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A Computational Approach for Score-Level Fusion Decision-Making of Multi-biometric Recognition System Using Ant Colony Optimisation

Manvi Khatri[1,*], Ajay Sharma[1]

[1] Department of Computer Science and Engineering, SRM University, Delhi-NCR, Sonepat, India

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ABSTRACT

This study presents a novel deep learning approach for improving the performance of a multi-biometric recognition system using Ant Colony Optimisation (ACO) at the score level. The proposed method integrates three biometric characteristics, the face, palm, and iris, into a single recognition input. A deep learning model, convolutional neural networks (CNNs), is employed to extract discriminative features from each attribute. The ACO algorithm optimizes the score-level fusion procedure, in which recognition scores from the combined input are combined to make the final determination. The experimental results show the method's efficacy in selecting the score level fusion method per the input biometric and implementation parameters. The ACO-based score-level fusion improves system performance by leveraging complementary information from multiple biometric characteristics, providing a promising solution for robust and accurate multi-biometric recognition in various applications, including access control and identity verification.

1. Introduction

Identifiers might come in the form of hand geometry, fingerprints, ear patterns, facial traits, patterns in the iris and retina, and other types of biometrics. Typing, signature, and voice are behavior-based identifiers. Biometric authentication is more trustworthy. They excel. Even advanced biometric systems have data type and methodological difficulties. Limited degrees of freedom, on-universality, noisy input data, and infraclass heterogeneity prohibit biometric verification systems from identifying people. Security strongly affects verification system performance [1]. Multimodal biometrics describes biometric data uniquely by combining data from different biometric features and sources. Multi-biometric systems may improve identification by preventing spoof attacks, decreasing the failure-to-enrol rate, improving population coverage, and adding degrees of freedom. Multi-biometric systems need more processing, computation, and storage than unimodal biometric systems, but their advantages make them suitable for real-time large-scale verification and authentication [2,3].

[*] *Corresponding author.*
E-mail address: manvi.khatri.18@gmail.com (Manvi Khatri)

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The unimodal system typically identifies users using one biometric trait. Although unimodal systems are trustworthy and much more advanced than their predecessors, they have drawbacks. These include within-class and between-class similarity, similarity across classes, noise in sensed data, non-universality, spoofing attacks, etc [4]. Multimodal biometric systems identify people using many characteristics [5]. They are widely used in real-world applications because they can overcome unimodal biometric system difficulties [4]. Multimodal biometric systems employ module data to integrate an individual's multiple traits. Four types of fusion are sensor, feature, score, and decision. Multimodal biometric systems are a popular secure recognition method because of their numerous advantages over unimodal ones [5].

Human biometrics vary. This category includes physiological and behavioural traits, including fingerprints, faces, irises, palm prints, finger knuckle prints, DNA, stride, voice, signature, and keystroke. Soft biometrics, including height, weight, skin colour, gender, age, moles, and scars, were included. Qualities have pros and cons [6]. The approach must scan the face in a steady backdrop since expression, surroundings, and age impact identification results. Military and access control prevail because identical twins appear the same [7]. Thin eye tissue is vascularized. Biometric retinal blood vessels may be difficult. Needs an eyepiece. "This method of picture capture is unpopular since it requires the user to touch the device and display their sensitive eyes. Single points, texture, microscopic points, and substantial lines may identify a person in the hand. High-security applications require high-resolution images, whereas commercial applications need low-resolution—easy sample collection [8]. Finger length, breadth, palm shape, and size measure hands. Attendance, building access, etc., can only employ geometric attributes for a small population. Time-varying hand geometry lacks discrimination [9]. Most organisms inherit DNA. Genes encode organ development and function. Twins vary genetically. Sampling and analysis are costly. Cloned DNA isn't unique. This helps forensics examine crime scenes. Blood, skin, etc., extract it.

