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TRACK 2: MEDICAL APPLICATIONS OF MULTIMEDIA

HDL-PI: hybrid DeepLearning technique for person identification using multimodal finger print, iris and face biometric features

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Abstract
Due of its uniqueness, biometric technologies are employed for security and access control in today's digital world. Global demand for biometric technology has led to the development of biometric systems integrating many features. The robustness depends on the capacity to derive meaningful information from single biometric features. Multimodal biometric security systems are thought to be more accurate and secure than unimodal ones. An attacker may still enter the system using a stolen or hacked biometric data, even the greatest multi-biometric architecture. A hybrid deep learning approach for person identification (HDL-PI) employing palm print, iris, and face biometric features is proposed. It eliminates undesirable artefacts from the raw input image. After feature extraction, we develop a modified group search optimization (MGSO) technique to optimize features and minimize data dimensionality. In order to improve prediction accuracy and minimize error metrics, teacher learning based deep neural networks (TL-DNN) is presented. Performance measurements include accuracy, precision, recall, and F-measure; error metrics include equal error rate (EER), false alarm rate (FAR), false rejection rate (FRR), and genuine acceptance rate (GAR).

Keywords Biometric · Person identification · Multimodal · Hybrid deep learning · Feature selection

1 Introduction

To validate or establish a person's identity, current systems need dependable personal identification systems. With the Personal Identity Program, only authentic real users may access

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the services [26]. Automated authentication technologies are widespread in any application related to security based on a person's behavior and physical characteristics. Biometric systems enable access to physical, informational, and other rights and advantages. Thus, these systems employ attributes to detect a person's private, legal, and social issues [11, 17]. Physiological and behavioral features are biometric identifiers. Face, Iris, voice, DNA, or handprints are examples of physiological biometrics. Behavior Biometrics is concerned with human behavior such as typing, walking, voice, and handwriting. Biometrics is currently employed practically everywhere [6]. These include birth certificates, naturalization certificates, passports, identification cards, and other government-issued proof of citizenship. Multimodal biometric systems provide an alternative when noise sensor data, variations of lighting, pricing for various events, biometric features and fraud attacks cannot be easily understood by a person [28]. In addition, additional information can be provided through various biometrics, resulting in a higher identification system. In fact, a multibiometric system can be divided into four categories: multiple sensors, multiple models, multiple mechanisms, and multiple events [14]. Linking information from multiple biometric sources is called information fusion. This can be divided into three different level combinations [18]. At the sensor level, the fusion process takes place in front of the recovery module, and this can only be done if the various acquisitions are instances of the same biometric module derived from multiple compatible sensors. Character-level merging is the process of combining different characteristic vectors generated from different biometric models to form a single model or characteristic vector [19, 20]. Only in the case of mutually compatible or homogeneous characteristic vectors can they be combined as a characteristic vector. The score level is matched after the competition module has created competition scores between the test sample and the database sample as an indicator of similarity or difference for each sample system.Recently, identification systems based on biometrics and security concerns have become areas of research interest. Because of the similarities between individuals, most studies in the literature review focus on fingerprints, face, fingerprints, and iris [9]. In particular, the challenges of facial recognition include appearance, age changes, beard and makeup. Ear images are less susceptible to changes in appearance or makeup than face images, and the combination of face / ear recognition gives less recognition and is easier to understand by recognizing face and ear [25].

Several techniques combining two or three biometric features have emerged in recent years.Multimodal biometric finger recognition integrates the functions of fingerprint, fingerprint, finger shape and finger-to-finger printing from a human finger. Multimodal biometrics uses a triangle standard with a four-finger biometric mark [24].The ROI local gradient system (SLG) of the Palmer axis and the annual axis are derived and modified using the brand, which allows for a strong image of a strong V code and an image of an index h [23].The confidence-based late integration framework used for audiovisual biometrics [2] shows that competitive confidence can be computed from competitive confidence scores and that a coefficient C can be computedto convert competitive scores. MFCC and PLP, both GMM speakers, were employed to develop the voice recognition model.The facial recognition model is based on clean face and Euclidean distance (EUD) [4]. Despite their importance in forensic and biometric applications, previous studies on lipprints have yielded very few results [34]. The multimodal detection system is based on the Multiple Vector Neural Network (MSVNN) based on Chloe Penguin search optimization algorithm [32]. The multimodal single-sensor approach to manual venous-based biometric detection is challenged. Image of hand nerves, structured palmar nerve and four ROIs of finger nerve were obtained [8]. The integration scheme [1] is used as a multimedia biometric system for human recognition to distinguish sounds and faces. The sound recognition process shows that the best results are obtained by simulating septal coefficients using the GMM classifier display. A multimodal biometric technique based on converting individual waves encoded for image analysis and recognition [29]. Multimodal biometric system using optimal score level fusion.To optimally integrate three additional biometric properties of the iris, face and fingerprint by using optimized biometrics with the help ofbacktracking search optimization algorithm (BSA) [33].

The three physiological biometrics Face, Fingerprint and Iris employed in ourresearch have receive significant benefits, since fingerprint is user friendly and robust. Iris texture is unique even for twins. Face is a reliable as reported in lots of literature. High priority of the system is to ease and improve efficiency of identification, by disallowing any fraudulent act. The above mentioned methods are enhanced in this proposed methodology that is briefly explained in our paper.

1.1 Our contributions

For further enhancing the detection accuracy and performance enhancement, we propose a Hybrid Machine Learning technique for Person Identification (HML-PI) using multimodal finger print, iris and face biometric features. The proposed HDL-PI approach has the following major contributions:

1. An Improved Whale Optimization (IWO) technique is developed for unwanted artifact removal from the input image in pre-processing.
2. Modified Group Search Optimization (MGSO) algorithm is used for feature optimization which gives best optimal features among multiple features to reduce data dimensionality issues.
3. Teacher Learning based Deep Neural Network (TL-DNN) is used for person identification which enhances the prediction accuracy and reduces all error metrics.
4. Finally, the effectiveness of proposed TL-DNN technique is analyzed with the standard benchmark multimodal SDUMLA-HMT database. In terms of quality and error metrics, simulation results are compared to existing methodologies.

2 Review of literature and development in the subject

In recent years, researchers throughout the world have examined multimodal person identification. Table 1 summarizes several research gaps.

An ensembled support vector machine based kernel mapping (ESVM-KM) technique was developed by Raja et al. [27] for multimodal biometric recognition. The ESVM-KM technique was designed for improving the accuracy of multimodal biometric recognition with human face, finger print and iris images. The ESVM-KM technique initially performed the preprocessing in order to remove noise and to improve the image quality for human recognition. After that, ESVM-KM technique carried outs Gabor wavelet transformation based feature extraction process in which features of human face, finger print and iris images are efficiently extorted for classification. Finally, the ESVM-KM technique used ensembled SVM classifier for enhancing the recognition rate of multimodal biometric system. The ESVM-KM technique conducts simulation worked on the metrics such as computational time, recognition rate, and true positive rate. The simulation results demonstrated that the ESVM-KM technique was able to improve the recognition rate and also reduced computational time of multimodal biometric recognition system when compared to state-of-the-art works. The results got through ESVM-KM are stored in cloud environment for easy and future access.

Ammour et al. [5] developed a new feature extraction technique for a multimodal biometric system using face–iris traits. The iris feature extraction is carried out using an efficient multi-resolution 2D Log-Gabor filter to capture textural information in different scales and orientations. On the other hand, the facial features are computed using the powerful method of singular spectrum analysis (SSA) in conjunction with the wavelet transform. SSA aims at expanding signals or images into interpretable and physically meaningful components. SSA was applied and combined with the normal inverse Gaussian (NIG) statistical features derived from wavelet transform. The fusion process of relevant features from the two modalities are combined at a hybrid fusion level. The evaluation process is performed on a chimeric database and consists of Olivetti research laboratory (ORL) and face recognition technology (FERET) for face and Chinese academy of science institute of automation (CASIA) v3.0 iris image database (CASIA V3) interval for iris. Experimental results showed the robustness.

Aleem et al. [3] presented local non-negative matrix factorization (LNMF) to reduce face subspace dimension. Face and fingerprint biometrics were employed in a multimodal biometric recognition system. The two biometric modalities were normal and acceptable. Elastic alignment extracted finger image features. Matching score fusion of selected modalities. Face recognition depended on high face space. Finding an inherently low-dimensional subspace that efficiently described the data was beneficial.

