

Article

Match-Level Fusion of Finger-Knuckle Print and Iris for Human Identity Validation Using Neuro-Fuzzy Classifier

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Abstract: Biometrics is the term for measuring human characteristics. If the term is divided into two parts, bio means life, and metric means measurement. The measurement of humans through different computational methods is performed to authorize a person. This measurement can be performed via a single biometric or by using a combination of different biometric traits. The combination of multiple biometrics is termed biometric fusion. It provides a reliable and secure authentication of a person at a higher accuracy. It has been introduced in the UIDIA framework in India (AADHAR: Association for Development and Health Action in Rural) and in different nations to figure out which biometric characteristics are suitable enough to authenticate the human identity. Fusion in biometric frameworks, especially FKP (finger-knuckle print) and iris, demonstrated to be a solid multimodal as a secure framework. The proposed approach demonstrates a proficient and strong multimodal biometric framework that utilizes FKP and iris as biometric modalities for authentication, utilizing scale-invariant feature transform (SIFT) and speeded up robust features (SURF). Log Gabor wavelet is utilized to extricate the iris feature set. From the extracted region, features are computed using principal component analysis (PCA). Both biometric modalities, FKP and iris, are combined at the match score level. The matching is performed using a neuro-fuzzy neural network classifier. The execution and accuracy of the proposed framework are tested on the open database Poly-U, CASIA, and an accuracy of 99.68% is achieved. The accuracy is higher compared to a single biometric. The neuro-fuzzy approach is also tested in comparison to other classifiers, and the accuracy is 98%. Therefore, the fusion mechanism implemented using a neuro-fuzzy classifier provides the best accuracy compared to other classifiers. The framework is implemented in MATLAB 7.10.

Keywords: FKP; iris; SIFT; SURF; biometric fusion; FAR; FRR; log Gabor wavelet

1. Introduction

In individual validation strategy, biometrics provide higher security than the traditional techniques, for example, utilizing tokens or passwords. For security reasons, the customary security strategies are, bit by bit, changing from passwords or keys to biometric techniques. In any case, the biometric confirmation frameworks which utilize a single biometric for verification have different constraints. Consequently, to conquer these above restrictions, numerous biometrics and different strategies are being considered and created. Various biometric frameworks comprise of numerous different biometric data for authentication. They provide higher confirmation rates and are more dependable. For fusing biometric frameworks, there are three degrees of fusion. Among the three levels, a combination at the matching score level is generally favored. Recent research shows that in numerous bio-metric frameworks, less work has been performed on testing and assessing the presentation of the system. Therefore, a test in multimodal biometrics is chosen as the correct technique to absorb or meld information from different sources. This has propelled the current work to check whether a biometric framework execution is improved by incorporating reciprocal data from various modalities.

Biometrics is a unique mechanism for authenticating a human. In biometric authentication, humans can be authenticated on the basis of behavioral or psychological characteristics. Physical characteristics involve the shape of the human body, while psychological characteristics are based on the behavior of humans. Frameworks based on a single biometric trait are termed unimodal, while the frameworks having two or more biometric traits are named multimodal biometrics. Multimodal biometrics overcomes the issues of noisy sensor data, non-comprehensiveness, parody assaults, and many more. Multimodal biometric frameworks combine the features introduced by various biometric wellsprings of data. The proposed approach presents a multimodal biometric framework dependent on the fusion of FKP and Iris [1] at the match score level. The features of FKP [2] are captured by the fusion of feature vectors by applying SIFT [3] and SURF [4]. By fusion of FKP and iris, the precision and execution of proposed multimodal biometric recognition are significantly high with respect to FKP [5] and iris separately [6]. In this, FAR (False Acceptance Rate) is decreased, and FRR (False Rejection Rate) is increased.

Biometric frameworks that perceive an individual utilizing a single biometric data are known as unimodal biometric frameworks. These frameworks face many difficulties, such as noisy data, intra-class contrasts, non-comprehensiveness, etc. These issues can be reduced through multimodal biometric frameworks that merge data introduced by numerous biometric sources [7]. Figure 1 shows a regular multimodal biometric framework in which three biometric features, for example, finger-knuckle print, iris, and face, are fused at the match score level to acquire the outcome. The images shown in the figure are taken from self and [8,9]. It is anticipated that multimodal biometric frameworks are more dependable than unimodal biometric frameworks because of the presence of numerous wellsprings of biometric data [9]. The utilization of numerous biometric wellsprings of data further develops the general framework precision. These frameworks are more costly than unimodal biometric frameworks since they require disk space, calculations for correlation and extraction of many features, numerous sensor gadgets, and extra user enrollment. Furthermore, the exhibition of these frameworks might be degraded if the appropriate combination procedure has not been utilized to fuse the data provided by various wellsprings of biometric data.

The sequence of obtaining and preparing in a multimodal biometric framework can be serial or parallel. In a serial architecture [10], different biometric sources are acquired and prepared consecutively, and the outcome acquired by one matcher might influence the handling of others. In a parallel design, distinctive biometric sources are handled freely, and their outcomes are matched utilizing the proper fusion approach. The decision of a particular biometric framework relies upon the application's necessities.

