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RESEARCH ARTICLE

Gender-Specific Characteristics for Hand-Vein Biometric Recognition: Analysis and Exploitation

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ABSTRACT In recent years, vein-based biometric recognition has received ever-increasing attention from both academia and industry, due to the advantages it offers over traditional biometric traits such as fingerprint, iris, and face. Nonetheless, some issues related to the use of vein biometrics still need to be investigated and understood. Specifically, in this study, we speculate about the gender-related variations in vein patterns, and their effects on biometric verification performance. An analysis on the feasibility of recognizing male and female subjects depending on their hand-vein patterns, and on the level of similarity characterizing the biometric templates extracted from male and female populations, are here carried out considering three different databases. Specifically, the public VERA dataset, containing samples of palm-vein patterns, and two datasets containing images of finger-vein patterns, i.e., the UTFVP public database, and an in-house dataset collected with an on-the-move contactless modality, are here considered. The obtained experimental results show that the approach here proposed to perform gender recognition allows to reach an accuracy up to 95.83% on the public finger-vein UTFVP dataset, and to outperform the current state-of-the-art on the public palm-vein VERA dataset, with accuracy at 93.55%. It is also shown that vein-based biometric systems can benefit from the exploitation of information regarding the gender of the considered subjects, with achievable recognition rates that can be significantly improved by designing a biometric verification system relying on gender-specific models for extracting the employed discriminative templates.

INDEX TERMS Biometric recognition, gender recognition, vein biometrics, deep learning.

I. INTRODUCTION

Biometric technologies are nowadays widely adopted in several applications dedicated to human recognition and identity management. A biometric system collects and exploits physical, behavioural, or cognitive traits, characterized by properties such as universality, uniqueness, permanence, measurability, performance, acceptability, and robustness to circumvention, to generate a set of discriminative features employed as user's identifiers. In the recognition phase, the features extracted from the biometric probe are compared with those stored in a database during the enrolment stage, in order to either verify the identity claimed by the presented user or to determine the identity itself.

It is worth remarking that, when collecting a subjects' biometric trait, ancillary information related to the individual such as age, gender, or height, to cite a few, can be estimated from the recorded data. Characteristics like the aforementioned ones are commonly indicated as soft biometric traits, since they are not discriminative enough to automatically distinguish among different individuals. Nonetheless, soft biometric traits can be helpful for a variety of uses [1]. First of all, they offer a semantic interpretation of the collected data, meaning that they can provide descriptions easily

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understandable by humans, and therefore useful in surveillance applications since the information they bring can be directly compared with what is perceived by human operators. Soft traits can be also exploited to design recommendation systems offering customized products and services depending on the users' age and gender. Furthermore, soft biometric characteristics can be employed to improve or expedite the recognition process performed through conventional biometric traits. In fact, soft attributes can be either fused with the primary biometric characteristics to generate more discriminative users' representations, therefore improving the achievable recognition performance, or employed to perform a search space reduction in identification systems, by filtering out irrelevant subjects on the basis of the available ancillary information.

Among soft biometric traits, gender is one of the most investigated one, also considering that gender recognition is a fundamental capability of human beings in social life, with people deemed capable of carrying out this task with an error rate of about 10% on average [2]. Automatizing this human capability would be crucial in domains such as surveillance, forensics, entertainment, and marketing. According to forensic studies, the skull of a person, and more specifically the chin and the jawbone, contains the most significant gender indicators [3]. Not surprisingly, most of the literature on automatic gender recognition has focused on the analysis of face traits [4]. Results in the range of 90% - 95% correct recognition have been achieved using facial features to determine a person's gender, with the attainable performance depending on several factors, such as the pose of the considered individual, the presence of occlusions, the acquisition environment, and so forth [5]. For scenarios where only profile face images are available, the shape of the ear has been exploited to infer a person's gender [6]. The characteristics of the eyes have been also deeply investigated to perform gender recognition, with discriminative characteristics found in a person's iris [7], as well as in the periocular region [8]. Also, fingerprints have been evaluated to perform gender recognition [9]. The hand shape has been instead extensively analyzed in several forensics studies, while few automatic approaches have been so far proposed [10]. Among behavioural traits, speech [11] and gait [12] are among the characteristics most investigated to perform gender recognition, and studies on signature and keystroke dynamics have been also recently proposed [13].

Within this framework, in this paper, we investigate the influence of individuals' gender on the discriminative capabilities of features extracted from the hand vein patterns, which have recently received an increasing level of attention from the biometric research community. In fact, hand vein patterns possess several interesting properties encouraging their exploitation for automatic people recognition. For instance, vein patterns can be captured through non-invasive devices, being also possible to design contactless acquisition procedures for their collection. As subcutaneous structures, they are intrinsically more robust to presentation attacks than exposed biometric traits, such as fingerprint, face, or iris. They also inherently guarantee liveness detection. More importantly, it has been shown that vein patterns are characterized by an entropy higher than many other widespread biometric traits, thus guaranteeing recognition performance comparable with those related to fingerprint and iris characteristics [14]. As a consequence, several commercial devices relying on vein patterns have been deployed in the last few years for real-life applications.

Nonetheless, soft characteristics related to hand vein patterns have been so far neither properly investigated nor exploited [15]. In this regard, the present study explores gender-specific effects on the hand vein patterns collected for automatic people recognition. In more detail, in this paper, we first investigate the possibility of performing gender recognition relying on hand vein patterns. Then, an evaluation of possible differences in the score distributions depending on the subjects' gender is carried out. Furthermore, we also evaluate whether a biometric verification process relying on hand vein patterns could benefit from the information related to the gender of the considered subjects. Such possibility has been for instance evaluated for face images in [16], where the soft characteristics extracted to perform gender recognition are jointly used together with the primary user-specific features, by resorting to a score-level fusion of the extracted information. Differently from the work in [16], in our approach, we employ strategies relying on neural networks to specifically learn hand vein feature representations in a way dependent on the gender of the presented user, with the aim of evaluating whether such gender-aware processing could improve the recognition performance.

