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Review

Wearable Fall Detectors Based on Low Power Transmission Systems: A Systematic Review

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Abstract: Early attention to individuals who suffer falls is a critical aspect when determining the consequences of such accidents, which are among the leading causes of mortality and disability in older adults. For this reason and considering the high number of older adults living alone, the development of automatic fall alerting systems has garnered significant research attention over the past decade. A key element for deploying a fall detection system (FDS) based on wearables is the wireless transmission method employed to transmit the medical alarms. In this regard, the vast majority of prototypes in the related literature utilize short-range technologies, such as Bluetooth, which must be complemented by the existence of a gateway device (e.g., a smartphone). In other studies, standards like Wi-Fi or 3G communications are proposed, which offer greater range but come with high power consumption, which can be unsuitable for most wearables, and higher service fees. In addition, they require reliable radio coverage, which is not always guaranteed in all application scenarios. An interesting alternative to these standards is Low Power Wide Area Network (LPWAN) technologies, which minimize both energy consumption and hardware costs while maximizing transmission range. This article provides a comprehensive search and review of that works in the literature that have implemented and evaluated wearable FDSs utilizing LPWAN interfaces to transmit alarms. The review systematically examines these proposals, considering various operational aspects and identifying key areas that have not yet been adequately addressed for the viable implementation of such detectors.

Keywords: LPWAN; wearable devices; fall detection; LoRaWAN; Sigfox; NB-IoT

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1. Introduction

Interest in biomedical telemonitoring research has significantly increased worldwide in recent years. This is due to its ability to monitor patients' and users' well-being remotely, enabling personalized treatments within familiar environments at a much lower cost than the traditional monitoring procedures carried out in specific facilities such as hospitals or nursing homes [1]. Technological advancements in sensors, electronic elements' miniaturization, the evolution of communication networks, and artificial intelligence have led to the development of low-cost wearable devices capable of monitoring vital and biometric signals [2]. The detection of critical, health-affecting events such as falls becomes a fundamental aspect in remote supervision of elderly individuals or those with mobility issues.

Falls occur when balance is involuntarily lost, resulting in the body impacting the ground or any other firm surface [3]. The World Health Organization (WHO) highlights that falls are a significant public health concern, being the second leading cause of accidental injury deaths worldwide. It is estimated that each year, approximately 684,000 individuals die worldwide due to falls, with the population of adults aged over 60 experiencing the highest number of fatal falls [4]. In addition, it has been projected that by 2050, the population of individuals aged 60 and above will reach around 2.1 billion, representing approximately 22% of the global population [5]. Currently, about 37.3 million falls result in severe injuries requiring medical attention. Nonetheless, timely medical intervention for individuals who have experienced a fall can lower the risk of hospitalization by 26% and reduce mortality rates by 80% [6]. For this reason, early detection of falls through remote telemonitoring systems can enhance medical care and prevent complications associated with fall accidents. In a generic manner, a fall detection system (FDS) can be defined as an architecture capable of autonomously detecting falls experienced by a particular subject and notifying caregivers as soon as these falls occur.

During the last decade, a wide variety of research related to fall detection has been developed, as evidenced in existing literature [6–34]. According to studies, a classic categorization of FDSs can be approached depending on the nature of the sensors involved in the fall detection process. In this vein, three types of sensors are normally considered: wearable devices, environmental systems, and video-based systems [26].

Video and environment-based systems, which can be grouped under the term "contextual detection systems" or "context-based systems", present similar advantages and drawbacks. Both methods use fall detection techniques involving the capture of environmental data to monitor and track body movement. Consequently, both tracking systems require the deployment and detailed configuration of sensors, cameras, and other devices in specific areas within the user's residence. Despite undeniable advancements in this type of detector, several issues that limit their effectiveness persist.

The primary limitation lies in the coverage area itself, as contextual systems demand sensor installation in constrained indoor spaces, typically within a room [10], where (in any case) dead zones or blind spots for detection may also occur. Therefore, operationality is significantly restricted to home monitoring scenarios while no ubiquitous user tracking (and freedom of movement) is permitted. Additionally, privacy concerns arise from the permanent use of cameras, while environmental sensors (such as microphones, motion detectors, etc.) can be affected by various sources of spurious noise. Furthermore, external items (furniture, pets, belongings) might fall within the tracking area and generate false alarms [35].

On the other hand, wearable fall detection devices can be seamlessly incorporated into clothing due to their reduced size. Due to the plummeting costs of wearables, they provide a more economical solution with a lower energy consumption compared to context-based systems. Typically, these devices include microcontrollers, IMU (Inertial Measurement Unit) sensors, and, in some cases, barometers, which enable fall detection based on the user's acceleration, angular velocity, orientation, or altitude. Moreover, they feature a wireless communication module, easing the remote monitoring and integration of the tracking system into IoT (Internet of Things) networked platforms [36].

Despite technological advancements in fall detection, current systems face significant challenges that limit their effectiveness in various contexts. One of the main issues is the rate of false positives [37,38], where everyday activities like sitting down quickly or bending over can be mistakenly identified as falls. This problem affects confidence in detection systems and can lead to an overload of emergency services and caregivers. Another critical challenge is user acceptance and comfort, as wearable devices need to be worn constantly to function effectively, and not all users are willing or able to adapt to this necessity [39]. Additionally, detection accuracy can be compromised in environments with electromagnetic or physical interference [33], which can affect the sensors' ability to monitor user movements properly. However, one of the major challenges is the limited autonomy of wearable devices due to data acquisition and transmission, which hampers their prolonged operation and decreases their viability for continuous monitoring without frequent recharges [40].

In this scenario, a technology emerges with significant potential for fall detection in telemonitoring contexts: LPWAN (Low Power Wide Area Network) communications are proficient in efficiently transmitting data across extensive distances while minimizing energy consumption, and hence, significantly increasing the autonomy of wearables, which are typically powered by lightweight batteries with limited capacity.

Most wearable-based FDSs integrate short-range communications, such as Bluetooth Low Energy (BLE) [41–43] or, to a lesser extent, ZigBee [44–46]. Although these technologies minimize battery drainage, they require placing a gateway or relay node in the close vicinity of the user, capable of forwarding the alarms received from the wearable to the remote monitoring point (e.g., via Wi-Fi or 3G networks). This role is usually performed by a smartphone, which the user must carry permanently, a situation that is not always possible in all the application scenarios. An alternative to a "transportable" gateway is directly integrating medium-range (Wi-Fi) long-range cellular communications, such as 3G or 4G, into the wearable. In fact, certain high-end smartwatches already incorporate these wireless interfaces. However, these technologies demand significant energy to operate [47–49]. This noticeably constrains the autonomy of the wearable, which is usually not powered by high-capacity batteries to reduce its weight. Additionally, these interfaces require being within the radio coverage of the corresponding Wi-Fi access point or cellular base station, which, depending on where the system is intended to be deployed, is not always available. In addition, the use of cellular communications adds a monthly service cost to the FDS application.

In contrast, LPWAN networks offer a low-power architecture with long-range coverage, making them particularly advantageous when deployed in outdoor environments [47,50]. LPWAN technologies, such as LoRaWAN (Long Range Wide Area Network) and Sigfox, are well-suited for IoT applications requiring extensive coverage and economical communication solutions. These networks operate in unlicensed frequency bands, significantly reducing operational costs and utilizing efficient communication protocols that allow devices to consume less energy when transmitting data [51,52]. Additionally, LPWAN solutions offer bidirectionality and the ability to establish public or private networks, providing flexibility and better adaptability to the specific needs of wearable-based monitoring systems. Each LPWAN access point or gateway can support thousands of end nodes over several kilometers, reducing implementation and maintenance expenses. This makes LPWAN architectures particularly suitable for applications in areas where traditional communication infrastructures are limited or costly to deploy [7].

In addition to the technological advancements in sensors and communication networks, the effectiveness of FDSs heavily relies on the algorithms implemented to process the data collected by wearable devices. These algorithms are designed to accurately identify falls by analyzing patterns in the inertial signals, such as acceleration, angular velocity, and orientation changes. Various algorithms, including threshold-based methods and machine-learning techniques, have been developed to enhance the accuracy and reliability of fall detection. Threshold-based methods (TBM) offer low computational complexity and can be executed directly on wearable devices without needing important hardware resources [6,8,16,26,34]. However, they may have severe limitations in distinguishing falls from other conventional activities involving energetic or fast movements. On the other hand, machine learning algorithms, including deep learning models, provide higher accuracy but require more computational resources [28,34,36,53,54]. Hybrid algorithms, which combine TBM and machine learning, leverage the advantages of both approaches to improve detection performance and energy efficiency. For instance, Yuan et al. [55] implemented a system using TBM for preliminary detection and GRU (Gated Recurrent Unit) for final classification, optimizing both accuracy and power efficiency.

In addition to technological advancements in sensors and communication networks, the effectiveness of FDSs largely depends on the algorithms implemented to process the data collected by wearable devices. These algorithms are designed to accurately identify falls by analyzing patterns in inertial signals, such as acceleration, angular velocity, and changes in orientation. Various types of algorithms have been developed for this purpose, each with its own advantages and limitations.

Threshold-based methods (TBM), which are among the simplest and most widely used, work by setting predefined limits on the inertial signals. When the data exceeds these thresholds, a fall alert is triggered. These methods offer low computational complexity [56] and can be executed directly on wearable devices without the need for significant hardware resources [6,8,16,26,34]. However, TBM methods often struggle to distinguish falls from other activities, leading to an increase in false positives and false negatives. Luque et al. [57] compared four TBM algorithms and demonstrated that simultaneously avoiding both types of errors is difficult. This is because the thresholds may be too sensitive, increasing false positives, or not sensitive enough, increasing false negatives. Adjusting these thresholds to find an optimal balance is complex and does not always guarantee consistent performance across all users and contexts.

On the other hand, machine learning algorithms have emerged as a powerful alternative to improve fall detection accuracy. These algorithms analyze large volumes of historical data to identify complex patterns and features that indicate a fall, allowing them to offer higher accuracy than threshold-based methods [28,34,36,53,54]. Among them, deep learning models, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), have proven particularly effective in fall recognition by capturing temporal dependencies in inertial signals. Salah et al. [36] developed an edge artificial intelligence FDS, achieving 95.55% accuracy using CNN and 96.78% with LSTM. However, this higher accuracy comes at a cost, as machine learning algorithms often require more computational resources [58], which can be challenging for wearable devices with limited processing and power capabilities.

To address the limitations of both approaches, hybrid algorithms have been developed that combine the strengths of TBM and machine learning. These systems typically use threshold-based methods for preliminary fall detection, taking advantage of their low energy consumption and then applying machine learning techniques for more detailed and accurate classification. However, the reverse is also possible, where the output of a Machine Learning or Deep Learning model is compared against a threshold to determine a fall. Therefore, either method can be used in any order [59]. For example, Yuan et al. [55] implemented a system that uses TBM for preliminary detection and GRU (Gated Recurrent Unit) for final classification, optimizing both accuracy and energy efficiency. These hybrid algorithms represent a trade-off between simplicity and accuracy but also introduce greater complexity in the design and implementation of the system, as they require the integration of multiple algorithmic components. While it is true that hybrid models face challenges related to selecting an appropriate threshold, these challenges can be addressed, as shown by Astriani et al. [60], who propose a method that not only relies on a simple threshold but also incorporates multiple critical features such as weightlessness, impact, post-fall immobility, and the comparison of accelerations before and after the fall. Additionally, the use of ROC (Receiver Operating Characteristic) curves is implemented to adjust the threshold dynamically, optimizing the balance between sensitivity and specificity [61]. The use of LPWAN technology in wearable devices for FDSs and biomedical telemonitoring, in general, is an ever-evolving area with noteworthy potential to enhance people's quality of life. It has clear advantages yet to be fully explored and evaluated compared to wearable systems employing short-range, low-power communications to which the literature on wearable FDSs has traditionally paid much more attention.

The primary aim of this review is to analyze and synthesize existing literature concerning the use of LPWAN technologies in wearable devices for fall detection, considering their benefits, limitations, opportunities for improvement, detection algorithms, and energy efficiency. The research focuses on the wearable devices employed, the nature of the sensors, and the algorithms that are implemented on the wearable to detect falls from the inertial signals. The main contributions of this paper are detailed below:

- It provides an overview of FDSs using wearable devices and LPWAN technologies.
- It offers a detailed examination of the predominant algorithms used in fall detection within the context of integrating LPWAN technologies.

- It conducts a comprehensive analysis of the recent state of the art, covering studies that implement LPWAN wearable technologies for fall detection and considers aspects such as the wearable devices used, their placement on the body, the sensors, and energy efficiency.
- It evaluates performance parameters such as accuracy, sensitivity, and specificity in different combinations of LPWAN technologies, detection algorithms, and sensors.
- It presents a detailed discussion on emerging trends in applying LPWAN in fall detection, as well as future research directions.

