Fusion of Finger Vein Images, at Score Level, for Personal Authentication

Bharathi Subramaniam[1], Sudha V Krishnan[1], Sudhakar Radhakrishnan[1] and Valentina E Balas[2]

[1]Department of Electronics and Communication Engineering, Dr.Mahalingam College of Engineering and Technology, Pollachi -642 003, Tamilnadu, India
E-mail: sbharathi@drmcet.ac.in, sudhashree@drmcet.ac.in, hod_ece@drmcet.ac.in

[2]Department of Automatics and Applied Software, Aurel Vlaicu University of Arad / Academy of Romanian Scientists, 77 B-dul Revolutiei, 310130 Arad, Romania; E-mail: valentina.balas@uav.ro

Abstract: A biometric system with a single biometric trait is less effective, owing to constraints, such as inter-class similarities, susceptibility to noisy pictures and spoofing. Integrating information from different biometric evidences aids in the resolution of difficulties in unimodal biometric systems. It is incredibly challenging in a biometric system to intrude into more than one trait at the same time. Researchers are becoming more interested in multimodal biometric systems due to benefits such as dependability, security, and robustness. A multimodal biometric system based on finger vein images is proposed in this paper, by combining information from the index, middle and ring fingers of the hand. The essential characteristics from the finger vein images are extracted using a Convolutional Neural Network with a ReLU activation function. The input test image features are then compared with the features stored in the database using the correlation-based matching technique, and the match scores are fused using the arithmetic mean-based score level fusion. The performance of the proposed work is analyzed using the finger vein images from STUMULA -HMT database. The results reveal that the suggested multimodal biometric system outperformed the existing techniques, with a maximum accuracy of 99.83%.

Keywords: Biometrics; finger vein authentication; score level fusion; Convolutional Neural Network

1 Introduction

Biometric authentication technology has majorly included the inherent characteristics of people like fingerprint, face, finger vein, iris, voice, gait and many more. In the beginning, fingerprints were paid more attention, and researchers have deployed fingerprint technologies in security applications and handheld devices. The possibility of changing the fingerprint through surgery [1], extracting latent print and spoofing attacks lead to distracting the researchers to another biometric trait. Similarly, face biometric also getting slows down by the possibility of sophisticated face masks [2] and the impact of accuracy because of the non-permanent facial makeup [3]. Nowadays, vein biometrics [4] gain more concentration among researchers because of its own security, reliability, liveness and hygiene. Even though finger vein biometrics provides security, still accuracy is deduced due to intra-class variation, noisy data, inter-class similarities and poor-quality images (Blurry, askew, dim and bright images [5]). Integrating several biometric modalities improves biometric data security and accuracy. The multimodal biometric system may be implemented in a variety of ways by combining biometric data at various levels. The two major possibilities for implementing fusion techniques in multimodal biometric system are at pre-matching and post-matching stages.

Usually, the biometric system learns user-specific identities in the enrollment phase and the identity is verified in the verification phase. Sensor level fusion is the process of amalgamating information obtained from multiple perspectives or different sensors. Feature level fusion integrates features from many sensors (several samples of the same trait, multiple characteristics) to create a concatenated resultant feature vector. Some feature reduction methods may be used to exemplify a larger facet of a fused feature vector. However, the fusion at this level also serves to improve system performance and is used for template creation [6]. The matching module in each biometric modality will deliver the matching score, after matching the input biometric template with the templates stored in the database. Score level fusion is frequently used in multimodal biometric systems [7] [8] because matching scores include enough information to discriminate between genuine and imposter situations while being fairly simple to acquire. The fusion of decisions derived from several modalities is referred to as decision level fusion. However, because the feature sets of the various modalities may be incompatible, fusion at this level is a tricky process to do in practice. Due to the limited availability of relevant data, fusion at the decision level might be seen as stringent.

As a result, the recommended technique utilizes score level fusion to improve the accuracy of the biometric system by merging the matching scores obtained from the index, middle, and ring finger vein images. The remainder of the paper is structured as follows. In Section II the related works identified with fusion of biometric traits for multimodal biometric recognition at various levels are examined. The proposed technique for Fusion of Finger Vein Images at Score Level is introduced in Section III. In Section IV the experimental results obtained by this proposed technique have been explained. The conclusion and future work are discussed in Section V.

