# CNN-based Model for Gender and Age Classification based on Palm Vein Images

Ruber Hernández-García
*Research Center CIEAM*
*Universidad Católica del Maule*
Talca, Chile
rhernandez@ucm.cl

Zheng Feng
*School of Electrical and Information Engineering*
*University of Sidney*
Sidney, Australia

Ricardo J. Barrientos
*Faculty of Engineering Sciences*
*Universidad Católica del Maule*
Talca, Chile
rbarrientos@ucm.cl

Francisco Manuel Castro
*Dept. of Computer Architecture*
*Universidad of Málaga*
Málaga, Spain

Julián Ramos-Cózar
*Dept. of Computer Architecture*
*Universidad of Málaga*
Málaga, Spain

Nicolás Guil
*Dept. of Computer Architecture*
*Universidad of Málaga*
Málaga, Spain

***Abstract*—Automatically predicting gender and age group from biometrics traits is an essential and challenging task in many real-world applications. There are several works about using machine learning methods to identify human gender or age through the face, iris, or fingerprint, but only limited research about using palm vein patterns. Considering the powerful feature representation ability of Convolutional Neural Networks (CNN) and the advantages of palm vein biometrics, this paper introduces a new CNN-based method for gender and age classification based on palm vein images. Experimental results show that the proposed model is able to learn discriminative features from palm vein images for these tasks, achieving state-of-the-art results on the VERA database by using a shallow CNN architecture. Besides, the obtained results suggest the feasibility of further studies on multi-task identification approaches and the reduction of the penetration rate in massive databases.**

***Index Terms*—Palm vein images, Gender classification, Age estimation, Convolutional neural networks, Soft biometrics**

## I. Introduction

Biometrics is a computer science field that aims to identify and authenticate individuals through their unique physiological (e.g. fingerprint, iris, or palm vein) and/or behavioral (e.g. gait, signature, or voice) characteristics. Biometric authentication matches individual's characteristics to the corresponding stored biometric template to determine their similarity allowing the authentication. On the other hand, biometric identification intends to determine the individual's identity based on the biometric traits. In recent years, with the increasing of identity theft, terrorism and cybercrime, biometric systems are very useful in many potential applications such as personal authentication, forensic sciences, and passive demographic data collection.

In addition to classical biometrics, which fulfills properties such as universality, distinctiveness, and permanence, people can also be differentiated (although not uniquely) by their soft biometric traits. Soft biometrics is defined as the set of individual characteristics that differentiate people, although they lack distinctiveness and permanence [1]. Soft biometrics include physical (e.g. age, gender, or ethnicity) and body-adherent (e.g. clothes, tattoos, or accessories) characteristics, which have several advantages such as non-obtrusiveness, human compliance, and not require enrollment. Besides, in a massive identification context, soft biometrics improves computational efficiency by reducing the searching space and speeding up the matching rate [2]. For example, a gender classification can reduce a search of only half of the subjects in the database. Moreover, soft traits can be used as auxiliary information to improve the accuracy of the recognition process [3].

In the literature for age and gender classification, different proposed investigations are based on fingerprint [4], [5], face [6], [7], gait [8], inertial information [9], iris [10], [11], palmprint [2], and palm vein [12]–[14]. Comparing palm vein patterns to other biometric traits is more stable, secure, and robust. Palm veins patterns are hidden biometric features because the blood vessels are underneath skins and turned visible under near-infrared (NIR) illumination [15]. The resulting palm vein pattern depends on several parameters, including gender, age, body build, skin color, body temperature, lighting conditions, among others [1], [12]. However, among the publicly available databases for palm vein recognition, only VERA-Palmvein database (hereinafter referred as VERA) [16] includes metadata about the age and gender of individuals. Hence, soft biometrics research based on the palm vein images is still preliminary.

