An Automated Deep Learning Framework for Human Identity and Gender Detection

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***Abstract*—Automated detection of human identity and gender offers several industrial applications in near future, such as monitoring, surveillance, commercial profiling and human computer interaction. In this paper, deep learning techniques have been used to investigate the problem of human identity and gender classification using hand images. First, pre-processing techniques have been applied to enhance the appearance of the hand images. The pre-processed image is passed through the convolution neural network to determine the gander. For identity detection, the network has been trained on the images for the determined gender for better recognition. To further enhance the result, the framework has been implemented using different optimizers and k fold cross-validation. Experimental results have shown that highly effective performance is achieved in both the human identification and gender classification objectives. High average accuracy of 97.75% using the dorsal hand side for human identification and 96.79% has been obtained for gender classification using the palm hand side. Conclusively, the proposed method has achieved more accuracy than the previous methods both for identification and gender classification.**

***Keywords*—human identification, gender classification, deep learning**

I. INTRODUCTION

Biometrics is an important physical human characteristic that is unique for every person and covers a wide range of personal information such as age, gender, and handedness [1]. In recent times, research has increased significantly in soft biometrics due to the tremendous development of applications, e.g., health care, criminal investigations, security, and many others. Among the personal information, human identity and gender are important biometric information for industrial and security purposes, such as monitoring, surveillance, commercial profiling and human computer interaction.

Automatically predicting gender and identity from biometrics traits is an essential and challenging task in many real-world applications. Recently, several methods have been reported in the literature to determine human identity and gender using different biometrics like face, iris, gait, and hand shape. The majority of such methods in the literature are based on facial information. However, the facial expression can vary due to moods and ages [2]. Unlike face images which are usually unconstrained, hand images are rarely changed and usually captured under a controlled position. Human hand not only possesses distinctive feature for identity and gender information, it is also considered one of the primary biometric traits used to identify a person and many devices can be grasped by hands such as tablets, laptops, mobile phones, and other smart devices.

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 [3]. 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 (see Fig. 1). 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: pre-processing 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. Section III explains the architecture of the proposed methodology. Section IV provides the experimental results and Section V concludes the paper.

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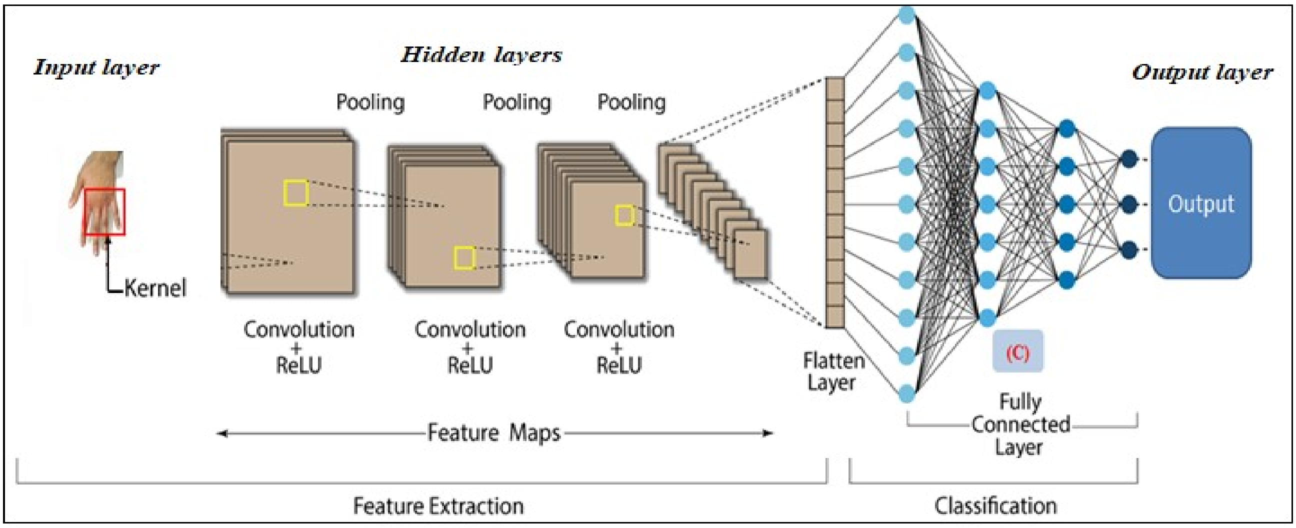

Figure 1. Convolution neural network architecture. In general, convolution neural networks contain many layers namely the input layer, convolutional layer, subsampling layer, and fully-connected layer.