2 Background of the Research Work

Many researchers presented their findings on the merging of biometric characteristics at several stages to enrich the biometric system's performance. Yan et al [9] used a feature level fusion approach to generate user-specific biometric templates by fusing data from numerous palm vein samples acquired from each and every individual. The palm vein is captured at a wavelength of 700 nm and they have obtained the EER is around 0.98%. Jinfeng yang et al. [10] presented feature level fusion-based personal identification by combining fingerprint and finger vein data with a unique supervised local-preserving canonical correlation analysis technique (SLPCCAM) and other feature fusion approaches. Among all their fusion approaches, the SLPCCA-based method has a low FAR of around 1.35%. Yong-Fang Yao et al [11] demonstrated a distance-based separable weighting method for fusing of face and palm print data at feature level with an average recognition rate of around 90.73%.

Jialiang Peng et al [12] developed a virtual multimodal biometric system by extracting GLBP, minutiae, Fourier descriptor, and phase congruency features from four biometric modalities: finger vein, fingerprint, finger shape, and finger knuckle print. Sugeno–Weber (SW) triangular norm is used to fuse the match scores. Maleika Heenaye et al. [13] demonstrated a hand vein based multimodal biometric system by utilizing dorsal and palmer vein biometrics of the hand. To normalize the matching scores into the range 0 to 1, min-max normalization techniques were employed. The sum rule, which creates the sum of the product of weights, is then used to fuse the matching scores together and normalized scores in each matching module. The fused biometric system has FRR of around 0.35%. Walia et al [14] presented fingerprint, finger vein, and iris-based multi-biometric systems, and matching was accomplished using Eigen distance, Euclidian distance, and hamming distance for each biometric system. Backtracking Search Optimization Algorithm (BSA) is used to optimize the classifier scores, and the match scores were transformed into belief masses using the Denoeux model. In the decision module, the belief mass is then compared to a threshold value, and they have obtained an EER of 1.57%. Sim et al. [15] suggested an iris and face biometrics-based multimodal system. Euclidian distance and hamming distance were utilized for matching the features of iris and face biometrics. Following that, the collected scores were fused together using weighted score level fusion. Dwivedi et al. [16] used the Rectangle Area Weighting (RAW) approach to show score level fusion of cancellable multi-biometric templates. Individual biometric system scores were computed using the mean-closure weighting (MCW) approach. The two-level cancelable fusion score approach outperforms unimodal cancelable systems. Khellat-Kihel et al. [17] presented finger vein, finger knuckle, and finger print biometrics based multimodal biometric system. Concatenating feature vectors from all three finger-based biometrics was used to achieve feature-level fusion. Then, at the decision level, unimodal judgments from a fingerprint, finger knuckle, and finger vein biometric system are merged to provide the final decision, with an accuracy of about 95.28%.

Kun Su et al [18] employed a multi-sample fusion approach to connect a finger vein and an ECG biometric system. The biometric system was built using feature-level and score-level fusion methods. The maximum EER of all methods was obtained by weighted sum rule-based score level fusion, which was about 1.27%. However, the serial and parallel feature fusion methods yielded an EER of around 7.5%. Ammour et al. [19] presented a multimodal biometric system by utilizing the face and iris. The fusion took place at the score and decision levels, with a recognition rate of around 86.66% for the min-max based normalization technique. Sengar et al [20] developed a palm print and fingerprint-based multi-biometric system based on Deep Neural Network that achieves an accuracy of around 91% with 1.10% FAR and 3% FRR.

3 Proposed Method

Figure 1 depicts the schematic of the proposed finger vein-based biometric system. Convolutional Neural Network [21-23] is utilized during the enrollment phase to extract deep feature sets from index, middle, and ring finger vein images from both the right and left hands. The acquired characteristics are saved in the database as the user's distinct identity. In the verification phase, matching takes place between the input image features and features in the database (stored enrolled templates) utilizing the correlation-based matching technique. Using arithmetic mean-based score fusion, the matching scores obtained from the matching modules are merged into a single number. If the final matching score is greater than the threshold value, the corresponding individual will be given access; otherwise, the person will be considered an imposter.

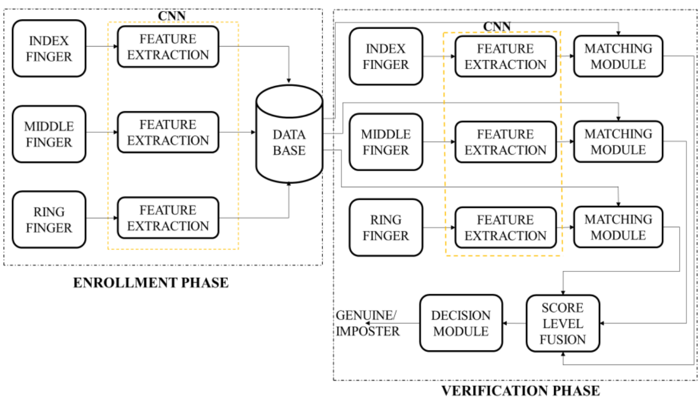


Figure 1
Block diagram of the proposed work

3.1 Database

The proposed research is carried out by utilizing the SDUMLA-HMT database [24], which comprises index, middle, and ring finger vein images taken from the hands of 106 people. Each finger was captured six times, and each image in the database is of size 320×240.

