperparameters, exploration of different technological pipeline options or architectures, and the introduction of a new line of machine learning / deep learning methods and models. These contributions are closely related to the three main pillars of the thesis.

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8 Data Analysis

This chapter will review the data analysis of the multidisciplinary topic of advanced remote diagnostics techniques and sensors in sports safety and health condition predictions. The layers are similar to the structure already introduced in the other chapters, layered into the following sections: (1) remote consultation, (2) radars and other sensors, (3) health condition monitoring, (4) disease detection and injury prevention, and (5) prediction and gamification of sports strategies. The scientific contributions are summarized at the end of the chapter.

8.1 Methods in remote consultancy and collaborative diagnosis

8.1.1 Multilingual remote consultancy

Visual Transformer types have higher fine-tunability and accuracy than traditional image processing NNs [36]. Each DETR thesis experiment and validation research in the same research phase was carried out on the same training and validation dataset, application categories, and object categories, resulting in (i) Phase 1: 248 images with 55 validations, 7 application categories, and 3 object categories, (ii) Phase 2: 512 annotated images, with 11 validation, 10 application categories, and 3 object categories. In addition, the prepared dataset contains manually prepared multioriented scene texts with quadrangle bounding box annotation. It also tested the model's limits using a minimum viable set of learned object queries. It tested the most best-known algorithms (see Tables 8.1 and 8.2) and their variations (see Table 8.3) to get the best performance index and to prove that if it is to choose the optimal setup, it will not face a well-known drawback: running the training process until infinity. The thesis experiment aimed to run relatively limited experiment rounds and summarize the results. It resulted in elaborations based on average precision (AP) and mean average precision (mAP) metrics for evaluation. Furthermore, some labeled validation examples were visually inspected for better human evaluation. The following variations were used: (1) different number of epochs: 50, 150, and 1000;

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(2) different categorizations: all 4 predefined categories, or 2 categories: text + others (static, no translate, container categories merged into one category) [36].

Table 8.1: Detectron Phase 1 - thesis experiments and results.

Model	Iterations	AP_1	AP_2	AP_3	mAP	Total Loss
faster_rcnn_R_50_C4_3x	500	0.07034	0.07367	0.09235	0.06877	1.320
faster_rcnn_R_50_DC5_3x	1,000	0.17659	0.23342	0.20921	0.17706	1.253
faster_rcnn_R_50_FPN_3x	700	0.30985	0.44342	0.36016	0.34255	1.154
faster_rcnn_R_50_FPN_3x	1,000	0.30560	0.42302	0.34745	0.34160	1.183
faster_rcnn_R_101_FPN_3x	1,000	0.29764	0.47187	0.43785	0.39341	1.129
faster_rcnn_X_101_32x8_FPN_3x	3000	0.42799	0.56096	0.56331	0.49369	0.458
faster_rcnn_X_101_32x8_FPN_3x	10000	0.45223	0.57821	0.55734	0.48758	0.343
retinanet_R_50_FPN_1x	1,000	0.31027	0.45998	0.47357	0.40872	0.495
retinanet_R_50_FPN_3x	1,000	0.32150	0.46114	0.46953	0.41103	0.477
retinanet_R_101_FPN_3x	3,000	0.36923	0.55230	0.55267	0.49589	0.250
retinanet_R_101_FPN_3x	10,000	0.37968	0.55938	0.57270	0.50513	0.189
rpn_R_50_C4_1x	1,000					0.320
rpn_R_50_FPN_1x	3,000					0.180

Table 8.2: Detectron Phase 2 - thesis experiments and results.

Model	Total Loss	mAP	Workers	BATCH/IMG	IMS/BATCH	Iterations
faster_rcnn_R_50_C4_1x	0.963	0.29753	4	128	6	1,000
faster_rcnn_R_50_DC5_1x	0.967	0.31446	4	128	6	1,000
faster_rcnn_R_50_FPN_1x	0.912	0.33348	4	128	6	1,000
faster_rcnn_R_50_C4_3x	0.912	0.34338	4	128	6	1,000
faster_rcnn_R_50_DC5_3x	0.886	0.34033	4	128	6	1,000
faster_rcnn_R_50_FPN_3x	0.912	0.36219	4	128	6	1,000
faster_rcnn_R_50_FPN_3x	0.707	0.39064	4	128	6	3,000
faster_rcnn_R_101_C4_3x	0.857	0.32096	4	128	6	1,000
faster_rcnn_R_101_DC5_3x	0.882	0.30924	4	128	6	1,000
faster_rcnn_R_101_FPN_3x	0.869	0.32056	4	128	6	1,000
faster_rcnn_X_101_32x8_FPN_3x	0.998	0.30455	2	64	3	1,000
retinanet_R_50_FPN_1x	0.661	0.24791	4	128	6	1000
retinanet_R_50_FPN_3x	0.568	0.25690	4	128	6	1000
rpn_R_50_C4_1x	0.350	0.24046	4	128	6	1000
rpn_R_50_FPN_1x	0.376	0.35200	4	128	6	1000

Based on the initial training results, two bottlenecks were recognized, which need to be managed: (a) the results do not meet the expected thresholds, and (b) the training still has some reserves. These are visible in Figures 8.1 and 8.2. Based on the findings, the system was redesigned to produce results despite the limitation of the training dataset [36]. The experimental findings showed that categorizing four classes for TVOD requires much more training data than is proposed by standards [36]. A broader complexity of options and outcomes will not be enough to support a feasible multilingual VC consulting solution. Therefore, the initial training dataset was modified by merging three categories into one, which produced the following model with the results shown in Figure 8.3, which can be

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Table 8.3: YOLO4 thesis experiments and results.

	YOLO4 TINY 640 (16)				YOLO4 TINY 416 (32)				YOLO4 TINY 800 (16)			
Epochs	**AP_1**	**AP_2**	**AP_3**	**mAP**	**AP_1**	**AP_2**	**AP_3**	**mAP**	**AP_1**	**AP_2**	**AP_3**	**mAP**
10					0.029	0.040	0.130	0.066	0.145	0.199	0.398	0.247
20	0.164	0.153	0.352	0.223	0.051	0.039	0.117	0.069	0.172	0.141	0.312	0.208
30	0.158	0.136	0.352	0.215	0.069	0.047	0.131	0.082	0.280	0.344	0.291	0.305
40	0.272	0.150	0.343	0.255	0.064	0.051	0.127	0.081	0.281	0.265	0.392	0.312
50	0.255	0.156	0.372	0.261	0.070	0.063	0.118	0.084	0.257	0.332	0.445	0.345
60	0.270	0.179	0.337	0.262	0.068	0.065	0.113	0.084	0.269	0.222	0.472	0.321
70	0.308	0.129	0.339	0.259	0.078	0.058	0.131	0.089	0.290	0.400	0.484	0.392
80	0.296	0.105	0.356	0.252	0.087	0.062	0.130	0.093	0.326	0.359	0.485	0.390
90	0.343	0.231	0.364	0.313	0.080	0.059	0.138	0.092	0.347	0.405	0.485	**0.412**
100	0.350	0.152	0.418	0.307	0.087	0.069	0.133	0.096	0.339	0.379	0.481	0.400
110	0.326	0.180	0.408	0.305	0.090	0.069	0.137	0.099	0.335	0.395	0.486	0.405
120	0.326	0.236	0.393	**0.348**	0.092	0.072	0.137	0.100	0.355	0.399	0.479	0.411
130	0.300	0.175	0.410	0.295					0.343	0.411	0.486	**0.413**
140	nan	nan	nan	nan					0.340	0.411	0.483	0.411
150									0.345	0.409	0.483	0.412
	YOLO4 LARGE 480 (16)				**YOLO4 TINY 416 (16)**				**YOLO4 TINY 800 (16, 0.005)**			
Epochs	**AP_1**	**AP_2**	**AP_3**	**mAP**	**AP_1**	**AP_2**	**AP_3**	**mAP**	**AP_1**	**AP_2**	**AP_3**	**mAP**
10	0.140	0.023	0.190	0.118	0.035	0.008	0.104	0.049	0.315	0.337	0.451	0.368
20	0.206	0.061	0.263	0.177	0.049	0.026	0.093	0.056	0.373	0.271	0.432	0.359
30	0.214	0.024	0.266	0.168	0.043	0.030	0.109	0.061	0.440	0.247	0.372	0.353
40	0.247	0.041	0.288	0.192	0.064	0.015	0.102	0.060	nan	nan	nan	nan
50	0.228	0.024	0.300	0.184	0.062	0.031	0.111	0.068				
60	0.268	0.057	0.371	0.232	0.049	0.028	0.118	0.065				
70	0.252	0.042	0.344	0.213	0.061	0.031	0.105	0.065				
80	0.272	0.057	0.323	0.217	0.076	0.027	0.120	0.074				
90	0.258	0.012	0.283	0.184	0.079	0.018	0.142	0.080				
100	0.281	0.040	0.316	0.212	0.084	0.029	0.110	0.074				
110	0.235	0.011	0.298	0.181	0.078	0.034	0.132	0.081				
120	0.262	0.034	0.299	0.198	0.080	0.027	0.140	0.082				
130					0.087	0.023	0.130	0.080				
140					0.086	0.022	0.135	0.081				
150					0.087	0.024	0.133	0.081				

compared with the unclustered solution (see Figure 8.4). The following are the changes to the classes: (1) *New Class 1*, which corresponds to the previous Class 1 and requires translation; (2) *New Class 2*, which corresponds to the union of previous Classes 2, 3, and 4 and does not require translation [36].

For evaluation, the average precision (AP) was used and mAP was computed as follows.

$$\text{mAP} = \frac{1}{n}\sum_{k=1}^{n} \text{AP}_k \ , \tag{8.1}$$

where AP_k represents the average precision of class k, and n is the number of classes.

Alternative No. 1: YOLO4 model and analysis

YOLO offers many model variations, versions, architecture types, implementations, and underlying AI frameworks [36]. Figure 8.5 shows the YOLO4 architectures, with *In-*

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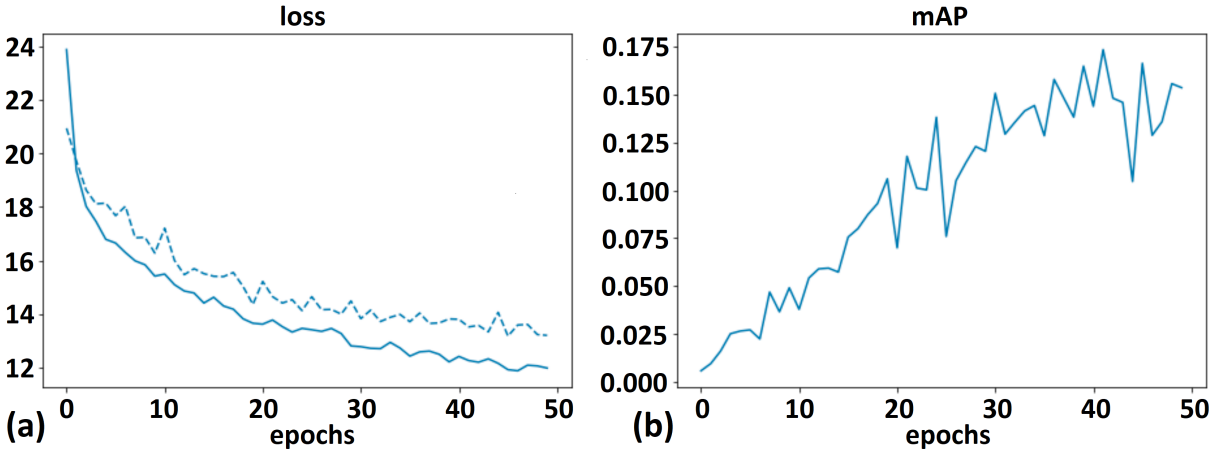


Figure 8.1: DETR results: (**a**) loss function obtained for the training set (solid line) and the validation set (dashed line) during 50 epochs, for all categories (1st thesis experiment); (**b**) mAP scores obtained for the validation set.

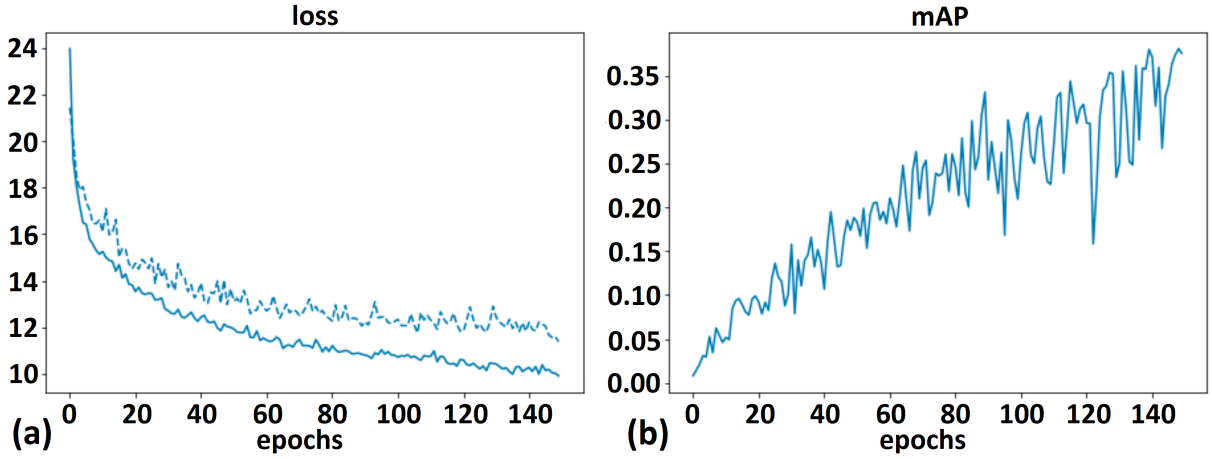


Figure 8.2: DETR results: (**a**) loss function obtained for the training set (solid line) and the validation set (dashed line) during 150 epochs, for all categories (2nd thesis experiment); (**b**) mAP scores obtained for the validation set.

put (like Images, Patches or Image Pyramid), *Backbone* (it could be: VGG16, ResNet-50, SpineNet, EfficientNet, ResNeXt-101, Darknet53, DenseNet, SqueezeNet, MobileNet, ShuffleNet), Neck (e.g., FPN, PANet, Bi-FPN, etc.), *Head* which could have *Dense Prediction* (RPN, YOLO, SSD, RetinaNet, FCOS, CornerNet, CenterNet, MatrixNet, etc.) in the case of One-Stage type Detector as well as *Sparse Prediction* (as Faster R-CNN, R-FCN, Mask R-CNN, Libra R-CNN, etc.) in the case of Two-Stage Detector.

As elaborated in article [36], the training started from randomly initialized weights or some pre-trained weight sets. This research focused on YOLO v4, using Python and TensorFlow. Data annotation was done with VOTT [157], and LabelImg [158]. Later ones always lead to better convergence. YOLOv4 has two primary variations: standard (large [257 MB]) and tiny (small [23 MB]). These were involved in evaluation with the following configurations over 120–150 epochs: (i) Different input image sizes (between

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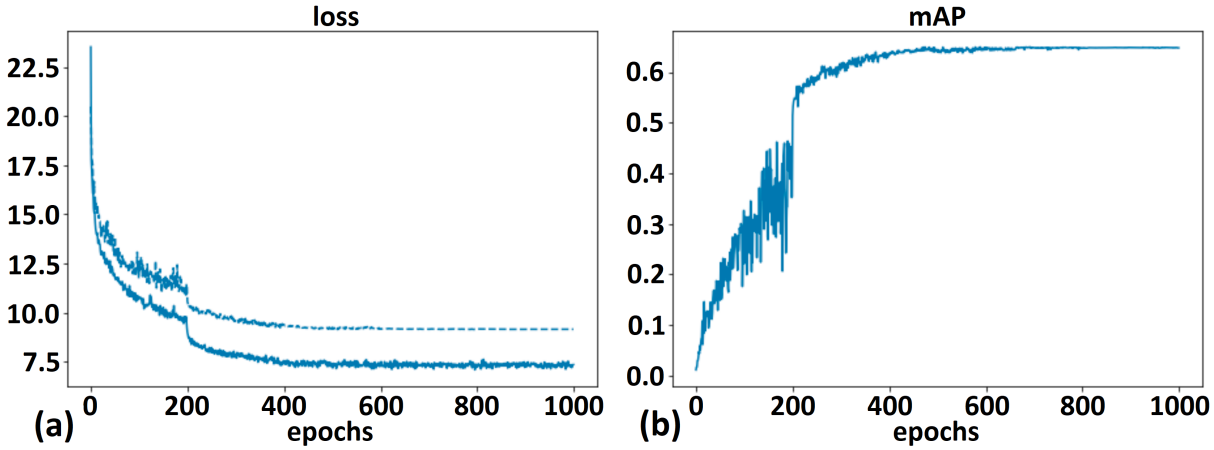


Figure 8.3: DETR results: (**a**) loss function obtained for the training set (solid line) and the validation set (dashed line) during 1000 epochs, for two categories (4th thesis experiment); (**b**) mAP scores obtained for the validation set.

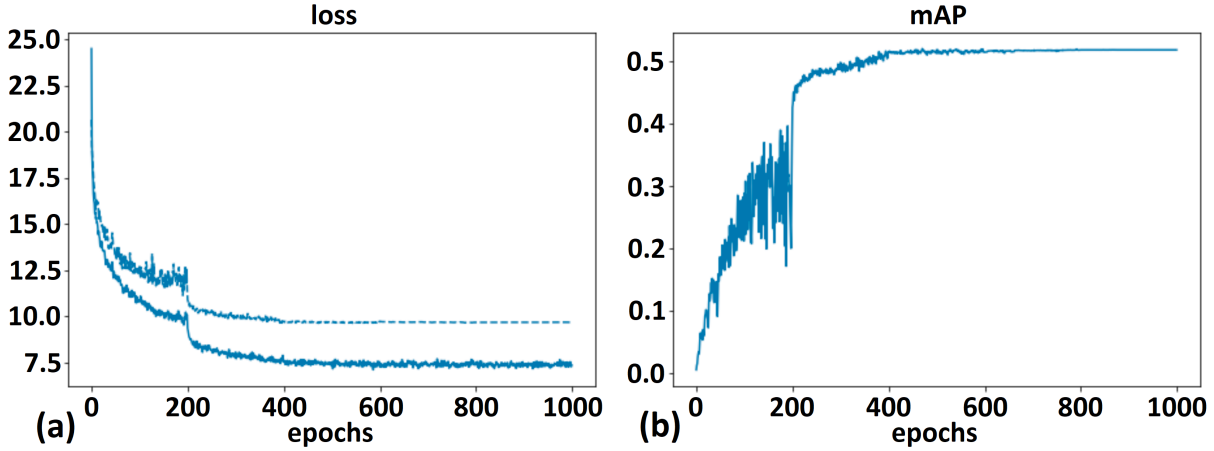


Figure 8.4: DETR results: (**a**) loss function obtained for the training set (solid line) and the validation set (dashed line) during 1000 epochs, for all categories (3rd thesis experiment); (**b**) mAP scores obtained for the validation set.

416 × 416 and 800 × 800 pixels), (ii) Different batch sizes (8–32), (ii) Different learning rates (0.005–0.02), (iii) Different optimizers (SGD, Adam, Nadam) [36].

Alternative No. 2: Detectron2 model and analysis

Detectron2 implements several widespread object detection/segmentation algorithms, such as Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, etc. As in Figure 8.6, it can distinguish three blocks: (1) *Backbone Network* for the extraction of feature maps from the input image, (2) the *Region Proposal Network* which detects the object regions from features and the (3) *Box Head*, which is one of the subclasses of ROI heads. In the studies, only algorithms with model zoo were involved in object detection [36]. The input data were not of the same shape, unlike in the case of YOLO. Therefore, the annotations were transformed into COCO JSON format. All proposed relevant algorithms (best

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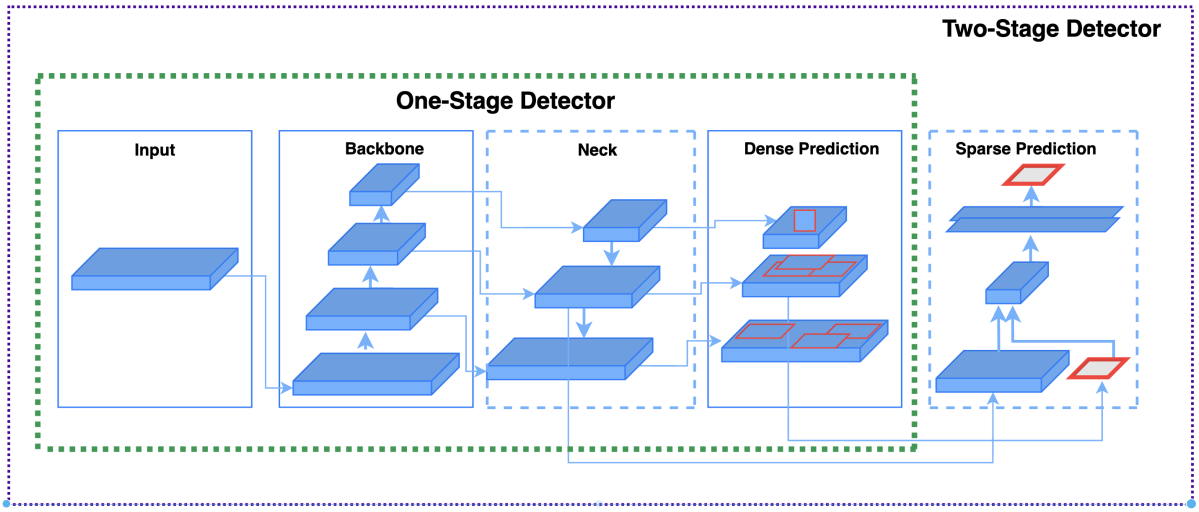


Figure 8.5: YOLO4 architecture according to Bochkovskiy, Wang, Liao [5].

practices) were tested and evaluated with the following variations: (i) different number of iterations (1000 to 10,000), (ii) different number of images per batch (4–16), (iii) different batch size per image (8–128), (iv) different warm-up iteration count (50 to 150), (v) different learning rates (0.001–0.02) [36].

8.1.2 Real-time synthesized and multilanguage OCR

Three different project types [38] were investigated during the thesis experiments shown in Table 8.4. The volume information of the training datasets was layered into three categories: (1) OCR_enhu: English and Hungarian example-only experiments, (2) OCR_hun: Hungarian examples-only experiments, and (3) OCR_multilang: when Japanese, English, and Hungarian languages are present in the dataset.

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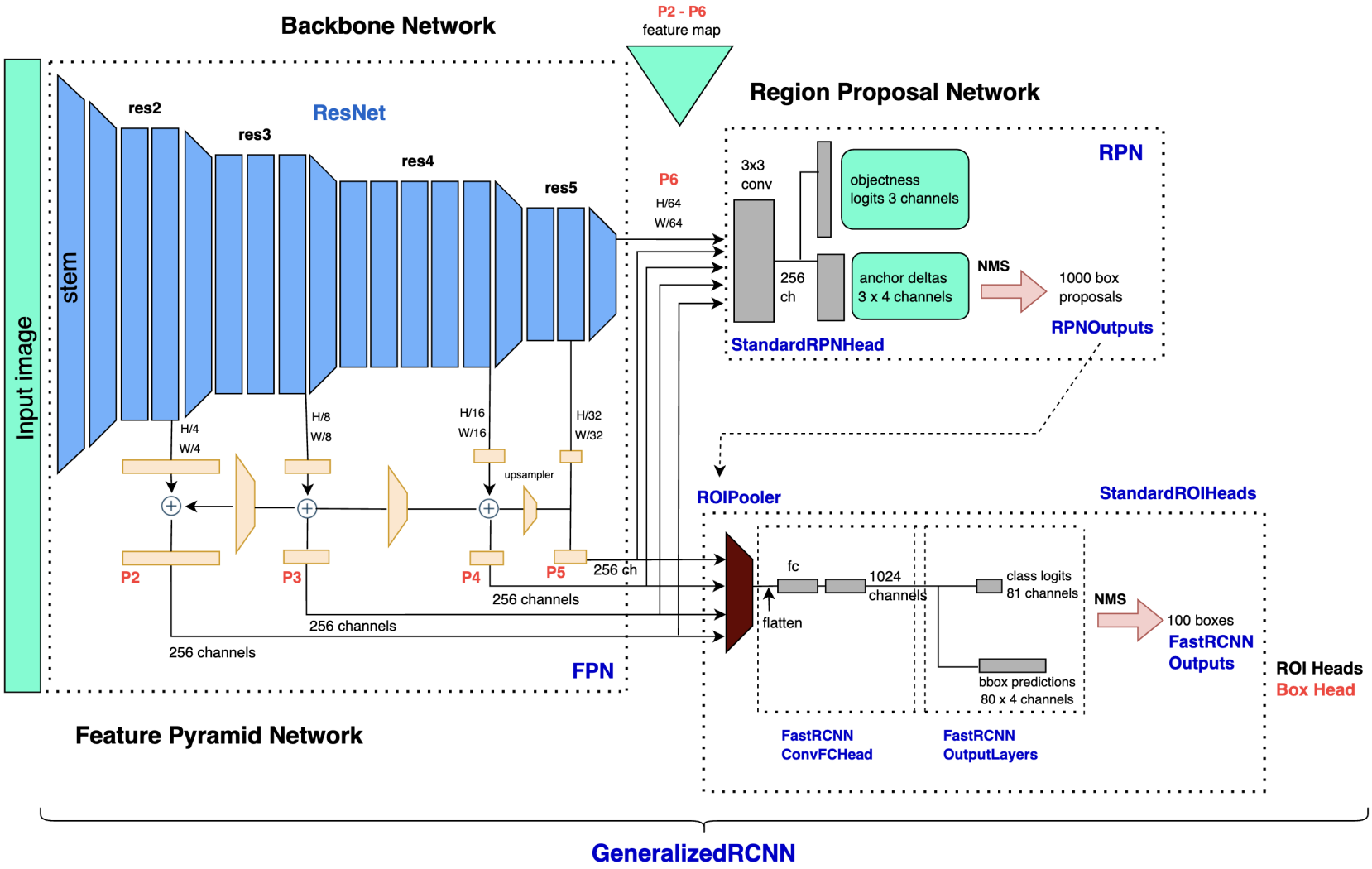


Figure 8.6: Detectron—detailed architecture of Base-RCNN-FPN according to Honda [6].

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Table 8.4: Training names, training data, and batch sizes.

Experiment name	Data	Character dictionary	Dictionary dize	Train batch size	Evaluation batch size	Training size	Evaluation size
155k_hu_v2_2	hun_train	606 k_hun_vocab.txt	112	128	128	77 k	15 k
155k_hu_v2_1	hun_train	606k_hun_vocab.txt	112	600	256	77 k	15 k
SVTR	training1	extended_vocab.txt	201	128	128	66 k	33 k
CRNN	training1	extended_vocab.txt	201	768	256	66 k	33 k
5M_enhujp_v2_8	training10-200	training9-200_vocab_min9500.txt	803	48	48	5 M	101 k
5M_enhujp_v2_6	training9-200	training9-200_vocab_min200.txt	2737	64	64	5 M	101 k
5M_enhujp_v2_5	training10-200	training9-200_vocab_min9500.txt	803	48	48	5 M	101 k
5M_enhujp_v2_4	training9-200	training9-200_vocab_min200.txt	2737	64	64	5 M	101 k
5M_enhujp_v2_3	training8-200	jpn_latin_dict.txt	4444	50	50	8.5 M	170 k
5M_enhujp_v2_2	training8-200	jpn_latin_dict.txt	4444	30	30	8.5 M	170 k
5M_enhujp_v2_1	training7-100	jpn_latin_dict.txt	4444	50	50	5 M	100 k
10M_enhujp_v3_1	training8-200	jpn_latin_dict.txt	4444	60	60	8.5 M	170 k
5M_enhujp_v3_4	training7-100	jpn_latin_dict.txt	4444	50	50	5 M	100 k
5M_enhujp_v3_3	training7-100	jpn_latin_dict.txt	4444	50	50	5 M	100 k
5M_enhujp_v3_2	training7-100	jpn_latin_dict.txt	4444	50	50	5 M	100 k
4M_enhujp_pre_v3_1	training6	jpn_latin_dict.txt	4444	24	24	4.4 M	88 k
4M_enhujp_pre_v3_1	training6	jpn_latin_dict.txt	4444	28	28	4.4 M	88 k
4M_enhujp_v3_5	training6	4M_vocab.txt	4721	28	28	4.4 M	88 k
4M_enhujp_v3_4	training6	4 M_min20_vocab.txt	3980	28	28	4.4 M	88 k
2M_enhujp_v2_2	training3	2M_min2k_vocab.txt	968	64	64	2 M	220 k
186 k_hu_v2_1	training2	186 k_extended_vocab.txt	112	128	128	186 k	34 k

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Exploratory data analysis

For the ease of processing, some EDA steps are performed on the training dataset after it has been generated: (1) counting images, (2) visualizing the distribution of training examples per category of application templates, (3) loading .tsv files into the DataFrame, and (4) visualizing the distribution of text length. From a scientific point of view, the fourth step is one of the most relevant topics. Figure 8.7 shows the visually represented text length distribution of the training dataset:

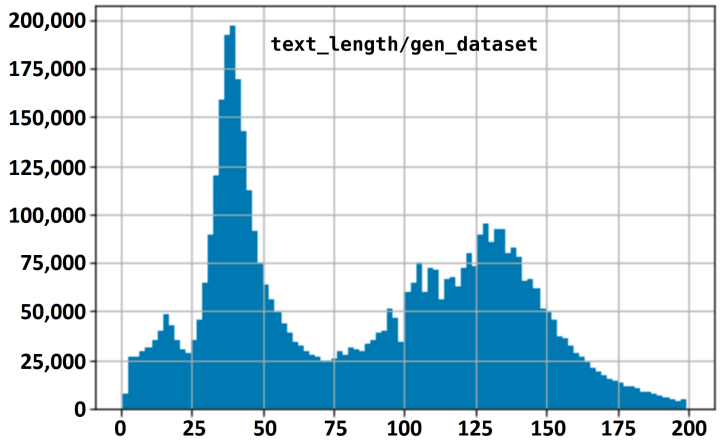


Figure 8.7: Visual representation of the distribution of the length of the texts in the training data.

Vocabulary generation

Two methods are available to create vocabulary (or dictionaries) in the training process: (1) create a unified vocabulary that human experts supervise and (2) generate vocabulary from training data. The process started by applying method (1), and then customize the vocabulary according to method (2). With the help of a Python script, the number of character occurrences in the dictionary was identified. It was analyzed whether it contained characters that appeared more than x times. Figure 8.8 visually represents character occurrences in the dataset, where the value 'x' represents the value on the x axis, which ranges from 0 to 2,000.

On the x-axis of the figure, the number 1,732 represents how many characters would be in the dictionary if every character that does not occur more than 1,732 times in the whole dataset was removed. In light of the analysis, let us select 200 as a value. This describes how frequently a character appears in the entire dataset before being included in the vocabulary. The characters were filtered and stored for subsequent study. This stage saved all characters that appeared at least 200 times in the vocabulary.

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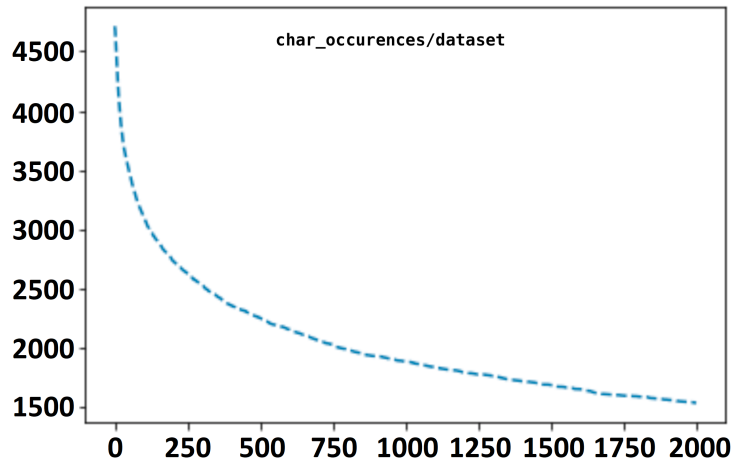


Figure 8.8: Character appearances in the generated training dataset.

Filter, split, and save the training dataset

A particular Python script must be used to ensure that the training dataset contains only instances of these vocabulary terms. Moreover, it must be checked that none of the non-permitted characters appear in the samples. Next, the dataset should be divided into training and validation parts. An essential part of model training is the validation of the training procedure. Let us cut off 1% of the training data sample for validation, exclude examples of non-permitted characters, and then save them in Paddle format.

8.1.3 Optimal dataset preparation in visual object detection

It is always challenging to prepare an optimal training dataset because it is subject to the following combined requirements: (1) comprehensive language representation [293], (2) high-quality data preparation [45], (3) diverse data sample utilization [294], (4) balanced dataset usage [10] – especially in the case of multi-language training [36, 295], (5) contextual understanding, (6) domain-specific adaptation, (7) scalability and extensibility, and (8) robustness and noise tolerance.

Training data in these thesis-relevant papers [36, 38, 40] was generated with a custom data generator tool developed in Python, which can manage customized templates to obtain ready-made annotated images in real life with metadata for further analysis. The tool can specify and/or customize the precise text sources to use and the proportions of these text sources to appear in the training data produced. For multilingual training, proper text distribution and optimal vocabulary preparation are two of the most critical areas where there was visible room for improvement in the case of the existing approaches.

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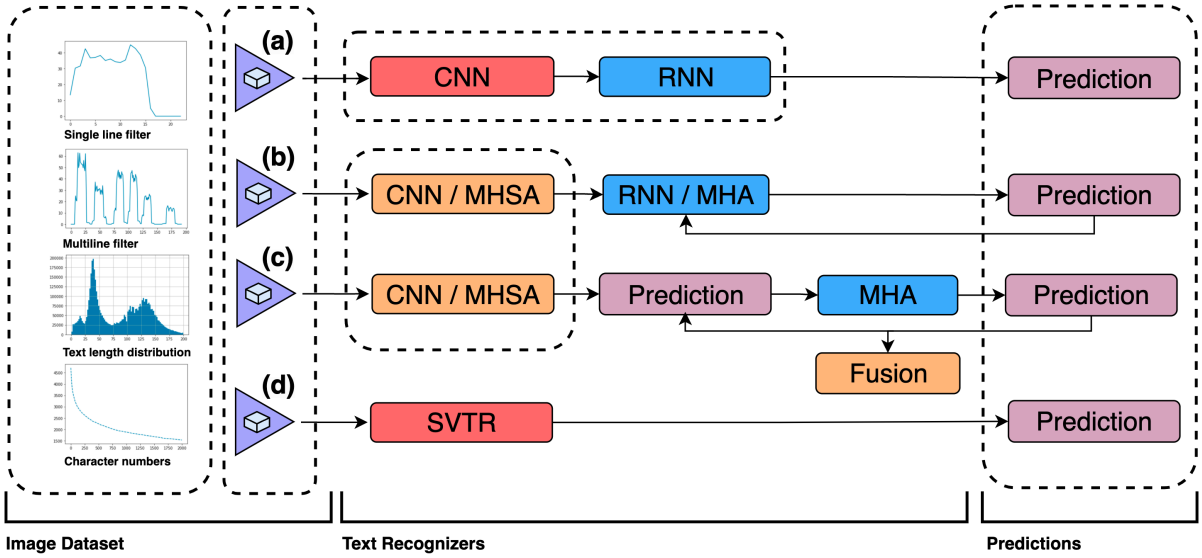


Figure 8.9: Dataset preparation for real-time OCR, adapted from Du, Chen, Jia *et al* [2]

8.2 Methods in the usage of radars and 3D accelerometers

8.2.1 RPA intensity with radars and 3D accelerometers

Modeling

The following ML experiments [15] were conducted within this research: *Energy Expenditure from HR*: Algorithm: linear regression, Libraries: numpy, pandas, sklearn; *Physical activity intensity from HR—option 1*: Algorithm: logistic regression with OLS, Libraries: numpy, pandas, sklearn; *Physical activity intensity from HR—option 2*: Algorithm: DecisionTreeClassifier, Libraries: numpy, pandas, sklearn; *Physical activity intensity from HR—option 3*: Algorithm: Lasso , Libraries: numpy, pandas, sklearn; *Level of the accuracy of predicted activity intens*: Algorithm: RandomForestClassifier OST, Libraries: pandas, sklearn; *RPE from time-series HR dataset*: Algorithm: RandomForestRegressor, Libraries: numpy, pandas, sklearn. During the pre-processing phase [15], athletes practicing moderate and vigorous activities were localized and selected from the relevant sports. Subsequently, the minimal and maximum HR intervals were established to initiate further investigation processes. In the following table 8.5, there is a predefined maximum HR per player with moderate and vigorous activity ranges. The details of calculations are listed in the upcoming Sections 8.2.1 and 8.2.1.

Monitoring RPE for a long period allowed it to adapt training intensity, volume, and recovery tactics to reduce overtraining and injuries. When RPE is replaced with session monitoring, a more advanced model (sRPE) can be set up. This will allow better management of the training load of athletes, ensuring that they are neither overworked

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Table 8.5: Pre-processing of PAMAP2 data: max HR, moderate and vigorous activity intervals.

			Moderate activity ranges		Vigorous activity ranges		
Subject ID	**Sex**	**Age (Years)**	**MAX HR (bpm)**	**Min HR (bpm)**	**Max HR (bpm)**	**Min HR (bpm)**	**Max HR (bpm)**
Player1	Male	27	193	124	147	149	179
Player2	Female	25	195	125	148	150	181
Player3	Male	31	189	121	144	146	176
Player4	Male	24	196	125	149	151	182
Player5	Male	26	194	124	147	149	180
Player6	Male	26	194	124	147	149	180
Player7	Male	23	197	126	150	152	183
Player8	Male	32	188	120	143	145	175
Player9	Male	31	189	121	144	146	176

nor undertrained, thus reducing the risk of injury and ensuring optimal performance. In addition, combining METs with other variables (such as RPE and sRPE) can produce a sophisticated model to thoroughly understand the training load and ACWR, thus optimizing training regimens and reducing the risk of injury per session. By monitoring, ACWR helps specialists manage the progression of their workload, gradually increasing intensity and volume to overcome overwork, and fostering appropriate adaptation while decreasing the risk of injury. By combining these variables, deeper knowledge of training loads, conditioning parameters and suitable training assets, fatigue levels, and risk factors for injury can be gained. With ML models [26], this information allows the creation of customized training programs, improves performance, and improves injury prevention techniques.

To proceed with MET, RPE and sRPE, it is necessary to collect data during and after activity sessions [15]. In the case of numerous sessions per day, a more extensive analysis of sRPE can be prepared, as shown in Figures 8.10 and 8.11. These data points can be compiled using radar sensor technology and 3D accelerometers, along with subjective reports from the athlete [15].

Sports safety specialists and health professionals will benefit from manual and ML-assisted data analyzes to identify trends and patterns that may be obvious or hidden, including changes in the HR, acceleration, and RPE/sRPE (see Figures 8.10–8.12) score over time. Thanks to these data, one may be able to determine the general physical condition of the athlete, as well as their level of weariness and injury risk. It will be possible to identify any performance changes (fatigue and injury risk assessment) or trends over time by comparing the estimated MET and RPE with the baseline data or the historical data of the athlete. As a result, a training or rehabilitation plan can be devised to assist the athlete in meeting their objectives. To reduce injuries and fatigue, this technique might be developed as a regularly monitoring asset to track progress and spot changes over time. This would ensure that athletes stay on track and achieve their predetermined goals.

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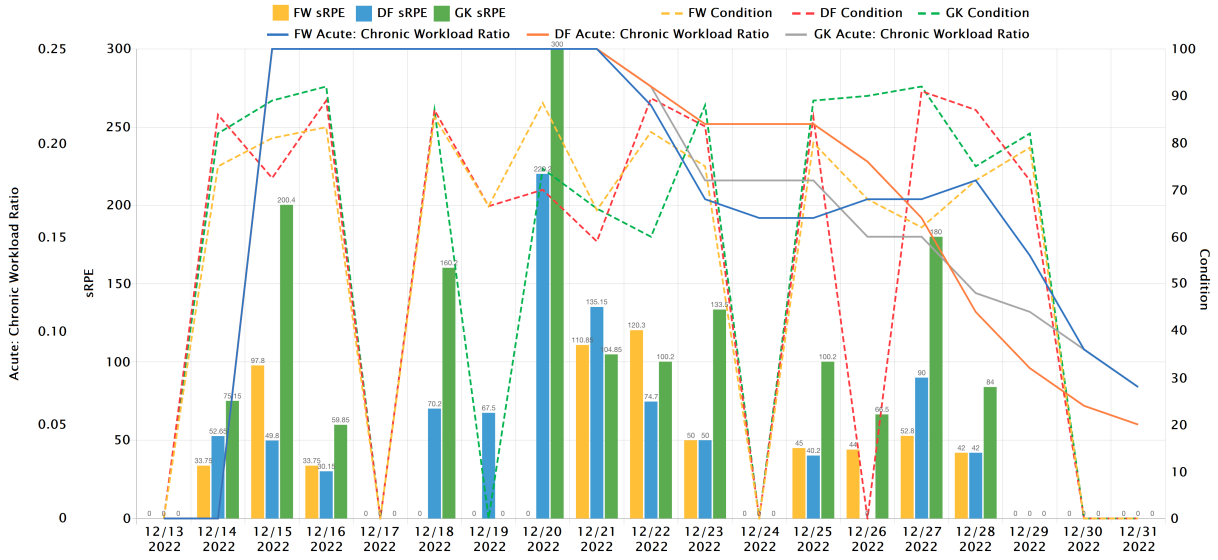


Figure 8.10: Daily sRPE, ACWR, Condition.

HR targets for moderate-intensity physical activity

Moderate-intensity physical activities are desired to be carried out at an HR between 64% and 76% of the maximum HR of the participant. A player can have a maximum HR of 220 beats per minute (bpm) minus his age.

Heart rate targets for vigorous-intensity physical activity

The HR target for vigorous-intensity physical activities should be between 77% and 93% of the maximum HR of the participants. The maximum HR is 220 min the age of the player.

8.2.2 Fatigue and stamina control on multivariate time series (MTS) datasets

IMU-generated multivariate time series datasets ensure AI-assisted fatigue and stamina regulation [42], a new performance sports paradigm with predictive precision and personalized training insights. IMUs and 3-axial accelerometer sensors can identify the onset of fatigue before symptoms appear, allowing pre-emptive training modifications to improve performance and reduce the risk of injury. Multiple synchronized sensors provide a detailed profile of an athlete's biomechanical functioning [296], including movement patterns and physiological reactions. This novel approach [42] also promotes dynamic, real-time models that adapt to the conditioning and performance of the athlete. Adding AI to this field also means moving toward coaching methods based on data rather than qualitative observation. In these methods [42], decisions are made based on continuous quantitative data. AI in multivariate time series dataset analysis will transform sports science by

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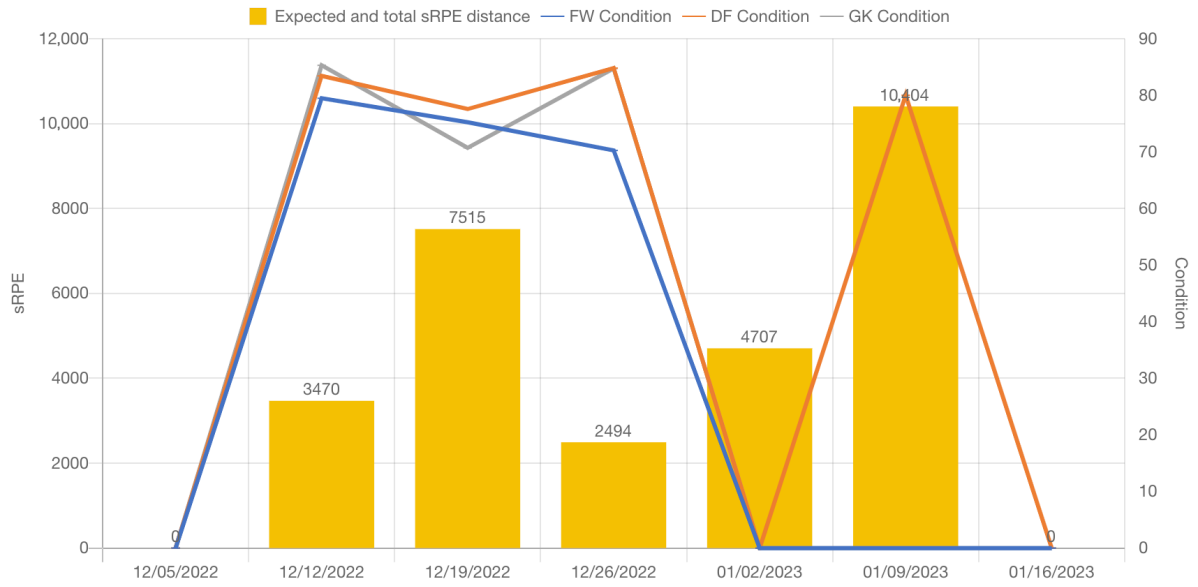


Figure 8.11: Weekly expected sRPE, Condition.

providing unprecedented personalization and precision in optimizing stamina and fatigue management.

During the pre-processing phase [42], it was localized and selected from the dataset. After that, a validation model was prepared using the 3-axial accelerometers to model and/or cross-validate the thesis experiments. Based on a standard beep test, the box plots show how the acceleration distribution changed during a 400-meter run for 19 healthy, experienced runners when they were tired (F) and when they were not tired (NF). The acceleration data from each participant's IMUs is split into "fatigued" and "not fatigued" states, so it can be easily visualized how fatigue changes their kinematic patterns. Across the box plots, there is a visible variation in the distribution of acceleration values between fatigued and unfatigued states. Most participants exhibit a higher median acceleration in the "Not Fatigued" state, suggesting a decrease in acceleration when fatigued. Additionally, wider boxes and longer whiskers indicate that some participants' acceleration values spread more when tired. This means that their performance is more variable when they are exhausted. The presence of outliers, particularly in the "fatigued" condition, suggests that there are instances where the acceleration deviates significantly from the typical range. This could indicate sporadic bursts or drops in energy levels due to fatigue.