The research described in this work aims to fill a notable void in the domain of multi-biometric recognition systems. The researchers believe in improving the system's performance by adding a unique deep learning approach integrating Ant Colony Optimisation (ACO) at the score level fusion. The amalgamation of three distinct biometric attributes, namely facial, palm, and iris traits, is accomplished through convolutional neural networks (CNNs). These CNNs are employed to extract distinctive and discerning qualities from each attribute. The utilization of Ant Colony Optimisation (ACO) in optimizing the score-level fusion process, which involves the amalgamation of recognition scores derived from the combined input, constitutes a pivotal novelty in this study. The findings provide evidence of the efficacy of this approach, underscoring the significance of choosing the suitable score-level fusion technique according to the input biometric and implementation parameters. ACO-based score-level fusion has effectively harnessed the synergistic information derived from several biometric traits. This study introduces an innovative and encouraging methodology for enhancing multi-biometric recognition systems by successfully integrating deep learning and ACO approaches, resulting in improved system performance. Section 2 covers relevant studies, section 3 covers the suggested technique, section 4 covers simulation findings, and section 5 concludes.

2. Related Work

2.1 Existing Work on Deep Learning

The DeepFace study by Taigman *et al.,* [10] from 2014 is one of the early applications of deep learning to the problem of facial recognition. For the first time, they came close to human performance on the unconstrained condition (DeepFace: 97.35% vs Human: 97.53%), achieving state-of-the-art accuracy on the LFW benchmark. One of the first uses of deep learning in facial recognition, this study is considered groundbreaking. Throughout 4 million training instances, DeepFace learned to identify human faces accurately. After this finding, many researchers started employing deep learning for face identification, which marked a major step forward in face recognition. In another promising work from the same year, Sun *et al.,* [11] proposed DeepID (Deep hidden Identity features) for facial verification. Deep convolutional networks retrieved the DeepID features from the final hidden layer. About 10,000 training images were used to teach this network to detect individual faces.

Tiong *et al.,* [12] developed a multimodal facial recognition system, emphasizing the periocular region and the face. They advocated employing a convolutional neural network (CNN) with seven layers for each feature separately and then combining the feature vectors at the end. They engaged the Multi-PIE dataset, on which they attained an accuracy rate of 98.35%. Geng *et al.,* [13] researched recognizing objects using video and audio. They employed a CNN that included six convolution levels, one completely coupled layer, and SoftMax as the output layer at the very end. In the end, they decided to integrate the qualities of both traits into one to improve recognition. They obtained their information from a television show titled "Friends." They achieved an accuracy of 97.85% as a result of this. Navdeep and Surinder [14] worked on a biometric identification system that uses palm prints and the face. They integrated NN with SVM to get higher levels of productivity. They finished the match with a combined score of 101.0414%. Priya and Mukesh [15] researched human skeletal and facial traits to develop a biometric system for human identification. They first preprocessed the photos, extracted their characteristics, and then used ANNs to classify the images. They were successful in achieving a 98.34% accuracy rate.

Recognition was achieved via the iris and eye thanks to the work of Silva *et al.,* [16]. They employed a customized version of VGG to extract iris and ocular features. They were experimenting with the NICE.II competition database helped them achieve a 5.55% efficiency improvement rate (EER). Using principal component analysis (PCA) for feature extraction and neuro-fuzzy neural networks (NFNN) for matching, Singh and Kant [17] worked on the identification of finger-knuckle prints (FKP) and iris patterns. PolyU FKP and the CASIA Iris database were the datasets that they used. With their model, they could attain an EER of 0.23%.

