



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 4, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

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Enhancing Hand Vein and Face Recognition Using Gender Traits

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ABSTRACT: In image preprocessing, ROI extraction methods and image enhancement methods were reviewed. In addition, the conventional feature extraction methods were classified into four groups (i.e., vein-based method, local binary-based method, dimensionality-based method and minutiae-based method) and introduced in detail. For the matching stage, the distance-based matching methods and classifier-based matching methods were both exemplified. Furthermore, we compared conventional and recently developed deep learning finger vein identification methods. However, deep learning methods showed significant improvement over traditional finger vein recognition techniques. The paper presented the most recent research advancements in the field of FVR during the past decade, despite the challenges that need to be resolved. In particular, during image acquisition, a good image acquisition device is needed to improve the quality of finger vein image. A large-scale database is needed; in fact, this will be useful in the evaluation of all kinds of FVR techniques. Moreover, a high recognition spoof detection finger vein identification method is needed to identify spoof attacks. Furthermore, machine learning approaches play an important role in finger vein recognition. Introducing deep learning approaches into FVR has the potential to enhance the recognition performance in a broad sense.

KEYWORDS: biometrics; finger vein recognition; feature extraction; matching; performance analysis

I. INTRODUCTION

The ability to identify individual attributes in the smart recognition field is a global security concern. In recent years, various algorithms have been developed to address the security problem, but there is still room for fast and efficient biometric recognition. Biometric recognition refers to an automatic recognition of individual properties acquired by their anatomic/behavioral characteristics. Several types of biometric techniques have been presented based on these anatomic/behavioral features such as fingerprint, palm print, hand veins, finger veins, palm veins, foot vein, iris, gait, DNA recognition, palates, voice recognition, facial expression, heartbeat, signature, body language, and face shape. These biometric recognition approaches can be divided into two categories: (i) extrinsic biometric features (palm print, iris, fingerprint, face) and (ii) intrinsic biometric features (palm vein, hand vein, and finger vein). Extrinsic features are more visible and have more adverse factors as compared to the intrinsic features. For instance, the retinal surface is affected by the high intensity of light during extraction of iris features. Similarly, the accuracy of face identification is also distorted due to brightness variance, style of facial, blockage of blood vein and pose. Present the merits, defects and other characteristics of some typical extrinsic and intrinsic features.