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.

Gender classification is a binary class problem in which the male and female are the two class labels into which the input feature is classified. Many researches have recently presented methods for gender detection based on different body features, such as iris [4], face [5–14], palmprint [15-17], fingerprint [18, 19], finger-vein [20], skin [21], etc. However, only limited researches used hand shape to determine gender due to the limited number of features in hand images, e.g., [22].

The majority of gender classification methods is based on face images as face contains more prominent features than other biometrics. For instance, the method introduced in [8] performs Local Binary Pattern (SLBP) and Histogram of Oriented Gradients (HOG) to extract features for gender classification with SVM classifier. A gender classification using the face image has been presented in [9]. The authors proposed Weber's Local Descriptor (WLD) to detect human gender using face images. Authors have engaged the WLD as it outperforms other descriptors and has better discriminatory power. To ensure the effectiveness of the proposed system, the FERET database has been utilized. In order to work with this methodology, first, the WLD is broadened by splitting an image into several parts and then calculating the WLD descriptor for all the blocks and concatenation. The proposed spatial WLD descriptor gives 99.08% accuracy.

Several CNN-based methods have been introduced for gender classification in the literature. For instance, a deep CNN-based method is proposed in [10] for age and gender classification using facial images. Primarily, Multi-task Cascaded CNN is utilized for the detection of faces in the input images. Then, the Efficient Net model is applied to extract feature vectors which are then passed into the One-Dimensional CNN for classification procedure. Another CNN-based method is introduced in [11]. In this study, the authors have used LFW datasets. They designed the model in a way that reduces memory and uptime requirements. The results exposed that this methodology is simple however it is efficient and achieved a prediction performance of 97.31%. Another methodology has been proposed which has the advantage of recognizing the age in addition to gender by focusing on the various parts of faces in the image [12]. To enhance the efficiency, the model has been trained using a novel learning framework to extract the most distinctive patches of groups, and MORPH II. The experimental results have shown that including attention mechanisms increase the strong effectiveness of CNNs.

A new descriptor based on the COSFIRE filters has been proposed for gender classification from facial images [13]. In this method, authors have combined an SVM of a chi-squared kernel and a GENDER-FERET dataset has been proposed that contains 474 images for a training and 472 images for testing. The results have shown that this method has outperformed three other classifiers that rely on the Local Binary Pattern (LBP) and Histogram of Gradients (HOG) handcrafted features. According to Dhomne [14], a high level of performance in gender classification can be achieved by engaging a classification method using the technique of Deep Convolutional Neural Network (D-CNN). The authors have presented a convolutional network namely Visual Geometry Group net (VGGnet) that can be used when the dataset is limited.

Although that face biometric has many information helping in gender detection, however, it has many challenges due to variations of pose, expression, aging, race, make-up, occlusion and illumination. Thus, many researchers tend to use more stable biometrics for gender classification. For hand images, various features can be used in biometrics, such as finger knuckle print, palm print, fingerprint, hand vein patterns, and hand geometry.

For instance, palm vein images are used with CNN for gender classification in [15]. This paper proves that CNN is able to learn discriminative features from palm vein images. In [16], another gender classification method is introduced based on palmprints using binarized statistical image features from Region-of-Interest (ROI) after filtering with a fixed length of 8bit that allows in capturing detail information from palmprints. Another gender classification method based on geometry features of palm image is also proposed in [17]. The classification is utilized by Polynomial Smooth Support Vector Machine (PSSVM) and the results are satisfactory with classification rate over 85%.