Participant 4 shows a slight decrease in median acceleration when fatigued. The interquartile range (IQR) expands during fatigue, indicating increased variability in acceleration; *Participant 5* exhibits a notable reduction in the median acceleration from "Not Fatigued" to "Fatigued". The presence of outliers in the "Fatigued" state suggests occasional deviations from typical performance levels; *Participant 7* has one of the most significant drops in the median acceleration due to fatigue, along with an increase in IQR, which shows that fatigue has a significant effect; *Participant 11* reveals a narrower IQR

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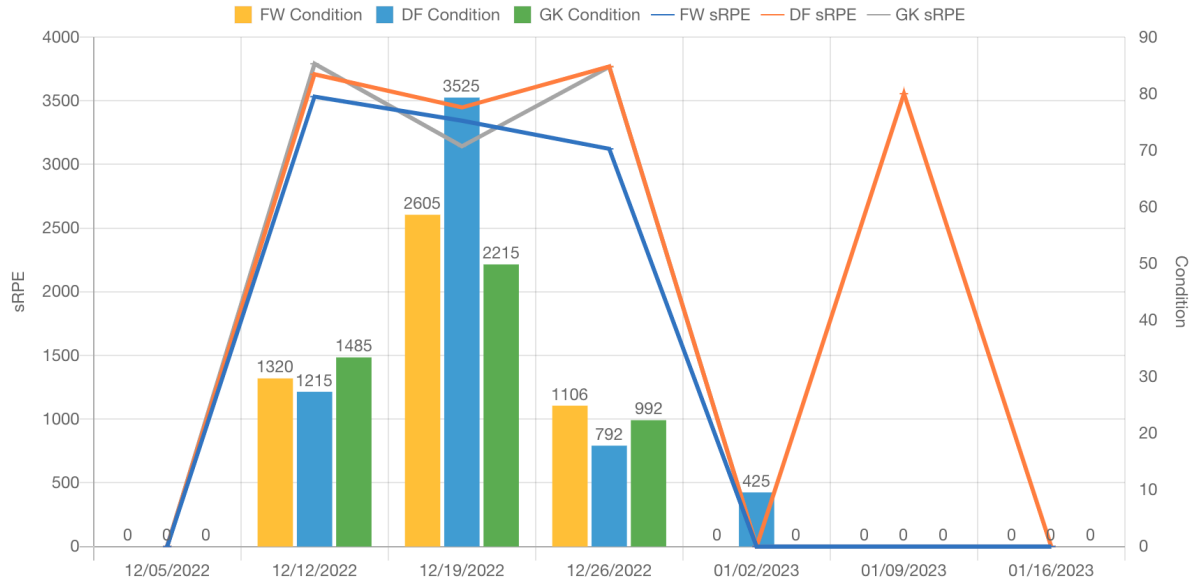


Figure 8.12: Weekly sRPE, ACWR, Condition.

in the fatigued state, which is unusual compared to other participants and may indicate more consistent performance under fatigue; *Participant 13* has a median acceleration that remains relatively stable across states, suggesting resilience to the effects of fatigue; in the case of *Participant 17*, and *Participant 7*, there is a large drop in the median acceleration when they are tired, along with a wide range of values showing that they are not performing consistently; *Participant 23* shows a significant number of outliers in the "Fatigued" state, suggesting erratic performance.

Highlighting *problematic participants* and *best performers*: *Problematic*: those with a substantial decrease in median acceleration and increased variability during fatigue – such as participants 7 and 17 – are considered problematic as they exhibit a pronounced negative impact of fatigue on their performance; *Best results*: participants like 13, who maintain a stable median acceleration and a consistent performance range despite fatigue, can be categorized as the best performers in managing fatigue.

Thesis experiments

The results (see Table 8.6) highlight the diverse capabilities of ML algorithms and the limitations of ML algorithms in predicting athletic fatigue and stamina. The moderate accuracy hovering around the 50% mark for most classifiers, including the *Extra Trees* (see Table 8.7 with parameters: n_estimators=100, random_state=42) and *Random Forest* (see Table 8.9 with parameters: n_estimators=100, random_state=42), suggests that while these models can capture some patterns in the data, there is substantial room for improvement. The trade-off between precision and recall in these models is evident, with none excelling distinctly in both metrics, indicating challenges in achieving high specificity and sensitivity. The *QDA classifier* shows a propensity for higher recall rates, suggesting

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Table 8.6: Results with most well-known clasifiers

No.	Classifier	Accuracy	Precision	Recall	F1-score
0	Extra Trees Classifier	**0.507515**	**0.526137**	0.486982	0.502192
1	Random Forest Classifier	0.505092	**0.523278**	0.476686	0.495675
2	QDA	0.489837	0.494120	**0.707237**	**0.527557**
3	K Nearest Neighbors Classifier	0.486452	0.502285	0.450020	0.472184
4	Decision Tree Classifier	**0.506605**	**0.521075**	0.505028	0.511507
5	Gradient Boosting Classifier	0.471260	0.495196	0.451750	0.459049
6	Logistic Regression	0.489593	0.485458	0.630432	0.510876
7	AdaBoost Classifier	0.484047	0.498580	0.489276	0.489536
8	Linear Discriminant Analysis	0.488134	0.483434	0.633499	0.510848
9	Ridge Classifier	0.488134	0.483434	0.633499	0.510848
10	Light Gradient Boosting Machine	0.495775	0.516807	0.445978	0.471630
11	SVM - Linear Kernel	0.491180	0.470230	**0.779147**	**0.543881**
12	Naive Bayes	0.481170	0.485005	0.694849	0.520882
13	Dummy Classifier	**0.512985**	0.512985	**1.000000**	**0.677771**

that it is susceptible to true positive cases; however, its lower precision rate points to a higher rate of false positives. This could imply that QDA is better suited for scenarios where missing a true positive is more critical than falsely identifying a negative case as positive. This could be more applicable in early diagnostic or screening settings than in precise performance prediction. In contrast, the *K Nearest Neighbors* (KNN) and *Decision Tree* (see Table 8.8 with parameters: random_state=42) classifiers, with their lower recall rates, indicate a tendency to miss true positives more often, which could be problematic in contexts where early detection of fatigue is crucial. The lower performance of the *Gradient Boosting Classifier* could be indicative of model underfitting, which, along with the lowest accuracy observed in the *Light Gradient Boosting Machine*, suggests that these models may struggle with the complex patterns present in the multivariate time series data from IMUs. The *Logistic Regression*, *Linear Discriminant Analysis*, *Ridge Classifier*, and *Naive Bayes* models show a consistent pattern of high recall rates, which could be valuable in early fatigue detection, but could also lead to a higher number of false alarms. This trade-off must be carefully managed in a sports context. Interestingly, the *AdaBoost Classifier* demonstrates a close balance between precision and recall, but its accuracy remains moderate. This balance might be beneficial in creating a baseline model upon which further fine-tuning could be performed. Finally, the anomalously high performance of the *Dummy Classifier*, which classifies all instances as positive, serves as a cautionary note on the importance of evaluating model performance within the context of the specific application and the cost-benefit analysis of different types of prediction errors. The findings demonstrate the precise performance of different classifiers in the context of AI-assisted sports performance. They emphasize the importance of carefully selecting and tuning models based on the specific demands and outcomes of correct or inaccurate predictions in sports training and health management. The findings lay the groundwork for future study, indicating the possibility of combining models or investigating more

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complicated algorithms to improve forecast accuracy and reliability.

Table 8.7: Results with ExtraTreesClassifier

Class	Precision	Recall	F1-score	Support
0	0.56	0.58	0.57	584
1	0.59	0.57	0.58	617
accuracy			0.58	1,201
macro avg	0.58	0.58	0.58	1,201
weighted avg	0.58	0.58	0.58	1,201

Table 8.8: Results with DecisionTreeClassifier

Class	Precision	Recall	F1-score	Support
0	0.53	0.55	0.54	584
1	0.56	0.53	0.55	617
accuracy			0.54	1,201
macro avg	0.54	0.54	0.54	1,201
weighted avg	0.54	0.54	0.54	1,201

Table 8.9: Results with RandomForestClassifier

Class	Precision	Recall	F1-score	Support
0	0.56	0.57	0.56	584
1	0.58	0.57	0.58	617
accuracy			0.57	1,201
macro avg	0.57	0.57	0.57	1,201
weighted avg	0.57	0.57	0.57	1,201

When dealing with IMU-generated multivariate time series datasets [42], LSTM networks often have advantages over traditional ML algorithms like *Random Forest*, *Extra Trees Classifier*, or *Decision Tree Classifiers*, and for this reason a dedicated LSTM DL thesis experiment was conducted (see Table 8.10 DL network (parameters: epochs=5000, batch_size=32, validation_split=0.1), with the DENSE layer (parameters: units=2, activation='softmax')), taking into consideration that LSTM comes with challenges such as higher computational complexity, more intensive hyperparameter tuning, and a need for larger datasets to train effectively without overfitting, as well as that the success of LSTMs highly depends on the quality of data pre-processing, feature engineering. The LSTM model was trained with a significant number of epochs (5000), a batch size of 32, and utilized a validation split of 10% of the training data – putting a proportion of the dataset aside for validation purposes is standard practice, providing a means to monitor

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and evaluate the model's performance on unseen data during training, thus helping in tuning and preventing overfitting. The proposed architecture included a DENSE output layer with two units and a softmax activation function, which is typical for binary classification tasks.

Table 8.10: Results with the LSTM

Class	Precision	Recall	F1-score	Support
0	0.58	0.59	0.59	584
1	0.61	0.60	0.60	617
accuracy			0.59	1,201
macro avg	0.59	0.59	0.59	1,201
weighted avg	0.59	0.59	0.59	1,201

8.3 Methods in health condition control calculation

8.3.1 sRPE and ACWR on fatigue and injury control

In the case of team sports (ice hockey), the dataset [26] was layered into player-type categories from an individual data collection, shown in Table. 8.11 The dataset was layered into player-type categories: datasets for forward (FW), defense (DF) and goalkeepers (GK). These categories were calculated together, to plan and control the FW, DF, and GK team velocities, progress, and fatigue control and to improve the player's training levels. It analyzes the performance or condition of three categories (possibly representing different groups or positions in a sports context) over time using various metrics such as average condition level, RPE units, strain, and monotony. There is an apparent drop in values around weeks 5/10 to 5/24 and a resurgence in week 5/31.

8.3.2 Personalized recovery

The *Pre-processing* phase has a *normalization phase*, where the input images are resized to a standard input size and the pixel values are normalized (usually between 0 and 1 or -1 and 1), which is followed by the *data augmentation phase* to enhance the robustness of the model, where variations of the input data (e.g., rotations, scale changes) can be introduced during training.

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Table 8.11: Ice hockey dataset segmented into FW, DF, GK player types

	10	11	12	13	4/5	4/12	4/19	4/26	5/3	5/10	5/17	5/24	5/31
WEEK Ave. Condition Level													
FW	514	622	498	492	418	466	505	524	523	551	538	545	541
DF	738	781	638	453	489	454	461	487	456	506	535	536	505
GK	705	711	553	410	381	387	362	375	412	448	476	494	414
WEEK Total RPE Unit													
FW	5,415	7,728	5,652	4,043	4,890	4,302	4,388	4,055	4,170	0	0	0	1,875
DF	5,277	7,677	5,520	3,882	4,721	4,277	4,232	4,004	4,076	0	0	0	2,153
GK	4,539	6,669	4,479	3,768	4,953	4,203	3,989	3,794	4,235	0	0	0	2,124
RPE Unit AC Ratio													
FW				0.71	0.88	0.91	1.00	0.92	0.99	0.00	0.00	0.00	4.00
DF				0.69	0.87	0.93	0.99	0.93	0.98	0.00	0.00	0.00	4.00
GK				0.77	1.00	0.97	0.94	0.90	1.04	0.00	0.00	0.00	4.00
Strain													
FW	5,597	15,398	6,011	5,617	14,306	5,868	7,373	7,633	5,483	0	0	0	1,502
DF	5,385	15,037	5,829	5,422	15,016	5,735	6,902	7,392	5,389	0	0	0	1,724
GK	4,562	13,635	4,731	5,029	13,529	5,581	6,515	6,704	5,546	0	0	0	1,693
Monotony													
FW	1.03	1.99	1.06	1.39	2.93	1.36	1.68	1.88	1.30	0	0	0	0.80
DF	1.02	1.96	1.06	1.40	3.18	1.34	1.63	1.85	1.32	0	0	0	0.80
GK	1.01	2.04	1.06	1.33	2.73	1.33	1.63	1.77	1.31	0	0	0	0.80
Strain AC Ratio													
FW				0.69	1.38	0.74	0.89	0.87	0.83	0.00	0.00	0.00	4.00
DF				0.68	1.45	0.72	0.83	0.84	0.85	0.00	0.00	0.00	4.00
GK				0.72	1.47	0.77	0.85	0.83	0.91	0.00	0.00	0.00	4.00

8.4 Methods in disease detection and injury prevention

8.4.1 Disease detection from voice

To identify the best AI classifier model, the following algorithms were tested on the dataset: Extra Trees Classifier, Random Forest Classifier, Light Gradient Boosting Machine, QDA, K Neighbors Classifier, Decision Tree Classifier, Gradient Boosting Classifier, Linear Discriminant Analysis, Ridge Classifier, Logistic Regression, Ada Boost Classifier, SVM - Linear Kernel, Naive Bayes, Dummy Classifier, the results are summarized in Table. 8.12.

Based on the best result, the Extra Trees Classifier was picked and then the model

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Table 8.12: Best model comparison

Model	Acc.	AUC	Prec.	MCC	TT(s)
Extra Trees Classifier	0.7166	0.8930	0.7196	0.5764	0.1980
Random Forest Classifier	0.7127	0.8935	0.7152	0.5704	0.6070
Light Gradient Boosting Machine	0.7071	0.8882	0.7078	0.5613	1.3080
QDA	0.6920	0.8628	0.7045	0.5424	0.0370
K Nearest Neighbors Classifier	0.6547	0.8237	0.6616	0.4857	0.2580
Decision Tree Classifier	0.6513	0.7401	0.6517	0.4772	0.1500
Gradient Boosting Classifier	0.6458	0.8223	0.6479	0.4699	9.0520
Linear Discriminant Analysis	0.5203	0.6894	0.5205	0.2807	0.0590
Ridge Classifier	0.5196	0.0000	0.5199	0.2797	0.0190
Logistic Regression	0.5185	0.6890	0.5189	0.2781	0.5780
AdaBoost Classifier	0.4939	0.6704	0.4944	0.2414	0.8090
SVM - Linear Kernel	0.4494	0.0000	0.4520	0.1748	0.1390
Naive Bayes	0.4000	0.5972	0.4208	0.1124	0.0190
Dummy Classifier	0.3359	0.5000	0.1128	0.0000	0.0180

was tuned (see the results in Table. 8.13).

Table 8.13: Tuned Extra Trees Classifier

	Accuracy	AUC	Prec.	MCC
Fold				
0	0.7037	0.8731	0.7144	0.5592
1	0.7233	0.8841	0.7323	0.5877
2	0.7037	0.8752	0.7068	0.5571
3	0.6863	0.8689	0.6900	0.5327
4	0.6776	0.8621	0.6991	0.5248
5	0.7364	0.8948	0.7430	0.6066
6	0.6885	0.8825	0.6925	0.5337
7	0.6841	0.8732	0.6934	0.5316
8	0.6856	0.8640	0.6902	0.5299
9	0.7293	0.8946	0.7362	0.5961
Mean	0.7018	0.8772	0.7098	0.5559
Std	0.0200	0.0109	0.0195	0.0291

8.4.2 Burnout in performance sport

Data annotation was performed by human experts. In future phases, a collaborative, AI-supported solution for more comprehensive dataset annotation will be used in the postdoctoral phase.

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8.4.3 Disease detection from written communication

In the thesis experiments, the most well-known classifiers were used, resulting in the following initial results. The most promising were (1) Random Forest, (2) Extra Trees, (3) Decision Tree, and (4) Light Gradient Boosting Machine [297].

Table 8.14: Experiments results with classifier comparisons

Classifier	Accuracy	Precision	Recall	F1-score
Extra Trees Classifier	**0.699941**	**0.697118**	**0.699941**	**0.679721**
Random Forest Classifier	**0.697592**	**0.693373**	**0.697592**	**0.676143**
QDA	0.459190	0.221843	0.459190	0.299158
K Nearest Neighbors Classifier	0.682032	0.667897	0.682032	0.656546
Decision Tree Classifier	**0.697005**	**0.694699**	**0.697005**	**0.676126**
Gradient Boosting Classifier	0.688784	0.681584	0.688784	0.663057
Logistic Regression	0.468878	0.261091	0.468878	0.304289
AdaBoost Classifier	0.483265	0.294791	0.483265	0.356398
Linear Discriminant Analysis	0.465942	0.260414	0.465942	0.303054
Ridge Classifier	0.474750	0.225388	0.474750	0.305663
Light Gradient Boosting Machine	0.687317	0.677241	0.687317	0.663735
SVM - Linear Kernel	0.474750	0.225388	0.474750	0.305663
Naive Bayes	0.459190	0.221843	0.459190	0.299158

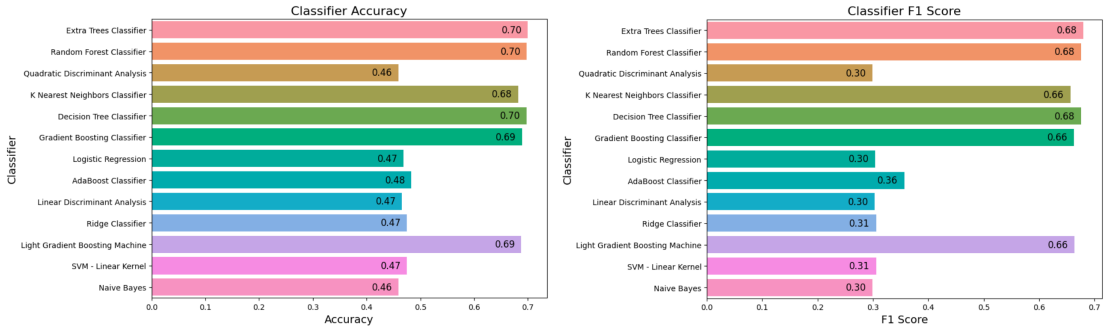


Figure 8.13: Classifier accuracy (left), classifier F1-score(right)

Examples of mental health disorder identification

Each mental health disorder has unique linguistic patterns that the algorithm must learn from the training data. The specific model and its parameters must be tailored based on empirical evidence from these data. This abstract representation simplifies many of the complexities involved in NLP and ML to better understand the approach. Implementing this algorithm requires careful consideration of representativeness and bias in training data, the interpretability of the model, and ethical considerations, especially given the sensitive nature of mental health. Identifying mental health disorders from text and its

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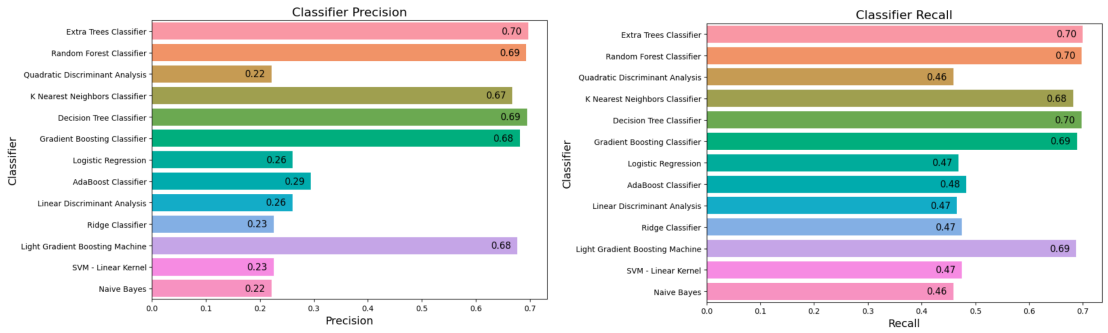


Figure 8.14: Classifier precision (left), Classifier Recall (right)

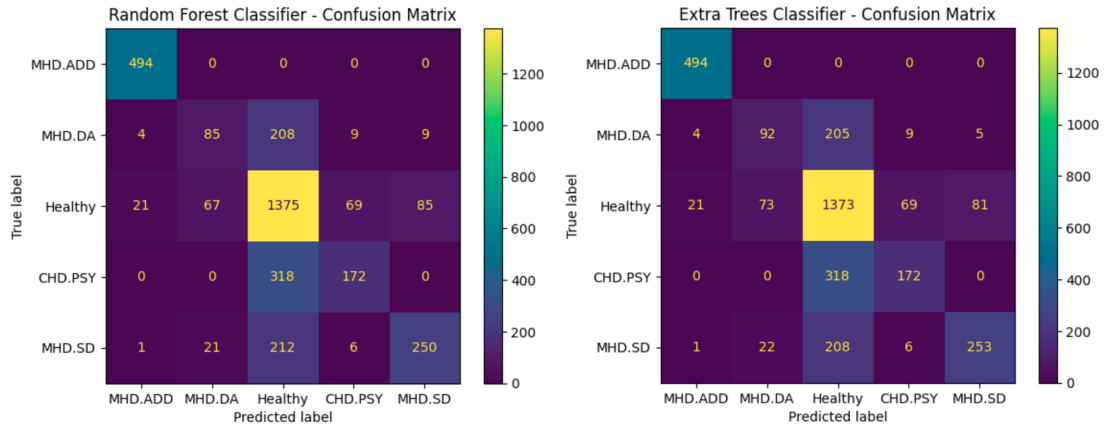


Figure 8.15: Confusion matrix - Random Forest (left), Extra Trees (right)

sentiment analysis involves the computational interpretation of language use, which may suggest underlying psychological conditions.

In practice, sentiment analysis can be performed using ML models trained on annotated datasets, where texts are labeled with associated mental health conditions. Models can learn to detect patterns that frequently correspond to specific disorders. However, validation of AI findings with clinical evaluations is essential, as sentiment analysis tools can complement but *NOT REPLACE* professional diagnosis.

Examples of neurodegenerative diseases or disorder identification

Identifying neurodegenerative diseases from text and sentiment analysis involves detecting language changes that may be symptoms of cognitive decline [19].

In sentiment analysis, although emotional content may not directly indicate a neurodegenerative disease, drastic changes in sentiment over time could reflect the emotional impact of living with such diseases, such as frustration or sadness due to loss of autonomy [19]. In addition, sentiment analysis could detect less obvious changes in emotional expression or response that could be associated with cognitive changes. It is vital to emphasize that these text-based observations are not conclusive for diagnosis, but may prompt further clinical evaluation. Neurodegenerative diseases are complex and require

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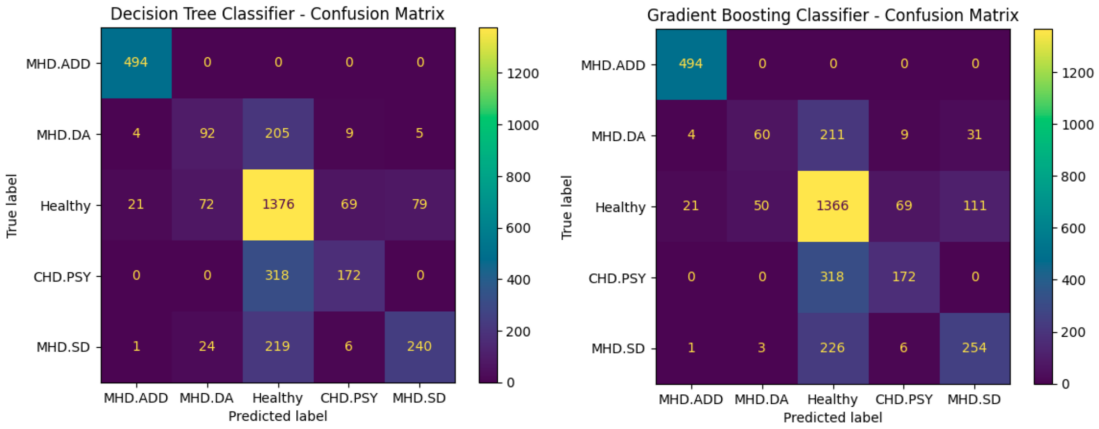


Figure 8.16: Confusion matrix - Decision Tree (left), Gradient Boosting (right)

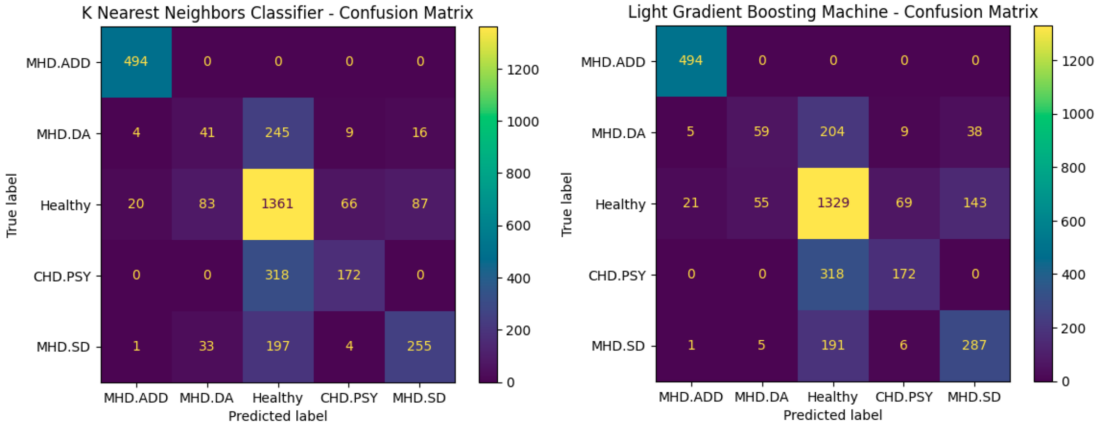


Figure 8.17: Confusion matrix - K Nearest Neighbors (left), LGBM (right)

a comprehensive medical evaluation, including neurological examination, cognitive tests, and imaging, to make an accurate diagnosis. Text and sentiment analysis can be supplementary tools that could identify potential issues for further investigation [19].

Examples of chronic diseases identification

Identifying chronic diseases through text and sentiment analysis typically involves looking for patterns that suggest that a person is experiencing symptoms or challenges associated with their condition. It is important to note that, while sentiment analysis can reveal emotions and concerns related to health, it is not a diagnostic tool for chronic physical diseases. Similar to the other categories, it can indicate when further medical evaluation is required. In these cases, sentiment analysis can assist in quantifying the emotional impact of symptoms or the disease management process. Negative emotions communicated through statements of specific symptoms can lead to a more comprehensive knowledge of the patient's experience. Although AI cannot detect chronic diseases based solely on text, it can provide useful information about a person's subjective health experiences. It is useful for healthcare providers to know when to investigate further or closely monitor

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symptoms.

Table 8.15: Text length distribution by label groups

No.	Disease	Text length
1	Alzheimer's Disease and Dementia	39.435497
2	Depression and Anxiety	91.884543
3	None (No symptoms)	85.082874
4	Psychosis	41.777778
5	Suicide and Depression	1,068.948119

Table 8.16: Text label distribution

No.	Disease	Text labels
1	None (No symptoms)	7,976
2	Suicide and Depression	2,525
3	Alzheimer's Disease and Dementia	2,496
4	Psychosis	2,448
5	Depression and Anxiety	1,585

8.5 Methods in sport strategy prediction and gamification

In the thesis experiments, the YOLO8 and YOLO-NAS models were used to analyze and test the feasibility of AI-based real-time object detection solutions [36] for digital tracking to identify strategies used in the game (e.g. drills, systems) for further analysis. Fig. 8.18 shows the YOLO8 confusion matrix.

Fig. 8.19 shows the YOLO-NAS confusion matrix.

For data annotation, the Roboflow platform was used for an ultra-fast labeling process, which provides an AI-assisted labeling solution that can handle advanced features like bounding boxes, polygons, and instance segmentation. I plan to use the platform in a real-time collaborating model as a future option. The annotations can be layered using the following categories: coach, goalkeeper, ice_hocley_puck, player1 (players of Team 1), player2 (players of Team 2).

8.6 Summary of scientific contributions

The primary scientific contribution of this chapter is a thorough validation using Exploratory Data Analysis (EDA) of the methods, models, technological pipelines, architectures, methodologies, adjustments, components, analysis of alternative approaches and

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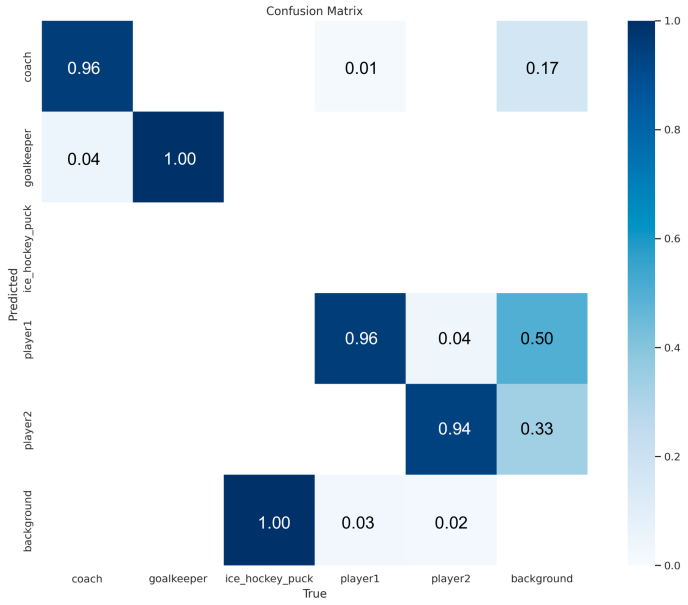


Figure 8.18: YOLO8 confusion matrix

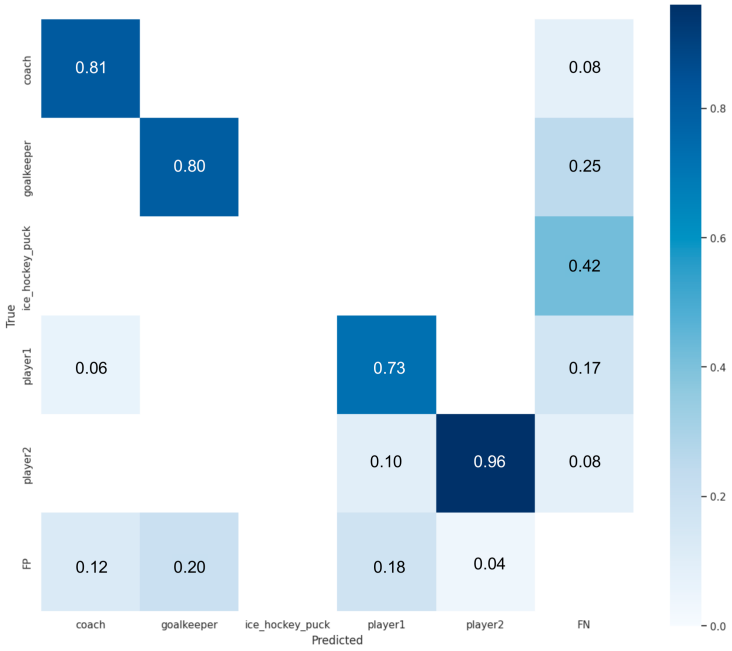


Figure 8.19: YOLO-NAS confusion matrix

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their variations, proposed fine-tuning of EDA results, and hyperparameter fine-tuning. These contributions are explained in detail through the experiments conducted in the thesis.

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9 Results and discussion

This chapter includes a summary of results and conversations related to the interdisciplinary field of advanced remote diagnostic techniques and sensors to predict health and safety conditions in sports. They will be examined in the following sections. Included are the following: (1) Remote consulting; (2) Radars and other sensors; (3) Health condition monitoring; (4) Disease identification and injury prevention; and (5) Prediction of sports strategies and gamification. The scientific contributions are summarized at the conclusion of the chapter.

9.1 Results in remote consultancy and collaborative diagnosis

9.1.1 Multilingual remote consultancy

DETR models

As mentioned in [36], the minimum VRAM required for the DETR thesis experiment is 6 GB. However, the minimum VRAM is a minimum standard requirement for efficient training. One of the advantages of this model is that it could not overfit with the prepared dataset. At approximately 500 epochs, all thesis experiments reached their peak performance (see Figures 8.3 and 8.4). The global loss values are a combination of the detection accuracy of the bounding box and the categorization accuracy. DETR had a reasonable training time: around 9.5 h for 1,000 epochs on the available training dataset. Based on the thesis experiments conducted, the number of categories affects the final performance of the model and can reach the top performance by using a clustering approach (synergizing the relevant classes). The best results with four categories were obtained in mAP > 0.5 (see Figure 8.4). However, it reached the best overall research outcome (mAP $= 0.65$) using a limited number of categories by clustering (see Figure 8.3); as a result, it obtained a better score mAP in almost the same number of epochs.

The results of the thesis experiments were analyzed and evaluated by the loss function values for the training dataset (solid line) and the validation dataset (dashed line), as

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well as the mAP scores for the validation dataset (solid line). In the results figures (see Figures 8.1–8.4), the graph on the left shows the loss function and the graph on the right the mAP score, both plotted against the epoch number. Figures 8.1, 8.2, and 8.4 show the results of the first, second, and third thesis experiments, with 50, 150 and 1,000 epochs, respectively, using the four predefined categories – text, static, no translate, container – and DETR specific N/A categories for disputable results [36]. Figure 8.3 shows the results of the fourth thesis experiment with 1,000 epochs using the cluster approach. Subsequently, three of the original categories were merged into one, which resulted in two new categories: (i) 'New Class 1' with original Class 1 (text) and (ii) 'New Class 2' for 'no translation object holder' composed from Class 2 (static) with Class 3 (no translate) with Class 4 (container) from original mode. As presented in [36], the OCR output is linked to the fourth thesis experiment and confirms that the algorithm is feasible even with mAP = 0.65.

Alternative No. 1: YOLO4 models

It is visible in Table 8.3 that YOLOv4 (tiny) reached mAP values of up to 0.41. It used the following settings: pre-training initial weights, input shape 800 × 800, 120 epochs, SGD optimizer, initial learning rate set to 0.01, and fixed scheduled rate decay during run epochs. Based on the thesis experiments, the following remarks were formulated: (1) the performance does not strictly correlate with training time (epochs); (2) the performance almost always plateaued before terminating the learning process; (3) the accuracy does not always correlate with the overall mAP and class-specific AP values; (4) in comparison with other experiment groups such as Detectron2 or DETR, YOLO requires more training time (around 3–6 minutes per epoch), which makes the hyperparameter tuning process very slow; (5) a very long training – over 150 epochs – becomes uncertain due to the vanishing gradient phenomenon. At this moment, the training is interrupted regardless of the original expected duration of the experiment. "YOLO large" and "YOLO tiny" have the same performance; "YOLO tiny" tends to give better results. It was realized that there is no reason to choose YOLO large for future experiments. A larger input image size provided better results than expected (at least up to the examined 800 × 800, at least); and finally (6) with a batch size of up to 8, the relevant models were unable to learn, so it had to set the batch size at 16 as the minimum value. At the same time, 32 was the maximum value used due to GPU memory constraints.

According to the thesis investigations [36, 38, 40], the optimizer type does not significantly affect performance. Although advanced ones (such as Adam and Nadam) are initially faster, they tend to have the same overall accuracy as vanilla SGD in the long run. However, Adam and Nadam lead to vanishing or exploding gradients more often.

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Alternative No. 2: Detectron2 models

In the experimental environment, 1,000 iterations last around 20–30 minutes, and the "iterations" here cannot correspond to YOLO epochs. The more advanced model types have higher memory requirements. In the case of Detectron2, the warm-up iteration number does not affect the outcome. The optimal learning rate is around 0.005–0.01, where the larger ones tend to explode gradients. In the case of a more advanced model, this type provides the most accurate outcome. According to the research results, performance is not strictly correlated with training time (epochs): performance almost always plateaued before the learning process was terminated. According to the thesis experiments, as indicated in Table 8.1, the RetinaNet and Faster-RCNN detectron models provided the best results, reaching around 0.5 mAP.

Detectron phase 2 research

Detectron2 benefits from models that have much more rapid training than YOLO. Using the same model architecture hyperparameters involved in previous thesis experiments [36], the research was renewed by performing the same experiments and refining the model architecture hyperparameters. However, a more suitable image processing algorithm was applied to the double number of training and validation images, improving the annotation protocol and the review process. The outcome of connected thesis experiments gives a much better loss value at the same mAP in the case of original classes. The second phase resulted in better accuracy through better adjustment of the training data. Table 8.2 shows the results of Detectron2 obtained in Phase 2. The result is quite impressive, even with four categories of objects. In this way, the goal of the thesis was achieved, which was to have the optimal minimal set of training and validation data and the feasible models proposed for a multilingual use case. The score achieved breaks the expected values in a specific OCR scope, resulting in high accuracy in the detection of textual data with mAP = 0.65. As visible in the graphs of Figures 8.1 and 8.2, during the first experiment with DETR (mAP = 0.174) and the second experiment with DETR (mAP = 0.39), there is room for improvement by increasing the number of epochs since the model did not yet produce overfitting. During the third experiment with DETR (mAP = 0.5) depicted in Figure 8.4, it can be seen that the model reaches its best after 400 epochs and there is only a small increment after that point. The model is not overfitting, but it cannot improve its performance. Very similar results were observed in the fourth experiment with DETR (mAP = 0.65) exhibited in Figure 8.3, but with a limited number of categories. However, a considerably higher mAP score was achieved in almost the same number of epochs. I checked the results of the detection of textual objects at this point of investigation [36]. The system had not reached the 0.90 value with mAP, just 0.65 (as presented in [36]); however, the focused objects were accurately identified [36].

In Phase 1 of this research, the DETR DL-based model structure was applied. It

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used only 248 manually collected and annotated training examples and 55 validation examples to fit the minimum viable technical model for practical statistical learning. To achieve the theoretical maximum with mAP exceeding 0.90 (e.g., in the case of context-sensitive language detection), the model requires a minimum set of 1,500 training with 200 validation data and 1,700 instances combined, according to the calculations based on the thesis experiments. The original goal of the research was to show that detecting textual elements with Visual Transformers and fully customizable ML models is possible with suitable accuracy by applying screenshot images [36].

Figure 8.1 shows room for refinement by enriching the number of epochs because the model is not yet overfitted. Overfitting can be determined from loss functions: It can reach the starting point of overfitting when the training loss decreases but the validation loss increases. Figure 8.2 shows the results of the second experiment, and it is observable that it can still increase the number of epochs. Figure 8.4 shows the results of the third experiment. The model is at its best after 400 epochs, with only a small increase after that point. Change the type of experiment if needed to improve the model. The model is not overfitted yet, but it cannot improve more through learning. mAP = 0.5 was obtained at this point. Figure 8.3 shows the results of the 4th experiment with 1,000 epochs using a clustered approach, and this experiment brings the real breakthrough; a much better score (mAP = 0.65) was achieved in almost the same number of epochs (see Figure 8.3). As presented in [36], the OCR output is connected to the fourth experiment [36].

The feasibility check and validation of the thesis experiment emphasize that the models recognize text boxes and categories with high accuracy, specific to the requirements of the textual topic approach. Each thesis experiment group gave the same level of performance (mAP between 0.4 and 0.65) regardless of the actual model types. The main bottleneck for further improvement is the limited quantity, quality, and coverage of data from all use cases. For this reason, annotation protocols, annotation review process, and image acquisition and selection guidelines were improved to start the second research phase.

YOLO reached its best (mAP = 0.413) with YOLOv4 Tiny (see Table 8.3). The disadvantage of YOLO was the slow training process. **Detectron**'s best score of mAP = 0.5 is coming from Retinanet R101 FPN 3x (see Table 8.1). The disadvantage of Detectron2 is the complex framework. Finally, **DETR**'s best of mAP = 0.65 came from DETR RESNET50 (see Figure 8.3). The disadvantages of this model are slow training, separated detection, and classification. In further investigation, it will be compared with the results of the most promising architectures. Based on the results, it can provide a new solution to support collaborative multilingual distant diagnostics, breaking language barriers with AI-supported solutions. The settings used by the best models are as follows: (1) *YOLO4 Tiny*: 800 × 800 input size, 120 epochs, SGD optimizer, learning rate 0.01, batch size 16; (2) *Detectron2 RetinaNet R 101 FPN 3x*: 10,000 epochs, learning rate 0.01, 6 images per batch, 128 batches per image, 150 warm-ups; (3) *DETR RESNET50*: variable input size, 500 epochs, learning rate 0.0001, batch size 2, LR decay 0.0001× every 200 epochs [36].

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It obtained almost the same level of mAP during the second-phase experiments but with much better loss values (see Table 8.2). Suppose that the clustering approach can be applied to the data classification; in other words, instead of four different classes (text, static, no-translate, container), the model can focus just on textual objects; then the models reach the best performance on a moderate number of training data with validation. In this way, it can adapt object detection models to real-time consultations and multilingual collaboration tools and solutions. From the investigated models, DETECTRON and DETR can serve best as these approaches because they will provide the same level of precision, but the best results will provide DETR [36].

DETR insights on textual object detection

The most important results of the thesis experiments can be summarized as follows: (1) approximately 6 GB of VRAM is required (at least) for efficient training; (2) the model could not be over-fitted during the thesis experiments, and this is promising; (3) at approximately 500 epochs, all experiments reached their maximum performance; (4) the global loss values are a combination of the detection accuracy of the bounding box and the categorization accuracy; (5) moderate training time (9.5 h/1,000 epochs with the available training data); and finally (6) the number of categories affects the final performance of the model; object detection with clustering [298] was a line of research connected to the scope.

AI for OCR and multilingual translations for video conference consultancies

Object detection with transformers (DETR) [49] reaches competitive performance with Faster R-CNN via a transformer encoder-decoder architecture [299]. The thesis experiment shows that even with a low number of pictures and moderate performance (mAP = 0.65), models can be built that recognize text box elements, e.g., phrases for collaborative work. Multilingual real-time neural translators can quickly deploy this approach as an interface for collaborative and interactive translation in real time. As a consequence of the thesis, to fit the model to a wide variety of languages, precise requirements can be defined for a highly accurate model, together with annotation guidelines and preparation policies [36].

9.1.2 Real-time synthesized and multilanguage OCR

Experiments, results and accuracies

Table 9.1 highlights the outcome (accuracy) information of the models [38], using a scaled highlighting table of the most promising results, where green shows the best results [38].

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Table 9.1: Results and accuracy.

Name	Image shape	Train batch size	Learning rate	Warmup epochs	Train epochs	Steps	Train best acc	Train min loss	Train best norm Edit Dist	Eval best acc
155k_hu_v2_2	[3, 32, 512]	128	0.0050	2	673	407,677	**0.949**	3.623	**0.985**	0.857
155k_hu_v2_1	[3, 32, 128]	600	0.0050	2	1,224	157,896	0.301	0.002	0.475	0.272
SVTR	[3, 48, 320]	128	0.0010	5	100	17,225	0.055	0.970	0.177	0.001
CRNN	[3, 32, 100]	768	0.0005	0	100	1,521	0.003	0.963	0.119	0.002
5M_enhujp_v2_8	[3, 32, 1024]	48	0.0005	1	21	1,287,568	**0.958**	0.260	**0.999**	**0.938**
5M_enhujp_v2_6	[3, 32, 1024]	64	0.0050	1	23	867,561	**0.938**	0.529	**0.997**	**0.909**
5M_enhujp_v2_5	[3, 32, 1024]	48	0.0050	2	4	350,376	0.885	4.871	**0.976**	0.850
5M_enhujp_v2_4	[3, 32, 1024]	64	0.0050	2	6	209,172	**0.922**	0.628	**0.998**	**0.902**
5M_enhujp_v2_3	[3, 32, 1024]	50	0.0050	2	2	314,836	0.780	13.366	**0.968**	0.736
5M_enhujp_v2_2	[3, 32, 2048]	30	0.0050	2	3	391,741	0.767	10.594	**0.976**	0.716
5M_enhujp_v2_1	[3, 32, 1024]	50	0.0050	2	39	921,738	**0.920**	2.545	**0.989**	0.888
10M_enhujp_v3_1	[3, 32, 1024]	60	0.0010	0	3	179,147	0.483	6.961	0.704	0.448
5M_enhujp_v3_4	[3, 32, 512]	50	0.0001	0	18	408,688	0.750	4.010	**0.904**	0.714
5M_enhujp_v3_3	[3, 32, 512]	50	0.0001	0	14	322,937	0.690	5.179	**0.901**	0.678
5M_enhujp_v3_2	[3, 32, 512]	50	0.0001	0	3	116,924	0.300	2.998	0.574	0.272
4M_enhujp_pre_v3_1	[3, 32, 768]	24	0.0005	0	6	537,619	0.500	1.427	0.681	0.443
4M_enhujp_pre_v3_1	[3, 32, 768]	28	0.0005	2	1	57,629	0.429	2.108	0.668	0.381
4M_enhujp_v3_5	[3, 32, 768]	28	0.0010	0	3	176,068	0.429	2.305	0.737	0.399
4M_enhujp_v3_4	[3, 32, 768]	28	0.0005	0	3	159,235	0.464	1.903	0.704	0.423
2M_enhujp_v2_2	[3, 32, 1024]	64	0.0050	2	100	1,644,300	0.672	41.946	**0.912**	0.648
186k_hu_v2_1	[3, 32, 512]	128	0.0050	2	267	194,505	**0.961**	2.341	**0.990**	**0.927**

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The following method was applied in the thesis experiments conducted [36, 38, 40]: (1) I analyzed both the CRNN and SVTR models, (2) fine-tuned the hyperparameters, (3) localized the limitations of PaddleOCR, CRNN, and SVTR models, (4) prepared a method for custom vocabulary preparation, and (5) continuously adjusted trained models to achieve the expected goals.