Face and finger vein identification were research areas for Cherrat *et al.,* [18]. CNN using three convolutional layers alongside a fully connected layer extracted finger vein characteristics, which Random Forest classified. They employed the same CNN architecture, SVM, and fusion score to obtain facial features. They achieved 99.89% accuracy using VERA Finger vein, Colour Feret, and the AR face database. Salem *et al.,* [19] focused on protecting personally identifiable information such as fingerprints and irises. Transfer learning allows for less training on individual users' data, which in turn results in an increased level of system security. For training purposes, they used AlexNet and DenseNet. They accomplished an F1 score of 95.47% because of their architecture. Kumari and Seeja [20] researched face and iris recognition from fuzzy images. Alex Net, Googlenet, Resnet18, Resnet50, Resnet101, VGG16, and VGG19 were among the CNNs tested on the UBIPr database. They achieved perfect accuracy in validation with VGG19 and reached 96% in maximum testing accuracy. Wang *et al.,* [21] employed pretrained and fine-tuned VGG, VIM, and VGM variants to study face and vein recognition. They conducted their experiments using the PolyU NIR-face database and a lab-made hand-dorsal vein database, and their results showed an accuracy of 91.60%.

2.2 Existing Work on Score Level

Classifiers from many fusion characteristics, including the front of the face, the profile of the beginning, and the voice, were suggested by Kittler *et al.,* [22]. The M2VTS database is used to verify the proposed module. Five minutes and eight seconds of video footage from 37 customers are included in this database's voice data. Classifier methods such as product, sum, min, median, and majority voting were utilized in the experiment [22].

Dalila *et al.,* [23] suggested a hybrid model based on the GA-PSO technique to merge biometric modalities at the score level. They employed a normalization strategy to run score modalities using the three publicly accessible multi-biometric datasets (NIST, XM2VT, and BANCA) to verify the fusion-level techniques they used. EER accuracy and ROC curve analyses were performed on the data.

As developed by Latha and Thangasamy [24], a multi-biometric system takes a person's palm print and iris score and mixes them. The final score is compared to the predetermined cutoff point to determine whether or not to accept the applicant. This system uses Ant colony optimization to find the best possible threshold for each worker. CASIA's iris and palm print databases provide more accurate results and more advanced recognition technologies. It is a leading paradigm for using ant colony optimization to raise standards in biometric authentication [24].

The ratio comprising likelihood with common densities was developed by Alford *et al.,* [25] as part of an ideal arrangement that incorporates various modalities of score matching. The fact that certain intervals of scores may be counted as separate is the primary motivation for generalized density [25]. They did this by offering two methods for combining evidence supporting a unified density. The sum rule determines whether or not two characteristics are independent. Dependence between various qualities may be evaluated using the copula rule. The trials are carried out using datasets from both MSU and NIST [26].

3. Proposed Methodology

3.1 Proposed System

The Score-level fusion approach is used further with ACO refinement, improving overall performance. The general working of the procedure is shown in Figure 1.