The paper is organized as follows. Section II outlines the physiological background of vein biometrics, also providing arguments regarding the gender-related anatomical characteristics of hand veins. Previous studies on gender recognition using vein patterns are also discussed. The deep learning approaches employed to analyze the considered traits are then described in Section III, while the databases used in our experiments are introduced in Section IV. The performed tests are then presented in Section V, which includes discussions regarding gender effects on the recognition rates achievable using hand vein patterns, the feasibility of performing gender recognition relying on hand veins, and the possibility of estimating gender-specific discriminative characteristics through the employed deep learning methods.

II. HAND VEIN PATTERNS

The uniqueness of vessel patterns on the back of hand has been first speculated in the late 19th century by Arrigo Tamassia, a professor of forensic medicine at Padua University [17]. Nevertheless, the real potential of vascular biometrics had not been noticed until 1987 when Joe Rice, considered the father of vein biometrics, introduced the first hand-vein-based biometric recognition system [18].

The acquisition of images depicting subcutaneous vein patterns, through non-invasive and contactless devices, relies on two properties of the human body, namely the *therapeutic*

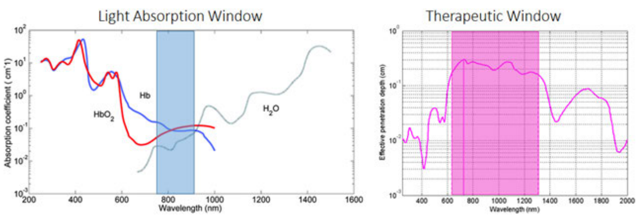


FIGURE 1. **Light absorption (left) and therapeutic (right) windows.**

and the *light absorption* windows, represented in Figure 1. The former window contains wavelengths in the range from 650*nm* to 1350*nm*, where the light has its maximum depth of penetration into the human tissue. The latter is instead the wavelength interval, within the therapeutic window, where oxygenated and deoxygenated haemoglobin reach their light absorption peaks (DeoxyHb: 760*nm*; OxyHb: 900*nm*), maintaining a level of absorption greater than that of water [19]. According to these characteristics, when a hand is illuminated with near-infrared (NIR) light in wavelength windows between 700*nm* and 900*nm*, the NIR absorption capability of haemoglobin makes the blood vessels appear dark, while the surrounding tissue let the light passing, thus appearing bright. A vein pattern capturing device is therefore constituted by a NIR camera equipped with a NIR illuminator, working in either transmission or reflection modality.

Besides these general characteristics of human tissues, there are also some gender-related differences in the anatomy of vein vessels, and in their NIR light absorption capability, which is also observable in the examples of Figure 2:

- the diameter of vein vessels can be notably different between male and female subjects. Medical studies have associated an increased vein diameter with greater age and male gender [20], [21];
- male and female subjects have different haemoglobin levels in the blood. In more detail, women have mean haemoglobin levels approximately 12% lower than men [22]. Since the vein pattern images are obtained because of the light absorption capacity of haemoglobin under NIR illumination, female vein patterns look paler than those of males because of such discrepancy in haemoglobin levels.

Due to the aforementioned differences, it is expected that the acquisition process of vein patterns from female subjects may produce images with characteristics quite different from those of male subjects. Some studies have been already conducted with the aim of investigating whether it is possible to perform gender recognition based on hand vein patterns. In an early attempt [23], it has been shown that information about the gender of subjects can be extracted from finger vein patterns by resorting to local binary patterns (LBP) features, and using a K-nearest-neighbour (KNN) classifier. Tests performed over the MMCBNU finger vein database [24], comprising images of finger vein patterns taken from 100 volunteers coming from 20 countries, have shown the possibility of reaching a gender recognition

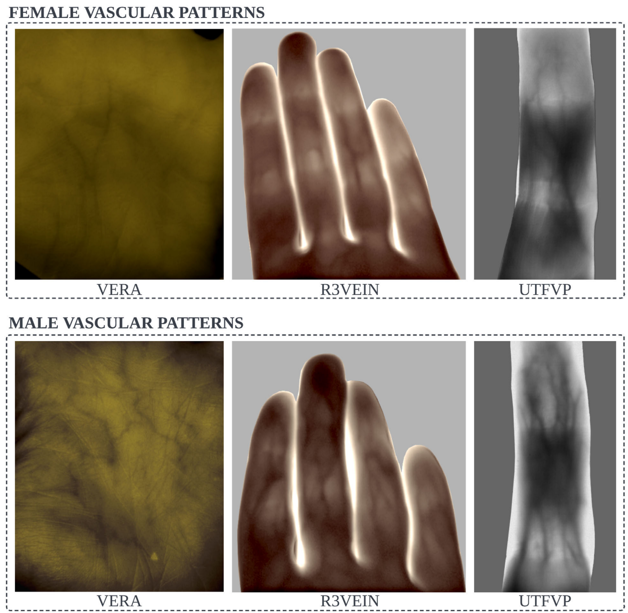


FIGURE 2. **Left-hand female and male vascular pattern samples from VERA palm, R3VEIN vein and UTFVP vein datasets, respectively.**

accuracy greater than 95%. The work in [23] has been also recently extended, using centre symmetric LBP descriptors and weighted KNNs, to investigate palm vein patterns [25]. Tests have shown the possibility of achieving an accuracy of about 95.8% over the public VERA dataset, which contains images of left and right-hand vein patterns recorded from 110 subjects [26]. However, as shown in [27], such performance is attainable only when training the employed classifiers with images from all the subjects in the VERA dataset, and including samples from both the available recording sessions in the training datasets. Conversely, when only samples from a single session are employed for training purposes, the achievable recognition rates notably worsen, with the approaches in [23] and [25] significantly outperformed by the method proposed in [27], which relies on a shallow neural network based on regularized extreme learning machines (ELMs), able to achieve an accuracy of 93.40% on the VERA dataset.