To systematically address these contributions, the paper begins by detailing the methodology used to screen the relevant literature in Section 2. This is followed by an overview of the most relevant LPWAN alternatives in Section 3. Next, Section 4 categorizes and analyzes the selected studies. Section 5 discusses the implications of the findings, while Section 6 summarizes the criticisms and limitations identified. Finally, Section 7 offers recommendations for future research and practical applications, with Section 8 presenting the main conclusions.

2. Methodology

This systematic review utilized the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, making specific adjustments to focus on advanced research concerning the use of LPWAN technologies in wearable devices for fall detection [62]. The methodological process consisted of the phases described in the following subsections:

2.1. Phase 1: Identification Relevant Studies (Identification)

2.1.1. Definition of the Research Question

The research question was formulated to address the topic of interest precisely: "What are the most commonly used LPWAN technologies in wearable devices for fall detection, and what is the effectiveness of their application in terms of accuracy and efficiency?".

2.1.2. Eligibility Criteria

For the selection of studies, eligibility criteria were established based on the following aspects:

Inclusion

- Full original articles published in peer-reviewed journals between 2010 and 2023.
- Research addressing the application of LPWAN technologies in wearable devices for fall detection.
- Focus on evaluating the accuracy and effectiveness of technologies in fall detection.
- Studies using inertial sensors combined with functional tests and/or daily life activities for fall detection.
- Articles that present the keywords defined in the search string in the abstract or title.

Exclusion

- Duplicated records that appear in more than one database.
- Papers not available in full-text format or not written in English.
- Works published before 2010, the year of Sigfox technology conception.
- Studies that do not present a prototype aimed at detecting falls and sending the corresponding alarm.
- Articles describing systems in which the alarm transmission technology does not involve the use of LPWAN technologies.
- Studies that do not include any type of evaluation of the developed prototype.
- Records about fall detection architecture that, although incorporating the use of LPWAN standards, are not based on wearable devices.

2.1.3. Information Sources

A comprehensive search for articles was conducted in renowned academic databases such as IEEE Xplore, MDPI, Scopus, Google Scholar, and Web of Science. While Web of Science was used to identify relevant articles, many of these were also available and downloaded from primary sources, such as IEEE Xplore.

Our search focused on articles that appeared between 2010 and 2023. The year 2010 was chosen as it marks the founding of Sigfox, the first sensor network operator with a large-scale market presence.

2.2. Phase 2: Selection of Relevant Studies (Screening)

Search and Selection of Studies

This section describes the process of searching and selecting relevant studies for the systematic review. The process is divided into several stages, starting with the design of the search string and finishing with the selection of studies that meet the established eligibility criteria.

2.2.1. Search

The terms for the bibliographic search included combinations of keywords such as ("LPWAN" OR "Low-Power Wide-Area Network" OR "LoRaWAN" OR "LoRa" OR "Symphony Link" OR "Sigfox" OR "NB-IoT" OR "LTE-M" OR "Ingenu RPMA" OR "Weightless LPWAN" OR "MIOTY" OR "DASH7") AND ("health AND fall" OR "elderly AND fall" OR "fall detection" OR "fall detection" OR "fall tracker" OR "fall detector" OR "fall sensor" OR "fall prevention" OR "fall monitoring"). These terms and logical operators, which are compatible with the search mechanisms commonly used in the databases, were alternatively introduced in the academic databases to identify the related literature.

As mentioned above, the search covered articles published in 2010, when Sigfox [63,64], the first widespread LPWAN technology, was created. However, significant research combining LPWAN and FDSs began to emerge in 2018, marking the beginning of specialized research in this specific area.

2.2.2. Title and Abstract Exploration

To evaluate the initial relevance of search results, a thorough examination of the titles and abstracts was carried out. Studies that clearly did not fit the research topic were discarded. Two researchers (M.L., E.C.P.) conducted independent reviews of the articles based on the set eligibility criteria. A consensus approach was followed since no relevant difference was found between the two independent analyses. Hence, no third reviewer was required to complete this exploration.

2.2.3. Potentially Relevant Studies Selection

The studies selected in the previous phase were evaluated in detail to determine whether they met the established inclusion criteria. Aspects such as focus on LPWAN technologies, application in wearable devices, and fall detection were considered. Studies that met these criteria progressed to the next stage.

2.3. Phase 3: Study Inclusion (Inclusion)

During this phase, the preselected studies were subjected to a comprehensive and rigorous evaluation. Additional exclusion criteria were applied to ensure that only the most pertinent studies were incorporated into the systematic review. The assessment also included an evaluation of the methodologies employed by the studies.

This multi-phase approach to the search and selection of studies ensured the systematic review was thorough and comprehensive, resulting in the inclusion of only the most relevant and high-quality studies in the final analysis.

Data Analysis and Quality Analysis of Articles

For the detailed synthesis of the selected studies, we employed several analysis methods:

- Classification of LPWAN technologies: Identifying and categorizing the LPWAN technologies (LoRaWAN, Sigfox, NB-IoT) used in each study.
- Sensor analysis: Evaluating the types of sensors (accelerometers, gyroscopes, magnetometers) and their placement on the body.
- Detection algorithm performance: Analyzing the performance of detection algorithms, focusing on accuracy, sensitivity, and specificity.
- Characteristics of the evaluation samples: Review sample sizes and the number of falls evaluated.
- Energy consumption analysis: Comparing reported battery life and power consumption of the devices.
- Comparative analysis: Highlighting strengths, weaknesses, and key findings across studies.

As mentioned above, the article selection process was divided into three fundamental stages. Figure 1 presents a visual representation of the application of these stages in the study selection process.s

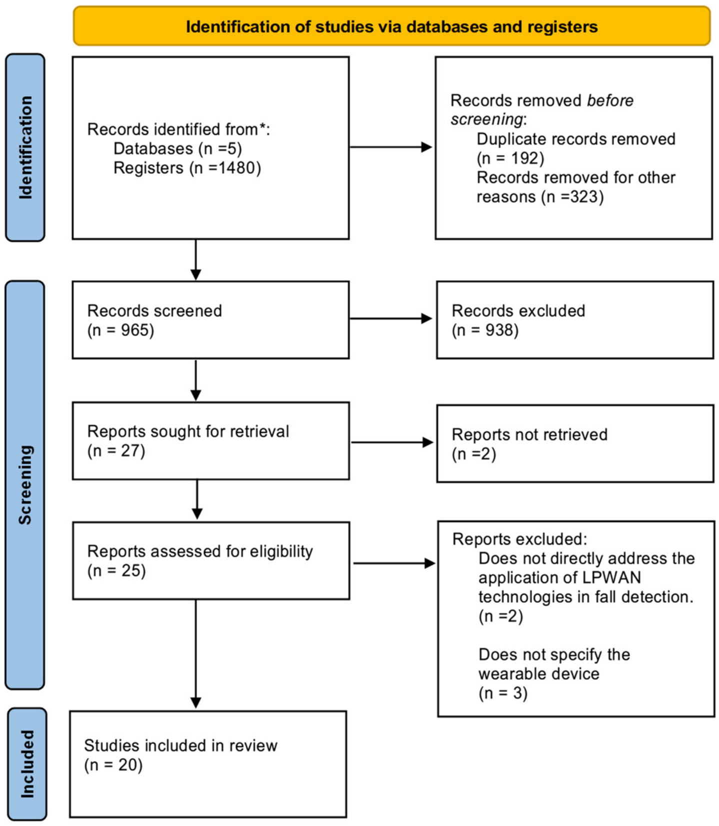

Figure 1. Proposed methodology: results of the screening for each stage in the bibliographic search.

Subsequently, in the third inclusion phase, a detailed review of the 25 retrieved reports was conducted to determine their eligibility. Among these, five works were excluded: two of them for not specifying the used fall detection algorithm, as well as three papers that omitted basic information about the employed wearable device. As a definite result of this three-stage process, 20 studies were preselected for inclusion in this review [6–8,11–14,16,20,22,26–28,33,34,36,53,54,65,66].

3. Overview of the LPWAN Concept

LPWAN technologies are a set of wireless communication solutions which enable the connection of low-power and cost-effective devices over long distances. These technologies are ideal for IoT and M2M (Machine-to-machine) applications requiring wide-area connectivity and sporadic and small data transmission. Examples of such applications can be found in the fields of environmental monitoring, asset tracking, smart agriculture, smart cities, or healthcare, among others [50,67,68].

The main characteristic of LPWAN networks is the ability to connect devices that require low power, enabling them to operate with batteries or even directly powered by energy harvesting sources. This is possible because LPWAN networks employ efficient communication protocols, which allow devices to consume less energy when transmitting data [69]. Figure 2 illustrates a qualitative comparison among the different communication technologies as a function of the energy efficiency and terminal and connection costs. In this context, LPWAN stands out significantly.

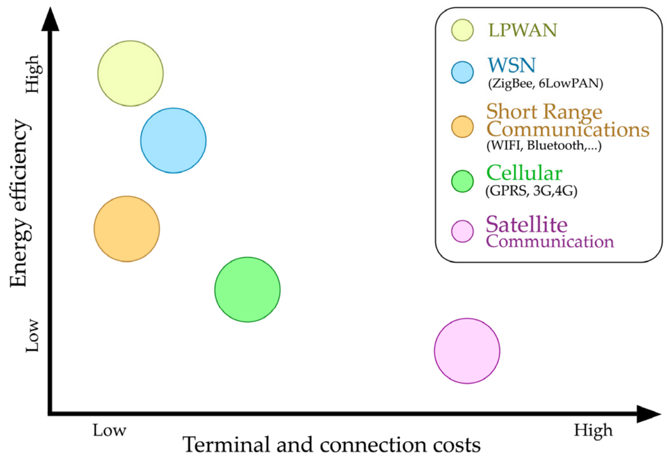

Figure 2. Comparison of energy efficiency with terminals and connection costs in various wireless communication technologies. Source: [51,69].

Apart from their low energy consumption and long-range capabilities, LPWAN networks offer extensive coverage and low implementation costs. Each access point or Gateway can support thousands of end nodes over several kilometers, thus favoring savings on network implementation costs. This makes them particularly suitable for applications in areas where traditional communication infrastructures are limited or costly to implement. IoT applications requiring the transmission of small data payloads across extensive distances while maintaining high energy efficiency are most ideally accommodated by LPWANs [70]. The former operates on licensed frequencies and is designed to function within frequency bands allocated for telecommunication services, leveraging existing infrastructures of mobile networks. In this regard, the 3GPP (3rd Generation Partnership Project) standards include several technologies that are meant for low-power, long-range, low-cost, and secure IoT applications, including NB-IoT (Narrowband- Internet-of-Things), LTE-M (Long Term Evolution for Machines), EC-GSM-IoT (Extended Coverage GSM for the Internet of Things), and 5G (5th Generation). Contrariwise, the latter uses unlicensed frequency bands. The so-called Industrial, Scientific, and Medical (ISM) radio bands are available for use without the need to pay a subscription fee. Examples of non-cellular LPWAN technologies include LoRaWAN and Sigfox. In the case of LoRaWAN, the technology can be employed to create public or private networks by incorporating new base stations that are free of license requirements [50,67].

In addition to their low energy consumption and long-range capacity, LPWAN networks are also characterized by their extended coverage and low implementation cost. LPWAN access points or gateways cost much less than any equivalent cellular base station.

Furthermore, an LPWAN gateway can support thousands of end nodes over several kilometers, which remarkably decreases the network's implementation and maintenance expenses. This makes LPWAN architectures particularly suitable for applications in areas where traditional communication infrastructures are limited or costly to deploy. Consequently, IoT applications requiring transmission of small data payloads across extensive distances (such as the medical alerts provided by FDSs) while maintaining high energy efficiency are most ideally accommodated by LPWANs [51].

Comparison of Most Popular LPWAN Technologies

The primary LPWAN technologies commonly employed in IoT applications comprise NB-IoT, LoRaWAN (Long Range Wide Area Network), and Sigfox (no relevant studies on FDSs using other LPWAN standards [47], such as Ingenu RPMA [Random Phase Multiple Access], Dash7 or Weightless LPWAN, was found). In contrast with Sigfox and LoRaWAN, NB-IoT is more focused on offering higher bandwidth and better coverage in urban areas with high node density at the cost of higher consumption and a more sophisticated protocol stack. Compared to Sigfox, LoRaWAN stands out for its greater capacity to transmit packets daily, long-lasting battery life, and lower operational costs. On the other hand, Sigfox provides a close, proprietary solution with a global network exclusively dedicated to IoT [47]. As in the case of traditional mobile telephony operators, Sigfox typically operates on a subscription-based model, according to which users can deploy their corresponding sensing nodes in an area covered by Sigfox gateways and pay for the connectivity services provided by the Sigfox network.

Table 1 provides a general comparison of these technologies, detailing aspects such as employed band, modulation, range, data rate, bidirectionality, energy consumption, and standardization.