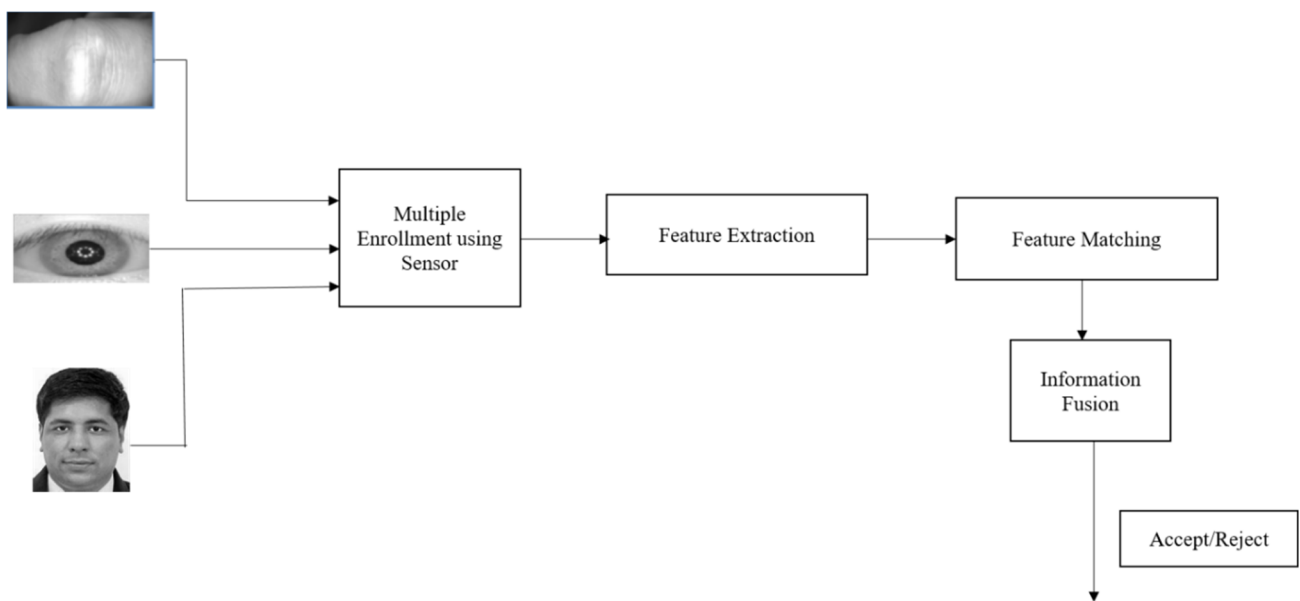


Figure 1. Multimodal biometric system.

1.1. Iris Recognition

Iris recognition is a computerized strategy for biometric verification that utilizes numerical pattern recognition procedures on pictures of either of the iris of a person's eye. Several hundred million people in several nations throughout the planet have been enrolled in iris recognition frameworks [11]. A benefit of using iris recognition [8] is that it has a fast speed of matching and is highly protective because the eyes are secured inside but are a remotely noticeable organ.

1.2. FKP Recognition

The FKP [2] is the inner skin of the back joint of a Fingerprint. As of now, the FKP [12] is exceptionally rich in surfaces and can be utilized to particularly distinguish an individual. Biometric features have been broadly utilized in the home validation framework since it is more solid when contrasted with ordinary strategies such as information-based techniques, for example, secret key, PIN, and token-based techniques [13], e.g., passports and ID cards. Diverse physical or social qualities such as unique finger impression, face, iris, palm print, voice, step, signature, and so forth have been generally utilized in biometric frameworks. Among these characteristics, hand-based biometrics, for example, palm print, fingerprint, and hand geometry, are extremely famous as a result of their high user recognition. It has more benefits when contrasted with fingerprints. First, it is not effectively harmed since just the inward surface of the hand and is utilized generally in holding articles. Furthermore, it is not related to any crimes and, subsequently, it has higher user recognition. Third, it cannot be manufactured effectively since individuals do not leave the hints of the knuckle surface on the articles contacted/taken care of. Figure 2 depicts the FKP acquisition device [14].

FKP features are extracted using SIFT and SURF methodology. After the extraction, the fusion of the feature vectors is performed using the Weighted Sum rule at the matching score level. At the time of verification, enrolled and query highlight vectors are contrasted with the closest neighbor to accomplish the individual matching scores

Multimodal biometric frameworks dependent on serial design are utilized in basic applications with less security for the users, for example, bank ATMs [15]. Conversely, multimodal biometric frameworks dependent on parallel design are more appropriate for basic applications with more security (for example, access to army bases). The greater part of the proposed multimodal biometric frameworks depends on the parallel approach since decreasing error rates was the fundamental objective [16,17].



Figure 2. FKP acquisition device.

The work directed a novel trial to build up the model that can authenticate human identity utilizing finger–knuckle print and iris biometric [18] modalities. The major advantage of this work is to plan a model that does not require an individual authentication mechanism, thereby making the authentication model more precise and accurate in validating human identity. This analysis is performed keeping in view that all the users are dependent on a single biometric trait for authentication, thereby making the system vulnerable to attack. The model created here had an accuracy of 99.58%.

The proposed method has an increased authentication rate and accuracy, which has increased the security for human validation. The approach also results in the modification of False Acceptance Rates (FARs) and False Rejection Rates (FRRs) of the existing system in order to provide a genuine authentication.

The rest of the paper is organized as follows. Section 2 provides a brief survey of relevant research regarding this topic. Section 3 demonstrates the proposed methodology, which indicates the score level fusion strategy of FKP and iris modalities using a PCA-based neuro-fuzzy classifier. Section 5 discusses the result analysis of the proposed methodology. This result analysis reveals that the proposed methodology has a better authentication rate compared to unimodal biometrics. A comparative analysis is also performed to verify the authentication of the proposed work.

2. An Overview of Related Research

In a multimodal framework, various modalities are fused, for example, fingerprint [19], face [20], palm print [21], iris [8], FKP, ear [22], and so forth. A portion of the FKP, iris, and fusion methodologies proposed by various authors are discussed.

In the paper of Zhang et al. [23], they proposed an amendment approach for dealing with the stance anomaly among the finger pictures and thereafter introduced a clever area coding-based component explanation method to also execute and incorporate a combination of FP, FV, and FKP attributes. In any case, for the coding plan, a bank of orchestrated Gabor channels is used for course remember overhaul for finger pictures.