Hand-dorsal vein patterns have been instead examined in [28], where an in-house database comprising samples collected from 98 females and 102 males, whose ages vary from 19 to 62, has been considered, and an unsupervised sparse feature learning approach has been employed to perform gender recognition. The same database has been exploited in [29], where methods relying on deep learning have been used by applying transfer learning to VGG [30] and AlexNet [31] architectures, and achieving a gender recognition accuracy at 91.6% with the former network.

However, none of the aforementioned studies has investigated whether any relevant difference exists between the score distributions obtained from male and female subjects when performing automatic biometric recognition.

TABLE 1. Network employed to process hand vein patterns for both gender and people recognition tasks. The original Densenet-161 CNN has been modified by adding a custom embedder preceding the final classification layer.

Layers		Input Size	Output Size
Convolution	7×7 conv, str.2	$224\times224\times1$	$112\times112\times96$
Pooling	3×3 max pool, str.2	$112\times112\times96$	$56\times56\times96$
Dense Block 1	$\begin{bmatrix}1\times1\text{ conv}\\3\times3\text{ conv}\end{bmatrix}\times6$	$56\times56\times96$	$56\times56\times384$
Transition 1	1×1 conv 2×2 avg pool, str.2	$56\times56\times384$	$28\times28\times192$
Dense Block 2	$\begin{bmatrix}1\times1\text{ conv}\\3\times3\text{ conv}\end{bmatrix}\times12$	$28\times28\times192$	$28\times28\times768$
Transition 2	1×1 conv 2×2 avg pool, str.2	$28\times28\times768$	$14\times14\times384$
Dense Block 3	$\begin{bmatrix}1\times1\text{ conv}\\3\times3\text{ conv}\end{bmatrix}\times36$	$14\times14\times384$	$14\times14\times2112$
Transition 3	1×1 conv 2×2 avg pool, str.2	$14\times14\times2112$	$7\times7\times1056$
Dense Block 4	$\begin{bmatrix}1\times1\text{ conv}\\3\times3\text{ conv}\end{bmatrix}\times24$	$7\times7\times1056$	$7\times7\times2208$
Custom Embedder	7×7 global avg pool batch normalization dropout (50%)	$7\times7\times2208$	1×2208
	fully connected layer batch normalization	1×2208	1×1024
Classifier	output layer	1×1024	$1\times U$

More importantly, the utility of designing gender-specific feature extraction processes, in order to improve the achievable biometric verification rates within the hand vein biometric framework, has not been evaluated so far.

The present paper is the first contribution trying to exploit information related to gender when performing biometric recognition on subjects whose hand vein patterns are collected for verification purposes.

III. HAND-VEIN FEATURE LEARNING

In the performed tests, the features employed to perform both gender and biometric recognition are learned through an approach relying on neural networks. While hand-crafted features such as the already mentioned LBP have been employed for a long time to perform biometric recognition, in the past 10 years we have witnessed an ever-increasing adoption of neural networks in biometric applications, thanks to the swift proliferation of novel deep learning techniques and low-cost computational units. The use of deep learning approaches has allowed to design algorithms that are more robust, convenient, and descriptive, in terms of feature extraction and comparison, than what has been possible using standard machine learning solutions. In more detail, several recent outstanding results have been attained by exploiting one of the most important features of neural networks, that is, transfer learning. In fact, this methodology allows transferring a well-performing approach from one domain to another, typically compensating for the lack of available training data in the target scenario, with the highly-effective representations estimated in the original context.

Such approach is employed also here to perform gender recognition based on hand vein patterns. Specifically, we exploit the same approach employed in [32] to extract discriminative features from hand vein patterns when performing automatic people recognition. A modified version of the Densenet-161 convolutional neural network (CNN) [33], described in Table 1, has been in fact introduced in [32] to process the considered traits through a stable and consolidated network, defined in literature for image classification tasks, after having performed a fine-tuning depending on the desired purpose. In the employed architecture, each *conv* layer comprises convolution, batch normalization, and ReLU stages. Having already proved the effectiveness of a transfer learning approach relying on the network described in Table 1 to perform biometric recognition based on hand vein patterns, this method is here evaluated also for gender recognition.

With reference to the employed network in Table 1, the hyperparameter U in the classification layer is set to 2 when performing gender recognition, which is therefore treated as a binary classification scenario. In this context, recent progress in the design of CNNs have shown that a soft-L_1 loss, which is the differentiable version of the F_1 function computing true positives, false positives, and false negatives as a continuous sum of likelihood values, has the capability of boosting the achievable classification performance [34]. For this reason, for gender recognition, the modified Densenet-161 is fine-tuned relying on a soft-L_1 loss.

Conversely, when employing the network in Table 1 for biometric recognition purposes, the parameter U refers to the total number of unique identities considered during the training phase. In this case, the additive angular margin penalty (AAMP) [35] has been employed as a loss function, due to its ability at reducing the intra-class variance, and increasing inter-class variance, as demonstrated in [36]. Differently from the standard softmax, commonly employed to train networks for identification purposes, the AAMP loss has shown better generalization capabilities, being therefore a suitable solution to train a network for generative representations that guarantee not only separability, yet also discriminability, among subjects not taken into account during the training stage. This is a fundamental requirement when taking into account realistic training and testing operating conditions as in Section V.

The initialization of the network parameters is performed using the weights of the pre-trained Imagenet model. As for the custom embedder layer of Densenet-161 in Table 1, unit weight initialization is employed for batch normalization, and Glorot uniform initialization is preferred for the fully-connected layers.

