MULTIMODAL BIOMETRIC SYSTEM FOR PERSONAL AUTHENTICATION BASED ON PALMPRINT AND PALMVEINS

Namrata Mahaveeragouda Patil [1] Bhavya D.N [2] Mahesha D.M [3] Sharath Kumar Y.H [4]
[1,2,3] Department of Studies and Research in Computer Science, Karnataka State Open University, Mysore-570006, India.
[4] Maharaja Institute of Technology Mysore, Department of ISE, MIT Mysore, India

Abstract- In this work, we will consider aforementioned systems as subsystems to combine them with aiming to design a contactless multimodal biometric system based on palmprint and palmveins. In this multimodal biometric system, we will use the above two unimodal biometric systems, contactless palmprint biometric system and contactless palmveins biometric system. Biometric systems fusion methods are considered as main methodologies in this regard. In this contribution, two methods of biometric fusion methods will be applied. Firstly, sensor level fusion method, and the second is score level fusion method. In both, we will consider the stages of preprocessing at palmprin and palmveins as it done above, while slightly differences in another sub-stages. This work proposes a multimodal biometric system based on convolutional neural network CNN, which uses palmprint and palm veins biometric traits. The input image of the user palm is captured, then it will be preprocessed in two ways, once as a palmprint trait, and the another as a palmveins trait. Then, the user identity will be recognized using the multimodal biometric system which is integrated of two fused CNNs palmprint and palm veins in order to determine the identity.

1. INTRODUCTION

In today's environment, authentication mechanisms are employed to prevent unauthorized access to data. Authentication is the method of identifying someone using a database-stored person template and distinguishing between real and fraudulent users. It has three levels of security, "what you have?", "what you know?", and "who are you?". In first level, authentication is performed via tokens, objects, or things. Such as token or card. Second level, authentication is based on information that is only known by the user such as password or PIN. Mostly, there is a combination between those two levels, where user asked to provide card and password. Finally, the highest level, authentication of a person based on one or more of their biometric traits. Physical and behavioural characteristics of a person are included in this form of authentication. Fingerprint, iris scan, face recognition, palmprint, signature, speech, gait, and other biometrics are examples. However, mechanisms based on things or objects like tokens and cards, may lost or broken, and mechanisms based on knowledge like passwords or pattern drawing, may forgot or stolen; but the mechanisms based on biometric traits considered a constant, because it is a part of the human body. Biometric systems is a pattern recognition, which obtains biometric data from recorded templates in the database to identify authentic users. It is found in unimodal systems which is depends on single trait, or multimodal systems which are used two traits or more. Moreover, biometric traits can be intrinsic which are hidden inside the human body and have more secure, or extrinsic which are visible and have ability to forge. Designing biometric systems is an issue that attracted more and more in the field of security. Traditionally, it needs to choose a proper algorithm based on the trait used. Then apply hand-defined algorithm to the image pixels, and in return receive a feature vector quantifying the image pattern. However, the feature vectors received, may not match what algorithm truly interested in, especially in multimodal biometric systems. Therefore, convolutional neural networks is an approach used instead of the hand-defined algorithm, which is learns the features of an image automatically through training process.

2. MULTIMODAL BIOMETRIC SYSTEMS LITERATURE REVIEW

Nagar et al proposed feature-level fusion framework for multibiometric cryptosystems to protects the multiple templates, they used three biometric traits fingerprint, iris, and face. They used fuzzy vault and fuzzy commitment with feature transformation [1]. Yang and Zhang have been fused fingerprint and finger veins at feature level fusion to propose a supervised (Local Preserving Canonical Correlation Analysis LPCCA) approach for feature extraction. In their study, classified two different databases using Nearest Nighboure NN classifier. They also, used Canonical Correlation Analysis (CCA) and local preserving CCA (LPCCA) [2]. Huang et al combined face and ear to design multimodal biometric system. They used Sparse Representation based classification (SRC) and sparse Coding Error Ratio (SCER) to measure the reliability of the system. In their study, they considered PCA extractor using two methods (MSRC, MRSC) [3]. Shekhar et al proposed a novel joint sparsity-based multimodal biometric system at feature level, using MVU multimodal dataset and AR face dataset. They applied sparse representation algorithm and feature selection for classification [4]. Goswami et al used iris, face, and fingerprint at feature level fusion. In their proposed work, applied feature combination and linear combination to propose a Group Sparse Representation based Classifier (GSRC) [5]. Marcilalis et al used face and fingerprint at score level fusion to propose a multimodal biometric system for personal identity verification. In their study, they applied PCA-LDA-based face, and Minutiae-based fingerprint algorithms, and they used serial of matchers [6]. Poh et al have been designed a multimodal biometric fusion strategy using face and speech at score level. In their study, they used OR-switcher to select most discriminative subsystems, and classification using Gaussian Mixture Model (GMM)-based fusion classifier [7]. Nguyen et al used Dampster-shafer algorithm for fusion of face, fingerprint, and iris at score level. They used weighted combination of quality measures and classifiers performance [8]. Mameta and Hanmandlu proposed a multimodal biometric system for surveillance purposes. They fused iris, face, and ear traits at score level fusion. They applied methods of fuzzy, Effective Gaussian Information (EGI), and Effective Exponential Information (EEI), and classify using Euclidean classifier [9]. Mehrotra et al fused fingerprint and iris at score level fusion. They proposed iGRVM classifier, which can be used as an alternative for biometric classification with faster testing as they stated in their study. They applied Relevance Vector Median (RVM) and proposed GRVM filter in their work implementation [10]. Bharadawaj fused ear, iris, and face traits at score level fusion. In his work, the author proposed (Quality-based context switching with online learning), author used Image Quality metrics and Context Switching algorithm, and for classification used an adaptive context switching algorithm to select best matchers [11]. Monwar and Gavrilova fused ear, iris, and face at decision level fusion using their chimerical dataset. Authors proposed method to integrate biometric ranking lists to obtain a consensus rank list in various scenarios. They used Markov chain approach and Hamming distance techniques [12]. Gogoi and Bhattacharyya fused fingerprint and iris biometric traits at decision level fusion. In their work, authors used Bayesian fusion rule and Ant Colony Optimization (ACO) algorithms, and for matching, they used 2D Gabor and SOM-MSOM techniques. They proposed fusion method for combination of multimodal biometrics [13]. Singh and Giaourova proposed a multimodal biometric system for face recognition using iris and face biometric traits. At feature level fusion, they normalized all features in one dimension and used wavelet domain and eigenspace domain to improve and robust recognition performance [14]. Ching and Eswaran fused face, gait, and speech biometric traits at score level fusion to design a surveillance system named as Human Visual System (HVS). They used adaptive weights and fuzzy logic techniques [15]. Manjunathswamy designed a biomodal biometric verification mechanism using fingerprint and face biometric traits. Author used Gabor filter and Nearest Neighbor classifier [16]. Zhou and Bhanu fused face and gait biometric traits at feature level fusion to design a Human recognition system at distance. They used Principal Component Analysis (PCA) and Multiple Discriminate Analysis (MDA) as a combined method [17]. Ghate and Patil combine face and fingerprint biometric traits at score level fusion. They applied fingerprint reconstruction approach and they used Gaussian mask and