In the paper by Chitroub et al. [24], they proposed a powerful plan for combination rule choice. The presentation displayed by score level combination calculations was regularly influenced by opposing choices delivered by the constituent matches for a similar person. Furthermore, the computational expense of these combination calculations that were influenced by conflicting scores rises radically. This paper introduced calculations to streamline both check exactness and calculation time. The creators had proposed a successive combination calculation by including the probability proportion test measurement in an SVM system [25] to arrange match scores delivered by various sources. The creators had additionally introduced a powerful determination calculation that brought together the constituent sources with the combination rules to streamline recognition exactness and calculation time. In light of the nature of the information biometric information, the

proposed calculations progressively pick between different matches and combination rules to perceive a person. The proposed calculations were utilized to lighten the impact of covariate factors in the face recognition framework [26] by coordinating with the scores delivered by two face recognition calculations. The examinations led on a heterogeneous face information base of 1194 subjects recommended that the proposed calculations proficiently further developed the confirmation exactness of a face recognition framework with low computational time. In the future, the proposed consecutive combination and dynamic choice calculations could likewise be reached out to other multimodal situations, including the face, unique mark, and iris [27] matches.

Yang et al. [28] introduced an outline of various biometric layout insurance plans proposed in the writing and examined their qualities and constraints as far as security and revocability are concerned. They have summed up various assaults against biometric framework security and procedures to overcome these assaults. Among these assaults, an assault against putting away biometric layouts is of significant worry because of the unavoidable idea of biometric formats. To delineate the issues associated with carrying out format security, they gave explicit executions of these methodologies on a typical unique mark information base. The current layout insurance plans are not yet fully grown enough for the enormous scope of the organization [29]. Once in a while, they do not meet the prerequisites of variety, revocability, security, and high-recognition execution. They clarified that the security investigation of existing plans is by and large dependent on the intricacy of beast power assaults, which assumes that the circulation of biometric highlights is uniform. Accordingly, an enemy might have the option to utilize the non-uniform nature of biometric components to perform an assault against the framework that might require extremely fewer endeavors to disregard the framework security. A solitary format security approach may not be adequate to meet all the application prerequisites. Henceforth, mixture approaches that utilize the benefits of various format security plans should be fostered. Likewise, with the developing interest in multi-biometric frameworks, plans should be fostered that save multi-biometric formats at the same time.

Zhang et al. [30] have proposed a clever recognition technique dependent on finger-knuckle prints. Key points are removed from the FKP utilizing scale-invariant element Transform. The extricated key points are then bunched utilizing K-Means Algorithm. The centroid of the K-Means is put away in the information base. For a provided question picture, the centroid is processed and contrasted to that in the dataset utilizing XOR activity. The exhibition is tried on the Poly-U FKP information base and is displayed to provide a high recognition rate for confirmation.

Muthukumar et al. [31], in their work, utilized the neighborhood highlights initiated by the stage congruency model, which is upheld by solid psychophysical and neurophysiologic confirmations for FKP recognition. In the calculation of stage congruency, the neighborhood direction and the nearby stage are likewise extricated from the neighborhood picture fix. These three neighborhood highlights are autonomous of one another and reflect various parts of the picture nearby data. The three neighborhood highlights are proficiently registered under the computation system of stage congruency utilizing a bunch of quadrature pair channels. These three neighborhood highlights are incorporated by score level combination to further develop the FKP recognition exactness. An EER [32] of 1.27% was accomplished for the FKP recognition utilizing neighborhood provisions, and a mix of nearby and worldwide components further developed it to 0.358%.

Amraoui et al. [33] proposed a method in which surface data separated from iris information [34] and dynamic pressing factor variety information removed from online marks was joined to shape a solid biometric framework. In this view, this paper is proposing a multimodal biometric recognition design, which uses another element vector extraction system dependent on the Webber Local Descriptor and the k-NN AI classifier. The TAR-TRR [35] results when utilizing iris recognition [36] alone came to 88.39%. When utilizing the dynamic pressing factor variety of information extricated from online marks, TAR-TRR came to 75.89%. When joining the information of the two modalities, the recognition

of TAR-TRR expanded to 90.18%. The proposed engineering uncovered that biometric frameworks which perform recognition utilizing two unique information channels are more solid than when utilizing single channel information.

Perumal et al. [37] proposed an original methodology for finger–knuckle-print recognition consolidating classifiers dependent on both miniature surfaces in the spatial area provided by nearby paired example (LBP) and large scale data in recurrence space procured from the discrete cosine change (DCT) to address the FKP picture. The arrangement of the two capabilities is finished by utilizing the support vector machine classifier (SVM) classifier. The choice level combination utilizing the larger part vote rule is displayed to beat the individual classifiers. The recognition rate accomplished is 98.2%, 98%, 98.7%, and 97.1% separately.

Kumar et al. [38] proposed to work on the security of multimodal frameworks by creating the biometric key from unique finger impression and FKP biometrics with its component extraction utilizing K-implies calculation. The mysterious worth is scrambled with a biometric key utilizing the asymmetric Advanced Encryption Standard (AES) Algorithm. This paper additionally examines the joining of the unique mark and FKP utilizing bundle model cryptographic level combination to work on the general execution of the framework. The encryption cycle will provide more validation and security for the framework. The Cyclic Redundancy Check (CRC) work shields the biometric information from malignant altering, and it provides mistake checking usefulness.

Subbarayudu et al. [39] have utilized unique finger impressions and finger–knuckle print pictures to plan a multimodal biometric framework. Components are extricated from the unique mark utilizing Discrete Wavelet Transform and that of a finger–knuckle print utilizing scale-invariant element change. In both cases, the provisions are bunched utilizing K-Means grouping calculation. The centroid of the groups is linked and put away as component vectors. XOR administrator is utilized for coordinating, and a recognition pace of 99.4% is accomplished.

In their research, Evangelin et al. [40] proposed a multimodal biometric framework utilizing unique finger impression and iris. Unmistakable printed components of the iris and finger impression are extricated utilizing the Haar wavelet-based strategy. A clever component level combination calculation is created to consolidate these unimodal provisions utilizing the Mahalanobis distance method. A help vector-machine-based learning algorithm is utilized to prepare the framework utilizing the element extricated for order. A most extreme recognition pace of 94% is accomplished.

As per the literature survey done in Table 1, it is concluded that FKP and iris biometric modalities have been proved to be the highly accurate system for Human Authentication. Based on this analysis, a fusion mechanism is proposed for the combined accurate authentication of human-based on two levels biometric verification and authentication.