9.1.3 Single and hybrid language results

English and Hungarian multilanguage experiments

There were no promising results from these thesis experiments with CRNN or SVTR [38]. The reason might be a relatively small dataset (66k examples) combined with a maximum text length extended. The size of the pre-processed images is another significant consideration. The CRNN model indicates that there will be less than half a pixel for each character in a 100-pixel width image, which means that 250 characters should appear in a 100-pixel-wide image. Furthermore, the SVTR-based model should have been configured to display 150 characters on 320 pixels, an average of about 2 pixels per character. Since hyperparameters were only tested in these experiments, they were shut down relatively early.

Hungarian single language experiments

These two thesis experiments ("Training 1" and "Training 2") used the CRNN architecture for testing purposes (vocabulary, parameters, image sizes), but with some modifications [38]. The size of the dictionary is minimal relative to the amount of training dataset based on the choice of parameters. Similarly to "Training 1", it made the same mistake with the image size; it was unable to display the width of 1 pixel for each character. In contrast, 'Training 2', which had a width of 512, was successful. Although 'Training 1' failed this experiment, 'Training 2' achieved a relatively high score (see the [38] Training section). The graphs indicate that the accuracy of the assessment stopped increasing after half of the training period. The training data were insufficient for proper model training, but everything else was satisfactory. Experimental parameter validation: The accuracy of this training run improved significantly compared to its predecessors. Since the final project requirements require a multilingual model, it was decided to stop its development [38].

Hybrid multilanguage experiments

The vocabulary used in both thesis experiments [38] ("Experiment 1" and "Experiment 2") was relatively large (both were generated from training data). In contrast, the training dataset contains only 4.4 M examples. In addition, the image size might not be sufficient for the 200 long text lines, since this would result in an average width of 3.2 pixels per

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character. These parameters indicate that these models can only reach an accuracy of around 40%. The first experiment was carried out with the v3_2 model ("Experiment 3") and the precision and evaluation results improved; however, the training accuracy appeared to stop, so the experiment ended. Similarly, the other two models ("Experiments 4" and "Experiment 5") could benefit from more training time. As a result – for details, see the Figures of Experiments 4 and 5 from [38] – of having more time to learn from the training data, the following two models achieved significantly higher scores. The precision of the training and evaluation correlates with better deals, as demonstrated by the loss value and precision of the training. Similarly to the two previous ones, they also had to be stopped because their learning slowed down after a while. This could be attributed to their excessive vocabulary.

'Experiment 6' (4M_enhujp_pre_v3_1) was built on a pretrained Japanese model created by the PaddleOCR team. Most of the characters in the vocabulary are Japanese, so it was determined that the Japanese pre-trained model would be the most appropriate method. As shown in [38], Figure of Experiment 6, the model did not produce the expected results, and the reliability could not be further increased. PaddleOCR's fine-tuning strategy contributed to this outcome. As a result, the user cannot cut down the top layer of the model and fine-tune it with new data; instead, the model's weights are trained.

'Experiment 7' (10M_enhujp_v3_1) has a big enough training dataset and the correct image size. However, it should be noted that the vocabulary used is relatively large. Moreover, this vocabulary is unified and may contain unnecessary and missing characters. However, training was only performed briefly (see [38], Experiment 7 for details), and training accuracy stopped increasing. Despite this, the accuracy of the evaluations has continued to grow simultaneously. As a result, the model cannot be trained by using the training data.

'Experiment 8' (V2_1) and 'Experiment 10' (v2_3) appear to have reached their maximum potential, based on the evaluation accuracy levels, which have not increased for some time. The evaluation data for these two experiments are shown in [38]. The evaluation of the accuracy (see [38]) in 'Experiment 9' (v2_2) appears to be improving, although the training accuracy seems to be stagnant. To date, 'Experiment 11' (v2_4) has shown the most promising results (see [38], Experiment 11), but after a few epochs, it reached its maximum potential. This is explained by a low learning rate. However, with a slightly lower learning rate, as seen in 'Experiment 12' (v2_6), it seems that the experiment can still have some potential (see [38], Experiment 12). Similarly to the previous two experiments, something similar happens to the first model, 'Experiment 13' (v2_5), which has an excessively high learning rate and stops improving after a while (see [38], Experiment 13 for details). With a sufficiently small learning rate, the last experiment (v2_8) reached the best score.

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9.1.4 Optimal dataset preparation in visual object detection

Developing an optimal dataset with well-defined evaluation metrics and benchmarks enables researchers and AI specialists to assess the performance of various OCR models, identify areas for improvement, and facilitate model comparison and selection.

Table 9.2: Experiment result on feasibility testing

Name	Steps	Epochs	Best_Acc	Dataset	Vocab size
3M_dashboard_eng_V1	1.83M	90	91%	3M	803
3M_dashboard_hun_v1	0.96M	47	89%	3M	112
3M_dashboard_enhujp_v2_1	1.61M	100	90%	3M	4,444
10M_enhujp_v2_1	3.96M	100	85%	8.5M	4,444
15M_enhujp_v2_1	1.32M	100	85%	15M	2,737
30M_enhujp_v2_4	0.7M	10	98.76%	30M	1,441
30M_enhujp_v2_1	0.15M	10	95.87%	30M	1,441
50M_enhujp_v2_2	1.71M	10	94%	50M	3,964

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The approach was validated in different datasets and is shown in Table 9.3, which shows the accuracy of the models, with the most prospective results highlighted in bold. The more in-depth elaboration of the thesis experiments is presented in the paper [36] pertaining to the thesis.

Table 9.3: Experiment result and accuracy information on validation testing sets, according to the experiments presented in

Project type	Name	Dictionary	Epochs	Text length	Training batch size	Evaluation batch size	Image shape	Learning rate	Train best acc	Training size	Evaluation size
Single language	155k_hu_v2_2	606k_hun_vocab.txt	2k	100	128	128	[3, 32, 512]	0.0050	**0.949**	77k	15k
Single language	155k_hu_v2_1	606k_hun_vocab.txt	2k	100	600	256	[3, 32, 128]	0.0050	0.301	77k	15k
Multilanguage	SVTR	extended_vocab.txt	100	150	128	128	[3, 48, 320]	0.0010	0.055	66k	33k
Multilanguage	CRNN	extended_vocab.txt	100	250	768	256	[3, 32, 100]	0.0005	0.003	66k	33k
Multilanguage	5M_enhujp_v2_8	training9-200_vocab_min9500.txt	100	200	48	48	[3, 32, 1024]	0.0005	**0.958**	5M	101k
Multilanguage	5M_enhujp_v2_6	training9-200_vocab_min200.txt	100	200	64	64	[3, 32, 1024]	0.0050	**0.938**	5M	101k
Multilanguage	5M_enhujp_v2_5	training9-200_vocab_min9500.txt	100	200	48	48	[3, 32, 1024]	0.0050	0.885	5M	101k
Multilanguage	5M_enhujp_v2_4	training9-200_vocab_min200.txt	100	200	64	64	[3, 32, 1024]	0.0050	**0.922**	5M	101k
Multilanguage	5M_enhujp_v2_3	jpn_latin_dict.txt	100	200	50	50	[3, 32, 1024]	0.0050	0.780	8.5M	170k
Multilanguage	5M_enhujp_v2_2	jpn_latin_dict.txt	100	200	30	30	[3, 32, 2048]	0.0050	0.767	8.5M	170k
Multilanguage	5M_enhujp_v2_1	jpn_latin_dict.txt	100	100	50	50	[3, 32, 1024]	0.0050	**0,920**	5M	100k
Multilanguage	10M_enhujp_v3_1	jpn_latin_dict.txt	50	200	60	60	[3, 32, 1024]	0.0010	0.483	8.5M	170k
Multilanguage	5M_enhujp_v3_4	jpn_latin_dict.txt	50	100	50	50	[3, 32, 512]	0.0001	0.750	5M	100k
Multilanguage	5M_enhujp_v3_3	jpn_latin_dict.txt	50	100	50	50	[3, 32, 512]	0.0001	0.690	5M	100k
Multilanguage	5M_enhujp_v3_2	jpn_latin_dict.txt	50	110	50	50	[3, 32, 512]	0.0001	0.300	5M	100k
Multilanguage	4M_enhujp_pre_v3_1	jpn_latin_dict.txt	50	200	24	24	[3, 32, 768]	0.0005	0.500	4.4M	88k
Multilanguage	4M_enhujp_pre_v3_1	jpn_latin_dict.txt	50	200	28	28	[3, 32, 768]	0.0005	0.429	4.4M	88k
Multilanguage	4M_enhujp_v3_5	4M_vocab.txt	50	200	28	28	[3, 32, 768]	0.0010	0.429	4.4M	88k
Multilanguage	4M_enhujp_v3_4	4M_min20_vocab.txt	50	200	28	28	[3, 32, 768]	0.0005	0.464	4.4M	88k
Multilanguage	2M_enhujp_v2_2	2M_min2k_vocab.txt	100	200	64	64	[3, 32, 1024]	0.0050	0.672	2M	220k
Single language	186k_hu_v2_1	186k_extended_vocab.txt	2k	100	128	128	[3, 32, 512]	0.0050	**0.961**	186k	34k

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Figure 9.1 shows the visualization of the distribution of text length in the English, Hungarian, and Japanese datasets for Experiment 1 (Experiment1_15M_enhujp_v2_1), where the horizontal axis represents the length of the text and the vertical axis the frequency on each subchart. Here, the mean, median, minimum and maximum values for the filtered text lengths and the overall text length without considering the language are as follows: (1) English dataset: Mean: 75.404116, Median: 75.0, Min/Max: 1/199; (2) Hungarian dataset: Mean: 79.014045, Median: 78.0, Min/Max: 1/99; (3) Japanese dataset: Mean: 34.984825, Median: 39.0, Min/Max: 1/162; (4) Full (EN-HU-JP) dataset: Mean65.619248, Median: 55.0, Min/Max: 1/199.

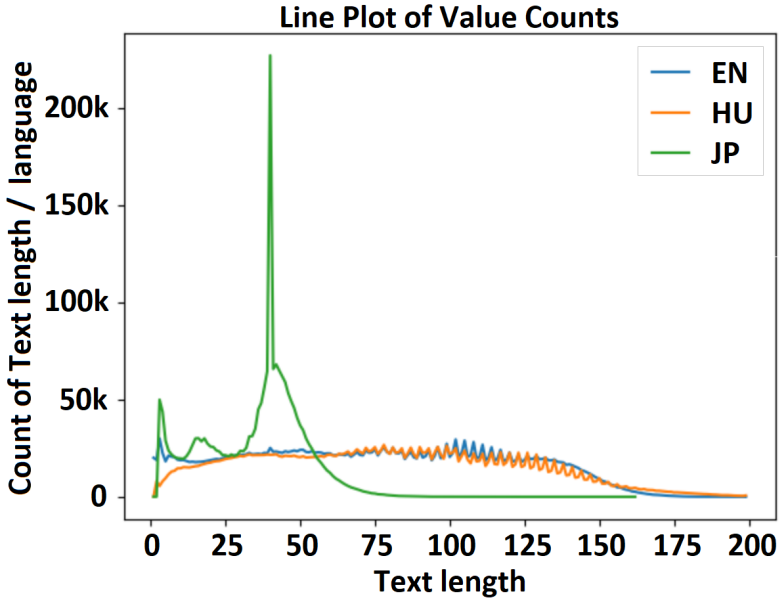


Figure 9.1: Text length distribution – Experiment 1 (15M_enhujp_v2_1): English - Hungarian - Japanese distribution

Figure 9.2 shows the visualization of the distribution of text length in the English, Hungarian, and Japanese datasets for Experiment 2 (Experiment1_30M_enhujp_v2_4), where the horizontal axis represents the length of the text and the vertical axis represents the frequency in each subchart. The mean, median, minimum, and maximum values for the filtered text lengths and the overall text length without considering the language are as follows: (1) English dataset: Mean: 73.695273, Median: 73.0, Min/Max: 1/199; (2) Hungarian dataset: Mean: 76.833792, Median: 75.0, Min/Max: 1/199; (3) Japanese dataset: Mean: 34.873541, Median: 38.0, Min/Max: 1/162; (4) Full (EN-HU-JP) dataset: Mean: 65.302173, Median: 57.0, Min/Max: 1/199.

Figure 9.3 shows the visualization of the distribution of text length in the English, Hungarian, and Japanese datasets for Experiment 3 (Experiment1_50M_enhujp_v2_2), where the horizontal axis represents the length of the text and the vertical axis represents the frequency in each subchart. The mean, median, minimum, and maximum values for the filtered text lengths and for the overall text length without considering the language are as follows: (1) English dataset: Mean: 76.840730, Median: 77.0, Min/Max: 3/199;

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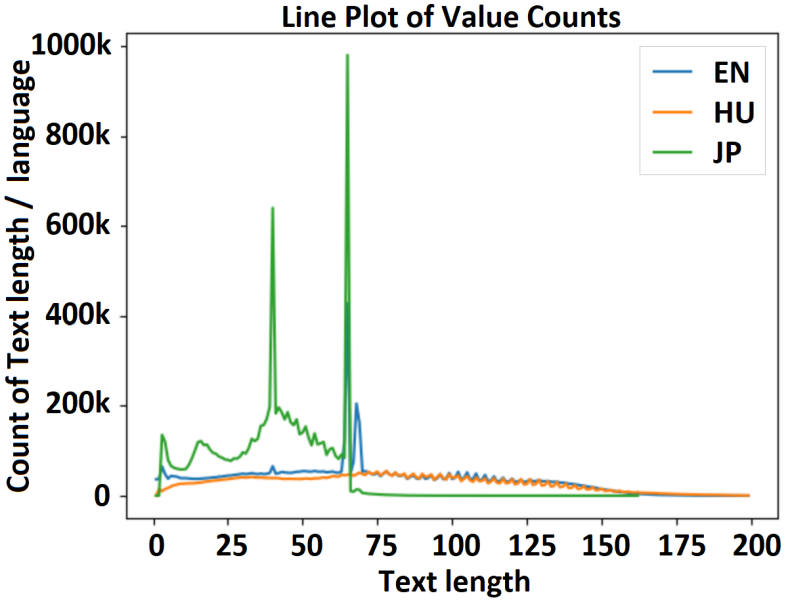


Figure 9.2: Text length distribution – Experiment 1 (30M_enhujp_v2_4): English - Hungarian - Japanese distribution

(2) Hungarian dataset: Mean: 79.699119, Median: 78.0, Min/Max: 3/199; (3) Japanese dataset: Mean: 35.632283, Median: 39.0, Min/Max: 3/162; (4) Full dataset (EN-HU-JP): 67.751759, Median: 59.0, Min / Max: 3/319. The approach was validated on different datasets. The results and experiments related to this pillar of the thesis were presented in the [36] paper.

The primary objective was to ensure that the dataset adequately represents the unique characteristics of each language (Japanese, English, Hungarian), including alphabets, the most frequently used characters, writing styles, and common vocabulary. This allows the OCR system to learn and recognize distinctions and combinations effectively between or among language scripts. The dataset used in the thesis studies includes high-quality, clear, and accurate text samples from well-known and current sources, allowing the OCR system to be efficiently trained. This guaranteed that the model learned to reliably recognize characters, words, and hybrid languages, ultimately enhancing its performance in real-time OCR jobs. The training dataset included examples with varying levels of noise, such as occlusions, distortions, or low-quality photos, to train the OCR system to be robust and noise-tolerant in real-world circumstances. A wide range of text samples, including diverse fonts, writing styles, and situations, were added during the thesis tests and workflow optimization process to generate the dataset, allowing the OCR system to generalize better and adapt to numerous scenarios. This data diversity allows the model to handle a wide range of text inputs from various sources. A balanced dataset was constructed to prevent the model from being biased toward a single language or character set.

As a future outcome, this involves the “equal representation of” of each language and mitigation of class imbalances, allowing the OCR system to recognize characters and words

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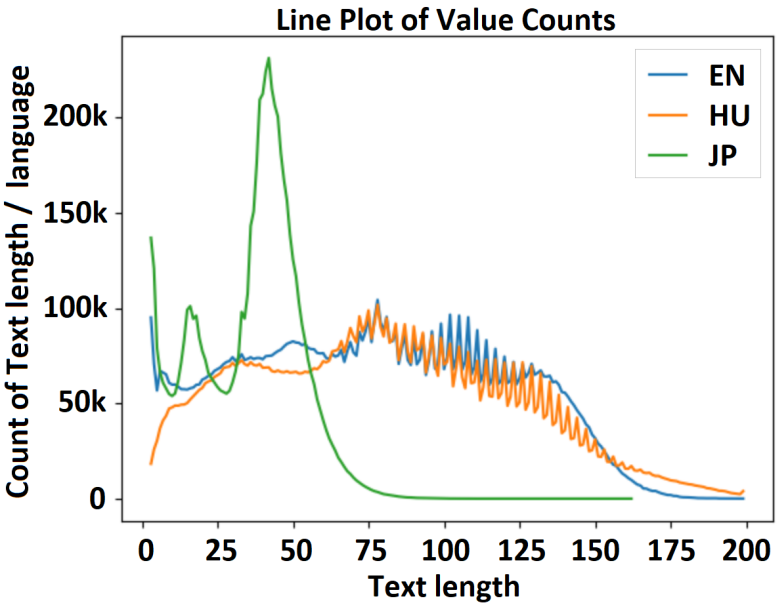


Figure 9.3: Text length distribution – Experiment 1 (50M_enhujp_v2_2): English - Hungarian - Japanese distribution

from the three languages equally well. It was ensured that the training dataset included samples that reflect the contextual variations of each language and their variations (e.g., English acronyms or technical terms in Hungarian or English phrases). This allows the OCR system to understand and interpret texts or phrases within different contexts, such as formal, informal, technical, or everyday settings.

Domain-specific data for each language have been incorporated to support the OCR system in specialized fields or use cases, such as legal, IT, medical, engineering, or technical contexts. This adaptation improves the model's ability to recognize and interpret domain-specific terminology and slang. To enable further expandability, a specific dataset was designed to allow easy integration of additional languages or new data samples in the future or to be ported to an HPC environment. This facilitates the ongoing improvement and expansion of the OCR system to accommodate new requirements and evolving language trends.

9.2 Results in the usage of radars and 3D accelerometers

9.2.1 RPA intensity with radars and 3D accelerometers

As shown in Figure 8.10, the daily sRPE (Figures 8.10 – 8.12 and 9.7), ACWR (Figures 8.10 and 8.12), and Condition (Figures 8.10 – 8.12) – per player type in an ice hockey team – provide a complete picture of an individual's level of physical activity and their progress toward achieving their short- and long term goals (see Figure 8.11), as well as

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allow the development of training plans and sessions that are best suited to meet their needs, either at the group or individual level (Table 8.5). Furthermore, they can help detect when an individual may be overtraining, taking into account the HR intervals per activity type as it was calculated in Sections 8.2.1 and 8.2.1. They can monitor how well the individual is recovering and ensure that the individual does not overtrain, which can cause injury. Changes in MET values over time, as well as sudden decreases or increases in these values, are the most important KPIs for assessing injury risk. In addition, detailed subjective reports of the individual about any discomfort or pain experienced by them can be valuable in identifying potential injuries or anomalies. Regular monitoring of these KPIs can prevent damage and ensure that the individual can perform at their top level [15].

RPE, ACWR in sports using subjective data from athletes

The following graphs show the RPE and sRPE, and the ACWR data of the athletes as a result of the manual data processing process [15, 26]. Using sRPE [138] instead of the classic RPE analysis provides a superior monitoring method for the training load, taking good consideration of the intensity of the training sessions. This part of the development has been implemented with the support of Cloud Campus [127] and Toyo University during the "sRPE/ACWR/Condition" research phase – to support student athletes and coaches with up-to-date conditioning state data – with the participation of sports specialists and coaches. Figure 8.10 shows the daily sRPE, ACWR, and Condition per player type in an ice hockey team. Figure 8.12 shows the weekly sRPE, ACWR, and Condition per player type in an ice hockey team [127]. Figure 8.11 shows the expected total of conditions and sRPEs per type of player on an ice hockey team [127].

RPE, METs in sports using HR data

Figure 9.4 shows HR during running, cycling, and football (soccer) with predicted variations in MET and RPE. The most significant metrics to consider when comparing these sports would be the level of MET, which provides an objective measure of energy expenditure [32, 33], and the RPE values, which offer a subjective estimate of exertion, both critical measurements to consider. As a result of these measures, customized training can be designed, progress monitored, and key performance indicators of sport safety (KPI) can be developed to prevent overtraining and/or injury among athletes.

Figure 9.5 shows the predicted variation in MET and RPE during running, cycling, and football (soccer) activities. The graph indicates that runners typically have a higher MET value than cyclists and soccer players, indicating a higher level of energy expenditure and a more significant amount of caloric expenditure in running. A higher perceived exertion rate (RPE) may also be present during running, indicating a higher exertion during activity [232].

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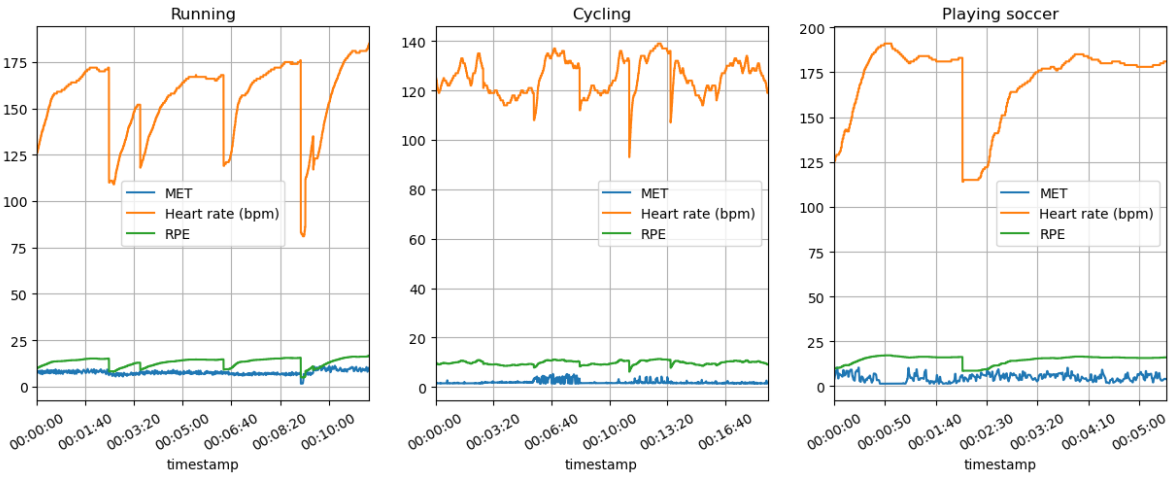


Figure 9.4: HR, MET, and RPE per sport.

The MET value of cycling is generally lower than that of running, indicating lower caloric and energy expenditures. Cycling cannot be considered a cardiac workout, but it can be useful, especially when the intensity is moderate or severe, as demonstrated by tests. Cycling is likely to have lower RPE values than running, indicating that it is a less demanding sport. Football (soccer) differs from many other sports in that it requires intense bursts of activity followed by brief rest periods. As a result, the values may be comparable to or slightly higher than those of intensive cycling. The RPE levels are likely higher in running due to its intensity and the fact that it is stop-and-go throughout.

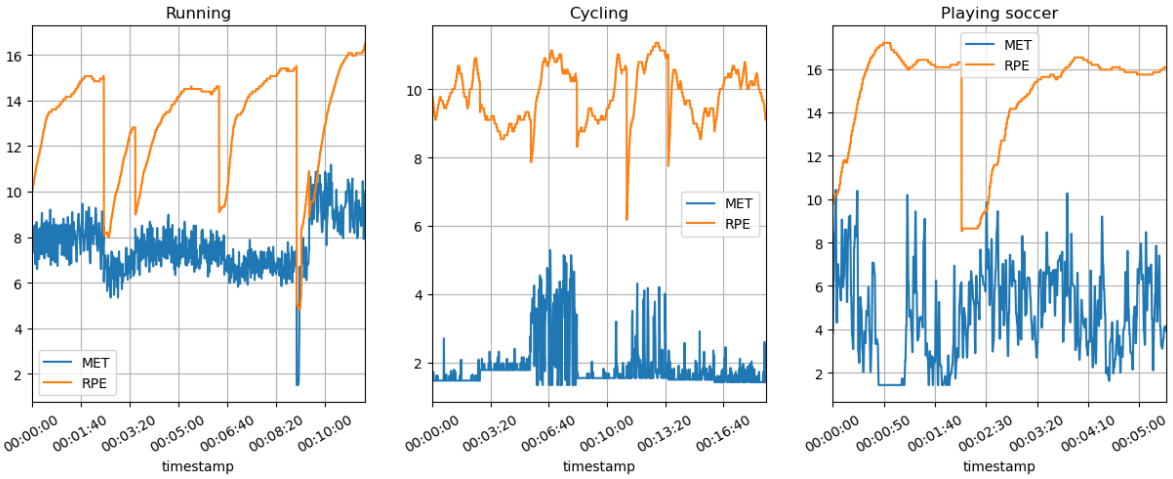


Figure 9.5: MET and RPE per sport.

Figure 9.6 shows the HR with the predicted variations of the MET and RPE segments during running, cycling, and football (soccer) activities.

Figure 9.7 shows the predicted variations in the MET and RPE segment during running, cycling, and football (soccer) activities.

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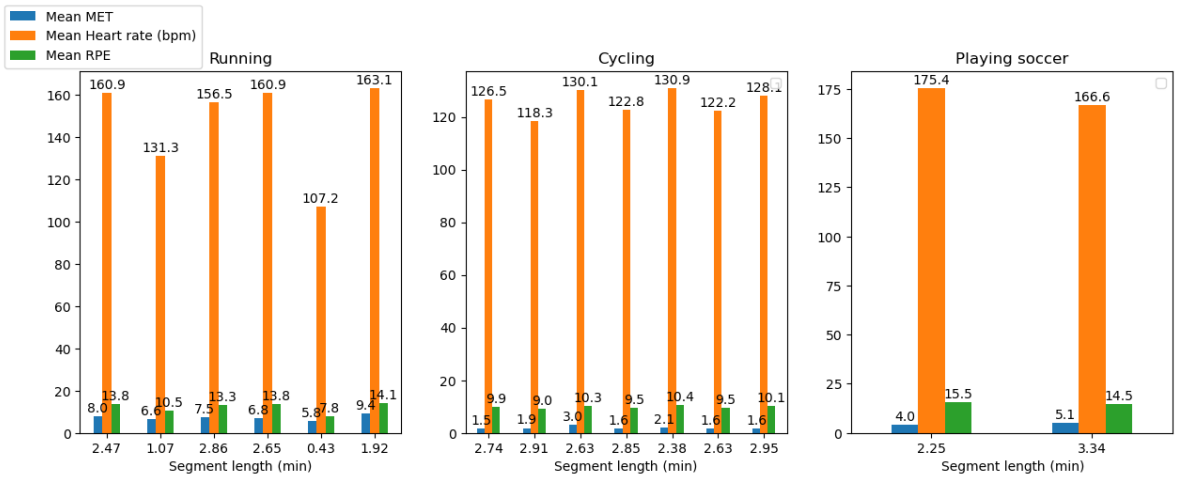


Figure 9.6: MET, HR, and RPE per sport on segments.

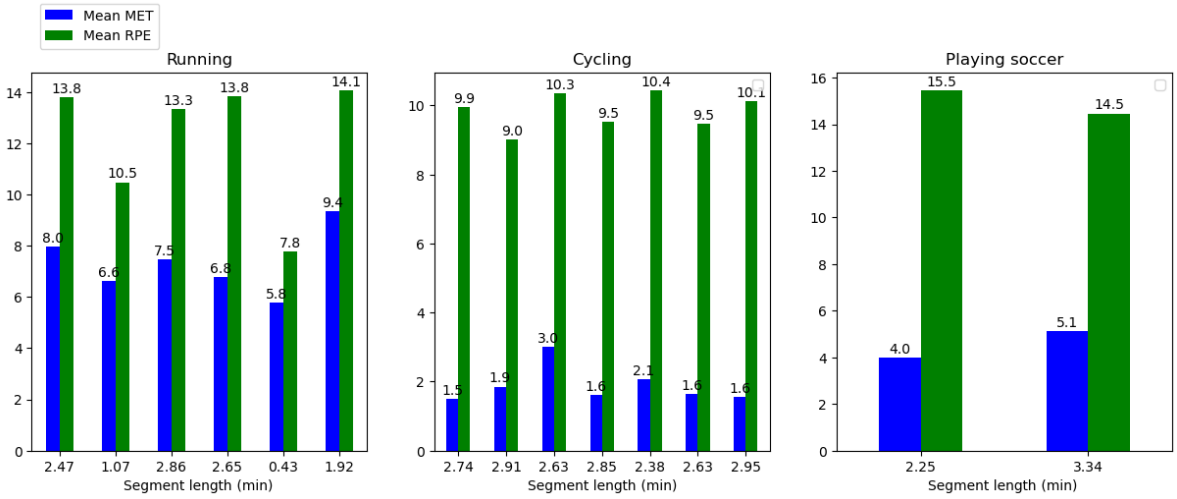


Figure 9.7: Predicted MET and RPE per sport on segments.

RPE, METs in sports using 3-axial acceleration data

Athletes must be monitored at predetermined intervals to find out why they are not providing top performance, for example, after every training session or every few weeks, to determine if there is a reason why they are not performing at their best level. Furthermore, it is essential to ensure that the athlete's subjective comfort and pain have also changed over time. To detect any changes in these values regularly, athletes are recommended to be checked frequently to detect any changes or anomalies as quickly as possible and take preventive measures to avoid additional injury and fatigue.

As part of regular monitoring [15], the athlete can also ensure that their goals and performance levels are achieved and they are performing at their peak. Due to the stop-and-go aspect of soccer, a player's MET values may change at a specific point, providing evidence that discomfort is experienced in a particular location. If the individual's MET values suddenly drop, it could also mean that the player cannot perform at the same

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level of intensity, possibly due to an injury or fatigue, which can affect their individual ability to perform. Figure 9.8 shows the measured acceleration data on three axes with the predicted METs during the activity of football (soccer).

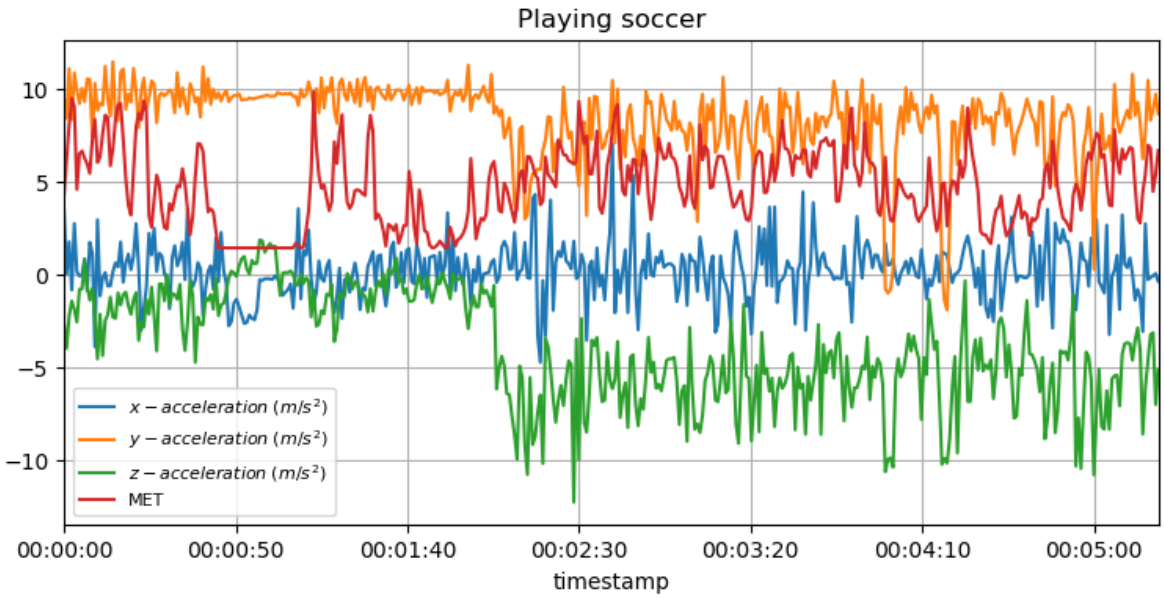


Figure 9.8: METs for football activity with acceleration data.

Unexpected changes in the cyclist's MET values during cycling may suggest that they cannot maintain their normal intensity due to injury or exhaustion, as a result of which they cannot perform their usual training. Furthermore, repetitive movements in cycling can put strain on some joints, such as the knees. As a result, monitoring MET levels on a frequent basis is critical for detecting any potential overload difficulties. Figure 9.9 shows the measured acceleration data on three axes with the predicted METs during cycling activity.

High MET values during intense jogging have been linked to an increased risk of overtraining and injury. A sudden drop in MET values may suggest inadequate training, such as due to injury or tiredness. Figure 9.10 depicts the measured acceleration data on three axes and projected METs during running activity.

Observing training results and physical flexibility in motion can assist discover physical indicators of injury or wear. Monitoring acceleration data allows for the detection of hidden trends or anomalies that may indicate an athlete's individual injury or fatigue risk. Suddenly shifting acceleration patterns can suggest muscle strain or joint injury, whereas a progressive decrease in acceleration could indicate tiredness or overload. The perceived exertion rating (RPE) can be used to measure exercise intensity and exhaustion levels. Increased RPE values may indicate that an athlete exerts excessive effort and is at risk of injury or fatigue, similar to acceleration data. In invisible, distant, or specific circumstances, wearable technology, such as accelerometers and HR monitors, can provide valuable information for continuous progress assessment.

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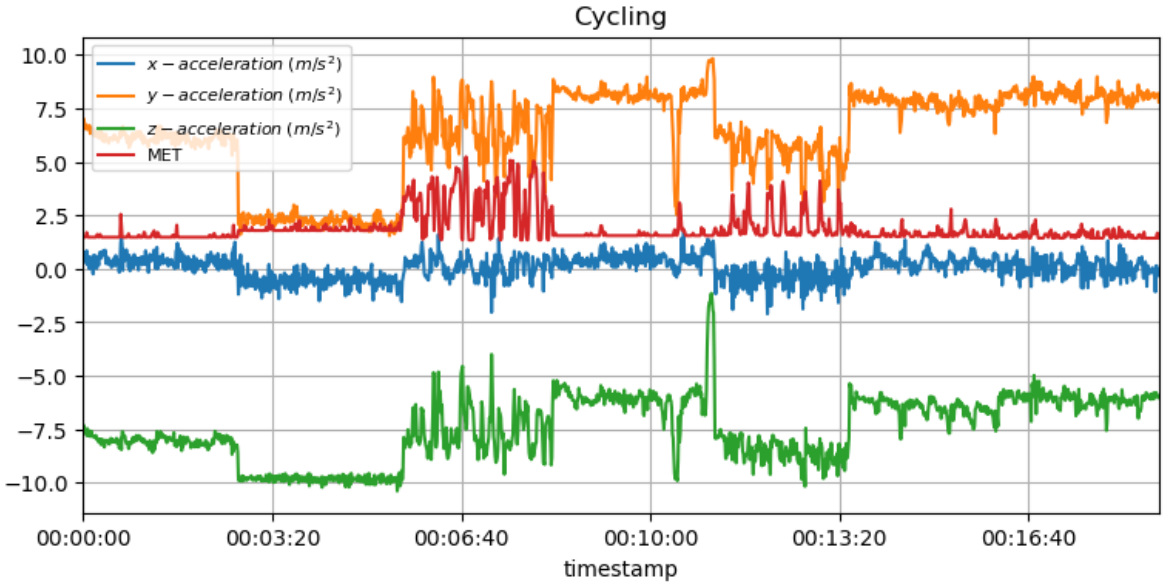


Figure 9.9: METs for cycling activity with acceleration data.

Figure 9.11 shows the measured acceleration data on three axes with the predicted RPE during football (soccer) activity.

Figure 9.12 shows the measured acceleration data on three axes with the predicted RPE during cycling activity.

Figure 9.13 shows the measured acceleration data on three axes with the predicted RPE during running activity.

Figure 9.14 shows the measured acceleration data on three axes with the predicted variations in RPE and MET during football (soccer) activity. It is possible to suggest exhaustion or injury if the athlete's HR is substantially lower than expected or if the acceleration data values fluctuate widely. Individuals may experience discomfort or pain in a particular area if their HR or acceleration data values change rapidly.

Figure 9.15 shows the measured acceleration data on three axes with the predicted variation in RPE and MET during cycling activity. An athlete with a low HR or whose acceleration data values vary considerably may be tired or injured. Rapid changes in HR or acceleration data may indicate discomfort or pain in a particular location.

Figure 9.16 shows the measured acceleration data on three axes with the predicted variations in RPE and MET during running activity. Low HR or significant fluctuations in acceleration data may indicate exhaustion or injury in an athlete. In addition to indicating pain or discomfort, it can indicate that the individual cannot maintain a normal level of intensity.

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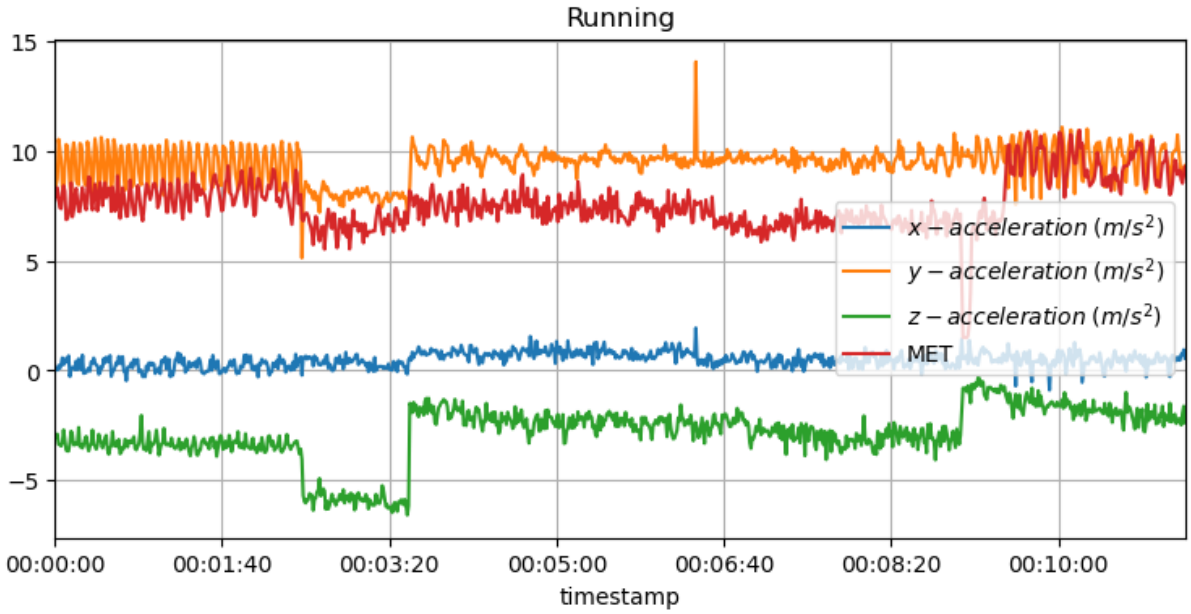


Figure 9.10: METs for running activity with acceleration data.

9.2.2 Fatigue and stamina control on multivariate time series (MTS) datasets

Table 8.6 presents the performance comparison metrics of the classifiers. Each row represents a different classifier algorithm, and the columns quantify their performance in terms of *Accuracy*, *Precision*, *Recall*, and *F1-score*. Details:

1. *Extra Trees Classifier* ensemble learning method yields a moderate accuracy of 50.75%, with a slightly higher precision rate of 52.61%. Its recall rate is lower at 48.70%, which, combined with precision, results in an F1-score of 50. 22%. This indicates a balanced trade-off between accuracy and recall, but suggests room for improvement in both specificity and sensitivity;

2. *Random Forest Classifier* performs similarly to the *Extra Tree Classifier* with an accuracy of 50.51% and a precision of 52.33%. The recall rate is slightly lower at 47.67%, leading to an F1-score of 49.57%, which points to a performance comparable to the Extra Trees Classifier but with a marginally lower recall;

3. *QDA* classifier, based on a statistical approach, has a lower accuracy of 48.98% but a higher recall rate of 70.72%, indicating that it is better at identifying true positive cases. However, the precision is lower at 49.41%, leading to an F1-score of 52.76%, which is the highest among classifiers with an accuracy below 50%;

4. *K Nearest Neighbors Classifier*, with an accuracy of 48.65%, is an instance-based classifier and tree-based method. It also has a precision of 50.23% and a recall of

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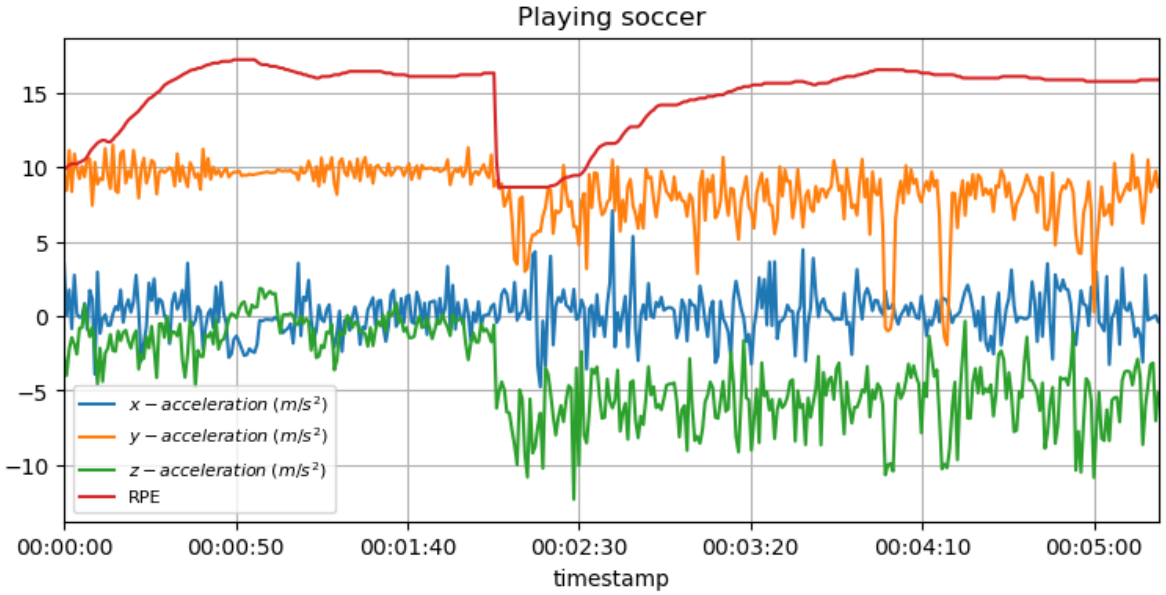


Figure 9.11: RPE for football activity with acceleration data.

45.00%, resulting in an F1-score of 47.22%, which suggests a need for parameter tuning or consideration of alternative models;

5. *Decision Tree Classifier* shows a competitive accuracy of 50.66% and an F1-score of 51.15%. Its precision and recall are balanced around 52%, indicating that it is a robust model, but not necessarily the most effective for this particular task;

6. *Gradient Boosting Classifier* has the lowest accuracy of 47.13% among the classifiers listed, with precision and recall rates near 49% and an F1-score of 45.90%. This indicates that the model might be underfitting or not capturing the complexity of the data well;

7. *Logistic Regression and Linear Discriminant Analysis* have similar accuracy rates of around 48.9%, with a higher recall rate exceeding 63% but lower precision around 48.5%. This high recall rate is reflected in a moderate F1-score of approximately 51%, suggesting that while these models are good at identifying positive cases, they may also include a larger number of false positives;

8. *AdaBoost Classifier* shows a close balance between precision and recall, both at approximately 49%, reflected in an almost equal F1-score of 48.95%. The precision is slightly lower at 48.40%, indicating that it performs moderately across all metrics;

9. *Ridge Classifier* mirrors the performance of *Logistic Regression* and *LDA*; this classifier also demonstrates an accuracy and an F1-score of 48.81% and 51.08%, respectively. This suggests that these linear models may share a common strength and weakness in predicting the positive class but also misclassifying the negative cases;

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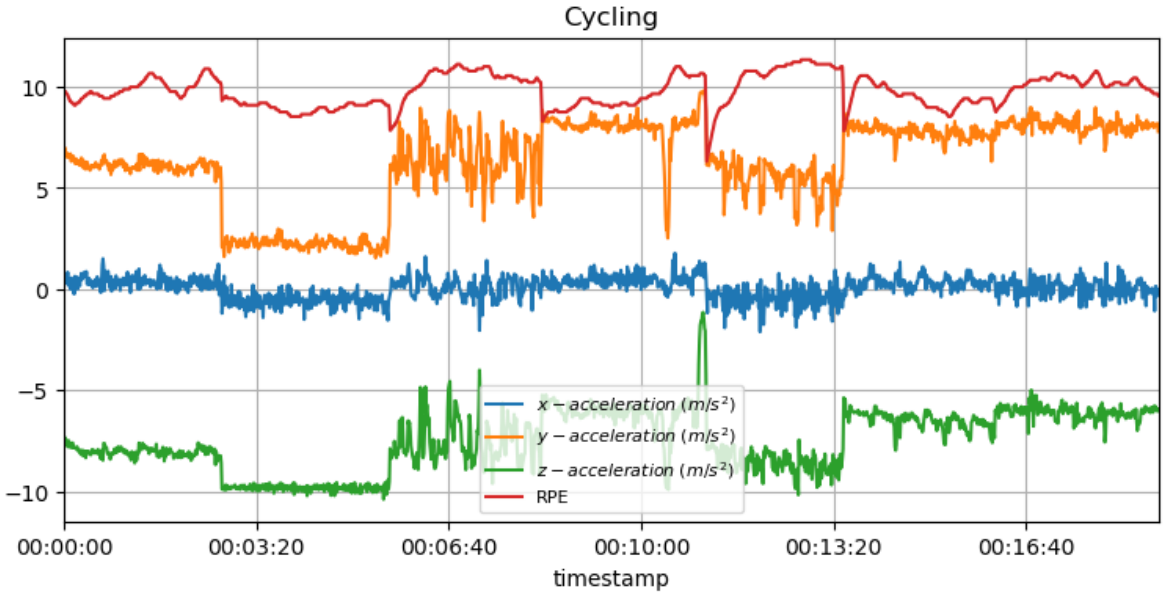


Figure 9.12: RPE for cycling activity with acceleration data.