According to the above, this paper introduces a new approach for gender and age classification based on palm vein images. The proposed model is based on a shallow architecture of a convolutional neural network (CNN) and evaluated on the VERA database [16]. The main contributions of this research are: (1) a new CNN-based method to automatically learn discriminative features from palm vein images for gender and age classification, which ensures robustness and simplicity in the identification of individuals, (2) a new multi-classification approach identifying gender and age simultaneously through palm vein patterns, based on a new age group distribution of the VERA database, and (3) the increase in terms of accuracy and efficiency due to the used shallow architecture. These contributions will undoubtedly allow the exploration of new multi-tasking identification approaches and the reduction of the penetration rate in massive databases (e.g. pruning the searching space for a finer identification process).

The rest of the paper is organized into four sections. Section II provides an overview of the related state-of-the-art methods. The proposed methodology is presented in Section III. Later, Section IV analyzes the experimental results of the proposed model. Finally, Section V concludes our work and discusses possible future works.

## II. Related Works

Soft biometrics contributes significantly to biometric recognition and has high potential in real-world applications. Therefore, there are many works have been done on this problem [2], [4]–[7], [11], [12], [14]. Based on our perspective, most gender and age group classification techniques can be divided into two main types. In the first category, researchers use various techniques to extract features from soft biometrics and train the classifier separately. On the other hand, the second type uses an end-to-end neural network to classify individuals from their soft traits. Particularly, this section briefly discusses the related works on gender and age classification through palm vein patterns. However, to the best of our knowledge, there are few works in the literature that have addressed gender and age classification tasks on palm vein images. Mainly, for palm vein images we have only found the reports by Damak *et al.* [12] and Zabala-Blanco *et al.* [14]. Hence, we extend our review to other kind of images such as dorsal hand veins [13], [17], [18] and finger veins [19].

For the first type of method, Damak *et al.*investigated texture analysis invariant to illumination and venous pattern gradient information by the Center Symmetric-Local Binary Pattern (CSLBP) descriptor. An essential step in their proposed method is the Region Of Interest (ROI) extraction which only keeps the core part of the NIR palm vein image and reduces the less important part. After that, the author extracted the CSLBP descriptor and applied a weighted k-Nearest Neighbor (KNN) classifier to recognize gender and ages groups. From the experimental results, gender and age recognition accuracy achieved 95.8% and 94.4%, respectively. In [13], Wang *et al.*differentiate young and older adults by dorsal hand veins (DHV) by using gray-level histogram and gray-level mean value as features from NIR dorsal hand veins images. Then, they applied k-means clustering to classify DHV images and used Euclidean distance for similarity measure. The best recognition rate for age was 82% and 85% by gray-level histogram for the old and young groups, respectively. On the other hand, Zheng [17] analyzes vein patterns and skin areas separately for old and young based on the statistical parameters of gray-level histograms of dorsal hand vein images. Their study obtained better prediction rates for the KNN with 92.6% for skin features and 90.4% for vein features. In addition, dorsal vein images have been used for gender classification in [18], using four feature extraction methods: mean curvature (MC), Two-Dimensional Principal Component Analysis (2DPCA), Local Binary Pattern (LBP), and Scale Invariant Feature Transform (SIFT). In order to improve the low accuracy results achieved with an Support Vector Machine (SVM) classifier, they also used an unsupervised learning model using sparse features, for which they achieved a 98.2% with 450 features. The work reported in [19] proposes an age and gender recognition system using finger vein patterns. To characterize the texture of the vein images, the LBP descriptor is used, while the classification is performed with three different classifiers: a Single Hidden Layer Neural Network, a SVM, and a KNN classifier. Their experimental results showed that the extracted finger vein features allow the identification of gender and age with a recognition rate of up to 98% and 97.33%, respectively, using the KNN classifier which was the best approach.

Despite the advantages presented by end-to-end neural networks, we only found one work in this category. Zabala-Blanco *et al.* [14] recently evaluated original and regularized Extreme Learning Machines (ELM) for age and gender classification on palm vein images. Their method uses ELMs to avoid the feature extraction process and reduce the computational cost. Based on the classification performance, in terms of accuracy, F-measure, geometric mean (G-mean), and execution time metrics, both evaluated models outperform the baseline state-of-the-art approach [12] on the VERA database. In spite of the benefits of the proposed method, it presents the limitation related to the exhaustive search of its parameters (number of hidden neurons and regularization parameter). On the other hand, it is observed that the classification performance (up to 93.4% for gender and 90.68% for age) can still be improved.