Compass mask in Gradient space. They proposed a robust combination method for privacy protection [18]. Ammour et al proposed a multimodal biometric system based on Hybrid level fusion using face and iris biometric traits. In their work, authors used Euclidean distance to compare the templates generated using multiresolution 2D Log-Gabor filter combined with Spectral Regression Kernel Discriminant Analysis (SRKDA) algorithm. i.e. for feature extraction, used Log-Gabor with SRKDA; and for matching, used Euclidean distance [19]. Kabir et al proposed a multimodal biometric recognition system by fusing ear, fingerprint and palmprint biometric traits. They proposed a Weighted Hybrid Fusion method using the Simple-Sum (SS) and Weighted-Sum (WS) matchers [20]. Meraoumia et al proposed a multimodal biometric person recognition system, they fused multi-spectral palmprint at score level. In their work, features extracted from palmprint images using 2D-OCT and 2D-Dwt methods, and they used fusion rules including SUM, MIN, MAX, and WHT [21]. Choras fused three biometric traits dorsal vein, periocular, and palmprint at feature level fusion to provide multimodal biometric system. In his work, author proposed Gabor's functions and LBP features using feature normalization and PCA method [22].

3. SENSOR LEVEL FUSION

Combining biometric traits at sensor level is an important methods used, where every biometric trait preproocessed independently, then, the enhanced biometric trait images will fused in a single image for further processes. Here, as it shown in the flow diagram presented at figure (1), palmprint ROI images are extracted for each subject, and palmvein ROI images are extracted for each subject; and then, for each subject palmprint ROI images and palmvein ROI images are fused together to combine a multi-biometric trait images for the subject. In the enrolment stage, features will extracted and then will be stored in the template database, while in the verification stage, the extracted features will matched with the available stored features to report the decision of the verification whether the subject is genuine (accepted) or imposter (rejected).

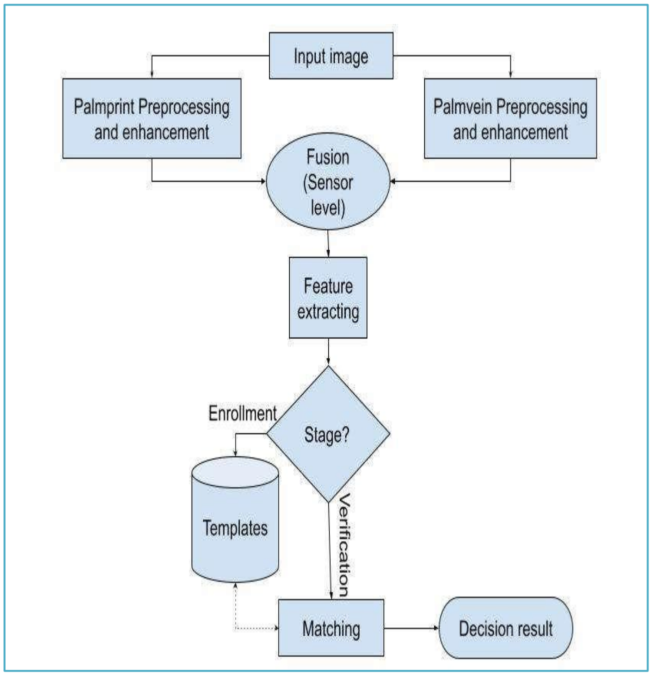

Figure 1: Flow diagram for sensor level fusion of palmprint and palmveins

3.1 Implementation of Multimodal Biometric System at Sensor level of Fusion

This section will implement the multimodal biometric system based on palmprint and palmveins biometric traits. The fusion will be at sensor level, where enhanced biometric traits are fused. Then, the fused/ multi biometric data will fed into the convolutional neural network model for training data in aims to extract features for each subject based on the subject biometric traits (both palmprint and palmveins). Finally, the extracted features will stored in the template as an enrollment process, or matched with the available data to recognition process that will accept the genuine or reject the imposter claimed subject.

3.1.1 Preprocessing for fusion at sensor level

Preprocessing of the proposed multimodal biometric system at sensor level can be considered as an integration of the same preprocessing used at the subsystems (a contactless palmprint biometric system, and a contactless palmveins biometric system). Here, each image will preprocessed in two ways, once, image will preprocessed as palmprint biometric image, hence, enhancing palmprint images using Gabor filter, blurs it using the median filter, and uses the Mean filter for binarizing and generating the last view of the enhanced palmprint biometric image. The difference in this section that the extracted images of biometric traits are combined together in a single image. That is, every image will separated into two copies for preprocessing as two different biometric traits, then after preprocessing, combine them to create a fused biometric trait image.

