An Implement Secure Authentication Multimodal Biometric System Using OAL-CNN (Optimized Featured-Based CNN) Model

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Abstract— Nowadays, the high demand for reliable authentication and security methods, lead to the development of the UMBS (uni-modal biometric system) so that the MBS (multimodal biometric system) has developed. The MBS will utilize multiple BTs (biometric traits) of an individual for security and authentication purposes. Generally, Fusion plays a main role in the MBS. Various fusion methods are utilized in BSs. FLF (feature level fusion) is a very famous approach as compared to the other methods. FLF, features are fetched from all BTs. After that features extracted are merged into an FV(feature vector) of high-dimensional. The proposed work is considering multimodal BS (biometric system) for score-level fusion such as palm, ear, and Fingerprint. The research model has four major procedures pre-processing, feature extraction, optimized score-level fusion, and recognition. At the initial, each input image is pre-processed; here the biometric image improvement method is carried out for overcoming the challenges like background noise. Then, the output is fed to the FE (feature extraction) procedure. From the palm image, the features are extracted by the PCA algorithm. For the ear image, both the text and shape feature sets are extracted by the same method. The next phase is optimized score level fusion, here the reliable features are chosen using the optimization method using ant lion optimization. For choosing the reliable feature sets, then the chosen feature sets are fused. The last and final phase of the research method is recognition, for recognition of CNN (convolutional neural network) is implemented. This method has been used to classify the MBS system and the performance of the proposed approach is calculated by parameters such as accuracy, specificity, and sensitivity. The proposed model has been implemented in the MATLAB with GUIDE platform. The proposed method (OAL-CNN) has improved the accuracy rate value of 94 percent, SP, and SN as compared with the existing model (OGWO).

Keywords—*Multimodal Biometric System; Feature Extraction (PCA) ; Optimized Ant Lion- CNN model; Convolutional Neural Networks; MATLAB.*

I. INTRODUCTION

In the scientific area, the technology of biometrics is wide-ranging in different technologies. Currently, these technologies are helpful in different sectors such as a bank, IT companies, etc. A biometric system (BS)[2] is required for different functions of the entrance society to the user identity between payment transactions. It is a dynamic zone of research in machine learning (ML) and pattern recognition (PR) which is an essential component of the science of identification. Several biometric modalities [3], such as the iris, face, fingerprint, and speech, provide appropriate individual recognition. It is also providing secure authentication and identification resolutions. It is required in applications such as electronic data security, log-in for computer networks (CNs), internet access (IA), credit cards (CC), mobile phones (MP), ATMs, e-commerce services, etc[4]. Two primary forms of biometric systems are uni-modal and multimodal biometric systems [1].

Multimodal is the composition of both or additional biometric modalities in an authentication or identification model. It detects the issue of non-universality, and then various traits confirm enough persons' coverage [9]. The multimodal biometric (MB) also reported the problem of spoofing[6,7] as it alarms different features and modalities[8]. Multimodal BS is a system that chains the results achieved from other than a single biometric feature for the motive of user authentication. Multimodal BSs are more consistent due to the many autonomous modalities required [5]. Multiple biometrics modalities are utilized for better accuracy and security, and unimodal is not provided because of non-universality. The multimodal BSs work in two stages [10]: (i) Enrollment and (ii) Authentication.

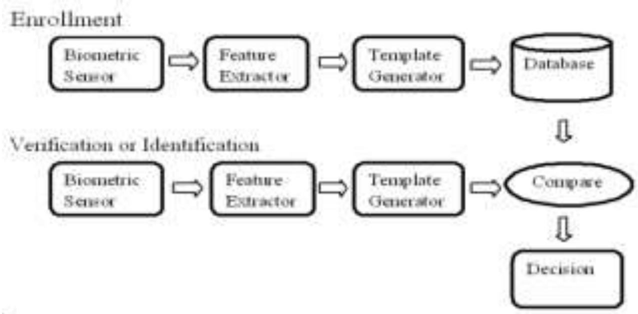

Figure 1. Multimodal Biometric Stages Diagram [4]

Figure 1 represents the **enrollment stage** is the biometric qualities of the person are taken and kept in the system's dataset in the terms of a template for that person and required for future use for the next phase. **The authentication stage [11]** also captures the user traits and is used for the authentication purpose of the user. ID (identity) is more similar and consists comparison of captured information using templates matching the person in the dataset.