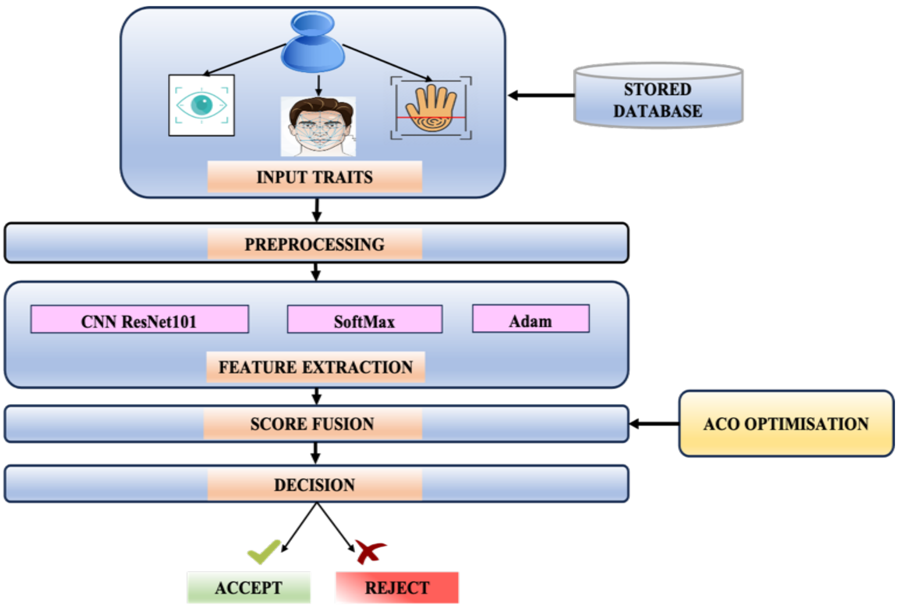

Fig. 1. Score-level fusion multimodal biometric model

3.2 Preprocessing and Feature Extraction

Resizing and improving the photos and the data was done as a sort of preprocessing. To use the Resnet model, the picture resolution was decreased to 224x224 pixels, and data augmentation was used to increase the training data quality and lower the possibility of issues caused by overfitting. These measures were taken to make the model compatible with the Resnet framework. The number of iris pictures rose directly from transformations such as rotation, shearing, magnification, width shifting, and height shifting. To improve visibility, the images of the face and palm were additionally rotated, sheared, enlarged, extended, resized, and horizontally inverted.

For biometric recognition systems to function, feature extraction is required. The process includes reducing the number of attributes used to describe the data while retaining its important properties. Different biometric characteristics need unique approaches to feature extraction. Here is a summary of some of the most often-used methods:

(i) Fingerprint Recognition
- Minutiae-based methods: Extract features like bifurcations and ridge endings.
- Ridge-based methods: Captures patterns of ridges and furrows on the fingerprint.
- Spectral Analysis: Utilizes Fourier or wavelet transforms.
- Texture Analysis: Local Binary Patterns (LBP), Gabor filters, etc.

(ii) Facial Recognition
- Eigenfaces: Principal Component Analysis (PCA) is used to reduce dimensionality.
- Fisherfaces: Linear Discriminant Analysis (LDA) is employed for feature extraction.
- Local Feature Methods: Extract individual features such as eyes, nose, and mouth.
- Deep Learning: Convolutional Neural Networks (CNNs) automatically identify features.

(iii) Iris Recognition
- Gabor Filters: Capture spatial characteristics.
- Wavelet Transform: Multi-scale representation of the iris texture.
- Laplacian of Gaussian: Captures fine details in the iris.

(iv) Voice Recognition
- Mel-Frequency Cepstral Coefficients (MFCC): Represents the short-term power spectrum of sound.
- Linear Predictive Coding (LPC): Models the prediction error in linear approximation of vocal tract.
- Formants: Resonant frequencies in human speech.

(v) Palmprint Recognition
- Principal Lines: Capture the main lines on the palm.
- Texture Features: Wavelet transforms, Gabor filters, or LBP methods.
- SIFT/SURF Features: Identify and describe local features in images.

(vi) DNA Sequencing
- Sequence Alignment: Features like Short Tandem Repeats (STRs) are compared.
- Genomic Variants: SNP (Single Nucleotide Polymorphism) profiles are often used.

(vii) Retinal Scan
- Blood Vessel Patterns: Extracted through segmentation algorithms.
- Zernike Moments: Captures the mathematical characteristics of the retina.

(viii) Signature Recognition
- Static Features: Length, height, width, angles, and area occupied by the signature.
- Dynamic Features: Speed, pressure, and stroke order are considered if available.

(ix) Keystroke Dynamics

- Timing Features: Measures dwell time (key press to release) & flight time (release to next key press).
- Rhythm Patterns: Looks at patterns in which keys are pressed and released.

There are distinguishing characteristics that can reliably identify a person based on each biometric attribute. Modern systems frequently apply machine learning algorithms to extract and pick the most discriminatory traits.

During the feature-level process, the traits relevant to a number of different attributes are combined into a singular collection of features. To provide additional characteristics that are representative of the user, the points that were collected from the three qualities that were examined were merged. In this study, a CNN deep learning model that takes into account palm, face, and iris traits is used. There are four primary stages involved in the process of biometric recognition. One method is taking a digital snapshot of a person using a specialized piece of hardware to get a biometric feature. The use of preprocessing enhances the quality of the picture. Data about features is derived using algorithms. Identifying a person by the matching of extracted attributes is helpful.