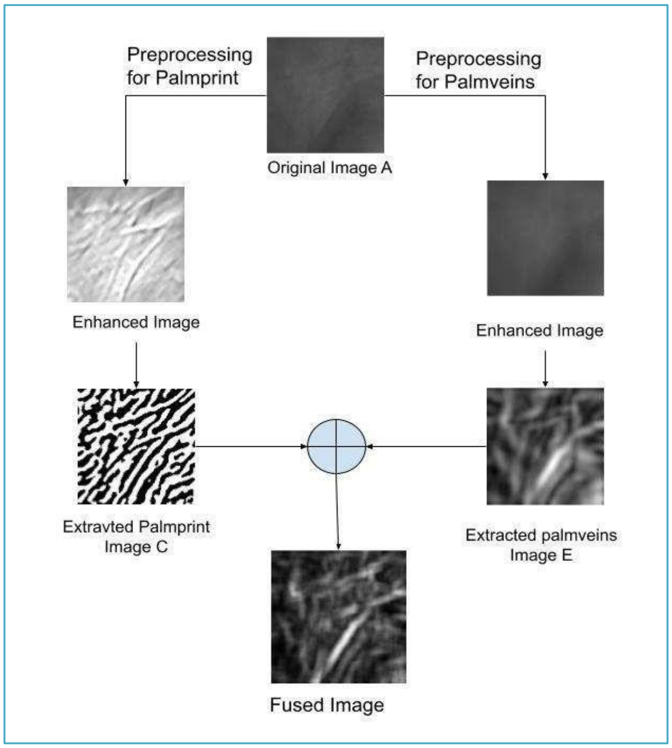

Figure 2: Preprocessing stages for multimodal based sensor level fusion

Proposed Palmprint Preprocessing Algorithm:

a. Read an input image A.
b. Preprocessing for palmprint trait:
   i. Apply Gabor filter on the image A as image B.
   ii. Smooth an image using Median filter on the image B.
   iii. Segment image B using an adaptive thresholding of Mean to create a binary image C**.**
c. Preprocessing for palmveins trait:
   i. On image A, apply Gaussian filter with 3 kernel filter as image D.
   ii. Apply Standard Deviation filter with 11 kernel filter on image D.
   iii. Rescale the image D to create a palmveins preprocessed image E.
d. Fusion of the palmprint and palnveins traits:
   i. Combine images C and E as image F.
   ii. Save the image F as a fused biometric trait. And add it into the fused dataset.
e. Repeat the above steps for each image in the dataset.

After preprocessing stage, we need to arrange the dataset to be suitable for feeding it to the neural network model. So that, dividing dataset into two main sets training set and testing set with rate of 70% and 30%, respectively. In addition, for best training, we have to validate the model using some trained data. For that, we will take a copy of part 30% from the training set, to be used in the model validation. In this regard, the algorithm of arranging dataset is provided below.

Arranging datasets (divided data into three sets using different sizes of samples):

1- From both sessions, separate images of each subject together (20 images for each palm).
2- Training set: Randomly, choose 70% (14 images) from each palm images.
3- Validation set: From training set, randomly choose 30% (5 images) from every subject in the dataset.
4- Testing set: The remaining are 30% (6 images) for each palm.

4. NEURAL NETWORK IMPLEMENTATION

Above all, the proposed model needs to build and reconstruct its layers. Where the VGG16 preprocessing functions used for feature extraction, weights will be fitted as VGG16 model with ImageNet weights. However, this section will cover all substages in designing the proposed system in relation with CNN works. From neural network point of view, the proposed "multimodal biometric system based on palmprint and palmveins biometric traits" can be designed as shown in the figure (3), where the preprocessing is done as in the previous section, then the image will fed into the CNN model, where training process through convolutional layers, feature extraction through maxpooling layers, and validation/ testing the model using softmax classifier.

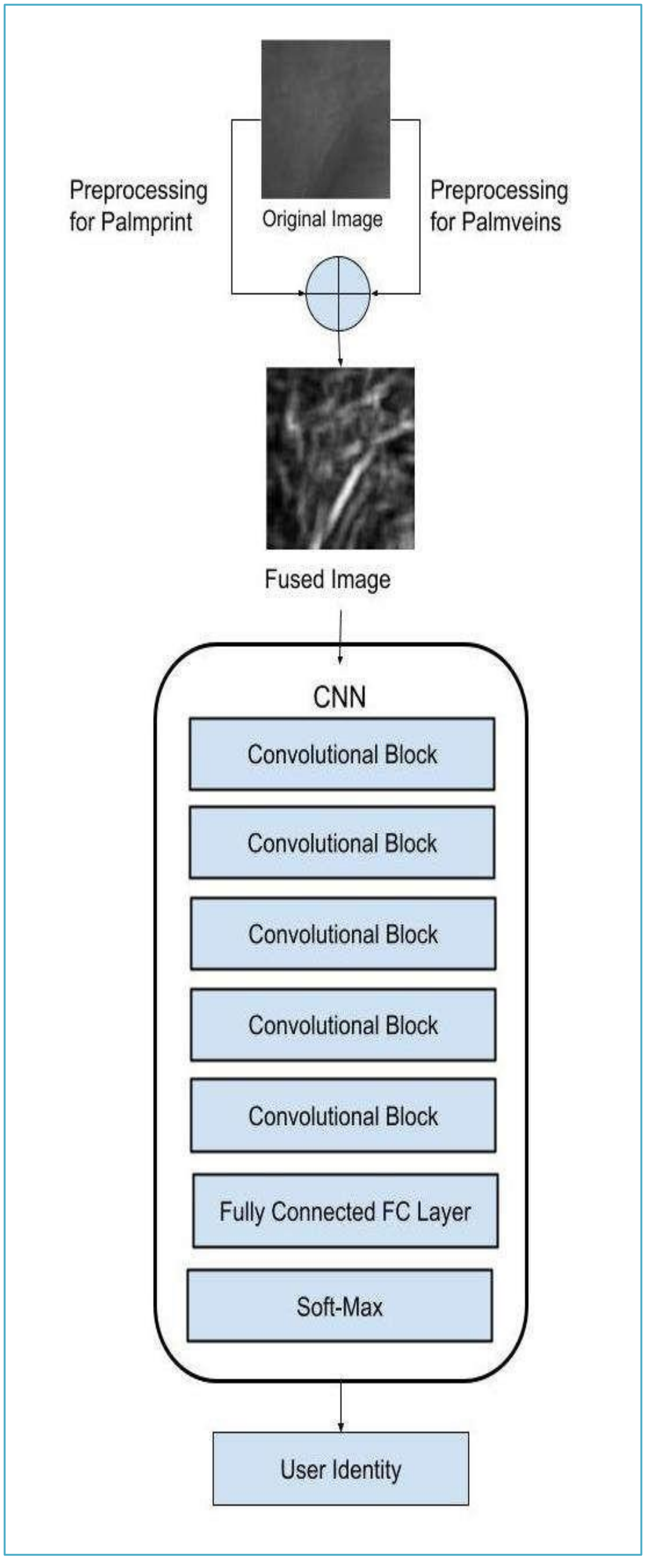

Figure 3: proposed multimodal biometric System based on sensor level fusion.