3.2 Feature Extraction

The convolutional neural network is a deep learning algorithm that extracts the feature sets from an image in the forward propagation and updates the weights and bias during backward propagation. After several iterations, CNN learns to extract the relevant features. The configuration of the proposed convolutional neural network is shown in Table 1. The input image is preprocessed and resized to 227×227. We have used six convolutional layers with different number of filters and filter sizes to extract relevant features. Filters convolve with the input image to produce feature maps. The decision of each neuron in the CNN is carried out by the activation functions used in the convolutional layers. In the proposed system, the CNN is trained and tested with ReLU activation function due to its own merits. In every convolutional layer, average pooling is done to reduce the size of the feature map. The architecture of the CNN is shown in Figure 2. Convolutional neural network was trained and tested with finger vein images from the database with various learning rates such as 0.03, 0.025, 0.01, 0.001, 0.0005, 0.0002 and 0.0001.

Table 1
Configuration of the proposed convolutional neural network

Layers	**No. of Filters**	**Filter size**	**Stride**	**Activation function**	**Size of feature map**
Input	-	-	-	-	227×227
Conv 1	32	3×3	1	ReLu	$227 \times 227 \times 32$
Avg. pooling 1		2×2	2		$114 \times 114 \times 32$
Conv 2	64	3×3	1	ReLu	$114 \times 114 \times 64$
Avg. pooling 2		2×2	2		$57 \times 57 \times 64$
Conv 3	64	3×3	1	ReLu	$57 \times 57 \times 64$
Avg. pooling 3		2×2	2		$29 \times 29 \times 64$
Conv 4	128	3×3	1	ReLu	$29 \times 29 \times 128$
Avg. pooling 4		2×2	2		$15 \times 15 \times 128$
Conv 5	256	3×3	1	ReLu	$15 \times 15 \times 256$
Avg. pooling 5		2×2	2		$8 \times 8 \times 256$
Conv 6	256	3×3	1	ReLu	$8 \times 8 \times 256$

Avg. pooling 6		2×2	2		4×4×256
Flattening	-	-	-	-	4096×1
Fully connected layer	-	-	-	Softmax	50×1

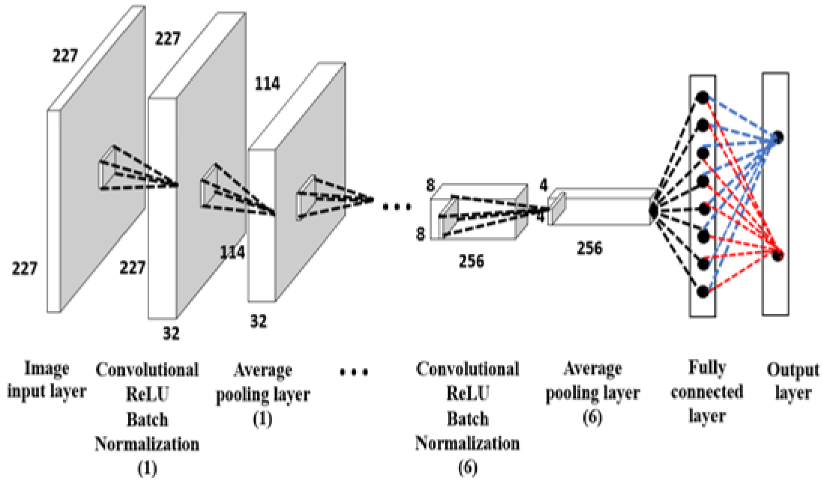


Figure 2
Architecture of CNN used for feature extraction

3.3 Enrollment Phase

CNN produces the hierarchical representation of an image as a feature vector after the completion of multiple iterations. The deep layers produce the higher-level features which are constructed using the lower-level features produced in the earlier layers. Then the user-specific feature vectors are stored as their identity.

3.4 Verification Phase

The convolutional neural network is given with images of the user's index, middle, and ring finger veins as input. CNN delivers the relevant feature vector for each finger vein image based on the weights and bias applied during the training phase.

