FA-CNN Classification Method Based On Multi-Modal Biometric System Model with a Fusion of Palm Print, Finger Print, and Ear Features

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Abstract*—Currently, the stage of development data, how to perfectly classify an individual's identity, and care for the security of information have become significant areasfor individuals from all walks of life. A more suitable and secure resolution to detect identification is the identification biometrics. However, a particular biometric identification does not provide gradually complex and varied authentication setups. So, a multi-modal biometric technology is required to improve performance accuracy and identification security. In this paper, an FA-CNN-based method is developed for a Multi-modal biometric system based on palm print, fingerprint, and ear bimodal feature layer fusion using the KPCA method. The proposed work is implemented in some steps, such as preprocessing; at this point, three types of datasets are used, then the KernelPCA (KPCA) method is used for feature extraction. The Firefly algorithm is used to select optimized features with the composition of the CNN method termed as FA-CNN classification model. The overall research results show that the proposed model's performance reaches 98.88% of accuracy, 0.990 sensitivity, and 0.998 specificity.*

Keywords*—*Multi-modal Fusion-levels, Firefly algorithm, KPCA, CNN model.

I. INTRODUCTION

The word "biometric" is a combination of two words, bio, and metrics. The word bio means life and metrics denotes degree. Biometric verification systems are attracting widespread due to augmented security and recognized superior presentation and growing global demand. It is a practice or process of determining human biological features to confirm an individual's uniqueness. It has the skill to differentiate between an approved individual and a phony. This system enhanced the recognition method of determining biological and communication traits. Biological or functional features which continue the permanent period contain several human body properties. These properties are significant for all persons. Communication traits that improve with time include a signature, speech, language patterns, way of walking, keystroke, etc. Because of several aspects such as age, sickness, fractures, injury, and numerous other affect activities. Biometric properties are single and designed for each individual. Operators cannot forget this and outperform skill. The biometric recognition system distinguishes an individual established on particular features resulting from behavioral or physical features. Feature extraction signifies essential parts of an image in the practice of a feature vector. It is utilized in every scientific, commercial, health, business foundation, border security, and banking domain. It has some limitations such as budget, precision, throughput, and simplicity of practice. Biometrics systems are two types based on particular individuality. They are identified as unimodal systems with difficulties such as noisy information, false elimination, intra-class dissimilarity, false biometric characteristic, non-universality, inter-class matches, and spoofy attacks. Multi-modal biometrics is required to overcome these difficulties. Different multi-modal indications and individualities are composed of various foundations of equivalent individuals [1].

The multi-modal biometric system (MBS) consists of two or more biological and physical or communications features employed for identification. The MBS system eliminates the difficulties of a unimodal biometric system (UBS). The MBS system expressively expands the recognition presentation of a biometric scheme, refining people's attention, preventing spoofing attacks, and dropping the disaster-to-enroll ratio. These systems also deliver antispoofing actions through production. It is tough for an impostor to spoof numerous biometric individualities concurrently. The core objective of MBS is to diminish the false acceptance ratio, etc. and the fusion of several biometric modality information is important in the MBS system. The data from different biometric characteristics are incorporated at the feature, score, and decision levels [2]. Most real-world difficulties use a UBS system determined by confirming a particular data source for verification. This system has various selected drawbacks, such as unwanted noise in the identified information, Intra-class dissimilarity, non-universality, and spoofing. These drawbacks are resolved by using multi-modal BS.

A multi-modal biometric system requires several sensors for data procurement which permits catching various characters of a particular biometric basis and characters of numerous biometric illustrations. These organizations are additionally consistent because of many unbiased, distinct, independent biometrics characteristics. Several types of MBS systems are described in figure1.

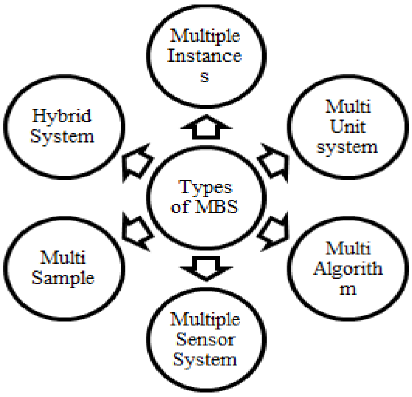


Fig. 1 Type of MBS [1] [3]