Building model is an important issue, it starts with an input convolutional layer with 32 filters of size three, "ReLU" activation function, and "same" of padding, where the input shape is 128 × 128, which is the size of the ROI image in the used dataset. Followed by max-pooling layer with a pool of size two, and two pixels of strides to avoiding overfitting. The second layer is another convolutional layer with 64 filters, and with the same settings on the first layer, except that there is no input shape here because the layer is a hidden layer. This is followed by a similar of max-pooling layer to prevent overfitting also. Finally, flatten and dense layers with "softmax" of activation function, to classify the images to specific number of classes (i.e. not binary classes). Figure (4) shows the structure of a similar model.

Feature extraction: using transfer learning, features is extracted based on VGG16 CNN, which is already trained on ImageNet weights. ImageNet dataset is a famous dataset consist of millions of images collected by Google [90].

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_1 (Conv2D)	(None, 64, 64, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 32, 32, 64)	0
flatten (Flatten)	(None, 65536)	0
dense (Dense)	(None, 600)	39322200

Total params: 39,341,592
Trainable params: 39,341,592
Non-trainable params: 0

Figure 4: CNN Model Structure sample.

Training: after building the model, model must be compiled, where its compilation in "Adam" optimization with a learning rate of 0.00001, using measures of accuracy in categorical cross entropy, because of multi classes we are working on. Figure (5) shows a view of the training process. Parameters used and result in measures are presented in the tables (2), with the results mentioned in correspondence.

```
Train for 420 steps, validate for 300 steps
Epoch 1/25
420/420 - 656s - loss: 9.5016 - accuracy: 0.3880 - val_loss: 0.3627 - val_accuracy: 0.9243
Epoch 2/25
420/420 - 650s - loss: 0.1998 - accuracy: 0.9542 - val_loss: 0.0499 - val_accuracy: 0.9863
Epoch 3/25
420/420 - 646s - loss: 0.0240 - accuracy: 0.9936 - val_loss: 0.0165 - val_accuracy: 0.9957
Epoch 4/25
420/420 - 643s - loss: 0.0025 - accuracy: 0.9995 - val_loss: 0.0115 - val_accuracy: 0.9983
Epoch 5/25
420/420 - 646s - loss: 0.0056 - accuracy: 0.9983 - val_loss: 7.6647e-04 - val_accuracy: 0.9997
Epoch 6/25
420/420 - 641s - loss: 1.7002e-04 - accuracy: 1.0000 - val_loss: 7.4630e-05 - val_accuracy: 1.0000
Epoch 22/25
420/420 - 642s - loss: 7.8849e-06 - accuracy: 1.0000 - val_loss: 6.6895e-06 - val_accuracy: 1.0000
Epoch 23/25
420/420 - 640s - loss: 6.7814e-06 - accuracy: 1.0000 - val_loss: 5.7627e-06 - val_accuracy: 1.0000
Epoch 24/25
420/420 - 644s - loss: 5.7871e-06 - accuracy: 1.0000 - val_loss: 4.9180e-06 - val_accuracy: 1.0000
Epoch 25/25
420/420 - 638s - loss: 4.9312e-06 - accuracy: 1.0000 - val_loss: 4.1986e-06 - val_accuracy: 1.0000
```

Figure 6: View of the Training process.

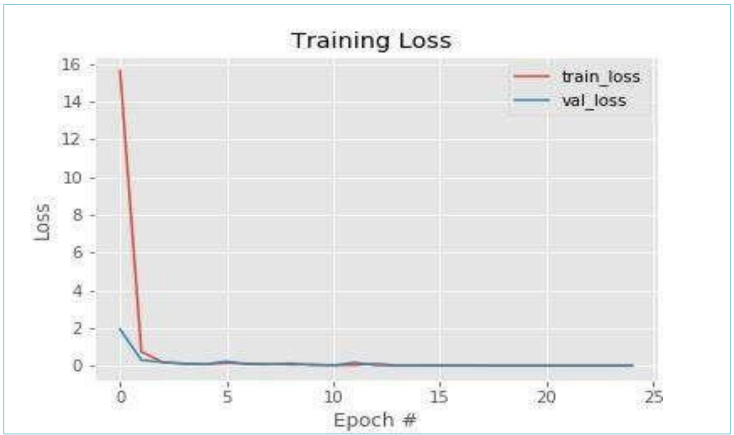

Figure 7: Training and Validation Loss for sensor fusion system.

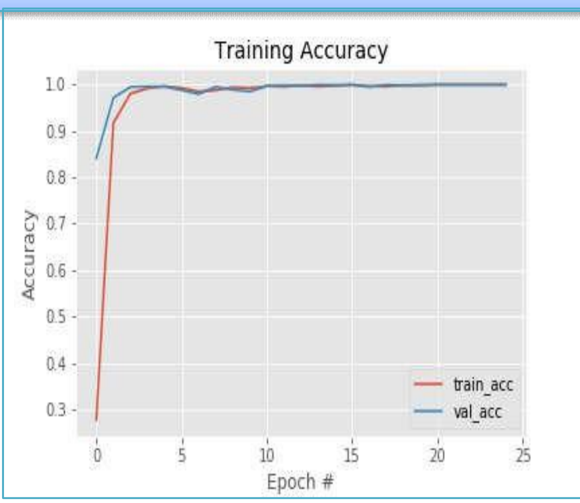

Figure 8: Training and Validation accuracy for sensor fusion system.

Testing: In testing stage we have to validate the model on some trained data, and then test the model using untrained data in the verification phase. In the first phase, called validation process, we randomly chosen 30% of the trained data and then fitted on the models built above. In this phase, we ensure that the model loss is low and accuracy is high as they are presented in the table (3), and figured out in the figures (6, and 7), where validation accuracy and loss are for pretrained data. The second phase, named verification/test/prediction process, is more important and considered to be the main result of the work. In this phase, untrained images have to be examined on the model. We use our testing set of images which are around 30% of the dataset — untrained before in the model. As shown in the table (5.2), FPR, FNR, TPR, TNR, and Accuracy of the system are figured out from the confusion matrix, which is built through this stage. Genuine and imposter figures are plotted in figure (5.8). ROC-AUC is plotted as a view for one class as shown in figure (5.9).