3.3 Why ACO Optimisation?

Marco Dorigo created Ant Colony Optimisation (ACO) in 1992. Using an ant's conduct as a model, this method is among the most effective ways to get the greatest possible answer. Every ant starts with the same pheromone level, which is then optimized via comparisons depending on resource availability and similarity between ants of different positions. Both the evaporation factor and the Q-pheromone constant (both of which are always smaller than 1) play crucial roles in ACO. Each ant's starting value is determined randomly within a predetermined range [27].

Ants are sociable insects that form large communities. For an ant, finding food is priority number one. It will watch over nearby colonies while out foraging. To find nourishment, ants go from one location to another. Pheromones are tiny organic components left behind by an organism moving from one place to another. Pheromone trails are a means of communication between ants. When a particular quantity of prey is discovered, it is transferred to the maximum extent. Depending on the amount and kind of pheromone, it is kept before being returned. The ant keeps a watchful eye on the victim. As a result, the remaining ants watch the leader's actions and replicate them. Most ants go in the same direction, which is determined by the strength and consistency of a pheromone. Meanwhile, there is a predictable rise in pheromone deposition.

Specifically, ACO employs a method known as "exploitation and exploration." The ants utilize exploitation to find the optimal option among all feasible ones and then force the other ants to adopt it [28]. Exploration is a tool for finding the best way forward in a given environment.

These procedures will be used in ACO:

(i) Ants forage randomly, going from the nest to their goal and back again through pheromone trails. Pheromone trails will be used to find the shortest routes.
(ii) Ants often choose the shortest route between two points.
(iii) After the pheromone trails have evaporated and the shortest route has been updated, the ants can no longer take the longer course. This evaporation process will ensure that the ant colony takes the quickest route possible rather than the lengthy way around. Pheromone trails are used for this purpose.

3.3.1 Algorithm for Updating Each Ant's Pheromones

Pheromone updates are used to determine an ant's goal function. If i^{th} solution is selected in i^{th} iteration:

$$\tau_i\ (t+1) = \rho^*\tau_i\ (t) + \left(\frac{Q}{E}\right) \tag{1}$$

$$\tau_i\ (t+1) = \rho^*\tau_i\ (t) \tag{2}$$

Where

$\tau_i(t)$ = i^{th} solution pheromone level
Q = Pheromone constant
E = Error calculated
ρ = Evaporation factor

4. Experimental Result and Analysis

Out of 16566 captured images, 11585 were used for training, and the remaining photos were used for testing. The images were taken from three databases: the PolyU-IITD Contactless Palmprint Images Database (Version 3.0), the PolyU Cross-Spectral Iris Image, and the Tufts Face datasets [27–30].

Our proposed computer system used both the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) as performance metrics. The FAR is used to determine the number of faulty inputs that were accepted by the system in error. The FRR evaluates the number of legitimate inputs processed by the system but rejected.

$$\text{FAR} = \frac{\text{How many times does the system accept faulty inputs}}{\text{Sample Size}} \tag{3}$$

$$\text{FRR} = \frac{\text{Valid inputs rejected incorrectly}}{\text{Sample Size}} \tag{4}$$

Error reduction is one of the primary focuses of the newly developed fusion system. FAR and FRR may be calculated by the use of their weighted sum as:

$$\text{E} = \text{CFA}^*\text{GFAR} + \text{CFR}^*\text{GFRR} \tag{5}$$

$$\text{CFR} = 2\text{-CFA} \tag{6}$$

Where

CFA = Cost function corresponding to False Acceptance Rate (FAR)
CFR = Cost function corresponding to False Rejection Rate (FRR)
GFAR and GFRR = = Global error rates estimated using ideally chosen fusion rules to reduce error (Eq. (1)).

To identify the fusion parameters for the ACO algorithm, Cost Factor Analysis (CFA) is used. It allows for a more rapid execution of the algorithm.