Based on the above review and considering the success of convolutional neural networks in similar tasks [2], [3], in the following, we present the proposed method that evaluates the performance of a CNN-based model to classify people's gender and age through palm vein patterns.

## III. Proposed Methodology

This study introduces a soft biometrics system based on a convolutional neural network for gender and age classification through palm vein images. An overview of the proposed method is presented in Fig. 1, which is divided into three main processes: image pre-processing, feature learning, and classification.

In the first step, a ROI detection procedure is performed on RAW images, and three different alternative image enhancement algorithms are applied for comparison: gray-level normalization, sharpening filter [20], and CLAHE [21]. We applied the dynamical ROI detection method proposed in [22] to prevent exceeding hand borders and adjust ROI images dynamically. Besides, due to the limited number of samples in the original VERA database, we adopt the proposal of [23] that consists of fixing a central window and performing 5-pixel translations on both axes, in addition to performing 5-degree

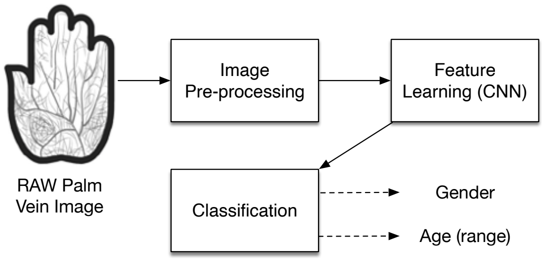


Fig. 1. Overall flowchart of the proposed method.

rotations with respect to the center of the palm. In this way, each original sample is augmented in 87 new images.

In the feature learning step, the CNN-based model is trained to extract the features from the ROI images as a feature map. After that, the classification process is performed, where three classifiers (Softmax, KNN, Support Vector Machine (SVM)) are evaluated on the extracted features to determine the gender and age group of testing samples.

### *A. CNN-based Feature Learning for Gender and Age Classification*

Most previous approaches have used hand-crafted features based on the image texture [12], [13], [17], [18]. However, CNN-based feature learning has demonstrated several advantages against traditional feature descriptors for computer vision tasks. Therefore, we use a CNN model to automatically learn the feature representation from ROI palm vein images. For this purpose, we adopt the CNN shallow architecture proposed in [23], which is called SingleNet. The architecture is composed of only five convolutional layers, providing a computational model as simple as possible with learning results comparable to the most complex state-of-the-art models.

The specification of the implemented architecture is depicted in Fig. 2, which is inspired by AlexNet model [24]. The network is composed of nine layers, including the input and output: five convolutional layers (*Conv1*-*Conv5*), two fully-connected layers (*Full1*, *Full2*), and a final Softmax classifier with cross-entropy loss. During the image pre-processing, ROI palm vein samples are resized to 64×64, which is the input size. According to experiments carried out for the refinement of the architecture, in order to reduce the overfitting, it was necessary to add batch normalization to convolutional layers and dropout after fully-connected layers. The activation function of every convolution layer is the Rectified Linear Unit (ReLU).

Each convolutional layer would repeatedly apply a set of filters on the input image and outputs the results in a feature map. As the number of filters increases, the feature map's size is reduced using max-pooling operations. Therefore, the kernel sizes also decreases from 7×7 to 2×2. The processing is performed using the Equation 1, where the input image is represented by $f$ and filter denoted by $h$. The column and row numbers of the resulting matrix $F$ are $x$ and $y$, and is computed as follows:

$$F[x,y] = (f*h)[x,y] = \sum_{m}\sum_{n} h[m,n]\times f[x-m,y-n] \quad (1)$$

The final feature map obtained by the *Conv5* layer is flattened and used as a feature descriptor (a 1024-positions vector) for the classification process.

### *B. Classification Strategies*

Once the feature representation is obtained, the last step consists of classifying the encoded samples to the corresponding class. In this study, we have two independent classification tasks: gender and age group. Whereas gender classification is a binary classification problem, on the other hand, age group classification becomes a multi-class classification problem.