The multimodal biometric system has four modules such as; sensor module, feature extraction, matching, and decision-making module. The **sensor module** is a suitable personal interface integrating the sensor of biometrics or scanner requirement to calculate or manage the basic biometric information of the person [11].

Score Level Fusion includes the composition of basic data accessed from several sensors. This level is suitable for different modalities and mostly well-defined with feature level in primary data recognized in current or expected accurately[12].

Feature level fusion, signals accessed from various biometric behaviors are executed first, and features are extracted by feature vector individually from each biometric quality. Then these individually extracted features convert into a combined feature vector required for classification. In this fusion level, a different method must be deployed for feature selection. Several kinds of experts have used fusion at the feature level. Features consist of comfortable data on biometric traits, then applied identically. Fusion at this level is estimated to give superior appreciation performance by observing various modalities' compatibility[13].

The main advantages are an advanced technology-based system that provides more straightforward utilization than traditional technology. Traditional technology is created on the physical inking of the user's fingertip. It is a complicated process ink eliminating advanced. The implementation cost of biometric systems is low because an optical sensor is an inexpensive device [5] [16] [7] [18]. The advanced biometric system reduced energy consumption [15]. The biometric method is employed in portable infrastructure such as mobile environments or smartphones (iPhone), which varieties the more required authentication method [17]. The biometric authentication approach has achieved more consideration due to the higher accuracy of samples developed from the acknowledgment of individuals[19].The palm print approach provides appropriate benefits as compared to other biometric systems.

Multimodal BS has different applications such as computer network, Banking sector, the internet, ATMs, etc[13][14].

II. LITERATURE OF REVIEW

Vijayakumar, et al., (2021) [20] proposed an innovative multimodal biometric user recognition system dependent on a DL (Deep Learning) model for identifying individuals utilizing biometrics dimensions of the eye, facial, and palm vein. The framework was structured around CNN (Convolutional Neural Network), which automatically extracted and then used the Softmax classification to identify images. Multiple convolutional networks were integrated to create the framework: one for the irises, the second for the facial, and another one for the fingerprint. The CNN model was constructed using the well-known generative VGG-16, the ADAM optimization approach, and categorized cross-entropy as the gradient descent. To prevent overfitting, multiple approaches were used, such as visual enhancement as well as dropping approaches. Multiple evaluation methods were used to fuse the CNN architectures to investigate the impact of fusing techniques on recognition rate, so attribute and match score merger methods were used.

Sarangi, P. P., et al., (2021) [21] designed a multimodal biometrics system that relies on the ears plus profiled faces suggested in this paper, which not only addresses the limitations of biometric traits but also increases the total detection accuracy. Separately, the ears plus profiled facing paradigms are depicted to use a mix of two additional localized feature descriptors: LDP and LPQ . The local descriptors (LD) based on histograms then were integrated into high-dimensional input vectors that maintain complementary information both in frequencies and spatial dimensions. Every extracted feature was subjected to PCA and the z-score standardization approach separately, as well as the shortened extracted features are then concatenated at the fusion. Subsequently, over the concatenated extracted features, the Kernels Discriminative Common Vector methodology is used to create stronger racist and discriminatory and non-linear attributes for authentication and identification that use the KNN classification algorithm.

Bala, N., et al., (2021) [22] studied biometric identification methods. Multimodal biometric recognition technology improves computerized network security as well as secrecy. A huge amount of research on data analysis over a previous couple of decades had been established. Emerging changes in biometric authentication had been examined in terms of the variety of fusing methods as well as the fusion degree, i.e. sensing layer or feature-based fusing, feature level integration, match score merging, as well as composite fusion level merging. The numerous forms of fusing were discussed in-depth, including their benefits and drawbacks. Furthermore, the methodology, datasets used, and the precision majority of various studies were shown to demonstrate the extensive use of biometric modalities architecture. The proposed study determined to deliver a complete indication of several fusion strategies for integrating multiple biometric modalities.