Table 1. Summary of LPWAN Technologies: LoRaWAN, NB-IoT, and Sigfox [47,51,52].

Features	LoRaWAN	NB-IoT	Sigfox
Range	5 km (urban), 20 km (rural)	1 km (urban), 10 km (rural)	10 km (urban), 40 km (rural)
Bidirectional	Yes/half-duplex	Yes/half-duplex	Limited/half-duplex
Frequency	Unlicensed ISM band (915 MHz in North America, 433 MHz in Asia, 868 MHz in Europe)	Licensed LTE frequency	Unlicensed ISM band (868 MHz in Europe, 915 MHz in North America, 433 MHz in Asia)
Modulation	CSS	QPSK	BPSK
Maximum Bit Rate ("on-the-air")	50 kbps	250 kbps	100 bps
Standardization	LoRa Alliance	3GPP	Sigfox collaborates with ETSI on Sigfox-based network standardization
TX (Transmission) power consumption	28 mA	74–220 mA	10–50 mA
RX (Reception) power consumption	10.5 mA	46 mA	10 mA
Sleep mode power consumption	1 µA	3 µA	6 µA

Acronyms: CSS (Chirp Spread Spectrum), QPSK (Quadrature Phase Shift Keying), BPSK (Binary Phase Shift Keying), TX (Transmission), RX (Reception), ISM (Industrial, Scientific, and Medical radio bands), 3GPP (Third Generation Partnership Project), ETSI (European Telecommunications Standards Institute).

LoRaWAN and Sigfox are well-suited for IoT applications demanding extensive coverage and economical communication solutions. As aforementioned, these technologies operate in unlicensed frequency bands, which results in a significant reduction of operational costs. In addition, both architectures are based on extremely simple communication protocols with minimal handshakes, greatly simplifying their implementation in devices (such as wearables) with heavily limited hardware resources. As for the maximum data transfer rate, LoRaWAN offers up to 50 kbps, whereas Sigfox only provides up to 100 bps, rendering them suitable options for low-speed data applications (such as FDSs, which only require sending medical alerts with little data). Nevertheless, it is important to highlight that LoRaWAN may enable bidirectional or half-duplex communication, while Sigfox has more constraints regarding packet exchange rate between the end nodes and the gateways. On the other hand, the NB-IoT standard [47] offers superior performance with speeds of up to 250 kbps, although it uses licensed frequencies, which may require additional costs and regulatory challenges. In terms of energy consumption, LoRaWAN stands out for its efficiency, consuming 28 mA during transmission and 10.5 mA during reception. Conversely, NB-IoT transceivers, despite their superior performance, exhibit higher energy consumption, ranging from 74 to 220 mA during transmission and 46 mA during reception. Sigfox, on the other hand, offers moderate energy consumption, ranging from 10–50 mA during transmission and 10 mA during reception.

In summary, LoRaWAN and Sigfox are ideal for IoT applications that need wide coverage, cost-effective communication, and energy efficiency, albeit they present limitations in data speed. Conversely, NB-IoT offers superior performance at the expense of higher costs, regulatory challenges, and increased energy consumption.

4. Analysis of Selected Studies

This section presents a comprehensive analysis of the selected studies for this systematic review. Key aspects such as the LPWAN technologies used, the sensors employed, the placement of wearable devices on the body, and the fall detection algorithms implemented are examined.

4.1. Selected Studies

Table 2 summarizes the articles reviewed, showing author(s), title, type, location, LPWAN technology, application, and sensors employed in each article.

Table 2. Papers Included in the Systematic Review.

Ref.	Year	LPWAN Technology *	Sensor **
Escriba et al. [20]	2018	Sigfox	Accelerometer
Patel et al. [14]	2018	LoRaWAN	Accelerometer
Valach et al. [12]	2018	LoRaWAN	Accelerometer
Manatarinat et al. [22]	2019	NB-IoT	Accelerometer and gyroscope
Pena Queralta et al. [53]	2019	LoRaWAN	Accelerometer, gyroscope and magnetometer
Scheurer et al. [65]	2019	LoRaWAN	Accelerometer
Cai et al. [54]	2020	NB-IoT	Accelerometer and gyroscope
Chang et al. [8]	2020	LoRaWAN	Accelerometer, gyroscope and IR (Infrared)
Huynh et al. [6]	2020	LoRaWAN	Accelerometer, gyroscope and magnetometer
Lachtar et al. [11]	2020	LoRaWAN	Accelerometer, gyroscope and magnetometer
Zanaj et al. [7]	2020	LoRaWAN	Accelerometer, gyroscope and magnetometer
Liu et al. [28]	2021	NB-IoT	Accelerometer, gyroscope and magnetometer
Lousado et al. [13]	2021	LoRaWAN	Accelerometer
Fan et al. [27]	2022	NB-IoT	Accelerometer and gyroscope

Table 2. *Cont.*

Ref.	Year	LPWAN Technology *	Sensor **
Li et al. [16]	2022	LoRaWAN	Accelerometer and gyroscope
Qian et al. [26]	2022	NB-IoT	Accelerometer and gyroscope
Salah et al. [36]	2022	LoRaWAN	Accelerometer
Wong et al. [33]	2022	LoRaWAN	Accelerometer, gyroscope and magnetometer
Wu et al. [34]	2022	NB-IoT	Accelerometer and gyroscope
Pierleoni et al. [66]	2023	NB-IoT	Accelerometer, gyroscope and magnetometer

Notes: * LPWAN technologies include Sigfox, LoRaWAN (which also includes studies using LoRa), and NB-IoT, which are used for long-range, low-power wireless communication. ** Sensors mentioned include accelerometers (triaxial acceleration), gyroscopes (triaxial angular velocity), magnetometers (magnetic field), and IR sensors (infrared radiation). Some measurements (such as orientation), also used by certain FDSs, can be computed from the signals captured by the inertial sensors.

4.2. Selection of the LPWAN Technology

Among the various types of LPWAN used in biomedical telemonitoring for fall detection, LoRaWAN and NB-IoT emerge as the most prominent standards. LoRaWAN leads in preference with a total of 12 implementations, closely followed by NB-IoT with 7. Additionally, Sigfox is employed in a single study. These findings are visually summarized in Figure 3.

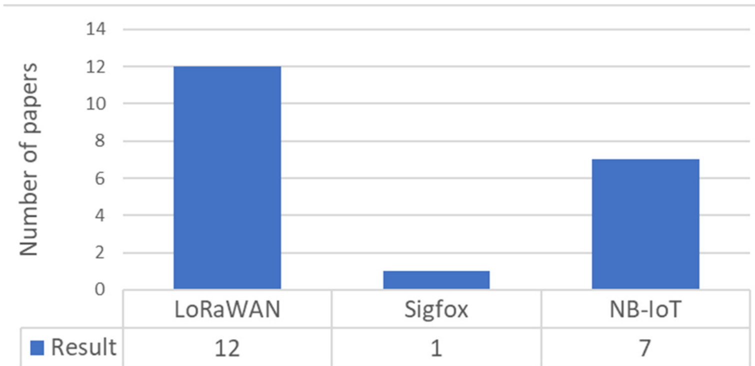

Figure 3. Distribution of LPWAN technologies used in studies of wearable fall detectors.

LoRaWAN and NB-IoT dominate the landscape of fall detection due to their balance of range and energy efficiency. However, the limited adoption of Sigfox, with only one study recorded, highlights its drawbacks. Its high latency and sensitivity to environmental conditions make it less suitable for critical applications such as fall detection [71].

4.3. Comparative Insights on LPWAN Technologies

Table 3 presents a comparative analysis of various studies on LPWAN technologies used in FDSs. This table highlights the main conclusions and limitations of each technology in the reviewed articles, providing a comprehensive overview of their application in health and safety monitoring for older adults.

The reviewed articles reveal key patterns regarding the conclusions and limitations of each LPWAN technology. The studies consistently indicate that Sigfox, while effective for low-power data transfer and suitable for fall detection, is limited by its low data rate and sensitivity to environmental conditions [20]. LoRaWAN stands out for its long-range communication capabilities and low power consumption. In fact, LoRaWAN is the most frequently used technology due to its operation in unlicensed frequency bands, which makes it a cost-effective option. However, the studies also agree that LoRaWAN can face network reliability issues, particularly in public networks and environments with physical obstacles [6–8,11–14,16,33,36,53,65]. NB-IoT, on the other hand, offers wide coverage, the ability to handle multiple connections, and low power consumption, making it suitable for health monitoring applications. The primary limitations of NB-IoT, according to the studies, relate to network coverage variability and potential data loss due to environmental interference [22,26–28,31,34,54]. Table 4 provides a summary of the performance of LPWAN technologies in fall detection across various environmental conditions (e.g., rural areas or environments with physical obstacles like cities with high building density) and mobility scenarios.

Table 3. Comparative Insights on LPWAN Technologies in Fall Detection Systems.

Ref.	Contribution	Conclusions on LPWAN Technology	LPWAN Limitations	Outcome
Escriba et al. [20]	Development of a smart wearable active patch for elderly health prevention, utilizing Sigfox for fall detection and GPS tracking.	Sigfox is effective for low-power data transfer and suitable for fall detection and geolocation.	A low data rate limits the amount of information transmitted; communication is affected by environmental conditions and device location.	The system effectively used Sigfox for low-power data transfer, with the patch maintaining communication reliability in 67.92% of tested positions, validating its capability for fall detection and location tracking.
Patel et al. [14]	Development of a LoRaWAN-based system for real-time monitoring of vital signs and fall detection, with alerts sent via LINE application.	LoRaWAN can extract data from weak signals in noisy environments, which is useful for delivering critical medical data.	No specific limitations are commented.	The system demonstrated high performance with LoRaWAN, achieving 100% sensitivity, 96.93% accuracy, 94.25% specificity, and 91.38% predictability, ensuring reliable transmission of fall alerts.
Valach et al. [12]	Research on the feasibility of using LoRaWAN in healthcare IoT devices, focusing on energy optimization and transmission reliability.	LoRaWAN is suitable for long-distance data transmission with low power consumption and is useful for patient location and monitoring vital signs.	The LoRaWAN connection was unreliable when the end node was on the ground during tests.	LoRaWAN showed reliability issues in fall detection when the end node is near the ground; using Arduino Pro Mini is suggested to reduce energy consumption.
Manatarinat et al. [22]	Development of an NB-IoT-based system for elderly healthcare, enabling automatic fall detection and alerts via the LINE application.	NB-IoT is suitable for health monitoring applications, providing efficient low-power communication with wide coverage.	No specific limitations.	Reliable fall alert communication and patient location using NB-IoT, ensuring immediate medical response. Achieved low latency and dependable alert delivery, with reliance on an NB-IoT operator for network functionality.
Pena Queralta et al. [53]	Developed and technically validated the AIDE-MOI fall detection algorithm using real-life data from older adults, utilizing LoRaWAN for effective long-range, low-power communication.	LoRaWAN is a promising option to overcome the limitations of traditional network infrastructures in remote health settings, providing long-distance, low-power data transmission.	LoRaWAN cannot support high data rate applications due to limited transmission bandwidth.	The AIDE-MOI system demonstrated significant improvement with LoRaWAN, achieving a sensitivity of 80% and a specificity of 99.9978%, ensuring reliable and efficient fall detection and data transmission in real-life environments.

Table 3. *Cont.*

Ref.	Contribution	Conclusions on LPWAN Technology	LPWAN Limitations	Outcome
Scheurer et al. [65]	Developed and technically validated the AIDE-MOI fall detection algorithm using real-life data from older adults, utilizing LoRaWAN for effective long-range, low-power communication.	LoRaWAN is used for long-range, low-power communication, allowing data transmission over several kilometers.	No specific limitations are commented.	The AIDE-MOI system using LoRaWAN achieved 80% sensitivity and 99.9978% specificity, ensuring reliable fall detection and efficient data transmission.
Cai et al. [54]	Developed a GBDT-based fall detection system using comprehensive data from posture sensors and human skeleton extraction, utilizing NB-IoT for effective data transmission to a cloud server for analysis.	NB-IoT provides wide coverage, multiple connections, low speed, and low power consumption.	No specific limitations are commented.	The system, using NB-IoT, achieved an I2 score of 0.878 on a fused dataset and 95% accuracy, demonstrating reliable and low-latency data communication.
Chang et al. [8]	This study proposes an intelligent assistive system for visually impaired individuals using smart glasses and a smart cane connected via BLE, with LoRaWAN for reliable fall detection and alert transmission.	LoRaWAN-based intelligent assistive system for aerial obstacle avoidance and fall detection for visually impaired people shows high accuracy and long-range communication.	Dependence on public LoRaWAN network coverage, which can vary based on geographical location and network infrastructure availability.	The system effectively uses LoRaWAN to transmit fall alerts, achieving long-distance coverage and low latency. The integration of both devices reduced false alarms, achieving an overall accuracy rate of 94.56%.
Huynh et al. [6]	Develops a LoRaWAN-based system for activity assessment and fall detection at home, using low-cost inertial sensors and a cloud platform for data analysis and emergency notifications.	LoRaWAN technology advantages of long-range capabilities and low power consumption. Wearable devices can operate 2–10 km from a LoRaWAN base station with an optimized battery life of one week between charges.	No specific limitations.	The system demonstrated a high specificity of 100% in fall detection during approximately 200 h of normal activities, proving the effectiveness of using LoRaWAN for reliable data transmission and emergency alerts.
Lachtar et al. [11]	Proposes a monitoring architecture using LoRaWAN and MQTT * for fall detection in elderly people within a smart city environment.	LoRaWAN technology is used for long-range, low-power communication in a smart city environment, effectively robust and efficient for elderly monitoring.	Reliance on public LoRaWAN network coverage, which can fluctuate based on geographic location and available infrastructure.	The system demonstrated efficient long-range communication with LoRaWAN, covering an average area of 6 km^2 with minimal packet loss, making it suitable for smart cities.