Multi-Sensor Systems are captured evidence from several sensors, such as fingerprint statistics obtained from an optical, compact state, and powerful sensors. Multiple spectral cameras are utilized to attain images of human attributes such as faces and fingerprints. A multi Algorithm form of MBS requires numerous features extracted according to several algorithms, such as face recognition using PCA and linear discriminant analysis and removing a novel highlighted face. Multi-Instance MBS systems, pool data of various occurrences from similar individual bodies. For instance, evidence is integrated across multiple fingers rather than a single-finger trial to attain a more reliable consequence of personal validation. This form of presentation is widely used in a large database. Also, a human-eye scanning system is not a decent optimal. Thus, both eyes' images are taken for a more reliable outcome. A single model is not enough in biometrics, so numerous samples are needed to comprehensively demonstrate a distinct characteristic in multiple sample MBS systems. For instance, a face recognition system (FRS) works on a person's front and side view 3D face modal. A multi-unit system combines pieces of evidence from numerous components like the iris. The hybrid system extracts the data with several modalities. For instance, it pools the match score of twofold different images of a face by using various individual postures and considering together irises which is the composition of algorithm and multi-sensor types of the MBS system [3].

In a multi-modal biometric system (BS), several attributes or properties of human bodies are initially detected through a sensor device such as a camera. Then its structures are eliminated and further coordinated or matched using a databank. The equivalent scores from whole structures are combined to acquire precise scores by using certain methods. The authentication procedure becomes unaffected if the score is equivalent or more than the threshold level; otherwise, it is a fraud or fake. Figure 2 represents two attributes, such as thumb expression and a handwritten signature is considered as input. The whole sensor initially resolves sense thumb expression, and then the feature extractor element extracts its properties. Further, these properties are matched with the dataset, and additional sensor element sense handwritten signatures. It will abstract its properties and match them with the dataset, then its score is computed. At that time, the scores from the inputs are fused using certain methods, and then it provides an absolute score. If this absolute score is more than or equivalent to the threshold, then the outcome is genuine; otherwise, it is fake.

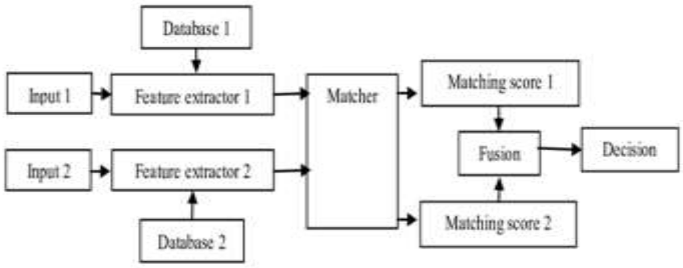


Fig 2. Working Process of Multi-modal BS [4]

Multi-modal BSs are used in different areas as multi-modal biometric applications. It provides more services as compared to Uni-modal BSs. Mostly Multi-modal biometric applications are associated with safety, privacy, and security. Also required in commercial, scientific, supervision, and community areas described in Figure 3. The Commercial applications of MBS systems involve computer system login, automated information security, e-commerce, internet usability, ATM, credit card, physical access controller, mobile phone, medical health records administration, and spatial learning. Government areas include domestic identity cards, accurate facilities, driving licenses, community security, welfare payment, etc. Mostly corpse credentials, illegal research, terrorism, ID, parenthood strength of character, and lost kids are considered in Forensic uses of the MBS system. The community uses canteen supervision, border regulator, elective or pooling system, and secure visitor organization. Landing field security and staying licenses are considered in transportation applications of the MBS system.

Applications of MBS					
Gover nment	Airpor ts	Banki ng	Hotal Retail Store	Corpor ate Institut es	Medic al Health care

Fig 3. Applications Areas of MBS [2]

A unimodal BS faces several difficulties, which are eliminated using a multi-modal biometric system. MBS offers various advantages; the MBS system offers a good outcome by using multiple features of modal biometrics. This system provides perfect precision than unimodal biometrics. The performance of the system is also upgraded than the single biometric system. It also protects from spoof attacks and stocks several appearances in the system record. For example, a databank is stolen through interlopers in a particular pattern, contributing to a great false rejection rate. It solves the non-universality subject. This system reflects the problem of unwanted information. Image filtration is accepted during image preprocessing, eliminating unwanted noise. This system is also observed fault tolerant scheme, which remains activated uniformly when positive biometric causes develop defective payable to the instrument or software fault or deliberate manipulator operation [5]. Multi-modal BSs utilized fusion for data accessibility in biometric systems. In Multi-modal BSs, various types of fusion are used for accurate performance. Fusion is a key component in Multi-modal BSs. Theyare constructed on evidence accessible in biometrics. There are consists of following levels of fusion are defined in Figure 4. Fusion is categorized into five categories as;

- *Sensor-Level Fusion*

MBSs illustrate a similar biometric characteristic using two or more particular several sensors [6]. A single method or permutation of a method completes the numerous illustrations' processing. Sample face recognition presentation required an observable light camera and an ultraviolet web camera attached through a particular rate of recurrence.