3.5 Matching

The correlation-based matching is performed here in order to compare the input biometric feature template with the enrolled feature templates. The sample values of the enrolled attributes and the test features of the person's index, middle, and ring finger images are given in Table 2. The matching score of enrolled and test features is obtained by finding the correlation between the enrolled and test features with the calculations shown in Tables 3,4 and 5 respectively for the index, middle, and ring finger.

Table 2
Sample values of Train and Test features

Enrolled features			**Test features**		
Index finger	**Middle finger**	**Ring finger**	**Index finger**	**Middle finger**	**Ring finger**
50.668	49.193	50.096	48.283	48.283	49.879
48.283	48.283	48.389	47.265	48.283	48.389
45.938	46.089	46.610	45.000	46.035	46.610
50.668	49.193	50.096	48.283	48.283	49.784
48.283	48.283	48.389	47.265	48.283	48.358
45.938	46.089	46.610	45.000	46.035	46.650
50.668	49.193	50.096	48.283	48.283	50.376
48.283	48.283	48.389	47.265	48.283	48.389
45.938	46.089	46.610	45.000	46.035	46.610
50.668	49.193	50.096	48.283	48.283	50.389
48.283	48.283	48.389	47.265	48.283	48.389
45.938	46.089	46.610	45.000	46.035	46.610
50.668	49.193	50.096	48.283	48.283	49.389

Table 3
Correlation calculation for index finger

$T_{in} - \overline{T_{in}}$	$T_{enrolled} - \overline{T_{enrolled}}$	$(T_{in} - \overline{T_{in}})^2$	$(T_{enrolled} - \overline{T_{enrolled}})^2$	$(T_{in} - \overline{T_{in}})(T_{enrolled} - \overline{T_{enrolled}})$
2.189	1.323	4.793	1.751	2.897
-0.196	0.305	0.038	0.093	-0.06
-2.541	-1.96	6.456	3.84	4.979
2.189	1.323	4.793	1.751	2.897
-0.196	0.305	0.038	0.093	-0.06
-2.541	-1.96	6.456	3.84	4.979
2.189	1.323	4.793	1.751	2.897
-0.196	0.305	0.038	0.093	-0.06
-2.541	-1.96	6.456	3.84	4.979
2.189	1.323	4.793	1.751	2.897
-0.196	0.305	0.038	0.093	-0.06
-2.541	-1.96	6.456	3.84	4.979
2.189	1.323	4.793	1.751	2.897
$\sum(T_{in} - \overline{T_{in}}) = 48.479$	$\sum(T_{enrolled} - \overline{T_{enrolled}}) = 46.960$	$\sum(T_{in} - \overline{T_{in}})^2 = 49.939$	$\sum(T_{enrolled} - \overline{T_{enrolled}})^2 = 24.490$	$\sum(T_{in} - \overline{T_{in}})(T_{enrolled} - \overline{T_{enrolled}}) = 34.163$

Table 4
Correlation calculation for middle finger

$T_{in} - \overline{T_{in}}$	$T_{enrolled} - \overline{T_{enrolled}}$	$(T_{in} - \overline{T_{in}})^2$	$(T_{enrolled} - \overline{T_{enrolled}})^2$	$(T_{in} - \overline{T_{in}})(T_{enrolled} - \overline{T_{enrolled}})$
1.235	0.692	1.525	0.478	0.854
0.325	0.692	0.106	0.478	0.225
-1.869	-1.556	3.493	2.422	2.909
1.235	0.692	1.525	0.478	0.854
0.325	0.692	0.106	0.478	0.225
-1.869	-1.556	3.493	2.422	2.909
1.235	0.692	1.525	0.478	0.854
0.325	0.692	0.106	0.478	0.225
-1.869	-1.556	3.493	2.422	2.909
1.235	0.692	1.525	0.478	0.854
0.325	0.692	0.106	0.478	0.225
-1.869	-1.556	3.493	2.422	2.909
1.235	0.692	1.525	0.478	0.854
$\sum(T_{in} - \overline{T_{in}}) =$ 47.958	$\sum(T_{enrolled} - \overline{T_{enrolled}}) =$ 7.591	$\sum(T_{in} - \overline{T_{in}})^2 =$ 22.021	$\sum(T_{enrolled} - \overline{T_{enrolled}})^2 =$ 13.994	$\sum(T_{in} - \overline{T_{in}})(T_{enrolled} - \overline{T_{enrolled}}) =$ 16.805