Another biometric used for gender classification is fingerprints [18, 19]. In [18], a three convolutional layer CNN with rectified linear (ReLu) and tanh activation functions is performed to discriminate gender of a person. A finger vein print is also used to recognize the gender of persons [20]. This method identifies the gender with average accuracy of 90%. Skin patches of different body parts, such as forehead, cheeks and opposite side of palm, are also used to classify the gender in [21].

Recently, hand shape has been used for gender classification as it is constrained, rarely changed and usually captured under a controlled position. However, research in this area remains limited and very preliminary. One of recent gender classification methods that use hand biometric is introduced in [22], where the hand silhouette into six different parts corresponding to the palm and fingers. Then, region and boundary features are extracted based on Zernike moments and Fourier descriptors. Then, the distance of a given part from two different eigenspaces, corresponding to the male and female classes is computed to classify the gender. This method is applied on a small database containing 20 males and 20 females, and it yields classification result close to 98%.

For biometric identification, several methods have been introduced by researchers using different biometrics, such as eye movement [23], lip-shape [24], periocular region appearance cues [25], finger knuckle [26], finger vein [27], eigen palm features [28], hand vein [29-31], and hand-shape [32, 33].

In [28], human hand features have been employed for biometric identification. They used the features of the eigen palm and the eigen finger with fusion that uses the matching score. This method has been tested on a dataset of 237 people. From the results, it can be claimed that the proposed methodology has resulted in an Equal Error Rate (EER) of 0.58% and a Total Error Rate (TER) of 0.72. An Application-Specific Processor (ASP) has been used to extract vein patterns for biometric identification purposes [29]. This method depends on a shift-and-add architecture. In this method, the preprocessing is done using a fixed-point operation. The results have confirmed the viability of this method in terms of personal identification and security. The results have reliability of 99.45%, and the maximum value of the False Acceptance Rate (FAR) is 0.001% and a verification speed of 150ms/person was obtained.

Statistical processing of the hand vein patterns has been employed by the researchers which proved to be a novel method for biometric identification [31]. 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.

A deep learning framework has been proposed in [33] for gender classification, and human identification. In this work a new dataset, i.e., 11K hand is proposed, which builds two streams of CNN that takes images as CNN input to detect gender and biometric identification from images. The previous model has used a feature extractor to feed the Support Vector Machine (SVM) using hand images. The results have shown that the framework of the Fisher vector with various feature descriptors such as AlexNet, GoogleNet, a bag of visual words, and VGG CNNs achieved the best gender classification accuracy using dorsal hand-side images. However, for the biometric identification, the method has not outnumbered other methods yet achieved better accuracy with the dorsal hand-side images.

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. The designed framework is summarized in Fig. 2.

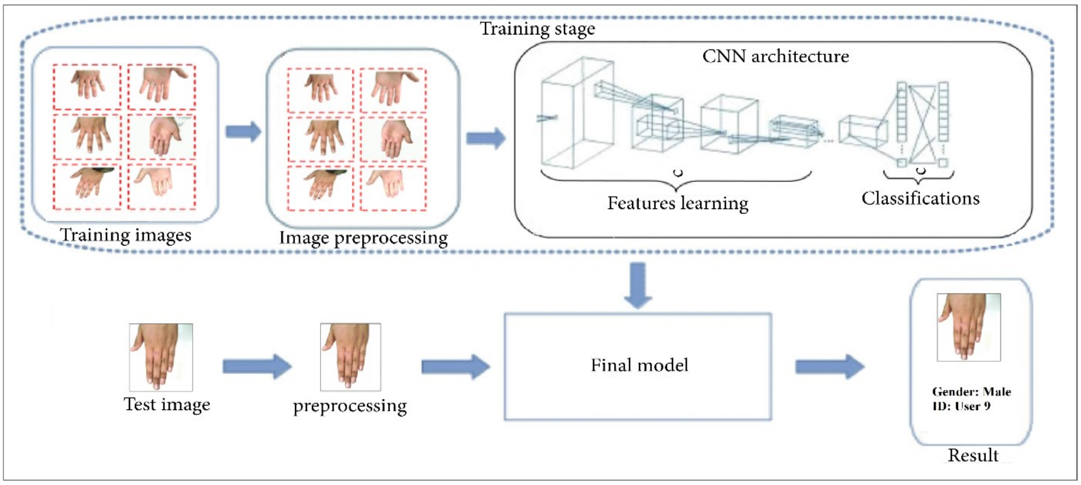

Figure 2. The proposed model.