Table 3. *Cont.*

Ref.	Contribution	Conclusions on LPWAN Technology	LPWAN Limitations	Outcome
Zanaj et al. [7]	Proposes a wearable fall detection system integrated into shoes, using LoRaWAN for long-range, low-power communication and MQTT for alert notifications.	LoRaWAN is an attractive and promising technology for health and wellness monitoring, enabling long-range communication with low battery consumption. It has been demonstrated to be effective for long-term use and reliable coverage with a single gateway.	Packet loss can occur due to obstacles affecting the connection between the end node and gateway.	Demonstrated efficient data transmission with a 95% success rate in various environments. The system operates for approximately 23 h on a 500 mAh battery, proving LoRaWAN's viability for fall detection.
Liu et al. [28]	Proposes a wearable fall detection system utilizing a 1D CNN deep learning model and NB-IoT communication to send alerts and GPS data to the cloud.	NB-IoT is key for data transmission and alerts in a successful fall detection system based on 1D CNN.	Lack of NB-IoT service coverage can cause interference and data loss due to variability in signal quality across different geographical environments and network conditions.	The system demonstrated a fall detection accuracy of 98.85%, with a sensitivity of 98.86% and specificity of 99.84%, highlighting the effectiveness of using NB-IoT for reliable data transmission and fall alerts.
Lousado et al. [13]	Proposes a cost-effective, energy-efficient monitoring system for elderly individuals using LoRaWAN and The Things Network (TTN) for long-range communication and data processing.	LoRaWAN offers an effective and low-cost solution for monitoring the health and home conditions of elderly people, especially in remote areas with limited mobile network coverage.	Variability in LoRaWAN public network coverage, which may be insufficient in certain geographical areas due to uneven infrastructure availability.	Demonstrated high predictive accuracy (99.73%) for detecting falls and other anomalies, showcasing the viability of using LoRaWAN for reliable and continuous monitoring of elderly individuals' health and movement in areas with limited mobile network coverage.
Fan et al. [27]	Design and development of a low-power wearable fall detection device for the elderly using NB-IoT technology, capable of remote positioning, tracking, fall detection, and one-touch emergency calls.	NB-IoT communication is of paramount importance for the successful implementation of this fall detection device for the elderly, providing an effective solution for monitoring elderly safety and reducing caregiving pressure on family members.	No specific limitations.	The device demonstrated effective fall detection in different directions during simulated tests. GPS positioning accuracy showed that 94% of the time, the positioning error was within 20 m, validating the device's capability for precise location tracking using NB-IoT technology.

Table 3. *Cont.*

Ref.	Contribution	Conclusions on LPWAN Technology	LPWAN Limitations	Outcome
Li et al. [16]	Design and development of an emergency communication system for elderly people living alone, using LoRaWAN technology for long-range, low-power communication, along with a fall detection algorithm based on the channel hopping strategy.	LoRaWAN, combined with channel hopping, enhances the communication quality and efficiency of emergency systems monitoring the elderly, facilitating remote monitoring.	Communication loss rate of 2% at distances up to 1800 m due to electronic interference, physical obstacles, and simulated environmental conditions.	The device achieved a fall detection rate of over 85% in simulated tests. The average communication latency was 9.5 s, and the effective communication distance reached 1800 m, validating the efficiency of LoRaWAN for emergency communication systems.
Qian et al. [26]	Design and development of a wearable fall detection system combining MEMS * sensors and NB-IoT, capable of integrating with public health systems for real-time monitoring and timely rescue.	NB-IoT, combined with MEMS sensors and a multilevel threshold algorithm, provides an efficient, low-power solution for real-time fall detection that is suitable for integration with public communication networks.	Signals are sensitive to the environment, and disturbances and noises can cause system faults.	The system demonstrated a fall detection accuracy of 94.88%, sensitivity of 95.25%, and specificity of 94.5% in experimental tests. This validates the effectiveness of the NB-IoT-based system for real-time fall detection and location tracking in elderly individuals.
Salah et al. [36]	Design of a fall detection system based on Edge artificial intelligence, combining a microcontroller and LoRaWAN communication.	LoRaWAN technology, used with edge AI, enables long-range, low-power communication, making it suitable for real-time fall detection systems with high accuracy and low latency.	Communication range decreases when moving from a direct line of sight to a non-line of sight due to obstacle interference, affecting system performance.	The device achieved a 95.55% accuracy in fall detection using a convolutional neural network (CNN). Local inference reduced latency and improved energy efficiency, with a battery life exceeding 53 h and a communication range of up to 180 m in line-of-sight using LoRaWAN.
Wong et al. [33]	Design of a fall detection system based on LoRaWAN communication, optimizing fall detection accuracy while reducing costs by eliminating the need for mobile phones.	LoRaWAN technology is highlighted for its low power consumption, reduced operational costs, and flexible data transmission rate, making it the best option for long-distance communication in emergency situations.	Communication can be affected by obstacles, electrical and magnetic interferences, leading to system instability and data transmission issues.	The system accurately detected falls in various scenarios with set thresholds, demonstrating reliable performance in both indoor and outdoor environments. The LoRaWAN protocol ensured stable signal transmission up to 318 m with minor obstructions, proving its effectiveness for long-range communication.

Table 3. *Cont.*

Ref.	Contribution	Conclusions on LPWAN Technology	LPWAN Limitations	Outcome
Wu et al. [34]	Design and development of a fall detection module based on NB-IoT technology and MEMS systems, capable of collecting acceleration and angle data and transmitting it for precise fall analysis.	NB-IoT, combined with MEMS sensors and a GRU-based algorithm, provides an effective, low-power solution for real-time fall detection, suitable for long-distance data transmission.	No specific limitations.	The module demonstrated an accuracy of 90.1% using the threshold method and 92.9% with GRU. Data was successfully transmitted via NB-IoT, enabling alerts to be sent to family members and rescue centers in the event of a detected fall.
Pierleoni et al. [66]	Design and development of a comprehensive architecture for Ambient Assisted Living (AAL) scenarios, incorporating a cross-protocol proxy for seamless communication between different IoT protocols and a wireless wearable fall detection device based on LPWAN technologies such as NB-IoT.	NB-IoT, used in combination with CoAP * and MQTT, provides an efficient and reliable communication solution for wearable fall detection devices, ensuring low latency and high throughput.	Latency issues due to network congestion and packet loss requiring retransmissions, with latency averaging 0.4 s and occasional peaks up to 10 s.	The system demonstrated low latency (approx. 0.4 s) and high reliability in transmitting fall detection alerts using NB-IoT and MQTT. The proxy improved interoperability, and the wearable device showed a high success rate in fall detection and alerting in an AAL environment. The packet loss rate was slightly above 0.1%, with recovery through retransmissions.

* Acronyms: CoAP (Constrained Application Protocol), MQTT (Message Queuing Telemetry Transport), MEMS es Micro-Electro-Mechanical Systems.

Table 4. Performance of LPWAN Technologies in Fall Detection According to Environmental Conditions and Mobility Scenarios.

Technology	Environmental Conditions	User Mobility Scenarios	Reference
Sigfox	Sensitive to environmental conditions; ideal for rural environments	Suitable for low mobility applications where data transmission is not continuous and can tolerate delays.	[20,71]
LoRaWAN	May face reliability issues in environments with physical obstacles; offers good interference resistance	Ideal for urban and rural applications with limited to moderate mobility due to its combination of long-range and low-power consumption.	[6–8,11–14,16,33,36,53,65,71]
NB-IoT	Can be affected by network coverage variability and environmental interference	Best for urban environments where support for mobile devices and high reliability in data transmission are required, making it ideal for critical applications such as fall detection.	[22,26–28,34,54,66,71]

There is no perfect option for fall detection applications requiring immediate and reliable message delivery. Sigfox is suitable for situations where latency is not critical, and energy efficiency is prioritized. NB-IoT, with its low latency and high reliability, is ideal for critical applications in urban environments. LoRaWAN offers a good balance with its combination of long-range, low-power consumption, and better average latency, making it versatile for various environments. It is crucial to consider the specific needs of the application and the conditions of the environment when choosing the appropriate technology for fall detection.

4.4. Employed Sensors

Within the field of biomedical telemonitoring for fall detection, Inertial Measurement Unit (IMU) sensors are predominantly used to feed detection algorithms that identify falls. These IMU sensors include accelerometers, gyroscopes, and magnetometers, which are employed in various combinations across the reviewed studies (see Figure 4). The most prevalent combination is the use of accelerometer, gyroscope, and magnetometer, employed in 7 studies (35%). The combination of accelerometer and gyroscope is used in 6 studies (30%), while another six studies (30%) rely solely on the accelerometer for detection. Finally, in one case (the work by Chang et al. [8]), the use of accelerometer and gyroscope is complemented by an infrared sensor located in a second wearable (a pair of glasses).

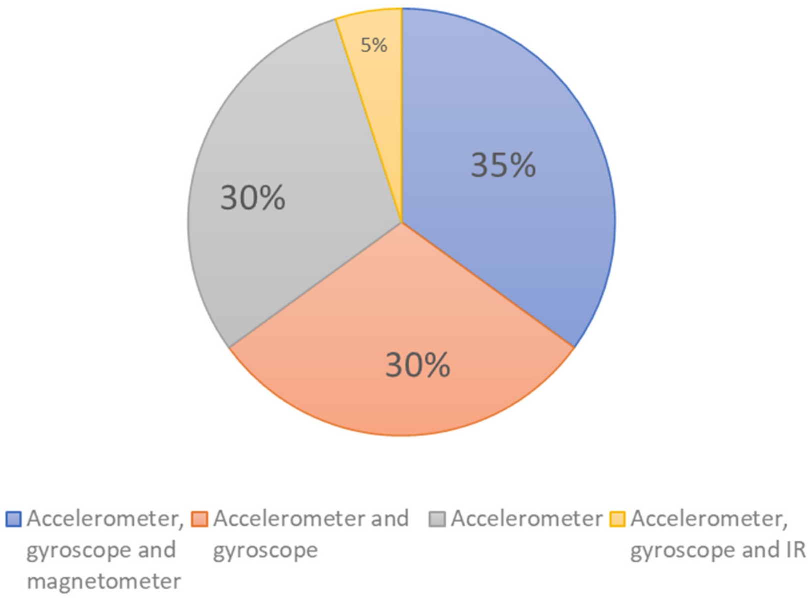

Figure 4. Types of sensors used in the selected articles.

Although IMU sensors, such as accelerometers, gyroscopes, and magnetometers, are widely used in wearable devices with LPWAN technology for fall detection, the system's lack of integration of additional sensors, such as a barometer, limits accuracy. As highlighted by Pierleoni et al. [31], the inclusion of a barometer could provide valuable information on altitude changes during a fall, improving detection reliability. The almost exclusive reliance on inertial sensors, with only occasional use of infrared sensors, suggests a missed opportunity to address more complex scenarios and enhance fall detection accuracy.

4.5. Location of the Wearable Device

The location of the wearable device is a crucial factor for accurate fall detection in LPWAN-based systems. Özdemir [39] study highlights that sensor placement can significantly influence readings and the system's ability to differentiate between normal movements and fall events. According to the study, average accuracies based on the sensor's location on the body vary considerably. The waist region is identified as the best position, with an average accuracy of 98.42% for six machine learning algorithms. The thigh sensor follows with an accuracy of 97.89%, and the ankle with 97.00%. On the other hand, the head, with an accuracy of 96.61%, and the chest, with 96.50%, also show good results. Wrist sensors have the lowest performance, with an average accuracy of 94.92%. These findings underscore the importance of carefully selecting the device's location to optimize fall detection. Table 5 presents the selected locations for wearable device placement in the LPWAN-based FDS under analysis.

Table 5. Location of the Wearable Device.