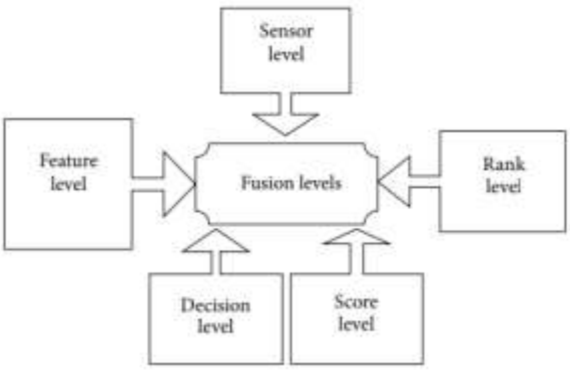


Fig 4. Fusion Levels in MBS [7]

1. Feature Level

Fusion is beneficial in taxonomy at this level [14]. Several feature vectors (FVs) are pooled, attained either with several beams or spread over some feature extraction methods to similar unprocessed data [8].

2. Decision Level

The whole biometric sub-system independently finalizes feature extraction, equivalent, and analysis developments. Decision schemes generally use Boolean utilities, where the analysis yields the common decision between existing sub-systems [9]

3. Rank Level

As an alternative to the whole pattern, partitions are utilized. Ranks from pattern panels are combined to evaluate the fusion rank for the organization [10]. This level contains merging authenticated ranks attained from various uni-modal biometrics. It associates with a recycled rank for building the ultimate decision [11].

4. Score Level

It states the permutation of similar scores provided through several systems. This level of fusion practices is separated into two leading groups: fixed and trained rules. The fixed rule consists of AND, OR, common, maxima, minima, addition, product, and mathematical rules. The trained rules include weighted addition, product, fisher linear discriminate (FLD), quadratic differentiation, LR, SVM, multiple layer perceptrons (MLP), etc. Various researchers are developing multi-modal BSs based methods and tools. Nguyen et al., [12] constructed iris detection with off-the-shelf CNN structures. The authors concentrated on the performance estimation of certain pre-accomplished CNN methods such as AlexNet, GoogleNet, VGG, denseNet, etc. This proposed method also eliminated the difficulty of computational density as exposed difficulty. O.G. Atanda et al., [13] employedface, right ear, and right iris images. These features were utilized due to their passive biometrics. and do not require individuals' active or full participation to be probed. The composition of several resources of biometric data is demonstrated to deliver additional consistency, accuracy, and precision as recognized. Three biometric personalities were captured and included to improve the presentation of the advanced multi-modal BS. O.G. Atanda[13] presented that the adapted CNN utilized for feature extraction (FE) and the classification of imageries in the established multi-modal biometric security system achieved the ordinary CNN in various performance parameters such as sensitivity, specificity, precision, recognition accuracy, and recognition accuracy and recognition-time. While ordinary CNN and adapted CNN Classifiers were DL methods, ordinary CNN is multiplication concentrated. This encounter by dropping the difficulties of ordinary CNN regarding recognition degrees and intervals. In existing feature-level fusion, concatenating numerous feature vectors is central to constructing a moderately big feature vector. This raises the computational and storing properties difficulties and ultimately needs a more difficult classifier strategy to control the composed dataset at the feature level space. An effective, feature-level fusion technique is recommended to overcome those problems [14].

This paper is arranged as: Section 2 defines the various research methodologies regarding MBSs. Section 3 analyzed required methods such as KPCA, Firefly, and CNN methods used in this proposed work. Section 4 represents the proposed methodology of the multi-modal biometric system and section 5 represents the simulation tool, Datasets, and results of the proposed MBS model. Section 6 defines the conclusion and future scope.