A method by Sujatha et al. [30] proved with experimental results on multimodal biometric algorithm for authentication using normalized score-level fusion techniques and hybrid Genetic Algorithm and Particle Swarm Optimization for optimization in order to reduce the parameters considered for evaluation as false acceptance rate and false rejection rate and to enhance accuracy. In their research work, it integrated iris, finger vein, and finger print biometric traits chosen for their best biometric characteristics. The experiment was conducted by SDUMLA-HMT database, and the state-of-art algorithm is evaluated by metrics as false acceptance rate, false rejection rate, equal error rate, and accuracy for proving that the claimed identity as genuine or imposter.

Chanukya et al. [10] used the multimodal biometrics for the purpose of person certification and proof. Lot of biometrics is used for human authentication in which ear and fingerprint are efficient one. There are three vital phases involved in the biometric detection which include the preprocessing, Feature extraction and the classification. Initially, preprocessing is done with the help of median filter which lends a helping hand to the task of cropping the image for choosing the position. Then, from the preprocessed Finger print and ear image texture and shape features are extracted. In the long run, the extracted features are integrated. The integrated features, in turn, are proficiently classified by means of the optimal neural network (ONN). The NN weights are optimally, selected with the help of firefly algorithm (FF). The biometric image was classified into fingerprint and ear if the identical person images are amassed in one group and the uneven images are stored in a different group. The performance of the developed approach was analyzed in terms of evaluation metrics.

A novel method for data augmentation technique have been introduced by Umer et al. [31]. For features extraction and classification tasks well-known, VGG16, ResNet50, and Inception-v3 CNN architectures have been employed. The performance due to iris and periocular are fused together to increase the performance of the recognition system. The extensive experimental results have been demonstrated in four benchmark iris databases namely: MMU1, UPOL, CASIA-Iris-distance, and UBIRIS.v2. The comparison with the state-of-the-art methods with respect to these databases shown the robustness and effectiveness of the developed approach.

Rahman et al. [12] studied the performance of different classification techniques and fusion rules in the context of unimodal and multimodal biometric systems based on the electrocardiogram (ECG) and fingerprint. The experiments are conducted on ECG and fingerprint databases to evaluate the performance of the presented biometric systems. MIT-BIH database was utilized for ECG, FVC2004 database is utilized for the fingerprint, and further experiments are being performed to evaluate the developed multimodal system with 47 subjects from virtual multimodal database. The performance of the developed unimodal and multimodal biometric systems was measured using receiver operating characteristic (ROC) curve, AUC (area under the ROC curve), sensitivity, specificity, efficiency, standard error of the mean, and likelihood ratio. The findings indicated AUC up to 0.985 for sequential multimodal system, and up to 0.956 for parallel multimodal system, as compared to the unimodal systems that achieved AUC up to 0.951, and 0.866, for the ECG and fingerprint biometrics, respectively. The overall performance of the developed multimodal systems was better than that of the unimodal systems based on different classifiers and different fusion levels and rules.

El-Bendary et al. [13] presented different fusion types in multimodal biometrics. There are two unimodal schemes have been presented based on using the voice and face image individually, those two biometrics have been used in the multimodal biometric scheme. The presented multimodal scheme was evaluated and applied using the feature and score fusion. The mechanism operation of presented algorithm started with capturing the biometics signals 'Face/Voice', the second step is the feature extracting from each biometric individually. The Artificial Neural Network (ANN), The Support Vector Machine (SVM) and the Gaussian Mixture Model (GMM) classifiers have been employed to perform the classification process individually. The computer simulation experiments reveal that the cepstral coefficients and statistical coefficients for voice recognition performed better for the voice scenario. Also, the Eigenface and support vector machine tools in the face recognition scheme performed better than other schemes. The multimodal results better than the unimodal schemes. Also, the results of the scores fusion-based multimodal biometric scheme was better than the feature fusion-based scheme. Hence, the biometric-based authentication was effective and applicable for the WBANs authentication and personality continuous authentication on these medical applications wireless networks.

Mustafa et al. [22] developed a decision fusion technique for the combination of iris and fingerprint biometrics in a process devoid of any form of pre-processing; their approach was proposed based on the review of the existing literature in the domain. It involved the combination of fingerprint and iris biometrics using the Gray-Level Co-occurrence Matrix (GLCM) with KNN for feature extraction, while the AND gate is used making the final decision. From the results, the developed fusion approach clearly performed better than approaches that are based on single modality; the developed method achieved 95% efficiency level in terms of making final decision on 20 test users.

3 Problem statement and system architecture

3.1 Problem statement

To ensure a secure cyber-physical system, a novel multi-modal biometric system based on face and finger print is developed by Sidra Aleem et al. [3]. Finger print matching is performed

Table 1 Summary of research gap

Ref.	Model	Features	Key algorithm	Notable Parameter	Advantages	Limitations
[27]	Multimodal	Human face, finger print and iris	ESVM-KM, Gabor Wavelet Transformation based Feature Extraction Algorithm	Computational time, recognition rate, and true positive rate	Improved the recognition performance of multimodal biometric system	Multi-spectral samples are collected in low, changing light.
[5]	Multimodal	Face–iris	Spectral Regression Kernel Discriminant Analysis (SRKDA)	Accuracy,Recognition rate	Robustness	No efforts were made to enhance two-phase system performance.
[3]	Multimodal	Face and finger print	LNMF	EER, FAR and FRR	Matchingspeed and accuracy	Distance to camera, equipment, and operator training impact performance.
[30]	Multimodal	Iris, finger vein, and finger print	Hybrid Genetic Algorithm and Particle Swarm Optimization	False acceptance rate, false rejection rate, equal error rate, and accuracy	Claimed identity as genuine or imposter	Dynamic time warping for classification.
[10]	Multimodal	Fingerprint and ear	ONN	Accuracy, sensitivity and specificity	Shape of the image is segmented proficiently	Consistent authentication is essential nowadays.
[31]	Multimodal	Iris and periocular	VGG16, ResNet50, and Inception-v3 CNN architectures	Accuracy	Robustness and effectiveness	As training samples increase, accuracy improves.
[12]	Multimodal	ECG and fingerprint	CNN	Accuracy and ROC	Minimize intrusion and minimize fraud ofcredentials.	Increased biometric identification methods.
[13]	Unimodal	Face	ANN, SVM	EER	The user do not need enter the biometric data again and again	The biometrics security is not suitable for the WBAN nodes
[22]	Multimodal	Fingerprint and iris	Gray-LevelCo-occurrence Matrix (GLCM) with KNN	Accuracy	The failure of a singleclassifier can be recovered by using the other classifier.	Choosing an algorithm is a time-consuming and difficult task.
[3]	Multimodal	Face and finger print	Elastic Alignment Algorithm	Accuracy	a) Effective face texture information extraction, b) dimensionality reduction of the facial subspace.	Biometric trait and uniqueness affect the single biometric systems

using alignment-based elastic algorithm. For the improved facial feature extraction, extended local binary patterns (ELBP) are used. For the effective dimensionality reduction of extracted ELBP feature space, local non-negative matrix factorization was used. Score level fusion is performed for the fusion.

Experimental studies show that multimodal biometrics provide enhanced identification ratios compared to Unimodal biometrics. In general, multimodal biometric authentication effectively modifies Unimodal biometric security system to address a wide range of technical shortcomings in identity management and authentication. Legitimacy is essential for secure, confidential data transfer in banking, the military, and healthcare. Fraudulent issues can be solved through combination of several independent biometric systems. The function extraction method significantly affects the performance of the system and ways to separate several functions. Data security is a centralized cloud's main limitation [16], complete computer management, lost storage and system capabilities.

Within these limits, security raises serious concerns about unapproved access to personal data. Biometric data, in particular, is protected under the Privacy Act. For edge-to-edge cloud environments, this paper proposes a multimodal authentication system incorporating cryptographic biometrics. A sorting system's error rate is generally expressed as a percentage of the database to search. The confusing matrix classifier provides detailed behavioral analysis. Now, some newer applications, such as Aadhaar card system, use facial, finger, and iris functions to identify person.