Table 5
Correlation calculation for ring finger

$T_{in} - \overline{T_{in}}$	$T_{enrooled} - \overline{T_{enrolled}}$	$(T_{in} - \overline{T_{in}})^2$	$(T_{enrooled} - \overline{T_{enrolled}})^2$	$(T_{in} - \overline{T_{in}})(T_{enrooled} - \overline{T_{enrolled}})$
1.598	1.431	2.553	2.048	2.287
-0.109	-0.059	0.012	0.003	0.006
-1.888	-1.838	3.565	3.378	3.470
1.598	1.336	2.553	1.785	2.135
-0.109	-0.090	0.012	0.008	0.010
-1.888	-1.798	3.565	3.232	3.395
1.598	1.928	2.553	3.718	3.081
-0.109	-0.059	0.012	0.003	0.006
-1.888	-1.838	3.565	3.378	3.470
1.598	1.941	2.553	3.768	3.102
-0.109	-0.059	0.012	0.003	0.006
-1.888	-1.838	3.565	3.378	3.470
1.598	0.941	2.553	0.886	1.504
$\sum(T_{in} - \overline{T_{in}}) =$ 48.498	$\sum(T_{enrooled} - \overline{T_{enrolled}}) =$ 48.448	$\sum(T_{in} - \overline{T_{in}})^2 =$ 27.074	$\sum(T_{enrooled} - \overline{T_{enrolled}})^2 =$ 25.589	$\sum(T_{in} - \overline{T_{in}})(T_{enrooled} - \overline{T_{enrolled}}) =$ 25.942

Then the correlation between input features (T_{in}) and enrolled features ($T_{enrolled}$) is calculated using equation (1) as follows:

$$\text{Score} = \frac{\sum_m \sum_n \left(\text{Tin}_{mn} - \overline{\text{Tin}}\right)\left(\text{Tenrolled}_{mn} - \overline{\text{Tenrolled}}\right)}{\sqrt{\sum_m \sum_n \left(\text{Tin}_{mn} - \overline{\text{Tin}}\right)^2 \left(\sum_m \sum_n \left(\text{Tenrolled}_{mn} - \overline{\text{Tenrolled}}\right)^2\right)}} \quad (1)$$

The correlation between input features and enrolled features are to be considered as matching scores.

3.6 Match Score Level Fusion

From each biometric matcher the generated scores are amalgamated into a single score by utilizing equation to get the arithmetic mean of matching scores in (2):

$$\text{Mean score} = \frac{1}{n}\sum_{i=1}^{n}\left(\text{Score}\right)_i \quad (2)$$

Where, n- number of biometric matchers and *(Score)$_i$* - matching scores obtained from corresponding matching modules.

3.7 Authentication Decision

The final decision is determined on basis of Mean score. The threshold is set such that the genuine user will not be rejected and imposter user will not be accepted. If the mean score is greater than the threshold, the corresponding individual is verified; otherwise, the person is classified as an imposter, and access to the system is prohibited.

3.8 Evaluation Metrics

The suggested approach is assessed using the following evaluation metrics, as depicted in equations (3) to (9), and the outcomes are presented in section IV.

Accuracy is the percentage ratio of correct predictions to total forecasts.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

False Acceptance Rate (FAR) is the ratio of erroneous positive forecasts divided by the total number of negatives.

$$\text{FAR} = \frac{FP}{FP + TN} \quad (4)$$

False Rejection Rate (FRR) is the ratio of erroneous negative estimates divided by the sum of positives.

$$\mathrm{FRR} = \frac{\mathrm{FN}}{\mathrm{FN} + \mathrm{TP}} \tag{5}$$

Equal Error Rate (EER) refers to the state where the false acceptance and rejection rates are equal

$$\mathrm{EER} = 0.5\left(\mathrm{FAR} + \mathrm{FRR}\right) \tag{6}$$

Precision: The number of positive class forecasts that really belong to the positive class is referred to as precision.

$$\mathrm{Pr\,ecision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{7}$$

Recall: The recall is the number of correct positive class predictions produced from all correct positive samples in a dataset.

$$\mathrm{Re\,call} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{8}$$

Specificity: The proportion of actual negatives, which got correctly predicted as the negative is defined in terms of Specificity.

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{9}$$

4 Results and Discussion

The empirical values of the finger vein-based biometric recognition system's proposed technique are provided here. The performance of the unimodal biometric system is given in Table 6.