During training, stochastic gradient descent (SGD) with a batch size of 32 is used for back-propagation, with a learning rate initially set to 0.01, and then divided by 10 after the loss reaches a plateau. Momentum is set to 0.9 for speeding up the convergence of gradient vectors, and the maximum number of training epochs is set to 120. While searching the best hyper-parameters of AAMP [35], the penalty margin is set to $m \in [0.3, 0.7]$ with step size 0.05, and the scale is set to $s \in [16, 96]$ with step size 16.

TABLE 2. Overview of vein databases used in this study.

Benchmark Database	Vein Modality	Database Statistics		Capturing Conditions	Capturing Parts
VERA [26]	Palm	# of Subjects	110	grayscale single channel	left and right hand palms
		# of Female Subjects	40		
		# of Male Subjects	70		
		# of Classes	220		
		# of Sessions	2		
		Samples per Session	5		
		Total Samples	2.200		
UTFVP [37]	Finger	# of Subjects	60	grayscale single channel	index-, middle- and ring-fingers from left and right hands
		# of Female Subjects	16		
		# of Male Subjects	44		
		# of Classes	360		
		# of Sessions	2		
		Samples per Session	2		
		Total Samples	1.440		
R3VEIN [38]	Finger	# of Subjects	200	4 different channels for varying exposure rates	4 fingers together (except thumb) from left and right hand
		# of Female Subjects	71		
		# of Male Subjects	129		
		# of Classes	400		
		# of Acquisitions	10		
		Samples per acquisition	9		
		Total Samples	144.000		

When testing the trained networks, a standard binary classification process is performed when carrying out gender recognition. On the other hand, the network trained for biometric recognition is employed as a feature extractor when comparing two distinct samples for verification purposes. In more detail, the Euclidean distance between a pair of feature representations, generated from enrolment and probe samples, is computed, and compared against a pre-set threshold to decide on the authenticity of the claimed identity. As it will be detailed hereafter in Section V, realistic open-set scenarios, in which data from a given class are used exclusively for either training or testing, but never both, have been considered in the performed tests for hand-vein-based gender and biometric recognition.

IV. EMPLOYED DATABASES

Three hand vein datasets including gender labels for each subject, described in the following sections, have been employed in the tests to evaluate the feasibility of vein-based gender recognition, and the feasibility of improving the verification performance of a biometric system relying on gender-specific representations of vein patterns. Detailed information about these databases is provided in Table 2. To use the considered images as input to the employed network in Table 2, all samples in each dataset are re-sized into 224 × 224 pixels and normalized to have zero mean and unit variance before feeding them into the recognition systems.

A. VERA DATABASE

The VERA palm vein dataset [26] has been collected in Haute Ecole Specialisee de Suisse Occidentale in Sion. The database contains 2.200 palm vein images taken from 40 women and 70 men subjects, whose ages are between 18 and 60, with an average of 33 years. For each subject, vascular patterns of the right and left palms have been captured during two distinct sessions, with five pictures taken for each hand during each session.

B. UTFVP DATABASE

The UTFVP dataset has been collected from 60 subjects at the University of Twente. The dataset contains 1440 images, taken from 16 female and 44 male subjects. For each subject, vascular patterns from the index, ring, and middle fingers of both hands have been captured twice during each recording session. A total of 360 different classes are therefore available. The dataset comprises samples collected during two sessions, separated by an average time-lapse of 15 days, for each subject. The width of the visible blood vessels ranges from 0.3–1.6 mm, with a pixel density for the acquired images of 126 pixels per centimetre.

C. R3VEIN DATABASE

The R3VEIN database has been introduced in [38], and contains acquisitions of vein patterns from subjects interacting with the employed device while passing their hands over it, therefore implementing an on-the-move recording strategy. Four different NIR cameras, with exposure rates set at $E_1 = 12\mu s$, $E_2 = 16\mu s$, $E_3 = 20\mu s$, and $E_4 = 24\mu s$, have been used in the employed acquisition device, to capture vein images with varying levels of received light. The database employed for tests in [38] contained finger vein patterns collected from 100 subjects. An extended version of that database, comprising data from an additional amount of other 100 subjects, for a total of 200 participants and 400 classes in the R3VEIN dataset, is here employed to perform tests investigating the role of gender on vein biometrics.

The whole dataset has been collected by recording sequences of frames depicting the moving hands. Each subject has provided 10 image sequences, each consisting of 9 frames, for left and right hands, with a total of 144.000 frames collected from 200 subjects, of which 71 are females and 129 males. In the present study, a total of 36.000 tone-mapped high-dynamic-range (HDR) samples are generated from the low-dynamic-range images captured by each of the 4 cameras at different exposure rates as detailed in [38], and employed in the performed tests as inputs to the network in Table 2.

It is worth remarking that, in terms of the number of samples, the used R3VEIN database is one of the largest datasets collected for vein biometrics in the academic literature.

V. EXPERIMENTAL ANALYSIS AND DISCUSSION

The performed tests are detailed in the following sections, each focusing on one of the three aspects considered in our research: Section V-A presents the results related to the two-class gender recognition performed on hand vein patterns. The differences between score distributions computed from male and female subjects in a biometric recognition system are then discussed in Section V-B. Finally, the possibility of discriminating between male and female subjects, and learning gender-specific characteristics when performing biometric verification using hand vein patterns, thus designing a two-step sequential recognition system, is outlined in Section V-C.

As already mentioned, open-set training and testing methodologies are considered for each experiment. This means that, when performing tests on each of the considered datasets, the available subjects are split into two equal-size disjoint partitions, each exclusively used either to train the employed networks or to perform recognition tests. When dealing with multi-session databases (VERA and UTFVP), biometric recognition tests are performed taking enrolment and verification samples from different recording sessions.

A. GENDER RECOGNITION BASED ON VEIN PATTERNS

Since all databases considered in this study are not balanced (female/male ratio on VERA, UTFVP and R3VEIN are 40:70, 16:44, 71:129, respectively), two different training and testing strategies are employed during the performed experiments:

- *unbalanced scenario*: all the available data are employed, with the original female/male ratio of each dataset preserved in both training and testing subsets, ensuring that female and male classes are represented in these partitions with the same proportions of the whole datasets;
- *balanced scenario*: only a subset of each dataset is used, in order to have an equal number of male and female classes in both training and testing subsets.