II. LITERATURE REVIEW

This section describes various existing research methods, tools, or models based on the multi-modal biometric system. These models are most important for security, authentication, and identification. Some of the investigations are defined as;**Basma Ammour et al., (2022) [15]** described multi-modal biometric tools lately growing significantly due to their capacity to reduce definite inherent restrictions of particular biometric modalities and recover the whole recognition frequency.A common biometric detection system included detection, feature extraction, and matching units.The system's robustness is subject to additional consistency in extracting appropriate evidence from the distinct biometric behaviors. So, the authors proposed a novel feature extraction method for a multi-modal biometric system (MBS) using face and iris personalities. The iris feature extraction utilized an effective multiple-resolution 2-D Log-Gabor filter to predict textural data in several scales and directions. The facial features were computed by the dominant singular spectrum analysis method (SSA) combined with the wavelet transform. For this proposed method, the authors utilized different types of datasets, such as an Olivetti research laboratory (ORL) and face recognition technology (FERET) for face and the Chinese Academy of science institute of Automation (CASIA). The proposed method achieved a better recognition ratio by using these datasets individually. **Yang Wang et al., (2022) [16]** described the data security concept as the most interesting and hot matter of societies from all gaits of natural life. Existing, a different suitable and protected resolution to uniqueness identification was biometric identification. On the other hand, a uni-biometric identification cannot care for gradually difficult and spread validation developments. So, the authors proposed a biometric technique based on finger-vein and face bi-modal feature-layer fusion using a convolutional neural network (CNN). The fusion occurred in the feature layer in the proposed technique development. The self-care tool was used to attain the weights of the dual biometrics and joined with the RESNET remaining construction. The bi-modal fusion feature network concatenation dropped the self-care weight feature. Alex Net and VGG-19 network models were nominated in the tentative portion designed for removing finger vein and face image structures as inputs to the feature fusion unit to demonstrate the extraordinary effectiveness of bi-modal feature layer fusion. The proposed technique reached an accuracy of 98.4%. **Susara S Thenuwara et al., (2022) [17]** described that border criminals and unauthorized immigrants dramatically increased worldwide within previous years due to the non-attendance of appropriate approval approaches at the border cities. Generally, customer switches were completed by accomplished immigration generals who associate the ID and the physical entrance at the border. In some countries was done by automated border control (ABC) systems. The author proposed a novel model for multi-modal biometric approval involved through the multi-agent system (MAS) to improve the optimum resolution by the co-feature of MAS. The investigation was completed with four existing multi-modal datasets: NIST, SDUMLA-HMT, BANCA, and PRIVATE. The experimental outcomes of the proposed model delivered an outstanding performance associated with earlier ABC schemes at the verification stage and were computationally fast. **Mikel Labayen et al., (2021) [18]** described individuality authentication and proctoring of available scholars as a key task of dynamic learning presently. In detail considered for online approval and authorization, the training supervisions were important to confirm that the online beginners who accomplished the educational development and predictable extract detection were those who competed for the developments. The authors proposed an exact resolution constructed on the validation of various biometric tools and a programmed proctoring scheme, such as system workflow and AI algorithms, including features. These features resolve the core alarms in the fair as extremely accessible, automatic, reasonable, through rare hardware and software supplies for the manipulator, dependable, and passive for the scholar. In conclusion, the scientific performance investigation of the large-scale system, the usability isolation sensitivity analysis of the user, and their outcomes were debated.**Hsu Mon Lei Aung et al., (2022) [19]** described biometric recognition as a major task in security control systems. While the face protracted widely recognized as an applied biometric human recognition, it can be appropriated and copied. Furthermore, procurement of reliable facial data from an image occupied at an extensive distance using a low-resolution camera was challenging in video investigation. The authors proposed an MBS model by facial and gait information composition using deep CNN and transfer learning (TL). The proposed model acquired discriminative spatiotemporal features of face imageries. The dual extracted features were merged into a collective feature space at the featurelevel. The proposed model was constructed with CASIA-B gait and Extended Yale-B databases and a dataset of walking videos of 25 users. The proposed model achieved better results as accuracy parameters (97.3%), ERR of 0.004, and F1-score of 0.97. **Li Jiang et al., (2021) [20]** described the multi-modal biometric system that included two serious subjects: feature an illustration and multi-modal combination. Traditional feature images challenge appearance preprocessing and different feature-extraction methods for different modalities. The authors conventional a Dual-Branch-Net-based recognition method to report these twofold problems through human appearance. The technique combined CNNs, TL, and triad loss function to widespread feature images, shortening and merging the twofold modalities' feature-extraction procedure. The dual-Branch-Net also achieved a deep multilevel fusion of the twofold modalities' features. The system with an available feature vector and IKP employed a homologous multi-modal dataset named PolyU-DB. Investigational outcomes

the presentation that the method accomplished excellent and achieved an EER of the recognition, the outcome of 0.422%.

Table I Defines the analysis of existing methods and problems. Various datasets and parameters are considered for specific research.

TABLE I
THE ANALYSIS OF EXISTING METHODS

Author's Name	**Proposed Method**	**Problem**	**Dataset**	**Parameters**
Basma Ammour et al., (2022) [15]	Proposed novel feature extraction method for the multi-modal biometric system.	Lack of robustness.	CASIA iris-FERET CASIA iris-ORL	Recognition Rate
Yang Wang et al., (2022) [16]	Proposed MBS based on finger vain and face features using CNN model.	Required large dataset.	CASIA-WebFace SDUMLA-FV datasets	Accuracy
Susara S Thenuwara et al., (2022) [17]	Proposed a novel design for multi-modal biometric approval involved with the multi-agent system (MAS).	This method is not suitable for small in size networks.	SDUMLA-HMT multi-modal, BANCA and PRIVATE datasets.	Accuracy, Sensitivity Specificity
Mikel Labayen et al., (2021) [18]	Proposed an exact resolution constructed on the validation of various biometric tools.	The accuracy of the model is average.	---------	Accuracy Specificity
Hsu Mon Lei Aung et al., (2022) [19]	The proposed model acquired discriminative spatiotemporal features of gait and facial features from face imageries.	It required huge datasets for accurate results.	CASIA-B, Extended Yale-B dataset and walking videos of 25 users.	Accuracy
Li Jiang et al., (2021) [20]	Proposed a precise resolution based on validating different biometric tools and an automatic protection scheme.	This method is not suitable for multiple-feature extraction.	PolyU-DB	Accuracy EER