Table 6

Performance of unimodal system with various learning rates

Learning Rate	INDEX FINGER			MIDDLE FINGER			RING FINGER		
	FAR	FRR	Accuracy (%)	FAR	FRR	Accuracy (%)	FAR	FRR	Accuracy (%)
0.03	0.28	0.24	97.43	0.22	0.25	97.79	0.26	0.28	97.7
0.025	0.25	0.27	97.71	0.24	0.27	97.72	0.22	0.21	97.5
0.01	**0.22**	**0.26**	**97.74**	**0.24**	**0.22**	**97.82**	**0.22**	**0.24**	**97.8**
0.001	0.23	0.25	97.63	0.23	0.25	97.8	0.28	0.29	97.6

0.0005	0.28	0.24	96.4	0.32	0.24	97.83	0.26	0.28	97.6
0.0002	0.45	0.46	97.12	0.42	0.25	97.8	0.42	0.41	97.5
0.0001	0.45	0.43	96.08	0.44	0.22	96.5	0.38	0.48	96.2

The CNN is tested with various learning rates such as 0.03, 0.025, 0.01, 0.001, 0.0005, 0.0002 and 0.0001 for index, middle and ring finger vein traits distinctly. The results show that the learning rate 0.01 achieves a maximum accuracy, low FAR and FRR compared to other learning rates employed. In the case of unimodal system, for learning rate of 0.01, accuracy of 97.74%, 97.82% and 97.8% are obtained for index, middle, and ring finger vein images respectively. As a consequence, the biometric system with ReLU activation function is examined with a learning rate of 0.01 for finger vein images and the obtained results are presented in Table 7.

Fundamental performance measures such as FAR and FRR guarantee that the matching algorithm does not make any erroneous positive and negative matches for single template comparison attempts. Metrics like as accuracy, specificity, precision, recall, and EER are used to validate the biometric system. The above-mentioned performance metrics are assessed so as to measure the performance of our proposed finger vein-based system and are presented in Table 7. The proportion of genuine positives and negatives in the entire data set is measured by accuracy. For the proposed system, we have obtained a higher accuracy for multimodal systems as 99.83% & 99.76% compared with unimodal systems. The proportion of false acceptance equals the proportion of false rejection, according to EER. The suggested multimodal system has an EER of around 0.125 for both left- and right-hand fingers.

Table 7

Performance analysis of proposed system in unimodal and multimodal modes

Metrics (%)	**Left-hand fingers**				**Right-hand fingers**			
	Index	Middle	Ring	Multi-modal	Index	Middle	Ring	Multi-modal
Accuracy	97.74	97.82	97.8	99.83	97.74	97.8	97.6	99.76
Precision	96.6	96.4	96.8	98.97	96.4	96.6	97.2	98.96
Recall	97.4	96.8	97.2	98.97	97.2	96.4	96.8	98.96
Specificity	97.2	97.8	97.4	98.8	97.4	97.6	97.2	98.8
EER	0.24	0.23	0.23	0.125	0.25	0.25	0.26	0.125
FAR	0.22	0.24	0.22	0.11	0.24	0.22	0.28	0.11
FRR	0.26	0.22	0.24	0.14	0.26	0.28	0.24	0.14

Table 8
Comparative analysis of related work

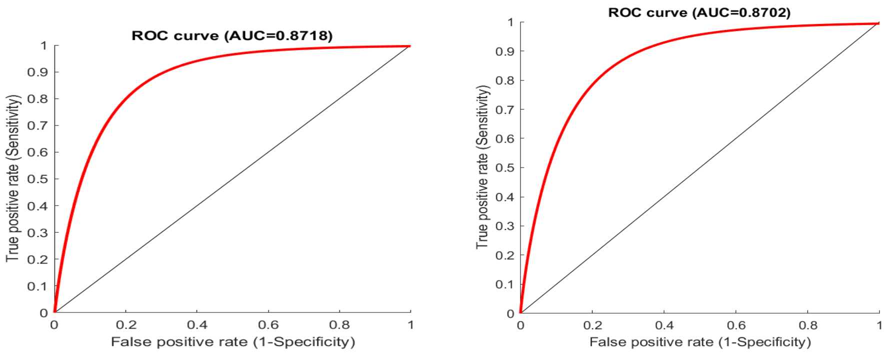
Authors	Biometric trait	Level of fusion	Methodology	Performance metrics
Yang Jinfeng and Zhang Xu [10]	Finger print & finger vein	Feature level	Supervised local-preserving canonical correlation analysis & nearest neighborhood classifier	FAR = 7.32 FRR = 5.00
Sengar et al [20]	Palm print & fingerprint	Feature level	Deep Neural Network	FAR = 1.10 FRR = 3.00
Lin et.al [25]	Palm and dorsal hand vein	Feature level	Hierarchical integrating function & Multi resolution analysis	FAR =1 FRR = 3.5 EER = 3.75
Kumar and Prathyusha[26]	Knuckle shape & dorsal hand vein	Score level	Matching vein triangulation and shape features	FAR = 1.14 FRR = 1.14
Raghavendra et al [27]	Palm print & palm vein	Score level	Log Gabor transform, weighted sum rule	FAR =7.4 FRR=4.8 EER=2.2
			Non-standard mask, weighted sum rule	FAR =2.8 FRR=1.4 EER=2.2
Proposed method	Index, middle and ring finger vein	Score level	CNN & correlation-based matching	FAR = 0.11 FRR = 0.14 EER =0.125