Table 1. Comparative analysis of different approaches.

S No.	Paper	Year	Methodology	Limitation
1.	Feature level fusion approach for personal authentication in multimodal biometrics [40]	2017	<ul style="list-style-type: none"> Gray Level Co-occurrence Matrix feature extraction technique is used for unique feature identification. ANN with Particle Swarm Optimization is deployed for Security Enhancement. Palm print and FKP is used for Fusion 	<ul style="list-style-type: none"> Accuracy is achieved only up to 78%. Complexity is too high
2.	Finger–knuckle print recognition system using a compound local binary pattern [33]	2017	<ul style="list-style-type: none"> Compound Local Binary Patterns for FKP identification An extra bit is added for each P bit encoded by LBP to a neighbor 	<ul style="list-style-type: none"> FKP Accuracy is achieved more than 90% Only one biometric is used.

Table 1. Cont.

S No.	Paper	Year	Methodology	Limitation
3	Finger–knuckle-print recognition system based on features level fusion of real and imaginary images [2]	2018	<ul style="list-style-type: none"> • Three Patch Local Binary Pattern technique is used for finger–knuckle Print Recognition • Cosine Mahalanobis distance is used at Matching Stage 	<ul style="list-style-type: none"> • 1 D log Gabor Filter is used which can be improvised • Only one Biometrics is used
4	Toward More Accurate iris Recognition Using Dilated Residual Features [41]	2019	<ul style="list-style-type: none"> • Residual Network Learning with dilated convolutional kernels is considered for training process • It alleviates the need for the down-sampling and up-sampling layers 	<ul style="list-style-type: none"> • MaskNet training is required. • Masked bits are not ignored
5	A Deep Learning iris Recognition Method Based on Capsule Network Architecture [42]	2019	<ul style="list-style-type: none"> • Deep Learning base method based on Capsule Network is proposed. • A modified Dynamic Routing technique is used to identify between two capsule layers 	<ul style="list-style-type: none"> • Need for other Vector forms and integration with other learning methods • For large categories need for identification for Processing methods
6	Local Binary Pattern based Multimodal Biometric Recognition using Ear and FKP with Feature Level Fusion [43]	2019	<ul style="list-style-type: none"> • LBP Feature Extraction method is used for FKP Feature Extraction • Canny Edge Detection method is used 	<ul style="list-style-type: none"> • Histogram Equalization is used which can be modified to a higher extent. • Intruding Chances are reduced but with single biometric
7	Towards Complete and Accurate iris Segmentation Using Deep Multi-Task Attention Network for Non-Cooperative iris Recognition [44]	2020	<ul style="list-style-type: none"> • A deep learning approach named irisParseNet is proposed • Unified into a multi task network 	<ul style="list-style-type: none"> • Segmentation Performance is less • Lightweight iris Segmentation Network is still to be developed
8	Contactless person recognition using 2D and 3D finger–knuckle patterns [12]	2022	<ul style="list-style-type: none"> • Contactless Verification of a person is proposed for fusion of 2D and 3D finger–knuckle prints • Kernel Fisher Analysis Technique is used for dimensionality reduction 	<ul style="list-style-type: none"> • Efficient Authentication based on only one biometric • Can be combined with other biometric modalities for better authentication

3. Introduction to MATLAB

The MATLAB system is a collection of tools and high-level languages. It provides an excellent environment for research work and simulation.

3.1. Development Environment

This is the huge arrangement of instruments and offices that assist you with utilizing MATLAB capacities and records. A significant number of these instruments provide an office of graphical Uis. Matlab likewise furnishes offices to collaborate with other languages, such as java, c, c++, prophet information base, and dab net. MATLAB has its own proofreader and furthermore supports another editorial manager. It incorporates the Command Window, an order history, and programs for review help, the work area, records, and the inquiry way. In the order window, we can run different orders and script records; in the order history, we can see the past history of orders. By utilizing assistance, we can acquire data about different inbuilt capacities, different devices, significant subjects, and procedures. The work area provides data on variables that are at present utilized by orders or content documents.

3.2. The MATLAB Mathematical Function Library

This is an enormous assortment of computational calculations going from rudimentary capacities such as total, sine, cosine, tan and complex number crunching to additional perplexing capacities such as quaternion number, complex number, grid reverse, lattice eigenvalues, differential condition, mix, Laplace change, Bessel capacities, quick Fourier changes, wavelet changes, and so forth. Each new adaptation of MATLAB incorporates different capacities in view of the new examination.

3.3. Geometric Transformations and Image Registration

Mathematical changes are helpful for errands, for example, turning an image, diminishing its goal, adjusting mathematical twists, and performing image enrollment. Image Processing Toolbox upholds straightforward tasks, for example, resizing, turning, and editing, as well as additional complex 2D mathematical changes, such as relative and projective. The tool kit likewise provides an adaptable and complete structure for making and applying redid mathematical changes and insertion techniques for N-layered exhibits.

Image enlistment is significant in remote detecting, clinical imaging, and different applications where images should be adjusted to empower quantitative investigation or subjective correlation. Image Processing Toolbox upholds power-based image enlistment, which consequently adjusts images utilizing relative force designs. The tool compartment likewise upholds control-point image enlistment, which requires the manual choice of control focuses in each image to adjust two images. Furthermore, the Computer Vision System Toolbox upholds feature-based image enrollment, which consequently adjusts images utilizing feature discovery, extraction, and matching, followed by mathematical change assessment.

3.4. Some MATLAB Functions Used

Imread: Read image from the design document
 Imwrite: Write images to the design document
 Imfinfo: Information about designs document
 Imshow: Display images
 Subimage: Display different images in a single figure
 Immovie: Make films from multiframe images
 Implay: Play motion images, recordings, or image arrangements
 Imcrop: Crop images
 Imresize: Resize images
 Imrotate: Rotate images
 Imshowpair: Compare contrasts between images
 Imellipse: Create a draggable oval
 Imellipse: Create a draggable oval
 Imfreehand: Create a draggable freehand district
 Impoly: Create a draggable, resizable polygon
 Imrect: Create a draggable square shape
 Bwboundaries: Trace district limits in a twofold image
 Bwtraceboundary: Trace object in parallel image
 Corner: Find corner focuses in images
 Cornermetric: Create a corner metric framework from images
 Edge: Find edges in a grayscale image

4. Proposed Methodology

The proposed method is based on the analysis of different approaches. The analysis is performed on the basis of different approaches of biometric fusion performed on the face, finger, FKP, and iris biometrics.