Reference	Device Position
Huynh et al. [6]	Waist or wrist
Zanaj et al. [7]	Foot (shoes)
Lachtar et al. [11]	Cane
Lousado et al. [13]	Backpack
Escriba et al. [20]	Back
Qian et al. [26]	Wrist
Fan et al. [27]	Wrist
Wu et al. [34]	Waist
Liu et al. [28]	Waist
Wong et al. [33]	Chest
Scheurer et al. [65]	Back, abdomen, or chest
Pierleoni et al. [66]	Ankle or shoe

Note: "Cane" refers to a walking stick used as an assistive device.

The studies presented in Table 5 highlight the diversity of locations used for wearable devices in fall detection. The selection of the device's location should consider both detection accuracy and user comfort and acceptance. Additionally, it is important to consider that different activities and contexts can influence the effectiveness of the sensor's location, suggesting the need to customize the device placement according to the user's individual needs. Comparing these results with Özdemir [39] findings, the accuracy on the wrist reported by Qian et al. [26] (94.88%) approximately corresponds. The accuracy on the waist reported by Liu et al. [28] (98.85%) also aligns significantly. In summary, the waist can be considered a reasonable location for a wearable fall detection device. This position not only offers high accuracy but is also close to the body's center of gravity, allowing for more precise detection of changes in body movement while minimizing interference with the user's daily activities. Although wrist devices are more comfortable and socially acceptable, similar to a conventional watch, specific arm movements can affect fall detection accuracy. On the other hand, placing the sensor on the back, abdomen, or chest, as indicated by Scheurer et al. [65], does not significantly affect fall detection effectiveness but may hamper ergonomics. Other locations, such as inside footwear or on a cane, aim to maximize comfort but at the cost of a lower accuracy of the detector.

4.6. Employed Detection Algorithms

The accuracy of fall detection in biomedical telemonitoring settings greatly relies on the detection algorithm, the "intelligence core" in charge of identifying anomalous mobility patterns from the gathered signals. However, evaluating their performance and comparing the selected studies according to a common evaluation framework becomes complex due to the significant differences in the test conditions (methodology, participants, use of fake falls, etc.) considered by the authors to validate their proposal.

In any case, a summary of outcomes from the relevant studies is presented in Table 6. In the second column, the table indicates the type of algorithm used to identify the falls.

Table 6. Summary of Performance Metrics of Fall Detection Algorithms.

Reference	Algorithm Type *	Accuracy	Sensitivity	Specificity	Sensor	Sample Size (Number of Participants)	No. of Evaluated Falls
Huynh et al. [6]	Thresholding policies	n.i.	96.3%	96.2%	Accelerometer, gyroscope and magnetometer	10	n.i.
Chang et al. [8]		98.3%	n.i.	n.i.	Accelerometer, gyroscope and IR (Infrared)	3	150
Li et al. [16]		85%	n.i.	n.i.	Accelerometer and gyroscope	6	500
Wu et al. [34]		90.1%	n.i.	n.i.	Accelerometer and gyroscope	n.i.	n.i.
Qian et al. [26]		94.88%	95.25%	94.5%	Accelerometer and gyroscope	20	400
Salah et al. [36]	K-NN (15 neighbors)	78.64%	81.07%	76.57%	Accelerometer	24	1798
Salah et al. [36]	K-NN (5 neighbors)	79.11%	80.06%	78.21%	Accelerometer	24	1798
Salah et al. [36]	CNN	95.55%	95.1%	94.86	Accelerometer	24	1798
Liu et al. [28]		98.85%	98.86%	99.84%	Accelerometer, gyroscope and magnetometer	35	1798 and 288
Salah et al. [36]	LSTM	96.78%	97.87%	95.21%	Accelerometer	24	1798
Pena Queralta et al. [53]		91.90%	95.3%	n.i.	Accelerometer, gyroscope and magnetometer	54	647
Salah et al. [36]	SVM	82.27%	87.21%	78.48%	Accelerometer	24	1798
Wu et al. [34]	GRU	92.9%	n.i.	n.i.	Accelerometer and gyroscope	n.i.	n.i.
Cai et al. [54]	GBDT (Acceleration Dataset)	89.2%	n.i.	n.i.	Accelerometer and gyroscope	10	n.i.

* Acronyms: CNN (Convolutional Neural Network), GBDT (Gradient Boosting Decision Tree), GRU (Gate Recurrent Unit), k-NN (K-Nearest Neighbors), LSTM (Long Short-Term Memory), n.i. (not indicated by the authors), SVM (Support Vector Machine).

The table shows that there are examples of the three families of algorithms typically considered to address the problem of fall detection in wearable systems: from simple thresholding strategies (which assume that a fall occurs when certain measurements—or combinations of measurements—received from the sensors exceed certain critical values) to machine learning algorithms (such as k-Nearest Neighbor, Support Vector Machine, Decision Trees, etc.) and deep learning models (such as convolutional or recurrent neural networks) [72].

To characterize the effectiveness of the classifier, the table also includes some basic performance metrics reported by the authors: accuracy (percentage of total movements that are correctly identified), sensitivity (ratio of falls properly detected), and specificity (ratio of non-falls or ADLs- Activities of Daily Living- that are adequately interpreted).

Table 6 illustrates that, for the prototypes under study, the best results are those obtained with CNNs. Liu et al. [28] conducted a study using CNN in combination with measurements provided by accelerometers, gyroscopes, and a magnetometer alongside NB-IoT technology, achieving an accuracy of 98.85%, a sensitivity of 98.86%, and a specificity of 99.84%. They utilized the SisFall [73] and Mobifall [74] datasets for training and validating their models, ensuring a comprehensive evaluation of fall detection accuracy. In a similar approach, Salah et al. [36] also implemented a detector using CNN and LoRaWAN technology but only leveraging the data from an accelerometer. The prototype achieved an accuracy of 95.55%, a sensitivity of 95.1%, and a specificity of 94.86%. Another algorithm of significant relevance is the LSTM. According to Salah et al. [36], this algorithm reached an accuracy of 96.78%, a sensitivity of 97.87%, and a specificity of 95.21% when employing an accelerometer sensor. It is worth noting that these models were also trained and validated with the SisFall dataset [73,75], providing a robust framework for evaluating the performance. These results emphasize the high potential of these algorithms for fall detection within this context.

At this point, it should be noted that many works on FDSs with wearable devices do not analyze in detail (or directly ignore) certain operational aspects of great relevance for the practical implementation of these architectures. Among these aspects, one can mention the consumption of battery, memory, and computational resources that the detection algorithms themselves demand in the wearables, which usually have significant hardware limitations.

In this context, there is a consensus on the idea that simpler algorithms, such as those based on thresholds or some machine learning solutions [76,77], require fewer resources than those based on deep learning. In some works, such as Lampoltshammer et al. [78], it is proposed to implement a very simple mechanism in the wearable (e.g., based on a simple threshold for the acceleration module), so that when a fall is suspected, the inertial signals (collected over a certain period) are sent to an external point with higher computational power for a more detailed analysis based on more complex algorithms. However, this approach may require frequent transmissions from the wearable, which can be counterproductive from an energy perspective (and impractical if LPWAN solutions with limited available bandwidth are used). Few works, such as the RNN presented by Musci et al. [79] or the Tiny CNN described by Yu et al. [41], consider a careful and optimized design of the deep learning algorithm for its implementation on low-power embedded devices. Regarding memory consumption, the recent work by Fernandez-Bermejo et al. [80] highlights the importance of minimizing the parsimony of the models used (i.e., the number of parameters that they require) to facilitate their implementability.

As for the sensor, the accelerometer is the least demanding in terms of energy and the most used in the literature for motor rehabilitation [81], so it is not surprising that most proposals are based on measuring acceleration. In this sense, the sampling rate can affect consumption. A sampling rate above 20 Hz increases recognition accuracy in HAR systems by just 1% while this quality metric stabilizes beyond 50 Hz [82]. Therefore, a sampling rate of 50 Hz is considered more than sufficient [83]. In some work, it has been proposed to adaptively modify the frequency to the user's activity. Hence, during low activity situations, the frequency could be reduced to a minimum to moderate consumption and augmented when greater mobility is detected. However, this scheme, apart from increasing the complexity of the detector, may cause false negatives if the fall occurs from a stationary or low-movement position.

On the other hand, deep learning can benefit from the ability to work with raw signals in the time domain without needing to perform sophisticated operations to extract features. For example, Casamassima et al. [81] analyze the consumption of body area networks and conclude that the computation of features based on the FFT of accelerometry signals requires many more MCU clock cycles than those directly obtained from the time series.

Activating the GPS to report the position of the faller can also be a significant cause of battery drain in wearables. Gharghan et al. [84] propose activating the GPS only when a fall is suspected.

In any case, regarding the specific literature on fall detectors using LPWAN technologies, it should be noted that these operational aspects are practically overlooked, which is paradoxical since one of the main objectives of using LPWAN communications is to minimize consumption and hardware complexity.

4.7. Energy Consumption

One of the crucial aspects to consider when designing a wearable fall detector is battery life. However, battery lifetime is only investigated in some works of the related literature (synopsized in Table 7). As it can be appreciated, results indicate that battery lifespan can significantly vary based on the algorithm used, LPWAN technology, and sensors employed. None of the selected works explicitly study which of these factors is the main cause of battery drain. Only the work by Salah et al. in [36] showed that implementing the CNN model on a LoRaWAN sensing unit results in an improvement of battery life: 53 h in contrast with the 38 h of lifetime attained when a similar prototype combines BLE and a CNN-based detector. This highlights the potential savings in battery consumption that can be achieved with LPWAN technology when compared to other wireless transmission standards traditionally used in FDSs. In any case, when examining the results in the table, a certain relationship between the type of detection algorithm used and battery life technology becomes evident. Simpler detection algorithms, such as those considered in the prototypes described by Huyn et al. [6], tend to contribute to longer battery life, whereas more complex algorithms like CNN [36], may require more resources and thus consume more energy.

Table 7. Energy Consumption in Fall Detectors using LPWAN Technology.

Reference	Battery Life *	Battery Capacity **	Algorithm Type	LPWAN Technology	Employed Sensor
Huynh et al. [6]	1 week–1 month	Not specified	Thresholding	LoRaWAN	Accelerometer, gyroscope and magnetometer
Zanaj et al. [7]	23 h (500 mA/h), 36 h (800 mA/h)	500 mAh 800 mAh	Thresholding	LoRaWAN	Accelerometer, gyroscope and magnetometer
Salah et al. [36]	More than 53 h	2000 mAh	CNN	LoRaWAN	Accelerometer
Escriba et al. [20]	3 days (low-power mode)–13 h (GPS tracking)	30 mAh	Not indicated	Sigfox	Accelerometer

Notes: * Battery life varies depending on the operational mode; for example, Escriba et al. reported different durations for. low-power mode versus GPS tracking mode. ** Battery capacity is measured in milliampere-hours (mAh).

In any case, it is noteworthy that a significant number of studies employing LPWAN technology with fall detectors do not analyze battery life or consumption of the prototype through field tests. This becomes particularly striking when considering that one of the major benefits of these long-range wireless communication standards is energy efficiency.

4.8. LPWAN Transceivers

A comprehensive understanding of the transceivers used in FDSs with LPWAN technology is of great interest for current research, as it enables the identification of trends in the design of these devices, especially considering that the radio transceiver is one of the components with the highest energy consumption [85]. Reducing the energy of wireless communication is crucial for improving the energy efficiency of wearable devices. Table 8 compiles the transceivers used by the reviewed works, detailing the associated LPWAN technology and their references.

Table 8. LPWAN Transceivers.

Reference	Transceiver	LPWAN Technology *
Zanaj et al. [7]	SX1257	LoRaWAN
Salah et al. [36]	RFM95W	LoRaWAN
Lachtar et al. [11]	RFM95/96/97/98(W)	LoRaWAN
Valach et al. [12]	RFM95W	LoRaWAN
Lousado et al. [13]	SX1276	LoRaWAN
Qian et al. [26]	BC-95	NB-IoT
Fan et al. [27]	M5310A	NB-IoT
Wong et al. [33]	SX1278 RA-02	LoRaWAN
Pierleoni et al. [66]	nRF9160	NB-IoT

Notes: * LPWAN technologies include Sigfox, LoRaWAN, and NB-IoT, which are used for long-range, low-power wireless communication.

The review identified a clear preference for LoRaWAN technology in FDSs, due to its balance between range, energy efficiency, and the use of unlicensed spectrum bands [7,11–13,33,36]. Transceivers such as the SX1257, RFM95W, and SX1276, with current consumption of 58–85 mA and 120 mA respectively [86–88] for the transmission mode, demonstrate their suitability for battery-dependent long-range wearable devices. Additionally, the presence of NB-IoT technologies is noted, albeit to a lesser extent, represented by transceivers like the BC-95, M5310A, and nRF9160 [89–91], showing transmission power consumption of up to 220 mA. NB-IoT, which operates in licensed bands, may involve higher operational costs due to this requirement, despite offering more robust coverage. The nRF9160 stands out for its efficiency in idle mode, with consumption as low as 2.7 µA in PSM (Power Saving Mode) and 18–37 µA in eDRX (Extended Discontinuous Reception) [91]. Although NB-IoT provides greater coverage, its higher energy consumption during transmission may limit the battery life of wearable devices, underscoring the need of optimizing energy efficiency for wearable applications.