In order to address the aforesaid challenges, many researchers put forth their ideas, but the problem is still remains. No single system is foolproof. Thus, using a multi-biometric system increases security (Here means improving recognition accuracy) and broadens support for and acceptance by the user population by offering alternatives. Researchers are endeavouring to improvise the performance of identification process by combining different biometric traits, strategies reducing the misclassification, enhancing the accuracy (recognition rate) and reducing computational cost. But obtaining a system having these qualities is still a challenging task. This circumstance has motivated me to deem it as my research. In order to achieve the aforesaid challenges, selecting efficient classifiers and reliable method for feature selection, introduce efficient method for feature extraction, introducing the novel method for multilevel segmentation, introducing multi-modal biometric comprising of face, fingerprint and iris traits, analyzing the performance measuring metrics with different fusion approaches and measuring performance of unimodal and multi-modal biometrics are the contributions of the research work. Finally, we show that fusion of uncorrelated modalities such as fingerprint, face and iris achieves better efficiency compared to unimodal biometric systems.

3.2 Research gap

For biometric systems to be efficient, the similarity between various inputs from one individual must be high, and it should be low between inputs taken from different individuals. Most of the research in the field of biometrics is centered on some main problems:

i) To find the best representation scheme for a particular trait. The feature extractor must be capable of minimizing intra-subject variations.
ii) To design robust algorithms for feature extraction is another major challenge in biometric systems. Matching algorithms should be chosen based on the characteristics of various traits.

iii) Permanence and distinctiveness of traits affect the performance of a biometric system. Hence it is important to analyze these properties while designing the system.
iv) Biometric templates can be compromised or stolen. In case an adversary replicates an individual's trait used for authentication, he could use it to gain access to crucial applications. Authors identified different points of attacks in a system, including those at the interface, modules, template database, etc.
v) Another issue arises with a unimodal system that do possess some inhibitions in the measures of exactness in recognition, spoofing and replacing some other forged prototype instead of the genuine one. Hence, we have decided to go in for an effectual multi-modal recognition algorithm.

In this paper, we survey some of these challenges and the role of deep learning in tackling them. These include detection of spoofing attacks, protection of biometric templates and identification of traits in unconstrained conditions. We highlight the superiority of deep learning algorithms over state-of-the-art methods and potential future directions thatwould be useful for researchers. For example, the role of multimodal biometric systems to enhance security is becoming important these days.

3.3 Objectives

The proposed method's major objectives are:

1. To develop a novel hybrid machine learning approach for person identification using multi-model biometrics.
2. To study and analyze the image pre-processing algorithms to enhance the input image quality.
3. To introduce optimization technique for feature fusion to improve the detection accuracy.
4. To propose hybrid neural network based classifier to predict the person which is more suitable for medical application such as dead body identification.

3.4 System architecture

Figure 1 illustrates the proposed hybrid deep learning technique for person identification (HDL-PI) system architecture. The proposed method's working process consistsset of process such as preprocessing, future extraction, future fusion, feature selection and person identification.Using the correlation criteria function, we aim to learn canonical correlation features from Face, Iris, and Fingerprint feature sets in canonical space. Then, using the fusion technique in canonical space, the dataset is generated with fused feature vectors for every training sample. Next, the optimally selected features have been used to identify person by using TL-DNN classifier which ensures the detection accuracy.

4 Proposed methodology

This section demonstrates the proposed HDL-PI technique working process which consists following set of process.

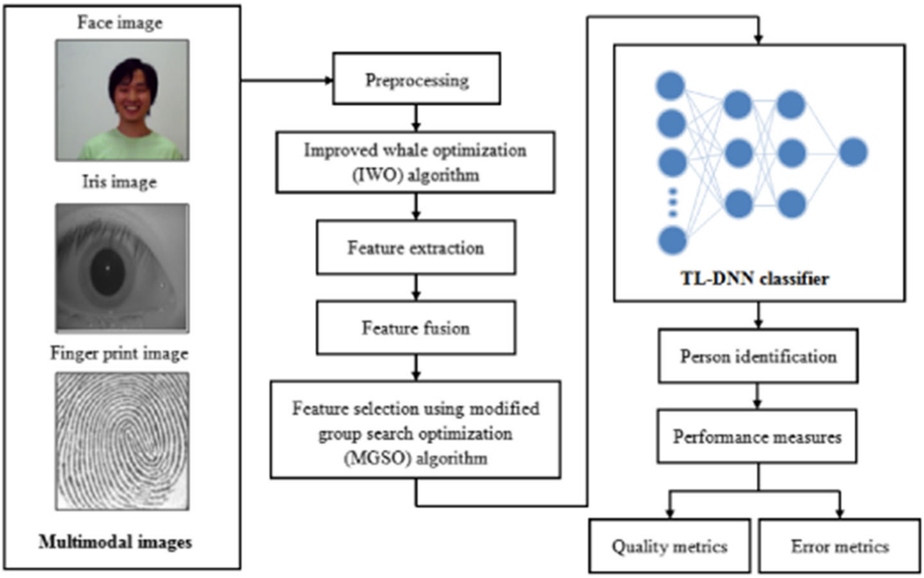

Fig. 1 Proposed HDL-PI method architecture

1. Dataset description
2. Data pre-processing
3. Feature extraction
4. Feature selection
5. Feature fusion
6. Person identification

4.1 Dataset description

SDUMLA-HMT was collected at Shandong University in Jinan, China, in 2010. The data collection technique included 106 people, 61 males and 45 females, aged 17 to 31. Each subject's face, finger vein, gait, iris, and fingerprint were collected. SDUMLA-HMT has five sub-databases: face, finger vein, gait, iris, and fingerprint. Significantly, in all five sub-databases, the same subject's biometric features are captured.

4.1.1 Fingerprint dataset

It is a popular biometric feature for authentication. The fingerprint database from 5 sensors also helps research on sensor interoperability in fingerprint identification, a current hotspot. Our fingerprint database contains thumb, index, and middle finger photos from both hands. Authentic Inc.'s AES2501 swipe fingerprint scanner; Zhongzheng Inc.'s FPR620 optical fingerprint scanner; Zhongkong Inc.'s URU4000 optical fingerprint scanner; and Changchun Institute of Optics, Fine Mechanics, and Physics' ZY202-B optical fingerprint scanner. Each of the 5 sensors captured 8 impressions for each of the 6 fingers. Figure 2 shows the some sample fingerprint images from the SDUMLA-HMT dataset.

Fig. 2 Fingerprint test samples from SDUMLA-HMT dataset which captured from multi-sensors AES2501, FPR62, FT-2BU, URU4000 and ZY202-B (top to bottom)

4.1.2 Iris database

Recent research has focused on iris recognition [15]. High quality image with many details has important role in segmentation. Using High Dynamic Range technique, image details can be increased. In this paper, using converting iris images into HDR iris images, segmentation operation is performed. Images are changed to different exposure manually, then are combined and produced HDR image using iris database. Statistical studies demonstrate that iris has the most dependable and stable biological features. So we incorporated an iris database to SDUMLA-HMT. We used an intelligent iris capture equipment created by the University of Science and Technology of China to acquire iris data. This meant that individuals had to remove their glasses and stay a distance of 6 cm to 32 cm from the apparatus. Each individual submitted 10 iris images, 5 for each eye. Figure 3 displays various SDUMLA-HMT iris images. SDUMLA-HMT dataset contains 1060 iris images. Each iris image is a 256 Gy-level "bmp" file with 768 × 576 pixels of image resolution is important for input images.

4.1.3 Face database

Face recognition is a mature biometric technique. SDUMLA-face HMT's database aims for real-world face recognition. Face data capture considers four variations: poses, facial expressions, illuminations, and accessories. Our face database contains images of people in 3 poses (upward, forward, and downward), 4 expressions (smile, frown, surprise, and close eyes), and 2 accessories (glasses and hat). Just "on" the one lamp and recorded 3 sorts of facial images. The database has 8904 images. All images with 24 bit "bmp" files of 640 × 480 pixels of image resolution is important for input images. Figure 4 shows the some sample face images from the SDUMLA-HMT dataset.