We implemented three strategies to evaluate classification performance on both tasks. First, the trained CNN model is used as an end-to-end classifier by using its Softmax top layer, where each layer unit represents a class, and its output corresponds to the class probability. Additionally, we utilized the learned feature representation as input of a K-Nearest Neighbor (KNN) classifier and a Support Vector Machine (SVM) classifier. The KNN classifier is a good alternative for replacing the Softmax layer and using the feature vectors extracted by the CNN model [23]. This second strategy allowed us to conduct a direct comparison with previous works of the state-of-the-art. The KNN was implemented using the Euclidean distance and $k = 1$, due to the fact that performance decreases as the $k$ value increases [23]. As final classification strategy, the SVM classifier was trained using a linear kernel. As age classification is a multi-class problem, we defined a $C$ binary SVMs ensemble, where $C$ is the number of age groups.

### *C. Palm Vein Dataset for Gender and Age Classification*

VERA-Palmvein database [16] is the only public dataset that contains information about the gender and age of individuals. Hence, we used it to evaluate the proposed method. The database is composed of 40 women and 70 men whose ages are between 18 and 60, with an average of 33 years old. It contains 2200 NIR images taken from 110 individuals with five samples of left and right hand in two separate acquisition sessions, for a total of 10 samples per individual. All images were captured by using a contactless device, and saved as 8-bit grayscale PNG format with a resolution of 480×680 pixels.

The classes were selected according to the classification task to be performed in the same way as the baseline work [12], which was also used in [14]. Table I shows the distribution of classes for each classification task. For gender classification, the classes are "male" and "female", while age groups are "teenager" (<20 years), "young" (20-40 years), and "adult" (41-60 years), which correspond to the classes used in the reference article "child", "young", and "adult", respectively. As can be noted, there is a significant unbalance between the age groups initially proposed, so we propose a new distribution of groups, dividing the subjects into ten-year age groups, as shown in Fig. 3. This new distribution was used to evaluate

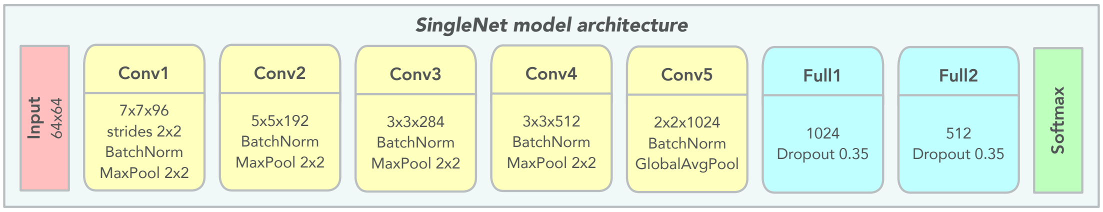


Fig. 2. Adopted CNN architecture for feature learning: five convolutional layers followed by two fully-connected layers. The last layer corresponds to the Softmax classifier, which can be replaced by another classification method.

the proposed method in a multi-classification approach identifying gender and age simultaneously, which is presented in Section IV-C.

TABLE I
DISTRIBUTION OF CLASSES FOR EACH CLASSIFICATION TASK.

| Classification Task | Classes | Individuals | Samples |
|---|---|---|---|
| Gender | Male | 70 | 700 |
| | Female | 40 | 400 |
| Age | Teenager | 4 | 40 |
| | Young | 78 | 780 |
| | Adult | 28 | 280 |

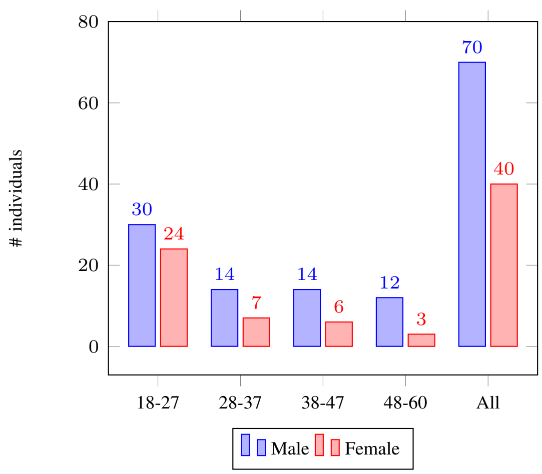


Fig. 3. Proposed distribution of age groups in the VERA database.