Joseph, et al., (2021) [23] designed a multimodal authentication scheme with the combination of extracted features of fingerprint, retinal, and fingerprint qualities. The relevant image processing methods, including pre-processing, standardization, extraction, and classification, had applied to each attribute. By merging the attributes in two steps, distinct cryptographic keys were formed from the features extracted. The platform's resilience was measured using the FRR measures and FAR. Three standard conventional encryption methods, like Blowfish, Advanced encryption standard, and Data encryption standard was used to analyze the performance 0of the model. In a cloud context, the proposed paradigm improves data identity and security management. **Moreno-Rodriguez, et al., (2021) [24]** presented a fully accessible dataset comprising concurrently collected EEG (Electroencephalography), and audio data, with the video stream. The dataset comprised 51 participants (25 females, 26 males), acquired for biometrics objectives and not restricted. While uttering single figures in Spanish, a total number of 140 data were gathered by each participant, accumulating 7140 cases. The 14-channel Emotiv-TM EPOC equipment was used to record EEG signals. While developing unimodal identification technologies, the generated set was quite useful, but it was much more so than when evaluating multimodal variations. Additionally, the acquired data might be used in applications such as brain-machine connections and computer vision, to mention a few examples. Six subscriber identification tests were introduced as an original investigation on information interpretability of the looking to identify: face detection and identification with 99 percent accuracy. **Soleymani, et al., (2021) [25]** described a Quality Aware Multimodal Identification model that links depictions from several biometrics attributes of different amounts and quality of data. The main impartial of the proposed model was to improve detection performance by retrieving complimentary identity information dependent on quality assessment. Authors created a quality-aware paradigm for integrating depictions of making connections by ranking their relevance by employing weakly-supervised classification results. The system employed two fusing units, each of which was comprised of a collection of quality-aware and aggregating systems. The authors suggested two task-specific losing properties about design modifications: MULTI-MODAL conditional independence reduction and bidirectional compaction damage.

III. PROBLEM STATEMENT

Biometric systems are used in a range of environments. The following are some of the drawbacks of biometric techniques.

a. Numerous tasks are carried out at different fusion stages in multimodal-based biometric identification; including decision level, perfectly matched score level, and, sensor level, and so on. According to the probable inconsistency of component facilities offered by distinct perceptions, multimodal fusing operations at this level are particularly complex to provide satisfying performance [26].
b. The CANONICAL correlation modeling approach falls short of revealing the complicated as well as nonlinear association relation between different selected features.
c. Whenever the extracted features of several perceptions are contradictory, the uncertain link between the feature map of different modalities, as well as the constraint of imbalanced datasets make it hard to integrate selected features in a multimodal biometric system [21] [22].
d. The feature-based fusion's restriction is that selected features with different behavior of complex systems are not approachable or acceptable.
e. Due to the existence of chaotic or overlapping inputs, conjunction in latent semantic merging might result in an extremely high dimensional feature matrix, resulting in an efficiency reduction.
f. The above-mentioned are the major flaws in different existing identification technologies that have prompted researchers to research a multifunctional biometric system. In this work, a method is recommended that will help to improve the effectiveness of the system.

IV. RESEARCH METHODOLOGY

The research methodology steps are discussed below and the block diagram is shown in figure 2.

A. ***Data Collection*** - Initially, explore the multimodal biometrics such as Fingerprint, Ear, and Palm print (IIT Delhi and CASIA) databases. All databases are presented in online repository sites.

B. ***Pre-processing*** - It steps are different modules such as; (i) noise level checking (ii) Smooth image evaluation (iii) edge detection (iv) histogram generated (v) RGB component evaluation (vi) Conversion 3D into 2D format.