4.2 Data pre-processing

The pre-processing process improves the quality of the finger print, iris, and facial images and extracts the regions of interest. The face is the most important part of the body. It is enhanced by histogram equalization that increases image contrast. The facial image is then cropped using the improved whale optimization (IWO) algorithm's left and right eye centre positions. The IWO algorithm detects local regions of the facial image (left and right iris, nose, mouth).Many high-level applications rely on feature extraction, which is one of the most important computer vision methods. In this study, the improved whale optimization method (IWO) is used for pre-processing to ensure preprocessed image for further feature extraction. In general, the whale optimization method is a meta-heuristic optimization system inspired by nature and modeled after the humpback whaleshunting behavior. In IWO algorithm, we generate real numbers $\overrightarrow{R_1}$ and $\overrightarrow{R_2}\, q\in[0, 1]$ and use them to compute $\overrightarrow{B}$ and $\overrightarrow{D}$, $\overrightarrow{B}$ and $\overrightarrow{D}$ calculations are as follows:

$$\overrightarrow{B} = 2 \cdot \overrightarrow{b} \cdot \overrightarrow{R_1} - \overrightarrow{b} \quad (1)$$

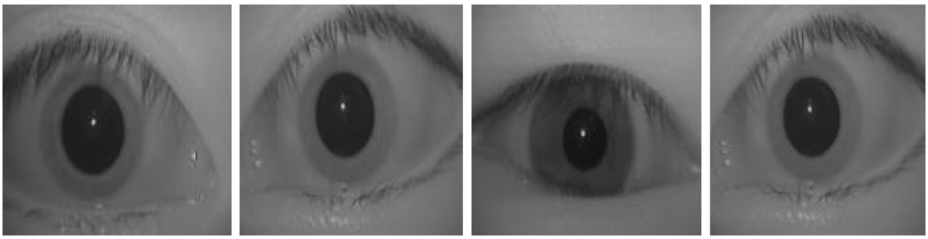

Fig. 3 Iris test samples from SDUMLA-HMT dataset

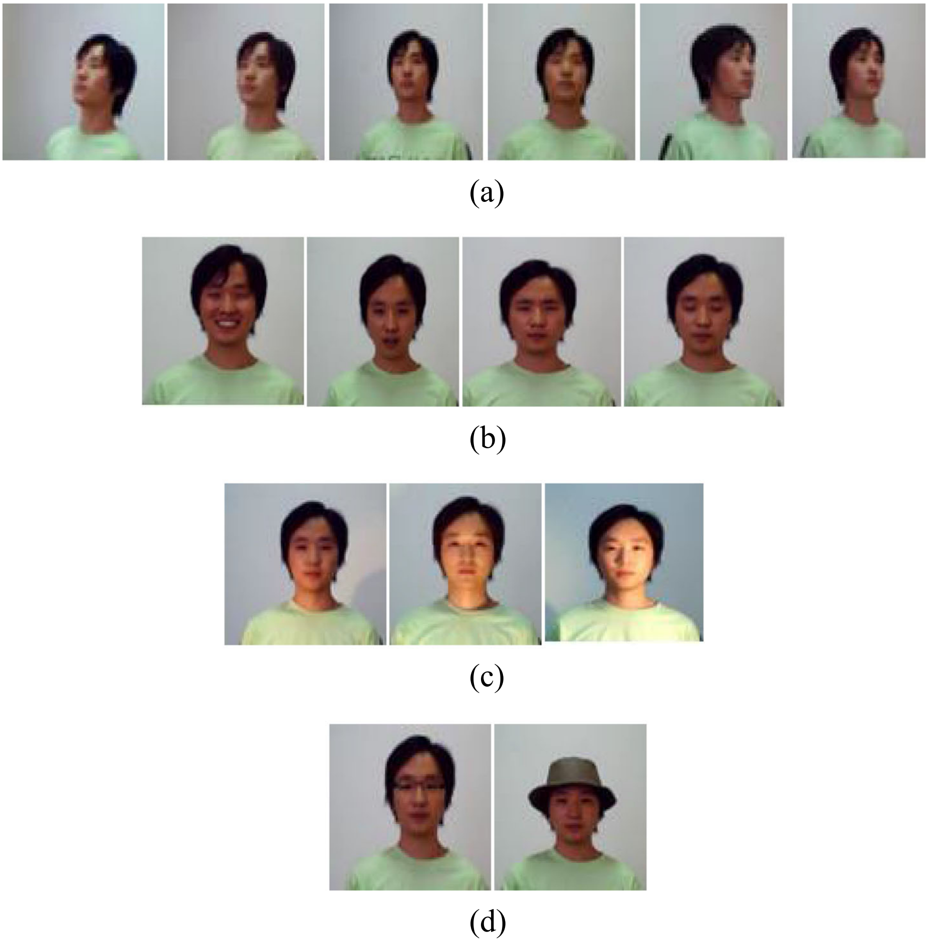

Fig. 4 Face test samples from SDUMLA-HMT dataset with **a** pose, **b** expression, **c** illumination and **d** accessory variations (top to bottom)

$$\overrightarrow{D} = 2 \cdot \overrightarrow{R_2} \tag{2}$$

where $\overrightarrow{b}$ implies real number that iterates from 2 to 0 linearly. The search agent is compelled to leave its present position and wander aimlessly across space in pursuit of prey with this strategy. The function of position update is described as follows:

$$\overrightarrow{C} = \left| \overrightarrow{D} \times \overrightarrow{Q_{rand}} - \overrightarrow{Q_L^s} \right| \tag{3}$$

$$\overrightarrow{Q_L^{s+1}} = \overrightarrow{Q_{rand}} - \overrightarrow{B} \times \overrightarrow{C} \tag{4}$$

Where $\overrightarrow{Q_{rand}}$ is approximately the generated level vector on the boundary line. $\overrightarrow{Q_L^s}$ i-th implies search agent status vector generation, $\overrightarrow{Q_L^{s+1}}$ which is the generation of the S + 1 search agent status vector. The position of the prey is determined and the prey is encircled throughout this procedure. The search agent approaches the appropriate search agent location. The position update summarized as follows:

$$\overrightarrow{C} = \left| \overrightarrow{D} \times \overrightarrow{Q_*^s} - \overrightarrow{Q_L^s} \right| \tag{5}$$

$$\overrightarrow{Q_L^{s+1}} = |\overrightarrow{Q_L^s - \overrightarrow{B} \times \overrightarrow{C}}| \tag{6}$$

where $\overrightarrow{Q_*^s}$ implies optimal search agent position vector generation t.Algorithm 1:Pre-process using IWO algorithm

Input	: $\vec{B}$ and $\vec{D}$
Output	: $\overrightarrow{Q_{*M}^s}$
1	Generate the initial population
2	Evaluate the fitness for each candidate solutions in
3	while stopping condition not satisfied do
4	For j=1 to nq do
5	Update the values
	$\overrightarrow{Q_L^{s+1}} = \overrightarrow{Q_{rand}} - \vec{B} \times \vec{C}$
6	Boundary range
	$\overrightarrow{Q_L^{s+1}} = \overrightarrow{C^s} \cdot E^{aL} \cdot \cos(2\pi L) + \overrightarrow{Q_*^s}$
7	Formula of whale optimization algorithm
	$\overrightarrow{Q_L^{s+1}} = \overrightarrow{q_L^s} + \vec{B} \cdot \tan(\pi \cdot (R_3 - 1/2))$
8	Global best search agent has a better fitness
	$\overrightarrow{Q_{*M}^s} = \begin{cases} \overrightarrow{Q_*^s} \cdot (1+n) & , R_4 > K \\ \overrightarrow{Q_*^s} & ,, R_4 \le K \end{cases}$
9	End

The search agent is compelled to leave its present position and wander aimlessly across space in pursuit of prey with this strategy. The position transformation formula and mathematical model are as follows:

$$\overrightarrow{Q_L^{s+1}} = \overrightarrow{C^s} \cdot E^{aL} \cdot \cos(2\pi L) + \overrightarrow{Q_*^s} \tag{7}$$

An arbitrary real value between [−1,1] is used as the logarithmic shape constant for the logarithmic helix. In the random stabilization phase, we use the general Cauchy's functionality of the search agent to counteract the cochlear mutation. The mathematical formula for the general function opposite the sofa is as follows:

$$f^{-1}(q; y_0; \gamma) = y_0 + \gamma \cdot tan(\pi \cdot (q - 1/2)) \tag{8}$$

It's based on this formula that the whale optimization strategy for random prey is updated as follows:

$$\overrightarrow{Q_L^{s+1}} = \overrightarrow{q_L^s} + \overrightarrow{B} \cdot tan(\pi \cdot (R_3 - 1/2)) \tag{9}$$

where, $\overrightarrow{q_L^s}$ signifies jth generation search agent position*s*. R_3 be random value between 0 and 1.A local mutation probability K is used to assure the algorithm's stability as follows:

$$\overrightarrow{Q_{*M}^s} = \begin{cases} \overrightarrow{Q_*^s} \cdot (1+n), R_4 > K \\ \overrightarrow{Q_*^s}, , R_4 \le K \end{cases} \tag{10}$$

Algorithm 1 describes the pseudo code of preprocessing using IWO.