5. Discussion

The results of this systematic review provide insight into the application of LPWAN technologies in wearable devices for fall detection. This field is growing significantly, and our analysis highlights current and future trends.

As a first observation, there is a notable concentration of research in China (6 studies) [16,26–28,34,54] and Taiwan (2 studies) [8,33], with other countries contributing one manuscript each [6,7,11–14,20,22,36,53,65,66]. This reflects the leadership of these regions in the research and use of low cost transmission technologies in IoT appliances. Although the review initially considered articles from 2010 due to the conception of Sigfox, it focused on studies from 2018 to 2023 due to the increase in relevant research during this period. The results do not show a clear temporal pattern, although an increase was noted in 2020 and 2022. The review shows a balance between journal and conference papers, with 10 references of each type, indicating attention to both established and recent research. The focus from 2018 onwards was due to the emergence of articles combining LPWAN with fall detection. Additionally, this review covered various LPWAN technologies, including LoRaWAN, Sigfox, and NB-IoT, for a comprehensive assessment [6–8,11–14,16,20,22,26–28,33,34,36,53,54,65,66].

The choice of LPWAN technologies is regarded by the authors of these papers as a acritical factor in implementing effective and efficient FDSs. Our findings support the predominance of LoRaWAN and NB-IoT in this field, a trend which has remained consistent and is sup-ported by previous research (Mekki et al. [47]). Nonetheless, the analysis conducted delves deeper into comparing these technologies, particularly regarding their energy efficiency and transmission speed. Particularly, LoRaWAN stands out in its energy efficiency, surpassing NB-IoT, a highly relevant aspect due to its potential impact on wearable devices' battery life [51]. This characteristic becomes critically important to ensure the continuous and effective operation of these devices. On the other hand, NB-IoT exhibits notable advantages in data transmission speed according to Sinha et al. [92], which could be relevant in applications requiring fast and reliable transmission of biomedical information.

As it refers to energy consumption, the main problem is that in most works on FDS based on LPWAN (as those using other standards), battery consumption is either not assessed or is analyzed in a very superficial way. Just one of the reviewed works (Salah et al. in [36]) provides evidence of the potential advantages of replacing a short-range, low-power standard with LPWAN technologies.

Regarding the sensors employed in wearable devices for fall detection, our findings align with prior research by Bet et al. [93], emphasizing the significance of Inertial Measurement Unit (IMU) sensors in this domain. The analysis conducted has identified a diversification in the combinations of these sensors used, suggesting that the selection of sensors might depend on specific contexts and precision requirements. Moreover, studies [6,7,13,20,26–28,33,34,65,66] have observed various locations for fall detection devices, ranging from the waist to the wrist, including the feet and different areas of the torso. Overall, the waist and chest are the most effective locations, offering higher accuracy. However, other studies note that placing the device in other areas of the torso does not significantly affect its detection capability, thus, providing more flexibility in placement [6,65]. Currently, researchers are exploring alternative positions such as the foot 'within shoes' or an auxiliary element like a walking stick, aiming to maximize comfort without compromising accuracy [7,11,66].

The analysis of fall detection algorithms has revealed consistency with prior research, such as the study by Liu et a. [28], emphasizing the advantages of employing neural network-based approaches, including CNN, and Salah et al. [36] using an LSTM architecture. However, our analysis has provided a deeper level of contextualization by considering the performance of these algorithms concerning LPWAN technologies and the sensors used. It is worth mentioning that while these approaches exhibit high potential in terms of accuracy, they may also be computationally resource-intensive, posing challenges in energy efficiency for resource-limited wearable devices [36].

In the study by Valach et al. [12], the reliability of fall detection was questioned when devices were placed in low-visibility areas like on the floor or under tables. During testing, the LoRaWAN base stations of the TTN (The Things Network) network failed to receive transmissions from these positions, which could jeopardize the detection of many falls. This suggests that further investigation into the shielding effects of the device's board and its impact on signal transmission is necessary to enhance reliability in critical scenarios. Nonetheless, compared to BLE and WiFi, LPWAN technology like LoRa offers better signal penetration through physical obstacles due to its sub-GHz frequencies, resulting in better coverage in challenging environments [94]. The sub-GHz band provides superior signal quality over wider areas and longer distances, experiencing less attenuation and multipath fading caused by obstacles and dense surfaces like concrete walls [95]. The actual reception ratio of LPWAN-transmitted alarms generated by wearable fall detectors should be carefully investigated in real application scenarios.

A critical aspect of wearable device design is user comfort, social acceptability, and ease of use, elements that were not considered by the authors reviewed [6–8,11–14,16,20,22,26–28,33,34,36,53,54,65,66], who focused exclusively on the technical aspect. According to Özdemir [39], the current elderly population avoids technology due to discomfort with wearable devices. This highlights the importance of user-centered designs to enhance their adoption. Studies like that of Gemperle et al. [96] have identified less intrusive areas of the body for wearable placement, such as the upper back of the arm, the waist area, and the back of the torso. Social acceptability is also crucial; Pasher et al. [97] found that the acceptance of wearable devices significantly depends on their ergonomics and how users perceive their comfort and aesthetics, often outweighing privacy concerns. Finally, Thilo et al. [98] emphasize that involving end-users in the design and development stage of a wearable prototype is well-received by older adults and allows for the exploration of their needs and preferences, indicating that older adults' perceptions of activity, independence, and familiarity should be considered to ensure the devices are functional, comfortable, and usable.

6. Criticisms and Limitations

- From the study conducted, it can be inferred that the application of LPWAN technologies to wearable FDSs is still in an embryonic state, having neither exploited nor systematically analyzed its main benefits. Therefore, it is necessary to remark on the following weaknesses in the reviewed literature:
- Limited coverage: Signal reliability can be challenging in low-visibility areas. However, the developed prototypes do not investigate realistic usage scenarios where coverage might fail.
- Energy consumption: When compared to short-range and local area technologies, LPWAN standards may excel in energy efficiency, which is a key factor in increasing the battery life of wearables. Nevertheless, the existing studies to date have barely evaluated the quantitative benefits of using LPWAN compared not only to other transmission technologies but also to other sources of consumption present in the detector, mainly the detection algorithm.
- Implementation difficulty and reliability: LPWAN networks offer greater flexibility than other types of networks, but they still involve certain operational costs (subscription to operators) or deployment costs (e.g., location, installation, and management of base stations) that the literature does not evaluate. Likewise, the low bandwidth provided for LPWAN networks may be sufficient to send certain types of alarms (encodable in a few bytes) but may be clearly insufficient if more complex information needs to be sent to an external node in real-time (such as long samples of inertial signals). This limitation is scarcely addressed in the reviewed works.
- Lack of large-scale and clinical studies: In any case, as with almost all literature dedicated to FDS systems (whether based on contextual or wearable sensor systems), there is an almost complete lack of large-scale clinical trials.

7. Recommendations

- Based on the limitations and deficiencies identified, we outline the main areas of action that future proposals for LPWAN-based FDS should consider to develop viable products for real-world applications:
- Analyze coverage: Prototypes should be tested in realistic environments to demonstrate that users can be monitored over long distances (both outdoors and indoors) without compromising signal quality.
- Characterize energy consumption: The energy consumption of prototypes should be 'budgeted' and characterized in detail to demonstrate that using LPWAN technologies contributes to a significant increase in wearable autonomy. In this regard, the consumption (not only of energy but also of hardware resources) of the transmission system should be compared with that required by the detection algorithm.
- Conduct large-scale clinical studies: Develop large-scale longitudinal studies to appraise the actual effectiveness of LPWAN-based FDSs. In that sense, clinical field tests and massive evaluations of the long-term performance of the detectors in real-world scenarios should be prioritized.
- Integrate with emerging technologies: Investigate the integration of LPWAN technologies with emerging technologies such as 5G and edge computing to enhance data processing capabilities and reduce latency. This could improve the overall performance and responsiveness of FDSs.

- Develop user-centric designs: Evaluate the prototypes not only from a purely technical point-of-view but also consider a user-centric perspective that does not neglect key aspects such as ergonomics or usability. Focus on developing user-friendly wearable devices that ensure comfort and social acceptability. Consider different placement locations on the body and the specific needs of various user groups to maximize the practicality and adoption of these devices.
- Remote Rural Areas: LPWAN technologies such as LoRaWAN and Sigfox are highly beneficial in remote rural areas where traditional communication infrastructures, such as cellular networks, are limited or nonexistent. The long-range and low-power characteristics of LPWAN make it an ideal choice for monitoring fall detection in environments where other communication networks might be impractical or too costly to implement.
- Urban Environments with High Building Density: NB-IoT is particularly well-suited for urban environments with high building density and potential signal interference. Its ability to penetrate buildings and provide reliable communication in densely populated areas makes it a valuable asset for FDSs deployed in cities, ensuring consistent performance even in challenging urban landscapes.
- Elder Care in Low-Cost Public Health Initiatives: In scenarios where cost-effectiveness is crucial, such as large-scale public health initiatives aimed at elder care in developing regions, the low operational costs and minimal infrastructure requirements of LPWAN provide a scalable solution for deploying FDSs to a broader population, making healthcare more accessible.

8. Conclusions

This systematic review provides a comprehensive analysis of LPWAN technologies in wearable FDSs, focusing on enhancing transmission reliability, energy efficiency, and sensor precision. LPWAN technologies, especially LoRaWAN, offer superior energy efficiency and better signal penetration than WiFi and BLE, resulting in improved coverage in challenging environments. However, low-visibility scenarios, such as devices placed on the floor, still pose challenges.

The review highlights the use of various IMU sensors (accelerometers, gyroscopes, magnetometers) and advanced detection algorithms (CNN, LSTM), which improve detection accuracy and system reliability. While threshold-based algorithms offer greater energy efficiency, machine learning and neural network-based algorithms enhance detection accuracy, albeit with higher energy consumption.

Balancing energy efficiency and data transmission speed is crucial when choosing between LoRaWAN and NB-IoT. Despite their potential, LPWAN technologies have not been fully investigated in FDSs, with limited studies on their benefits. Further research is needed to explore these aspects comprehensively, emphasizing large-scale field tests and clinical evaluations to fully realize the potential of LPWAN technologies in wearable FDSs.

Overall, enhancing transmission reliability, optimizing energy use, and improving sensor precision are vital for advancing FDSs. This review guides future developments in enhancing the precision, energy efficiency, and global effectiveness of these systems.

Future research should focus on conducting large-scale field tests and clinical evaluations to validate the long-term effectiveness of LPWAN-based FDSs. Additionally, exploring hybrid detection algorithms and integrating LPWAN technologies with emerging technologies like 5G and edge computing could further enhance system performance. Practical applications include not only FDSs but also remote health monitoring, smart home integration, and use in rehabilitation and assisted living facilities to improve elderly care and emergency response times.