5. EXPERIMENTAL RESULT OF MULTIMODAL AT SCORE FUSION LEVEL

As it shown in the table (1), accuracy is 98.38%, we have been tested 3600 images for 600 subject with 6 images for each subject. So, the confusion matrix shows that the verification will be distributed as 3600 × 600 processes; where 3600 processes have to recognized as a genuine, and 2,156,400 processes as an imposter, as it figured out in the figure (8). As it appeared in the ROC curve at figure (9), it visualized that the proposed multimodal biometric system performed a well classification, where the Area Under the Curve AUC is equal to one**.**

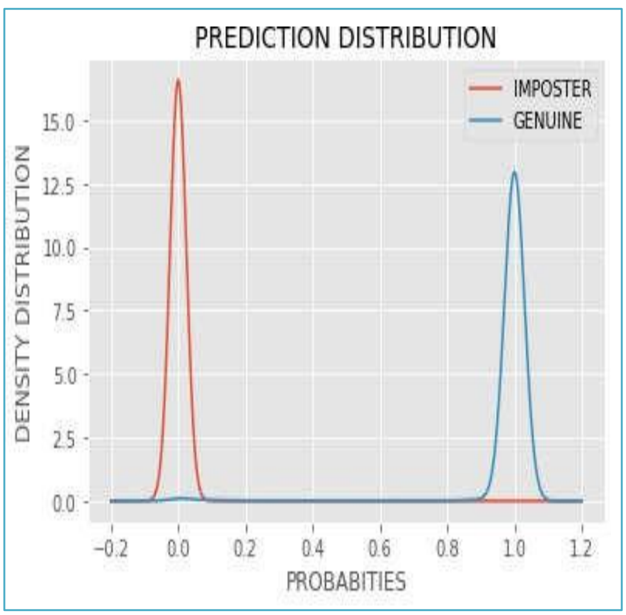

Figure 8: Imposter/Genuine Distribution of Multimodal based on sensor level fusion.

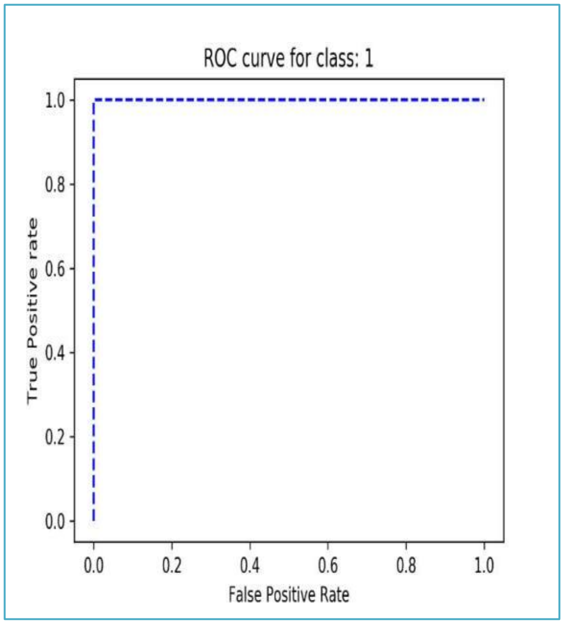

Figure 9: ROC Curve sample of the multimodal system based on sensor level fusion.

5.1 Score Level Fusion

As shown in the framework diagram presented in the figure (10). Basically, two stages are included, as the requirements of the biometric systems, i.e. enrolment, then verification stages. When the system acquired an image, it will process it in two ways simultaneously, such that, inputted image will get preprocessing as a palmprint biometric trait, and the same image i.e. the original image will preprocessed as a palmvein biometric trait.

In case of the enrolment stage, features of each will be extracted and stored in the template database. In case of the verification stage, after feature extraction, the features will feuded to the matcher, which will match these features with the available stored in the template, and then return the score of matching against the same subject. Continuously, to fuse the two modals, in the fusion process will test whether both of the features are for the same subject or not. In positive case, fuse their scores using arithmetic mean method of score fusion. Then the decision of the verity will be based on the result of fusion.

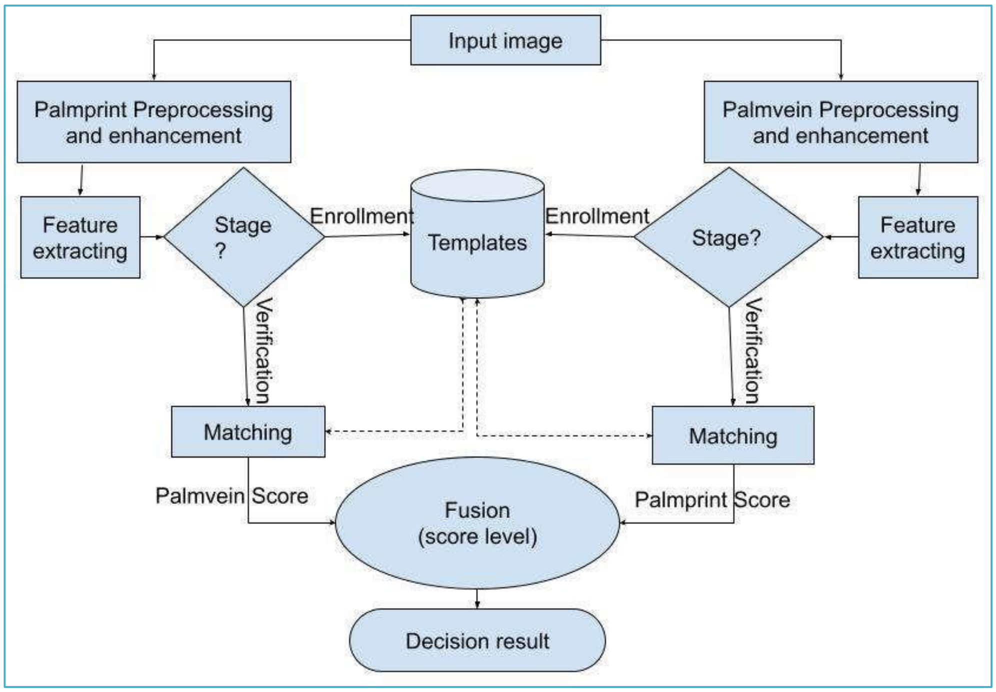

Figure 10: Flow daigram for Score level fusion of palmprin and palmveins systems

5.2 Implementation of Multimodal Biometric System at Score Level of Fusion

This section will implement the multimodal biometric system based on palmprint and palmveins biometric traits. The preprocessing will done independently, then, the fusion will be at score level, where the scores gained from the matching process are fused.