Considering the unbalanced classes of the dataset, we calculated the class weight based on its number of samples in order to take into account the weights for training and classification processes. The weight of the $i$-th class ($C_i| \; i = 1..N$) is computed as:

$$W(C_i) = \left( \frac{min(|C_i| \;\; i = 1..N)}{|C_i|} \right)^{\frac{1}{2}}, \quad (2)$$

where $N$ is the number of classes. Equation (2) is mathematically equivalent to the method used in [12] and [14]. Accordingly, the weights will be in the range $[0, 1]$, the higher the number of samples of the class the lower will be its corresponding weight, whereas the value 1 corresponds to the minority class.

In order to properly use the database, we used 80% of individuals for training and 20% for testing in a 5-fold cross-validation scheme. Thus, the reported performance metrics are the average of the five evaluation iterations.

### *D. Performance Metrics*

Usually, the Accuracy metric is used to evaluate the classification performance. However, it corresponds to a general prediction metric, so it is not appropriate for unbalanced classes problems. Hence, an accurate comparative analysis should be done on diverse metrics. This research compared the performance of the proposed method through F-measure and G-mean metrics, which are more appropriate for unbalanced data. The G-mean represents the product of *Sensitivity* and *Specificity*, corresponding to positive and negative samples, respectively. The F-measure corresponds to the harmonic mean of *Precision* and *Recall*. Both metrics allow a comparison of the obtained results with the works reported in the state-of-the-art, and are defined from the confusion matrix as follows:

$$F-measure = \frac{TP}{TP + (FP + FN)/2} \quad (3)$$

$$G-mean = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}} \quad (4)$$

where TP, TN, FP and FN denote the categories of true positive, true negative, false positive and false negative, respectively.

## IV. EXPERIMENTAL RESULTS

This section shows the results obtained by the proposed method for gender and age classification on the VERA database. In the experiments, a dedicated server were used running Debian GNU/Linux 10 (buster) operating system (kernel 4.19.0-17-amd64 x86 64), consisting of two Intel Xeon Gold 6140 CPUs, with 128 GB of RAM, and two NVIDIA GeForce GTX 1080Ti GPUs. The proposed methods were implemented with Python (v.3.7.3), making use of the OpenCV (v.4.1), Tensorflow (v.1.15.0), Keras (v.2.3.1), and Scikit-learn (v.0.24) libraries.

### *A. Training Details*

For training the CNN model, we configured 100 epochs with a $batchsize = 32$ and an initial learning rate $lr = 0.01$, with a reduction of the learning rate by 0.2 when the loss function is kept unchanged (*ReduceLROnPlateau*). After the first set of training epochs, 25 additional epochs were established in which all available training data were used without considering the validation set. In this way, we reduced the limitations associated with the lack of training samples. Additionally, in both training phases, an early stopping criterion was established if the validation error did not improve for seven epochs. For the SGD optimization, the $momentum = 0.9$ and the $weight\_decay = 1 \times 10^{-5}$.

It is worth mentioning that we used the same training set used in the CNN training for training the SVM classifier. Whereas for the KNN classifier, this training set was used as our *gallery set*.

### B. Performance Results for Gender and Age Classification

We trained the CNN model to learn a feature representation for gender and age classification tasks from palm vein images. In order to find the optimal method, we examined different pre-processing techniques with the classification strategies. Tables II and III summarize the performance of gender and age classification based on the studied metrics, respectively. Best results are highlighted in bold font. Each value corresponds to a different combination of pre-processing techniques (rows) and classifiers (columns). For pre-processing techniques, '*gray-normal*' represents gray-level normalization, '*sharpen*' is the sharpening filter, and '*clahe*' corresponds to the homonymous technique. In the columns, the three classification strategies studied are presented: Softmax as '*SM*', '*SVM*' and '*KNN*' for the classifiers of the same name.