C. ***Feature Extraction*** - Feature Extraction scheme using PCA algorithm to extract the multimodal biometric features. It extracts the unique and reduces the dimensionality size of the pre-processed images. PCA is used to shrink the measurement of the statistics set comprising a large amount of the related variables and recalls the maximum change in actual data. This method has defined four major objectives:

- It extracts significant biometric images from the data table.
- It reduces the size of the database by keeping only vital data.
- Easy to describe the database.
- Analyse the model of the observations and the variables.

D. ***Feature Selection*** - This method is a newly developed optimization method planned by mirjalili [26]. This method copycats the shooting component of antlions in the environment. This method consists of two main components such as inspiration and operators. This method follows these steps such as building traps, catching prey and re-construction the hole, moving the ants toward the action, random walk of ants, and elitism.

E. ***Classification*** - It is a form of feed-straight neural network (NN) that is commonly specified in image-processing (IP), such as multi-array data. The model of the CNN construction efficiently preserves the formation of accurate data and develops the layered image. A standard CNN model contains multiple levels of processing layers arranged from left-hand to right-hand. The CNN has four primary layers: convolution layer, pooling layer, FCL, classification layer, and normalized layer (ReLU) [27]. The first two are the strategy's main layers and are primarily utilized in the initial phases. Additional layers are required for complex systems, and figure 4.6 represents the CNN model [28].

F. Fusion - This is the highest practice of the investigation MMB system. It is determined by the well-organized hybridization of facial and iris modalities. In this proposed work, the MMB system employs score-level fusion at a parallel time direction to accomplish the qualities of distinct fusion and boosted the system execution. This research model has fulfilled the score-level fusion, the scores are coordinated with the min, max, addition, and biased addition (sum) rule procedures.

*F. **Metric Evaluation*** - In this research work estimated the system performance through the accuracy rate, specificity (SP), and sensitivity (SN). It is associated with using existing technologies such as the OGWO model.

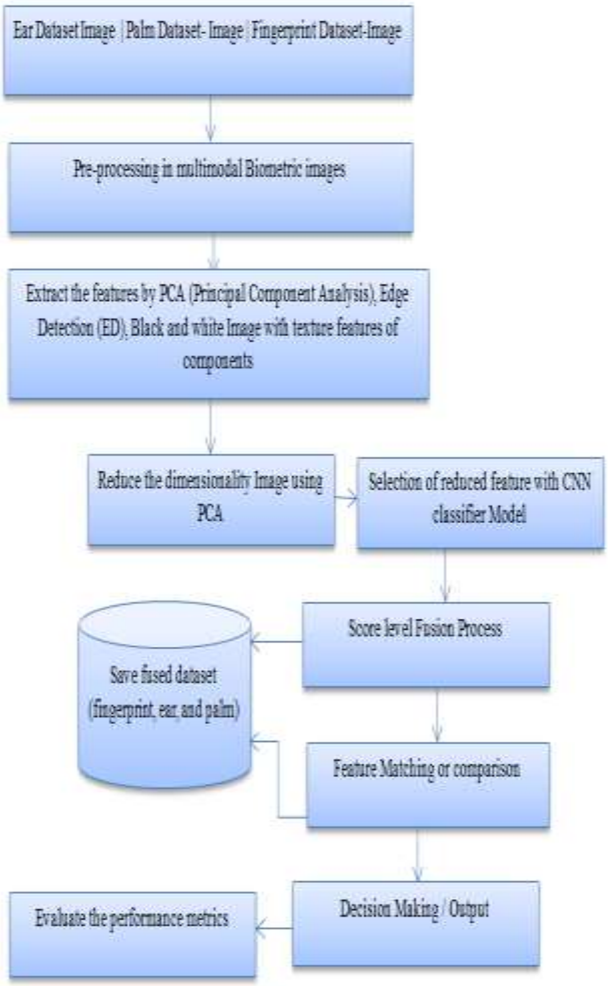

Figure 2. Proposed Model using OAL-CNN algorithm

V. Result and Discussions

This section elaborates on the simulation and outcomes that help in studying and comparing multi-model biometric models. Outcomes are elaborated in several multimodal biometrics related to different performance metrics such as; Accuracy, SP, and SN.