5.2.1 Neural Network Implementation

These unimodal systems, will be used as a subsytems to design the multimodal biometric system based on palmprint and palmveins. In this regards, preprocessing is done simultaneously as it in the proposed subsystems, with some differences in the arranging dataset, such that every image have to take the same position in the training set or testing set in both subsystems. In another hand, if the image A for the subject X is putted in the palmprint training set, then, the image A for the subject X must be putted in the palmveins training set, likewise to all images. Then, the dataset for each subsystem will be fed into its CNN model, where training, validating, and testing processes will done separately. The result of each subsystem is the confusion matrix, which is the matching probabilities or can to be considered as a recognition rate for each image in the testing set against the extracted features for each subject, this is for both palmprint and palmveins. However, finally the score fusion will applied using the confusion matrices for both subsystems. This is will create another confusion matrix for the fused system, which is can be used to generate the metrics of recognition rate and distributed of genuine and imposter and plotting the ROC-AUC diagram.

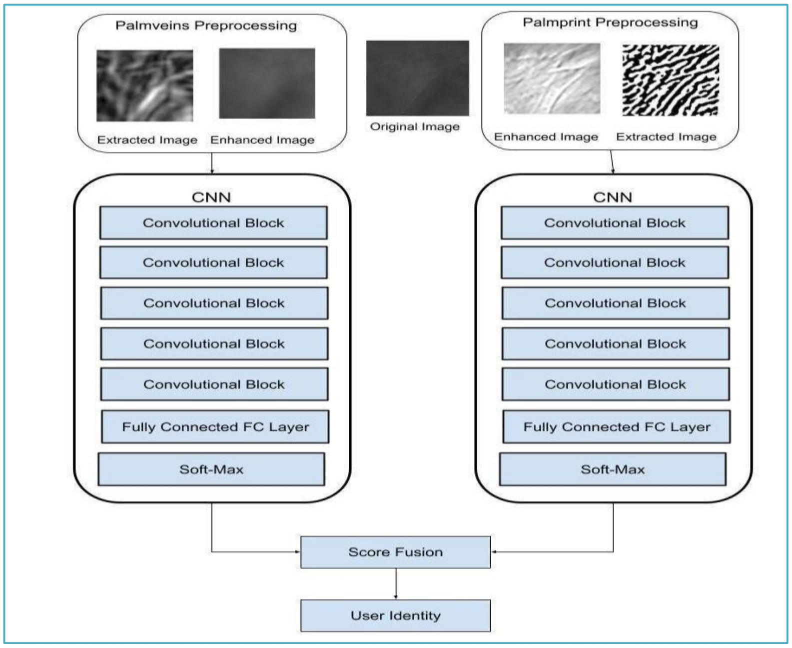

Figure 11: Proposed multimodal biometric system based on score level

6. EXPERIMENTAL RESULT OF MULTIMODAL AT SCORE FUSION LEVEL

As it shown in the table (2) mentioned above, accuracy is 98.12%, we have been tested 3600 images for 600 subject with 6 images for each subject. So, the confusion matrix shows that the verification will be distributed as 3600x600 processes; where 3600 processes have to recognized as a genuine, and 2,156,400 processes as an imposter, as it figured out in the figure (13). As it appeared in the ROC curve at fig (5.12), it visualized that the proposed multimodal biometric system performed a well classification, where the Area

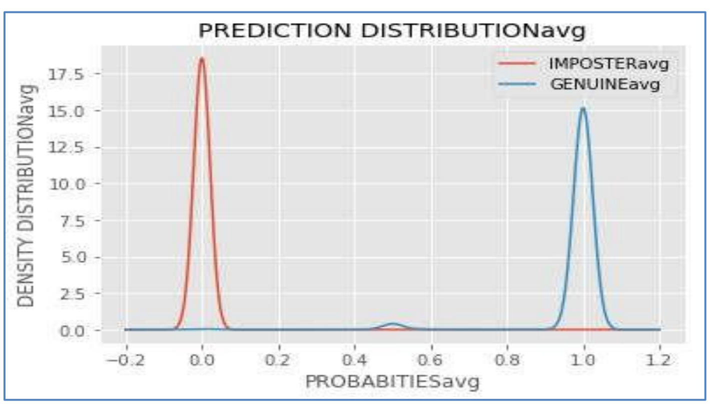

Figure 12: Impster/Genuien Distribution for Multimodal at Score level Fusion

Under the Curve AUC is equal to one**.**

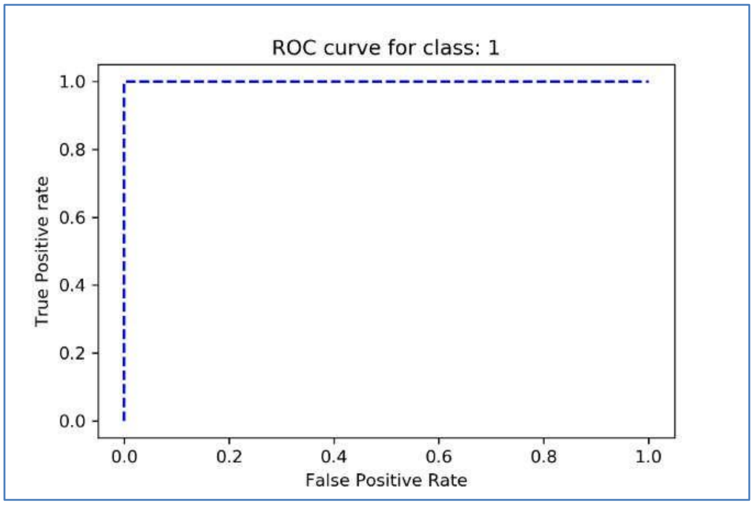

Figure 13: ROC cuve for Multimodal at Score level Fusion

6.1 Evaluation

The proposed work is a multimodal biometric system based on palmprint and palmveins is designed through using CNN. In sensor level of fusion, the recognition rate is 89.38%, which is lead to high performance of the system, with minimum of EER which is 0.0161. in addition the multimodal at sensor level has advantages of enhancing the biometric traits images and fuses it at the earlier stage of the biometric stages, so, the followed stages computations will decreases, and the CNN work will done on the multimodal as it a single model. because of the images of the traits are already fused as a single image. i.e. the features will extracted from only one image, this is a benefit of sensor fusion. The demerit, of this model that the features will fused early, so, it may leak the features detection.