In addition to evaluating the effectiveness of the customized Densenet-161 proposed in [32] for gender recognition, other two CNNs have been considered for comparative purposes in the performed tests. Specifically, also the Resnext-101-32 $\times$ 8d [39] and VGG19-bn [30] architectures have been taken into account. The latter network allows performing a comparison between the proposed approach and the one exploited in [29] for gender recognition.

The results obtained on the VERA database are reported in Table 3 in terms of *precision*, *recall*, and their harmonic mean, the F_1 *score*, obtained when considering either female or male subjects as the positive class. The weighted average of the values computed for the two classes is also reported, as well as the overall *accuracy*. The comparison across the recognition models shows that the modified Densenet-161 outperforms the other benchmark CNN architectures, with the proposed approach being therefore preferable to alternatives relying on other networks such as VGG in [29].

In the unbalanced scenario, resorting to the proposed modified Densenet-161 CNN guarantees an F_1 score at 91.07% and 94.95%, respectively considering female and male subjects as a positive class, for an overall 93.55% accuracy and 93.54% F_1 score. Such results are slightly better than those obtained by the state-of-the-art gender-recognition approach in [27] over the VERA database. It is yet to be remarked that the training here performed has been conducted only on half of the available subjects, while samples from the first recording session of all the subjects in the VERA database have been employed for training purposes in [27], according to an unrealistic closed-set experimental scenario. Actually, training the employed network on more subjects would allow for achieving even better performance. In order to prove this point, we have also evaluated the performance achievable in an open-set scenario where 80% of the available subjects are used for training, and the remaining 20% are employed for testing. In a 5-fold cross-validation, our approach has reached an accuracy at 96.82%, with F_1 scores of 95.71% and 97.47% for female and male classes, respectively, therefore achieving results notably better than those obtained, with the same experimental protocol, using LBP descriptors and weighted KNNs in [25].

The higher performance observed for male subjects may be due to the larger amount of data available for training, which therefore has a significant effect on the fine-tuning of the considered network. Conversely, in a balanced scenario, the behaviours observed for female and male classes get very close, respectively resulting in 93.38% and 93.37% F_1 scores. In this condition, the performance for female subjects actually improves, achieving a result comparable to the one obtained for male subjects. Yet, the overall accuracy slightly drops to 93.37%, which might be due to the lower sample size available during the training period.

As for the other considered databases, Table 4 shows the results obtained over the UTFVP database, with the overall accuracy in unbalanced and balanced scenarios at 95.83% and 94.27%, respectively. On the other hand, the results in Table 5 show that, for the R3VEIN database, the accuracy in unbalanced and balanced scenarios are 89.47% and 88.07%, respectively. Even here, the performance on male subjects is better than that for female classes in the unbalanced scenarios, while very close results are instead obtained when considering a balanced condition.

The recognition performances achieved on UTFVP and VERA databases are significantly higher than what is accomplished on the R3VEIN dataset. Such a gap in gender recognition rates can derive from the differences in acquisition hardware and data collection procedures. For instance, in the UTFVP database, fingers have been placed on a platform for image capturing. The images on the R3VEIN database have been instead collected with a contactless and on-the-move acquisition protocol.

The results obtained on all three considered datasets confirm that hand vein patterns can be employed to perform gender recognition, with performance levels similar to those accomplished with face, ocular, or speech traits.

B. EFFECTS OF GENDER ON VERIFICATION SCORE DISTRIBUTIONS

The analysis so far performed highlights that differences between the vein pattern images acquired from male and female subjects exist and can be used to perform gender recognition. It is yet to be investigated whether such differences may have an effect on the performance of a biometric recognition system relying on hand vein patterns. In order to shed light on this aspect, tests are conducted separately

TABLE 3. Gender recognition performance on VERA.

	Modified Densenet-161						Resnext-101						VGG-19					
	Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario		
Positive Class	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.
Precision	91.65%	94.61%	93.53%	93.27%	93.48%	93.38%	88.67%	94.24%	92.21%	92.29%	92.71%	92.50%	89.30%	91.91%	90.96%	88.44%	93.35%	90.90%
Recall	90.50%	95.29%	93.55%	93.50%	93.25%	93.37%	90.00%	93.32%	92.18%	92.75%	92.25%	92.50%	85.50%	94.14%	91.00%	93.75%	87.75%	90.75%
F_1 Score	91.07%	94.95%	93.54%	93.38%	93.37%	93.37%	89.33%	93.83%	92.19%	92.52%	92.48%	92.50%	87.36%	91.01%	90.96%	91.02%	90.46%	90.74%
Accuracy	93.55%			93.37%			92.18%			92.50%			91.00%			90.75%		

TABLE 4. Gender recognition performance on UTFVP.

	Modified Densenet-161						Resnext-101						VGG-19					
	Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario		
Positive Class	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.
Precision	90.10%	98.07%	95.94%	90.48%	98.85%	94.66%	88.12%	97.30%	94.85%	88.37%	98.82%	93.59%	90.58%	96.41%	94.85%	88.84%	99.41%	94.12%
Recall	94.79%	96.21%	95.83%	98.96%	89.58%	94.27%	92.71%	95.45%	94.72%	98.96%	86.98%	92.97%	90.10%	96.59%	94.86%	99.48%	87.50%	93.49%
F_1 Score	92.39%	97.13%	95.87%	94.53%	93.99%	94.26%	90.36%	96.37%	94.76%	93.37%	92.52%	92.94%	90.34%	96.50%	94.86%	93.86%	93.07%	93.47%
Accuracy	95.83%			94.27%			94.72%			92.97%			94.86%			93.49%		

TABLE 5. Gender recognition performance on R3VEIN.