The results shown in Table II suggest that the proposed CNN model is able to learn a good feature representation for different pre-processing inputs, being '*clahe*' better than the rest. Thus, the combination of the CLAHE technique with the KNN classifier achieves the best performance values: a 97% for F-measure and 96.3% for G-mean. However, the SVM classifier performs slightly more stable than the other two strategies taking into account the mean values of F-measure and G-mean metrics for the three pre-processing techniques.

TABLE II
RESULTS FOR GENDER CLASSIFICATION

| **Pre-processing** | **F-measure** | | | **G-mean** | | |
|---|---|---|---|---|---|---|
| | **SM** | **SVM** | **KNN** | **SM** | **SVM** | **KNN** |
| gray-normal | 92.3 | 93.6 | 92.9 | 89.1 | 91.5 | 90.8 |
| sharpen | 93.4 | 94.3 | 94.3 | 92.3 | 93.3 | 92.9 |
| clahe | 96.4 | 96.5 | **97.0** | 95.4 | 95.9 | **96.3** |

For age group classification, Table III shows that the results for '*gray-normal*' and '*sharpen*' are significantly lower than '*clahe*'. In this case, the combination CLAHE+SVM was only 0.1% better than CLAHE+KNN for the G-mean metric and similar results for F-measure. Despite that, SVM has the drawback that it needs a second training stage after learning the feature representation.

The above results for both classification tasks make the combination CLAHE+KNN better than others because it performs better than parametric classifiers (i.e. Softmax and SVM) on average. Moreover, KNN does not require a training stage in the case of increasing the number of individuals in the database. This behavior also confirms previous results for identification purposes [23].

TABLE III
RESULTS FOR AGE GROUP CLASSIFICATION

| **Pre-processing** | **F-measure** | | | **G-mean** | | |
|---|---|---|---|---|---|---|
| | **SM** | **SVM** | **KNN** | **SM** | **SVM** | **KNN** |
| gray-normal | 87.9 | 85.4 | 89.5 | 84.4 | 82.1 | 86.2 |
| sharpen | 85.9 | 86.8 | 87.7 | 81.0 | 83.2 | 84.8 |
| clahe | 96.8 | **97.5** | 97.5 | 96.3 | **96.8** | 96.7 |

### C. Performance Results for Gender and Age Multi-classification

In addition to the baseline experiments, we applied our model for classifying gender and age at the same time. For this goal, we trained the CNN model with composite labels consisting of the gender and age groups shown in Fig. 3, e.g. male/female+*age-group*, for a total of eight classes. Table IV shows the classification performance based on the same metrics. In this experiment, the overall performance is slightly lower than single classification tasks due to the increasing classes and lacking individuals in some of them. The results for '*clahe*' are higher than 95% in all cases. Also, both SM and SVM perform similarly and slightly better than KNN. These results suggest that further studies could be carried out on multi-task classification based on palm vein patterns. Besides, a multi-classification scheme allows us to split a massive database into smaller parts and thus speed up the final identification process.

TABLE IV
RESULTS FOR GENDER AND AGE MULTI-CLASSIFICATION

| **Pre-processing** | **F-measure** | | | **G-mean** | | |
|---|---|---|---|---|---|---|
| | **SM** | **SVM** | **KNN** | **SM** | **SVM** | **KNN** |
| gray-normal | 87.9 | 87.5 | 90.0 | 83.1 | 82.5 | 87.4 |
| sharpen | 91.1 | 89.5 | 90.5 | 86.6 | 85.7 | 87.4 |
| clahe | 95.6 | **96.5** | 95.0 | **96.6** | 95.6 | 95.9 |

### D. Comparison against State-of-the-Art

Table V compares our three classification strategies based on CNN feature learning from CLAHE images of palm vein patterns, which was the best pre-processing technique in our experiments. We only consider the state-of-the-art approaches on the VERA database for gender and age classification. It is noteworthy that our method is significantly better than ELM [14], which is also based on a neural network and does not use hand-crafted features. Comparing to CSLBP [12], the proposed approach improves their results with the advantage of avoiding a feature extraction process. Furthermore, the database partitions in [12] bring them certain advantageous conditions because their cross-validation scheme was based on samples instead of individuals. Due to this, in some way, the classifier can know a priori features of the testing set from samples of one of the acquisition sessions.