The proposed parameters are discussed as;

$$Accuracy = \frac{Tn+Tp}{Tp+Tn++Fp+Fn} \ldots\ldots\ldots\ldots\ldots\ldots \quad (i)$$

$$Specificity = \frac{Tn}{Tn+Fp} \ldots\ldots\ldots\ldots\ldots. \quad (ii)$$

$$Sensitivity \ = \frac{Tp}{Tp+Fn} \ldots\ldots\ldots\ldots\ldots (iii)$$

Here, Eq (i), (ii), and (iii) represent the Tp (true positive); Tn (true negative), Fp (false positive), and Fn (false negative).

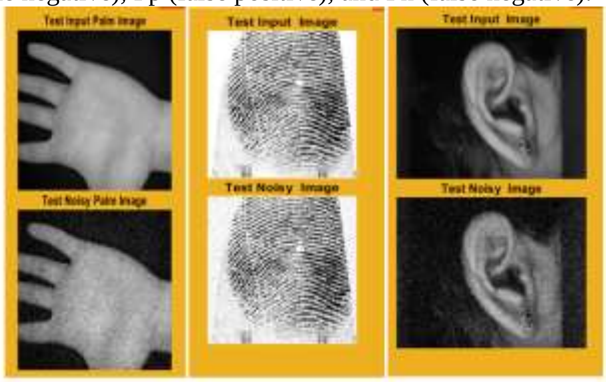

Figure 3. Input Image

Fig 3 represents the multimodal BS such as palm, fingerprint, and ear biometric traits. Firstly, upload the input dataset and include the false noise attack in the uploaded images. The noise attack is used SALT and PEPPER noise. This category of noise can be caused by severe and unexpected distortions in the sign of the image. It shows itself as infrequently defining white and black image pixels.

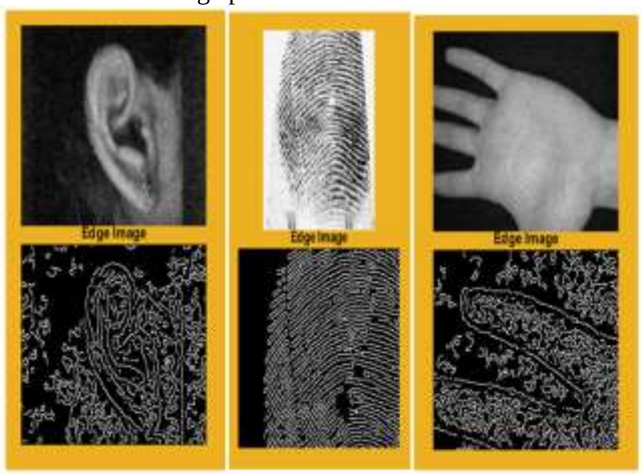

Figure 4. Image Preprocessing

Fig 4. represents the filtered image using the bilateral filter method and edge detection using the canny edge detector method. A bilateral filter (BF) is a non-linear, edge-preserving, and artificial noise reduction leveling filter for biometric images. It exchanges the intensity of each image pixel with a weighted avg. of IVs (intensity values) from neighbor image pixels. This weight may depend on a GD (Gaussian distribution). After that, it developed the canny edge operator. It is an ED that utilizes a multiple-phase method to sense a wide range of edges in uploaded BS traits images.