	Modified Densenet-161						Resnext-101						VGG-19					
	Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario			Imbalanced Scenario			Balanced Scenario		
Positive Class	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.	Female	Male	W. Avg.
Precision	84.97%	92.05%	89.50%	95.46%	80.68%	89.16%	84.46%	89.94%	87.97%	92.92%	82.81%	88.37%	85.45%	89.59%	88.04%	92.89%	82.01%	88.04%
Recall	85.96%	91.45%	89.47%	83.17%	94.68%	88.07%	81.81%	91.54%	88.03%	84.39%	92.12%	87.86%	82.20%	91.63%	88.10%	83.77%	92.02%	87.45%
F_1 Score	85.46%	91.75%	89.49%	88.89%	87.12%	88.14%	83.11%	90.73%	87.99%	88.45%	87.22%	87.89%	83.79%	90.60%	88.05%	88.09%	86.72%	87.48%
Accuracy	89.47%			88.07%			88.03%			87.86%			88.10%			87.45%		

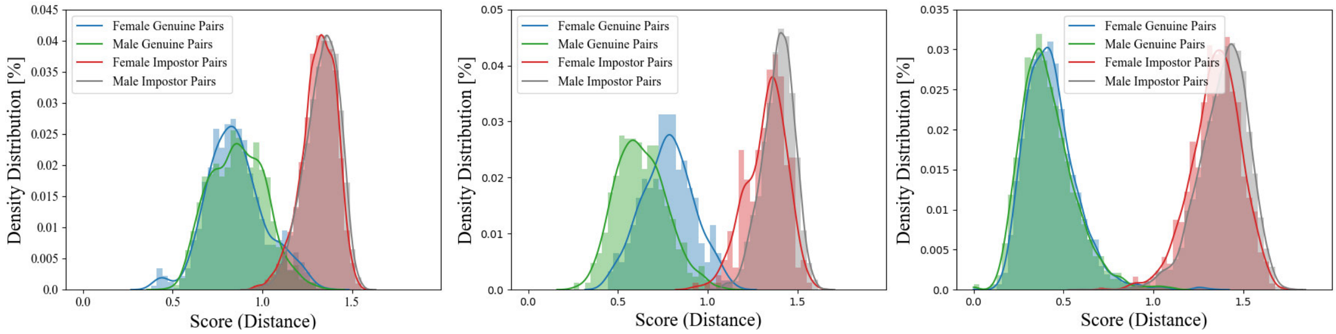
on the female and male populations, for both the considered databases. The proposed modified Densenet-161 network in Table 1 has been employed for such tests on biometric recognition capabilities, having already shown in [32] and [36] that this approach guarantees recognition rates better than alternatives relying on other CNN architectures.

In more detail, the employed network has been trained for 120 epochs according to both the balanced and imbalanced strategies described in Section V-A. Using the trained network as feature extractor, the following dissimilarity score distributions have been estimated for a biometric verification task:

- male genuine scores (M-gen), obtained by comparing pairs of vein patterns extracted from the same hands of male subjects only;
- male impostor scores (M-imp), obtained by comparing pairs of vein patterns extracted from two distinct male subjects, considering the same hand. This kind of impostor attempt resembles what would happen in a real-life application, where it is expected that a male subject is employed to impersonate a male legitimate user. Besides being a condition dictated by common sense, the differences observed in Section V-A between vein patterns from male and female subjects would in fact not recommend to use impostors with a gender different than the target user when carrying out impersonation attacks;
- female genuine scores (F-gen), obtained by comparing pairs of vein patterns extracted from the same hands of female subjects only;
- female impostor scores (F-imp), obtained by comparing pairs of vein patterns extracted from two distinct female subjects, considering the same hand.

The distributions obtained in the imbalanced scenario, with all the available data employed, are depicted in Figures 3(a), 3(b) and 3(c), respectively referred to VERA, UTFVP and R3VEIN databases. Tables 6, 7 and 8 report relevant statistical information regarding the estimated distributions, in terms of mean and standard deviation, for both balanced and imbalanced scenarios.

The obtained results confirm that notable differences between the score distributions referred to male and female populations are present. This is more evident in the UTFVP database. In more detail, the dissimilarity scores in the female genuine distributions are typically greater than those referred to the male population. Moreover, the impostor dissimilarity distributions related to female subjects are characterized by values smaller than those achievable when considering the male population. In brief, when vein patterns are processed without taking into account gender-specific characteristics, the intrinsic anatomical differences mentioned in Section II make it harder, for the female population with respect to the male one, to perform genuine comparisons characterized by



(a) Score distributions for VERA (b) Score distributions for UTFVP (c) Score distributions for R3VEIN

FIGURE 3. Dissimilarity score distributions of a vein-based biometric verification system, for male and female populations, in the imbalanced scenario, with Modified Densenet-161.

TABLE 6. Statistics of distributions computed on VERA.

	Imbalanced Scenario				Balanced Scenario			
Scores	F-gen	F-imp	M-gen	M-imp	F-gen	F-imp	M-gen	M-imp
Mean	0.853	1.316	0.863	1.332	0.862	1.321	0.867	1.320
Std	0.166	0.097	0.152	0.097	0.186	0.105	0.173	0.111

TABLE 7. Statistics of distributions computed on UTFVP.

	Imbalanced Scenario				Balanced Scenario			
Scores	F-gen	F-imp	M-gen	M-imp	F-gen	F-imp	M-gen	M-imp
Mean	0.779	1.326	0.629	1.392	0.717	1.342	0.559	1.338
Std	0.140	0.111	0.139	0.088	0.168	0.128	0.183	0.125

TABLE 8. Statistics of distributions computed on R3VEIN.