The vital image preprocessing is finished by choosing the image index. The edges for perceiving a face, fingerprint, and iris can be changed at run time to permit clients greater adaptability. For reasonable utilization of this framework, the database contains particular subdirectories of faces, ears, and irises that are consequently associated with the acknowledgment framework. The various biometrics of an individual can be chosen by picking the template, which includes face, ear, and iris images of that person. For adaptability, the outer databases need to duplicate the images in the current index or need to distribute the current registry to the outside dataset.

In order to make the framework intense, first limits are chosen so that the framework can recognize a face and a non-face image. Moreover, for changing the edge, there is a menu-driven arrangement in the framework. For proficient use, the framework has an activity-button-driven choice to free the pre-owned memory and clear all the chosen images.

The autonomy of the characteristics guarantees the improvement in execution. The raw biometric information captured by different sensors was handled and coordinated to produce other information. The preprocessor unit extricated the fundamental features. The layout will be created for the separated features. The information will be contrasted with dataset information for matching. During enlistment, these characteristics are used by the relating biometrics, and the features of the face, iris, FKP, and fingerprint are put away in the database. During verification, this cycle is again rehashed and the features acquired are contrasted with the information kept in the dataset, and the choice module will choose whether the individual ought to be acknowledged or dismissed. One such method is the Histogram of Gradients, which is defined in Section 4.1.

4.1. Histogram of Gradients (HOG)

HoG is a broadly utilized technique in the area of image preparing and design acknowledgment for applications, for example, face acknowledgment, object acknowledgment, image sewing, and scene acknowledgment.

It is an intriguing descriptor intended for design location. The general thought of this descriptor is to distinguish the layout of an article in an image by figuring the inclination direction is little contiguous districts that spread the whole image. In HOG [20], we are going to separate an image into various little associated areas of cell size $N * N$. We create the HOG headings for each pixel in the area and the entire image. HoG descriptor speaks to the mix of the considerable number of histograms created for districts in the image.

For feature extraction, the image will be separated into little nearby areas $R_0, R_1, R_2 \dots R_{m-j}$ and autonomously extricate surface descriptors from every locale. At that point, we develop a histogram with every single imaginable mark for each district [32]. Leave the number of names delivered by the administrator and m be the number of nearby districts in the isolated image. At that point, we can speak to a histogram (H) of marked image $d1(x, y)$. At last, an exceptional HOG histogram is worked by linking all the registered histograms.

In this paper, a novel approach is proposed in which FKP and iris are fused using score level fusion for human identity validation. Features from FKP are extracted with the assistance of SIFT and SURF. After extraction, the element vectors are fused with the assistance of the weighted sum rule at the matching score level. After the individual matching score generation, the nodule features are classified using a neuro-fuzzy classifier for identification of genuine and imposter at the time of verification, enrolled, and query vectors are contrasted with the closest neighbor to accomplish the individual matching scores. The process is demonstrated in Figure 3. The proposed methodology is divided into 2 sections.

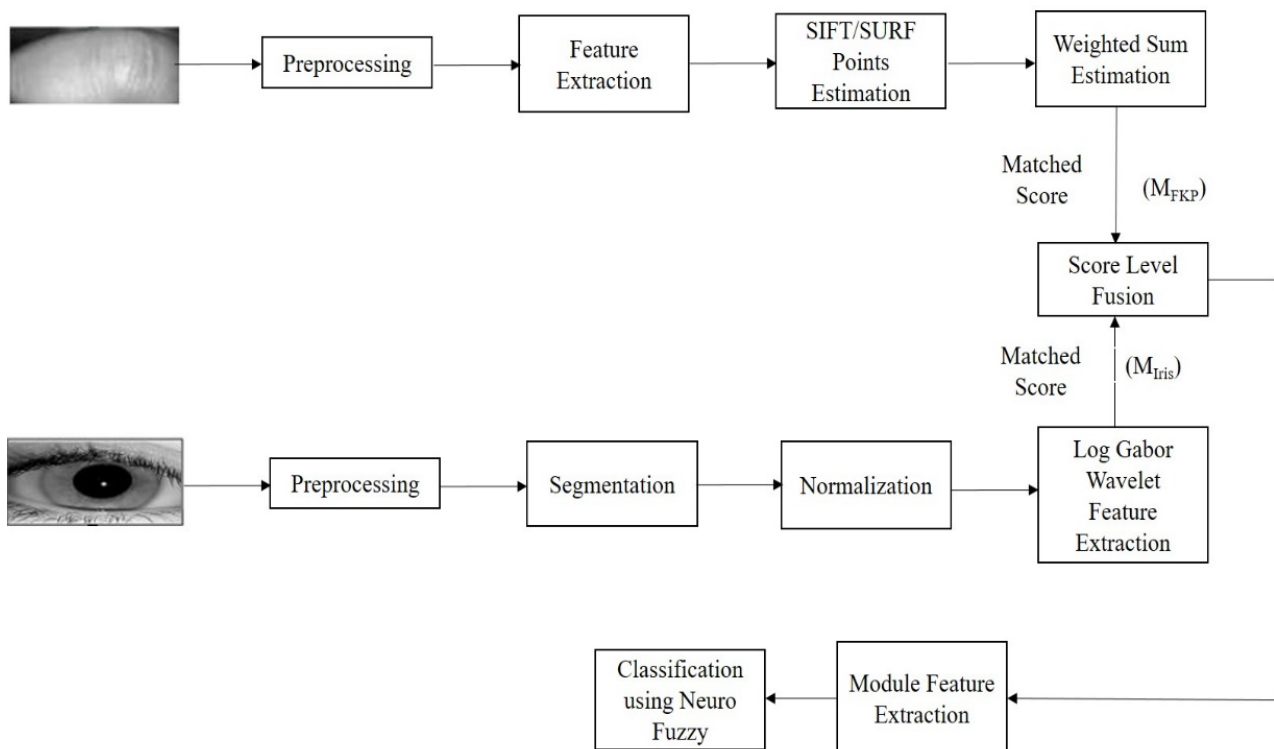


Figure 3. Block diagram of proposed model.