4.3 Feature extraction

Feature extraction is a kind of dimensionality reduction in which a large number of pixels are effectively represented to capture relevant image portions. In this section, we possible to extracts hidden features from the multimodal finger print, iris, and face biometrics using multi-block local binary pattern. A local binary pattern (LBP) feature vector describes the texture of the periocular region. It splits the image into identical blocks without overlap. Local image features are computed per block. For a block's pixels, LBP values are computed and a histogram is constructed. The histograms of every block are merged to generate a global image vector.

4.4 Feature selection

After the feature extraction, a modified group search optimization (MGSO) algorithm is used for the feature optimization which gives best optimal features among the multiplefeatures to reduce the data dimensionality issues. In this section, the optimal feature selection is described by using the MGSO algorithm. Using a group of candidate agents (population), each agent is a member. The j-th iteration has current solution positions in N-dimensional research space. The j-th agent's search area that is a member vector $D_j^K\left(\phi_j^K\right) = D_{j1}^K, D_{j2}^K, \ldots D_{jN-1}^K, D_{jN}^K) \in r^N$, based on ϕ_j^K from a polar-to-Cartesian array transformation, is as follows:

$$D_{j_1}^K = \prod_{p=1}^{N-1} cos\left(\phi_{j_p}^K\right) \tag{11}$$

$$D_{j_1}^K = sin\left(\phi_{j_{i-1}}^K\right)\prod_{p=1}^{N-1} cos\left(\phi_{j_{i-1}}^K\right)(i = 2, 3, \ldots\ldots N-1) \tag{12}$$

$$D_{j_1}^K = sin\left(\phi_{j_{N-1}}^K\right) \tag{13}$$

For example, in three dimensions, if the ith agent's head angle at the kth exploring round is $\phi_j^K = (\pi\backslash 3, \pi\backslash 4)$, using the given unit vector search area attain $d_j^K = \left(1\backslash 2, \sqrt{6}\backslash 4, \sqrt{2}\backslash 2\right)$. The height of each cone is when the fish catches and searches for prey.The producer's current position is the apex. In MGSO, at iteration K (K-th), the producer Y_q runs as:

The process tests at zero and three locations in the checking area using stochastic testing.

$$Y_Z = Y_q^K + R_1 l_{\max} d_q^K\left(\phi^K\right) \tag{14}$$

One point in the right and left hand faction hypercubes are:

$$Y_R = Y_q^K + R_1 l_{\max} d_q^K\left(\phi^K + R_2\Theta_{\max}\backslash 2\right) \tag{15}$$

$$Y_l = Y_q^K + R_1 l_{\max} d_q^K\left(\phi^K + R_2\Theta_{\max}\backslash 2\right) \tag{16}$$

where $R_1 \in \mathbb{R}^1$ impliesa randomly distributed random variable with mean 0 and standard deviation 1and $R_2 \in \mathbb{R}^{N-1}$impliesuniformly assigned stochastic values (0, 1). The producer then finds the near-best position and fitness function. If the best position has a higher fitness function, it moves there. Alternately, it will wait and move its caption to a random position.

$$\phi^{K+1} = \phi^K + R_2\alpha_{\max} \tag{17}$$

Where ($\alpha_{\max} \in \mathbb{R}^1$) implies maximum adjusting position. If the producer can't find a better search space after iterations, it sets the leader to 0 degrees.

$$\phi_{K+\alpha} = \phi_K \tag{18}$$

where ($\alpha \in \mathbb{R}^1$) be constant value. Some group agents are scroungers at every iteration. The scroungers will keep looking for improved fitness to achieve the producer's fitness function. MGSO uses space copying, the most frequent sparrow scrounger behavior. Scrounger behavior at K-th redundancy may be depicted as a stochastic walk towards the producer.

$$Y_j^{K+1} = Y_J^K + R_3 \circ \left(Y_q^K - Y_j^K\right) \tag{19}$$

where ($R_3 \in \mathbb{R}^N$) impliesuniform stochastic sequence value (0, 1). "∘" represents the product that computes the two vectors' product. When scrounging, the j-th scrounger searches for additional opportunities. Represent this behavior by implementing the ith scrounger's start to a newly generated position.An exploration stage that starts with external signs pointing to a device. MGSO algorithm classification is difficult if the i-th group agent is distributed. Rangers use stochastic walks and systematic exploration to find resources. Algorithm 2:Optimal feature selection using MGSO

Input	: φ_j^K Cartesian assortment
Output	:producer Y_q
1	Randomly initialize agent y_j and head angles φ_j of all positions
2	Calculate the fitness function of initial agents
3	Right-hand faction hypercube $Y_R = Y_q^K + R_1 l_{\max} d_q^K (\varphi^K + R_2 \Theta_{\max} \setminus 2)$
4	j=0, i=1 Do
5	Get the values of chaotic map C
6	Randomly created position $\varphi^{K+1} = \varphi^K + R_2 \alpha_{\max}$
7	Stochastic walk near the producer $Y_j^{K+1} = Y_J^K + R_3 \circ (Y_q^K - Y_j^K)$
8	An arbitrary distance $L_j = \alpha \cdot R_1 l_{\max}$
9	End for
10	Set K: =K+1
11	End

Rangers employ the first strategy in MGSO to search for scholastic fitness values. The kth search develops a scholastic front position ϕ_j by Eq. (17), and chooses an arbitrary distance:

$$L_j = \alpha \cdot R_1 l_{\max} \tag{20}$$

The model progresses to the new position as follows:

$$Y_j^{K+1} = Y_J^K + l_j d_j^K \left(\phi^{K+1}\right) \tag{21}$$

Limiting exploration to successful patch increases the possible resource maximization (fitness function). Uncovering a way of turning the next into a piece. With this method, the MGSO algorithm re-orients an agent away from the exploring region by rearranging the variables that disturbed the limits to its previous preferences. The algorithm 2 describes working function of optimal feature selection using MGSO algorithm.

4.5 Feature fusion

Feature level fusion aims to identify a single vector more discriminative than the feature vectors used as input. The proposed multimodal biometric system combines finger print, iris, and facial modalities. Our approach combines score and decision level fusion to maximise the benefits of each fusion level and increase the biometric system's performance. The scores are adjusted using min-max and Z-score methods, while the fusion is done using the min, max, sum, and weighted sum rules. We employed OR rule in decision level fusion.

4.6 Person identification

We introduce a pre-trained Teacher Learning based Deep Neural Network (TL-DNN) for person identification which enhances the prediction accuracy and reduces all error metrics.In this study, TL-DNN used to predict a patient's condition, which would improve the accuracy of medical examination.