	Imbalanced Scenario				Balanced Scenario			
Scores	F-gen	F-imp	M-gen	M-imp	F-gen	F-imp	M-gen	M-imp
Mean	0.432	1.348	0.413	1.392	0.477	1.360	0.470	1.363
Std	0.147	0.138	0.150	0.136	0.161	0.162	0.167	0.152

small dissimilarities, and impostor comparison resulting in high distances. It is worth noting that, although such observations are less evident in the balanced scenario, where the employed networks are trained with an equal number of male and female classes, they are indeed still valid, testifying the need for properly addressing such gender-dependent discrepancies. Toward this aim, it would be desirable to process the considered vein traits differently, depending on whether they belong to male or female populations. The following section details how a gender-aware biometric verification system could be designed, in order to improve the overall achievable recognition performance.

C. GENDER-AWARE VEIN BIOMETRIC VERIFICATION

In order to lower the observed performance disparity, and to enhance the verification capabilities of a biometric system by taking into account gender information, a gender-aware verification system has been designed as depicted in Figure 4. It is there assumed that different networks, specifically trained for male and female populations, extract discriminative features during enrolment. For verification, the proposed processing pipeline first performs gender recognition based on the acquired trait, and then further processes the provided input depending on the output of the first stage. As described in Section III, the Euclidean distance between L_2-normalized enrolment and probe features are computed, and a genuine/impostor decision is taken depending on a preset threshold.

In more detail, the training procedure performed to define the employed networks consists in an initial baseline training, where the employed custom Densenet-161 network in Table 1 is trained for 60 epochs with the whole set of available data, comprising male and female classes altogether. After this first step, gender-specific training is performed, fine-tuning the computed parameters generating two distinct branches for the two populations, till reaching the 120th epoch.

The effects of such gender-aware processing are quantitatively shown in Figure 5, which reports the receiver operating characteristic (ROC) curves obtained, in the imbalanced scenario, when resorting to gender-specific representations of the acquired vein patterns. Following the proposed approach, an improvement in recognition capability, with respect to a baseline, gender-unaware system such as the one employed to compute the score distributions discussed in Section V-B, is achieved.

In more detail, for the VERA palm vein dataset, the overall equal error rate (EER) goes from 4.37% to 4.08%, with a notable improvement in the false non-match rate (FNMR) achieved for false match rate (FMR) equal to 0.1%, which goes from 48.10% to 36.00%. For tests on the UTFVP dataset, the EER improves from 0.42% to 0.30%, with an improvement on the FNMR @ FMR = 0.1% going from 1.32% to 0.71%. For tests on the R3VEIN dataset, the EER improves from 0.64% to 0.55%, with the FNMR @ FMR = 0.1% going from 14.50% to 6.25%.

Additional results are provided in Tables 9, 10 and 11, which respectively report the EERs obtained on female and male populations over the VERA, UTFVP, and R3VEIN databases, for both a baseline (gender-unaware) and the

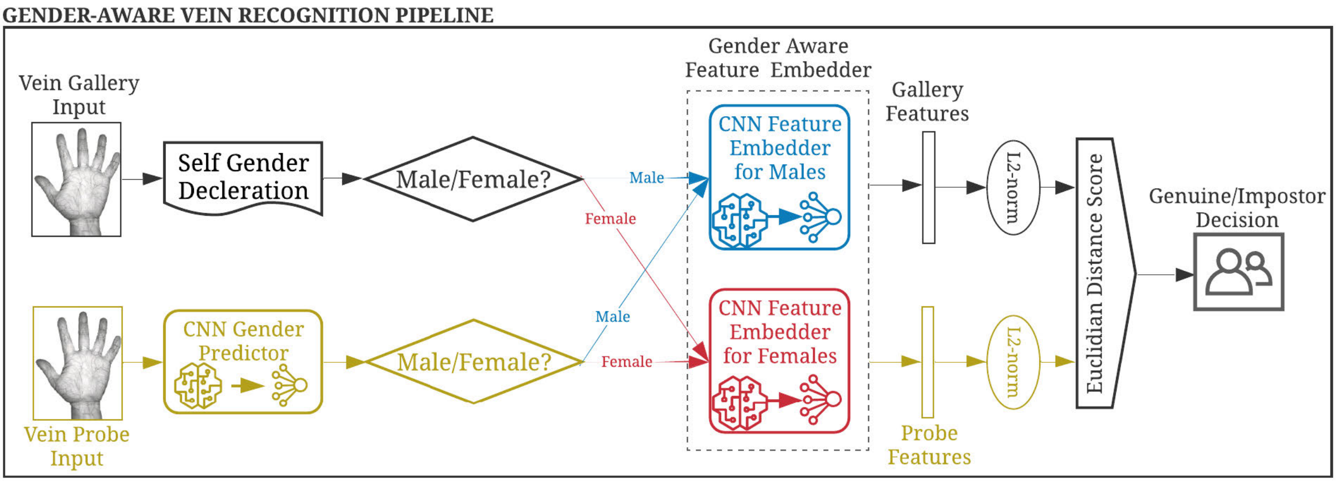
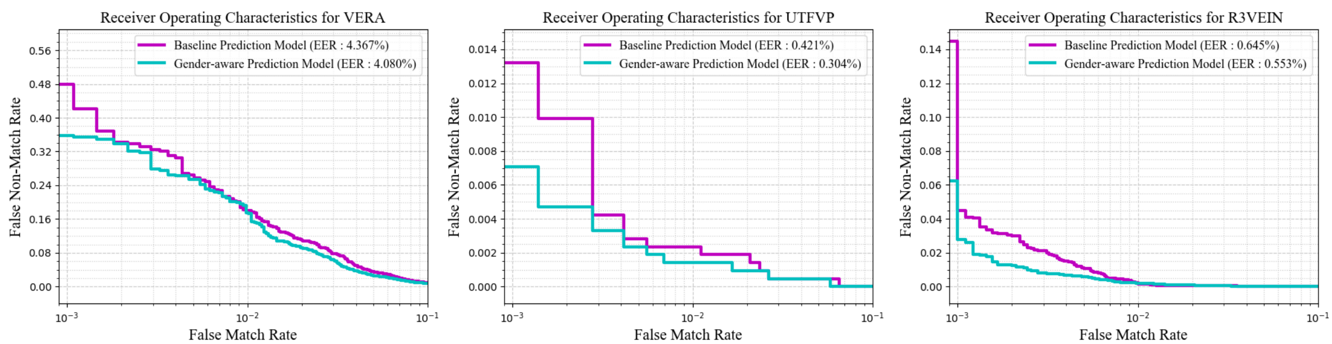
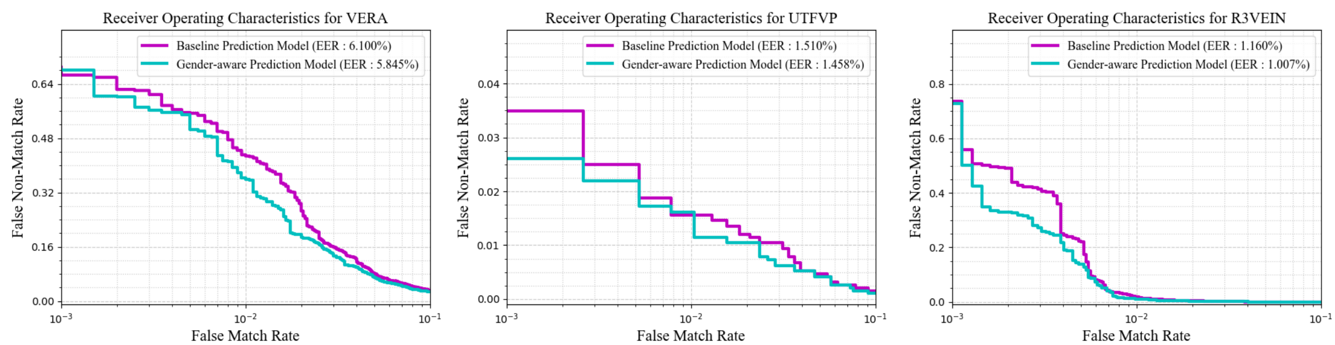