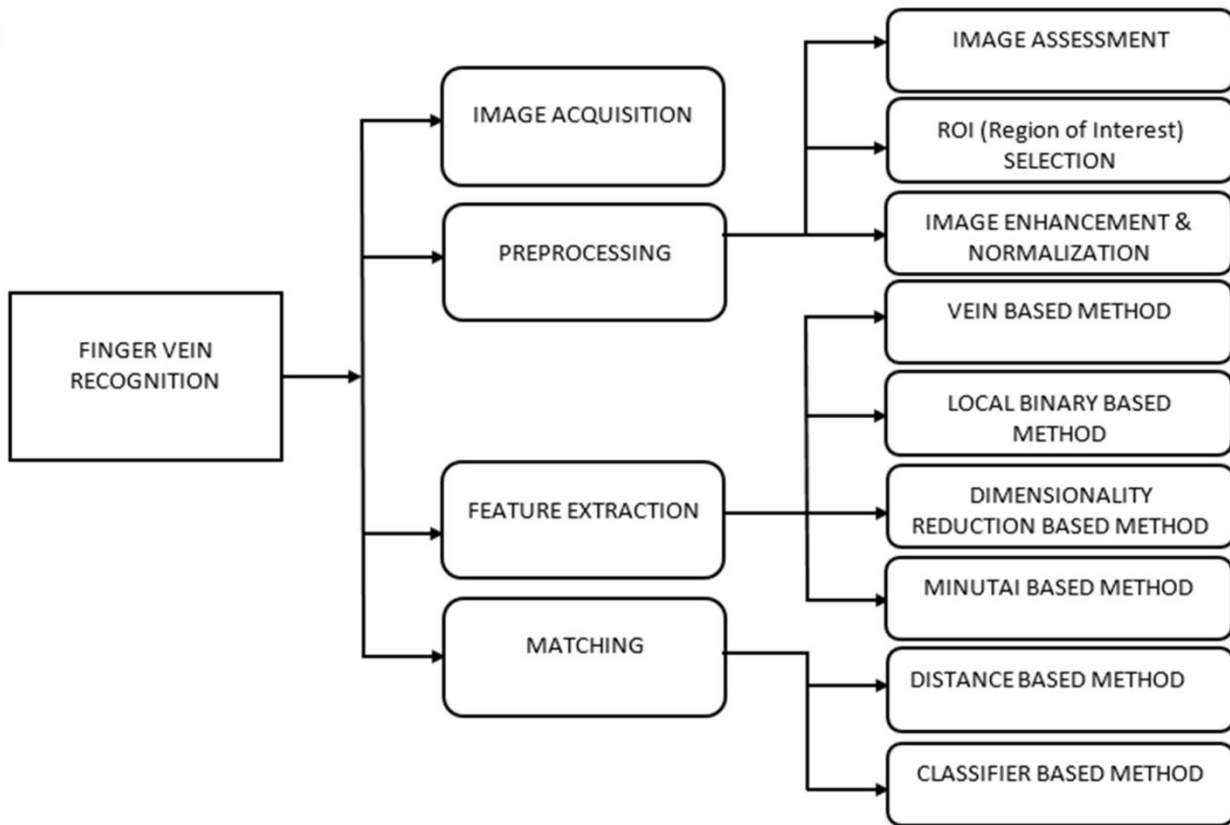


Fig 1: System Work Flow

Convolution Neural Network (CNN) has been recognized as the best classification algorithm used effectively for various kinds of problems due to its high accuracy and speed. The major difference between CNN and normal neural networks lies within the hidden neural layer that is connected to a subset of neurons in the prior layer only. This specific connection enables them to learn the characteristics implicitly. CNN can take an image as input, define biases learnable, and assign weights to different objects in the image in order to distinguish different objects. A CNN applies the filters to layers during image analysis and uses the same set of weights by all neurons to extract the features from various input images. Further, CNN uses the same weight and collection of parameters, which results in lesser translation variances, and helps in less error and more precision when categorizing images. Lastly, CNN provides local connectivity, which makes the computation more effective because each neural is connected only to a subset of images. In this paper, a deep learning-based framework has been proposed for identity and gender classification. The proposed method is subdivided into three phases: preprocessing phase, where the hand images are segmented and enhanced. The second phase uses the enhanced images with CNN model to determine gender. Based on the gender, CNN is trained on images for the same gender for more accurate identification result in the third phase. The remaining paper is organized as follows. Section II describes the earlier work done in the field of gender and identity detection.

II. RELATED WORK

Determining gender is essential in social interactions, where different salutations and grammar structures are held for male and female in different languages. Moreover, the gender information is a very informative clue that can be used by intelligent systems in healthcare, smart spaces, biometric-based access control domains and for many other applications, such as human computer interaction, advertisements, marketing analysis, and demographic research.

Despite the importance of these attributes in our daily lives, the fully automated gender classification is still far from meeting the requirements of intelligent applications. The automated gender classification system is challenged by many factors like diminished clarity, distortion of inputs, etc.

Statistical processing of the hand vein patterns has been employed by the researchers which proved to be a novel method for biometric identification. They have used a database of hand veins data which has been collected from 100 people to test the performance of their model. Although, the accuracy of the method has not outnumbered other techniques, however, results depict that it is nearest to other competitor methods. A color image of the hand is used for biometric identification in [32] which comes from scanning on a platform. From the image, certain features of the hand are extracted, and various pattern recognition techniques are used for the classification process. The experimental results reveal that the proposed methodology gives a medium to the high-security environment and 97% accuracy of identification is achieved.

III. METHODOLOGY

The suggested framework is subdivided into three principal phases: The first phase is regarding the preprocessing of hand images for gender classification and biometric identification. The hand images are segmented via three methods namely automatic thresholding, morphological filtering, and active contour deformation. Lastly, the hand images are improved by enhancing the background of the images. The second phase uses the enhanced images from the first phase for gender classification, which is carried out in two steps: testing and training steps. The third phase is human identification which is carried out using the CNN model trained on sufficient samples of the previously determined gender.

This step plays a fundamental role in optimizing the gender classification, and hence, enhancing the identity detection results. To implement this phase, the average filter is applied on the hand images with the aim to reduce the noise and enhance the appearance of the Region-ofInterest (ROI) in order to obtain better classification results. Next, an antistrophic diffusion filter is performed with a k-value of 0.08 and it is repeated three times to reduce the noises and unnecessary information and details while preserving the edges of the hand image. In the next step, automatic Otsu’s thresholding is utilized to get the initial segmentation of the ROI, followed by dilating the obtained object to recover the boundary pixels that may have been missed during the previous operation. Hand regularization is then utilized by applying an erosion filter. To achieve the final segmentation of the ROI, the active contour is performed using the Chan-Vese algorithm, which is characterized by the flexible, and accurate implementation.

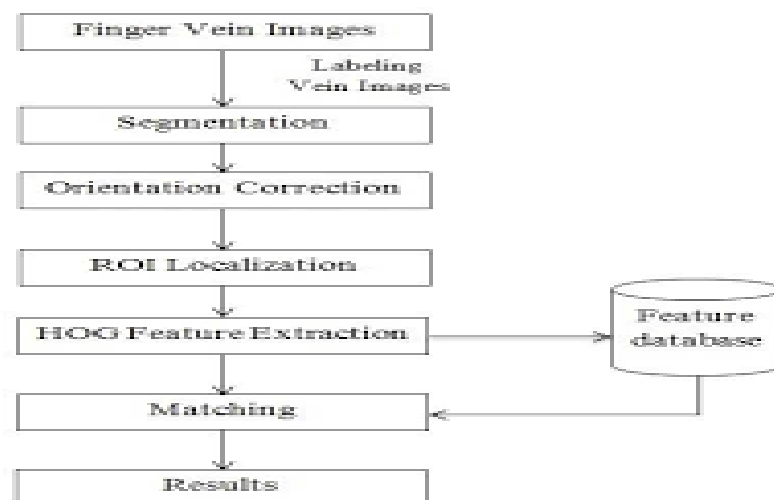


Fig 2: Work Flow

For gender classification purpose, 7-layer CNN model is trained on the enhanced images of both left or righthand images. Two activation functions are used; one is applied to the hidden layer while the other is to the output layer. In the hidden layer, a Rectified Linear Unit (ReLU) activation function is utilized to increase the nonlinearities in the network [34] and the Logistic function is engaged for the output layer. Accurate classification result in this phase can improve the performance of biometric systems such as human authentication and identification.