In addition to the above, if we compare the results obtained by our proposal against those obtained by other approaches based on different vein patterns such as dorsal hand veins [13], [17], [18] and finger veins [19], it can be noted that our method performs similarly or even better than them.

TABLE V
COMPARISON OF THE STATE-OF-THE-ART APPROACHES ON THE VERA DATABASE FOR GENDER AND AGE CLASSIFICATION

| Method | Gender | | Age | |
|---|---|---|---|---|
| | F-measure | G-mean | F-measure | G-mean |
| CSLBP [12] | 95.8 | 95.9 | 94.2 | 94.4 |
| ELM [14] | 90.8 | 92.6 | 88.3 | 78.9 |
| CNN+SM (ours) | 96.4 | 95.4 | 96.8 | 96.3 |
| CNN+SVM (ours) | 96.5 | 95.9 | **97.5** | **96.8** |
| CNN+KNN (ours) | **97.0** | **96.3** | **97.5** | 96.7 |

## V. CONCLUSIONS

This paper proposed a new CNN-based model for gender and age classification based on palm vein images. Based on the experimental results, the proposed method is able to learn discriminative features from palm vein images for these tasks. Our proposal outperforms the state-of-the-art results on the VERA database by using a shallow CNN architecture. Besides, we introduced a new multi-classification scheme for simultaneous gender and age classification, which achieves promising results for further studies.

Despite the above, we think the model's performance is limited by the quality and size of the dataset. Thus, it is required the creation of new palm vein datasets with a greater number of subjects containing additional information regarding soft biometric traits such as age and gender, among others. Likewise, it would be interesting to perform further ablation studies related to the CNN architecture used, evaluating different variants of the proposed architecture or other efficient architectures, such as SqueezeNet or ShuffleNet. Finally, considering the multi-classification results and once a more appropriate palm vein database is available, the creation of multi-task recognition models using biometric identification traits and soft biometric traits can be considered.

## ACKNOWLEDGMENT

R.H.-G. thanks to the Research Project ANID FONDECYT Iniciación en Investigación 2022 No. 11220693 "End-to-end multi-task learning framework for individuals identification through palm vein patterns", Ministerio de Ciencia, Tecnología, Conocimiento e Innovación, Gobierno de Chile. Portions of the research in this paper used the VERA-Palmvein Corpus made available by the Idiap Research Institute, Martigny, Switzerland.

## REFERENCES

[1] A. K. Jain, S. C. Dass, and K. Nandakumar, "Soft biometric traits for personal recognition systems," in *International conference on biometric authentication*. Springer, 2004, pp. 731–738.

[2] Z. Xie, Z. Guo, and C. Qian, "Palmprint gender classification by convolutional neural network," *IET Computer Vision*, vol. 12, pp. 476–483, 6 2018.

[3] M. J. Marín-Jiménez, F. M. Castro, N. Guil, F. De la Torre, and R. Medina-Carnicer, "Deep multi-task learning for gait-based biometrics," in *2017 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2017, pp. 106–110.

[4] M. R. Kaur, M. Susmita, G. Mazumdar, and M. D. Bhonsle, "A Study on Various Methods of Gender Identification Based on Fingerprints," p. 532, 2012.

[5] D. G. Rajesh and M. Punithavalli, "An efficient fingerprint based gender classification system using dominant un-decimated wavelet coefficients," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 8, pp. 1259–1265, 2014.

[6] G. Levi and T. Hassner, "Age and gender classification using convolutional neural networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2015, pp. 34–42.

[7] M. M. Dehshibi and A. Bastanfard, "A new algorithm for age recognition from facial images," *Signal Processing*, vol. 90, pp. 2431–2444, 8 2010.