These unimodal systems, will be used as a subsytems to design the multimodal biometric system based on palmprint and palmveins. In this regards, preprocessing is done simultaneously as it in the proposed subsystems, with some differences in the arranging dataset, such that every image have to take the same position in the training set or testing set in both subsystems. In another hand, if the image A for the subject X is putted in the palmprint training set, then, the image A for the subject X must be putted in the palmveins training set, likewise to all images. Then, the dataset for each subsystem will be fed into its CNN model, where training, validating, and testing processes will done separately. The result of each subsystem is the confusion matrix, which is the matching probabilities or can to be considered as a recognition rate for each image in the testing set against the extracted features for each subject, this is for both palmprint and palmveins. However, finally the score fusion will applied using the confusion matrices for both subsystems. This is will create another confusion matrix for the fused system, which is can be used to generate the metrics of recognition rate and distributed of genuine and imposter and plotting the ROC-AUC diagram.

In the result, score level fusion method gained a recognition rate of 98.12%, which is make the system in high performance with minimum of EER of 0.0183. and, as it visualized in the fig (5.13) the Area Under the Curve will be a full unit, that leads to the consideration that the system is a high classification.

In the point of view of other benefits of the multimodal biometric system, as it summarized in the table (5.2). the proposed system has high usability, and much more friendly and safe of infection because it uses a contactless, high secure because it uses intrinsic trait (palmveins) which cannot to affect by any external factors and difficult to replicate or forge. i.e. the proposed system uses a single part of the human body to collect two biometric trait, in a single shot, with a single device, in contactless. Moreover it uses a Deep Convolutional Neural Network through using transfer learning techniques of VGG16 pretrained model. To the best of our knowledge none conduct palmveins with palmprint to provide a fully contactless multimodal biometric system with these properties. Table (5.3) summary similar works comparing to the proposed work.

Table (5.2): result parameters

Parameter/Metric	Value/ Result using sensor fusion	Value/ Result using score fusion
No. of subjects	**600**	**600**
Training images	8400	8400
Validating images	3000	3000
Testing images	3600	3600
Total images	**12000**	**12000**
TP	3542	3534
FN	58	66
FP	58	66
TN	3542	3534
TAR/TPR	0.98388888	0.9816667
FAR/FPR	0.0161111	0.0183333
TRR/TNR	0.98388888	0.9816667
FRR/FNR	0.0161111	0.0183333
EER	**0.0161111**	**0.0183333**
ACCURACY	**98.38%**	**98.13%**

Table (7): comparing multimodal systems Results with the proposed system

Ref. Year	Traits used	Fusion level	Dataset used			Usability measures					ACC
			Dataset name	Images Size	Same dataset	Contactless	Lifeness	Single sensor	Single part	Single shot	
[151] 2015	Multifaces	Feature	CASIA-WebFace &LFW	9000	☒	✓	☒	✓	✓	✓	99% 76.53%
[152] 2016	Mouse, keystrock				☒	☒	☒	☒	☒	☒	68.8%

	e										
[153] 2017	Face, iris	Featur e	ORL, CASIA-IrisV3	280 4700	☒	√	☒	√	☒	☒	98.8%
[154] 2017	Ear, palmprint	Featur e	IIT Delhi-2 IIT Delhi P.P.	221 235	☒	√	☒	☒	☒	☒	100%
[155] 2017	Finger vein and knuckles	feature	SDUMLAH M T IIT Delhi	3816 500	☒	☒	☒	☒	√	☒	95%
[156] 2017	Face, L&R irises	Score	SDUMLA-HMT	8904 1060	√	√	☒	√	√	√	100%
[55] 2018	L&R irises	Score	SDUMLAH MT CASIA-IrisV3 IIT Delhi	3816 2655 500	☒	√	☒	√	√	√	100%
[157] 2020	Fingerpri nt, ear	Featur e			☒	☒	☒	☒	☒	☒	97.33 %
[158] 2020	Face, Iris	Score	ORL, CASIA-IrisV3	400 2655	☒	√	☒	☒	√	☒	99.2%
Prop osed work	Palmprint and Palm veins	Sensor	Tongji **contactless** palmveins dataset	**12000**	√	√	√	√	√	√	**98.38 %**
Prop osed work	Palmprint and Palm veins	Score	Tongji **contactless** palmveins dataset	**12000**	√	√	√	√	√	√	**98.12 %**

7. CONCLUSION

In this work, a multimodal biometric system is proposed. We fused these subsystems using biometric fusion methods in two levels. Firstly, in sensor level, where the two biometric images (palmprint and palmveins) are extracted as their done in the subsystems. Then, they fused using sensor level of fusion to form a multimodal biometric trait. Therefore, the convolutional neural network model is built for extracting the feature set for each subject through training data, then; classify extracted features into determined subjects. However, the matching of the testing data is done through prediction process, which is form a confution matrix that that consist of the result of matching every tested image in the testing set against every subject feature set. In the another level, it is score level, where the two biometric images (palmveins and palmprint) extracted and trained as in their subsystems. Then at score level of fusion, the result of matching every image against each subject from palmprint biometric subsystem, will fused using an arithmetic mean with the corresponding score from palmveins biometric subsystem. Finally, based on the fused score, the subject identity will determined. Firstly, at sensor level of fusion, the palmprint and palmveins biometric trait are fused after their extraction. Then the system is continuously built based on CNN techniques. The sensor level multimodal biometric system has been gained high performance as shown in its accuracy of 99.83%, ROC curve, and distribution of imposter/genuine. Secondly, at score level of fusion, the palmprint and palmveins biometric trait are fused after their scored as a single biometric systems.