III. MATERIAL AND METHODS

This section utilizes feature extraction and optimization methods for the proposed MBS. Feature extraction is a process that identifies the most discriminating features in signals. It is also defined as eliminating discriminated features in a dataset by generating novel features from the remaining ones. In the Feature extraction step, the KPCA method is utilized. The kernel PCA method, KPCA, makes and is a non-linear and widely used PCA. This method requires the "kernel trick" to indirectly plot the unique data to a specific high-dimensional (HD) repeating kernel Hilbert location, and this location is used for PCA implementation.Feature Selection (FS) is the process of dropping the input values to the proposed model with the help of appropriate data and eliminating noise in the data. It is also defined as automatically selecting relevant features of the proposed model to solve a specific problem.Optimization is the development in which the proposed model is trained iteratively and provides outcomes in the form of max and min function estimation. It is a fundamental phenomenon in ML to become improved outcomes. Further, the CNN method is widely used for classification. In this proposed work, the Firefly method comprises the CNN method, termed the FA-CNN method, utilized to perform optimized classification. These methods are briefly described as;

A. Kernel PCA Method

This method is non-linear and mostly utilizes PCA. The KPCA method is employed in different arenas and set up directly to show the features as a min to max depth space. Cause of this aspect, these are separately exposed in the linear formula. The KPCA method requires a kernel matrix for evaluating the eigenvector's Matrix. This method is called the alteration of the covariance matrix. It improves the renewal feasible PCA in a straight line, and many communication features are very dimensional space and construct a kernel function. The KPCA method is very active in dimensions non-linear design associated with other approaches [21]. The KPCA estimates the Kernel (Kp) matrix of features according to eq. (i).

$$Kp_{cd} = \quad (\quad) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(i)}$$

Eq (ii) represents kernel fn(). , with pq conversion attributes.

$$_{cd} = \quad _{cd} - {}^{1}/_{n}\sum_{l} \quad _{l} - {}^{1}/_{n}\sum_{l} \quad _{dl} + {}^{1}/_{n^2}\sum_{qr} \quad _{rs} \ldots \text{(ii)}$$

The integrated method is to calculate the mean for features in predictable PCA. It carries the agreement of higher mathematics space of features described with Kernel funs

(k_{P0}) as a 0 mean. The eigenvectors "EiVec" standard is

assessed at the mid of the *Kp* clear in eq. (iii), the **covariance matrix "CoVe"** is drawn from the EiVec of the *Kp.*

CoVe = ……………………………….……… (iii)

B. Firefly Method

This method was recommended by Xin-She Yang in 2007, the flashing behavior-based procedure and discovering food for fireflies at night. After extensive alterations of fireflies, the author distinguished a colossal firefly interchange near the Firefly, which is more positive at the food search time. It is very suitable for reducing the space between two fireflies. This method has extended far in acceptance due to its easy implementation process and better performance parameters. So, for easiness, the Yang model is implemented in three vital steps for developing the Firefly Algorithm (FA) [22].

- All fireflies are unisexual; as a result, fireflies are involved in other ones.
- Attraction skill is similar to their radiance. Thus, the bright Firefly will appeal to fewer glowing fireflies. The attractiveness is relative to the brightness. If both diminish, then increase their reserves. If not, someone's Firefly is more optimistic than direct Firefly swaps random.
- A firefly is recognized by using the objective function to be of better quality.

C. CNN Method

It is a prominent model of a DL. It represents various layers that perform a specific task. This model automatically gets a detailed demonstrationof the rare data over non-linear alterations and rough non-linear studies. A classic CNN model involves a feature extractor composition of various convolutional layers in Figure 5, commonly tracked by pooling layers (PLs) and a softmax classifier. The convolutional layer (CL) eliminates features of the signal, while the PL layer diminishes the magnitudes. Thus, it shrinks the computing delay. CNN model can reach a regularization type through it. The extracted features are transferred to the softmax layer classification.