A. ROI Detection and Enhancement

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-of-Interest (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. Finally, the hand region, i.e., ROI, is highlighted by refining the Region of Non-Interest (RONI), see Fig. 3.

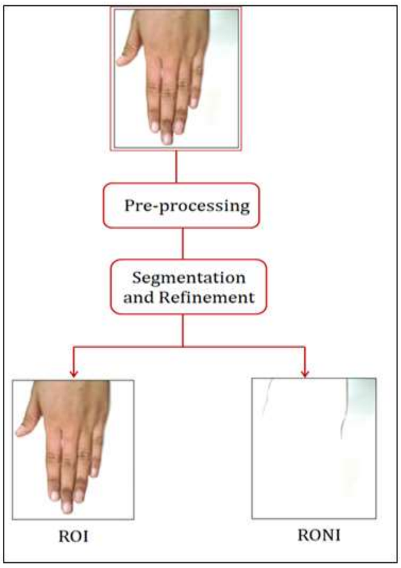

Figure 3. The pre-processing phase.

B. Gender Classification

For gender classification purpose, 7-layer CNN model is trained on the enhanced images of both left or right-hand 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.

C. Human Identificaiton

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 max-pooling 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

A. Experiment Setting

To evaluate the proposed framework, a publicly available 11K hand dataset has been used [33], which includes 11,076 hand images with size as 1200−1600 pixels, of 190 persons whose ages lie between 18–75 years. Each hand has been filmed from both dorsal and palm hand-sides. For human identification, various testing and training datasets are used. Specifically, the left/right-hand images of 80th, 100th, and 120th subjects are used, that contain dorsal and palm hand side images. Sample of hand images are portrayed in Fig. 4 from the 11K hand dataset.

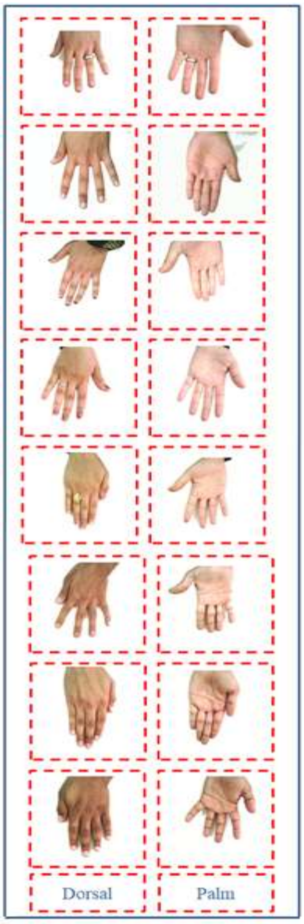

Figure 4. Samples of the hand images from the 11K hand dataset.

B. Performance Evaluation

Firstly, numerous experiments have been performed on randomly chosen images from the dataset to select the most fitting parameters to get the best performance. The proposed framework evaluation in this paper has two sections: A) the evaluation of gender classification using dorsal and palm hand images, B) the evaluation of human identification using dorsal and palm side recognition performance. The details of the experimental results are discussed below.

1) Gender classification performance

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 have provided the highest performance in gender classification.