REFERENCES

1. J. Yang and X. Zhang, “Feature-level fusion of fingerprint and finger-vein for personal identification, ”Pattern Recognit. Lett., vol. 33, no. 5, pp. 623–628, 2012, doi: 10.1016/j.patrec.2011.11.002.
2. S. Shekhar, V. M. Patel, N. M. Nasrabadi, and R. Chellappa, “Joint sparse representation for robust multimodal biometrics recognition,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 36, no. 1, pp. 113–126, 2014, doi: 10.1109/TPAMI.2013.109.
3. S. Shekhar, V. M. Patel, N. M. Nasrabadi, and R. Chellappa, “Joint sparse representation for robust multimodal biometrics recognition,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 36, no. 1, pp. 113–126, 2014, doi: 10.1109/TPAMI.2013.109.
4. A. Nagar, K. Nandakumar, and A.K.Jain,“Multibiometric crypto systems based on feature-level fusion,”IEEE Trans. Inf. Forensics Secur., vol. 7, no. 1 PART 2, pp. 255–268, 2012, doi: 10.1109/TIFS.2011.2166545.
5. Z. Huang, Y. Liu, C. Li,M. Yang, and L. Chen, “A robust face and ear based multimodal biometric system using sparse representation,”Pattern Recognit., vol. 46, no. 8, pp. 2156–2168, 2013, doi: 10.1016/j.patcog.2013.01.022.
6. G. Goswami, P. Mittal, A. Majumdar, M. Vatsa, and R. Singh, “Group sparse representation based classification for multi-feature multimodal biometrics,” Inf. Fusion, vol. 32, pp. 3–12, 2016, doi: 10.1016/j.inffus.2015.06.007.
7. G. L. Marcialis, F. Roli, and L. Didaci, “Personal identity verification by serial fusion of fingerprint and face matchers,” Pattern Recognit., vol. 42, no. 11, pp. 2807–2817, 2009, doi: 10.1016/j.patcog.2008.12.010.
8. N. Poh, A. Ross, W. Lee, and J. Kittler, “A user-specific and selective multimodal biometric fusion strategy by ranking subjects,” Pattern Recognit., vol. 46, no. 12, pp. 3341–3357, 2013, doi: 10.1016/j.patcog.2013.03.018.
9. K. Nguyen, S. Denman, S. Sridharan, and C. Fookes, “Score-level multibiometric fusion based on dempster-shafer theory incorporating uncertainty factors,” IEEE Trans. Human-Machine Syst., vol. 45, no. 1, pp. 132–140, 2015, doi: 10.1109/THMS.2014.2361437.
10. Mamta and M. Hanmandlu, “Multimodal biometric system built on the new entropy function for feature extraction and the Refined Scores as a classifier,” Expert Syst. Appl., vol. 42, no. 7, pp. 3702–3723, 2015, doi: 10.1016/j.eswa.2014.11.054.
11. H. Mehrotra, R. Singh, M. Vatsa, and B. Majhi, “Incremental granular relevance vector machine: A case study in multimodal biometrics,” Pattern Recognit., vol. 56, pp. 63–76, 2016, doi: 10.1016/j.patcog.2015.11.013.
12. S. Bharadwaj, H. S. Bhatt, R. Singh, M. Vatsa, and A. Noore, “QFuse: Online learning framework for adaptive biometric system,” Pattern Recognit., vol. 48, no. 11, pp. 3428–3439, 2015, doi: 10.1016/j.patcog.2015.05.002.
13. M. M. Monwar and M. Gavrilova, “Markov chain model for multimodal biometric rank fusion,” Signal, Image Video Process., vol. 7, no. 1, pp. 137–149, 2013, doi: 10.1007/s11760-011-0226-8.

14. M. Gogoi and Dhruba Kr. Bhattacharyya, "Fusion of Fingerprint and Iris Biometrics Using Binary Ant Colony Optimization," no. October, 2015, doi: 10.1007/978-81- 322-1771-8.
15. S. Singh and A. Gyaourova, "Infrared and visible image fusion for face recognition," Def. …, 2004, [Online]. Available: http://proceedings.spiedigitallibrary.org/proceeding.aspx?articleid=843506.
16. H. C. Ching and C. Eswaran, "A nature based fusion scheme for multimodal biometric person identity verification at a distance," 2009 Int. Conf. Signal Acquis. Process. ICSAP 2009, pp. 94–97, 2009, doi: 10.1109/ICSAP.2009.28.
17. B. E. Manjunathswamy, J. Thriveni, and K. R. Venugopal, "Bimodal Biometric Verification Mechanism using fingerprint and face images(BBVMFF)," 2015 IEEE 10th Int. Conf. Ind. Inf. Syst. ICIIS 2015 - Conf. Proc., pp. 372–377, 2016, doi: 10.1109/ICIINFS.2015.7399040.
18. X. Zhou and B. Bhanu, "Feature fusion of face and gait for human recognition at a distance in video," Proc. - Int. Conf. Pattern Recognit., vol. 4, no. May, pp. 529– 532, 2006, doi: 10.1109/ICPR.2006.556.
19. M. D. J. Ghate and S. B. Patil, "Robust combination method for privacy protection using fingerprint and face biometrics," 2015 4th Int. Conf. Reliab. Infocom Technol. Optim. Trends Futur. Dir. ICRITO 2015, 2015, doi: 10.1109/ICRITO.2015.7359312.
20. B. Ammour, T. Bouden, and L. Boubchir, "Face-Iris Multimodal Biometric System Based on Hybrid Level Fusion," 2018 41st Int. Conf. Telecommun. Signal Process. TSP 2018, pp. 1–5, 2018, doi: 10.1109/TSP.2018.8441279.
21. W. Kabir, M. O. Ahmad, and M. N. S. Swamy, "Weighted Hybrid Fusion for Multimodal Biometric Recognition System," Proc. - IEEE Int. Symp. Circuits Syst., vol. 2018-May, pp. 3–6, 2018, doi: 10.1109/ISCAS.2018.8351048.
22. A. Meraoumia, S. Chitroub, and A. Bouridane, "Multimodal Biometric Person Recognition System Based on Multi-Spectral Palmprint Features Using Fusion of Wavelet Representations," Intech, vol. i, no. tourism, p. 13, 2016, doi: http://dx.doi.org/10.5772/57353.
23. R. S. Choras, "Multimodal Biometrics for Person Authentication," Intech, vol. i, no. tourism, p. 13, 2016, doi: http://dx.doi.org/10.5772/57353.
24. B. Rajalakshmi and S. Sumathi, "survey of multimodal biometric using ear and finger knuckle image," Int. Conf. Commun. Comput. Internet Things (IC3IoT). IEEE, vol. 6859, pp. 48–53, 2018.