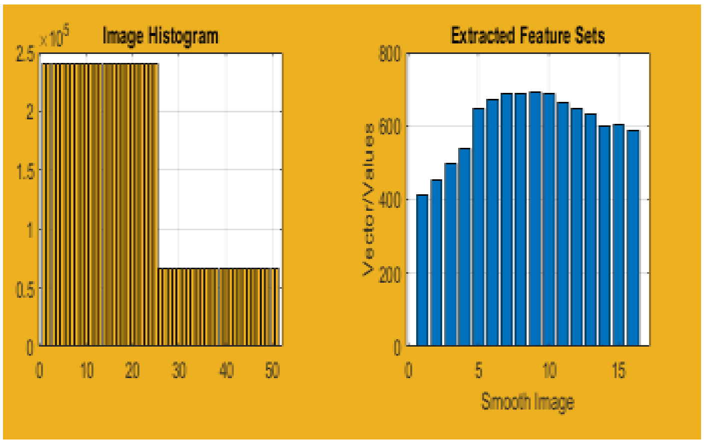

Figure 5. Image Histogram and Feature Extraction Process

Fig 5 represents an IH (image histogram) is a GSV (gray scale value) distribution defining the frequency of incidence of individual gray value levels. For an edge detector image size of 102 *1024*8 bits, the ranges from 0-255; the total no. of image pixels is equal to 1024*1024. After that, it developed a feature extraction method using the PCA algorithm. Feature extraction defines as the procedure of transforming raw information into a mathematical feature vector that can be processed while preserving the data in the uploaded original database. It produces better outcomes than implementing DL directly to the input data images.

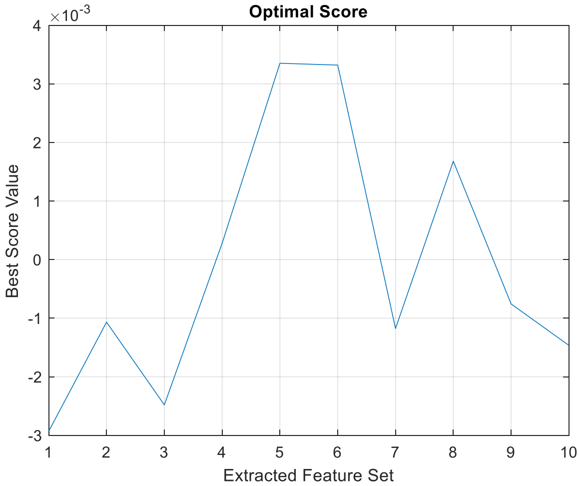

Figure 6. Optimizer with Best Score

Fig 6 represents the feature selection process with the best score values. The proposed model has been designed as an ALO method to choose the feature vector with the help of the fitness function. This feature selection method is a new swarm-based meta-heuristic method it chooses the smooth feature vector and passes them into the classification.