10. *Light Gradient Boosting Machine* exhibits an accuracy of 49.58%, with a precision of 51.68% and a recall of 44.60%, leading to an F1-score of 47.16%. The model is somewhat precise, but struggles with recall, suggesting that improvements are needed in identifying true positives;

11. *SVM - Linear Kernel* SVM model has an accuracy of 49.12%, with a notably high recall rate of 77.91% but a lower precision of 47.02%, which results in the highest F1-score of 54.39% among all models. This indicates a tendency of the model to favor recall over precision;

12. *Naive Bayes* is a probabilistic classifier and achieves an accuracy of 48.12% with a recall rate of 69.48% and a precision of 48.50%. Its F1-score of 52.09% is relatively high considering moderate precision, suggesting that it may be better at identifying true positives at the expense of accruing more false positives;

13. *Dummy Classifier* achieves an accuracy of 51.30%, with a precision and a recall of 100%. This results in an F1-score of 67.78%, which is significantly higher than other classifiers. However, this high score is deceptive, as it comes from a model that does not make real predictions, but classifies all instances as the positive class, hence the perfect recall and disproportionate F1-score.

The *Extra Trees Classifier* (see Table 8.7), configured with 100 estimators and a fixed random state for reproducibility, was applied to a binary classification task. The precision, recall and F1-score performance metrics are disaggregated for each class alongside the aggregate scores that encapsulate the overall performance of the model. The *precision*

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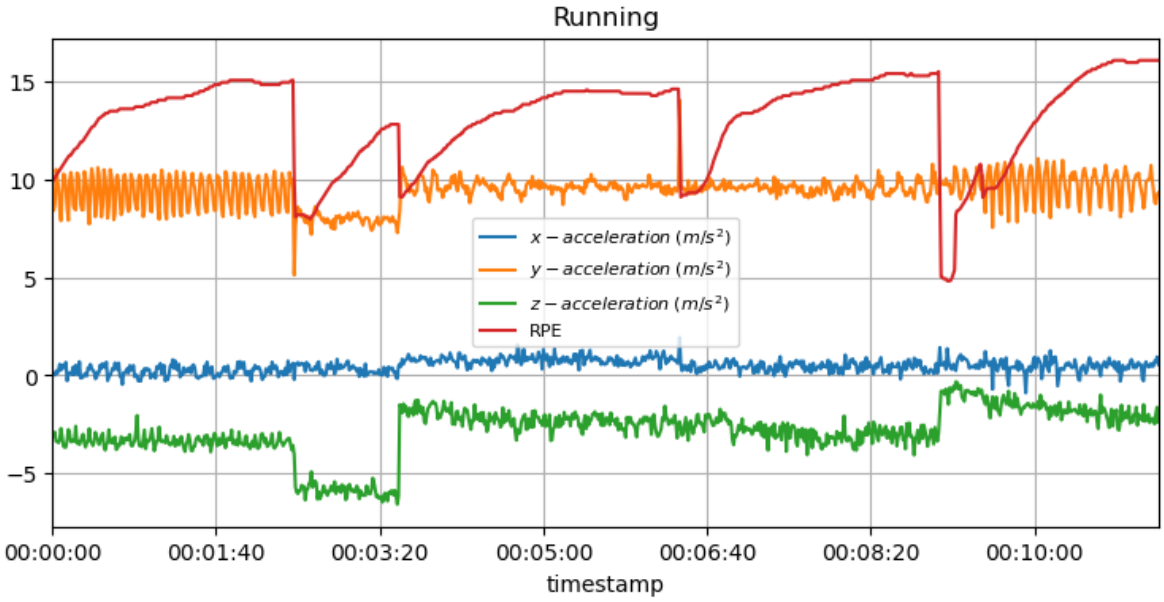


Figure 9.13: RPE for running activity with acceleration data.

metric indicates the proportion of true positives compared to all positive calls made by the model.

For class 0, a precision of 0.56 suggests that 56% of the instances predicted as class 0 are indeed class 0. For class 1, the precision is slightly higher at 0.59, implying that this class is predicted with marginally better accuracy. *Recall*, or sensitivity, measures the model's ability to identify all relevant instances. For class 0, the recall is 0.58, indicating that the model correctly identifies 58% of all actual class 0 instances. Class 1 has a recall of 0.57, which means that it correctly identifies 57% of all actual cases in class 1. The *F1-score* is the harmonic mean of precision and recall and serves as a single metric that balances false positives and false negatives. An F1-score of 0.57 for class 0 and 0.58 for class 1 suggests moderate agreement between precision and recall. The precision of the *model*, which is the ratio between correct predictions and total predictions, is 0.58. This indicates that the model correctly predicts the class of an instance 58% of the time in the dataset of 1,001 instances. The weighted average precision, recall, and F1-score are all 0.58, indicating that when the model's performance is weighed by the prevalence of each class in the data, the result is consistent with the macro average.

The class-specific performance of the *Decision Tree Classifier* (see Table 8.8) shows that for class 0, precision is 0.53, which indicates that when the model predicts that an instance is class 0, it is correct 53% of the time. The recall for class 0 is slightly higher at 0.55, which means that the model successfully identified 55% of all actual class 0 instances within the dataset.

The F1-score, a balanced measure of precision and recall, is 0.54, suggesting a modest equilibrium between the two metrics for this class. For class 1, the precision is marginally better at 0.56, indicating a slightly higher rate of correct predictions for positive instances.

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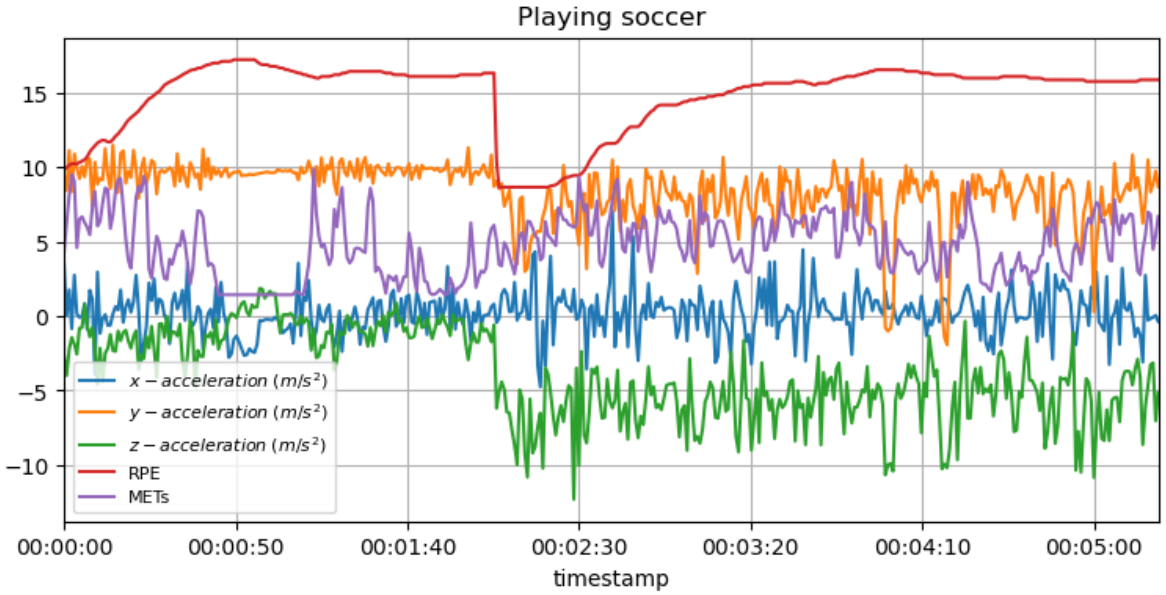


Figure 9.14: METs and RPE variations for football activity with acceleration data.

However, the recall is 0.53, indicating that the model captures 53% of the actual class 1 instances. The F1-score for class 1 is 0.55, as a function of the precision and recall values, again indicating balanced performance, although slightly favoring precision over recall. The overall accuracy of the model is 0.54. This implies that, in both classes, the model correctly predicts the class of a given instance 54% over time for the 1.201 instances tested. The macro average for precision, recall, and F1-score is 0.54 across both classes. This average does not take into account the class imbalance and considers both classes equally. A macro average of 0.54 suggests that the model's performance is generally consistent across both classes. The weighted average for precision, recall, and F1-score is also 0.54. Unlike the macro-average, the weighted average considers the number of instances (support) for each class, thus adjusting the average for class imbalance. The fact that the weighted average, the macroaverage and the accuracy are all the same suggests that any class imbalance in the dataset does not affect the way the model works.

Class-Specific Performance of a *Random Forest Classifier*'s performance (see Table 8.9) shows that for class 0, precision is 0.56. This indicates that 56% of the instances predicted to be class 0 were correctly identified, suggesting a moderate ability of the classifier to discern the true class 0 instances among all predicted as such.

The recall for class 0 is 0.58, which means that the classifier correctly identified 58% of all actual class 0 instances, reflecting a slightly higher sensitivity than its precision. Class 1 exhibits a precision of 0.59, indicating that the model is slightly more precise in identifying valid Class 1 instances than class 0. The recall for class 1 is 0.56, slightly lower than that for class 0, suggesting that the classifier is somewhat less sensitive in detecting all actual class 1 instances.

Detailed Analysis of the LSTM model: The class-specific performance of the LSTM

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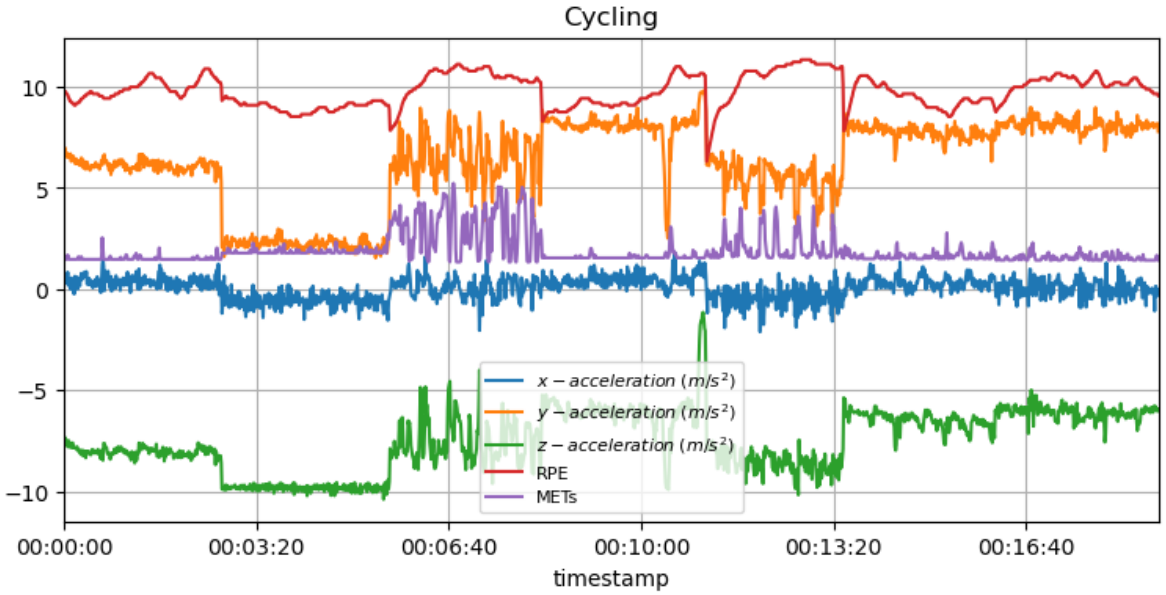


Figure 9.15: METs and RPE variations for cycling activity with acceleration data.

model performance metrics (see Table 8.10) shows that for Class 0, the model attains a precision of 0.58, meaning that 58% of the predictions made as Class 0 are accurate. The recall, indicating the model's ability to identify actual instances of Class 0 correctly, is slightly higher at 0.59. This suggests a reasonably balanced detection of this class by the model. The F1-score, which balances precision and recall, is 0.58, indicating a reasonable compromise between precision and recall rates. Class 1 has a precision of 0.61, which is somewhat greater than that of Class 0, showing that the model is slightly more accurate at predicting Class 1 instances. The recall for Class 1 is 0.60, indicating that the model accurately detects 60% of all actual Class 1 cases. The F1-score for this class is 0.60, which reflects precision and recall, indicating a similarly balanced performance with a small preference for precision.

The model's overall accuracy is 0.59, which indicates that the model accurately predicts the class of an instance in 59% of the cases in the dataset of 1,001 instances. This level of precision is moderate, reflecting a fair degree of effectiveness in classification but indicating room for improvement. The macro-average, which treats both classes equally important, is 0.59 for precision and recall. The macro-average's homogeneity indicates that both classes performed consistently. Taking into account the predominance of each class, the weighted average for precision, recall, and F1-score is 0.59, which matches the macro average. This congruence shows that the classes perform similarly, independent of their representation in the dataset.

Participant 4 exhibits relatively high fluctuations in stamina with a range of approximately 0.025 to 0.095, indicating considerable variability in their performance; *Participant 5* demonstrates moderate fluctuations in stamina values, yet overall less variability than Participant 4; *Participant 6* (see Table 9.23) shows a dense clustering of stamina values

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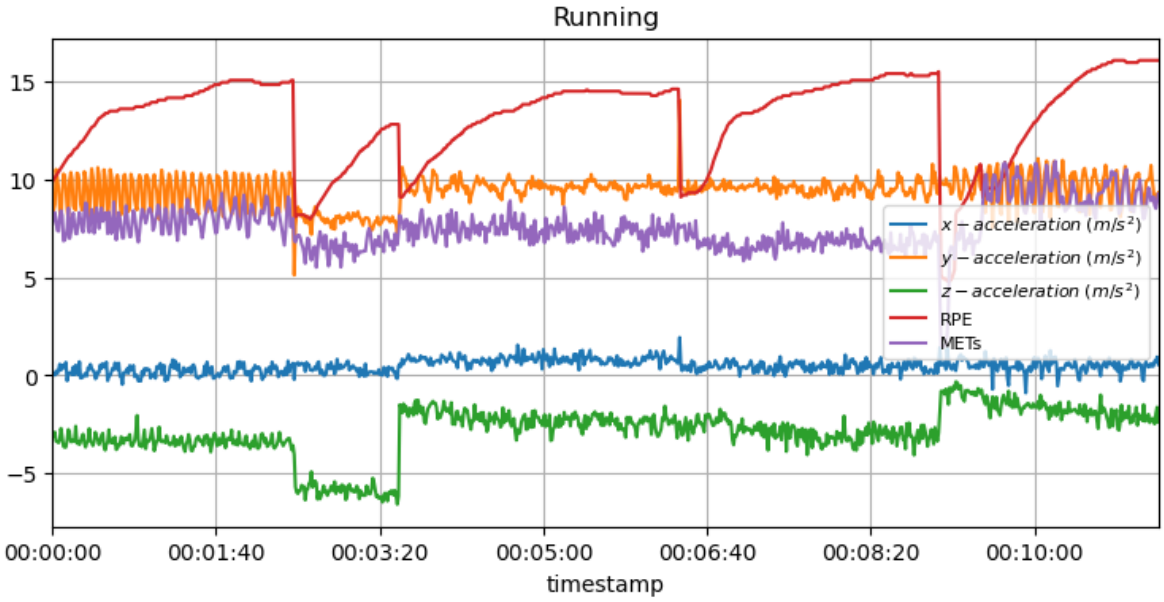


Figure 9.16: METs and RPE variations for running activity with acceleration data.

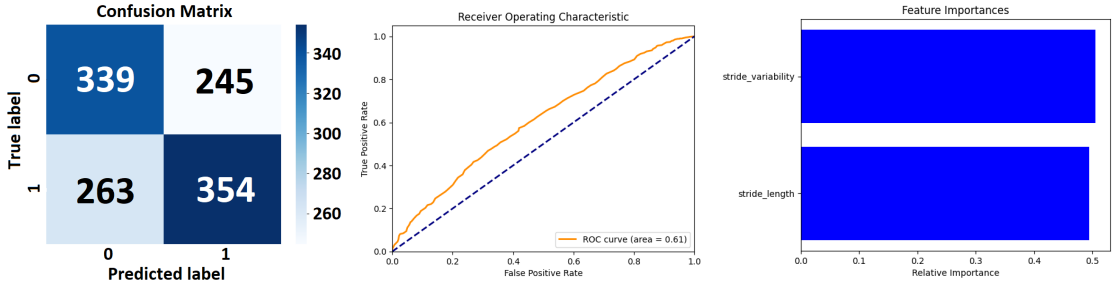


Figure 9.17: Extra Trees Classifier experiment results

with fewer peaks and troughs, suggesting a more consistent performance; *Participant 7* results indicate significant variability with some extremely high stamina values, which might suggest errors in data capture or exceptional moments of performance stability; (5) *Participant 8*: the stamina readings appear to be an anomaly, with values significantly higher than those of other participants, possibly indicating a data recording error or an issue with the calculation of stamina for this individual; *Participant 9 - Participant 23* display varying ranges of stamina, with some (such as *Participant 19*) having a particularly broad spread of values, suggesting inconsistent performance. Others, such as *Participant 13*, have a tighter group of values, which may point to a more stable performance;

Overall analysis: *Variability in performance*: The degree of fluctuation of the stamina values between strides varies markedly between participants (see Table 9.24). Some demonstrate tight clusters, indicative of consistent performance, while others have wide variances, suggesting fluctuations in their kinematic efficiency; *Potential data anomalies*: certain participants (e.g., Participant 8) show data patterns that deviate significantly from the norm, which can necessitate a review of data quality or methodological approaches

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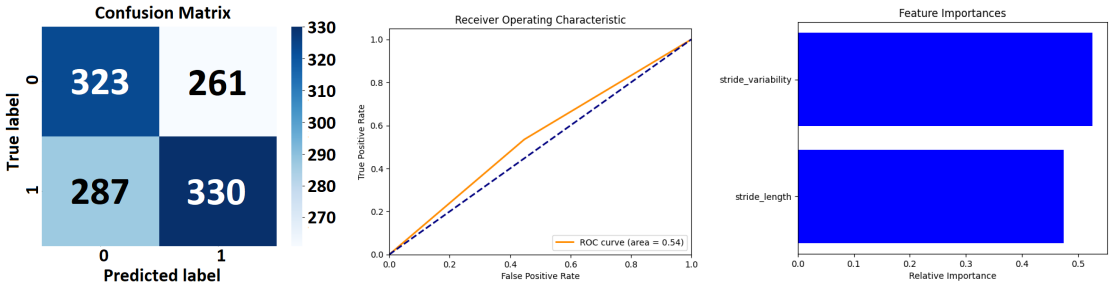


Figure 9.18: Decision Tree Classifier results

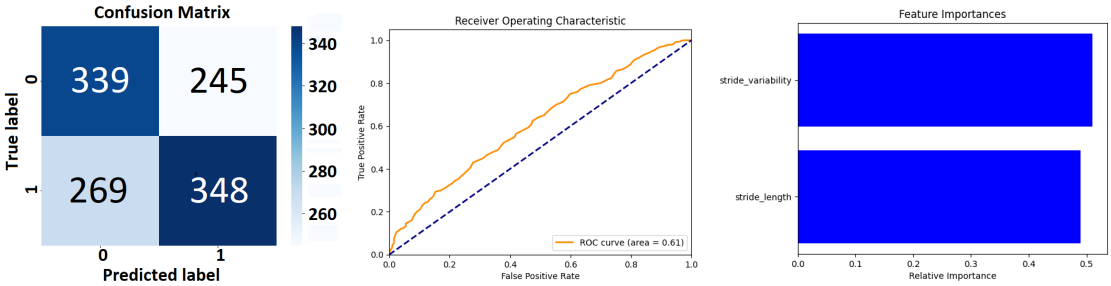


Figure 9.19: Random Forest Classifier results

specific to those cases; *Identification of Outliers*: Participants such as 7 and 19, with a wide range of stamina values, could be considered outliers in terms of the consistency of their running performance; *Implications for training and rehabilitation*: understanding stamina variability can inform tailored training programs to improve consistency and efficiency in running. It may also help identify the need for interventions to address specific kinematic deficits.

The evaluation of the classifiers presented in Table 8.6 suggests that no single model outperforms the others in all metrics. The choice of the best classifier would depend on the specific requirements of the classification task at hand.

The result of Table 8.7 of *Extra Trees Classifier* demonstrates a *balanced performance* between the two classes, with a slight variance that favors class 1 in precision and class 0 in recall. The general precision of the model and the average F1-score suggest that *it performs moderately*, although there *may be room improvement*, possibly by tuning the hyperparameters or incorporating features. The consistency of the macro- and weighted averages suggests that the model's performance is stable across the classes despite their slight differences in support within the dataset (see Figure 9.17).

The Decision Tree Classifier (see Table 8.8) shows a balanced but moderate performance in distinguishing between the two classes, with a slight propensity towards class 1 in terms of precision and towards class 0 in terms of recall. The overall accuracy and the macro- and weighted averages indicate symmetric performance across classes. Given the decision tree's inherent susceptibility to overfitting, the observed performance may also reflect the limitation of this model in generalizing from the training data to unseen data.

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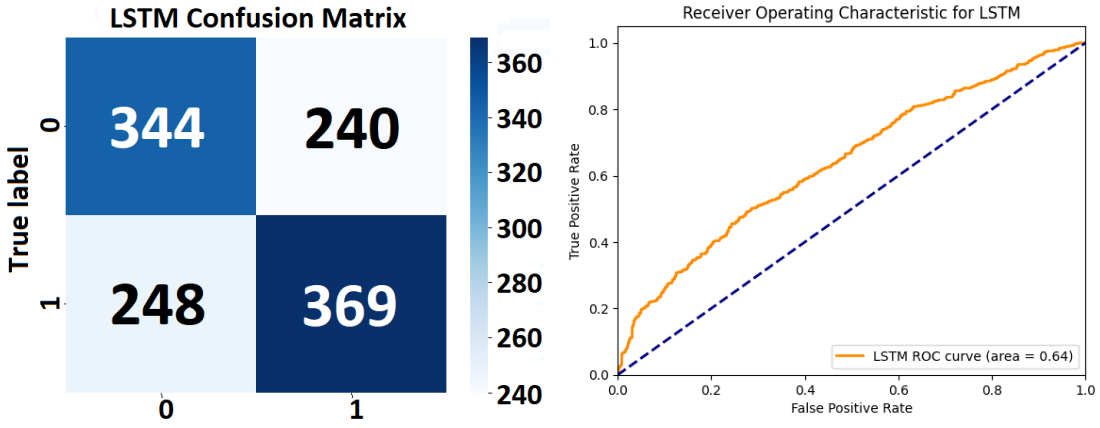


Figure 9.20: LSTM results

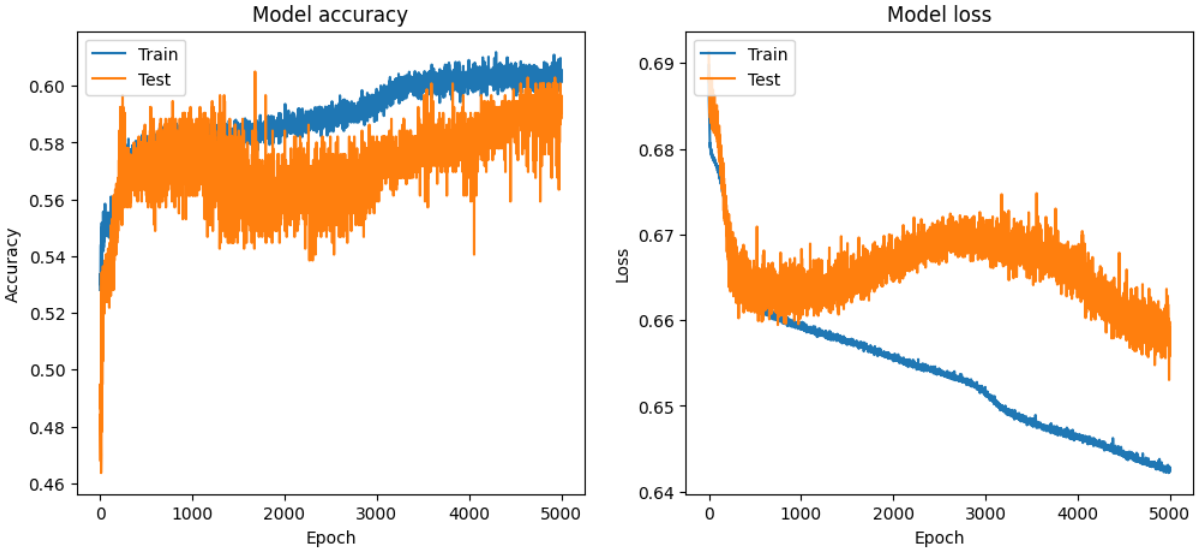


Figure 9.21: LSTM model accuracy (left) and model loss (right)

Improvements to the model, such as pruning, could potentially improve its predictive prowess. Furthermore, results may benefit from examining the depth and complexity of the decision tree, which could contribute to its overall performance (see Figure 9.18).

The *RandomForestClassifier* as shown in Table 8.9 exhibits a balanced classification ability in both classes with moderate precision and recall. The uniformity of the macro- and weighted averages indicates that the performance metrics are consistent across the classes. Given these results, the classifier appears to be a competent model for the dataset, although there is room for improvement. Potential steps to enhance the model's performance could include hyperparameter tuning, feature selection, engineering, and increasing the training data's size or diversity. Furthermore, depending on the application, different costs can be associated with false positives and negatives, which could lead to adjustments in the model to favor precision or recall (see Figure 9.19).

The research results [42] reveal performance results in various classifiers applied to AI-

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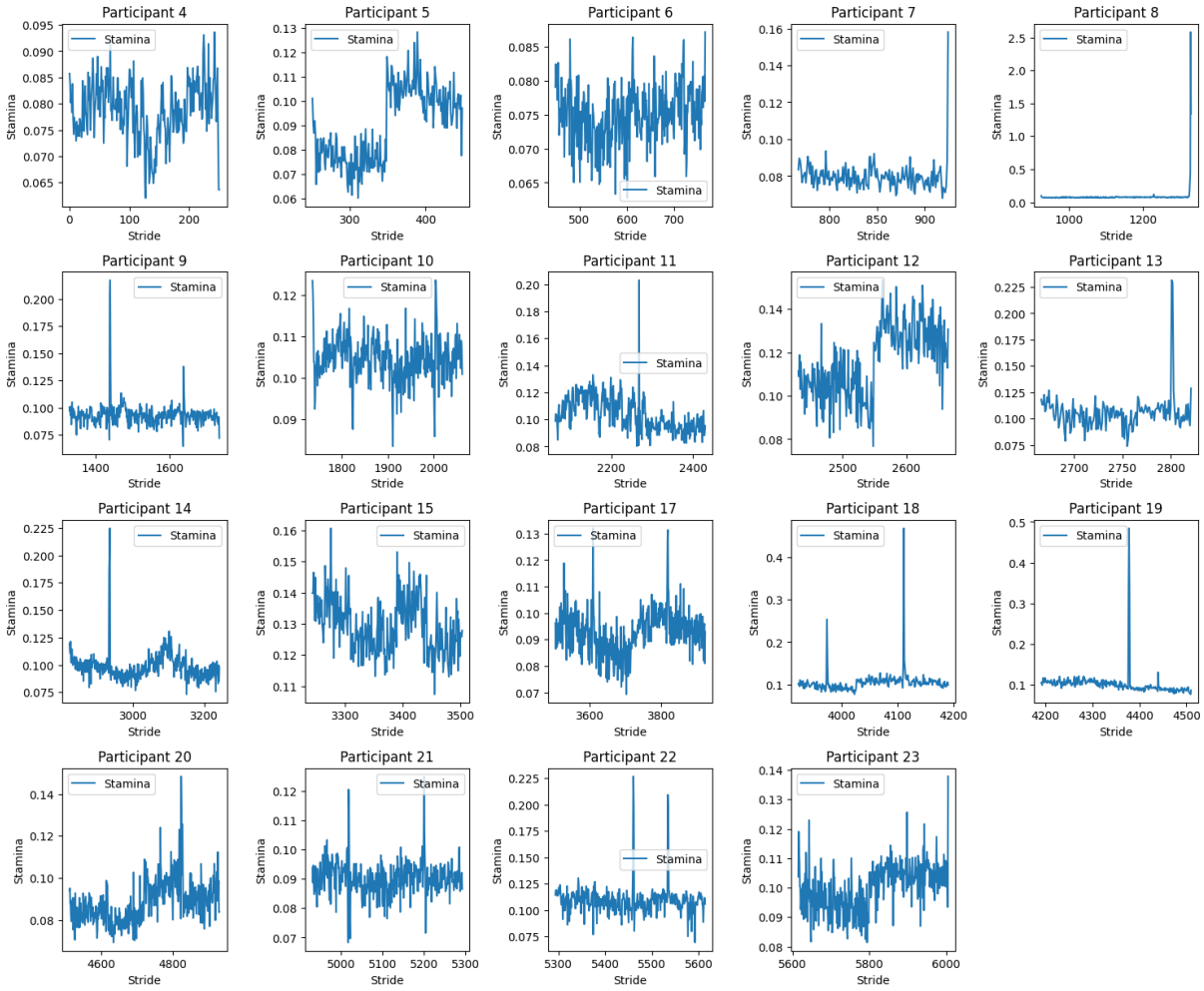


Figure 9.22: Stamina for analysis

assisted fatigue and stamina control using IMU-generated multivariate time series datasets in performance sports. The *Extra Trees* and *Random Forest* classifiers, both tree-based ensemble methods, demonstrate moderate effectiveness, with a precision slightly above 50% and balanced precision and recall rates. However, their equivalent F1-scores of approximately 50% highlight the need for higher specificity and sensitivity enhancement. These models are proficient but not ideal for this specific job. In contrast, the *QDA* classifier, which depends on a statistical technique, displays an interesting trade-off: It has lesser accuracy but excels in recall, indicating that its strength rests in identifying actual positive cases, although at the expense of precision. This model has a higher F1-score than other classifiers with sub-50% accuracy, demonstrating its potential in cases where strong recall is prioritized.

The classifiers *K Nearest Neighbors* and *Decision Tree* show lower performance metrics than the ensemble methods. Their lower F1-scores and balanced precision recall suggest that these models might benefit from parameter optimization or may not be entirely suitable for the complex nature of the data.

The lower performance metrics of the *Gradient Boosting Classifier* imply possible un-

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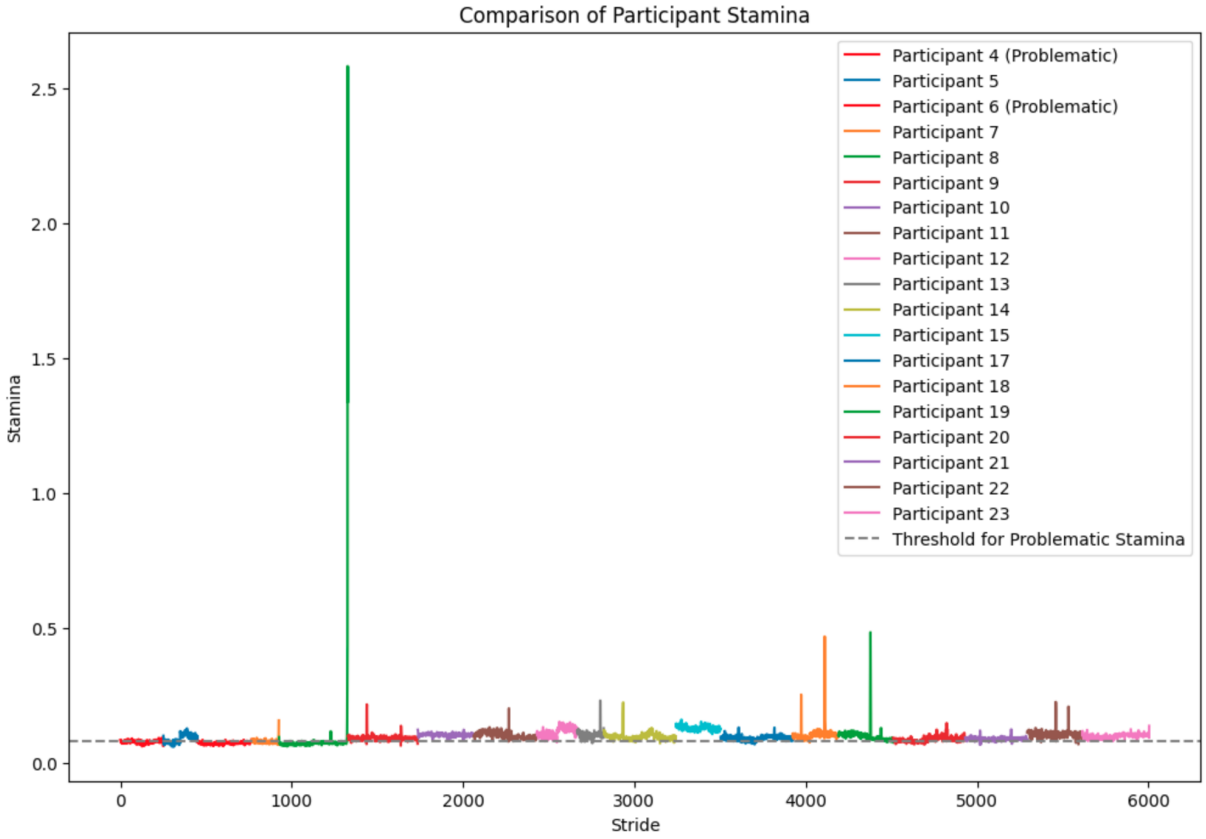


Figure 9.23: Comparison of participants' stamina

derfitting, indicating that this model might be overly simplistic for intricate data patterns in the domain. *Logistic Regression*, *Linear Discriminant Analysis*, and *Ridge Classifier*, all linear models, exhibit similar patterns of higher recall rates but lower precision. This consistency suggests a common tendency in these models to favor identifying positive cases, even at the risk of increasing false positives. The *AdaBoost Classifier* presents a balanced performance but with general moderate effectiveness, indicated by its almost equal precision, recall, and F1-score, all around 49%.

The *Light Gradient Boosting Machine* demonstrates reasonable precision but struggles to recall, suggesting its efficacy in classifying true negatives, but the need for improvement in detecting true positives. In particular, the *SVM* with a *Linear Kernel* stands out for its high recall rate and the highest F1-score among the models, implying a strong inclination toward identifying true positives, albeit at a compromise in precision. *Naive Bayes*, with its probabilistic approach, also tends to favor recall over precision, reflected in its relatively high F1-score despite moderate accuracy. Lastly, the *Dummy Classifier*, while exhibiting high accuracy and F1-score, serves as a reminder of the importance of interpreting these metrics in context. Its high scores are misleading, as they result from a simplistic approach of classifying all instances as positive, underscoring the necessity of a nuanced understanding of model performance beyond superficial metrics. These results highlight the complexities and trade-offs inherent in the application of various AI classifiers

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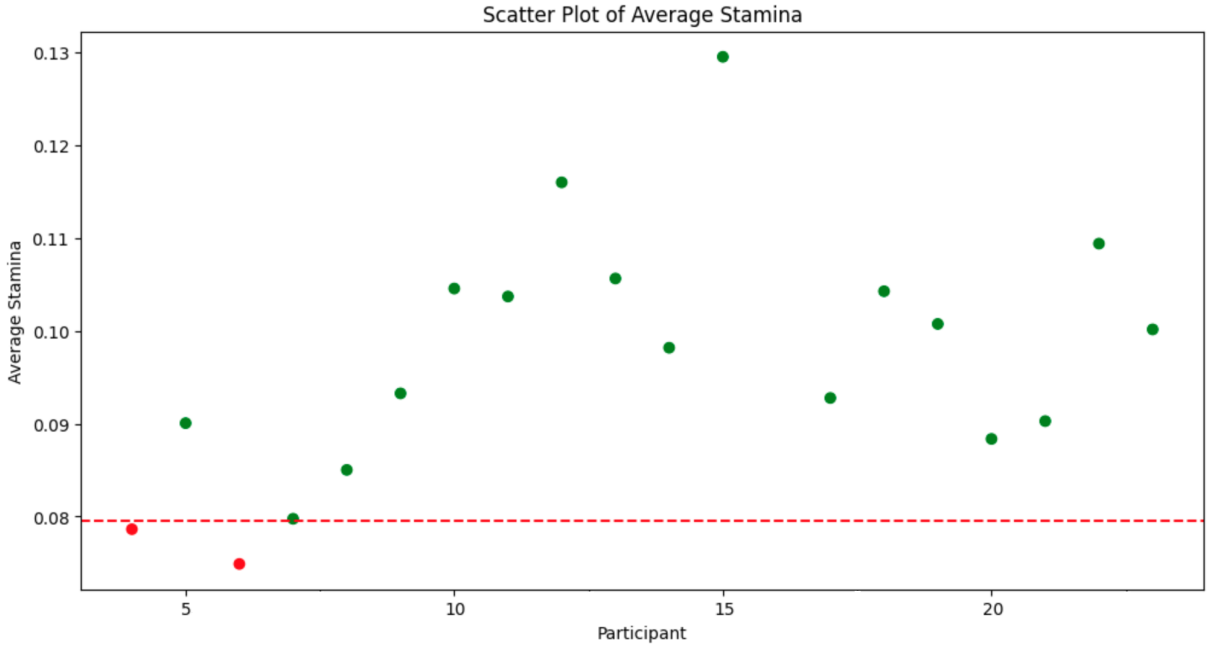


Figure 9.24: Scatter plot of average stamina

to predict fatigue and stamina in sports. The findings underscore the importance of the preparation of datasets and the need for careful selection and optimization of models tailored to the specific requirements and nuances of the sports health domain.

The *Light Gradient Boosting Machine* has reasonable precision but struggles with recall, indicating that it is effective in categorizing genuine negatives but needs to improve in detecting real positives. The *SVM* with a *Linear Kernel* has the highest recall rate and F1-score among the models, indicating a strong predisposition toward detecting true positives, but at a cost of precision. The probabilistic technique of *Naive Bayes* favors recall over precision, resulting in a relatively high F1-score despite poor accuracy. Finally, the *Dummy Classifier* demonstrates good accuracy and F1-score, but emphasizes the need to interpret these metrics in context. Its high results are deceiving since they are the consequence of a naive approach that classifies all instances as positive, emphasizing the importance of a comprehensive understanding of model performance beyond superficial metrics. These findings illustrate the difficulties and trade-offs inherent in the use of several AI classifiers to predict fatigue and stamina in sports. The findings highlight the necessity of dataset preparation, as well as the need for thorough model selection and optimization adapted to the unique requirements and complexities of the sports health domain.

In general, lower medians and more variability in fatigue state "Fatigued" compared to state "Not Fatigued" indicate that fatigue negatively affects the acceleration characteristics of the participants, according to the acceleration distribution box plots. These findings could have implications for the design of training regimens, where monitoring acceleration could serve as a proxy for fatigue levels and, therefore, the effectiveness of the

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training session. More statistical analysis would be required to confirm these observations and understand the underlying factors that contribute to the observed patterns. On the other hand, stamina plots suggest a significant inter-individual variation in the kinematic consistency of runners as measured by stamina across strides. The findings highlight the importance of individualized approaches to performance monitoring and coaching. More research on the biomechanical and physiological causes of these differences could give us more information about the endurance profiles of regular runners. Furthermore, the accuracy of abnormal data points is crucial to ensure the integrity of the thesis's conclusions.

Importance of the research and applicability to diverse disciplines

The research results [42] on AI-supported fatigue and stamina management in competitive sports, using IMU-generated time series datasets, have substantial relevance outside the sports domain, particularly in physical therapy and rehabilitation. The precision of AI in identifying movement patterns can play a crucial role in assessing patient progress during physical therapy [42]. This allows therapists to customize rehabilitation [22] activities according to each individual's specific recovery requirements. AI predictive abilities, developed in sports to detect weariness early, modified patterns, or anti-patterns, can be applied to prevent excessive strain in patients during rehabilitation, reducing the likelihood of injury relapse or worsening.

Furthermore, ongoing surveillance of AI-supported IMU technology allows therapists to receive immediate feedback on the biomechanical responses of patients to therapy, improving the efficacy of treatment plans. AI models can be used in postoperative rehabilitation [22] to predict recovery trajectories, facilitating more precise prognoses and customized rehabilitation regimens. The data-driven technique can also uncover slight improvements or losses in patients' conditions that might otherwise be overlooked in traditional exams, resulting in quick action. Furthermore, the application of this research in rehabilitation settings demonstrates the potential of AI and wearable technologies to treat chronic pain and enhance mobility. This technique uses data analysis to provide patient care. The use of these AI approaches in several disciplines has the potential to completely transform rehabilitation practices, making a substantial contribution to patient recovery and improving their overall quality of life [22]. Novelties also highlight the importance of multimodal learning, which will connect different domains and fields.

Ethical considerations

Using AI technology to tailor training programs (revealing hidden patterns and segments that can be improved or fine-tuned) and improve athlete performance results raises ethical concerns. First, the issue of data privacy and security arises due to the need for AI systems to gather and analyze athletes' sensitive personal and physiological data. The risk of improper use or unauthorized access of these data raises concerns regarding athlete

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confidentiality and data ownership management. This may alter the typical relationship between a coach and an athlete. The ethical consequences of using AI in sports require a thorough examination and regulatory supervision to ensure that its implementation adheres to the standards of equity, confidentiality, and the preservation of the athlete's independence.

9.3 Results in health condition control

9.3.1 sRPE and ACWR on fatigue and injury control

ACWR, sRPE, and fatigue score can monitor athletes' fatigue levels and make informed decisions about adjusting their training load [26]. A higher score indicates greater fatigue, which can justify a reduced intensity or training volume to facilitate recovery and prevent injury. In contrast, a lower fatigue score may indicate that the athlete is well recovered and can tolerate an increase in training load.

Individual results

Fig. 9.25 shows the distribution of the ACWR dataset in the "PM Data" dataset. Fig. 9.26 shows the distribution of the sRPE dataset in the "PM Data" dataset. Fig. 9.27 shows the distribution of the ACWR dataset per athlete in the "PM Data" dataset. Fig. 9.28 shows the distribution of the sRPE dataset per athlete in the "PM Data" dataset. Fig. 9.29 shows the distribution of the sRPE dataset by athlete type in the "Ice Hockey" dataset, showing the level of condition of the team. Fig. 9.30 shows the condition plan for coaches based on the sRPE results of the team on the "Ice Hockey" dataset .

Teamsport results

Based on Table 9.4 the best results were in the linear regression model. The results of using this model are highlighted in a subsequent part of the thesis. All other results are also available.

Predictions

Fig. 9.31 shows the accuracy of the model in the manually calculated and predicted ACWR dataset (with linear regression) from "PM data". Fig. 9.32 shows how the predicted ACWR values are connected with the sRPE at the same intensity level. This gadget could help coaches adjust the duration and intensity of training or activity sessions. The dataset was "PM Data". Fig. 9.33 shows the activity and fatigue control chart per day in "PM Data".

Coaches can identify unexpectedly low activities (0.4-0.8), in addition to expected activities (1.0 - 1.5). There were no high-risk activities in this case, but in performance

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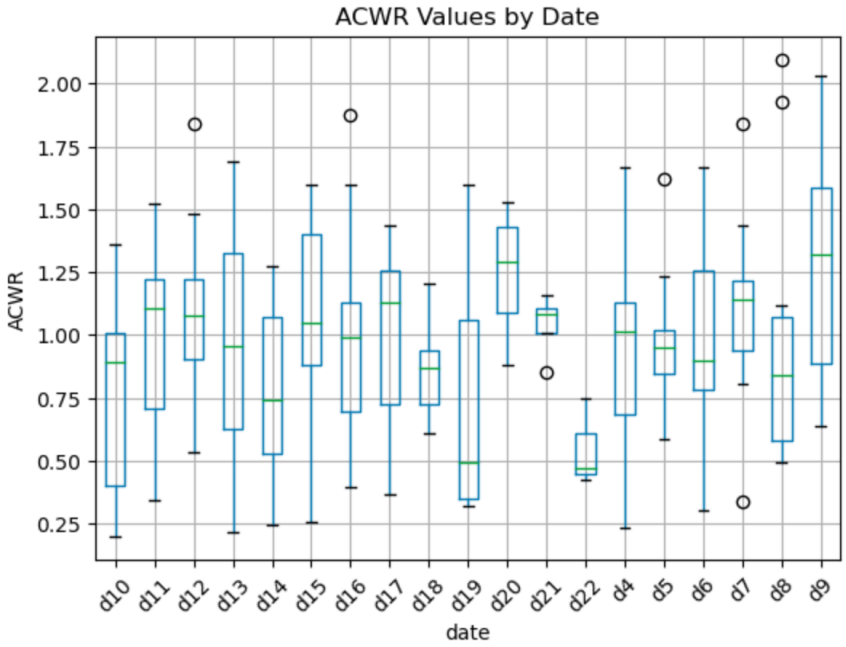


Figure 9.25: ACWR dataset distribution

Table 9.4: Regression model comparisons for P1 athlete

Experiment	Model	MSE	R-squared
1	Linear Regression	0.012088	0.953959
2	Ridge	0.012088	0.953958
3	Lasso	0.012152	0.953714
4	ElasticNet	0.012120	0.953837
5	Lars	0.012088	0.953959
6	LassoLars	0.012763	0.951386
7	OMP	0.012088	0.953959
8	BayesianRidge	0.012705	0.951607

sports, pushing the limit is a case of regular use. With the proposed tool, coaches can control the levels of risk of fatigue and injury. The figure illustrates how the predicted ACWR values are connected with the sRPE on the same intensity level. This gadget could help coaches adjust the duration and intensity of training or activity sessions. The dataset was "PM Data".