For biometric identification, only image samples of the same detected gender in the previous phase are used for training. Then, CNN is applied with 30 epochs and a batch size of 32. The hidden layers in the CNN architecture contain 3 convolutional filters on the convolutional layer. The following layer is the maxpooling with a subsampling ratio of 2 by 2. With such iterative implementation of CNN, the gender and identity of the person can be predicted by using their hand images.

IV. RESULTS AND DISCUSSION

To evaluate the gender classification performance, the CNN model has been trained with 3933 samples and validated using 1687 samples. Therefore, with the total number of hand images used in this work are 5620, with 30 epochs and a batch size of 32. It is worth mentioning that there is little difference between the training and validation accuracy and it has increased significantly with the increase in epochs. Likewise, there is a small difference between validation and training loss initially, however, the values have declined sufficiently with an increase in epochs and the difference has increased a bit. Therefore, it can be concluded that the model produces the best results using 30 epochs. Fig. 5 presents the training and validation accuracy, and training and validation loss with 30 epochs for gender classification using the dorsal hand side. It can be noted that 30 epochs.

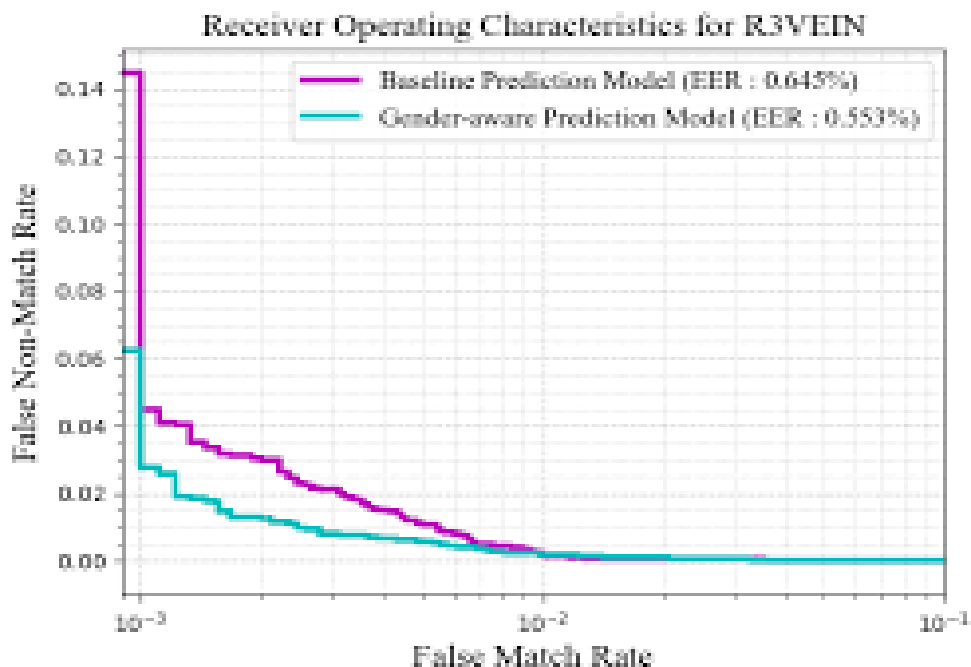


Fig 3: Gender Analysis

The corresponding empirical ROC curve and confusion matrix are displayed in Fig. 6. It is revealed that the proposed model has achieved 8 false negative instances, 1947 true negative instances, 3659 true positive instances, and 6 false positive instances. Based on the number of correct and incorrect predictions which have been made using the proposed model, it is concluded that the classifier has performed well. In accordance with these values, the proposed method

demonstrated that it can be used to accurately classify the gender of a person using dorsal hand side images if it is female or male.

V. CONCLUSION

Human Identity and gender play an active role in several applications such as biometrics, criminology, surveillance, human computer interaction, commercial profiling. In this paper, we have introduced a deep learning-based framework for automatically predicting human gender and identity by hands. The designed framework has been evaluated using a huge hand dataset image containing 11,076 hand images. The results have proved that the proposed framework has effectively worked for both gender classification and human identification problems. High accuracy of 96.79% has been achieved for gender classification using palm hand side, whereas 97.75% using dorsal hand side. Furthermore, the deep learning-based framework has also helped to achieve high accuracy for biometric identification using dorsal within an accuracy range of 93.7 to 97.25%, and within 95.07 to 96.41% for the palm hand side images using the different number of subjects. The proposed method achieved a high accuracy both for gender classification and human identification, which makes it suitable for practical commercial usage.

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