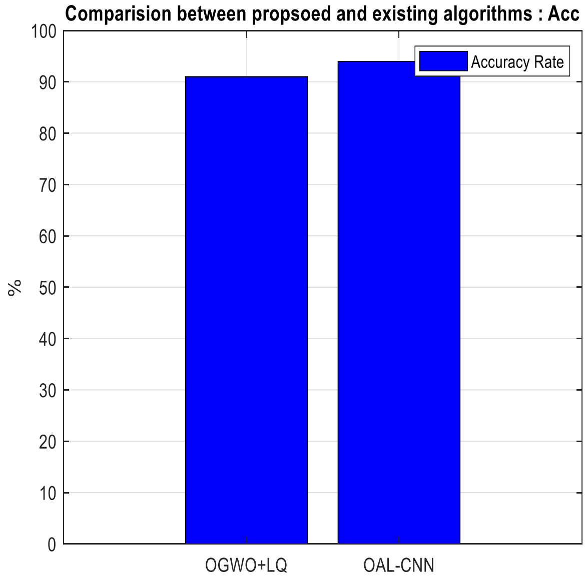

Figure 7 Comparison between proposed and existing work : Accuracy rate

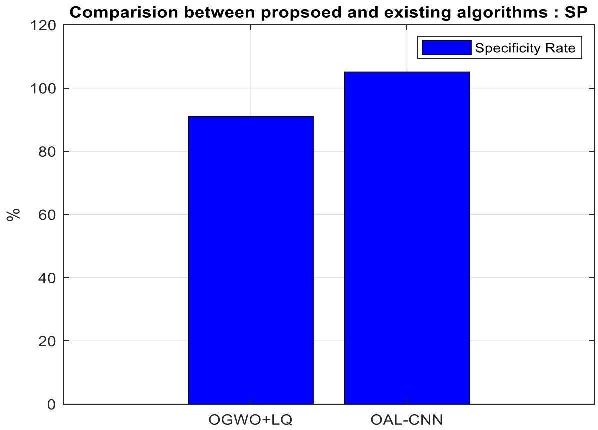

Figure 8. Comparison between proposed and existing work : SP

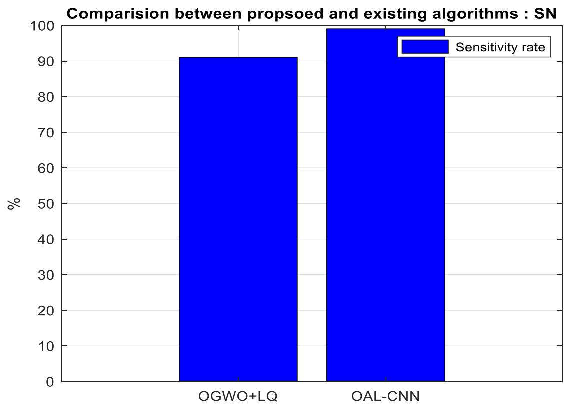

Figure 9. Comparison between proposed and existing work : SN

Figures 7, 8, and 9 present the comparison between the proposed and existing models with different parameters such as SP, SN, and Accuracy rate. It shows the comparison between different models like OGWO-LQ and OAL-CNN models. With the smaller difference between the proposed ad existing models. The proposed OAL-CNN method gives a maximum performance rate in the classification and all other parameters. Table 1 defines the comparison analysis with the proposed and existing models with different parameters such as; SP, SN, and accuracy rate.

Table 1 Comparison Analysis

Parameters	Accuracy %	SP %	SN%
OAL-CNN model	94	95	99
OGWO-LQ	91	91	91

Table 2. Proposed Parameters

Parameters	Values
MSE	1.40
SP (%)	95
SN (%)	99
Accuracy (%)	93.9~94
FAR	0.050
FRR	1.05

Table 2 shows the proposed model performance with parameters such as an accuracy value of 94 percent, SP value of 95 per cent, SN value of 99 percent, MSE value of 1.40, FAR 0.05, and FRR value of 1.05.

VI. CONCLUSION AND FUTURE SCOPE

This section has concluded the effective ear, palm, and fingerprint biometric traits that have attractively reduced complexity. The main objective at different and reliable feature vectors. Multimodal BS represents the several traits used together at a certain stage of fusion to authenticate users. The multimodal BS includes the use of several approaches called classifiers at Enrollment and feature comparing stages for the same biometric traits or the utilization of multiple sensors of the same traits like using different devices to measure the biometric data. Using several feature sets of the same biometric traits like the use of FINGERPRINT, PALM, and EAR. The multimodal biometric features are extracted by the image multiple resolution bilateral filters for withdrawing the attacks in the defined images and smoothing the image pixels. PCA method has been developed as a non-linear technique to reduce the high dimensionality of extracted feature sets. It is a linear format technique that is it may only be functional to datasets which are linear division. This feature extraction method uses kernel functions to the dataset into high dimensional feature space. Where it is linear separately, and the same as the main objective of the classification model. It extracts reliable features in the form of a matrix (rows, columns). This approach evaluated the high dimensional features, resolves the previous problems, and enhanced the authentication and accuracy rate of the multimodal BS. The research model operates in an authentication phase, in that the feature vectors are equated to save the features in the dataset for each biometric trait in the enrolment section. Between the most significant new optimized ant-lion CNN model used for classification. It explored the ALO method used and selected the extracted feature sets, through this research work developed and enhanced the ALO with CNN model for the multimodal BS model for the classification or authentication phase.This proposed work has been used for the fingerprint dataset using CASIA, ear IIT Delhi dataset to construct a multimodal BS simulation database with that it validated the research methods (OAL-CNN) and calculates the multimodal BS performance.This experiment results from analysis define multimodal authentication as much more précis and reliable than the unimodal BS approach. It evaluates the research model achieved an enhancement of 94 percent in term of accuracy rate and compared it with the existing model using OGWO. The further enhancement will plan deep learning using RNN with the LSTM model for taking out the high-level depictions of the data that will be merged with a novel ML algorithm. It will develop novel Soft computing methods to select the high-level features to evaluate the performance parameters.

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