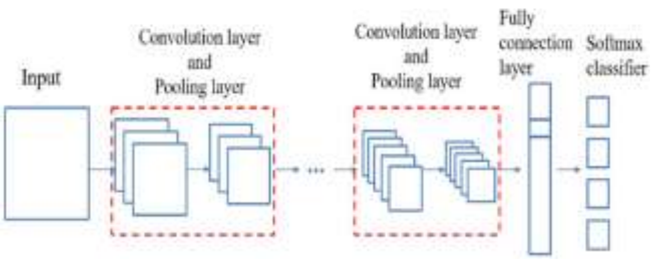


Fig 5. CNN Layered Model [23]

IV. Proposed Methodology

The proposed methodology is represented in Figure 6 and these are discussed in some steps as;

- In the beginning, explore IIT Delhi and CASIA datasets such as Fingerprint, Ear, and Palmprint for multi-model biometrics. All datasets are accessible in available repository places.

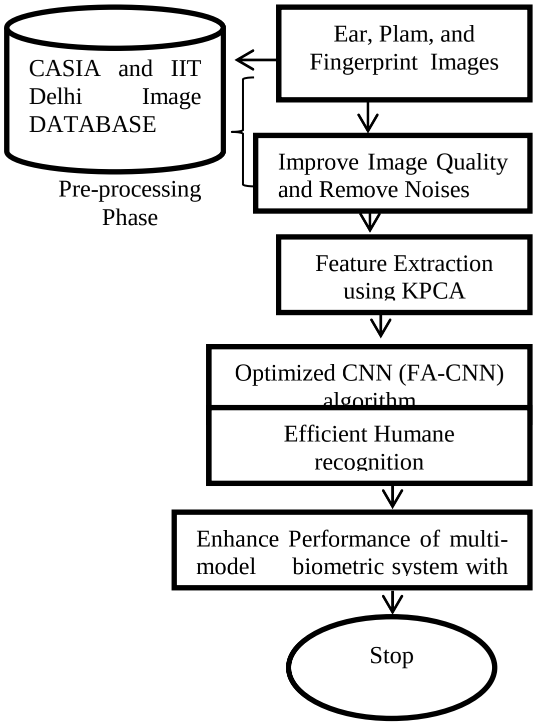


Fig. 6 Process of the Proposed FA-CNN Model for MBS

- The KPCA method extracts the multi-modal biometric features in Feature Extraction (FE) step. It extracts the exclusive and eliminates the dimensionality magnitude of the preprocessed images.
- The reliable features are selected to classify and increase the security and accuracy rate using Optimized (FA) with the CNN model.
- Calculate and confirm the performance parameters such as accuracy rate, SN, and SP.

V. Experimental Results

In this section, the simulation tool such as MATLABis used as a simulation tool. MATLAB is a fundamental virtual-reality tool that offers better results through customization throughout the learning process. Matlab tool is effectively used in different domains such as scientific research, mathematics, plotting, deep learning, etc. Next, three types of Datasets such as CASIA- palm print, CASIA fingerprint, and IIT Delhi EAR datasets and performance parameters are discussed;

A. Datasets

This proposed work uses three types of datasets: CASIA-palm print, CASIA fingerprint, and IIT Delhi EAR datasets. These datasets are represented in Figure 7 and also described as;

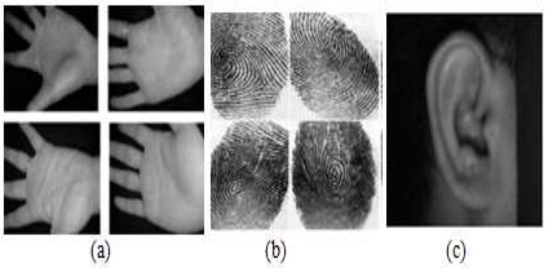


Fig. 7 (a)CASIA-Palm print(b**)** CASIA Fingerprint (c) IIT Delhi Ear Dataset

- *CASIA- palm print Dataset*

This dataset includes 5502 palm print imageries reserved by 312 subjects. Chinese Academy of Sciences reserves this dataset for the institution of Automation. This dataset is arranged in eight bits gray–levels and in JPEG format. It is utilized for any subject and eight palm print imageries have been collected with left and right palms. The resolution of original palm print images is 640*480 pixels [24].

- *CASIA Fingerprint Dataset*

Fingerprint identifications compare two, or binary designs of friction fact skin influences from human fingers to outline during these simulations resulting from the related species. The main fingerprint models include minutia, elevation finish, splitting up, and small ridge or spot. The elevation decision is an argument on elevation dismissal. Figure 7 (b) displays the CASIA fingerprint dataset that operates as feature-based image matching, where some minutiae are extracted from the detailed and input fingerprint descriptions [25].