Most previous research considered NT (Negative Transfer) a significant problem, but they pay less attention to solving it [21]. Our study will propose a TL-DNN classifier for person identification to alleviate the NT issue. For this, In TL-DNN, a cluster of understudies is thought of as the quantity of occupants in courses of action, and the wellbeing of the plans is considered as results or grades. Learning is a critical cooperation by which everyone gains from others and chips away at their knowledge. Let us assume $R_\varepsilon = \{R_{\varepsilon 1}, R_{\varepsilon 2}, \ldots R_{\varepsilon c}\}$ represents ϵ-th learner position in F_T iteration, where c indicates the amount of learns and subjects. R_{mean} means middle class, Y_{fbest} is the best grade in all subjects, i.e. teacher F_T. Due to the difference in the average level of class and teachers, and the new level has been changed and has the following advantages:

$$R_\varepsilon^{new} = R_\varepsilon + z_\varepsilon \left(R_{fbest} - f_t R_{mean}\right) \tag{22}$$

z_ϵ denotes the number selected from the approximate range [0, 1]. The optimal function ft. is utilized to ascertain the convertible normal. The optimal function of f_t can be 1 or 2, which is determined by the accompanying condition.

$$f_t = Ran(1 + Ran(0, 1)) \tag{23}$$

Select the second grade of the R_L class, where $L = \epsilon$. Here, R_ϵ is changed to the following expression. The updated position represents as follows:

$$R_\varepsilon^{new} = \left\{ \begin{array}{ll} R_\varepsilon + z_\varepsilon (R_\varepsilon - R_L), & \Delta(R_\varepsilon) < \Delta(R_L) \\ R_\varepsilon + z_\varepsilon (R_L - R_\varepsilon), & \Delta(R_\varepsilon) > \Delta(R_L) \end{array} \right\} \tag{24}$$

Therefore, the reading after the combination depends on the condition of the integration.

$$R_\varepsilon^{new} = \left\{ \begin{array}{ll} R_\varepsilon + z_\varepsilon(R_\varepsilon - R_L) = R_\varepsilon; & f_{t1} = 1 \\ R_\varepsilon + z_\varepsilon(R_\varepsilon - 2R_L) = 1 - z_\varepsilon; & f_{t2} = 2 \end{array} \right. \tag{25}$$

The new position is calculated by the following equation:

$$R_\varepsilon^{new} = R_\varepsilon + z_\varepsilon \left(Q_{fbest} - f_{t1} Q_{mean}\right) - z_\varepsilon \left(Q_{fworst} - f_{t2} Q_{mean}\right) \tag{26}$$

The worst and best performances are called Q_{fworst} and Q_{fbest}, respectively. Estimates for $z_{\epsilon 1}$ and $z_{\epsilon 2}$ from 0 to 1 were selected. The two expression variables are called f_{t1} and f_{t2}, which are represented by the following equations.

$$f_{t1} = \frac{2}{1 + e^{-sum\left(Abs\left(Q_{fbest} - Q_{\varepsilon}\right)\right)}} \tag{27}$$

$$f_{t2} = \frac{2}{1 + e^{-sum\left(Abs\left(Q_{fworst} - Q_{\varepsilon}\right)\right)}} \tag{28}$$

At the highest level, Q_{fbest} will always be z_{ϵ}

$$R_{\varepsilon}^{new} = R_{\varepsilon} + z_{\varepsilon 1}\left(Q_{\varepsilon} - Q_{rab}\right) - z_{\varepsilon 2}\left(Q_{\varepsilon} - Q_{ran}\right) \tag{29}$$

Students learn about a particular area that is central to each student's language research, which can be explored.

$$R_{\varepsilon}^{new} = R_{\varepsilon} + \frac{\left(N_R - 0.5\right)\left(B_U - B_L\right)}{2\varepsilon} \tag{30}$$

All lower and upper boundaries of the study area are marked B_L and B_U, respectively. Here, N_R is shown as the approximate selected number in the range 0 to 1. The DNN relative gravity vector (VW) is defined for each individual

$$\sum_{y=1}^{J} VW_{x,y}^{F_T} \quad y = 1, 0 < VW_{x,y}^{F_T} \quad x = 1, 2, \ldots J \tag{31}$$

Algorithm 3: Person identification using TL-DNN classifier

Input	: Learners
Output	: Weighted solution
1	Initialize input values
2	Update the new position
3	Determine the teacher factor
4	Examine a new position.
5	Estimate the origin bias
6	Evaluate the corresponding weight vector
7	Calculate the weighted solution at time T
8	Calculate the weighted solution at time T+1
	$R_x^{F_T+1} = R_x^{F_T} + R_x^{new} \qquad x = 1, 2, \ldots J$
9	End

The population size is shown in M and current frequency is shown in F_T.

$$R_x^{new} = \sum_{y=1}^{J} VW_{x,y}^{F_T} \times z_x^{F_T} \quad y = 1, 2, \ldots, J \tag{32}$$

$$R_x^{F_T+1} = R_x^{F_T} + R_x^{new} \quad x = 1, 2, \ldots J \tag{33}$$

The i^{th} individual's weighted solution is referred to as i^{th} at time T + 1 and T, y_j^T implies the j^{th} individualsolution. The algorithm 3 illustrates TL-DNN person identification working process. Our model will thus alleviate the NT (Negative Transfer) issue for person identification.

5 Results and discussion

5.1 Performance metrics

In this section, we validate our proposed hybrid deep learning technique for person identification (HDL-PI) technique by using benchmark multimodal SDUMLA-HMT dataset with the finger print, iris and face biometrics. The simulation results of our proposed TL-DNN classifier is compared with the existing classifiers in terms of two major performance measures such as quality and error metrics. The proposed TL-DNN classifierperformanceis analyzed through quality metrics (accuracy, precision, Recall and F-measure) and the error metrics (EER, FAR and FRR).

This paper provides a method for increasing the resolution using an input image inspired by [7]. In the proposed method, we improved the image super-resolution based on local regression and nonlocal means. The proposed method consists of a learning phase. After the initial implementation, we compared the results with a quick and accurate method and found the difference. Then, using the TL-DNN algorithm, these differences were applied to the initial image. Results showed that our proposed method performed efficient in terms of error metrics EER, FAR, FRR and GAR.

5.2 Comparative analysis of error performance

In this sub section, we validate our proposed TL-DNN classifier with the error measures using the standard benchmark multimodal SDUMLA-HMT dataset. The error measures of proposed TL-DNN classifier is compared with the existing state-of-art classifiers LNMF [3] and CCA [16] in terms of EER, FAR, FRR and GAR. Table 2 describes error measures comparison of proposed andexisting classifiers for SDUMLA-HMT dataset. Figure 5 describes the equal

Table 2 Comparative analysis in terms of Error metrics

Classifiers	Modalities	Error metrics			
		EER (%)	FAR	FRR	GAR
LNMF [3]	Face, finger print	4.678	0.089	0.85	0.911
CCA [16]	Iris, fingerprint	0.8474	0.89	0.25	0.11
TL-DNN (proposed)	Finger print, iris and face	0.654	0.96	0.14	0.04

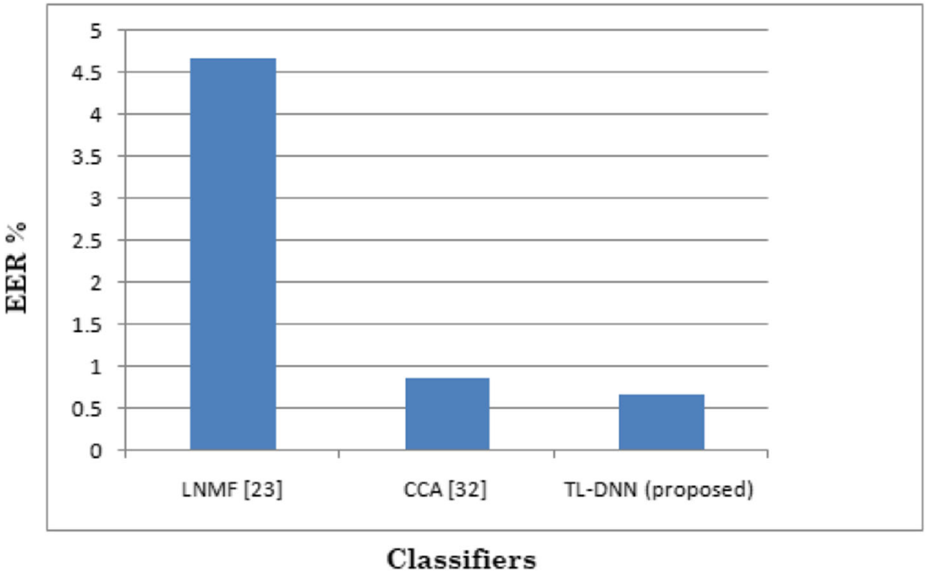

Fig. 5 EER analysis

error rate (EER) comparative analysis of proposed TL-DNN classifier is 86.020% and 22.823% better than the existing state-of-art LNMF [3] and CCA [16] classifiers. Figure 6 describes the false acceptance rate (FAR) comparative analysis of proposed TL-DNN classifier is 90.729%, and 7.292% better than the existing state-of-art LNMF [3], and CCA [16] classifiers. Figure 7 describes the false rejection rate (FRR) comparative analysis of proposed