4.2. FKP Methodology

The architecture of the proposed FKP method is depicted in Figure 4. It involves the following modules:

(a) FKP Image Enhancement

The finger–knuckle picture has a little contrast and irregular intensity. To accomplish a texture image following steps are taken:

Stage 1: Image is partitioned into sub-blocks 10×10 pixels to assess the impression of the square.

Stage 2: Bi-cubic insertion is utilized to grow gauge coarse reflection for FKP unique size.

Stage 3: Subtraction of assessed reflection to attain the regular intensity of FKP.

Stage 4: Improve differentiation of squares (10×10) of FKP surface through histogram leveling.

(b) FKP Feature Extraction

Feature vectors are extricated from FKP images utilizing SIFT and SURF, both SIFT and SURF were intended to separate invariant features from images. Figure 5 shows the extracted SIFT and SURF points. Filter calculation includes the following steps:

Stage 1: Find out the approximate area and key points.

Stage 2: Filter their area and scale

Stage 3: Find direction for each point.

Stage 4: Find descriptors for each point.

(c) Fusion of Feature Vectors

The features of FKP are represented by the component vector of features separated by SIFT and SURF calculation. The matching scores between the corresponding feature key points are determined utilizing the closest neighbor relationship technique as follows:

Let S and U are feature vector matrices of the key points of the query and the enrolled FKPs acquired utilizing SIFT and SURF:

$$S = \{s_1, s_2, s_3, \dots, s_m\} \quad (1)$$

$$U = \{u_1, u_2, u_3, \dots, U_n\} \tag{2}$$

where S_i , and U_j , is the feature vector of key points I in S and j in U separately. If $\|S_i - U_j\|$ are the Euclidian separation among S_i and its first closest neighbor U_j at that point:

$$S_i = \|S_i - U_j\| < TH \text{ Matched with } U_j \tag{3}$$

where TH is an estimation of the limit matched and unequaled key points. Figures 6 and 7 show the distribution of matched and non-matched points for SIFT and SURF.

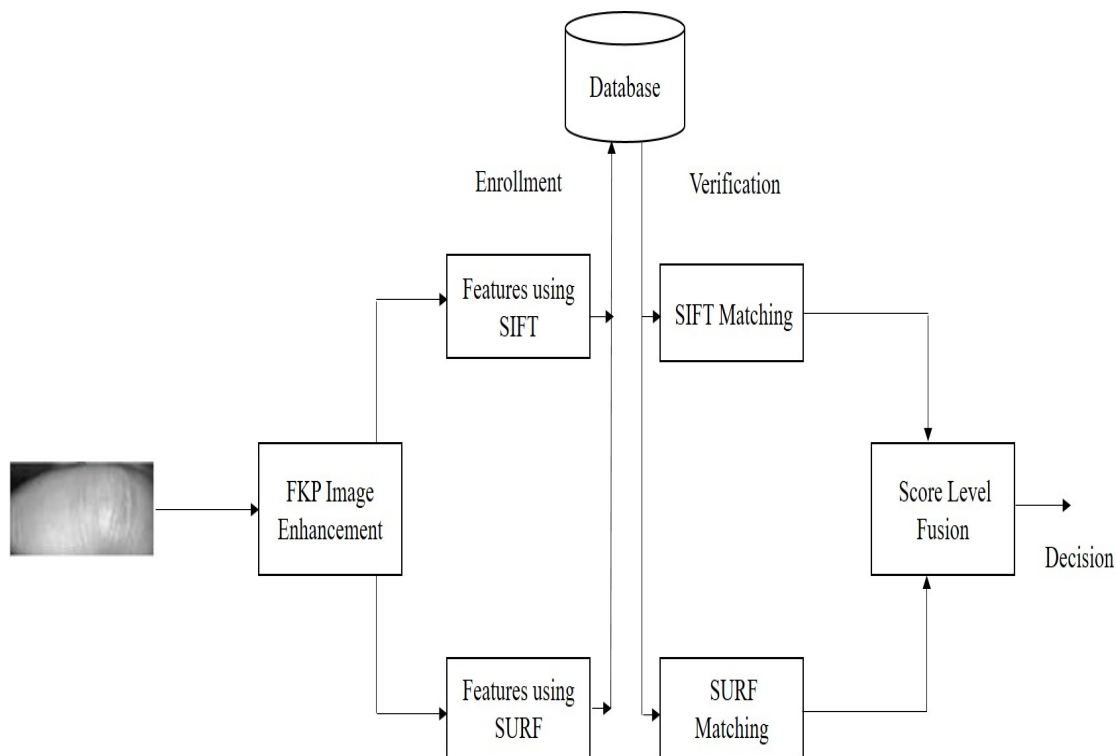


Figure 4. Proposed FKP method.

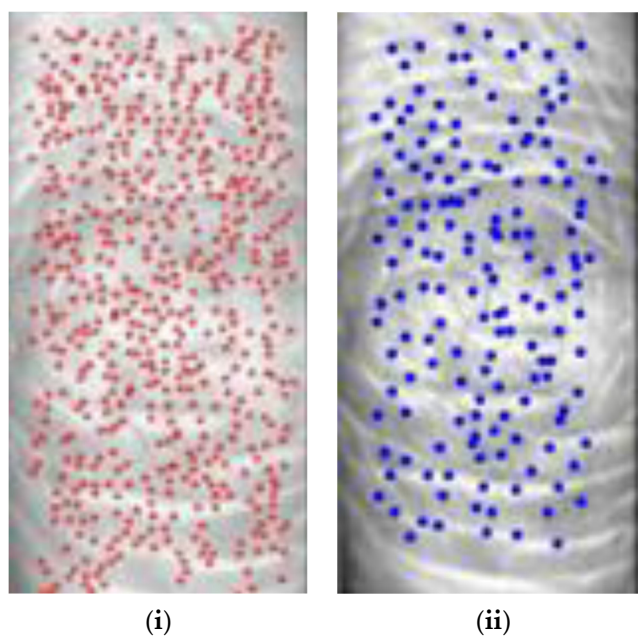


Figure 5. (i) SIFT key points (ii) SURF key points.