Experiments [26] suggest that AI-based ACWR prediction using regression models [300] such as Linear Regression [301], Ridge, Lasso, ElasticNet, LARS, OMP, and BayesianRidge can provide more accurate and precise estimates of ACWR and fatigue scores. These models consider complex relationships between variables [302] and can capture non-linear patterns in the data, leading to better performance than manual calculations that may rely on simplified assumptions or not account for all contributing factors. The predicted ACWRs allow for selecting and validating the best model based

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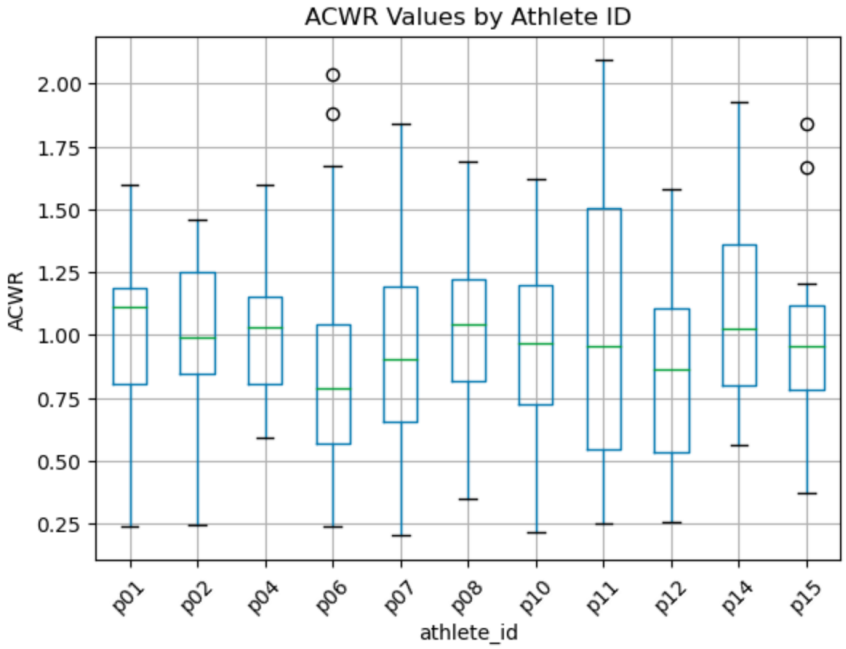


Figure 9.26: ACWR dataset distribution

on performance metrics such as R-squared, MSE, or cross-validation scores. This process helps to ensure that the chosen model is the most suitable for the data, leading to more reliable predictions of ACWR and fatigue scores. The models can be fine-tuned with parameters. Manual calculations, on the other hand, may not have a built-in mechanism for model validation or comparison, which can lead to less reliable results. Advanced regression models such as Ridge, Lasso, ElasticNet, and BayesianRidge incorporate regularization techniques that can help prevent overfitting and address problems related to multicollinearity [303] in the data. This makes AI-based ACWR predictions more robust and reliable, even when the data have complex interdependencies between variables or limited training samples. Manual calculations, on the contrary, may not account for these issues, potentially leading to less reliable or biased estimates of ACWR and fatigue scores.

9.3.2 Microsleep thesis experiments results

Table 9.5 provides a detailed overview of the EEG signal data derived from the *SC4451F0-PSG* segment of polysomnographic sleep recordings, which includes EEG data from *Fpz-Cz* and *Pz-Oz* electrodes at designated temporal junctures where microsleep events have been documented, as indicated by Yes in the column. "Microsleep Event". The column "Time (s)" details the timestamps of the EEG recording in seconds, and each timestamp corresponds to a data entry where a microsleep event is presumed to have occurred. "Original EEG Signal (µV)" shows the recorded EEG signal in microvolts at these moments, capturing the unfiltered raw electrical activity measured by the EEG. "Filtered EEG Signal (µV)" presents the signal post-processing, presumably by the Kalman filter, which aims to clarify the interpretation of the signal by reducing noise and artifacts.

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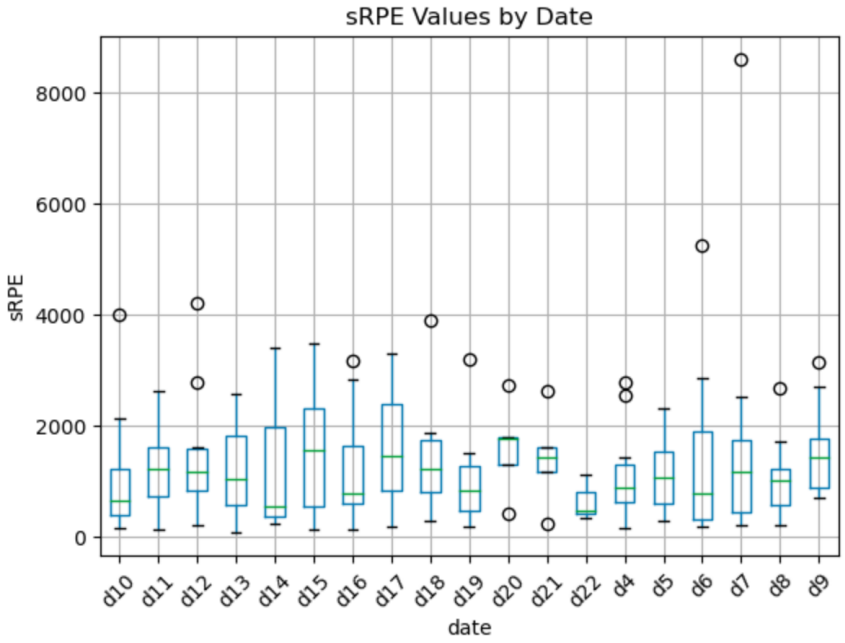


Figure 9.27: sRPE data distribution per athletes

The microvolt values for the filtered signal are notably different from the original, which could reflect the filter's effect in isolating the significant characteristics of the EEG signal associated with microsleep. Positive and negative amplitudes imply different brain activity in the EEG readings. The mentioned time points and signal values reflect discrete bouts of microsleep over a long recording period, which may help analyze their patterns and prevalence. Figure 9.34 presents an examination of the EEG data related to microsleep events, showing the corresponding fluctuations in the EEG signal over time. In the tessellations, the highlighted regions indicate areas of the scalp with detected microsleep events, suggesting localized changes in brain activity. The time series on the right reveal episodic disturbances in the EEG signals, marked as microsleep events, char-

Table 9.5: Microsleep event detection sample results from dataset

Nr	Time (s)	Filtered EEG Signal (µV)	Microsleep Event
1	0.03	-0.000024	No
2	0.04	-0.000018	No
3	0.06	-0.000024	No
4	0.07	-0.000030	No
..	...	...	...
5	2265.75	1.738347e-07	Yes
6	5620.99	6.540699e-06	Yes
7	13247.23	-4.272715e-07	Yes
8	21986.62	-1.756352e-06	Yes
..	...	...	...

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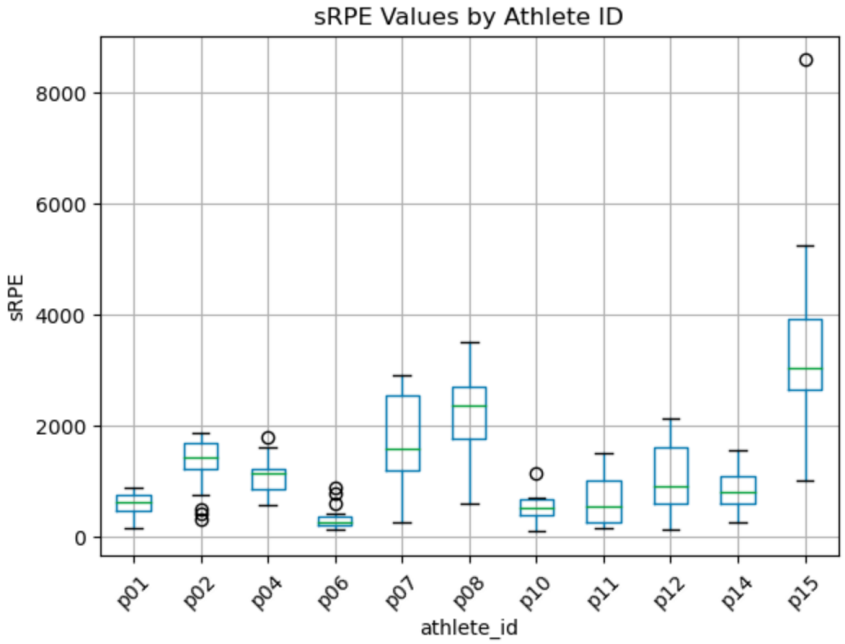


Figure 9.28: sRPE data distribution per athletes

acterized by abrupt deviations from the baseline signal pattern. These visualizations collectively underscore the spatial-temporal dynamics of microsleep, facilitating a nuanced understanding of its manifestation across the scalp's geography as recorded by EEG monitoring.

9.3.3 Personalized recovery

Figure 9.35 shows the velocity and acceleration differences over frames between the reference video (optimal exercise) and a *first video from the injury recovery period [22].* Figure 9.36 shows the difference in velocity and acceleration in frames between the reference video (optimal exercise) and a second video *from the recovery period of the injury.* Figure 9.37 shows the estimated motion intensity per video with percentage differences compared to the reference video (Video 1). The graph shows on one graph the *motion scores* and the *percentage differences*, highlighting the importance of perfect execution of simple exercises. Figure 9.38 shows the set of results in which exercises are executed incorrectly or execution is unbalanced.

The AI pipeline [22] provides instant feedback on the sections where the athlete needs to apply corrections. In these cases, execution accuracy usually fails because of speed or acceleration in specific sections. Based on the result, it can be confirmed that the integration of AI-supported pipelines into sports, especially in safety domains, to improve performance or adjust the injury recovery or rehabilitation process [22] has produced several groundbreaking innovations and value propositions. AI analyzes videos of training sessions or matches, highlighting key moments, patterns, or areas for improvement. Figure 9.39 shows a later phase where only minor adjustments are required.

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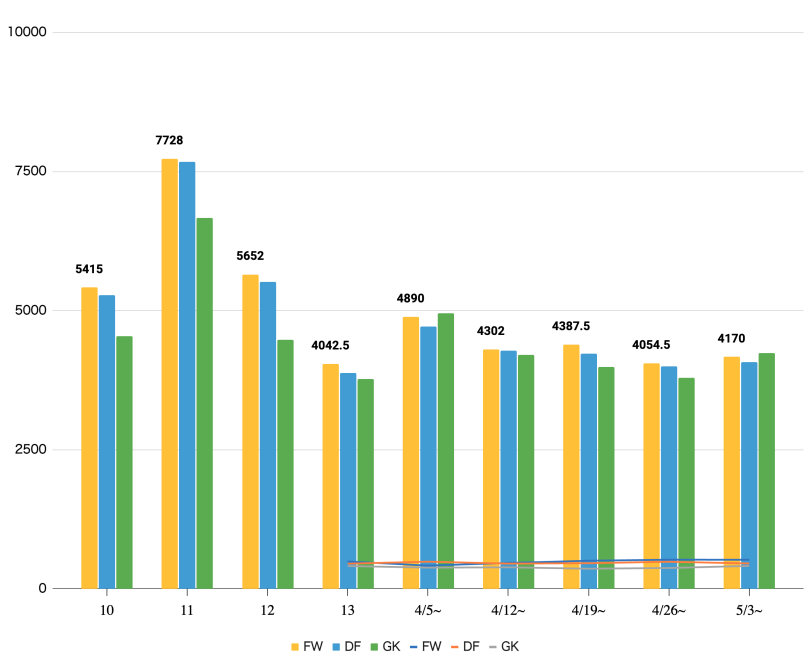


Figure 9.29: FW Total weekly load (bars) and average weekly condition (line)

With AI, the athlete's physical metrics, historical data, and performance benchmarks can be analyzed to build a customized training plan on this basis.

The body of each athlete is unique and a one-size-fits-all approach may not produce optimal results. High-speed cameras and sensors track the movements of athletes. AI then uses this information to deliver feedback on the movement, posture, and technique. Such an analysis can lead to corrections in technique, potentially leading to improved performance and reduced risk of injury, especially in sports such as running or swimming. The thesis experiments examined a limited number of specific exercises, but the results were promising. During thesis experiments, emotion recognition was realized as another specifically targeted domain that might expand the results of real-time analysis. AI can gauge an athlete's emotional state using facial recognition and voice patterns. Mental health is paramount. Recognizing stress, anxiety, or other emotional problems early can help provide timely interventions, ensuring that athletes remain mentally fit.

9.4 Results in disease detection and injury prevention

9.4.1 Disease detection from voice

A set of cough audio files were processed [16], and the relevant features were extracted (using MFCC, Chroma, Mel spectrogram, Spectral contrast) and the features were stored from each cough segment and the characteristics along with the corresponding file names

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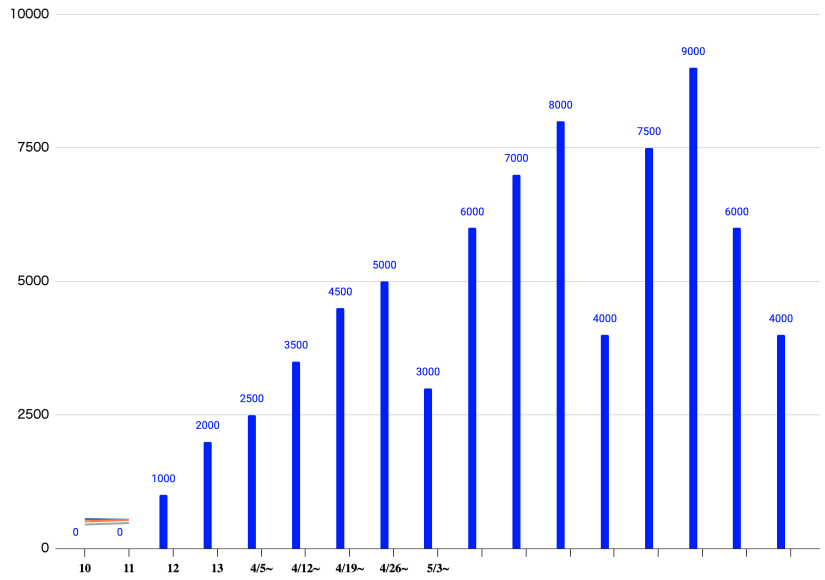


Figure 9.30: Conditioning plan

for further analysis, such as training an ML model for disease /anomaly detection.

Table 9.6: Feature extraction

uuid	status	cough_type	dyspnea	wheezing	severity
p1	healthy	wet	FALSE	FALSE	mild
p2	symptomatic	wet	FALSE	FALSE	pseudocough
p3	healthy	wet	FALSE	FALSE	pseudocough
p4	COVID-19	unknown	FALSE	FALSE	mild

uuid	status	stridor	choking	congestion	severity
p1	healthy	TRUE	FALSE	FALSE	mild
p2	symptomatic	FALSE	FALSE	FALSE	pseudocough
p3	healthy	FALSE	FALSE	FALSE	pseudocough
p4	COVID-19	FALSE	FALSE	FALSE	mild

Based on the results, it was essential that the model started to give relevant results, starting from a 50% score, and the model it recognized the labeled data at the expected accuracy.

A multidimensional scaling figure is presented in Fig. 9.40, which shows how detected anomalies (or patients with COVID) can be localized among healthy samples. The prepared pipeline provided the expected range scores. The worst results were obtained between 30% and 37%, and false positive results began to appear from 38%. From 50%, the accuracy achieved the expected range of precision. As a next phase, I would like to involve a focus group in a controlled environment to validate the results. I also plan to expand the ML algorithms to include more advanced ones.

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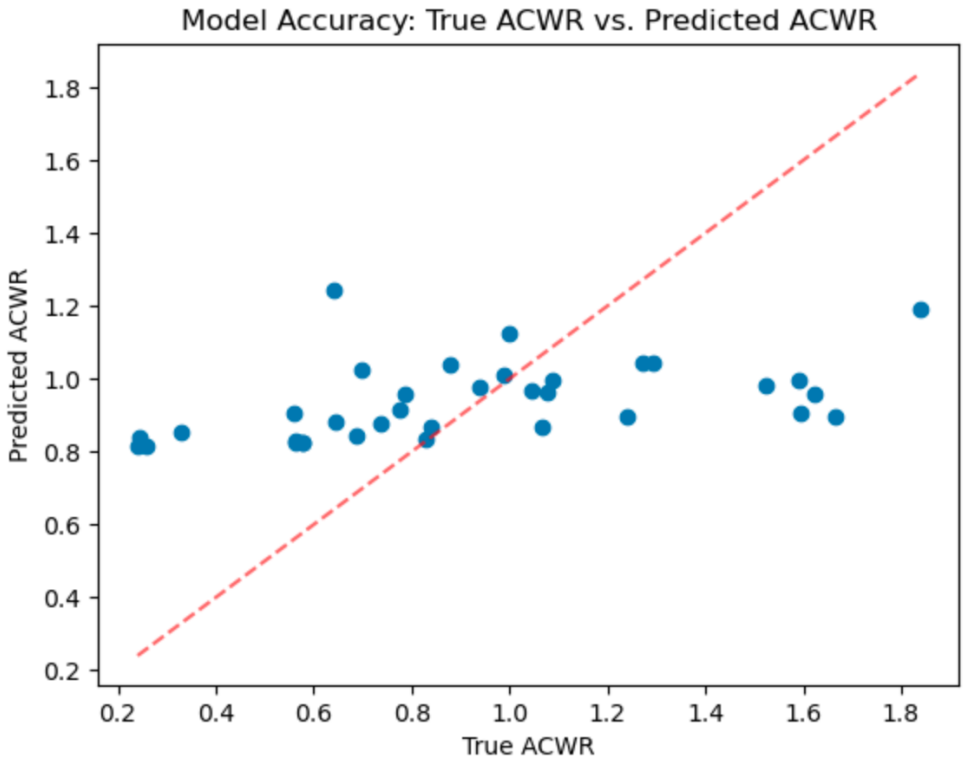


Figure 9.31: Model accuracy for calculated and predicted ACWR

Table 9.7: Predicted model

uuid	status	Label	Score
PM1	COVID-19	healthy	0.3741
PM2	COVID-19	healthy	0.4070
PM3	healthy	symptomatic	0.3800
PM4	healthy	symptomatic	0.3883
PM5	**symptomatic**	**symptomatic**	**0.5000**
PM6	**symptomatic**	**symptomatic**	**0.5100**

Some of the most important and relative conclusions and findings of this approach [16] include: (1) *High accuracy*: AI-based voice analysis models have demonstrated high accuracy in detecting and differentiating between various diseases (e.g., cough and COVID-19 [12, 17, 142, 143]), respiratory illnesses and neurological disorders; (2) *Early detection*: Voice-based AI models have the potential to identify subtle changes in speech patterns and acoustic characteristics, allowing early detection of diseases and timely intervention; (3) *Non-invasive and cost-effective*: Voice-based disease detection is a non-invasive method, which requires only a microphone and an audio recording device, making it more accessible and affordable compared to traditional diagnostic procedures; (4) *Scalability*: AI-driven voice analysis can be easily scaled and deployed in various settings, such as telemedicine, mobile health applications, and large-scale population screenings; (5) *Multimodal data integration*: Combining voice-based features with other data types, such as clinical data,

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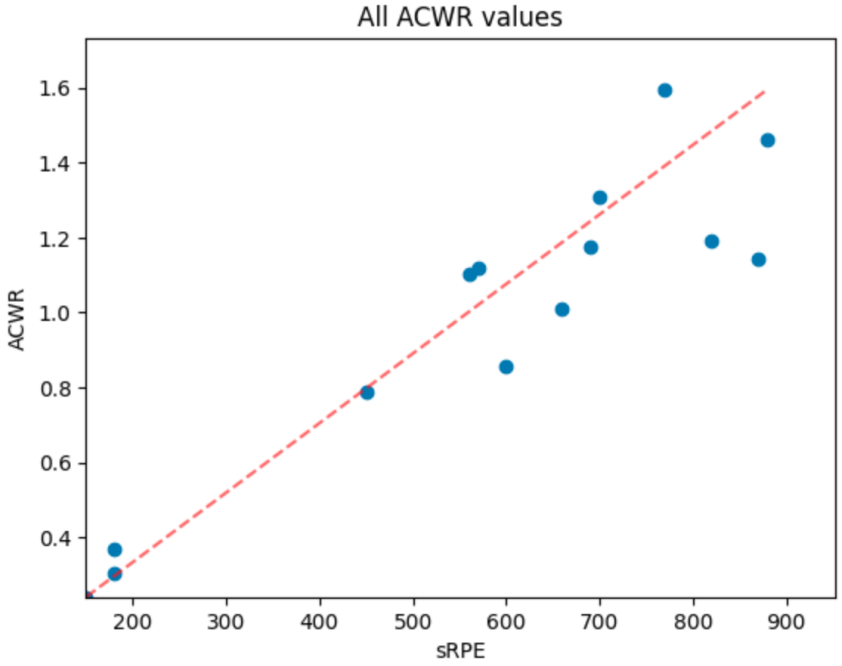


Figure 9.32: ACWR and sRPE on moderated activity intensity

imaging, or genetic information, can improve the precision and reliability of AI-driven disease detection models; (6) *Personalized medicine*: Voice-based AI models can be customized to individual patients, enabling personalized risk assessment, disease progression monitoring, and treatment response evaluation.

The following development lines linked to the voice-based disease detection pipeline were identified: (1) *Validated dataset from the sports sector*: Thesis experiments in student sports athletes to understand much better the specific diseases and anomalies in the field of sports; (2) *Identifying multiple conditions*: Advanced AI algorithms can analyze voice patterns to detect a variety of diseases, such as Parkinson's [106], Alzheimer's [304], respiratory diseases, and even mental health disorders such as depression and anxiety. This broad applicability makes voice-based diagnostics a powerful tool in the medical field; (3) *Real-time monitoring*: AI-powered voice-based diagnostic tools can provide the opportunity to continuously monitor an athlete's health, enabling doctors to track disease progression and make timely decisions on treatment plans. This real-time feedback can also empower athletes to better manage their health.

9.4.2 Pneumonia detection in performance sport

In case of Experiment 1 (see Table 9.8), the Gelan-c summary as is follows: 467 layers, 25412502 parameters, 0 gradients, 102.5 GFLOPs. Speed data of Experiment 1: 0.5 ms pre-process, 31.1 ms inference, 1.8 ms NMS per image at shape (32, 3, 640, 640).

In case of Experiment 2 (see Table 9.9) the speed data are as follows: 0.3 ms pre-process, 31.7 ms inference, 1.5 ms NMS per image at shape (32, 3, 640, 640).

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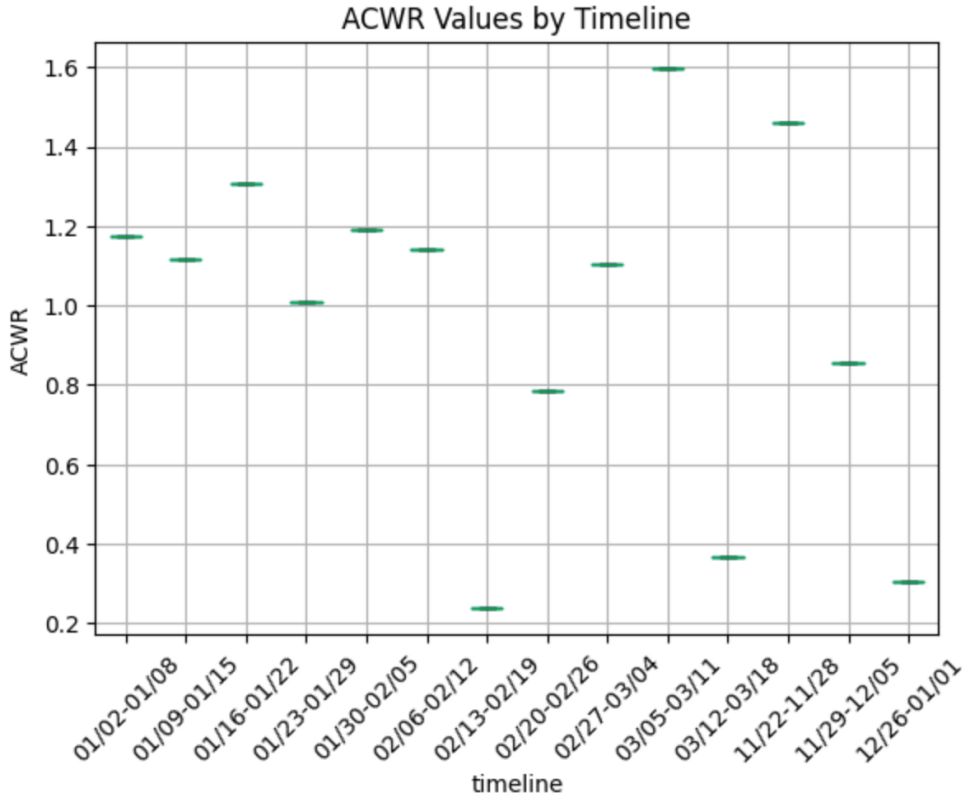


Figure 9.33: ACWR control board

Table 9.8: Experiment 1 results (100 epocs)

Class	Images	Inst.	P	R	mAP50	mAP[50:95]
all	861	858	0.970	0.960	0.970	0.830
Normal	861	281	0.981	0.929	0.972	0.807
Pneumonia	861	577	0.959	0.991	0.969	0.852

The results of *Experiment 1* indicate an effective model training and validation performance, with steady improvements in loss metrics and high stability in precision and recall 9.41. The mAP metrics suggest robustness in detecting objects across various thresholds. However, fluctuations in validation losses and the gradual increase in mAP across stricter IoU thresholds highlight areas where further model tuning and possibly more diverse training data might be needed to achieve even better generalization and accuracy. The *train/box_loss* and *val/box_loss* show a decreasing trend, indicating that the model is learning to predict the location of objects more accurately over time. The *train/cls_loss* and *val/cls_loss* both decrease over time, with the training loss showing a smooth decline and the validation loss appearing more variable but generally trending downward. This variability in validation loss could be due to model sensitivity to different data batches or slight overfitting. The *train/df1_loss* and *val/df1_loss* both decrease over time. The loss plateaus in df1 training, suggesting that the model has largely optimized this aspect of

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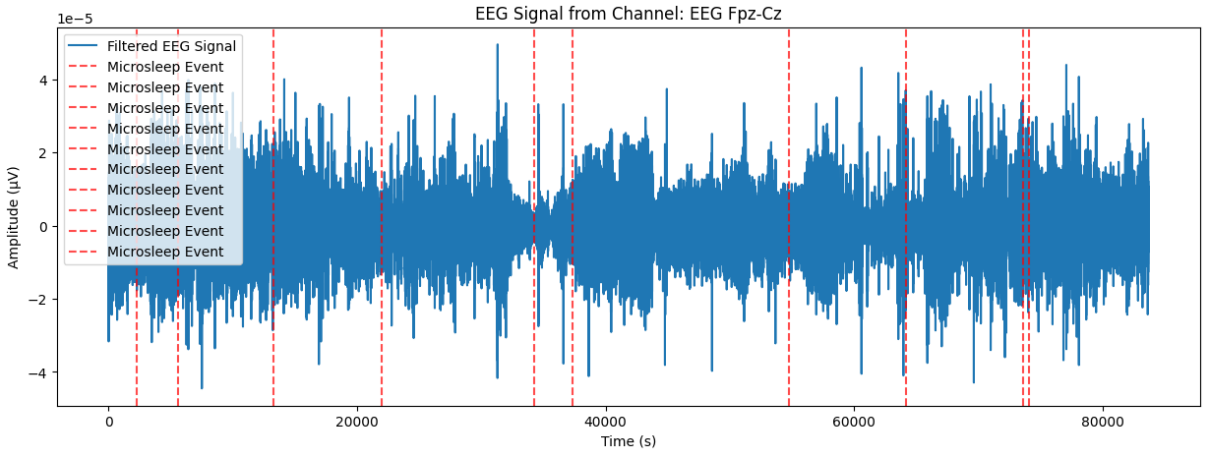


Figure 9.34: Identified microsleep areas

Table 9.9: Experiment 2 results (200 epocs)

Class	Images	Inst.	P	R	mAP50	mAP[50:95]
all	861	858	0.971 ↑	0.963 ↑	0.970	0.830
Normal	861	281	0.978 ↓	0.939 ↑	0.972	0.807
Pneumonia	861	577	0.964 ↑	0.986 ↓	0.971 ↑	0.854 ↑

its learning capability by later epochs. The *metrics/precision* and *metrics/recall* metrics are quite high and stable, indicating that the model performs well both in identifying relevant objects accurately and in retrieving most of the relevant objects. In the case of *metrics/mAP_0.5* and *metrics/mAP_0.5:0.95*, the mAP_0.5 is relatively stable and high, indicating good model performance at the 0.5 IoU threshold. The mAP for the range (0.5:0.95) increases gradually, suggesting improved accuracy across a range of stricter criteria for object detection as training progresses.

The comparison of two experiments (see Table 9.8 and Table 9.9) aimed at enhancing the detection of pneumonia from chest radiographs using DL techniques over varying training durations presents intriguing insights into the model performance dynamics. The first experiment, conducted over 100 epochs, established baseline metrics for precision, recall, and mean Average Precision (mAP) across different IoU thresholds. Upon extending the training to 200 epochs in the second experiment, subtle yet notable variations in these metrics were observed, highlighting the complex relationship between training duration and model efficacy. Overall precision increased slightly from 0.970 to 0.971, suggesting a marginal improvement in the model's ability to correctly identify positive samples. This improvement was more pronounced in the pneumonia class, where precision increased from 0.959 to 0.964. Precision for normal cases decreased slightly, indicating potential overfitting difficulties as the model grew overly tuned to traits unique to the training set.

Similarly, the recall rate, which measures the model's ability to detect all relevant instances, improved overall from 0.960 to 0.963. This increase was mirrored in the pneu-

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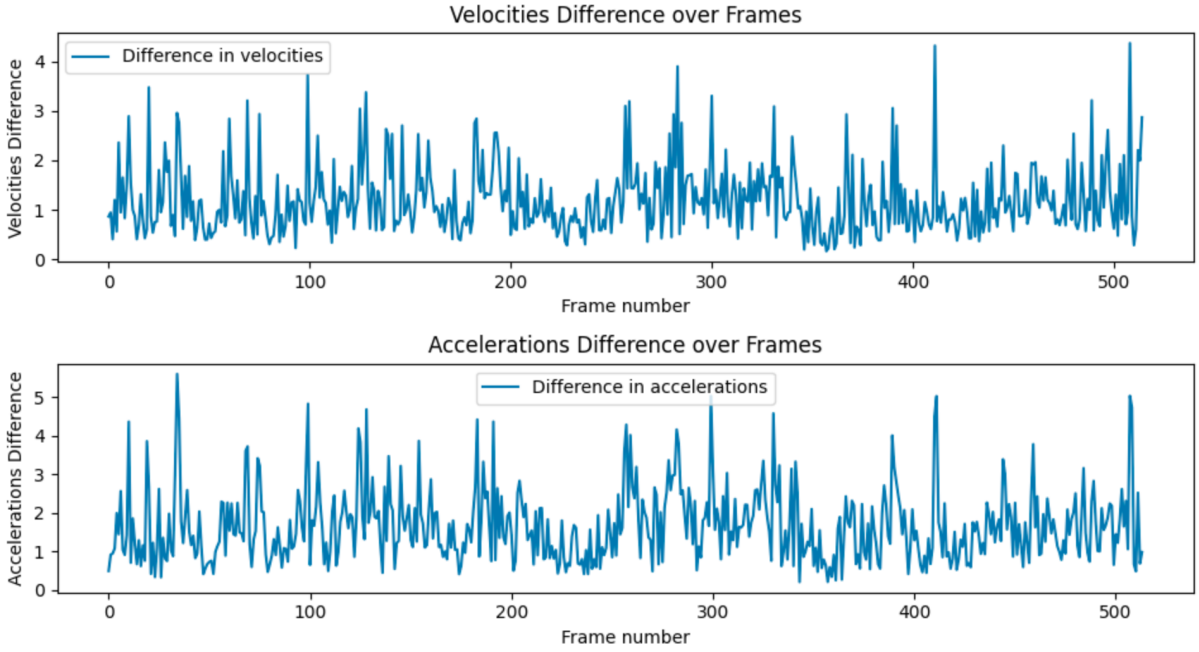


Figure 9.35: Comparing velocities and accelerations - first video from dataset

monia class, but was accompanied by a decrease in the normal class, further suggesting the onset of overfitting. Regarding mAP values, stability in mAP at an IoU of 0.5 across both experiments indicates that the model's ability to detect objects under a less stringent criterion did not benefit significantly from extended training. However, a slight improvement in the mAP for IoU thresholds ranging from 0.5 to 0.95 in the pneumonia class of 0.852 to 0.854 suggests incremental gains in the detection of objects under more rigorous conditions.

These results underscore the delicate balance required in model training for object detection tasks (see Figure 9.43). Increasing the number of epochs can increase condition detection but can also cause overfitting, as shown by the normal class's lower performance measures. This research shows the need for tactics that increase the duration of training and improve the generalization of the model to provide consistent improvements in all assessment measures without compromising the robustness of the model. These strategies should be refined using better regularization approaches [28] or more diversified training datasets to optimize performance in a wider range of diagnostic circumstances.

9.4.3 Burnout in performance sport

The best results come from interdisciplinary collaboration [18]. AI experts, sports scientists, nutritionists, psychologists, and others must work together to create a cohesive strategy (see Table 6.3).

Although AI offers quantitative insights (see Table 9.10), human expertise remains crucial. Coaches, trainers, and psychologists bring a nuanced understanding, which com-

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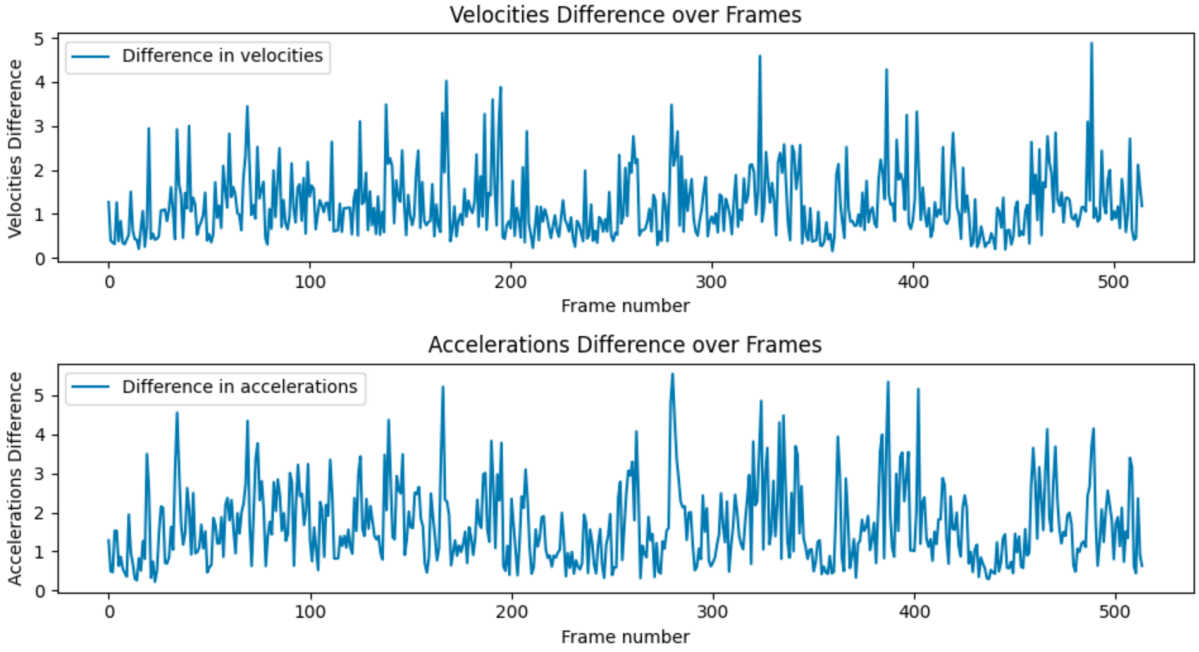


Figure 9.36: Comparing velocities and accelerations - second video from dataset

Table 9.10: Model training and prediction

Classifier	Accuracy	Precision	Recall	F1-score	Support
Random Forest	0.400791	0.387345	0.400791	0.366366	1,517
Logistic Regression	0.396177	0.401628	0.396177	0.356608	1,517
SVM	0.393540	0.394108	0.393540	0.329759	1,517
KNN	0.108108	0.292953	0.108108	0.118139	1,517
Decision Trees	0.340145	0.330424	0.340145	0.331814	1,517
Gradient Boosting	0.405405	0.395510	0.405405	0.354742	1,517

plements AI predictions (see Fig. 9.46 and Fig. 9.47). The optimal approach combines AI-driven data and human intuition and expertise. Fig. 9.44 shows the distribution of the sentiment scores.

An important remark from the specialists involved: The ability of AI to integrate data from multiple sources underscores the importance of a holistic approach to athlete management. Fig. 9.45 shows the top 10 importance of the characteristics of the texts 9.11.

Factors such as sleep, nutrition, mental health, and external stressors play an important role in stamina and burnout and should be part of any comprehensive strategy. Projects often find that AI can detect patterns indicative of burnout in textual data before they manifest themselves more explicitly. This makes early intervention possible. AI models perform better when trained on rich and diverse datasets (see Fig. 9.47). They might show increased negativity, reduced future orientation, or increased self-focus. As burnout progresses, there is a clear shift in sentiment from positive/neutral to more

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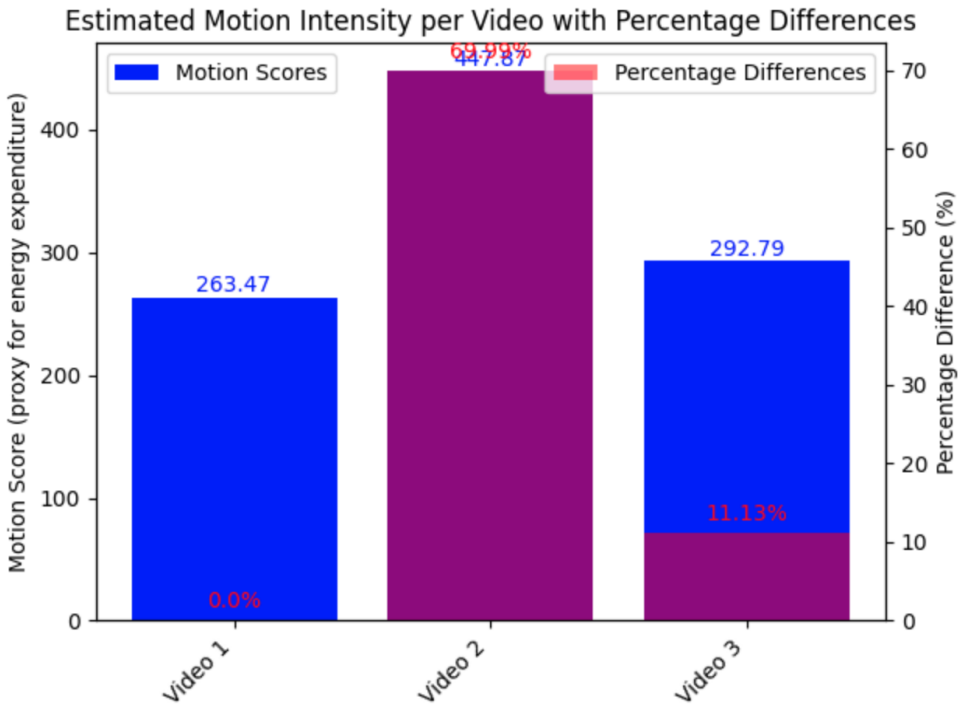


Figure 9.37: Comparing motion intensity per captured videos

negative in most cases [18]. This change can be tracked quantitatively using sentiment analysis.

Fig. 9.46 shows the confusion matrix of an unbalanced dataset of 7,583 texts. Fig. 9.47 shows the confusion matrix of a balanced dataset of 2,792 texts. Needs to be highlighted the importance of combining text analysis with additional data sources, such as work hours, sleep patterns, or even biometric information. Combining these data sources can increase forecast precision. No model is perfect. There is always the possibility of misclassifying someone's status, which can have real-world consequences.

In healthcare settings, early detection of burnout can lead to timely interventions, which could prevent more serious mental health problems [18]. Using pre-trained models (like BERT or GPT variants) and fine-tuning them for burnout detection has shown promise in achieving high accuracies with relatively minor datasets.

9.4.4 Disease detection from written communication

The use of AI for text parsing (using the label distribution presented in Table 8.16) and sentiment analysis has yielded promising results in the realm of precognition of mental health and NDD [19]. Studies using these technologies have demonstrated the ability of AI [18] to identify linguistic patterns (see Table 8.15 for the text length distribution) that correlate with symptomatic manifestations of various conditions. Research has shown that people with depression tend to exhibit a higher frequency of negative affect words and self-referential pronouns in their communication, which can be detected by AI algorithms

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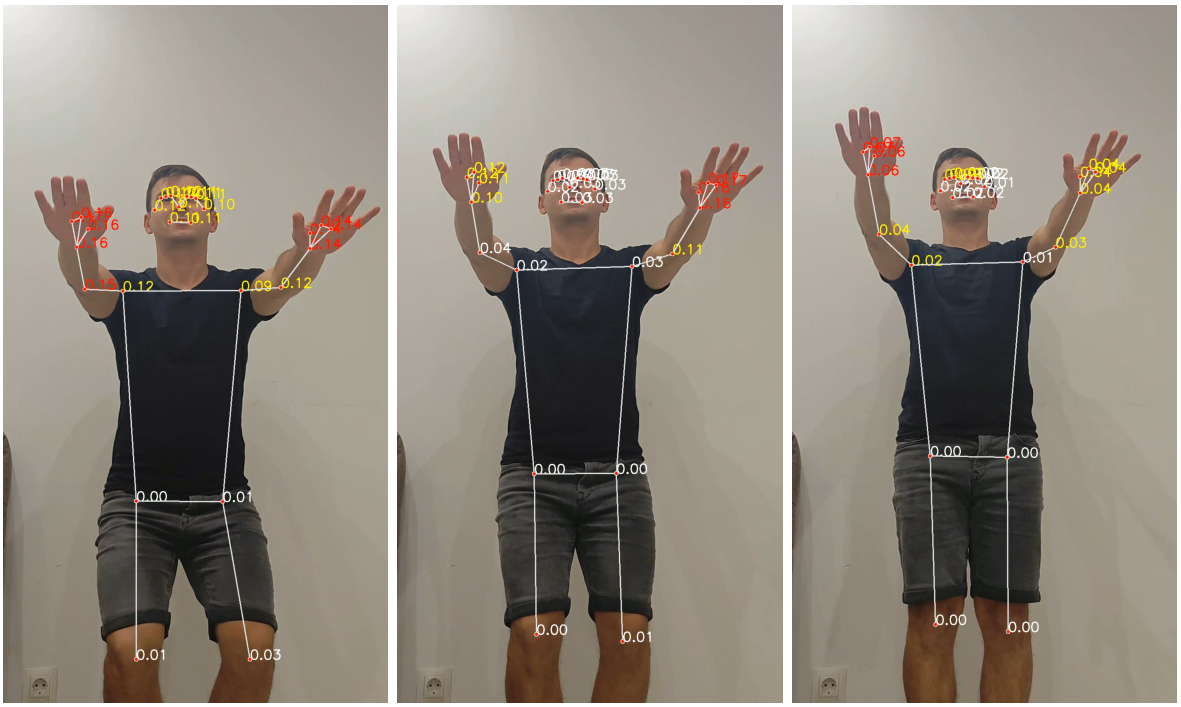


Figure 9.38: Type 1 identified problems - imbalanced results

with notable precision (see Figure 9.48 and Figure 9.49).

In the domain of neurodegenerative diseases, preliminary findings suggest that changes in language complexity, such as simplified syntax and diminished vocabulary diversity (Table 9.11 and 9.12), may be quantifiable through AI analysis before these symptoms are clinically evident. This can be mainly observed in conditions like Alzheimer's disease, where progressive cognitive decline has a direct impact on language function. In addition, sentiment analysis monitors fluctuations in mood and affect, which are integral to mental health assessment, providing a non-invasive, supplementary tool to track patient well-being.

The paper [18, 19] related to the thesis facilitates the monitoring of individual communication over time, allowing the identification of trends that can indicate the onset or progression of a disorder. This approach offers a continuous objective evaluation that complements intermittent clinical evaluations. In addition, it has the potential for remote monitoring, which is invaluable for patients with limited access to regular healthcare services (see Figure 9.50).

These advancements must be balanced by the fact that they are not alternatives for established diagnostic approaches. The ethical issues of using personal communication data for health monitoring are also being investigated, needing open data processing and strict privacy safeguards.

The presented methods are emerging as significant contributors to the early detection and monitoring of mental health and NDD, offering a novel lens through which to understand and manage these complex conditions. The continued refinement of these tools, alongside advances in ML and NLP (see Table 9.12), promises to improve the capabilities

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Figure 9.39: Type 2 identified problems - adjustable results

of medical professionals and improve outcomes for patients.