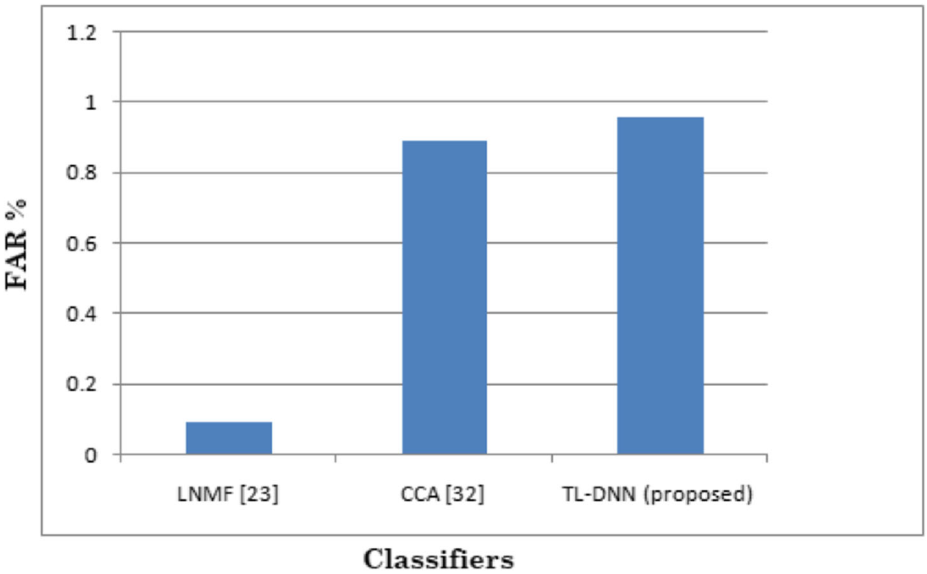

Fig. 6 FAR analysis

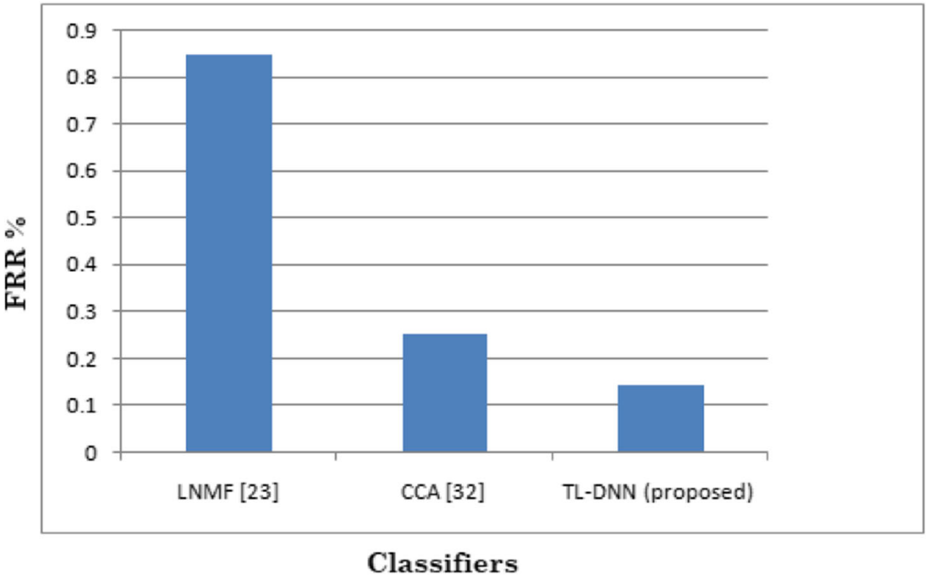

Fig. 7 FRR analysis

TL-DNN classifier is 83.529% and 44% effective than the existing state-of-art LNMF [3], and CCA [16] classifiers. Figure 8 describes the genuine acceptance rate (GAR) comparative analysis of proposed TL-DNN classifier is 95.69% and 63.636% effective than existing state-of-art LNMF [3] and CCA [16] classifiers.

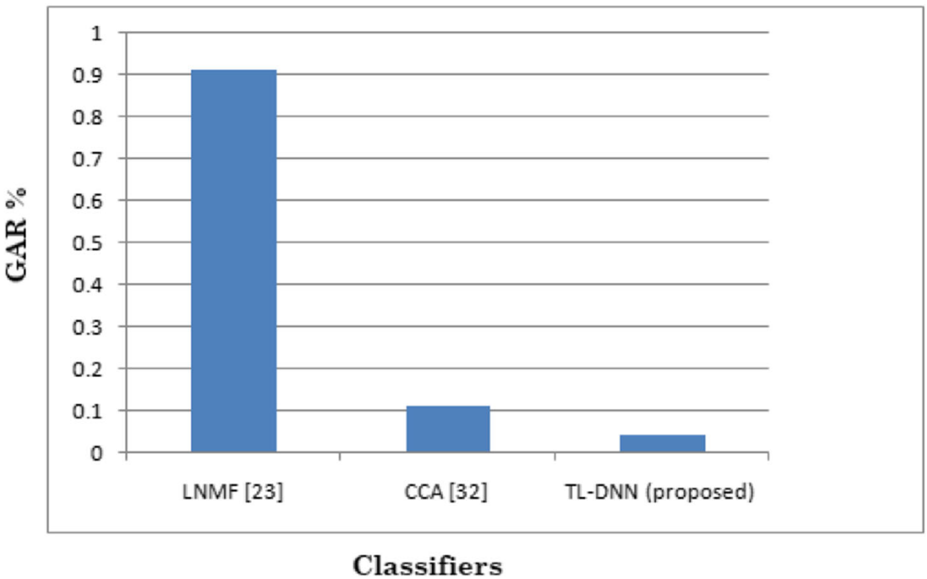

Fig. 8 GAR analysis

Table 3 Comparative analysis in terms of Quality metrics

Classifiers	Quality metrics (%)			
	Accuracy	Precision	Recall	F-measure
LNMF [3]	87.520	87.063	87.765	87.413
CCA [16]	95.280	94.823	95.525	95.173
TL-DNN (proposed)	98.760	98.303	99.005	98.653

5.3 Comparative analysis of quality performance

In this sub section, we validate our proposed TL-DNN classifier with the quality measures using the standard benchmark multimodal SDUMLA-HMT dataset. The quality measures of proposed TL-DNN classifier is compared with the existing classifiers LNMF [3] and CCA [16] in terms of accuracy, precision, Recall and F-measure. Table 3 describes the quality measures comparison of our proposed and existing classifiers for SDUMLA-HMT dataset.

Figure 9 shows the accuracy of our proposed TL-DNN classifier is 11.381 and 3.524% effective than the existing state-of-art LNMF [3] and CCA [16] classifiers respectively. Figure 10 shows the precision of our proposed TL-DNN classifier is 11.434% and 3.540% effective than the existing state-of-art LNMF [3] and CCA [16] classifiers respectively. Figure 11 shows the Recall of our proposed TL-DNN classifier is 11.353% and 3.515% effective than the existing state-of-art LNMF [3] and CCA [16] classifiers respectively. Figure 12 shows the F-measure of our proposed TL-DNN classifier is 11.39% and 3.528% effective than the existing state-of-art LNMF [3] and CCA [16] classifiers respectively.