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References

1. Aledhari, M.; Razzak, R.; Qolomany, B.; Al-Fuqaha, A.; Saeed, F. Biomedical IoT: Enabling Technologies, Architectural Elements, Challenges, and Future Directions. *IEEE Access* **2022**, *10*, 31306–31339. [CrossRef] [PubMed]
2. Costin, H.; Rotariu, C.; Adochiei, F.; Ciobotariu, R.; Andruseac, G.; Corciova, F. Telemonitoring of vital signs—An effective tool for ambient assisted living. *IFMBE Proc.* **2011**, *36*, 60–65. [CrossRef]
3. World Health Organization. WHO Global Report on Falls Prevention in Older Age. Available online: https://apps.who.int/iris/handle/10665/43811 (accessed on 26 February 2023).
4. World Health Organization. Falls. Available online: https://www.who.int/en/news-room/fact-sheets/detail/falls (accessed on 26 February 2023).
5. World Health Organization. Ageing and Health. Available online: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed on 10 April 2023).
6. Huynh, Q.T.; Nguyen, U.D.; Tran, B.Q. A Cloud-Based System for In-Home Fall Detection and Activity Assessment. In *IFMBE Proceedings, Proceedings of the 7th International Conference on the Development of Biomedical Engineering in Vietnam (BME 7), Ho Chi Minh City, Vietnam, 27–29 June 2018*; Springer: Singapore, 2020; Volume 69, pp. 103–108. [CrossRef]
7. Zanaj, E.; Disha, D.; Spinsante, S.; Gambi, E. A wearable fall detection system based on LoRa LPWAN technology. *J. Commun. Softw. Syst.* **2020**, *16*, 232–242. [CrossRef]
8. Chang, W.J.; Chen, L.B.; Chen, M.C.; Su, J.P.; Sie, C.Y.; Yang, C.H. Design and Implementation of an Intelligent Assistive System for Visually Impaired People for Aerial Obstacle Avoidance and Fall Detection. *IEEE Sens. J.* **2020**, *20*, 10199–10210. [CrossRef]
9. Newaz, N.T.; Hanada, E. The Methods of Fall Detection: A Literature Review. *Sensors* **2023**, *23*, 5212. [CrossRef]
10. Tanutama, L.; Wijaya, H.; Ardianti, D. Elderly Fall Detection and Warning System. In *IOP Conference Series: Earth and Environmental Science, Proceedings of the 4th International Conference on Eco Engineering Development 2020, Banten, Indonesia, 10–11 November 2020*; IOP Publishing Ltd.: Bristol, UK, 2021; Volume 794, p. 794. [CrossRef]
11. Lachtar, A.; Val, T.; Kachouri, A. Elderly monitoring system in a smart city environment using LoRa and MQTT. *IET Wirel. Sens. Syst.* **2020**, *10*, 70–77. [CrossRef]
12. Valach, A.; Macko, D. Exploration of the LoRa Technology Utilization Possibilities in Healthcare IoT Devices. In Proceedings of the 2018 16th International Conference on Emerging eLearning Technologies and Applications (ICETA), Stary Smokovec, Slovakia, 15–16 November 2018. [CrossRef]
13. Lousado, J.P.; Pires, I.M.; Zdravevski, E.; Antunes, S. Monitoring the health and residence conditions of elderly people, using lora and the things network. *Electronics* **2021**, *10*, 1729. [CrossRef]
14. Patel, W.D.; Ramani, B.; Pandya, S.; Bhaskar, S.; Koyuncu, B.; Ghayvat, H. NXTGeUH: LoRaWAN based NEXT Generation Ubiquitous Healthcare System for Vital Signs Monitoring & Falls Detection. In Proceedings of the 2018 IEEE Punecon, Pune, India, 30 November–2 December 2018. [CrossRef]
15. Wu, H.H.; Lee, D.H. Monitoring of driver's biomedical signals using LoRa-based wireless communications. *IEICE Electron. Express* **2021**, *18*, 20210104. [CrossRef]
16. Li, Y.; Lin, Z.; Huang, Z.; Cai, Z.; Huang, L.; Wei, Z. A Channel Hopping LoRa Technology Based Emergency Communication System for Elderly People Living Alone. In Proceedings of the 2022 21st International Symposium on Communications and Information Technologies ISCIT, Xi'an, China, 27–30 September 2022; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2022; pp. 19–26. [CrossRef]
17. Han, J.; Song, W.; Gozho, A.; Sung, Y.; Ji, S.; Song, L.; Wen, L.; Zhang, Q. LoRa-Based smart iot application for smart city: An Example of Human Posture Detection. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 8822555. [CrossRef]
18. Fernandes Carvalho, D.; Ferrari, P.; Sisinni, E.; Bellitti, P.; Lopomo, N.F.; Serpelloni, M. Using LPWAN Connectivity for Elderly Activity Monitoring in Smartcity Scenarios. *Lect. Notes Electr. Eng.* **2020**, *627*, 81–87. [CrossRef]
19. Vimal, S.; Robinson, Y.H.; Kadry, S.; Long, H.V.; Nam, Y. IoT Based Smart Health Monitoring with CNN Using Edge Computing. *J. Internet Technol.* **2021**, *22*, 173–185. [CrossRef]
20. Escriba, C.; Roux, J.; Hajjine, B.; Fourniols, J.Y. Smart wearable active patch for elderly health prevention. In Proceedings of the 2018 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2018, 12–14 December 2018; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2018; pp. 1040–1043. [CrossRef]

21. Much, M.D.; Marcon, C.; Hessel, F.; Cataldo Neto, A. LifeSenior—A Health Monitoring IoT System Based on Deep Learning Architecture. In *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Proceedings of the 7th International Conference, ITAP 2021, Washington, DC, USA 24–29 July 2021*; Springer Science and Business Media Deutschland GmbH: Berlin, Germany, 2021; Volume 12787, pp. 293–306. [CrossRef]
22. Manatarinat, W.; Poomrittigul, S.; Tantatsanawong, P. Narrowband-internet of things (NB-IoT) system for elderly healthcare services. In Proceedings of the 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST), Luang Prabang, Laos, 2–5 July 2019; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2019. [CrossRef]
23. Islam, M.S.; Islam, M.T.; Almutairi, A.F.; Beng, G.K.; Misran, N.; Amin, N. Monitoring of the Human Body Signal through the Internet of Things (IoT) Based LoRa Wireless Network System. *Appl. Sci.* **2019**, *9*, 1884. [CrossRef]
24. Dammak, B.; Turki, M.; Cheikhrouhou, S.; Baklouti, M.; Mars, R.; Dhahbi, A. LoRaChainCare: An IoT Architecture Integrating Blockchain and LoRa Network for Personal Health Care Data Monitoring. *Sensors* **2022**, *22*, 1497. [CrossRef] [PubMed]
25. Song, W.; Liao, J.; Han, J. A Real-Time Human Posture Recognition System Using Internet of Things (IoT) Based on LoRa Wireless Network. In *Lecture Notes in Electrical Engineering, Proceedings of the CSA-CUTE 2019, Macau, China, 18–20 December 2019*; Springer Science and Business Media Deutschland GmbH: Berlin, Germany, 2021; Volume 715, pp. 379–385. [CrossRef]
26. Qian, Z.; Lin, Y.; Jing, W.; Ma, Z.; Liu, H.; Yin, R.; Li, Z.; Bi, Z.; Zhang, W. Development of a Real-Time Wearable Fall Detection System in the Context of Internet of Things. *IEEE Internet Things J.* **2022**, *9*, 21999–22007. [CrossRef]
27. Fan, X.; Li, Z.; Zhang, L. Design and Implementation of Fall Detection Equipment for the Elderly Based on NB-IoT. In Proceedings of the 2022 International Conference on Artificial Intelligence and Computer Information Technology (AICIT), Yichang, China, 16–18 September 2022. [CrossRef]
28. Liu, P.; Pan, J.; Zhu, H.; Li, Y. A Wearable Fall Detection System Based on 1D CNN. In Proceedings of the 2021 2nd International Conference on Artificial Intelligence and Computer Engineering (ICAICE), Hangzhou, China, 5–7 November 2021; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2021; pp. 200–203. [CrossRef]
29. Saleh Alhassoun, N. Cross-Layer Energy Optimization for IoT-Enabled Smart Spaces. In Proceedings of the 2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Austin, TX, USA, 23–27 March 2020.
30. Chen, X.; Jiang, S.; Lo, B. Subject-Independent Slow Fall Detection with Wearable Sensors via Deep Learning. In Proceedings of the 2020 IEEE Sensors, Rotterdam, Netherlands, 25–28 October 2020; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2020. [CrossRef]
31. Pierleoni, P.; Belli, A.; Maurizi, L.; Palma, L.; Pernini, L.; Paniccia, M.; Valenti, S. A Wearable Fall Detector for Elderly People Based on AHRS and Barometric Sensor. *IEEE Sens. J.* **2016**, *16*, 6733–6744. [CrossRef]
32. Makma, J.; Thanapatay, D.; Isshiki, T.; Chinrungrueng, J.; Thiemjarus, S. Toward Accurate Fall Detection with a Combined Use of Wearable and Ambient Sensors. In Proceedings of the 2022 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), Chiang Rai, Thailand, 26–28 January 2022; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2022; pp. 298–301. [CrossRef]
33. Wong, W.-K.; Hou, L.-Y.; Pan, T.; Wu, C.-C.; Chen, Y.-H. An IoT Application Based on LoRa Data Transmission. *InternatIonal J. IntellIgent Technol. Appl. Stat.* **2022**, *15*, 87–100. [CrossRef]
34. Wu, Y.; Zeng, P.; Ge, H. A Research of Fall Detection Module Based on NB-IOT. In Proceedings of the 2022 7th International Conference on Computer and Communication Systems (ICCCS), Wuhan, China, 22–25 April 2022; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2022; pp. 197–201. [CrossRef]
35. Ren, L.; Peng, Y. Research of fall detection and fall prevention technologies: A systematic review. *IEEE Access* **2019**, *7*, 77702–77722. [CrossRef]
36. Salah, O.Z.; Selvaperumal, S.K.; Abdulla, R. Accelerometer-based elderly fall detection system using edge artificial intelligence architecture. *Int. J. Electr. Comput. Eng.* **2022**, *12*, 4430–4438. [CrossRef]
37. Fanca, A.; Puscasiu, A.; Gota, D.I.; Valean, H. Methods to minimize false detection in accidental fall warning systems. In Proceedings of the 2019 23rd International Conference on System Theory, Control and Computing (ICSTCC), Sinaia, Romania, 9–11 October 2019; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2019; pp. 851–855. [CrossRef]
38. Igual, R.; Medrano, C.; Plaza, I. Challenges, issues and trends in fall detection systems. *Biomed. Eng. Online* **2013**, *12*, 66. [CrossRef]
39. Özdemir, A.T. An analysis on sensor locations of the human body for wearable fall detection devices: Principles and practice. *Sensors* **2016**, *16*, 1161. [CrossRef]
40. Nguyen Gia, T.; Sarker, V.K.; Tcarenko, I.; Rahmani, A.M.; Westerlund, T.; Liljeberg, P.; Tenhunen, H. Energy efficient wearable sensor node for IoT-based fall detection systems. *Microprocess. Microsyst.* **2018**, *56*, 34–46. [CrossRef]
41. Yu, X.; Park, S.; Kim, D.; Kim, E.; Kim, J.; Kim, W.; An, Y.; Xiong, S. A practical wearable fall detection system based on tiny convolutional neural networks. *Biomed. Signal Process. Control* **2023**, *86*, 105325. [CrossRef]
42. De Raeve, N.; Shahid, A.; De Schepper, M.; De Poorter, E.; Moerman, I.; Verhaevert, J.; Van Torre, P.; Rogier, H. Bluetooth-Low-Energy-Based Fall Detection and Warning System for Elderly People in Nursing Homes. *J. Sens.* **2022**, *2022*, 9930681. [CrossRef]
43. Freitas, R.; Terroso, M.; Marques, M.; Gabriel, J.; Marques, A.T.; Simoes, R. Wearable sensor networks supported by mobile devices for fall detection. *Proc. IEEE Sens.* **2014**, *2014*, 2246–2249. [CrossRef]