Incorporating AI-based text and sentiment analysis into the diagnostic context of mental health and NDD heralds a novel frontier in early detection and monitoring. This computational approach can transcend conventional constraints by analyzing linguistic and paralinguistic elements in patient speech or written text, potentially unveiling subtle deviations from normative communication patterns indicative of cognitive decline or emotional distress.

The ***Extra Trees Classifier*** (see Table 9.13) reveals insights into the model's performance across various classes, which are different mental health conditions in this case. The report includes precision, recall, F1-score, support for each class, and overall accuracy and averages. (1) *Alzheimer's Disease and Dementia*: the model demonstrates high precision (0.95) and perfect recall (1.00) in identifying Alzheimer's Disease and Dementia, leading to an excellent F1-score of 0.97. This suggests that the classifier is highly effective in identifying this condition, with a low rate of false negatives and false positives; (2) *Depression and Anxiety*: performance decreases significantly in this category, with a precision of 0.49 and a recall of 0.29, resulting in an F1-score of 0.37. This indicates challenges in accurately classifying cases of Depression and Anxiety, with a higher probability of both false positives and false negatives; (3) *None (Healthy)*: the model performs reasonably well in identifying healthy subjects, with a precision of 0.65 and a higher recall of 0.85, culminating in an F1-score of 0.74. This suggests that while the model can reliably identify healthy individuals, there is still room for improvement in reducing false positives; (4) *Psychosis*: for Psychosis, the model shows a moderate precision

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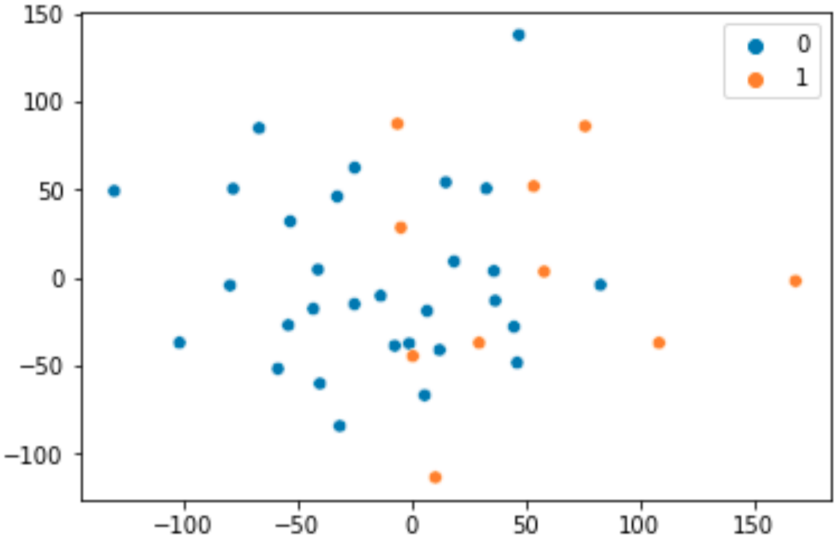


Figure 9.40: Multidimensional scaling of healthy subjects and patients with COVID

Table 9.11: Top 10 features with Importance levels

No.	ID	Feature	Importance
1	3254	plotting	**0.051509**
2	5000	sentiment	0.045933
3	4747	voices	0.044404
4	3164	people	0.037201
5	1994	hear	0.034005
6	2610	lost	0.032294
7	3520	real	0.028020
8	3231	places	0.027559
9	3606	remember	0.025091
10	1039	dates	0.024884

of 0.67 but a lower recall of 0.35, leading to a F1-score of 0.46. This implies that while the classifier is relatively reliable when it identifies a case as Psychosis (fewer false positives), it misses a significant number of true Psychosis cases (higher false negatives); (5) *Suicide and Depression*: the model shows fairly good precision (0.75) but moderate recall (0.52) in this category, with a resulting F1-score of 0.61. This suggests a better balance between false positives and false negatives, although there is still a notable number of missed cases; (6) *Overall Performance*: the overall accuracy of the model is 0.70, which is satisfactory but indicates potential for improvement. The macro average F1-score (0.63) and the weighted average F1-score (0.68) reflect moderate performance between classes, with better precision in some (such as Alzheimer's disease and dementia) and challenges in others (like Depression and Anxiety); In conclusion, the *Extra Trees Classifier* shows varying levels of effectiveness in identifying different mental health conditions. Its strength lies in identifying *Alzheimer's Disease* and *Dementia* and the general healthy population. At the same time, it faces challenges in accurately classifying Depression and Anxiety,

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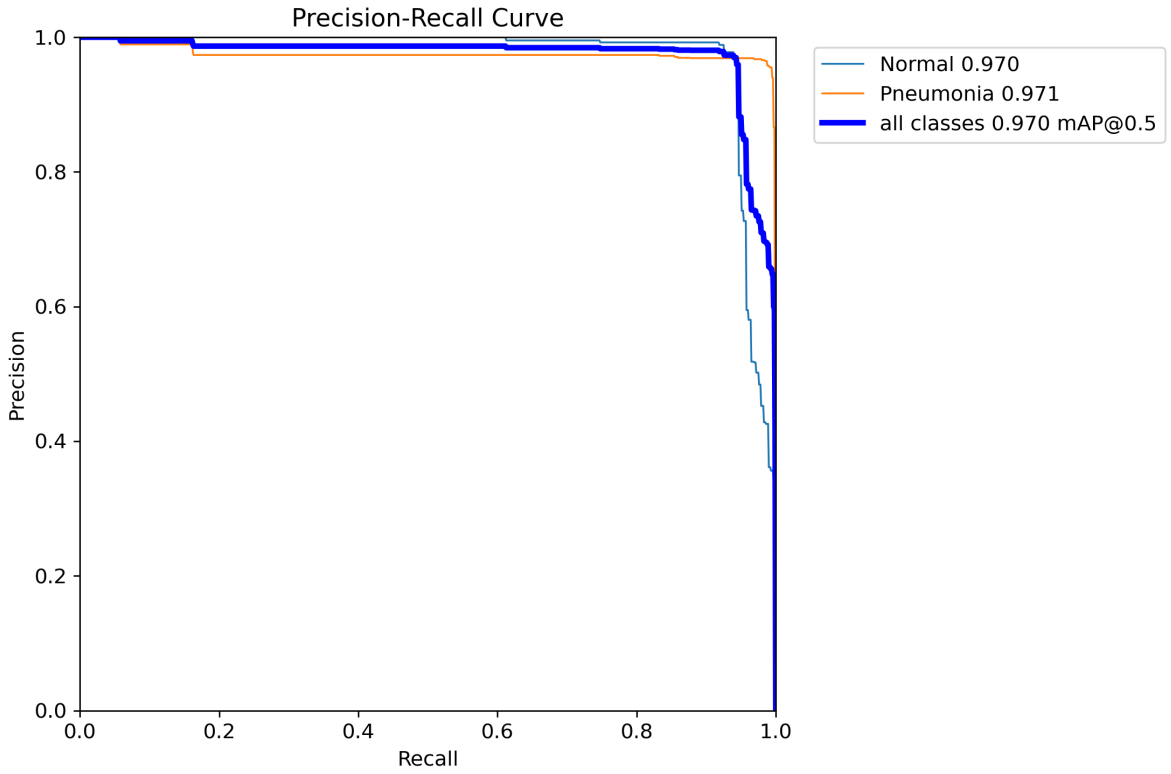


Figure 9.41: YOLO 9 precision-recall chart for pneumonia research

Table 9.12: Top six features with Importance levels per labels

Rank	Alzheimer's & Dementia		Depression & Anxiety		None		Psychosis		Suicide & Depression	
No.	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**
1	familiar	**5.775062**	anxious	**6.343930**	morning	**1.450505**	hear	**8.617279**	suicide	**5.172760**
2	places	5.702947	restless	5.998787	coffee	1.445807	plotting	8.378585	help	4.807741
3	remember	5.150686	worried	5.552964	buy	1.287901	arena	5.983609	kill	4.515317
4	lost	5.135937	nervous	4.982023	cool	1.249352	people	4.887970	life	4.319223
5	hard	4.962242	worry	4.118800	holiday	1.237574	voices	4.455395	just	4.166109
6	dates	4.882358	sleep	2.832804	tweet	1.230690	things	3.417450	wish	4.115592

ID = feature name, IMP - feature importance

Psychosis, and Suicide and Depression. This variance suggests the need for further model tuning or exploration of alternative features that could improve classification accuracy, especially for the underperforming categories. Furthermore, the imbalanced performance across classes indicates the potential benefit of effectively employing techniques to handle class imbalances.

The ***Random Forest Classifier*** (see Table 9.14) provides a detailed view of the performance of the model in different categories related to mental health disorders. This analysis focuses on precision, recall, F1-score for each category, and overall accuracy. (1) *Alzheimer's Disease and Dementia*: the Random Forest Classifier demonstrates excellent performance in identifying Alzheimer's Disease and Dementia, evidenced by high precision (0.95) and perfect recall (1.00), culminating in an F1-score of 0.97. This indicates a

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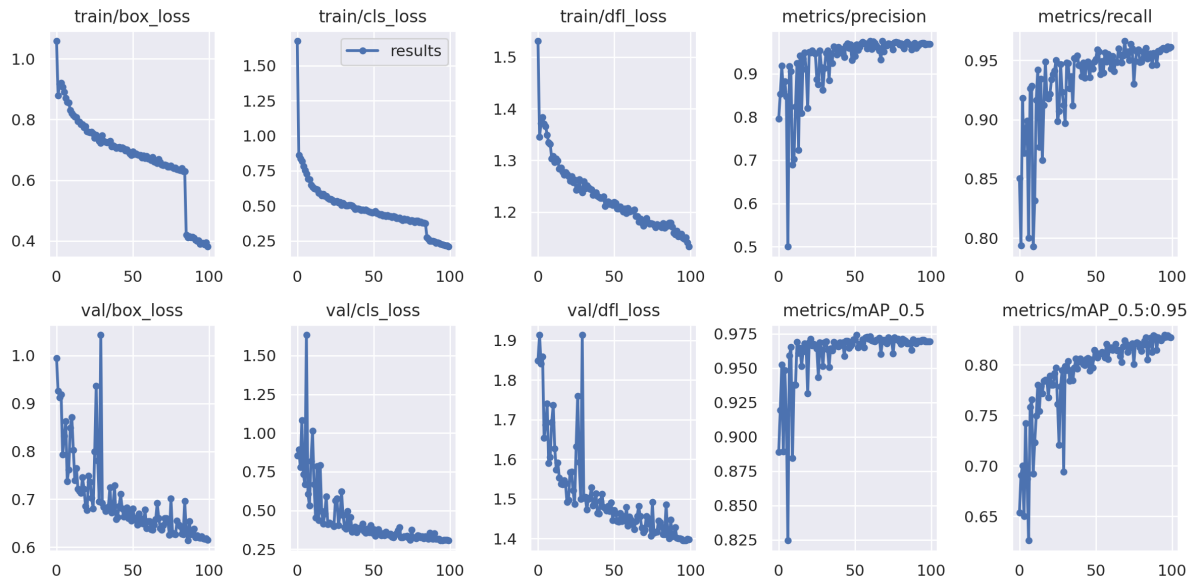


Figure 9.42: Pneumonia detection results with YOLOv9, 100 epochs, batch: 16, epochs: 200, img: 640, close-mosaic: 15

Table 9.13: Extra Trees Classifier classification report

Disease	Precision	Recall	F1-score	Support
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.29	0.37	315
None	0.65	0.85	0.74	1,617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.75	0.52	0.61	490
accuracy			0.70	3,406
macro avg	0.70	0.60	0.63	3,406
weighted avg	0.70	0.70	0.68	3,406

strong ability of the model to correctly classify cases of Alzheimer's Disease and Dementia with minimal false positives and negatives; (2) *Depression and Anxiety*: the model shows reduced effectiveness in this category with a precision of 0.49 and a lower recall of 0.27, leading to an F1-score of 0.35. This suggests a significant challenge in correctly identifying cases of Depression and Anxiety, as indicated by a considerable number of false negatives and a moderate rate of false positives; (3) *None (Healthy)*: in classifying healthy individuals, the model exhibits decent performance with a precision of 0.65 and a higher recall of 0.85, resulting in a F1-score of 0.74. This indicates a relatively reliable identification of healthy cases, although there is some room to reduce false favorable rates; (4) *Psychosis*: for the category of Psychosis, the model displays a moderate precision of 0.67 but a lower recall of 0.35, giving an F1-score of 0.46. This points to a reasonable precision when the model predicts psychosis (lower false positives) but a substantial number of missed actual

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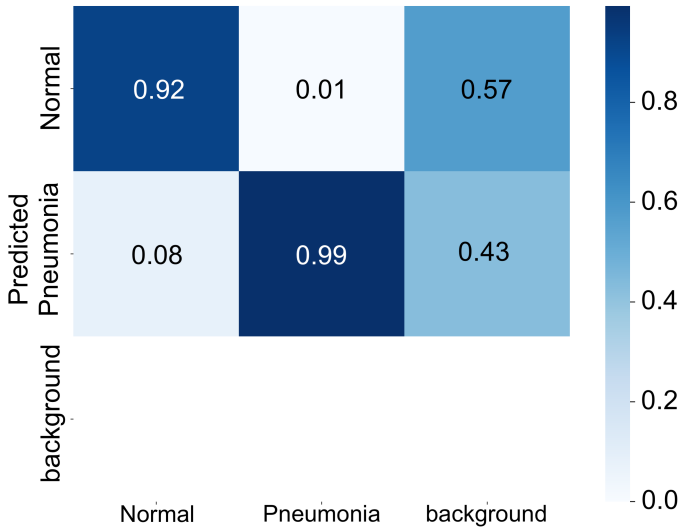


Figure 9.43: YOLOv9 Confusion matrix of Experiment 1 of pneumonia detection

Table 9.14: Random Forest Classifier classification report

Disease	Precision	Recall	F1-score	Support
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.27	0.35	315
None	0.65	0.85	0.74	1,617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.73	0.51	0.60	490
accuracy			0.70	3,406
macro avg	0.70	0.60	0.62	3,406
weighted avg	0.69	0.70	0.68	3,406

cases (higher false negatives); (5) *Suicide and Depression*: the model achieves a relatively good precision of 0.73 and a moderate recall of 0.51, resulting in an F1-score of 0.60. This suggests a somewhat balanced performance in terms of false positives and false negatives, although there is room for improvement in recall; (6) *Overall Performance*: the overall precision of the model stands at 0.70, reflecting a competent level of performance across all categories. However, the macro average F1-score (0.62) and weighted average F1-score (0.68) indicate a disparity in performance across different categories, with strengths in certain areas like Alzheimer's Disease and Dementia and weaknesses in others such as Depression and Anxiety. In summary, the Random Forest Classifier demonstrates robust capability in identifying Alzheimer's Disease and Dementia and reasonably good performance in distinguishing healthy individuals. The disparity in classification effectiveness across different mental health conditions also suggests the potential utility of more tailored approaches or models for specific situations and the importance of considering class imbalance in training data.

The ***Decision Tree Classifier*** (see Table 9.15) elucidates its performance in diag-

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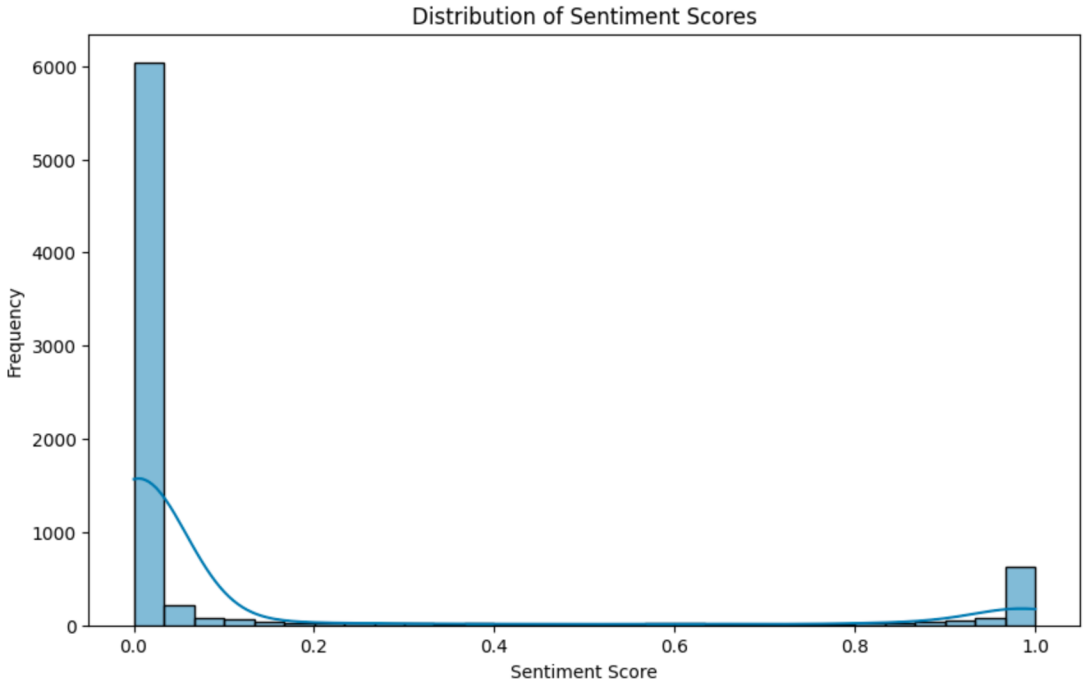


Figure 9.44: Distribution of sentiment scores

Table 9.15: Decision Tree Classifier classification report

Disease	**Precision**	**Recall**	**F1-score**	**Support**
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.29	0.37	315
None	0.65	0.85	0.74	1,617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.74	0.49	0.59	490
accuracy			0.70	3,406
macro avg	0.70	0.60	0.63	3,406
weighted avg	0.69	0.70	0.68	3,406

nosing various mental health conditions. The report details the model's precision, recall, F1-score for each category, and overall accuracy, offering a comprehensive assessment of its predictive capabilities. (1) *Alzheimer's Disease and Dementia*: in this category, the Decision Tree Classifier exhibits exemplary performance, as evidenced by its high precision (0.95) and perfect recall (1.00), leading to an impressive F1-score of 0.97. This indicates the robust ability of the model to accurately identify cases of Alzheimer's Disease and Dementia with minimum error; (2) *Depression and Anxiety*: the model shows limited effectiveness in classifying Depression and Anxiety, with a precision of 0.49 and a recall of 0.29, resulting in an F1-score of 0.37. This suggests considerable challenges in accurately detecting cases of Depression and Anxiety, as indicated by a high rate of false negatives and a significant number of false positives; (3) *None (Healthy)*: the classifier

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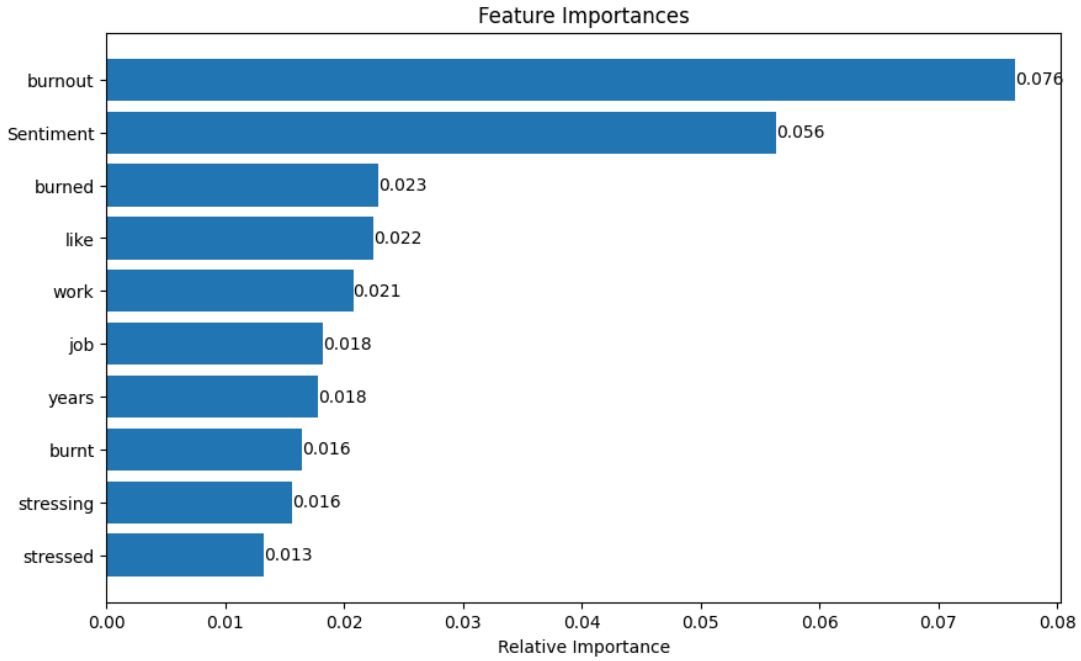


Figure 9.45: Burnout detection using sentiment analysis and performance parameters

demonstrates reasonable performance in identifying healthy individuals, with a precision of 0.65 and a higher recall of 0.85, yielding an F1-score of 0.74. This suggests a reliable identification of healthy cases, although there is scope for improvement in precision; (4) *Psychosis*: in the psychosis category, the model achieves moderate precision (0.67) but a lower recall (0.35), resulting in an F1-score of 0.46. This points to a moderate level of precision in predicting psychosis (fewer false positives), but with a notable number of missed true cases (higher false negatives); (5) *Suicide and Depression*: the classifier shows fairly good precision (0.74) but moderate recall (0.49), culminating in an F1-score of 0.59. This balance suggests a better equilibrium between false positives and false negatives, although the number of missed cases is still significant; (6) *Overall Performance*: the Decision Tree Classifier achieves an overall accuracy of 0.70, indicating satisfactory performance across all classes. However, the macro average F1-score (0.63) and weighted average F1-score (0.68) highlight disparities in performance across different categories, with significant effectiveness in some areas (such as Alzheimer's Disease and Dementia) and limitations in others (notably Depression and Anxiety); In conclusion, the Decision Tree Classifier shows a solid capacity to accurately identify Alzheimer's Disease and Dementia and reasonably good ability to distinguish healthy individuals. However, it faces considerable challenges in effectively classifying conditions such as depression and anxiety, psychosis, and suicide and depression. These variances underscore the need for further refinement of the model or exploration of more sophisticated or specialized features to enhance its predictive accuracy, particularly in the underperforming categories. The observed disparities also suggest strategies to address potential class imbalances in training to improve the model's diagnostic capabilities across a broader spectrum of mental health

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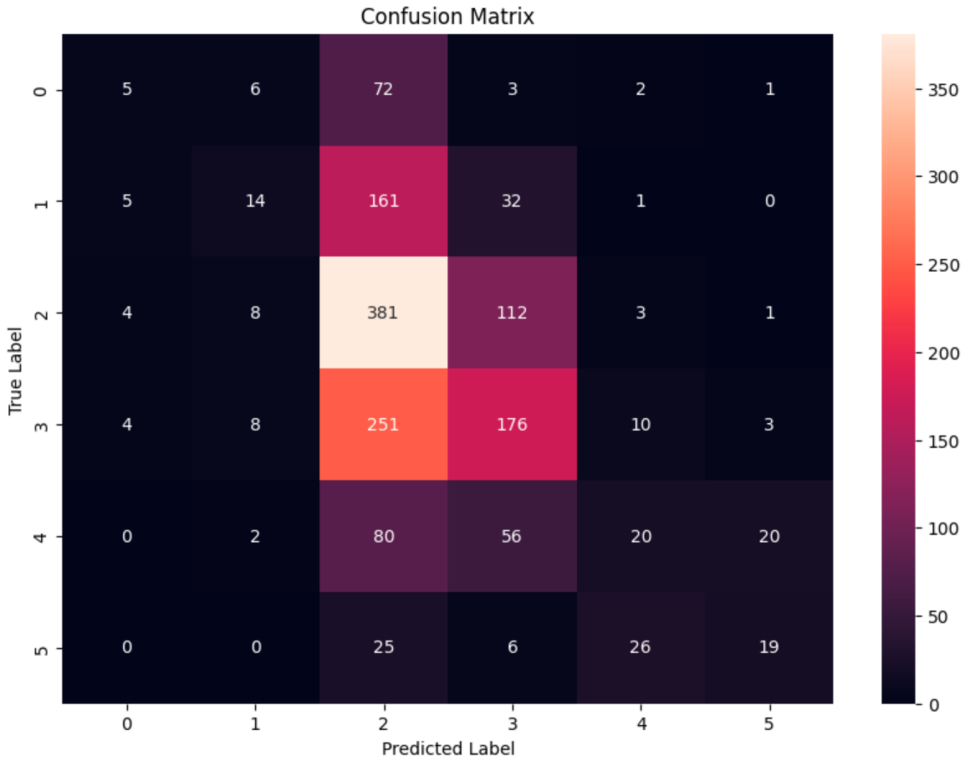


Figure 9.46: Confusion matrix for an imbalanced dataset

conditions. In the domain of NDD, text analysis might track longitudinal changes in language usage over time, facilitating a more dynamic understanding of disease progression. Collectively, these advances are expected to refine diagnostic precision, improve patient participation in mental health conditions, and tailor interventions to the linguistic and emotional profiles discerned through AI analysis.

9.4.5 Lesions and tumor detection on severe head injuries

Object detection

Fig. 6.15 shows the YOLO8-based tumor object detection results [28]. The model summary is as follows: 268 layers, 68,124,531 parameters, 0 gradients, and 257.4 GFLOPs. Processing speed: 0.5ms preprocess, 49.9ms inference, 1.6ms postprocess per image at shape (1, 3, 608, 608).

HGG and LGG detection

A critical part of the planning of treatment strategies for brain tumor patients involves separating LGG patients from HGG patients. In the conducted thesis experiments [28] LGG and HGG object detection was investigated with YOLO8 and YOLO-NAS algorithms to check whether the real-time detection pipeline could be a feasible approach [211,305]. Fig. 6.17 shows the YOLO8-based HGG and LGG object detection results with a processing

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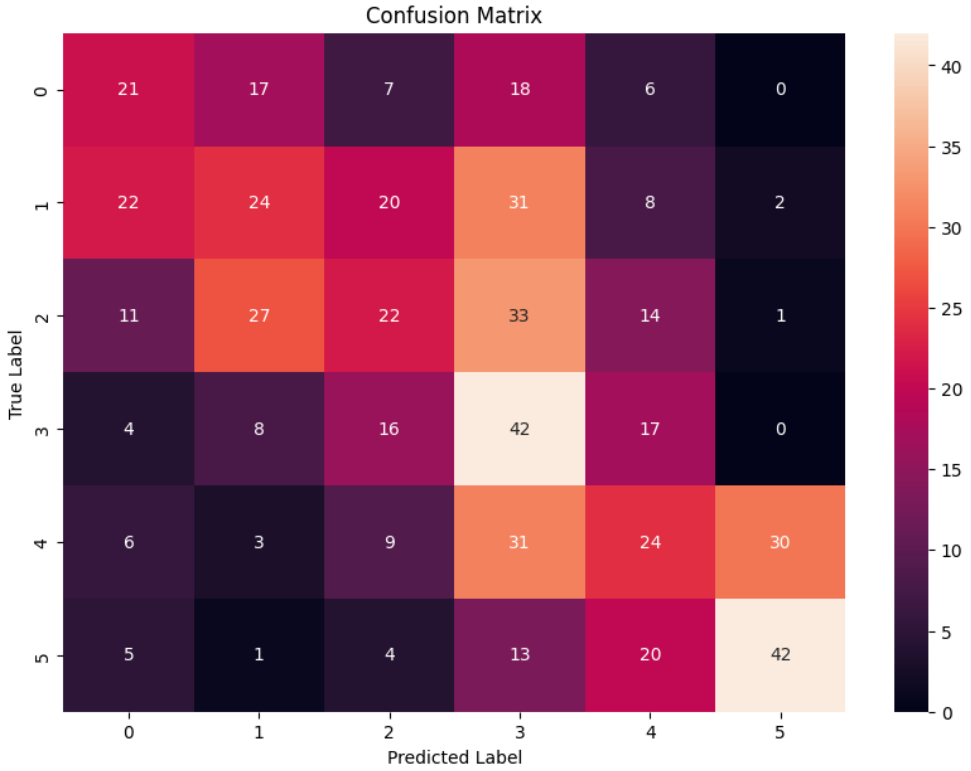


Figure 9.47: Confusion matrix for a balanced balanced dataset

speed of 0.5 ms preprocess, 17.7 ms inference, 1.4 ms postprocess per image in shape (1, 3, 608, 608). Fig. 6.16 shows the YOLO-NAS-based HGG/LGG detection results with the train epoch speed of 2.71it/s. The validation epoch speed 1 is 7.15it/s in this case.

The underlying research activities [28] of the thesis involving experts highlighted some fundamental topics linked to the future of healthcare and applied AI systems and pipelines as follows: (1) AI-based anomaly detection systems will provide sometimes unexpected results that need to be reviewed and understood as well, which opens the secondary topic, (2) AI explainability and transparency, which means that stakeholders, including athletes and medical practitioners, need to understand how AI makes its decisions to be able to define future strategies; (3) to achieve high accuracy and detailed diagnosis, some technical challenges will emerge, such as the requirement for large, high-quality datasets for model training, and the need for robust, real-world validation; (4) for a deeper analysis and better assessment, it will be important to validate the borders of further integrations, and it does not only mean diverse data types – from medical images to wearable sensor data – but also AI systems within existing medical and sports synergies; (5) it will be important to understand and manage the potential discrepancies between AI predictions and human expert opinions to adjust or prepare a valid human-machine recommendation system, and finally it is crucial to elaborate the (6) ongoing advancements and future,

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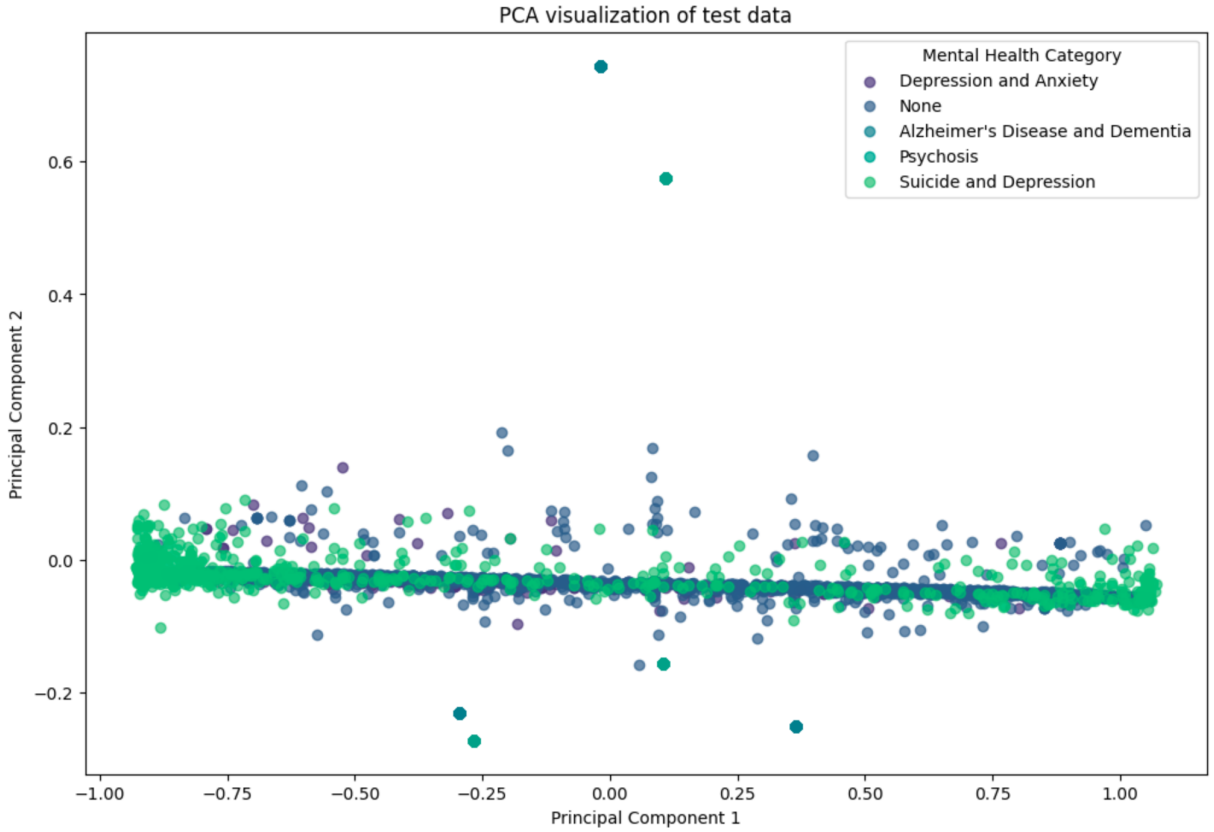


Figure 9.48: PCA visualization of test data

9.5 Results in sport strategy prediction and gamification

The YOLO8 model that was used in the thesis experiments [28, 41] (see Table 9.16) has the following summary with 13 images: 268 layers, 68,128,383 parameters, 0 gradients, 257.4 GFLOPs, Speed: 0.2ms preprocess, 58.2ms inference, 0.0ms loss, 1.0ms postprocess per image.

Table 9.16: NAS8 model summary

Class	Instances	Box(P	R	mAP50	mAP50-95)
all	155	0.93	0.772	0.772	0.519
coach	23	0.915	0.942	0.958	0.594
goalkeeper	10	0.86	1	0.94	0.68
ice_hockey_puck	4	1	0	0	0
player1	68	0.934	0.956	0.986	0.653
player1	50	0.98	0.96	0.973	0.667

The real-time approach for post processing strategy evaluation [41]: if 8 pictures are extracted from a video stream, it will result in a model summary (fused) of 268 layers, 68,128,383 parameters, 0 gradients, 257.4 GFLOP as shown in the inferences of the 8

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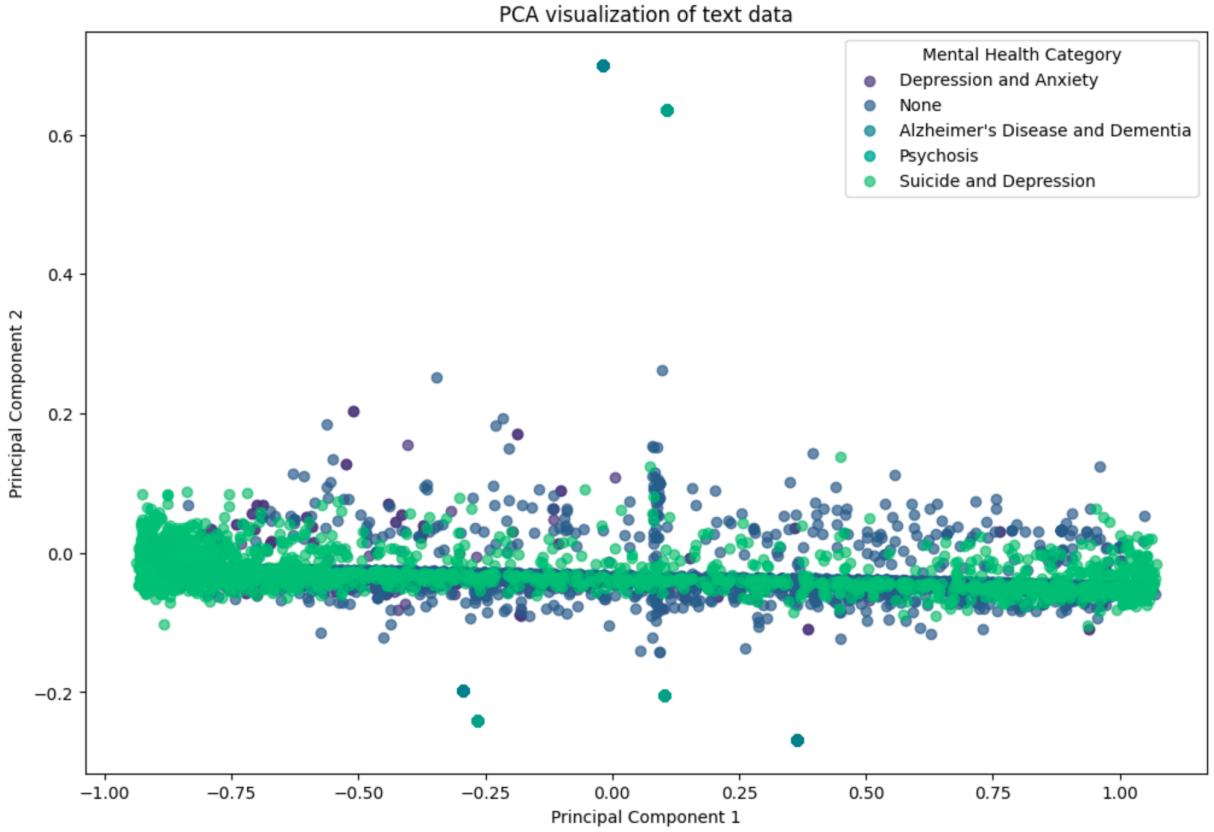


Figure 9.49: PCA visualization of text data

extracted pictures (jpg: 608x608) with speed: 0.5ms pre-process, 56.2ms inference, 1.7ms post-process per image at shape (1, 3, 608, 608). In the case of YOLO-NAS, it will show a lower accuracy (see Fig. 8.19) with the same dataset because YOLO-NAS requires more annotated data.

YOLO and YOLO-NAS results in digital tracking and strategy extraction from ice hockey videos: (1) *accurate player tracking*: both YOLO (see Fig. 9.51 showing the YOLO 8 precision confidence graph) and YOLO-NAS enable accurate tracking of players in ice hockey videos, providing precise positional information throughout the game. This allows coaches and analysts to analyze player movements, positioning, and interactions in real time (see Fig. 9.52, which shows a shooting practice drill and the N-Z forecheck system). The only issue that was faced during the thesis experiments was puck recognition, but this can be handled in a High-Performance Computing (HPC) environment (next research phase);

(2) *Object detection*: these models can effectively detect and track various objects in ice hockey videos, including pucks, sticks, and other equipment. This helps to understand the game's dynamics and extract relevant information for strategy development. Figures 9.53 and 9.54 show the prediction results – coaches, players from team 1 (player 1), players from team 2 (player 2), and goalkeepers with YOLO8 and YOLO-NAS respectively.

(3) *Tactical insights*: YOLO and YOLO-NAS provide valuable insights into offensive and defensive strategies in ice hockey. Coaches can analyze player positioning, team

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Figure 9.50: t-SNE visualization of text data

formations, passing patterns, and defensive coverage to identify strengths, weaknesses, and patterns in gameplay;

(4) *Near real-time decision making*: the AI-supported real-time analysis capabilities of YOLO and YOLO-NAS enable coaches to make informed decisions during the game. They can adjust strategies, make player substitutions, or implement tactical changes based on the analyzed data and insights;

9.5.1 New collaborative method options for defensive /offensive strategies

By combining real-time tracking and strategy extraction with historical data analysis, athletes and coaches can gain valuable insights into defensive and offensive strategies, improving team performance and decision making in ice hockey.

(1) *Historical game analysis*: coaches and analysts can use historical game videos to analyze defensive and offensive strategies used in previous games.

(2) *Opponent analysis*: retrospective learning methods can be applied to study the strategies and patterns of opposing teams in historical ice hockey videos. This allows coaches to develop effective defensive and offensive plans by identifying the strengths, weaknesses, and preferred tactics of their opponents.

(3) *Performance elaboration*: by comparing historical game footage, coaches can as-

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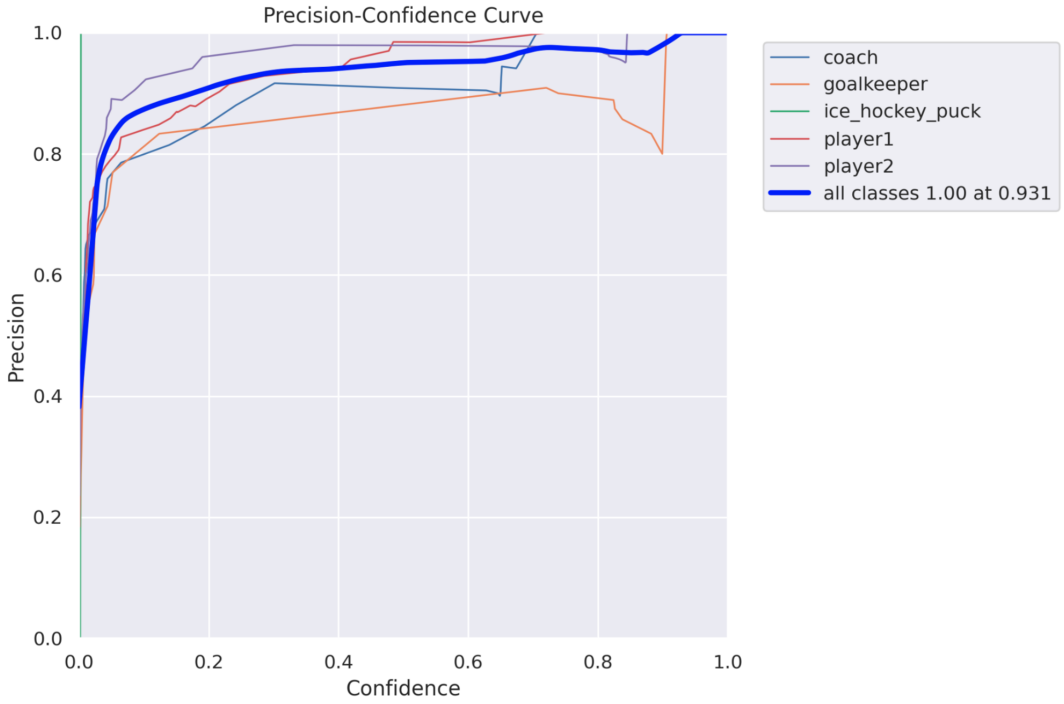


Figure 9.51: YOLO 8 precision confidence chart

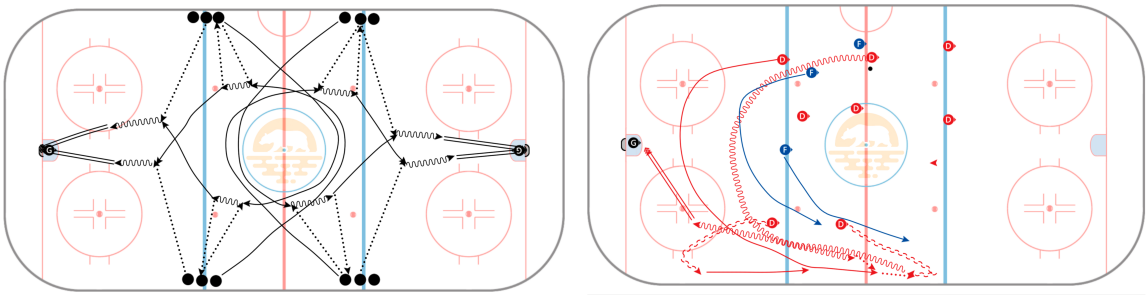


Figure 9.52: Shooting practice drill and N-Z forecheck system

sess the effectiveness of different defensive and offensive strategies used over time. This retrospective analysis helps refine game plans and optimize strategies for future matches.

(4) *Player development*: the system outcomes enable coaches to evaluate the progress and performance of individual players over multiple seasons. By analyzing historical data, coaches can identify specific areas for player development and tailor training programs accordingly;

(5) *Adaptive strategies*: coaches can adapt defensive and offensive strategies based on the analysis of past performances. By understanding successful strategies in similar game situations, coaches can adjust tactics to maximize team performance and exploit opponents' weaknesses.

Using YOLO and YOLO-NAS in performance sports as assistive AI assets can introduce a retrospective learning method that empowers athletes and coaches with data-driven insights, enabling them to make informed decisions, optimize strategies and improve over-

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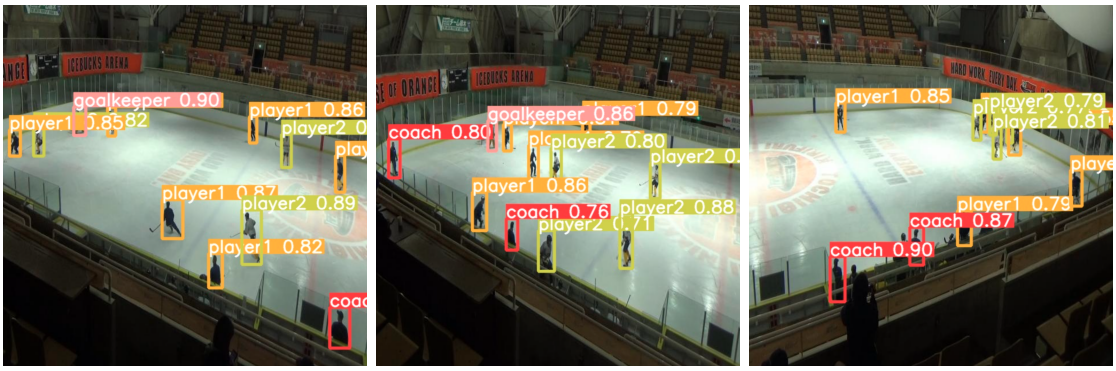


Figure 9.53: YOLO 8 predictions: players from Team1/2, coach, goalkeeper

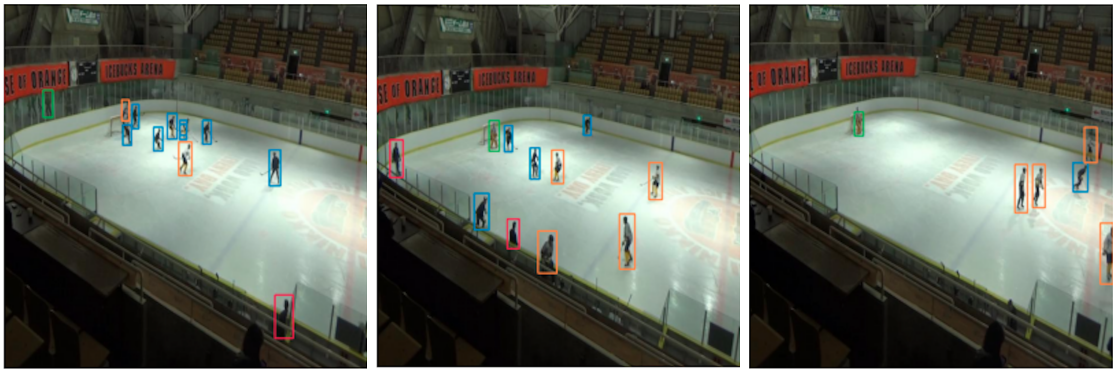


Figure 9.54: YOLO-NAS predictions: players from Team1/2, coach, goalkeeper

all performance in sports. Value propositions: (1) athletes and coaches can use historical video data to analyze past performances, identify trends, and evaluate the effectiveness of strategies and tactics used in previous games or drills; (2) by analyzing historical data, athletes and coaches can identify recurring patterns, both at the individual and team level, which can help understand strengths, weaknesses, and areas of improvement; (3) retrospective learning allows athletes and coaches to adapt strategies based on analysis of past performances. By understanding what has worked well in similar situations, they can modify game plans and make more informed decisions during future competitions; (4) analyzing historical video footage can provide insights into an athlete's progress and skill development over time, helping coaches design personalized training programs and target specific areas for improvement; (5) retrospective learning methods can be used to establish performance benchmarks based on historical data, enabling athletes and coaches to set realistic goals and track progress over time.