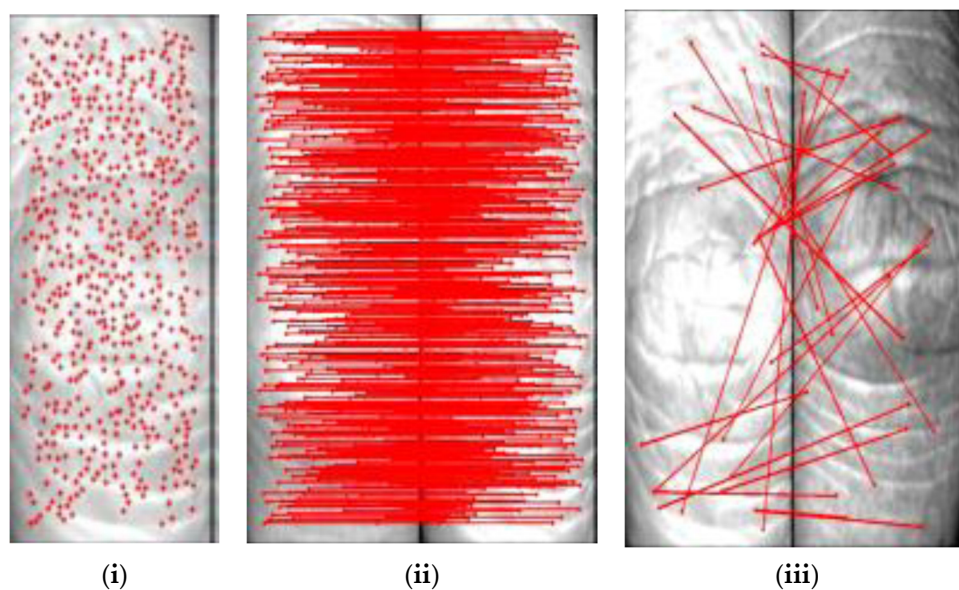


Figure 6. (i) SIFT points (ii) Matched points (iii) Non-matched points.

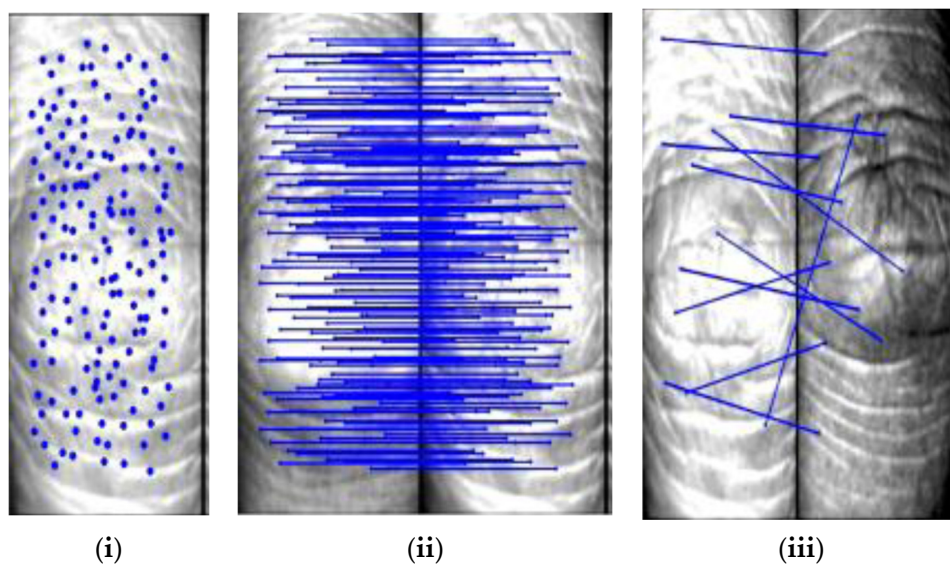


Figure 7. (i) SURF points (ii) Matched points (iii) Non-matched points.

Let M_S and M_U are matching scores of SIFT and SURF individually among the query FKP and a selected FKP. The individual matching scores M_S and M_U are combined with the weighted rule to accomplish the last matching score S as:

$$S = W_S \times M_S + W_U \times M_U \tag{4}$$

where, W_S and W_U are loads allotted to SIFT matching score M_S and SURF matching score M_U individually with $W_S + W_U = 1$. Here, $W_S = CS / (CS + CU)$, and $W_U = CU / (CS + CU)$ are viewed as where CS and CU are the right recognition rate of the strategy for SIFT and SURF.

4.3. Iris Methodology

Iris is the most secure biometric characteristic because of its general performance. It is the ring-molded region of our eye confined by the pupil and sclera area on both sides. The iris has many tangled properties, for example, crisscross collarets, spots, spirals, wrinkles, crowns, stripes, and so forth, which all make the iris a solid attribute. Figure 8 depicts the iris feature extraction model proposed by Daugman [45].