44. Cruz, F.R.G.; Sejera, M.P.; Bunnao, M.B.G.; Jovellanos, B.R.; Maaño, P.L.C.; Santos, C.J.R. Fall Detection Wearable Device Interconnected Through ZigBee Network. In Proceedings of the 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Manila, Philippines, 1–3 December 2017. [CrossRef]
45. Rao Gannapathy, V.; Fayeez, A.; Ibrahim, B.T.; Zakaria, Z.B.; Rani, A.; Othman, B.; Latiff, A.A. Zigbee-based smart fall detection and notification system with wearable sensor (e-safe). *IJRET: Int. J. Res. Eng. Technol.* **2013**, *2*, 337–344. [CrossRef]
46. Huang, C.N.; Chan, C.T. A ZigBee-Based Location-Aware Fall Detection System for Improving Elderly Telecare. *Int. J. Environ. Res. Public. Health* **2014**, *11*, 4233–4248. [CrossRef]
47. Mekki, K.; Bajic, E.; Chaxel, F.; Meyer, F. A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT Express* **2019**, *5*, 1–7. [CrossRef]
48. Devalal, S.; Karthikeyan, A. LoRa Technology—An Overview. In Proceedings of the 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 29–31 March 2018; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2018; pp. 284–290. [CrossRef]
49. Alkhayyal, M.; Mostafa, A. Recent Developments in AI and ML for IoT: A Systematic Literature Review on LoRaWAN Energy Efficiency and Performance Optimization. *Sensors* **2024**, *24*, 4482. [CrossRef] [PubMed]
50. Chaudhari, B.S.; Zennaro, M.; Borkar, S. LPWAN technologies: Emerging application characteristics, requirements, and design considerations. *Future Internet* **2020**, *12*, 46. [CrossRef]
51. Chilamkurthy, N.S.; Pandey, O.J.; Ghosh, A.; Cenkeramaddi, L.R.; Dai, H.N. Low-Power Wide-Area Networks: A Broad Overview of Its Different Aspects. *IEEE Access* **2022**, *10*, 81926–81959. [CrossRef]
52. Nolan, K.E.; Guibene, W.; Kelly, M.Y. An evaluation of low power wide area network technologies for the Internet of Things. In Proceedings of the 2016 International Wireless Communications and Mobile Computing Conference (IWCMC), Paphos, Cyprus, 5–9 September 2016; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2016; pp. 439–444. [CrossRef]
53. Pena Queralta, J.; Gia, T.N.; Tenhunen, H.; Westerlund, T. Edge-AI in LoRa-based health monitoring: Fall detection system with fog computing and LSTM recurrent neural networks. In Proceedings of the 2019 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 1–3 July 2019; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2019; pp. 601–604. [CrossRef]
54. Cai, W.Y.; Guo, J.H.; Zhang, M.Y.; Ruan, Z.X.; Zheng, X.C.; Lv, S.S. GBDT-Based Fall Detection with Comprehensive Data from Posture Sensor and Human Skeleton Extraction. *J. Healthc. Eng.* **2020**, *2020*, 8887340. [CrossRef] [PubMed]
55. Yuan, J.; Tan, K.K.; Lee, T.H.; Koh, G.C.H. Power-efficient interrupt-driven algorithms for fall detection and classification of activities of daily living. *IEEE Sens. J.* **2015**, *15*, 1377–1387. [CrossRef]
56. Siong Jun, S.; Rashidi Ramli, H.; Che Soh, A.; Ain Kamsani, N.; Kamil Raja Ahmad, R.; Anom Ahmad, S.; Juraiza Ishak, A. Development of fall detection and activity recognition using threshold based method and neural network. *Indones. J. Electr. Eng. Comput. Sci.* **2020**, *17*, 1338–1347. [CrossRef]
57. Luque, R.; Casilari, E.; Morón, M.J.; Redondo, G. Comparison and Characterization of Android-Based Fall Detection Systems. *Sensors* **2014**, *14*, 18543–18574. [CrossRef] [PubMed]
58. Kausar, F.; Mesbah, M.; Iqbal, W.; Ahmad, A.; Sayyed, I. Fall Detection in the Elderly using Different Machine Learning Algorithms with Optimal Window Size. *Mob. Netw. Appl.* **2023**, *1*, 1–11. [CrossRef]
59. Chai, X.; Lee, B.G.; Pike, M.; Wu, R.; Chieng, D.; Chung, W.Y. Pre-Impact Firefighter Fall Detection Using Machine Learning on the Edge. *IEEE Sens. J.* **2023**, *23*, 14997–15009. [CrossRef]
60. Astriani, M.S.; Bahana, R.; Kurniawan, A.; Yi, L.H. Threshold-based low power consumption human fall detection for health care and monitoring system. In Proceedings of the Proceedings of 2020 International Conference on Information Management and Technology (ICIMTech), Bandung, Indonesia, 13–14 August 2020; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2020; pp. 853–857. [CrossRef]
61. Šeketa, G.; Vugrin, J.; Lacković, I. Optimal threshold selection for acceleration-based fall detection. *IFMBE Proc.* **2018**, *66*, 151–155. [CrossRef]
62. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*. [CrossRef]
63. Sigfox, S.A. Sigfox 0G Technology. Available online: https://www.sigfox.com/what-is-sigfox/ (accessed on 16 May 2024).
64. Mekki, K.; Bajic, E.; Chaxel, F.; Meyer, F. Overview of Cellular LPWAN Technologies for IoT Deployment: Sigfox, LoRaWAN, and NB-IoT. In Proceedings of the 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Athens, Greece, 19–23 March 2018; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2018; pp. 197–202. [CrossRef]
65. Scheurer, S.; Koch, J.; Kucera, M.; Bryn, H.; Bärtschi, M.; Meerstetter, T.; Nef, T.; Urwyler, P. Optimization and technical validation of the AIDE-MOI fall detection algorithm in a real-life setting with older adults. *Sensors* **2019**, *19*, 1357. [CrossRef]
66. Pierleoni, P.; Belli, A.; Palma, L.; Concetti, R.; Sabbatini, L.; Raggiunto, S. A complete architecture for Ambient Assisted Living scenarios using a cross protocol proxy. *J. Ambient. Intell. Humaniz. Comput.* **2023**, *15*, 2757–2764. [CrossRef]

67. Kautsarina; Kusumawati, D. The Potential Adoption of the Internet of Things in Rural Areas. In Proceedings of the 2018 International Conference on ICT for Rural Development: Rural Development through ICT: Concept, Design, and Implication (IC-ICTRuDEv), Badung, Indonesia, 17–18 October 2018; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2018; pp. 124–130. [CrossRef]
68. Lykov, Y.; Paniotova, A.; Shatalova, V.; Lykova, A. Energy Efficiency Comparison LPWANs: LoRaWAN vs Sigfox. In Proceedings of the 2020 IEEE International Conference on Problems of Infocommunications Science and Technology (PIC S & T), Kharkiv, Ukraine, 6–9 October 2020; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2021; pp. 485–490. [CrossRef]
69. Qadir, Q.M.; Rashid, T.A.; Al-Salihi, N.K.; Ismael, B.; Kist, A.A.; Zhang, Z. Low power wide area networks: A survey of enabling technologies, applications and interoperability needs. *IEEE Access* **2018**, *6*, 77454–77473. [CrossRef]
70. Rama, Y.; Alper Özpınar, M. A Comparison of Long-Range Licensed and Unlicensed LPWAN Technologies According to Their Geolocation Services and Commercial Opportunities. In Proceedings of the 2018 IEEE 18th Mediterranean Microwave Symposium (MMS), Istanbul, Turkey, 31 October–2 November 2018; pp. 398–403. [CrossRef]
71. Stanco, G.; Botta, A.; Frattini, F.; Giordano, U.; Ventre, G. On the performance of IoT LPWAN technologies: The case of Sigfox, LoRaWAN and NB-IoT. In Proceedings of the IEEE International Conference on Communications, Seoul, Republic of Korea, 16–20 May 2022; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2022; Volume 2022, pp. 2096–2101. [CrossRef]
72. Xu, T.; Se, H.; Liu, J. A fusion fall detection algorithm combining threshold-based method and convolutional neural network. *Microprocess. Microsyst.* **2021**, *82*, 103828. [CrossRef]
73. Sucerquia, A.; López, J.D.; Vargas-Bonilla, J.F. SisFall: A fall and movement dataset. *Sensors* **2017**, *17*, 198. [CrossRef]
74. Vavoulas, G.; Pediaditis, M.; Spanakis, E.G.; Tsiknakis, M. The MobiFall dataset: An initial evaluation of fall detection algorithms using smartphones. In Proceedings of the 13th IEEE International Conference on BioInformatics and BioEngineering, Chania, Greece, 10–13 November 2013. [CrossRef]
75. Casilari, E.; Santoyo-Ramón, J.A.; Cano-García, J.M. Analysis of public datasets for wearable fall detection systems. *Sensors* **2017**, *17*, 1513. [CrossRef]
76. Saleh, M.; Jeannes, R.L.B. Elderly Fall Detection Using Wearable Sensors: A Low Cost Highly Accurate Algorithm. *IEEE Sens. J.* **2019**, *19*, 3156–3164. [CrossRef]
77. Guvensan, M.A.; Kansiz, A.O.; Camgoz, N.C.; Turkmen, H.I.; Yavuz, A.G.; Karsligil, M.E. An Energy-Efficient Multi-Tier Architecture for Fall Detection on Smartphones. *Sensors* **2017**, *17*, 1487. [CrossRef]
78. Lampoltshammer, T.J.; de Freitas, E.P.; Nowotny, T.; Plank, S.; da Costa, J.P.C.L.; Larsson, T.; Heistracher, T. Use of Local Intelligence to Reduce Energy Consumption of Wireless Sensor Nodes in Elderly Health Monitoring Systems. *Sensors* **2014**, *14*, 4932–4947. [CrossRef]
79. Musci, M.; De Martini, D.; Blago, N.; Facchinetti, T.; Piastra, M. Online Fall Detection Using Recurrent Neural Networks on Smart Wearable Devices. *IEEE Trans. Emerg. Top. Comput.* **2021**, *9*, 1276–1289. [CrossRef]
80. Fernandez-Bermejo, J.; Martinez-del-Rincon, J.; Dorado, J.; del Toro, X.; Santof imia, M.J.; Lopez, J.C. Edge computing transformers for fall detection in older adults. *Int. J. Neural Syst.* **2024**, *34*, 2450026. [CrossRef]
81. Casamassima, F.; Farella, E.; Benini, L. Context aware power management for motion-sensing body area network nodes. In Proceedings of the 2014 Design, Automation & Test in Europe Conference & Exhibition (DATE), Dresden, Germany, 24–28 March 2014; pp. 1–6. [CrossRef]
82. Gao, L.; Bourke, A.K.; Nelson, J. Evaluation of accelerometer based multi-sensor versus single-sensor activity recognition systems. *Med. Eng. Phys.* **2014**, *36*, 779–785. [CrossRef]
83. Noor, M.H.M.; Salcic, Z.; Wang, K.I.K. Dynamic sliding window method for physical activity recognition using a single tri-axial accelerometer. In Proceedings of the 2015 10th IEEE Conference on Industrial Electronics and Applications (ICIEA), Auckland, New Zealand, 15–17 June 2015; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2015; pp. 102–107. [CrossRef]
84. Gharghan, S.K.; Fakhrulddin, S.S.; Al-Naji, A.; Chahl, J. Energy-efficient elderly fall detection system based on power reduction and wireless power transfer. *Sensors* **2019**, *19*, 4452. [CrossRef] [PubMed]
85. Ballerini, M.; Polonelli, T.; Brunelli, D.; Magno, M.; Benini, L. NB-IoT Versus LoRaWAN: An Experimental Evaluation for Industrial Applications. *IEEE Trans. Industr Inform.* **2020**, *16*, 7802–7811. [CrossRef]
86. Semtech SX1257 Datasheet. Available online: https://www.semtech.com/products/wireless-rf/lora-core/sx1257 (accessed on 22 August 2024).
87. HopeRF. RFM95/96/97/98(W) LoRa Transceiver Module Datasheet. Available online: https://www.hoperf.com/modules/lora/RFM95W.html (accessed on 22 August 2024).
88. Semtech. SX1276/77/78/79 Datasheet. Available online: https://www.semtech.com/products/wireless-rf/lora-connect/sx1276 (accessed on 22 August 2024).
89. Quectel. BC95 NB-IoT Module Datasheet. Available online: https://www.es.co.th/Schemetic/PDF/QUECTEL_BC95B.PDF (accessed on 22 August 2024).
90. China Mobile IoT Company. M5310A AT Command Manual. Available online: https://iot.10086.cn/Uploads/file/product/20180827/M5310A%20AT%20%E5%91%BD%E4%BB%A4%E7%94%A8%E4%B9%A6%E4%BD%BF%E7%94%A8%E6%89%8B%E5%86%8C_V1_20180827154312_20506.pdf (accessed on 22 August 2024).

91. Nordic Semiconductor. nRF9160 System-in-Package Datasheet. Nordic Semiconductor. Available online: https://www.nordicsemi.com/Products/nRF9160 (accessed on 22 August 2024).
92. Sinha, R.S.; Wei, Y.; Hwang, S.H. A survey on LPWA technology: LoRa and NB-IoT. *ICT Express* **2017**, *3*, 14–21. [CrossRef]
93. Bet, P.; Castro, P.C.; Ponti, M.A. Fall detection and fall risk assessment in older person using wearable sensors: A systematic review. *Int. J. Med. Inform.* **2019**, *130*, 103946. [CrossRef] [PubMed]
94. Ferreira, C.M.S.; Oliveira, R.A.R.; Silva, J.S. Low-energy smart cities network with lora and bluetooth. In Proceedings of the 2019 7th IEEE International Conference on Mobile Cloud Computing, Services, and Engineering (MobileCloud), Newark, CA, USA, 4–9 April 2019; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2019; pp. 24–29. [CrossRef]
95. Muteba, F.; Djouani, K.; Olwal, T. A comparative Survey Study on LPWA IoT Technologies: Design, considerations, challenges and solutions. *Procedia Comput. Sci.* **2019**, *155*, 636–641. [CrossRef]
96. Gemperle, F.; Kasabach, C.; Stivoric, J.; Bauer, M.; Martin, R. Design for Wearability. In Proceedings of the 2nd IEEE International Symposium on Wearable Computers, Pittsburgh, PA, USA, 19–20 October 1998. [CrossRef]
97. Pasher, E.; Popper, Z.; Raz, H.; Lawo, M. WearIT@work: A wearable computing solution for knowledge-based development. *Int. J. Knowl.-Based Dev.* **2010**, *1*, 346–360. [CrossRef]
98. Thilo, F.J.S.; Bilger, S.; Halfens, R.J.G.; Schols, J.M.G.A.; Hahn, S. Involvement of the end user: Exploration of older people's needs and preferences for a wearable fall detection device—A qualitative descriptive study. *Patient Prefer. Adherence* **2017**, *11*, 11–22. [CrossRef]