9.6 Summary of scientific contributions

The primary scientific contribution of this chapter is the comprehensive analysis of the multifold results of the thesis – based on conducted research experiments and technological pipelines, which establish a connection between Computer Science and Health

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Sciences in various ways – by using advanced technological solutions and /or AI. The results reinforce the synergies between different domains such as performance sports, sports safety, medical radars, and sports sensors, control of health conditions (including mental health, detection of disease and health anomalies, injury prevention methods), sport psychology, athlete behavior analysis, sport strategy analysis, athlete performance analysis, physiotherapy and rehabilitation control, communication, sentiment analysis, retrospective learning, ethical implications, and artificial intelligence. The results and conducted discussions also highlight the future perspectives and room for improvement.

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10 Conclusions

10.1 Scientific conclusions

All research objectives of Chapter 1.3 – elaborated in detail in Chapter 3 – were achieved, and the results of Chapter 9 with novelties elaborated in Chapter 7 were published and distributed. The most important scientific results and contributions in alignment with the research objectives per thesis group level are shown in Table 10.1, and are as follows:

Table 10.1: Research objectives' (RO) fulfilment per thesis groups and per scientific results and contributions

Research objectives	**Fulfillment of objectives**	
ID and short RO description	**Thesis group**	**Thesis IDs**
RO1: Enhancement of real-time diagnostics and monitoring	S1, S2, S3	1.1, 1.5, 1.2, 2.1, 3.3
RO2: AI-based health and performance prediction	S1, S3	1.6, 1.5, 3.1, 3.2
RO3: Development of multilingual and multimodal collaboration tools	S1	1.1, 1.3, 1.4
RO4: Optimization of training and rehabilitation processes	S1, S2, S3	1.6, 1.7, 2.1, 2.4, 3.4
RO5: Integration of AI in strategic sports analysis	S2	2.3, 2.4
RO6: Innovative approaches to disease detection and prevention	S1, S3	1.7, 3.3
RO7: Psychological and mental health monitoring	S3	3.5, 3.6
RO8: Gamification and adaptive training enhancements	S3	3.4
RO9: Comprehensive data analysis for performance improvement	S2	2.2, 2.4

- **RO1**, about the *enhancement of real-time diagnostics and monitoring*, is fullfiled by: (1) implemented DETR model for visual and textual data recognition (Thesis 1.1); (1) developed sensor-based pipeline for energy expenditure estimation (Thesis 1.5); (3) comparative analysis of YOLO, Detectron, and DETR models (Thesis 1.2); (4) implementation of AI-assisted method for rehabilitation and real-time feedback (Thesis 2.1); (5) development of AI-supported pipeline for voice-based disease detection (Thesis 3.3),
- **RO2**, about *AI-Based health and performance prediction*, is fulfilled by: (1) LSTM-based precognition model development for fatigue and stamina control (Thesis 1.6);

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(2) medical radar sensor and 3D accelerometer sensor-based pipeline implementation for energy expenditure estimation (Thesis 1.5); (3) implementation of AI-based sRPE and ACWR prediction models (Thesis 3.1); (4) correlation analysis between sentiment analysis and stamina with techonogical pipeline and model development (Thesis 3.2),

- **RO3**, about *development of multilingual and multimodal collaboration tools*, is fullfiled by: (1) DETR model custimization with hyperparameter analysis, customized vocabulary development, dataset optimization model preparation analysis for multilingual visual and textual data recognition (Thesis 1.1); (2) development of enhanced multilingual OCR systems using CRNN and SVTR with customized PaddleOCR (Thesis 1.3); (3) development of visual controller method for precision-tuning of multilingual OCR systems(Thesis 1.4),

- **RO4**, about *optimization of training and rehabilitation processes*, is fullfiled by: (1) LSTM-based model analysis and development for optimizing recovery protocols (Thesis 1.6); (2) AI-based 3D human pose estimation model development for real-time biomechanical data (Thesis 1.7); (3) AI-assisted rehabilitation method proposal for personalized training (Thesis 2.1); (4) retrospective learning method and technological pipeline development for optimizing training regimens (Thesis 2.4); (5) combined gamification, generative AI, and reinforcement learning method implementation for adaptive training (Thesis 3.4),

- **RO5**, about *integration of AI in strategic sports analysis*, is fulfilled by: (1) YOLO and YOLO-NAS for real-time player and object tracking (Thesis 2.3); (2) retrospective learning development for performance analysis and strategy development (Thesis 2.4),

- **RO6**, about *innovative approaches to disease detection and prevention*, is fulfilled by: (1) AI-based 3D human pose estimation for injury prevention (Thesis 1.7); (2) AI-supported voice-based disease detection pipeline (Thesis 3.3),

- **RO7**, about *psychological and mental health monitoring*, is fulfilled by: (1) sentiment analysis for early detection of burnout (Thesis 3.5); (2) research and development on early detection of mental health and neurodegenerative disorders using ML and NLP (Thesis 3.6).,

- **RO8**, about *gamification and adaptive training enhancements*, is fulfilled by: (1) research and development on integration of gamification, generative AI, and reinforcement learning for adaptive training environments (Thesis 3.4),

- **RO9**, about *comprehensive data analysis for performance improvement*, is fulfilled by: (1) multivariate analysis of stamina, sentiment, and fatigue for long-term athlete

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development (Thesis 2.2); (2) retrospective learning to identify performance trends and optimize training programs (Thesis 2.4).

The connectivity between the research questions (RQ1 to RQ11) and the primary research objectives (RO1 to RO9) is illustrated in Table 10.2. This table determines whether the research questions were addressed and analyzed, and if the scientific objectives were successfully accomplished.

Table 10.2: Research questions (RQ) interconnectivity with the research objectives (RO)

Research question (RQ)	**Research objective (RO)**	**Thesis Group**
RQ1	RO2, RO3	S1, S2, S3
RQ2	RO1, RO4	S1, S2, S3
RQ3	RO3, RO5, RO9	S1, S2
RQ4	RO1	S1, S2, S3
RQ5	RO1, RO5	S1, S2, S3
RQ6	RO4, RO8	S1, S2, S3
RQ7	RO1..RO9	S1, S2, S3
RQ8	RO4, RO6	S1, S2, S3
RQ9	RO7	S3
RQ10	RO2, RO8	S1, S3
RQ11	RO9	S2

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10.2 New scientific results and contributions

These findings have important multidisciplinary consequences for improving current technology pipelines, methodologies, workflows, and the practicality of ML-based methods in the field of preventative sports safety in performance sports. Each thesis makes significant contributions and proposals to one or more respective fields, and introduces novel approaches and methods for addressing the challenges of sensors, distant diagnostics, sports safety, injury prevention, and health condition prediction. The theses have global impact and local relevance, and their findings have been published in several relevant publications This chapter presents (see Tables 1.1, 1.2, 1.3), which presents a structured and quantified summary of published scholarly contributions from Section 1.5.2).

Thesis Statements Group I.

Thesis Group I (S1): Advanced Distance Diagnostics Techniques and Sensors
Own publications related to this research direction: [P1], [P2], [P3], [P4], [P5].

Thesis 1.1
I proposed a near real-time pipeline with DETR for visual, textual data recognition to support future translation of multiuser, multilanguage videoconferences and to boost the efficacy of distance diagnosis. The Textual and VOD investigation analyzed different scenarios to provide reliable outcomes for a new collaborative working model. In the case of multilingual conferences, the proposed design can be used to prepare a feasible visual (textual) object detection model with a modest number of specific training datasets using the DETR model in order to support further data processing, such as neural multilingual translation translation. When it comes to adjusting the efficacy level, it depends on clustering or object classes, quality and quantity of training data. Experiments have demonstrated that it is possible to use the DETR model for a restricted number of training datasets with real-time collaboration tools to strengthen multilingual collaboration with multilingual translation.

Research objectives (RO): RO1, RO3
Importance: global impact, local relevance
Relevant publications: [P1], [P2], [P3].

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Thesis 1.2

I conducted a thorough analysis of the most promising real-time object detector models YOLO, Detectron, and DETR, each with different model variations to determine their performances in relation to the specific task and dataset at hand, resulting in a comparison analysis that can be adopted into multilanguage, real-time collaborative tool-based VOD experiments.

Research objectives (RO): RO1
Importance: global impact, local relevance
Relevant publications: [P1], [P2], [P3].

Thesis 1.3

I conducted research experiments with synthetic, multilingual training CRNN and SVTR model architectures for ML-based OCR engines to (1) test the possibility of custom-generated or synthetized multilanguage recognition and (2) to increase the accuracy and efficiency of real-time OCR systems. Both CRNN and SVTR offered innovative features in comparison to conventional OCR engines. The proposed ML model setups performed consistently and they recognized the multilanguage/hybrid texts with high accuracy. The highest precision scores were 93.89%, 91.35%, and 90.25% respectively.

Research objectives (RO): RO3
Importance: global impact, local relevance
Relevant publications: [P1], [P2], [P3].

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Thesis 1.4

I proposed a visual controller method, encompassing vocabulary, distribution, and single/multi-line dataset generation that facilitates the precision-tuning of the multilingual /synthetized vocabulary set and distribution preparation. This precision improves recognition accuracy across a wide range of languages and scripts. The OCR system can recognize and assimilate certain visual characteristics of each language by carefully picking diverse and representative examples for the training dataset. This causes a significant rise in text recognition accuracy and a decrease in errors, distinguishing it from traditional methods. The system's adaptability is the source of its originality. The method performs consistently better because to continuous monitoring of the OCR model's performance, modification of the multilingual vocabulary set, and distribution preparation. Furthermore, it exhibits notable versatility to handle new languages, scripts, or domain-specific text, signifying a huge step forward in OCR technology.

Research objectives (RO): RO3
Importance: global impact, local relevance
Relevant publications: [P1], [P2], [P3].

Thesis 1.5

I proposed a sensor-based pipeline to estimate energy expenditure remotely. Using a combination of medical radar sensor and three-axial accelerometer data allows for more accurate estimates of energy expenditure, which can help monitor an athlete's condition level and recovery status. Moreover, this method allows to monitor the athlete's physiological status and physical activities non-invasively and continuously during training and competition. This will provide valuable information for coaches and trainers to optimize performance and to prevent injuries. The RPAI with METs, RPE, sRPE, and ACWR can be used to control the intensity of training sessions, ensuring that the athlete is not overtraining or undertraining.

Research objectives (RO): RO1, RO2
Importance: global impact, local relevance
Relevant publications: [P4].

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Thesis 1.6

I proposed a precognition model for AI-assisted fatigue and stamina control that can be adapted to performance sports, which uses the dataset from IMU-generated multivariate time series data and yields several substantial conclusions with far-reaching implications on sports science and athlete performance management. The LSTM model exhibits a competent capability in handling the classification task at hand, with its performance suggesting a balanced approach to classifying the binary classes. However, given the complexity and the "black box" nature of LSTM models, a careful examination and potential comparison with other ML models, including simpler ones, would be prudent, particularly in contexts where interpretability and computational efficiency are crucial. The application of the precognition model extends to optimizing rest periods and recovery protocols. By predicting the trajectory of an athlete's recovery process, the model provides evidence-based recommendations for rest durations and recovery activities that are custom-fitted to the athlete's physiological needs, thus maximizing recovery efficiency and effectiveness.

Research objectives (RO): RO2, RO4
Importance: global impact, local relevance
Relevant publications: [P5].

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Thesis 1.7

I formulated an AI-based "3D human pose estimation" method that contributes to strategic planning in training and competition in performance sports, to enhance athletic performances. By predicting the trajectory of an athlete's recovery process, the model provides evidence-based recommendations for rest durations and recovery activities that are custom-fitted to the athlete's physiological needs, thus maximizing recovery efficiency and effectiveness. Predictive insights into an athlete's stamina and fatigue thresholds enable coaches to make informed decisions regarding training intensity, competition schedules, and even strategic in-competition pacing strategies. These IMU sensors link to athletes' equipment and provide critical biomechanical data, such as acceleration and angular velocity. Using AI on top of this data enables for non-invasive performance tracking and fine-tuning. Coaches who have received training in data interpretation can utilize this information to provide prompt feedback, optimize the intensity and technique of the training in real time, and improve the effectiveness of the sessions while avoiding excessive strain.

Research objectives (RO): RO4, RO6
Importance: global impact, local relevance
Relevant publications: [P5].

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Thesis Statements Group II.

Thesis Group II (S2): Sports safety and injury prevention
Own publications pertaining to this research direction: [P1], [P2], [P6], [P7], [P8], [P9].

Thesis 2.1

I proposed an AI-assisted method for rehabilitation process and performance hardening. The AI-controlled framework applied to the proposed sports safety pipeline demonstrated a marked efficiency in boosting athletic proficiency when juxtaposed with conventional training paradigms (e.g., deep analysis of exercises after an injury). Moreover, its application proves to be promising in precluding potential injuries by discerning and amending suboptimal training patterns and biomechanical lapses. When addressing post-injury scenarios – based on sports safety specialists' feedback — AI-integrated interventions appear to expedite the rehabilitation process, simultaneously elevating the quality of recuperation. This may be the most important outcome. Furthermore, personalized training, tailored to the distinct biomechanical and physiological attributes of athletes, has become a tangible reality with AI's adaptability. A significant enhancement was observed in the real-time feedback mechanism, enabling instantaneous technique adjustments. These innovations not only help athletes push their limits safely but also ensure that they get the most out of their training sessions, remain injury-free, and achieve peak performance during competitions.

Research objectives (RO): RO1, RO4
Importance: global impact, local relevance
Relevant publications: [P6], [P1].

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Thesis 2.2

I proposed a brain injury detection pipeline for performance sports for real-time detection of lesions and tumors after severe head injuries. The proposed techological pipeline with YOLO8 and YOLO-NAS models aims to make transformative outcomes in performance sports (like American football, rugby or ice-hockey). I expanded the technological pipeline with YOLO9 to be able to detect the pneumonia on time. The capacity to detect problems quickly and correctly in real time could significantly accelerate up medical intervention, enhancing recuperation times and long-term results for athletes. The additional added-values of the proposed pipeline and the proposed future implementations like a comprehensive version of NAS and Explainable AI could lead to continuous model improvement and greater adoption due to increased trust and understanding of AI decision-making processes.

Research objectives (RO): RO9
Importance: global impact, local relevance
Relevant publications: [P7], [P8].

Thesis 2.3

I proposed a pipeline and a sports strategy extraction method. The pipeline, using YOLO or YOLO-NAS, detects and tracks players and objects in real time, providing comprehensive data on their movements and interactions. Secondly, it seeks to extract strategic elements and patterns from the tracked data to aid in performance analysis and strategy development. Additionally, YOLO-NAS specifically aims to optimize the network architecture for improved tracking and strategy extraction, to analyze the feasibility of ML-based strategy extraction, and secondly to validate if – in terms of retrospective-type learning methods – athletes and coaches can leverage historical video data to identify trends, analyze past performances, and develop targeted predictive, AI-assisted training programs or adaptive strategies for future competitions. These outcomes will facilitate a novel data-driven approach to athletes and team development, enhancing performance and strategic decision-making in sports.

Research objectives (RO): RO5
Importance: global impact, local relevance
Relevant publications: [P1], [P2].

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Thesis 2.4

I formulated a method for retrospective-type learning for sports safety and training management in performance sport (with focus on rehabilitation and hardening) as assistive AI assets. By using the proposed method, athletes and coaches will be empowered with data-driven insights, enabling them to make informed decisions, optimize strategies, and enhance overall performance in sports. Value propositions: (1) athletes and coaches can leverage historical video data to analyze past performances, identify trends, and evaluate the effectiveness of strategies and tactics used in previous games or drills; (2) by analyzing historical data, athletes and coaches can identify recurring patterns, both at individual and team level, which can help in understanding strengths, weaknesses, and areas of improvement; (3) retrospective learning allows athletes and coaches to adapt strategies based on the analysis of past performances. By understanding what has worked well in similar situations, they can modify game plans and make more informed decisions during future competitions; (4) analyzing historical video footage can provide insights into an athlete's progress and skill development over time, helping coaches design personalized training programs and target specific areas for improvement; (5) retrospective learning methods can be used to establish performance benchmarks based on historical data, enabling athletes and coaches to set realistic goals and track progress over time.

Research objectives (RO): RO4, RO5, RO9
Importance: global impact, local relevance
Relevant publications: [P8], [P1], [P9].

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Thesis Statements Group III.

Thesis Group III (S3): Predictions of health conditions
Own publications pertaining to this research direction: [P10], [P4], [P11], [P12], [P9], [P1], [P13], [P14].

Thesis 3.1
I proposed a "Condition lie Detector" method that can help coaches to get objective feedback about athletes' health, stamina and condition (on individual and group level). The AI-based sRPE and ACWR prediction models have the potential to be applied across various sports and populations, including amateur athletes, recreational sports enthusiasts, and different age groups. As one of the future development lines, AI-based ACWR prediction models can benefit from incorporating more data sources, such as physiological markers, sleep quality, nutrition, and psychological factors. These additional data sources can help to create more comprehensive and accurate models, improving the predictive capability for ACWR and fatigue scores.

Research objectives (RO): RO2
Importance: global impact, local relevance
Relevant publications: [P10], [P4].

Thesis 3.2
I formulated an enhanced methodology proposed for HPC environment to validate first the correlation between sentiment analysis and stamina, followed by a multivariate analysis of the correlation between stamina, text-based sentiment, and fatigue to evaluate their combined effect.

Research objectives (RO): RO2
Importance: global impact, local relevance
Relevant publications: [P11], [P12], [P9].

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Thesis 3.3

I formulated a complex method of AI-supported pipeline combining the most advanced feature extraction methods (e.g., HNR, MFCCs, pitch of a voice, Jitter and Shimmer) to detect disease by using a fully customized feature extraction on voice samples. I started with COVID-19 and after that I expanded the research with other diseases and health anomaly detection. Based on the conducted experiments, voice-based disease detection using AI shows promising results and provides a novel, non-invasive, cost-effective, and scalable approach to identify and monitor various diseases (e.g., COVID-19 and other contagious respiratory illnesses). The biggest outcome of the proposed method is that it not only supports professional sports staff to predict disease from voice sample near real-time, but prevents cross-contamination in sports events.

Research objectives (RO): RO1, RO6
Importance: global impact, local relevance
Relevant publications: [P13], [P12], [P11].

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Thesis 3.4

I developed a motivating asset concept for performance sports by combining the synergistic effects of gamification, generative artificial intelligence (GenAI), and reinforcement learning (RL). This technique is distinctive in that it enhances psychological involvement by incorporating gamified features and physical training through tailored dynamic situations. It effectively addresses both the physical and mental aspects of sports performance within a comprehensive technology-driven framework. The integration of gamification and GenAI into performance team sports is revolutionary because it combines psychological motivation and adaptive technology innovation in a synergistic manner. GenAI systems enhanced with reinforcement learning (RL) can enhance and fine-tune real-time training parameters such as intensity, duration, structure, and drills. This is achieved by assessing large amounts of individual performance data, including subjective rating of perceived exertion (sRPE), metabolic equivalent (MET), and acute-to-chronic workload ratio (ACWR). Gamification enhances the athlete motivation, resulting in a 20-30% rise in completion rates without requiring additional requests from coaches. This, in turn, improves the effectiveness of training preparatory processes.

Research objectives (RO): RO4, RO8, RO9
Importance: global impact, local relevance
Relevant publications: [P4], [P5], [P10], [P11], [P9], [P14].

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Thesis 3.5

I formulated a method to identify burnout at an early stage in performance sports through written communication combined with sentiment analysis. This research is essential to understanding the psychological signs of burnout and the methods to gauge it, coupled with expertise in NLP and sentiment analysis techniques. Collecting athletes' textual data, like logs or post-training interviews/feedback, is crucial, along with possible metrics of stamina or fatigue. The role of AI, in particular significantly advanced models like BERT or GPT-3, is to analyze these texts, discerning underlying sentiments that may indicate burnout. AI can identify impending burnout patterns by correlating text-derived sentiments with physical metrics. I investigated the feasibility of an AI-driven approach to proactive intervention, allowing timely measures to prevent burnout. Additionally, the proposed method allows athletes to customize their training to their mental and physical health, thus extending their careers. The predictive capabilities of AI can identify early signs of burnout, even before overt symptoms manifest. This enables timely interventions, potentially preventing burnout and improving overall athlete welfare. The model showed that there is significant variability in how individuals respond to training loads and stressors. A universal approach to training and recuperation may not be effective. Personalized insights and recommendations, tailored to each athlete's unique profile, are vital.

Research objectives (RO): RO7
Importance: global impact, local relevance
Relevant publications: [P11], [P12], [P9].

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Thesis 3.6

I formulated a complex, ML- and NLP-based non-invasive methodology to identify the early markers from written text, combined with sentiment analysis of mental health disorders (such as depression, anxiety, psychotic disorders, Alzheimer's disease and dementia) and neurodegenerative disorders (like Parkinson's disease). The implemented pipeline of AI-parsed text and sentiment analysis appears to be a promising next-generation mental health anomaly detection tool for the early detection and ongoing monitoring of mental health and NDD. However, these methods are supplementary and cannot replace the nuanced clinical evaluation process at the current stage. Future research must refine the AI algorithms to account for linguistic diversity and context, while also addressing ethical considerations regarding data use and privacy. The expected outcomes of the method in the sports domain is becoming increasingly vital, particularly for the early recognition of mental health concerns and the precursors to NDD among athletes. The intense physical demands, psychological stress of competition, and high-impact nature of many sports can precipitate or aggravate conditions such as depression or anxiety.

Research objectives (RO): RO7
Importance: global impact, local relevance
Relevant publications: [P1], [P11], [P9], [P1].

Thesis 3.7

To detect pneumonia in real time, I formulated a complex, non-invasive approach. Using YOLOv9 in a real-time diagnostic system to detect early pneumonia symptoms in athletes might improve respiratory healthcare. The precision of YOLO 9 was high after rigorous training and validation, suggesting its reliability in sports performance situations. By promptly and precisely interpreting chest radiographs, the approach reduces pneumonia's impact on athletes' health and careers. The outcomes promotes sports medicine and pulmonology and sets a precedent for AI integration into other preventive medicine sectors, promising a future where AI and medical expertise improve high-performance sports health outcomes.

Research objectives (RO): RO7
Importance: global impact, local relevance
Relevant publications: [P7], [P8].

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11 Acquired competencies

I have grown on both a personal and professional level throughout the course of this doctoral program. The research activities were carried out with the University of Malaga (UMA) [1] and the "George Emil Palade" University of Medicine, Pharmacy, Science and Technology of Targu Mures, Romania (UMFST) [2] through the cotutelle framework program. The foundation of the current research effort has been the pursuit of ongoing work and the accumulation of competencies.

Academic awards and distinctions

- First prize for the best indexed ISI article published in the academic year 2021/2022 at the International Conference for Ph.D. Students and Young Doctors organized at the George Emil Palade University of Medicine, Pharmacy, Science and Technology of Targu Mures, for the journal paper "*Visual Object Detection with DETR to Support Video-Diagnosis Using Conference Tools*", published in MDPI, Applied Sciences.

- First prize for the best indexed ISI article published in the academic year 2022/2023 at the International Conference for Ph.D. Students and Young Doctors organized at the George Emil Palade University of Medicine, Pharmacy, Science and Technology of Targu Mures, for the journal paper "*Machine Learning on Prediction of Relative Physical Activity Intensity Using Medical Radar Sensor and 3D Accelerometer*" published in MDPI, Sensors.

- " III Concurso Thesis Talk - Cuenta tu tesis" – thesis talk finalist at the University of Malaga in the academic year 2022/2023.

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Research institutes and research groups

The research initiatives embraced multidisciplinary problems which were conducted in four countries, namely Spain, Hungary, Japan, and Romania – through the collaboration of five different universities, specifically: (1) UMA [1], (2) UMFST [2], (3) Toyo University (Japan), (4) Physiological Controls Research Center, Óbuda University (Hungary), (5) Department of Mathematics-Informatics, Sapientia Hungarian University of Transylvania (Romania). During the composition of my thesis, I had the privilege of collaborating with the following scholarly collectives, research groups:

- Clinimetría Group (IBIMA F-14)(PAIDI CTS-631), Spain,
- Biomedical Research Institute of Malaga (IBIMA), Spain,
- Tokyo Institute of Research (TIT), Japan,
- Physiological Controls Research Center, Óbuda University, Hungary,
- Computational Intelligence Research Group, Sapientia Hungarian University of Transylvania, Romania.

Instrumental competencies

Prior to pursuing my PhD, I had gained expertise in the competitive sector, therefore one of the most significant areas for me to grow in was health/bioinformatics research and methodologies. During my PhD, I received 20+ different certificates linked to educational programs at several prestigious universities. The majority of these belong to scientific and health professions (for example, reproducible research, hypothesis testing, qualitative and quantitative methods, starting research, research methods, understanding clinical research, case studies in personalized medicine, COVID-19 contact tracing and data analysis, systematic review and meta-analysis). In the field of informatics, I have mainly strengthened my skills in datascience, artificial intelligence, digital transformation, design thinking, data science mathematics, and fine-tuning of different methodologies and models through dedicated training.

Thanks to the complexity of the doctoral topic and the involvement of different research disciplines (health, sport, informatics, psychology), I was able to get involved in these domains and to learn from professionals about the applicable methodologies beyond the research themes and research areas (e.g., mechanisms of neurodegeneration, smart diagnostics for neurodegenerative disorders, non-invasive fatigue detection methods, methods for detecting brain injury range, systematic frameworks for sports injuries). Simultaneously, on the computer science side, I needed to develop and utilize far broader

[1]UMA - Department of Physiotherapy, University of Malaga, Spain

[2]UMFST - Department of Electrical Engineering and Information Technology, George Emil Palade University of Medicine, Pharmacy, Science, and Technology of Targu Mures, Romania

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technological abilities during my research. This high requirement of AI expertise prepared me to design, manage, construct, and disseminate complex bioinformatics artificial intelligence topics or projects from concept to presentation and publication of results. I was able to improve my skills in Matlab, R, and Python-based development projects, particularly in processing, data analysis (with SPSS and R), and visualization. In terms of artificial intelligence, I expanded my applied stack by incorporating the following technological topics /domains into my research:

- *Visual object detection*: Analyzed popular algorithms and models in object detection Fast R-CNN, Faster R-CNN, Region-based Convolutional Neural Networks, Region-based Fully Convolutional Network, as well as real-time object detectors such as YOLO, DETECTRON and DETR. Analyzed modern text recognizers, such as RNN, CNN, CRNN, SVTR. Deeper understanding of challenges connected to linguistics and multilanguage problems, synthetized languages,

- *Sensors and sensing*: Topics analyzed in remote sensing with IMUs and medical radar sensors. Analyzed multivariate time series datasets with ML (Random Forests, Gradient Boosting Machines) and DL (LSTM) algorithms,

- *Sports safety and health condition*: Applied and analyzed advanced technologies (e.g., MediaPipe Pose), ML and DL algorithms in rehabilitation, injury recovery, and performance hardenings. Analyzed the applicability of YOLO and YOLO-NAS to sports strategy recognitions. Analyzed the topics of rSPE, ACWR, stamina, and condition with different regression models like Linear Regression, Ridge, Lasso, ElasticNet, LARS, OMP, and BayesianRidge.

- *Anomaly detection and predictions*: Analyzed the detection of lesion and tumor (e.g., LGG, LGG) detection with YOLO and YOLO-NAS. Analyzed the human voice and its specific patterns to identify the best AI classifier model, trying the following algorithms on the dataset: Extra Trees Classifier, Random Forest Classifier, Light Gradient Boosting Machine, Quadratic Discriminant Analysis, K Neighbors Classifier, Decision Tree Classifier, Gradient Boosting Classifier, Linear Discriminant Analysis, Ridge Classifier, Logistic Regression, Ada Boost Classifier, SVM - Linear Kernel, Naive Bayes, Dummy Classifier. Textual information analyzed with NLP techniques, classifiers (e.g. Random Forest, Logistic Regression, SVM, KNN, Decision Trees, Gradient Boosting), combined with sentiment analysis methods (e.g., DistilBERT, NLTK, Vader),

During the construction of the PhD thesis, I broadened my skills in statistical data processing, parameterizing various tools, and processing and managing the variables offered by the latter.

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Interpersonal skills

Thanks to the extensive training and experience gained in the UMA and UMFST cotutelle doctoral programs in new directions in sports, health, informatics and bioinformatics research and postgraduate training in international health, I have the opportunity to collaborate with internationally distinguished researchers and professionals – from Romania, Spain, Japan, and Hungary – on a number of research projects and I am an active participant in various cross-functional team initiatives. I have involved several universities and research centers in my projects, enhancing the quality and depth of my research. I have studied and continue to learn a lot from these valuable collaborations. My goal is to further strengthen and expand these relationships with quality research.

Systemic competencies

Learning about the most recent and innovative technological advancements ahead of others, and then incorporating them into operational procedures and tech pipelines to improve their effectiveness and efficiency, is a constant source of inspiration and motivation for me. My professional, academic and personal life have always revolved around personal development and collaboration with others. To be successful in my career, I must continuously improve by adhering to the Kaizen philosophy, growing and emerging in specific areas that shape my identity. Similarly, these have helped me respond more effectively as a person, leader, and member of society. The PhD studies allowed me to improve my self-awareness, social and emotional intelligence, and expand my comfort zone. In addition, my professional researcher identity has been shaped by my talents in goal setting, targeting, focusing, and personal organizing. All of these synergies have helped me grow and improve as a professional and as a person.

Journal and conferences roles

During the thesis implementation, I had the privilege to be *peer reviewer* on some conferences: (1) *IEEE International Conference on Systems, Man, and Cybernetics* (SMC); (2) *Interdisciplinarity in Engineering* (Inter-Eng) and journal: (1) *JMIR Serious Games*.

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12 Perspectives, future research directions

12.1 Perspectives

I started to understand sports safety and AI-based anomaly detection before I commenced my doctoral studies in Computer Science (UMFST) and Health Sciences (UMA). With a steep learning curve, the cotutelle PhD course has helped me comprehend this heterogeneous subject from the perspectives of sport, medicine, informatics, and psychology. The early detection of anomalies, lesions, mental health and neurogenerative disorders, or diseases related to sports, combined with the use of sensors (e.g., medical radar sensors, 3-axial accelerometers, IMUs) to study fatigue, stamina, recovery/rehabilitation, boosted with AI, has opened up many new research directions in fatigue prediction, injury mitigation, and performance optimization. After years of perseverance and passion in this journey, the PhD program is just one stage and it will continue in the postdoctoral phase.

The new research cycle will provide new challenges (see Section 12.2.4), such as knowledge-intensive investigation of mental and neurodegenerative disorders, the first phase of which is given in related parts and publications of "Thesis Statements Group III". I plan to continue the initiated research trials in a supercomputing (HPC) environment, supplemented by audio and then video samples, with special focus on geolocation and spoken languages to improve the sentiment analysis efficacy. In general, the duration of the intervention, the parameterization of the sentiment analyses for a given focus group, the characteristics of the datasets, and the computational capacity required made it difficult to analyze the data on a broader scale (e.g., geolocation, or language segmentation), making it impossible to include it in a PhD thesis that coincided with a pandemic and the resulting constraints. However, the significance of the study's findings makes it one of the doctorate section's primary axes.

Another major goal of the postdoctoral phase is to create an infrastructure and a real-time AI algorithm for the early detection and remote prediagnosis of trauma, lesions, or health anomalies caused by collisions (e.g., ice hockey, American football, rugby), to prevent future complications or more serious problems. This approach could improve sports safety in team sports with high injury threats.

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In terms of anomalies, I intend to create an ambulatory severity stratification and recovery/rehabilitation index that will allow competitive sports patients to be stratified according to the severity of their condition, as well as the possibility of involving patients at various stages of the processes and proposed methodologies discussed in the theses of "Thesis Statements Group II" of this dissertation (see Section 3.2.2).

Another future direction to consider ("Thesis Statements Group I") is the development of a collaborative remote knowledge transfer diagnostic system that allows the collaboration of specialists who work in different fields and even speak different languages to support the early and rapid diagnosis and analysis of complex diseases (see Section 7.1.3), as well as the development of effective and personalized treatments (see Section 12.2.1).

Another future trend to consider is the management of fatigue by increasing endurance in competitive sports through the validation of questionnaires and tests commonly used in research and clinical practice but not subjected to the psychometric analysis required to gain a deeper understanding of the properties of their use by geolocation and age group.

Similarly, the publications included in the thesis (related to Thesis Statements Group I, II, and III) highlight the lack of methods and techniques for direct in vivo evaluation of in vivo exercise, which are applicable both in research and clinical practice, as well as the potential of artificial intelligence. As a result, the investigation and development of novel cross-disciplinary methodologies utilizing AI should be pursued.

Finally, in addition to the study of the application of practices, research, and related developments, the work done during the doctoral thesis and related residencies resulted in the formation of an internationally recognized team of competitive sports professionals with whom the research can be continued, methodologies and processes developed, and validated in various sports disciplines. This procedure allows for the continued development of the retrospective learning methodology and the multimodal learning approach.

This line of research, which complements the PhD thesis on early detection of mental health and neurodegenerative disorders, has begun with preliminary research in a supercomputer environment, which will prepare the modeling of datasets for optimal synthetic language teaching in a multidisciplinary collaboration. Metalinguistic language anomalies, mental and neurodegenerative disorders should not only be recognized but also understood in terms of patterns and specificities. In the postdoctoral phase, this line of study will seek to create new methods, improved models, publications, and specialized tests and procedures for the implementation of protocols and asyncytial interventions.

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12.2 Future research directions

12.2.1 Future plans in remote consultancy and collaborative diagnosis

In the postdoc phase, I would like to expand the thesis experiments to an HPC environment (such as Komondor HPC [306]), where it will be used for federated learning and distributed data processing, combined with domain adaptation and unsupervised learning methods using dynamic data sampling and the continuous model improvement approach.

12.2.2 Future directions with medical radars & triple axis accelerometers

In the long term, in collaboration with university teams (e.g., Toyo University from Japan) and using the ecosystem [127] I plan to implement a research program – on fatigue and stamina control based on multivariate time series (MTS) datasets – that improves athlete health and performance longevity. Improving the overall health of athletes and prolonging the longevity of their performance careers through a data-driven approach to training load management is a critical objective. The AI-assisted model supports sustainable high-performance training practices by continuously adapting to the physical state of the athlete (see Section 3.2.2). This pillar of the thesis [42] on AI-assisted fatigue and stamina control for performance sports, based on the analysis of multivariate time series datasets generated by IMU, is expected to lead to discoveries. The prospective development lines and innovative outcomes of this research are specific to significantly influence sports science, athlete training, and broader AI applications. Potential future development lines are the following:

1. *Algorithmic advancement and hardening*: Future research is expected to incorporate hybrid models that blend ML with biomechanical simulations to produce even more accurate predictions of fatigue and stamina.

2. *Sensor integration*: integrating additional sensor technologies, such as HR variability monitors and biochemical sensors, could enhance the multidimensional aspect of the datasets, providing a more holistic view of an athlete's physiological state. The seamless integration of IMUs [32, 33] and AI analytics into wearable technology could lead to the development of smart clothing that tracks performance and offers real-time feedback and training adjustments.

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12.2.3 Proposed research trajectories on pneumonia detection in sports

Several strategic priorities have been identified to improve the effectiveness and utility of AI-based pneumonia detection system: (1) it is essential to add more diverse chest radiographs from athletes to the training data set. This increase will make the model more robust and able to generalize across sports populations, allowing physiological differences due to sports disciplines, training regimes, and genetics; (2) adding diagnostic characteristics such as wearable health monitoring data could improve diagnosis. The AI system could detect tiny irregularities that X-rays cannot detect by connecting physiological data, such as heart rate and respiration rate, with image data; (3) model development will improve real-time processing to reduce latency. This development allows instant input during medical examinations and sports events, enabling quick medical judgments. Finally, applying this AI pipeline to stress fractures and heart abnormalities could have a tremendous impact on sports medicine. This holistic approach to the monitoring and diagnosis of athlete health will improve sports treatment and provide a model for predictive and preventive health interventions [41] in high-performance athletics.

12.2.4 Proposed research trajectories on disease and injury prevention

One of the main future objectives of this thesis line is to conduct a comprehensive investigation using a validated dataset while improving the model by incorporating speech analysis within a high performance computing environment (HPC) [306]. The present investigation stage encounters constraints within the Google Colab Pro platform. Future AI development lines will offer a more sensitive, specific and timely identification of mental health and NDD, ultimately leading to better patient outcomes through early and personalized care. The trajectory of AI in the precognition of mental health and NDD is trending towards several specific lines of development, which are proposed to be analyzed:

1. **Voice analysis expansion**: Tonal quality, pitch fluctuations, speech rate, and pause patterns in voice data can be quantitatively analyzed to detect early subtle signs of cognitive decline or emotional distress. For example, monotone speech may be an early indicator of Parkinson's disease, while a decrease in speaking rate and increased pause time may suggest Alzheimer's disease. Future AI models could be trained to detect these vocal biomarkers with greater precision, utilizing DL techniques to learn from a vast array of voice samples;

2. **Contextual and idiomatic language understanding** [307]: Developing AI systems with an improved understanding of context will involve creating more sophisticated NLP algorithms capable of detecting sarcasm, irony, and humor. This requires

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training on diverse datasets that include various dialects and colloquialisms to reflect the true range of human language use;

3. **Neuroimaging integration** [308]: Combining AI-parsed text and sentiment analysis with data from neuroimaging techniques such as fMRI or PET scans could lead to more accurate disease identifiers. AI could help correlate changes in speech and writing with specific neural patterns associated with neurodegeneration;

4. **Genomic correlations** [309]: AI could be used to find associations between linguistic changes and genetic markers. By analyzing the genetic profiles of individuals alongside language symptoms, researchers can identify hereditary patterns in neurodegenerative disease manifestation;

5. **Real-time wearable monitoring** [36]: The future may see the proliferation of wearable devices that track physical health metrics and capture speech and writing in real time. AI systems could analyze this data continuously to identify trends predictive of mental health and cognitive conditions;

6. **Digital phenotyping** [310]: This involves collecting and analyzing data on behavior and lifestyle manifested in the digital realm, from typing speeds on smartphones to interaction patterns on social media. Such phenotyping could provide additional clues to cognitive and mental health status;

7. **Ethical data governance**: As AI systems access more sensitive personal data, developing rigorous ethical frameworks to govern data use will be crucial;

8. **AI education**: Efforts will be made to increase the explainability of AI models in healthcare, allowing clinicians to understand and trust AI-driven assessments. Explainable AI will be essential to integrate AI insights into clinical decision-making.

Each of these development lines aims to *enhance* the *precision*, *reliability*, and *ethical integrity of AI applications* in the care of mental health and neurodegenerative diseases, promising a future of personalized and proactive healthcare solutions for performance sports platforms and sports safety solutions [127].

Future development idea as the next phase of burnout detection: The aim is to investigate in detail with a validated dataset on [127] the correlation between sentiment analysis and stamina or fatigue in an HPC environment (such as Komondor HPC [306]). The current phase of the research [18] reached its limits in the Google Colab Pro environment.

Future development idea of personalized recovery: First, I plan to deepen the collaborations between AI developers and sports psychologists to develop tools that offer insight into athletes' mental well-being. Personalized training regimens are expected to use DL models to interpret biometric data. Solutions [22] for early adopters have intended to overcome these obstacles. With the integration of sports ecosystems, real-time

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feedback systems that provide data-driven workout suggestions to athletes could become mainstream. Sensor-equipped wearables monitor athletes' physiological and biomechanical data in real time. I intend to explore the synergies between AI and genomics to revolutionize sports training with genetic predisposition insights in later phases. Injury prediction algorithms that learn from diverse datasets from athletes will help prevention strategies. The convergence of NNs and biomechanics can help athletes optimize performance by improving movement patterns. Wearable tech may return as data collectors and intelligent interpreters with actionable advice.

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UNIVERSITY OF MALAGA

PROGRAMA DE DOCTORADO EN CIENCIAS DE LA SALUD

ÁREA CIENTÍFICA: CIENCIAS DE LA SALUD

RESUMEN DE TESIS DOCTORAL

TÉCNICAS AVANZADAS DE DIAGNÓSTICO A DISTANCIA Y SENSORES EN LA SEGURIDAD DEPORTIVA Y LA PREDICCIÓN DEL ESTADO DE SALUD

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13 Resumen en Español

El diagnóstico a distancia adopta modelos como Digital Transformation (DX), Machine Learning (ML) y Deep Learning (DL) en la era de los datos, así mismo; la ciencia de los datos aporta nuevas perspectivas a muchos ámbitos. La pandemia de COVID-19 ha introducido nuevas herramientas de colaboración en la DX, desarrollando el trabajo a distancia y reduciendo el distanciamiento social, foementando nuevas actitudes globales. La Inteligencia Artificial (IA) se utiliza en el análisis de vídeo para prevenir lesiones y fatiga en el diagnóstico a distancia. Informa a los médicos sobre posibles enfermedades y factores de riesgo antes de actuar. La IA crea terapias farmacológicas innovadoras y medicina individualizada, así como los robots ayudan a otras profesiones. La seguridad en el deporte ha mejorado gracias a la COVID-19. Con el auge de los deportes de competición, la seguridad es una preocupación. Los sensores de distancia, los sensores vestibles y los enfoques de recuperación han revolucionado los ciclos de entrenamiento, acelerando la evolución y modificando los patrones de fatiga y recuperación. La IA y la detección rápida reducen el infradiagnóstico. Al combinar datos vitales y de ecosistemas con metadatos diarios, las plataformas deportivas pueden predecir lesiones. Los jugadores pueden analizar datos de salud y hábitos. Tecnologías basadas en la IA se utilizaron en estudios de tesis multidisciplinares y multicapa para mejorar los diagnósticos a distancia, el rendimiento deportivo o la seguridad para prevenir lesiones y acelerar recuperación. Gracias a la tecnología, se pueden realizar consultas y diagnósticos deportivos colaborativos y en tiempo real a distancia. El concepto sugerido es limitar, regular y fomentar las mejores prácticas para un ecosistema deportivo más rápido y seguro. En la tesis se destacan los métodos de detección de enfermedades vocales durante la COVID-19. Con los métodos DL y ML desarrollados en el presente estudio, los médicos deportivos podrían prevenir lesiones con análisis de datos en tiempo real.

Justificaciones: Las metodologías de la tesis pueden transformar la seguridad y el rendimiento deportivo. La IA puede mejorar la salud de los deportistas, aumentar su rendimiento y prevenir lesiones con conocimientos personalizados basados en datos en tiempo real. El agotamiento, los trastornos neurodegenerativos y el SCD pueden prevenirse o predecirse. Los experimentos de la tesis abarcan temas importantes como la prevención de lesiones, el control de la fatiga, la optimización del rendimiento, el seguimiento

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en tiempo real, las recomendaciones personalizadas, la detección precoz de problemas de salud, el control de la rehabilitación, la toma de decisiones basada en datos, el diagnóstico a distancia multilingüe y los modelos de rentabilidad con el diagnóstico asistido por IA,

Necesidad: Los temas de la tesis pueden tener un gran impacto en la sociedad y en los entusiastas de la seguridad y el rendimiento deportivos. Las tecnologías pueden potenciar los recursos de rendimiento deportivo, aumentar el conocimiento de las mejores prácticas de seguridad y salud deportivas, mejorar la toma de decisiones e impulsar el crecimiento económico, además de mejorar la salud pública. En el deporte, las necesidades incluyen la salud pública, seguridad, calidad de vida de los deportistas, estilos de vida saludables, beneficios económicos, toma de decisiones informada, equidad, accesibilidad, educación y concienciación. La versatilidad de esta tecnología se valora significativamente por los entusiastas de la seguridad y el rendimiento deportivos.