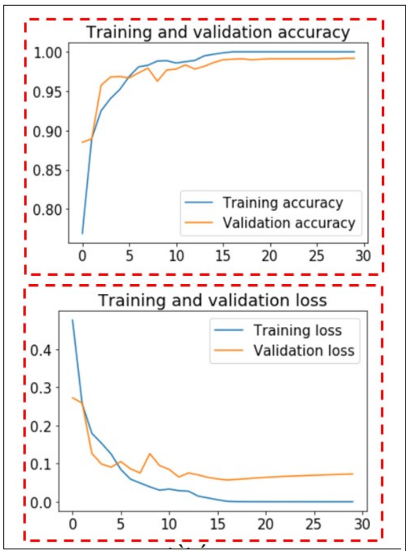

Figure 5. Evaluation model of gender classification using the dorsal hand side.

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.

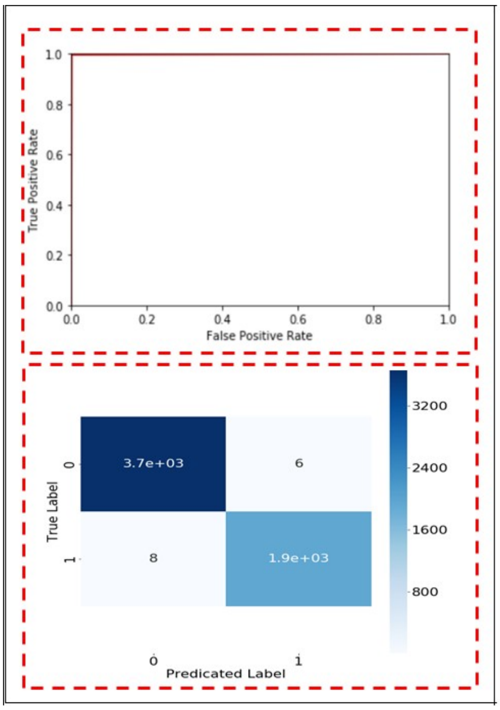

Figure 6. ROC chart and confusion matrix for gender classification using dorsal hand side.

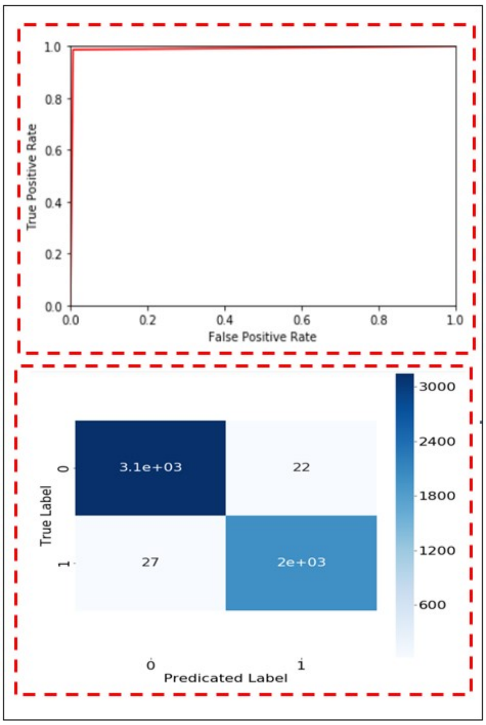

Figure 7. ROC chart and confusion matrix for gender classification using palm hand side.

To train the proposed framework for gender classification using palm hand-side images, the dataset is divided into two parts: training and validation with 0.3. The total number of samples which has been employed for the palm hand side is 5177. Among this, 3623 samples have been used to train the CNN model while it has been validated on 1554 samples and it has been performed with 30 epochs for the CNN model.

In Fig. 7, the ROC curve and confusion matrix has been shown for palm-side hand images processing. It is revealed from this figure that the model is highly able to discriminate gender detection from the palm-hand side. The information regarding actual and prediction classifications is also included which has been used to ensure the effective performance of the classifier for gender classification. The proposed model has achieved 12 false-negative instances, 51 false-positive instances, 3614 true positive instances, and 1943 true negative instances.

Fig. 8 displays the training and validation accuracy and loss with different epochs. As shown in the figure, the 30 epochs provide the best performance in gender classification using the palm hand side. The difference between training and validation for both accuracy and error is higher than the dorsal side hand images. However, the performance for palm side hand-images is slightly inferior in terms of accuracy than dorsal hand side images. Our model has produced the best results for training the given data with a high degree of flexibility with a minimum value of validation and training loss.