The ACO algorithm uses the parameters Q= 0.01 and ρ=1, where ρ is gradually lowered by 0.005 with each algorithm iteration. We experiment with CFA costs ranging from 0.1 to 1.9, and we choose optimum thresholds and related fusion rules for each CFA. To determine the probability of rule selection corresponding to each CFA, the whole algorithm was performed 100 times, as shown in Table 1.

Table 1
GFAR and GFRR of significant fusion rules

Rule	GFAR	GFRR
Iris Only	FAR1	FRR1
Face Only	FAR2	FRR2
Palm Only	FAR3	FRR3
Iris and Palm (OR)	FAR1+FAR3-FAR1*FAR3	FRR1*FRR3
Iris and Palm (AND)	FAR1*FAR3	FRR1+FRR3-FRR1*FRR3
Face and Iris (OR)	FAR2+FAR1-FAR2*FAR1	FRR2*FRR1
Face and Iris (AND)	FAR2*FAR1	FRR2+FRR1-FRR2*FRR1
Palm and Face (OR)	FAR3+FAR2-FAR3*FAR2	FRR3*FRR2
Palm and Face (AND)	FAR3*FAR2	FRR3+FRR2-FRR3*FRR2
Iris, Face and Palm (OR)	FAR1+FAR2+FAR3-(FAR1*FAR2)-(FAR1*FAR3)-(FAR2*FAR3)+(FAR1*FAR2*FAR3)	FRR1*FRR2*FRR3
Iris, Face and Palm (AND)	FAR1*FAR2*FAR3	FRR1+FRR2+FRR3-(FRR1*FRR2)-(FRR1*FRR3)-(FRR2*FRR3)+(FRR1*FRR2*FRR3)

The three biometric characteristics of the same individual were employed in our system so that we could assess how well our suggested task would operate. The score level could potentially improve by the application of score-level fusion. It was accomplished using normalized scores of combined inputs from three characteristics, which were merged by applying a simple sum rule or a product rule to carry out the fusion. The work that we are proposing covers three different instances.

The terms GFAR (Genuine Acceptance Rate) and GFRR (Genuine False Rejection Rate) are used to measure the accuracy of biometric systems. The more frequent FAR and FRR acronyms are False Acceptance Rate and False Rejection Rate. On the other hand, GFAR and GFRR require context-specific understanding if you're dealing with a particular system or research that employs them. The percentage of genuine identification attempts the biometric system accepts is the Genuine Acceptance Rate. If the system successfully recognizes the people it should, then the GFAR will be high. That is to say, if the GFAR is high, the system will likely be easy to use and won't create unnecessary roadblocks for legitimate users. The percentage of honest efforts at identification that were wrongly rejected by the biometric system is expressed as the Genuine False Rejection Rate.

A lower GFRR is preferred since a higher GFRR increases the likelihood that valid users would be refused access. This might be problematic in situations where fast access is essential, such as with emergency services, and would make the system less user-friendly overall. Optimizing for one might impair the other regarding security and usability. Therefore, it's important to strike a balance between the two. Using these measures, a sweet spot may be discovered. These percentages are the metrics by which every biometric system may be evaluated. They are also useful for contrasting the efficiency of various setups. Since it would be less likely to identify authorized users incorrectly, a system with a high GFAR and low GFRR would provide a better user experience. Some sectors and applications have specialized rate requirements, making these rates essential for meeting legal or industry standards. A high GFRR may necessitate additional time-consuming and expensive manual operations to ensure accuracy. A low GFAR, on the other hand, might jeopardize security and result in monetary or data loss.

The values of FAR and FRR for each characteristic are shown in Table 2.