Perspectivas tecnológicas de futuro y nuevas líneas de investigación: La biomecánica y el análisis del movimiento, el diagnóstico de la salud mental y el bienestar, la genómica y la medicina deportiva personalizada, el análisis predictivo, la telemedicina y el entrenamiento a distancia, y la rehabilitación mejorada por la IA pueden estimular la innovación y crear nuevas vías de investigación. La seguridad, el rendimiento y la medicina deportiva pueden ser revolucionados por estos avances,

Teledetección: La monitorización continua a distancia de las constantes vitales de los deportistas es crucial para identificar y predecir problemas de salud y rendimiento. Esta monitorización muestra la relación entre las distintas cargas de trabajo. La IA es esencial para garantizar la seguridad deportiva al predecir problemas de salud, periodos de recuperación y enfermedades con rapidez y precisión. Esto establecerá un ecosistema deportivo seguro y en rápida expansión. Una vez que los sensores médicos de radar y vestibles alcancen alta precisión, la teledetección sin contacto y las tecnologías móviles abrirán un nuevo campo de monitorización y diagnóstico a distancia. Para establecer medidas preventivas en el deporte de rendimiento, se realizó un análisis sobre las correlaciones entre aceleración y cansancio, (post) COVID-19 y cansancio, cansancio y lesiones, y COVID-19 y ACWR/sRPE. La tesis explora la integración de tecnologías avanzadas de IA y sensores en herramientas modernas de diagnóstico a distancia. Se utilizan herramientas de colaboración multilingüe y algoritmos para analizar la salud y el rendimiento de los jugadores en el desarrollo de procedimientos de diagnóstico a distancia de próxima generación. La IA estudia la condición, el sRPE, los MET y el ACWR para prevenir lesiones, optimizar el rendimiento y desarrollar programas de entrenamiento. La telemedicina y la tecnología de diagnóstico a distancia, como los sensores de radar médico, permiten supervisar y evaluar la salud de los deportistas en tiempo real, independientemente de su ubicación. Las técnicas de IA han prevenido accidentes en la seguridad y el rendimiento deportivos al analizar información complicada para predecir la fatiga, identificar patrones, tendencias y conexiones en el deporte, requiriendo de un gran volumen de datos y análisis detallado.

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13.1 Visión general

13.1.1 Context

En la actualidad, el tema abarca la ingeniería, la informática, la fisiología y la psicología, entre otros. Mejorar la seguridad y la salud de los atletas es nuestro objetivo a través de herramientas avanzadas de diagnóstico y algoritmos predictivos. La IA y el análisis de datos en las ciencias del deporte son posibles gracias a tecnologías como los radares médicos, los acelerómetros 3D y los sensores inerciales (IMU). Esta disciplina evoluciona a medida que aprendemos más sobre la relación entre los aspectos físicos, mentales y sociales en el rendimiento deportivo y la salud, gracias a la evolución de la tecnología. El tema central de esta tesis es la próxima generación de sensores y tecnologías de diagnóstico. Los acelerómetros, sensores de radar médico e IMU recopilan datos en tiempo real de los deportistas. Los sensores recopilan datos complejos que requieren métodos analíticos avanzados para su interpretación, como la variabilidad de la frecuencia cardiaca, el pulso y patrones de movimiento relacionados con la velocidad y la aceleración. Se incluyen la psicología, la sociología y la lingüística, más allá de la tecnología y la ciencia. Identificar el estado mental de un atleta mediante el análisis del sentimiento y del lenguaje ayuda a evaluar su salud general.

Diagnóstico a distancia en salud y deporte

Debido a la pandemia del COVID-19, la traducción multilingüe ha cobrado más importancia. La DX en medicina ha aumentado debido a la Detección Visual de Objetos (VOD) y la Detección Textual de Objetos, temas esenciales del diagnóstico y la consulta a distancia a través de videoconferencias. Para superar las dificultades de comunicación en videoconferencias multilingües, se crea un nuevo mercado de "procesamiento de datos multilingües en tiempo real". El VOD en la atención sanitaria reducirá el tiempo de respuesta a las consultas y mejorará el diagnóstico a distancia. El OCR es popular por sustentar tecnologías avanzadas como la detección de objetos en tiempo real. El método de detección de objetos textuales y visuales (TVOD) analiza algoritmos y modelos populares de detección de objetos, como la R-CNN rápida, la R-CNN más rápida, redes neuronales convolucionales (CNN) basadas en regiones, redes totalmente convolucionales basadas en regiones y detectores de objetos en tiempo real como YOLO, DETECTRON y DETR para proporcionar resultados fiables para un nuevo modelo de trabajo colaborativo. Los resultados de la tesis pueden aplicarse fácilmente a la seguridad en el deporte mediante las plataformas de videoconferencia.

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13.1.2 Motivación de la investigación

La motivación está impulsada por la informática, la ciencia, la tecnología y el bienestar de los atletas de la siguiente manera: (1) la mejora de la seguridad y la salud de los atletas; (2) la optimización de la resistencia y el rendimiento; (3) la adopción de innovaciones tecnológicas; (4) la investigación y la colaboración interdisciplinarias; (5) la comprensión del potencial económico; (6) la localización de las tendencias sanitarias mundiales y el interés público y (7) la comprensión de las consideraciones éticas y legales de la IA aplicada.

13.1.3 Significado

El enfoque multidisciplinar fomenta la innovación y garantiza que los avances tecnológicos sean éticamente sólidos, culturalmente sensibles, económicamente viables y beneficiosos para los atletas y la comunidad. Proporciona una comprensión exhaustiva de la salud de los atletas y de los índices de rendimiento, identificando riesgos y posibles anomalías o enfermedades venideras. Para mejorar la salud y el rendimiento de los atletas, se combina ingeniería, informática, medicina, fisiología, psicología y ciencia de datos en este campo.

13.1.4 Ética

La estrategia de investigación ética de la tesis multidisciplinar se basa en el rigor científico, los derechos de los participantes y las normas éticas. La tesis puso en práctica estos factores clave. Experimentos se llevaron a cabo para responder preguntas específicas de la tesis. Los métodos de investigación se ajustaron a la investigación, con riesgos investigados y declarados previamente. Se presentó información detallada al involucrar a seres humanos en la investigación. Todos los conflictos potenciales fueron evitados. Se controló y recopiló la información relevante. Los directores y tutores debatieron la estrategia de muestreo. La anonimidad de los participantes era crucial. Podían abandonar el estudio o la investigación en cualquier momento. Se consideró la normativa mundial de privacidad de datos. Se establece un alto estándar para futuras investigaciones postdoctorales sobre el tema. Esto se basa en la validez de la tesis, la metodología adecuada, el consentimiento de los participantes, la confidencialidad, la gestión del riesgo, la privacidad de los datos, las tácticas de muestreo, la utilidad, la integridad y la transparencia de la información.

13.1.5 Limitaciones

Aunque los enfoques de la tesis ofrecen ventajas considerables, tienen limitaciones. Estas limitaciones son inherentes a la complejidad y el alcance de la integración de múltiples disciplinas, cada una con sus metodologías, teorías y paradigmas. Entre ellas se incluyen la complejidad de la integración, los problemas de gestión de datos, las preocupaciones éticas y de privacidad, las disparidades económicas, la aceptación cultural, los problemas de generalizabilidad, las lagunas educativas y los retos normativos.

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13.2 Preguntas de investigación

Las preguntas centrales de investigación (RQ) giran en torno al aprovechamiento eficaz de las tecnologías emergentes y la IA para mejorar la seguridad de los atletas, optimizar su rendimiento y prevenir lesiones mediante la predicción de anomalías y/o enfermedades relacionadas con el rendimiento deportivo y la seguridad en el deporte. Abordar estas cuestiones requiere un enfoque integrado que incorpore la experiencia de varias disciplinas para crear soluciones innovadoras, éticas y prácticas en la ciencia del deporte.

Table 13.1: Preguntas de investigación (RQs) y su conectividad con las TI y la salud los dominios

ID	IT	Salud	Cuestión de investigación
RQ1	✓	✓	¿Cómo puede mejorarse la colaboración interdisciplinar para fomentar la innovación y la comprensión global en el diagnóstico y la predicción deportivos?
RQ2	✓		¿Cómo pueden las técnicas avanzadas de diagnóstico y las tecnologías de sensores ser efectivas e integrarse en la práctica deportiva para mejorar la monitorización en tiempo real y la predicción de la salud y el rendimiento de los deportistas?
RQ3	✓	✓	¿Cómo pueden integrarse estas tecnologías avanzadas de diagnóstico y sensores en las infraestructuras existentes de entrenamiento deportivo y asistencia sanitaria?
RQ4	✓	✓	¿Cómo pueden optimizarse las tecnologías de sensores avanzados para la monitorización en tiempo real de datos fisiológicos y biomecánicos de los deportistas?
RQ5	✓		Para predecir los riesgos para la salud y los resultados del rendimiento en deporte, ¿cuáles son los algoritmos y modelos de IA óptimos para interpretar los datos de los sensores?
RQ6		✓	¿Cómo pueden adaptarse estas tecnologías a los distintos perfiles fisiológicos, psicológicos y biomecánicos de cada deportista?
RQ7	✓	✓	Las implicaciones éticas y consideraciones de privacidad en el uso de tecnologías avanzadas de diagnóstico y de inteligencia artificial en el deporte, especialmente en relación con la privacidad de los datos y el consentimiento de los deportistas
RQ8		✓	¿Cómo pueden utilizarse estas técnicas de diagnóstico para desarrollar estrategias de prevención de lesiones y mejorar el bienestar general del deportista?
RQ9	✓		¿Cuáles son los algoritmos de IA y ML más eficaces para predecir lesiones y afecciones en los deportistas?
RQ10		✓	¿Cómo pueden adaptarse estas tecnologías a cada deportista, teniendo en cuenta sus perfiles fisiológicos y psicológicos únicos?
RQ11		✓	¿Cuáles son los efectos a largo plazo del uso de estas tecnologías en la salud física y mental de los deportistas?

Estas RQ (véase la tabla 13.1) definen colectivamente, en general, los problemas de los experimentos que subyacen a la tesis para aprovechar los avances tecnológicos con el fin de mejorar la salud, la seguridad y el rendimiento de los atletas, teniendo en cuenta al mismo tiempo factores de variabilidad individual, económica y ética. Abordan el desarrollo tecnológico, el análisis de datos, la medicina personalizada, las consideraciones éticas, la aplicación práctica, las repercusiones a largo plazo y las influencias culturales y económicas. Responder a estas preguntas requiere un enfoque multidisciplinar que integre conocimientos de ingeniería, informática, medicina deportiva, ética, psicología y sociología.

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13.3 Objetivos de investigación

Para abordar los diversos puntos focales interdisciplinarios, se establecieron tres pilares principales para la tesis: (S1) **Grupo de tesis I** – *Técnicas avanzadas de diagnóstico a distancia y sensores*; (S2) **Grupo de tesis II** – *Seguridad deportiva y prevención de lesiones*; (S3) **Grupo de tesis III** – *Predicción de estados de salud.* Basándose en las preguntas de investigación definidas en el capítulo 1.2 y en los pilares de la tesis, se han establecido objetivos de investigación (OR) específicos para abordar estos pilares, que son las direcciones de investigación. Estos RO (véase la tabla 13.2) pretenden aprovechar el poder de la IA, el aprendizaje automático (ML) y el análisis avanzado de datos para mejorar el diagnóstico, el entrenamiento, la rehabilitación y el apoyo a la salud mental de los deportistas, mejorando en última instancia el rendimiento, la seguridad y el bienestar en el deporte.

Table 13.2: Objetivos de la investigación (RO)

ID	Objetivo
RO1	Mejora del diagnóstico y la supervisión en tiempo real
RO2	Predicción de la salud y el rendimiento basada en la IA
RO3	Desarrollo de herramientas de colaboración multilingües y multimodales
RO4	Optimización de los procesos de formación y rehabilitación
RO5	Integración de la IA en el análisis estratégico del deporte
RO6	Detección y prevención de enfermedades mediante enfoques innovadores.
RO7	Seguimiento psicológico y de salud mental
RO8	Gamificación y mejoras de la formación adaptativa
RO9	Análisis exhaustivo de datos para la mejora del rendimiento

13.4 Metodología de la investigación

Teniendo en cuenta el tipo multidisciplinar de la tesis, se ha llevado a cabo una Investigación de Método Mixto (IRM), integrando técnicas tanto cualitativas como cuantitativas con la ayuda de las universidades implicadas (UMA[1], UMFST[2], SAPIENTIA[3], OBUDA[4]) y profesionales del deporte de rendimiento (por ejemplo, entrenadores, preparadores físicos, fisioterapeutas) de Hungría y Japón (Toyo University), se utilizó con desarrolladores de estrategias deportivas de la siguiente manera:

[1]UMA - Universidad de Málaga
[2]UMFST - G.E. Palade Universidad de Medicina, Farmacia, Ciencia y Tecnología de Targu Mures
[3]SAPIENTIA - Sapientia Universidad Húngara de Transilvania, Targu Mures
[4]OBUDA - Centro de Investigación de Controles Fisiológicos, Óbuda Universidad, Budapest

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13.4.1 Técnicas cualitativas

La investigación cualitativa se centró en mejorar la predicción de problemas de salud y seguridad en el deporte, enfocándose en el bienestar de los jugadores con diversos métodos. Los grupos de discusión se ampliaron a otros equipos deportivos universitarios, aunque se centraron en el equipo de hockey sobre hielo de la Universidad de Toyo en Tokio. Los algoritmos se validaron con conjuntos de datos públicos. Se utilizaron investigaciones in situ y conceptuales para comprender el entorno de la seguridad deportiva. Se examinaron las arquitecturas de sistema, algoritmos, modelos de aprendizaje automático, hiperparámetros y soluciones de teledetección propuestos. Se examinaron las arquitecturas de sistema, algoritmos, modelos de aprendizaje automático, hiperparámetros y soluciones de teledetección propuestos. Los comentarios de entrenadores y preparadores abarcaron aplicaciones teóricas y prácticas en las observaciones. Se evaluaron informes deportivos y de salud para analizar la influencia de COVID-19 en sRPE/ACWR, burnout y estado de ánimo. Las revisiones sistemáticas y el metaanálisis se basaron en el análisis documental de revistas académicas y conferencias.

13.4.2 Técnicas cuantitativas

La tesis mejora la tecnología deportiva con métodos cuantitativos para aumentar la seguridad y el rendimiento de los atletas. Las encuestas y cuestionarios fueron esenciales para diseñar sistemas de sensores remotos. Los sensores requerían información exhaustiva para plantear retos a los jugadores de deportes. Se complementaron las encuestas con experimentos usando acelerómetros de 3 ejes y dispositivos de medición inercial. Las herramientas proporcionaron datos para crear nuevos métodos de seguimiento y análisis deportivo. Los algoritmos de diagnóstico se perfeccionaron mediante observaciones sistemáticas durante varias fases de la investigación. Los datos cuantitativos fueron obtenidos a partir de observaciones cualitativas en el campo deportivo. Los datos ayudaron a los sistemas de aprendizaje a reconocer y anticipar acontecimientos en el campo. Se desarrollaron algoritmos precisos y realistas para su uso en el mundo real, utilizando percepciones de grupos de discusión y observaciones cuantitativas. Los experimentos fueron cruciales para probar las hipótesis de la investigación. Se utilizaron tanto el laboratorio controlado como las circunstancias naturales in situ para construir y probar el PdT, el PdC y los MVP. Se probaron correlaciones causa-efecto en la vida real utilizando hockey sobre hielo, carreras, fútbol sala y fútbol. Los ensayos ampliaron los conocimientos sobre tecnología deportiva y seguridad de los jugadores al ser publicados.

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14 Conclusiones en Español

Se alcanzaron todos los objetivos de investigación del capítulo 1.3 y se publicaron y distribuyeron los resultados. Los resultados y contribuciones científicas más importantes en consonancia con los objetivos de investigación por nivel de grupo de tesis se muestran en la tabla 14.1, y son los siguientes:

Table 14.1: Cumplimiento de los objetivos de investigación (RO) por grupos de tesis y por resultados y contribuciones científicas

Objetivos de la investigación	**Cumplimiento de objetivos**	
ID y breve descripción de la RO	**Grupo de tesis**	**ID de tesis**
RO1: Enhancement of real-time diagnostics and monitoring	S1, S2, S3	1.1, 1.5, 1.2, 2.1, 3.3
RO2: AI-based health and performance prediction	S1, S3	1.6, 1.5, 3.1, 3.2
RO3: Development of multilingual and multimodal collaboration tools	S1	1.1, 1.3, 1.4
RO4: Optimization of training and rehabilitation processes	S1, S2, S3	1.6, 1.7, 2.1, 2.4, 3.4
RO5: Integration of AI in strategic sports analysis	S2	2.3, 2.4
RO6: Innovative approaches to disease detection and prevention	S1, S3	1.7, 3.3
RO7: Psychological and mental health monitoring	S3	3.5, 3.6
RO8: Gamification and adaptive training enhancements	S3	3.4
RO9: Comprehensive data analysis for performance improvement	S2	2.2, 2.4

The connectivity between the research questions (RQ1 to RQ11) and the primary research objectives (RO1 to RO9) is illustrated in Table 14.2. This table determines whether the research questions were addressed and analyzed, and if the scientific objectives were successfully accomplished.

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Table 14.2: Interconectividad de las preguntas de investigación (RQ) con los objetivos de investigación (RO)

Pregunta de investigación (RQ)	Objetivo de la investigación (RO)	Grupo de tesis
RQ1	RO2, RO3	S1, S2, S3
RQ2	RO1, RO4	S1, S2, S3
RQ3	RO3, RO5, RO9	S1, S2
RQ4	RO1	S1, S2, S3
RQ5	RO1, RO5	S1, S2, S3
RQ6	RO4, RO8	S1, S2, S3
RQ7	RO1..RO9	S1, S2, S3
RQ8	RO4, RO6	S1, S2, S3
RQ9	RO7	S3
RQ10	RO2, RO8	S1, S3
RQ11	RO9	S2

14.1 Nuevos resultados y contribuciones científicas

Los hallazgos tienen importantes consecuencias multidisciplinares para mejorar las actuales líneas tecnológicas en el ámbito, metodologías, flujos de trabajo y viabilidad de los métodos basados en ML en la seguridad deportiva preventiva en deportes de rendimiento. Las tesis hacen contribuciones significativas a campos como los sensores, el diagnóstico a distancia, la seguridad deportiva, la prevención de lesiones y la predicción del estado de salud con enfoques y métodos novedosos. Las tesis ha tenido un gran relevancia tanto a nivel global como local al realizarse publicaciones derivadas de la misma en revistas de impacto.

Grupo de enunciados de tesis I.

Tesis Grupo I (S1): Técnicas y sensores avanzados de diagnóstico a distancia
Publicaciones propias relacionadas con esta dirección de investigación: [P1], [P2], [P3], [P4], [P5].

Tesis 1.1
Objetivos de investigación (RO): RO1, RO3
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P2], [P3]

Propuse un pipeline casi en tiempo real con DETR para el reconocimiento de

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datos visuales y textuales. El objetivo es apoyar la futura traducción de videoconferencias multiusuario y multilingües y mejorar la eficacia del diagnóstico a distancia. La investigación textual y VOD analizó diferentes escenarios para proporcionar resultados fiables a un nuevo modelo de trabajo colaborativo. Se analizaron diferentes escenarios para proporcionar resultados fiables a un nuevo modelo de trabajo colaborativo mediante la investigación textual y VOD. El diseño propuesto puede utilizarse para preparar un modelo viable de detección de objetos visuales con un número modesto de conjuntos de datos de entrenamiento específicos. Esto apoyaría el procesamiento posterior de los datos en conferencias multilingües, como la traducción neuronal multilingüe. El nivel de eficacia al ajustar depende de la agrupación o clases de objetos, y de la calidad y cantidad de datos de entrenamiento. Es posible utilizar el modelo DETR para reforzar la colaboración multilingüe con traducción multilingüe en tiempo real a través de experimentos con un número restringido de conjuntos de datos de entrenamiento.

Tesis 1.2
Objetivos de investigación (RO): RO1
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P2], [P3]

Se realizó un análisis comparativo de los modelos de detector de objetos en tiempo real más prometedores: YOLO, Detectron y DETR, evaluando sus rendimientos en diferentes variaciones de modelo y conjuntos de datos específicos. Este análisis puede ser útil para experimentos de detección de objetos en tiempo real con herramientas de colaboración multilingües.

Tesis 1.3
Objetivos de investigación (RO): RO3
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P2], [P3]

Con el fin de aumentar la precisión y eficacia de los sistemas de OCR en tiempo real, se llevaron a cabo experimentos de investigación con arquitecturas de modelos CRNN y SVTR sintéticos y multilingües de entrenamiento para motores de OCR basados en ML para probar la posibilidad de un reconocimiento multilingüe generado a medida o sintetizado. CRNN y SVTR ofrecieron características innovadoras en comparación con los motores OCR

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convencionales. Las configuraciones de modelos ML propuestas reconocieron los textos multilingües/híbridos con gran precisión y tuvieron un rendimiento constante. Las puntuaciones de precisión más altas fueron 93,89%, 91,35% y 90,25%.

Tesis 1.4

Objetivos de investigación (RO): RO3
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P2], [P3]

Facilita el ajuste de precisión del conjunto de vocabulario multilingüe / sintetizado y la preparación de la distribución mediante un método de controlador visual que engloba el vocabulario, la distribución y la generación de conjuntos de datos unilingües / multilingües. Mejora la exactitud del reconocimiento en una amplia gama de lenguas y escrituras. El sistema de OCR elige cuidadosamente ejemplos diversos y representativos para el conjunto de datos de formación, reconociendo y asimilando ciertas características visuales de cada lengua. Se distingue de los métodos tradicionales por su aumento significativo de precisión en el reconocimiento de textos y disminución de errores. La originalidad del sistema proviene de su adaptabilidad. La supervisión continua del rendimiento del modelo de OCR, la modificación del conjunto de vocabulario multilingüe y la preparación de la distribución son clave para obtener mejores resultados de forma constante. Es un gran avance en la tecnología OCR, mostrando notable versatilidad para manejar nuevas lenguas, escrituras o textos específicos de un dominio.

Tesis 1.5

Objetivos de investigación (RO): RO1, RO2
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P4]

Se propuso una metodología basada en sensores para estimar el gasto energético de forma remota.a. El uso de un sensor de radar médico y datos de acelerómetro triaxial permite estimaciones precisas del gasto energético en atletas, lo que ayuda a controlar su nivel de condición y recuperación. El método permite al atleta controlar su estado fisiológico y actividades físicas de forma no invasiva y continua durante el entrenamiento y la competición. Optimizar el rendimiento y prevenir lesiones es clave para entrenadores y

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preparadores físicos, por lo que esta información será valiosa para ellos. El RPAI con MET, RPE, sRPE y ACWR puede controlar la intensidad del entrenamiento para evitar el sobreentrenamiento o infraentrenamiento del deportista.

Tesis 1.6
Objetivos de investigación (RO): RO2, RO4
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P5]

Se propuso un modelo de precognición asistido por IA para controlar la fatiga y la resistencia en deportes de rendimiento, utilizando datos de series temporales multivariantes generados por la IMU. Este modelo arrojó conclusiones sustanciales con implicaciones en la ciencia del deporte y la gestión del rendimiento de los atletas. El rendimiento del modelo LSTM sugiere un enfoque equilibrado para clasificar clases binarias, mostrando una capacidad competente para manejar la tarea de clasificación. Sería prudente examinar y comparar los modelos LSTM con otros modelos de ML más sencillos en contextos donde la interpretabilidad y la eficiencia computacional son cruciales, debido a la complejidad de los modelos LSTM. Se extiende la aplicación del modelo de precognición a la optimización de los periodos de descanso y recuperación. El modelo proporciona recomendaciones basadas en pruebas sobre la duración del descanso y las actividades de recuperación que se ajustan a las necesidades fisiológicas del deportista, maximizando así la eficiencia y la eficacia de la recuperación al predecir la trayectoria del proceso.

Tesis 1.7
Objetivos de investigación (RO): RO4, RO6
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P5]

El método de "estimación de postura humana en 3D" basado en IA mejora el rendimiento atlético en deportes de alto rendimiento al contribuir a la planificación estratégica del entrenamiento y la competición. El modelo proporciona recomendaciones basadas en pruebas sobre la duración del descanso y las actividades de recuperación para maximizar la eficiencia y eficacia de la recuperación de un atleta. La información predictiva sobre la resistencia y los umbrales de fatiga de un atleta permite a los entrenadores tomar decisiones

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informadas sobre la intensidad del entrenamiento, los calendarios de competición e incluso las estrategias de ritmo en competición. Los sensores IMU proporcionan datos biomecánicos críticos, como la aceleración y la velocidad angular, conectados al equipamiento de los atletas. Permite un seguimiento y ajuste no invasivos del rendimiento mediante la IA. Los entrenadores pueden utilizar la formación en interpretación de datos para proporcionar retroalimentación inmediata, optimizar la intensidad y técnica del entrenamiento en tiempo real, y mejorar la eficacia de las sesiones evitando un esfuerzo excesivo.

Grupo de enunciados de tesis II.

Tesis Grupo II (S2): Seguridad deportiva y prevención de lesiones
Publicaciones propias relacionadas con esta dirección de investigación: [P1], [P2], [P6], [P7], [P8], [P9].

Tesis 2.1
Objetivos de investigación (RO): RO1, RO4
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P6], [P1]

Se propuso un método asistido por IA para endurecer el rendimiento y rehabilitación. El marco controlado por IA aplicado a la metodología de seguridad deportiva propuesta demostró eficacia en aumentar la destreza atlética al compararse con los paradigmas de entrenamiento convencionales. Su aplicación parece prometedora para prevenir posibles lesiones al discernir y enmendar patrones de entrenamiento subóptimos y lapsus biomecánicos. Además, según especialistas en seguridad deportiva, las intervenciones integradas en la IA aceleran el proceso de rehabilitación y aumentan la calidad de la recuperación en situaciones posteriores a una lesión. En este sentido el resultado más importante puede ser: la capacidad de adaptación de la IA ha hecho posible el entrenamiento personalizado para deportistas, considerando sus atributos biomecánicos y fisiológicos. Se ha observado una mejora significativa en el mecanismo de retroalimentación en tiempo real, permitiendo ajustes instantáneos de la técnica. Las innovaciones garantizan que los atletas saquen el máximo partido de sus sesiones de entrenamiento, se mantengan libres de lesiones y alcancen el máximo rendimiento durante las competiciones, ayudándolos a superar sus límites con seguridad.

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Tesis 2.2
Objetivos de investigación (RO): RO9
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P7], [P8]

Se propuso una metodología para la detección de lesiones cerebrales en deportistas de alto rendimiento para la detección en tiempo real de lesiones y tumores tras traumatismos craneoencefálicos graves. La metodología basada en modelos YOLO8 y YOLO-NAS fue aplicada en deportes como el fútbol americano, rugby y hockey sobre hielo. En este sentido, se aplicó la metodolgía YOLO9 para detectar la antes posible la neumonía. Detectar problemas rápidamente en tiempo real aceleraría la intervención médica, mejorando la recuperación y los resultados a largo plazo para los deportistas. Las futuras implementaciones propuestas, como una versión integral de la NAS y la IA explicable, podrían mejorar el modelo y aumentar la adopción al generar mayor confianza y comprensión de los procesos de toma de decisiones de la IA.

Tesis 2.3
Objetivos de investigación (RO): RO5
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P2]

Se ha propuesto un método para extraer estrategias deportivas mediante una tubería. El sistema diseñado detecta y rastrea a jugadores y objetos en tiempo real, proporcionando datos exhaustivos sobre sus movimientos e interacciones. Utiliza YOLO o YOLO-NAS. Ayuda en el análisis del rendimiento y el desarrollo de estrategias extrayendo elementos y patrones estratégicos de los datos rastreados. YOLO-NAS pretende optimizar la arquitectura de la red para mejorar el seguimiento y la extracción de estrategias, analizar la viabilidad de la extracción de estrategias basada en ML y validar si atletas y entrenadores pueden aprovechar datos históricos de vídeo para identificar tendencias, analizar rendimientos pasados y desarrollar programas de entrenamiento predictivos y asistidos por IA o estrategias adaptativas para futuras competiciones. Estos sistemas, facilitarán un enfoque basado en datos para mejorar el rendimiento de atletas y equipos en el deporte.

Tesis 2.4
Objetivos de investigación (RO): RO4, RO5, RO9

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Importancia: impacto global, relevancia local
Publicaciones relevantes: [P8], [P1], [P9]

Se elaboró un método retrospectivo de aprendizaje para la seguridad deportiva y la gestión del entrenamiento en deportes de alto rendimiento, focalizado en la rehabilitación y el fortalecimiento, utilizando IA como herramienta de apoyo. Los atletas y entrenadores podrán tomar decisiones informadas, optimizar estrategias y mejorar el rendimiento en el deporte utilizando el método propuesto. Esto, supone un valor añadido, debido a que el análisis de datos históricos permite a los deportistas y entrenadores identificar patrones recurrentes a nivel individual y de equipo, comprender puntos fuertes, débiles y áreas de mejora, y adaptar estrategias basadas en actuaciones pasadas. Esto permite a deportistas y entrenadores fijar objetivos realistas y realizar un seguimiento de los progresos a lo largo del tiempo. Al comprender lo que ha funcionado bien en situaciones similares, pueden modificar los planes de juego y tomar decisiones más informadas durante futuras competiciones. Del mismo modo, el análisis de secuencias de vídeo históricas proporciona información sobre el progreso y el desarrollo de las habilidades de un deportista, lo que ayuda a los entrenadores a diseñar programas de entrenamiento personalizados y a centrarse en áreas específicas de mejora.

Grupo de enunciados de tesis III.

Tesis Grupo III (S3): Predicciones de las condiciones de salud
Publicaciones propias relacionadas con esta dirección de investigación: [P10], [P4], [P11], [P12], [P9], [P1], [P13], [P14].

Tesis 3.1
Objetivos de investigación (RO): RO2
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P10], [P4]

El método "Detector de mentiras sobre la condición" puede proporcionar a los entrenadores información objetiva sobre la salud, resistencia y condición de los deportistas, tanto a nivel individual como grupal. Los modelos de predicción de sRPE y ACWR basados en IA tienen potencial para aplicarse en diversos deportes y poblaciones. Esto incluye atletas aficionados, entusiastas de deportes recreativos y diferentes grupos de edad. Los modelos de predicción de

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ACWR basados en IA pueden beneficiarse de la incorporación de más fuentes de datos, como marcadores fisiológicos, calidad del sueño, nutrición y factores psicológicos, como una futura línea de desarrollo. Las fuentes de datos adicionales pueden mejorar la capacidad de predicción de las puntuaciones de ACWR y fatiga al crear modelos más completos y precisos.

Tesis 3.2
Objetivos de investigación (RO): RO2
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P11], [P12], [P9]

Se propuso una metodología mejorada para validar la correlación entre el análisis del sentimiento y la resistencia en el entorno HPC, seguida de un análisis multivariante de la correlación entre la resistencia, el sentimiento basado en texto y la fatiga para evaluar su efecto combinado.

Tesis 3.3
Objetivos de investigación (RO): RO1, RO6
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P13], [P12], [P11]

Se diseñó un método de analisis de datos asistido por IA que combina avanzados métodos de extracción de características para detectar enfermedades a través de muestras de voz. Se amplió la investigación con otras enfermedades y la detección de anomalías de salud después de empezar con COVID-19. La detección de enfermedades basada en la voz utilizando IA muestra resultados prometedores en los experimentos realizados. Proporciona un enfoque novedoso, no invasivo, rentable y escalable para identificar y controlar diversas enfermedades, como COVID-19 y otras enfermedades respiratorias contagiosas. El método propuesto ayuda al personal deportivo profesional a predecir enfermedades a partir de la muestra de voz casi en tiempo real y evita la contaminación cruzada en los eventos deportivos.

Tesis 3.4
Objetivos de investigación (RO): RO4, RO8, RO9
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P4], [P5], [P10], [P11], [P9], [P14]

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Se combinaron los efectos sinérgicos de la gamificación, la IA generativa y el aprendizaje por refuerzo para crear un concepto de activo motivador para deportes de rendimiento. La técnica se distingue por potenciar la implicación psicológica con características gamificadas y entrenamiento físico en situaciones dinámicas adaptadas. Dentro de un marco tecnológico integral, aborda eficazmente los aspectos físicos y mentales del rendimiento deportivo. La integración de la GenAI y la gamificación en los deportes de equipo de alto rendimiento es revolucionaria al combinar la motivación psicológica y la innovación tecnológica adaptativa de forma sinérgica. Los sistemas GenAI mejorados con aprendizaje por refuerzo (RL) ajustan en tiempo real parámetros de entrenamiento como la intensidad, la duración y la resistencia. Se evalúa el rendimiento individual mediante la valoración subjetiva del esfuerzo percibido (sRPE), el equivalente metabólico (MET) y el ACWR, analizando grandes cantidades de datos. La gamificación aumenta las tasas de finalización de los atletas en un 20-30% sin necesidad de solicitudes extra de los entrenadores, al mejorar su motivación. Mejora la eficacia de los procesos de preparación del entrenamiento.

Tesis 3.5
Objetivos de investigación (RO): RO7
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P11], [P12], [P9]

Identificar el burnout en una fase temprana del rendimiento deportivo mediante la comunicación escrita y el análisis de sentimientos. La investigación es esencial para comprender los signos psicológicos del burnout, los métodos para medirlo, la experiencia en PNL y técnicas de análisis de sentimientos. La recopilación de datos textuales de los deportistas es crucial, junto con posibles métricas de resistencia o fatiga, como registros o entrevistas/comentarios posteriores al entrenamiento. La IA, como BERT o GPT-3, analiza textos para detectar sentimientos que revelen agotamiento. La IA puede identificar patrones de agotamiento inminente correlacionando sentimientos de textos con métricas físicas. Se ha investigado un enfoque proactivo impulsado por la IA para prevenir el burnout; prolongando así sus carreras, el método propuesto permite a los atletas adaptar su entrenamiento a su salud mental y física. La IA puede identificar signos tempranos de burnout antes de que se manifiesten síntomas obvios. Prevenir el agotamiento y mejorar el bienestar general del atleta al intervenir a tiempo. Existe una variabilidad significativa en la forma en que los individuos responden a las cargas de entrenamiento y a los factores

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estresantes, según el modelo. Puede no ser eficaz un enfoque universal del entrenamiento y la recuperación, por lo que es vital contar con ideas y recomendaciones personalizadas para cada atleta, adaptadas a su perfil único.

Tesis 3.6

Objetivos de investigación (RO): RO7
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P1], [P11], [P9], [P1]

Se desarrolló una metodología no invasiva basada en ML y NLP para identificar marcadores tempranos de trastornos de salud mental y neurodegenerativos a partir del texto escrito. La técnica implemnetada para el análisis de texto basada en IA y análisis de sentimientos es una prometedora herramienta de detección de anomalías de salud mental de nueva generación. Sin embargo, los métodos complementarios no pueden sustituir la evaluación clínica en la etapa actual. Es necesario perfeccionar los algoritmos de IA para considerar la diversidad lingüística y el contexto, abordando las consideraciones éticas sobre el uso de datos y privacidad en la investigación futura. En el ámbito deportivo, los resultados esperados del método son vitales para el reconocimiento precoz de problemas de salud mental y precursores del TND entre los deportistas. La competición deportiva puede precipitar o agravar trastornos como la depresión o la ansiedad debido a las intensas exigencias físicas y el estrés psicológico.

Tesis 3.7

Objetivos de investigación (RO): RO7
Importancia: impacto global, relevancia local
Publicaciones relevantes: [P7], [P8]

Se formuló un enfoque complejo y no invasivo para detectar la neumonía en tiempo real. La atención respiratoria podría mejorar al utilizar YOLOv9 en un sistema de diagnóstico en tiempo real para detectar síntomas tempranos de neumonía en deportistas. La alta precisión de YOLO9 tras un riguroso entrenamiento y validación sugiere su fiabilidad en situaciones de rendimiento deportivo. El método reduce el impacto de la neumonía en la salud y la carrera de los deportistas al interpretar con prontitud y precisión las radiografías de tórax. Los resultados promueven la integración de la IA en la medicina preventiva, lo que promete mejorar la salud de los deportistas de alto rendimiento.

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15 Perspectivas y futuras líneas

15.1 Perspectivas

Empecé a comprender la seguridad deportiva y la detección de anomalías basada en la IA antes de iniciar mis estudios de doctorado en Informática (UMFST) y Ciencias de la Salud (UMA). Con una pronunciada curva de aprendizaje, el curso de doctorado cotutelle me ha ayudado a comprender este tema heterogéneo desde las perspectivas del deporte, la medicina, la informática y la psicología. La detección precoz de anomalías, lesiones, trastornos mentales y neurogenerativos, o enfermedades relacionadas con el deporte, combinada con el uso de sensores (por ejemplo, sensores de radar médico, acelerómetros triaxiales, IMU) para estudiar la fatiga, la resistencia, la recuperación/rehabilitación, potenciados con IA, ha abierto muchas nuevas vías de investigación en la predicción de la fatiga, la mitigación de lesiones y la optimización del rendimiento. Tras años de perseverancia y pasión en este viaje, el programa de doctorado es sólo una etapa y continuará en la fase postdoctoral.

En cuanto a las anomalías a considerar ("Tesis del Grupo I") es el desarrollo de un sistema de diagnóstico colaborativo de transferencia remota de conocimientos que permita la colaboración de especialistas que trabajan en distintos campos e incluso hablan idiomas diferentes para apoyar el diagnóstico y el análisis precoces y rápidos de enfermedades complejas, así como el desarrollo de tratamientos eficaces y personalizados (véase la sección 12.2.1). Otra dirección futura a las anomalías, pretendo crear un índice ambulatorio de estratificación de la gravedad y de recuperación/rehabilitación que permita estratificar a los pacientes deportistas de competición según la gravedad de su afección, así como la posibilidad de implicar a los pacientes en las distintas fases de los procesos y metodologías propuestas que se tratan en las tesis del "Grupo de Tesis II" de esta disertación. Otra tendencia futura a tener en cuenta es la gestión de la fatiga mediante el aumento de la resistencia en los deportes de competición a través de la validación de cuestionarios y pruebas utilizados habitualmente en la investigación y la práctica clínica pero no sometidos al análisis psicométrico necesario para conocer en profundidad las propiedades de su uso según la geolocalización y el grupo de edad. La investigación intensiva centrada en el conocimiento de trastornos mentales y neurodegenerativos será un nuevo reto en el

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próximo ciclo de investigación. Esta fase se dará en las partes relacionadas y las publicaciones de "Declaraciones de tesis Grupo III" (véase la sección 12.2.4). Continuaré los ensayos de investigación en un entorno de supercomputación (HPC), centrándome en la geolocalización y los idiomas hablados para mejorar el análisis de sentimientos con muestras de audio y vídeo. Las dificultades para analizar los datos a una escala más amplia, como la geolocalización o la segmentación lingüística, impidieron su inclusión en una tesis doctoral debido a la duración de la intervención, la parametrización de los análisis de sentimientos, las características de los conjuntos de datos y la capacidad computacional requerida, coincidiendo con una pandemia y sus limitaciones. El estudio se convierte en uno de los ejes principales de la sección de doctorado debido a la importancia de sus resultados. Crear una infraestructura y un algoritmo de IA en tiempo real para detectar y prever lesiones causadas por colisiones en deportes como hockey sobre hielo, fútbol americano o rugby es otro objetivo principal de la fase posdoctoral. Estos factores, mejorarían la seguridad deportiva en deportes de equipo con alto riesgo de lesiones.

Las publicaciones incluidas en la tesis (relacionadas con los enunciados I, II y III de la tesis) ponen de manifiesto la falta de métodos y técnicas para la evaluación directa in vivo del ejercicio, aplicables en la investigación y la práctica clínica, así como el potencial de la IA. Debe proseguirse la investigación y desarrollo de nuevas metodologías interdisciplinares que utilicen la IA. El trabajo realizado durante la tesis doctoral y las residencias relacionadas formó un equipo reconocido internacionalmente de profesionales del deporte de competición con los que se puede continuar la investigación, desarrollar metodologías y procesos, y validarlos en diversas disciplinas deportivas. Además, se estudió la aplicación de prácticas, investigación y desarrollos relacionados. El procedimiento permite desarrollar la metodología de aprendizaje retrospectivo y el enfoque de aprendizaje multimodal. Se ha comenzado una investigación preliminar en un entorno de superordenador para preparar el modelado de conjuntos de datos y enseñar de manera óptima el lenguaje sintético en una colaboración multidisciplinaria, complementando la tesis doctoral sobre la detección precoz de trastornos mentales y neurodegenerativos. Es importante comprender las anomalías metalingüísticas del lenguaje en relación con los trastornos mentales y neurodegenerativos. En la fase postdoctoral, se crearán nuevos métodos, modelos mejorados, publicaciones y pruebas especializadas para la aplicación de protocolos e intervenciones asíncronas en esta línea de estudio.

15.2 Futuras líneas de investigación

15.2.1 Planes de futuro en teleconsulta y diagnóstico colaborativo

En la fase de posdoctorado, me gustaría ampliar los experimentos de la tesis a un entorno HPC, donde se utilizará para el aprendizaje federado y el procesamiento de datos

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distribuidos, combinados con métodos de adaptación de dominios y aprendizaje no supervisado mediante el muestreo dinámico de datos y el enfoque de mejora continua de modelos.

15.2.2 Futuras direcciones con radares médicos & acelerómetros de triple eje

A largo plazo, en colaboración con equipos universitarios (por ejemplo, la Universidad Toyo de Japón) y utilizando el ecosistema, tengo previsto poner en marcha un programa de investigación -sobre el control de la fatiga y la resistencia basado en conjuntos de datos de series temporales multivariantes (MTS)- que mejore la salud de los atletas y prolongue su rendimiento. Mejorar la salud general de los atletas e incrementar la duración de su etapa de alto rendimiento mediante un enfoque de la gestión de la carga de entrenamiento basado en datos es un objetivo fundamental. El modelo asistido por IA apoya las prácticas de entrenamiento sostenibles de alto rendimiento adaptándose continuamente al estado físico del atleta. Se espera que este pilar de la tesis sobre el control de la fatiga y la resistencia asistido por IA para los deportes de rendimiento, basado en el análisis de conjuntos de datos de series temporales multivariantes generados por la IMU, conduzca a descubrimientos. Las líneas de desarrollo prospectivo y los resultados innovadores de esta investigación son específicos para influir significativamente en la ciencia del deporte, el entrenamiento de atletas y las aplicaciones más amplias de la IA. Las posibles líneas de desarrollo futuras son las siguientes (1) *avance algorítmico con endurecimiento* y (2) *integración de sensores*.

15.2.3 Trayectorias de investigación propuestas sobre la detección de la neumonía en el deporte

Se han identificado varias prioridades estratégicas para mejorar la eficacia y utilidad del sistema de detección de neumonía basado en IA: (1) es esencial añadir más radiografías de tórax diversas de atletas al conjunto de datos de entrenamiento. Este aumento hará que el modelo sea más robusto y capaz de generalizar entre poblaciones deportivas, teniendo en cuenta las diferencias fisiológicas debidas a las disciplinas deportivas, los regímenes de entrenamiento y la genética; (2) añadir características de diagnóstico como datos de monitorización de la salud vestibles podría mejorar el diagnóstico. El sistema de IA podría detectar pequeñas irregularidades que los rayos X no pueden detectar al incluir los datos fisiológicos, como la frecuencia cardiaca y la frecuencia respiratoria, con los datos de las imágenes; (3) el desarrollo de modelos mejorará el procesamiento en tiempo real para reducir la latencia. Por último, la aplicación de este sistema de IA a las fracturas por estrés y a las anomalías cardíacas podría tener un enorme impacto en la medicina deportiva.

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15.2.4 Trayectorias de investigación propuestas sobre la prevención de enfermedades y lesiones

Uno de los principales objetivos futuros de esta línea de tesis es llevar a cabo una investigación exhaustiva utilizando un conjunto de datos validado, al tiempo que se mejora el modelo incorporando el análisis del habla dentro de un entorno informático de alto rendimiento (HPC). La fase de investigación actual se encuentra con limitaciones dentro de la plataforma Google Colab Pro. Las futuras líneas de desarrollo de la IA ofrecerán una identificación más sensible, específica y oportuna de la salud mental y el TND, lo que en última instancia redundará en mejores resultados para los pacientes gracias a una atención temprana y personalizada. La trayectoria de la IA en la precognición de la salud mental y los TNE tiende hacia varias líneas de desarrollo específicas, que se propone analizar: (1) *Ampliación del análisis de voz*; (2) *Comprensión del lenguaje contextual e idiomático*; (3) *Integración de neuroimágenes*; (4) *Correlaciones genómicas*; (5) *Monitorización portátil en tiempo real*; (6) *Fenotipado digital*; (7) *Gobernanza ética de datos*, y (8) *Educación en IA*. Cada una de estas líneas de desarrollo pretende *mejorar* la *precisión*, *fiabilidad* e *integridad ética de las aplicaciones de IA* en el cuidado de la salud mental y las enfermedades neurodegenerativas, lo que promete un futuro de soluciones sanitarias personalizadas y proactivas para plataformas deportivas de rendimiento y soluciones de seguridad deportiva. *Idea de desarrollo futuro como próxima fase de la detección del agotamiento*: el objetivo es investigar en detalle con un conjunto de datos validado la correlación entre el análisis de sentimientos y la resistencia o la fatiga en un entorno HPC. La fase actual de la investigación alcanzó sus límites en el entorno Google Colab Pro. *Idea de desarrollo futuro de la recuperación personalizada*: en primer lugar, tengo previsto profundizar en las colaboraciones entre desarrolladores de IA y psicólogos deportivos para desarrollar herramientas que ofrezcan una visión del bienestar mental de los atletas. Se espera que los regímenes de entrenamiento personalizados utilicen modelos de IA para interpretar los datos biométricos. Se han diseñado soluciones para los primeros usuarios con el fin de superar estos obstáculos. Tengo la intención de explorar las sinergias entre la IA y la genómica para revolucionar el entrenamiento deportivo con conocimientos de predisposición genética en fases posteriores. La convergencia de las NN y la biomecánica puede ayudar a los atletas a optimizar su rendimiento mejorando los patrones de movimiento. La tecnología vestible puede volver como recolectores de datos e intérpretes inteligentes con consejos procesables.

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16 References

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