In addition, the proposed model has been compared with the state-of-the-art model proposed in [33] using the same dataset, i.e., 11K hand dataset, and the results have been summarized in Table I. According to the results shown in Table I, the proposed framework has shown high performance in gender classification using the dorsal hand side. The average accuracy of 97.79%, precision of 99.78%, and F1 score of 99.80%, have been obtained for dorsal hand images. The proposed framework has also achieved a high recall value, i.e., 99.38%. It is clear from the table that our model achieves higher accuracy for gender classification using both dorsal and palm hand-side images than [33]. The reason behind the better results is the optimization processes that have been made on the hand images. With this optimization, the non-important parts of the image have been eliminated, and the quality of the important parts has been improved. Further, the training plays an important role in eliminating the noise in images and several training phases in pre-processing of the images have enormously improved the model performance.

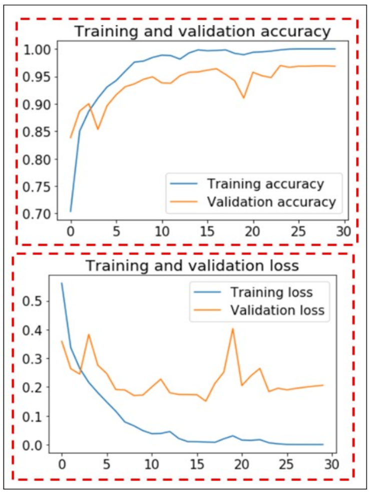

Figure 8. Evaluation model of gender classification using the palm hand side.

TABLE I. GENDER CLASSIFICATION PERFORMANCE

Palm side	Dorsal side	Hand side
0.874	0.910	CNN [33]
0.942	0.973	SVM [33]
96.75	**97.79**	Our model

2) *Human identification performance*

Table II shows the obtained results for human identification using several numbers of subjects. As shown in the table, the proposed methodology obtained a good accuracy for most of the samples. In some cases, the proposed model represents higher values while for some cases model in literature [33] has achieved higher values of accuracy. For instance, for the palm hand-side of the 120th person, the literature model has obtained an accuracy of about 93.3% and 95.6% for the palm hand-side while 96.2 and 97.0 for the dorsal hand-side respectively. Contrary to this, the proposed method in this work, the accuracy of 96.41 and 97.25 for palm hand-side dorsal hand-side are observed respectively. Therefore, the proposed method has obtained high results, indicating the efficiency and effectiveness of the proposed method for biometric identification.

TABLE II. HUMAN IDENTIFICATION PERFORMANCE

Method	CNN [33]	CNN+LBP [33]	Our model
80-Palm	94.8	**96.0**	95.07
100-Palm	92.9	95.3	**95.47**
120-Palm	93.3	95.6	**96.41**
80-Dorsal	**96.4**	96.2	93.7
100-Dorsal	96.0	96.7	**96.91**
120-Dorsal	96.2	97.0	**97.25**

Overall, the proposed model has the highest predictive ability and efficiency to discriminate female from male gender from both hand side. The proposed framework has achieved high accuracy, i.e., 96.75%, F1 score of 99.22%, precision of 99.14%, and recall of 99.30% using the dorsal hand side. Furthermore, the proposed model has successed in determining the identity of person using dorsal hand side with an average accuracy of 96.24, as well as a high precision, recall, and F1 score of 99.98, 98.55, and 99.26, respectively. The obtained correlation coefficient was 0.9 and the false positive rate was very low, i.e., 0.001.

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.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to the study's conception and design. Afaf Tareef, Hayat Al-Dmour, and Afnan Al-Sarayreh conducted the research by defining research frameworks and designing a research methodology. Afaf Tareef and Afnan Al-Sarayreh conducted and conceived the experiments and performed analysis. The initial draft of the manuscript was written by Hayat Al-Dmour and all authors commented on previous versions of the manuscript. All authors discussed the results and approved the final manuscript.

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