Table 2
FAR and FRR values of traits

	TRAITS	FAR	FRR
Case 1	IRIS	0.1	0.1
(All are equal)	FACE	0.1	0.1
	PALM	0.1	0.1
Case 2	IRIS	0.2	0.3
(Any two equal)	FACE	0.01	0.02
	PALM	0.01	0.02
Case 3	IRIS	0.0015	0.021
(All are different)	FACE	0.002	0.025
	PALM	0.001	0.03

The experimental findings of three scenarios with varying CFA values are shown in Table 3 and Figure 2, along with their respective minimal E-value comparisons. Case 1 demonstrates that when the values of FAR and FRR of all three characteristics are the same, the OR fusion rule will be selected with whichever two aspects have the lowest value of CFA. In addition, if the value of CFA is high enough, it will cause the AND fusion rule to be applied to any two characteristics. The results of Case 2 demonstrate that if the values of any two features are the same, the CFA parameter with the lower value will choose the OR fusion rule. In contrast, the CFA parameter with the higher value will select the AND fusion rule with the two lower characteristics' values. Lastly, Case 3 demonstrates that the lower and greater the value of CFA, the more likely it is that the OR fusion rule will be chosen, with the two characteristics having the lowest FAR and FRR values.

Table 3
Minimum error rates corresponding to CFA and fusion rules selected with the ACO algorithm

	Case-1		Case-2		Case-3	
CFA	Min-E	Rule Selected	Min-E	Rule Selected	Min-E	Rule Selected
0.1	0.029	All-OR	0.00275	FP-OR	0.000479	All-OR
0.2	0.0561	All-OR	0.00474	FP-OR	0.000929	ALL-OR
0.3	0.076	FP, PI, FI-OR	0.00673	FP-OR	0.001378	FP-OR
0.4	0.095	FP, PI, FI-OR	0.00872	FP, PI, FI-OR	0.001827	ALL-OR
0.5	0.114	FP, PI, FI-OR	0.01071	FP-OR	0.002277	FP-OR
0.6	0.133	FP, PI, FI-OR	0.0127	FP-OR	0.002696	PI-OR
0.7	0.152	FP, PI, FI-OR	0.01469	FP-OR	0.002946	PI-OR
0.8	0.171	FP, PI, FI-OR	0.01668	FP-OR	0.003196	PI-OR
0.9	0.19	FP, PI, FI-OR	0.01867	FP-OR	0.01867	FP-OR
1	0.2	FP, PI, FI-AND	0.02066	FP-OR	0.003696	PI-OR
1.1	0.182	FP, PI, FI-AND	0.02265	FP-OR	0.003945	PI-OR
1.2	0.076	FP, PI, FI-OR	0.00673	FP-OR	0.001378	FP-OR
1.3	0.164	FP, PI, FI-AND	0.02464	FP, PI, FI-AND	0.004195	PI-OR
1.4	0.146	FP, PI, FI-AND	0.02663	FP-OR	0.004445	FP-OR
1.5	0.11	FP, PI, FI-AND	0.01995	FP-AND	0.004945	PI-OR
1.6	0.092	FP, PI, FI-AND	0.016	FP, PI, FI-AND	0.005195	PI-OR
1.7	0.074	FP, PI, FI-AND	0.01205	FP-AND	0.005444	PI-OR
1.8	0.056	All-AND	0.0081	FP-AND	0.005694	PI-OR
1.9	0.029	All-AND	0.00415	FP-AND	0.004553	FI-AND