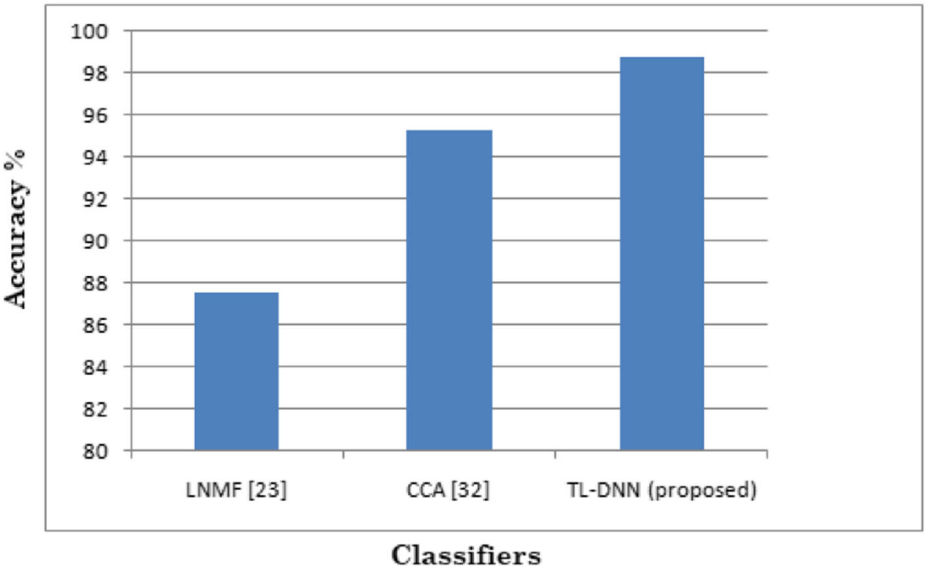

Fig. 9 Accuracy analysis

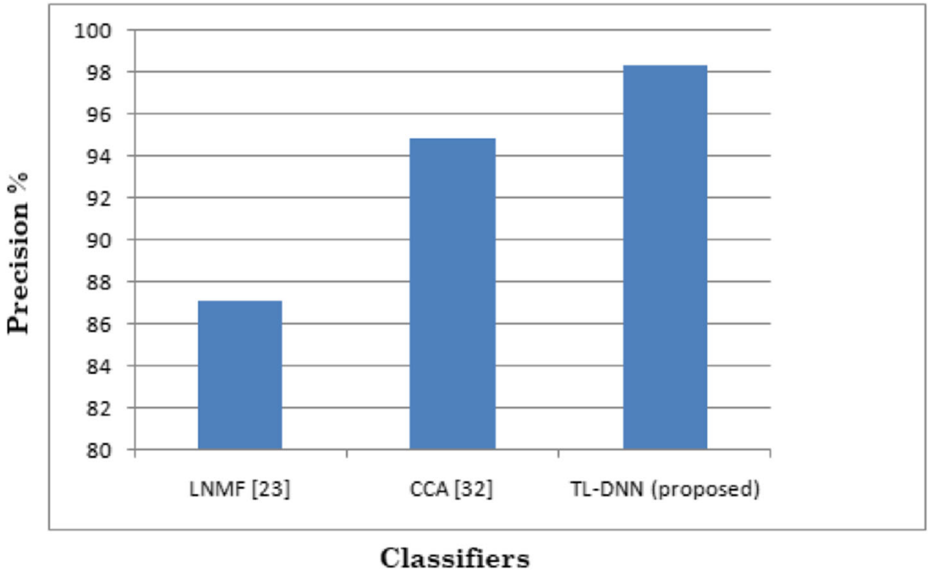

Fig. 10 Precision analysis

5.3.1 Computational analysis and efficiency analysis in terms of time

Analysis of computation time It is important to analyze the computation time of the proposed method for TL-DNN biometric recognition, and we give the time cost of the recognition process on fingerprint, iris and face database. We cannot obtain the source codes of the other methods for TL-DNN biometric recognition, so we only give the time cost of our proposed method in Table.

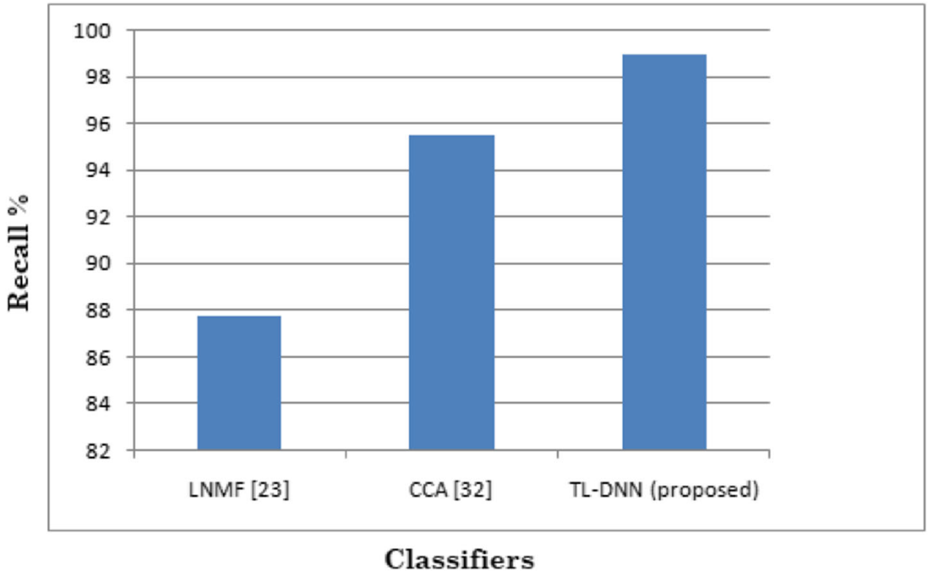

Fig. 11 Recall analysis

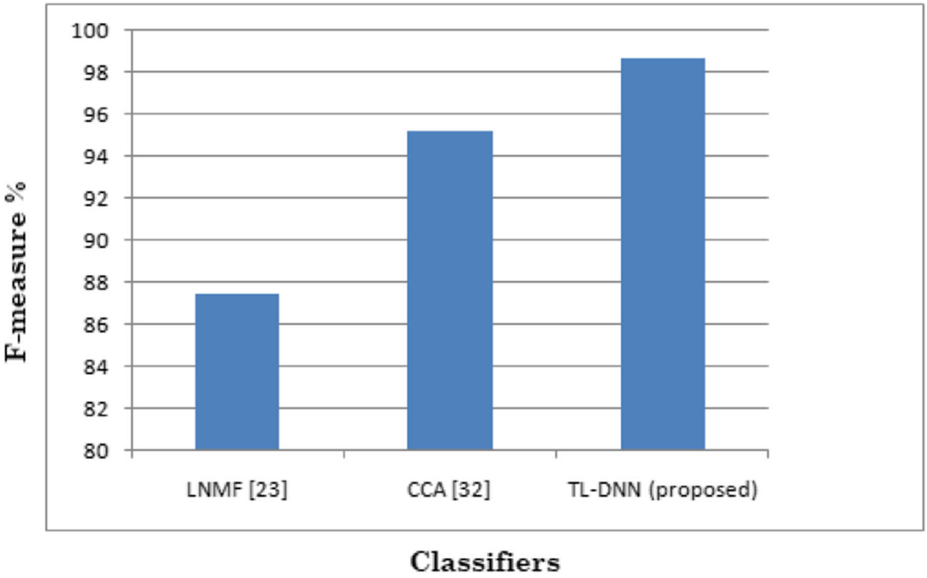

Fig. 12 F-measure analysis

As shown in Table 4, we can see that the feature-extraction time of TL-DNN is fast. The training time of TL-DNN without gradient back propagation is acceptable, as the deep learning training is known to take more time.

6 Conclusion

The three physiological biometrics Face, Fingerprint and Iris employed in our research have receive significant benefits, since fingerprint is user friendly and robust. Iris texture is unique even for twins. Face is a reliable as reported in lots of literature. High priority of the system is to ease and improve efficiency of identification, by disallowing any fraudulent act. The above mentioned methods are enhanced in our paper. We have proposed a hybrid deep learning approach for person identification (HDL-PI) using multimodal biometrics. The main contributions of our proposed HDL-PI technique is described as follows: An improved whale optimization (IWO) technique is developed for unwanted artifact removal from the input image in pre-processing. A modified group search optimization (MGSO) algorithm is used for feature optimization which gives best optimal features among the multiplefeatures to reduce the data dimensionality issues. Next, teacher learning based deep neural network (TL-DNN) is

Table 4 Time cost of TL-DNN on fingerprint, iris and face database

Process	Time (seconds)
Training	684
Pre-processing	0.0001
Feature extraction	0.4355
Matching	0.0011

introduced for person identification which enhances the prediction accuracy and reduces all error metrics. From the simulation results we proved the effectiveness of our proposed TL-DNN approach over the existing approaches of various performance and error metrics. The proposed TL-DNN approach's accuracy achieved the maximum range as 98.76% which is 11.38% and 3.54% efficient than existing state-of-art LNMF and CCA classifiers respectively. In future, we extend our method for palm print for biometric in person recognition.

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Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare that they do not have no Conflict of Interest.

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