The precision of 98.97% and 98.96% is obtained for left and right-hand fingers respectively, specifies that the proposed system perfectly predict the genuine user. At the same time, recall ensures a measure of the proportion of actual genuine users got predicted as genuine. The proposed method achieves a recall of about 98.97% and 98.96% for left- and right-hand fingers. Hence the model is authoritative to the genuine users. The specificity of about 98.8% ensures that the system is faithful in the sense of identifying the imposter user.

The comparative analysis of the proposed work with existing methodologies has been done and is illustrated in Table 8.

The Receiver Operating Characteristic (ROC) curve of the suggested method is depicted in Figure 3. The ROC curve is a depiction of the True Positive Rate versus the False Positive Rate at different thresholds. The area under the curve

(AUC) shows a trade-off between genuine positive and false positive rates. The higher the AUC, the better the model distinguishes between real and impostor users. The suggested technique yields an AUC of around 0.8718 for the left-hand finger vein and 0.8702 for the right-hand finger vein, demonstrating that the proposed method accurately discriminates genuine and impersonating users.



(a) (b)

Figure 3

ROC-AUC curve (a) for Left hand (b) for Right hand

Conclusions

A multimodal, finger vein-based biometric system, that emphasizes on the fusion of index, middle and ring finger vein images of hand at the score level is proposed in this paper. The SDUMLA-HMT finger vein database was used to analyze the performance of the system. The essential traits from the finger vein images were extracted using CNN with the ReLU activation function. The correlation-based matching approach is then utilized to match the input template and the enrolled templates, and the match scores are fused using the arithmetic mean-based approach. The proposed multimodal system has maximum accuracy of 99.83% compared to average accuracy of 97.8% in unimodal case. As a result, the suggested multimodal biometric system provides a better solution to the difficulties in the unimodal biometric system. Moreover, in terms of FAR, FRR, EER, the proposed system outperforms the existing methodologies.

Security of biometric traits is essential, because the risk goes all the way up to the database, this work will be further developed, to strengthen the security of the biometric system by keeping encrypted templates, as a reliable, user-specific identification.

References

[1] Munish Kumar and Priyanka, "Finger print Recognition System: Issues and Challenges", International Journal for Research in Applied Science & Engineering Technology, Volume 6, Issue 2, pp. 556-561, 2018

[2] Noyes E., Davis JP., Petrov N., Gray K. L. H and Ritchie K. L., "The effect of face masks and sunglasses on identity and expression recognition with super-recognizers and typical observers", . R. Soc. Open Sci. 8: 201169, 2021

[3] A. Dantcheva, C. Chen and A. Ross, "Can facial cosmetics affect the matching accuracy of face recognition systems?," IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS), Arlington, VA, USA, pp. 391-398, 2012

[4] Xie. C., and Kumar.A., "Finger Vein Identification Using Convolutional Neural Network and Supervised Discrete Hashing," . In: Bhanu, B., Kumar, A. (eds) Deep Learning for Biometrics. Advances in Computer Vision and Pattern Recognition, Springer, 2017

[5] Akintoye. K. A., Mohd Rahim. M. S and Abdullah A. H, "Challenges of Finger Vein Recognition System: A Theoretical Perspective," Journal of Computational and Theoretical Nanoscience, Vol. 8, No. 2, pp. 196-204, 2018

[6] Khellat-Kihel. S, Abrishambaf. R, Monteiro. J. L and Benyettou. M, "Multimodal fusion of the finger vein, fingerprint and the finger-knuckle-print using Kernel Fisher analysis," Applied Soft Computing, Vol. 42, pp. 439-447, 2016