FIGURE 4. High-level representation of gender-aware (bi-modal) vein recognition pipeline where CNN models are based on Densenet-161 architecture.



(a) ROC curves for VERA (b) ROC curves for UTFVP (c) ROC curves for R3VEIN

FIGURE 5. ROC curves for the used datasets, for baseline and gender-aware recognition systems, in the imbalanced scenario.



(a) ROC curves for VERA (b) ROC curves for UTFVP (c) ROC curves for R3VEIN

FIGURE 6. ROC curves for the used datasets, for baseline and gender-aware recognition systems, in the balanced scenario.

proposed gender-aware systems. On UTFVP, in the unbalanced scenario, the achieved improvement is exclusively due to the better discriminatory capability achieved for templates of female subjects, while a notable improvement is also observed for the male population when considering the VERA and the R3VEIN datasets. For all the considered databases, better results are obtained for the male population, with respect to the female one.

In order to evaluate whether this result is actually due to the intrinsic anatomical differences mentioned in Section II, instead of only to the availability of more training samples from male classes, the ROC curves achieved for balanced

TABLE 9. Verification performance, in terms of EER, on VERA.

	Imbalanced Scenario			Balanced Scenario		
Class	Female	Male	W. Avg.	Female	Male	W. Avg.
Baseline	5.72%	3.65%	4.37%	7.12%	5.69%	6.10%
Gender-aware	5.10%	3.15%	4.08%	6.59%	5.11%	5.84%

TABLE 10. Verification performance, in terms of EER, on UTFVP.

	Imbalanced Scenario			Balanced Scenario		
Class	Female	Male	W. Avg.	Female	Male	W. Avg.
Baseline	1.87%	0.03%	0.42%	2.13%	0.94%	1.51%
Gender-aware	1.14%	0.03%	0.30%	2.08%	0.78%	1.46%

TABLE 11. Verification performance, in terms of EER, on R3VEIN.

	Imbalanced Scenario			Balanced Scenario		
Class	Female	Male	W. Avg.	Female	Male	W. Avg.
Baseline	0.89%	0.61%	0.64%	1.34%	0.95%	1.16%
Gender-aware	0.88%	0.31%	0.55%	1.13%	0.88%	1.01%

training strategies are depicted in Figure 6, with the corresponding EERs also reported in Tables 9, 10 and 11. Besides the overall performance worsening with respect to the unbalanced scenario, due to the usage of fewer training samples, the same behaviour already observed is also obtained in these conditions, with a notable performance improvement obtained using the proposed gender-aware recognition system with respect to the baseline one, and better discriminatory representations obtained for both female and male classes.

VI. CONCLUSION

The relevance of gender-specific characteristics in the exploitation of hand vein patterns for biometric recognition purposes has been investigated in this paper. Tests performed on three databases have been first conducted to evaluate the feasibility of performing gender recognition through the analysis of hand vascular patterns. The obtained results testify that recognition rates similar to those achievable with face data can be actually accomplished. It has been then evaluated whether the anatomical specific characteristics of female and male populations could affect the discriminatory capabilities of the templates extracted from the considered traits, and employed for user recognition purposes. Actually, it has been observed that the score distributions associated to vascular patterns from female subjects are characterized by larger intra-class and lower inter-class values, with respect to those related to male subjects. Furthermore, a novel gender-aware pipeline to be used for people verification has been eventually proposed. The obtained EERs show that it is actually possible to improve the achievable recognition performance and reduce the gender-dependent discrepancy of recognition capabilities, by designing frameworks taking into account gender-dependent characteristics to extract discriminative biometric templates.

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The source code of the architecture given in this study can be found at: https://github.com/ridvansalihkuzu/vein-biometrics

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