- *IIT Delhi Ear Dataset*

This dataset consists of human ear images composed between Oct 2006 as well as June 2007 at the IIT Delhi in New Delhi, signified in Figure 7 (c). This dataset consists of 121 matters; three images occupy each subject in an interior background, containing four hundred twenty-one imageries [26].

B. Performance Parameters

This proposed work has three performance parameters: accuracy, sensitivity, and specificity. These are detailed as;

- *Accuracy*

It is defined as the fraction of the total sum of true positive (TP), true negative (TN), and complete sum of TP, false negative (FN), false positive (FP), and TN. It is represented in eq (i).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \text{....(i)}$$

- *Specificity*

Specificity is the ratio or fraction of true negative (TN) divided by the sum of TN and false positive (FP). It is also termed as FP rate.It is represented in eq (ii).

$$Specificity = \frac{TN}{FP+TN} \text{.... .....(ii)}$$

- *Sensitivity*

It is defined as the fraction or ratio of the true positive (TP) and the addition of the true positive (TP) and false negative (FN). It is represented in eq (iii).

$$Se \text{.....(iii)}$$

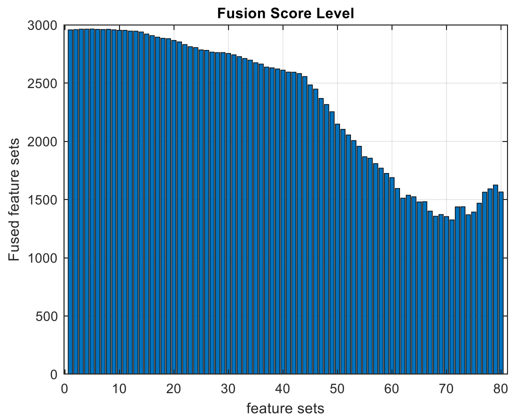


Fig. 8 Fusion Score Level

Figure 8 displays a bar graph depicting the score level fusion in an MBS. Score level fusion refers to the process of combining matching scores obtained from several biometric modalities to make a final decision regarding the verification of an individual. In an MMBS, various biometric traits such as fingerprint, palm, and ear are utilized together to enhance the overall accuracy rate and reliability of the system.

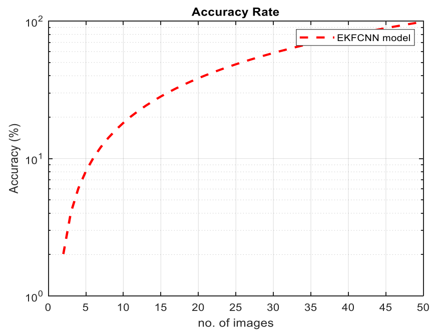


Fig. 9 Accuracy Rate

Next, Figure 9 shows the performance parameters and accuracy rates of a research model using the EKFCNN (Enhanced Kernel Firefly Convolutional Neural Network) model. As the number of images surges, the accuracy rate also increases. The accuracy rate of a Multimodal Biometric System (MMBS) can vary depending on various metrics, including the specific modalities used, the quality of biometric samples, the fusion methods employed, and the characteristics of the target population. The EKFCNN (Enhanced Kernel Firefly CNN) method has achieved a 99 percent accuracy rate.

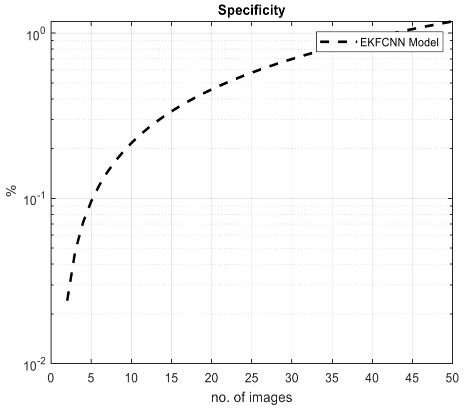


Fig. 10 Specificity

Figure 10, defines the proposed model (EKFCNN) performance metric with a specificity rate. It is also called as TN rate. It is a performance parameter used to calculate the efficiency of a multimodal BS in accurately verifying fraud or non-matching individuals. The maximum specificity rate defines a minimum acceptance rate and better reliability of the multi-model BS to accurately reject imposters.