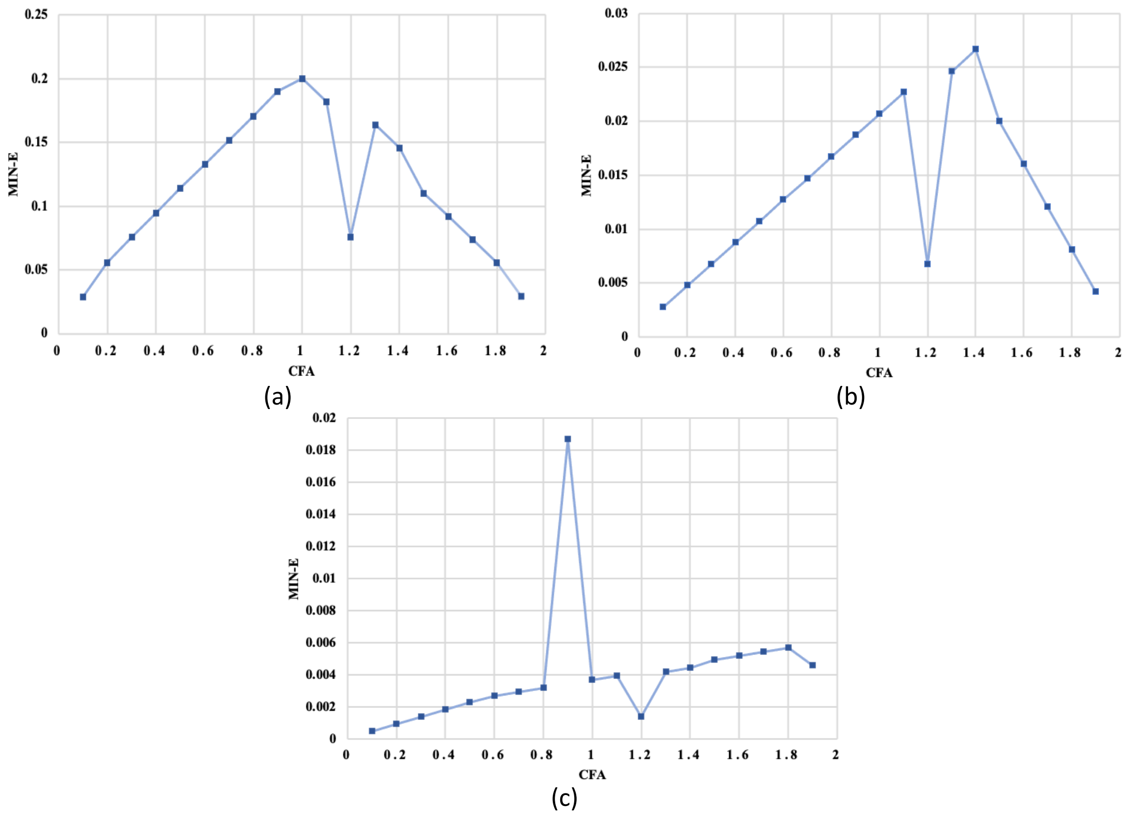

Fig. 2. Error plotted over CFA in three different scenarios: (a) when all values are identical, (b) when any two values are identical, and (c) when all values are different

The experimental findings of existing and proposed works are shown in Table 4, along with the accuracy gained by these models.

Table 4
Result Comparison

S. No.	Authors	Technology used	Result gained
1	Taigman *et al.,* [10]	Deep learning	97.35%
2	Tiong *et al.,* [12]	Convolutional neural network (CNN)	98.35%.
3	Geng *et al.,* [13]	CNN	97.85%
4	Priya and Mukesh [15]	ANNs	98.34%
5	Proposed Method	CNN with ACO	99.66%

5. Conclusions and Discussion

In this work, we provide an ACO approach to score fusion decision-making based on deep learning. Within the scope of this study, the ACO is used to determine the score-level decision rule (i.e., AND or OR) and the number of biometric characteristics (i.e., Face, Palm, and Iris) necessary to arrive at a productive conclusion. In addition, the findings show that the choice of fusion rule and modalities of biometric features depends on the FAR, FRR, and CFA. The chance of picking the OR rule for combining the results of multiple qualities is high when the value of CFA is low, but the AND rule will be directed towards it when the value of CFA is high.

Further, suppose the FAR and FRR parameters are set too high. In that case, choosing the maximum number of biometric characteristics will be forced upon the user. However, selecting only one biometric trait will be enough if the FAR and FRR parameters are too low. The work may be expanded even further to incorporate additional score-level fusion, such as the mean, the minimum, the maximum, the tanh, and the median.

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