[7] Bharathi, S, Sudhakar, R and Balas, VE, 'Biometric Recognition Using Fuzzy Score Level Fusion', International Journal of Advanced Intelligence paradigms, Vol. 6, No. 2, pp. 81-94, 2014

[8] Bharathi, S, Sudhakar, R and Balas, VE, 'Hand vein based Multimodal biometric Recognition,' Acta Polytechnica Hungarica, Vol. 12, No. 6, pp. 213-229, 2015

[9] Xuekui Yan, Wenxiong Kang, Feiqi Deng and Qiuxia Wu, "Palm vein recognition based on multi-sampling and feature-level fusion," Neurocomputing, Vol. 151, No. 2, pp. 798-807, 2015

[10] Jinfeng Yang and Xu Zhang, "Feature-level fusion of fingerprint and finger-vein for personal identification," Pattern Recognition Letters, Vol. 33, No. 5, pp. 623-628, 2012

[11] Yong-Fang Yao, Xiao-Yuan Jing and Hau-San Wong, "Face and palm print feature level fusion for single sample biometrics recognition", Neurocomputing, Vol. 70, No. 7, pp. 1582-1586, 2007

[12] Ialiang Peng, Ahmed A. Abd El-Latif, Qiong Li and Xiamu Niu, "Multimodal biometric authentication based on score level fusion of finger biometrics," Optik, Vol. 125, No. 23, pp. 6891-6897, 2014

[13] Maleika Heenaye and Mamode Khan, "A Multimodal Hand Vein Biometric based on Score Level Fusion," Procedia Engineering, Vol. 41, pp. 897-903, 2012

[14] Gurjit Singh Walia, Tarandeep Singh, Kuldeep Singh and Neelam Verma, "Robust multimodal biometric system based on optimal score level fusion model," Expert Systems with Applications, Vol. 116, pp. 364-376, 2019

[15] Hiew Moi Sim, Hishammuddin Asmuni, Rohayanti Hassan and Razib M. Othman, "Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images," Expert Systems with Applications, Vol. 41, No. 11, pp. 5390-5404, 2014

[16] Udresh Dwivedi and Somnath Dey, "Score-level fusion for cancelable multi-biometric verification," Pattern Recognition Letters, Vol. 126, pp. 58-67, 2019

[17] Khellat-Kihel. S., Abrishambaf. R, Monteiro. J. L and Benyettou. M, "Multimodal fusion of the finger vein, fingerprint and the finger-knuckle-print using Kernel Fisher analysis," Applied Soft Computing, Vol. 42, pp. 439-447, 2016

[18] Kun Su, Gongping Yang, Bo Wu, Lu Yang, Dunfeng Li, Peng Su and Yilong Yin, "Human identification using finger vein and ECG signals," Neurocomputing, Vol. 332, pp. 111-118, 2019

[19] Ammour. B., Boubchir. L., Bouden. T and Ramdani. M, "Face–Iris Multimodal Biometric Identification System," Information analysis and processing, Vol. 9, No. 1, 2020

[20] Sengar. S. S., Hariharan. U and Rajkumar. K, "Multimodal Biometric Authentication System using Deep Learning Method," International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, pp. 309-312, 2020

[21] Balas. V. E., Roy. S. S., Sharma. D and Samui, P. (Eds.). "Handbook of deep learning applications" Springer, Vol. 136, 2019

[22] Macsik. P., Pavlovicova. J., Goga. J and Kajan. S, "Local Binary CNN for Diabetic Retinopathy Classification on Fundus Images" Acta Polytechnica Hungarica Vol. 19, No. 7, 2022

[23] Dobes. M and Sabolova. N, "Emotion Recognition Using Pretrained Deep Neural Networks", Acta Polytechnica Hungarica Vol. 20, No. 4, 2023

[24] The SDUMLA-HMT database [Online] Available link: http://mla.sdu.edu.cn/sdumla-hmt.html

[25] Lin C. L and Fan K. C, "Biometric Verification Using Thermal Images of Palm-Dorsa Vein Patterns", IEEE Transaction on Circuits System Video Technology, Vol. 14, pp: 199-213, 2004

[26] Kumar. A and Prathyusha K. V, “Personal authentication using hand vein triangulation and knuckle shape”, IEEE Transaction on Image Processing, Vol. 18, pp: 2127-2136, 2009

[27] Raghavendra. R., Imran. M. Rao. A and Kumar. G. H, “Multi modal biometrics: analysis of hand vein and palm print combination used for personal verification”, Proceedings of IEEE International Conference on Emerging Trends and Engineering Technology, 2010