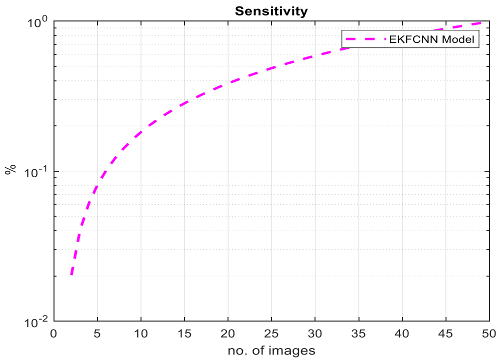


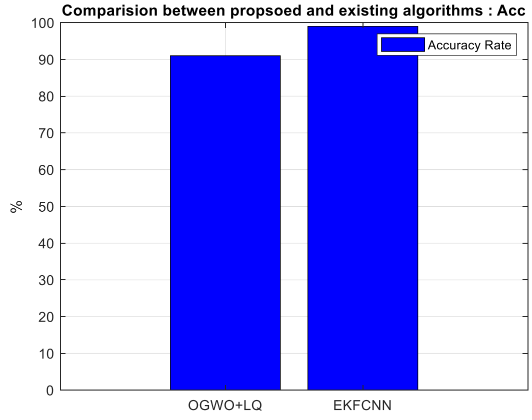
Fig. 11 Sensitivity

Figure 11 shows the performance metric with the sensitivity rate proposed (EKFCNN) model. It calculates the proportion of real attempts that are accurately verified by the system. The maximum sensitivity rate defines a minimum false rejection rate and better reliability of the MMBS to accurately verify real users. These parameters areespecially significant in ensuring the system's user satisfaction by reducing the chances of genuine customers being inaccurately rejected by false non-matches.

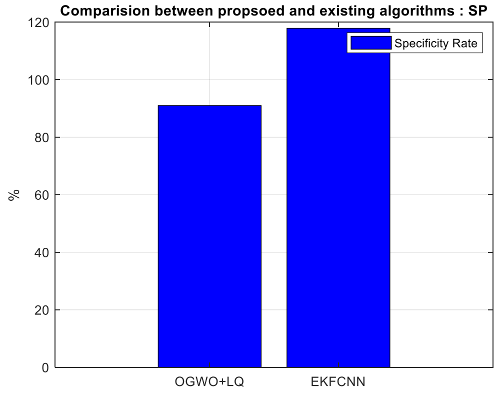
TABLE II
Comparative Analysis with Proposed EKFCNN and OGWO+LQ Models

Parameters| Methods	EKFCNN	OGWO-LQ
Accuracy	98.88	91.6
SP	0.998	91.6
SN	0.990	91.6

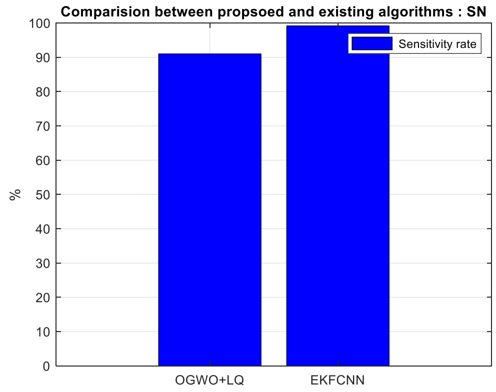
Table II shows the comparative analysis with proposed EKFCNN and existing OGWO-LQ models based on accuracy, SP, and SN rates. The proposed model has achieveda 98.8% accuracy rate as compared with the existing models. The research model has achieved an 8% improvement as compared with the OGWO - LQ model.



(a)



(b)



(c)

Fig. 12 (a) Comparison analysis with different methods and metrics (a) Accuracy (b) Specificity (c) Sensitivity

Figure 11 (a), (b), and (c) defines the comparison analysis between proposed (EKFCNN) and existing (OGWO+LQ) models in the form of accuracy, specificity, and sensitivity rate, which are the most important performance metrics. The proposed model (EKFCNN) accuracy and sensitivity rate has achieved maximum performance as compared with the existing model.

V. CONCLUSION AND FUTURE WORK

This paper presented detailed information on various types of fusion utilized in the multimodal biometric system. That has been proposed for Multimodal fingerprint, palm print, and ear features based on information found from different indications in a multi-modal biometric system. This paper, explored the different types of fusion of multimodal biometric systems, and develop a novel approach to fusion at the feature level using optimized feature-level Fusion (FLF). In this research work, the firefly optimization and CNN (FA-CNN) method are used to select reliable features and feature sets. Three types of MBS datasets, such as ear, palm, and fingerprint, are used for FLF. The implementation of the proposed method completes in different steps, such as preprocessing, FE, FS-optimized FLF, and classification. Each input dataset image is pre-processed initially to detect the issues such as background noise. The KPCA (kernel principal component analysis) is utilized for feature extraction from multi-modal biometric datasets. An optimal feature is selected using the firefly optimization method required for an optimal selection of features, and they are fused. The CNN method is used to classify the research method and is developed in MATLAB. The proposed method reached better performance by using a comparative analysis of different biometric parameters such as accuracy, specificity, and sensitivity.

In the future, this method will be implemented as another multimodal biometric feature like finger vein, iris, etc. It will implement the hybrid segmentation methods to expand the quality and of features the dataset images.

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