[8] F. M. Castro, M. J. Marín-Jiménez, and N. Guil, "Multimodal features fusion for gait, gender and shoes recognition," *Machine Vision and Applications*, vol. 27, no. 8, pp. 1213–1228, 2016.

[9] R. Delgado-Escaño, F. M. Castro, J. R. Cózar, M. J. Marín-Jiménez, and N. Guil, "An end-to-end multi-task and fusion CNN for inertial-based gait recognition," *IEEE Access*, vol. 7, pp. 1897–1908, 2018.

[10] S. Lagree and K. W. Bowyer, "Predicting ethnicity and gender from iris texture," in *2011 IEEE international conference on technologies for homeland security (Hst)*. IEEE, 2011, pp. 440–445.

[11] J. E. Tapia, C. A. Perez, and K. W. Bowyer, "Gender classification from iris images using fusion of uniform local binary patterns," in *European Conference on Computer Vision*. Springer, 2014, pp. 751–763.

[12] W. Damak, R. B. Trabelsi, A. D. Masmoudi, and D. Sellami, "Palm Vein Age and Gender Estimation Using Center Symmetric-Local Binary Pattern," in *International Joint Conference: 12th International Conference on Computational Intelligence in Security for Information Systems (CISIS 2019) and 10th International Conference on EUropean Transnational Education (ICEUTE 2019)*. Springer, 2019, pp. 114–123.

[13] Y. Wang and H. Zheng, "A preliminary analysis of the aging dorsal hand vein images," in *2013 5th International Conference on Intelligent Human-Machine Systems and Cybernetics*, vol. 2. IEEE, 2013, pp. 271–274.

[14] D. Zabala-Blanco, R. Hernández-García, R. J. Barrientos, and M. Mora, "Evaluation of the standard and regularized ELMs for gender and age classification based on palm vein images," in *2021 40th International Conference of the Chilean Computer Science Society (SCCC)*. IEEE, 2021, pp. 1–8.

[15] W. Wu, S. J. Elliott, S. Lin, S. Sun, and Y. Tang, "Review of palm vein recognition," *IET Biometrics*, vol. 9, no. 1, pp. 1–10, 2019.

[16] P. Tome and S. Marcel, "Palm vein database and experimental framework for reproducible research," in *2015 International Conference of the Biometrics Special Interest Group (BIOSIG)*. IEEE, 2015, pp. 1–7, database available online at: https://www.idiap.ch/dataset/vera-palmvein.

[17] H. G. Zheng, "Static and dynamic analysis of near infra-red dorsal hand vein images for biometric applications," Ph.D. dissertation, University of Central Lancashire, 2017.

[18] J. Wang, G. Wang, and Z. Pan, "Gender attribute mining with hand-dorsa vein image based on unsupervised sparse feature learning," *IEICE Transactions on Information and Systems*, vol. 101, no. 1, pp. 257–260, 2018.

[19] W. Damak, R. B. Trabelsi, A. D. Masmoudi, D. Sellami, and A. Nait-Ali, "Age and gender classification from finger vein patterns," in *International Conference on Intelligent Systems Design and Applications*. Springer, 2016, pp. 811–820.

[20] J. Chaki and N. Dey, *A beginner's guide to image preprocessing techniques*. CRC Press, 2018.

[21] K. Zuiderveld, "Contrast Limited Adaptive Histogram Equalization," in *Chapter VIII.5, Graphics Gems IV*, P. S. Heckbert, Ed. Academic Press Professional, Inc., 1994, pp. 474–485.

[22] R. Hernández-García, R. J. Barrientos, C. Rojas, and M. Mora, "Individuals identification based on palm vein matching under a parallel environment," *Applied Sciences*, vol. 9, no. 14, p. 2805, 2019.

[23] J. I. Santamaría, R. Hernández-García, R. J. Barrientos, F. M. Castro, J. Ramos-Cózar, and N. Guil, "Evaluation of end-to-end CNN models for palm vein recognition," in *2021 40th International Conference of the Chilean Computer Science Society (SCCC)*. IEEE, 2021, pp. 1–8.

[24] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 25, pp. 1097–1105, 2012.