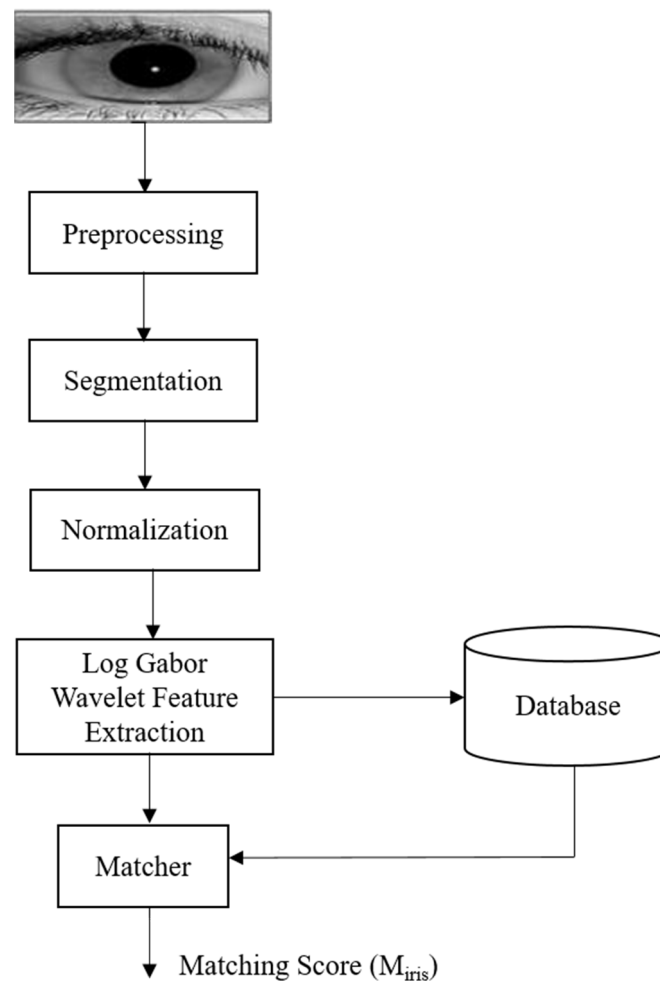


Figure 8. Iris recognition working by Daugman.

In the proposed method, the feature extraction is performed in three steps:

(i) Preprocessing and Segmentation

This progression is performed to attain the iris area of intrigue (ROI) from the image of the iris. Hough transform is utilized to discover the district of intrigue (ROI) in this cycle.

(ii) Normalization

This methodology assigns every pixel inside the ROI to a couple of polar directions. The focal point of the pupil is assumed as a direct point, and the radial vector goes through the ROI.

(iii) Iris Feature Extraction

Feature extraction is a key cycle in which 2D image attains transformed into vector boundaries. The significant element of the iris should be coded so correlations can be made between the selected layout and query format. There are numerous strategies to separate the element from the iris picture, for example, Gabor channel, wavelet transform, and so on. The log Gabor wavelets are utilized here for the said reason.

(iv) Matching of iris feature

The matching cycle decides if two-element vectors are indistinguishable or not, dependent on which genuine or imposter is chosen.

(v) Fusion of Match Scores

The proposed technique is intended for the verification process to decide the validity of the client. The scores created by biometrics features are consolidated utilizing the

weighted sum principle. The M_{fkp} and M_{iris} are matching scores generated from FKP and iris individually. The normalization of these scores is examined beneath:

$$NS_{fkp} = (M_{fkp} - \min_{fkp}) / (Max_{fkp} - \min_{fkp}) \quad (5)$$

$$NS_{iris} = (M_{iris} - \min_{iris}) / (Max_{iris} - \min_{iris}) \quad (6)$$

Utilizing normalization (min–max), the normalized scores NS_{fkp} and NS_{iris} are captured for FKP and iris individually. Before score level fusion, these scores are changed over into closeness scores.

4.4. Neuro-Fuzzy Classifier

For classification, the feature vector is provided as an input to a hybrid classifier which is based on the combined approach of neural network and a fuzzy called neuro-fuzzy. It is composed of 2 different subnetworks: self-organizing fuzzy-based network and multi-layer perceptron in a combined way. The feature vector is provided as an input to the fuzzy layer to generate the pre-classification vector, which is provided as an input to the multi-layer perceptron for classification of the input image. In the fuzzy layer, the grouping of pixels based on the closest neighbor relationship is performed, and clusters are generated. Based on the estimation scores, the nodules are classified into single and multiple values. Based on the experimental results, it is concluded that the proposed fuzzy neural network is more tolerant of noisy data.

5. Result Analysis

The proposed work is the fusion of two biometric modalities: FKP and iris, to authenticate a person. The implantation analysis reveals that the proposed work provides an accuracy of 99.68%, which is extremely high as compared to other biometric modalities. The proposed approach is validated on the basis of two different datasets: CASIA for iris biometrics and Poly-U for FKP biometrics. The proposed approach is implemented using different classifiers with different patterns and activation functions. The accuracy of the proposed approach is compared to all the classifiers: ANN, BPN, MLP, and neuro-fuzzy. The neuro-fuzzy classifier provides the best outcome in terms of accuracy, i.e., 99.8%.

In the proposed method, the fusion is trained and tested for four different classifiers. First is the artificial neural network in which the images are trained and tested for a predefined pattern. The second classifier is a multi-layer perceptron (MLP) in which multiple hidden layers are there on which different patterns are analyzed. The third classifier is a back propagation network (BPN) in which weights of the layer are adjusted by activation function to classify different patterns. The fourth is the hybrid combination of fuzzy-based and MLP in a combined way to classify the patterns.

The proposed technique is implemented in MATLAB with Poly-U (FKP information base) and CASIA (iris dataset) with 8-bits grayscale levels JPEG images. The matching is performed using a neuro-fuzzy neural network. In this, the image is improved by linking Gabor filter data. The performance of the proposed approach tested with a Neuro-fuzzy classifier provides the best outcome in terms of FAR (False Acceptance Rate), FRR (False Rejection Rate), and EER (Equal Error Rate).

Biometric frameworks are regularly assessed exclusively based on recognition framework execution. Yet, it is vital to take note that different variables are engaged with the deployment of a biometric framework. One variable is the quality and roughness of the sensors utilized. The nature of the sensors utilized will influence the exhibitions of the related recognition calculations. In the case of a verification system, two different error rates are defined: False Rejection Rate (FRR), the rejection of a legitimate user, and False Acceptance Rate (FAR), the acceptance of an imposter.

FAR is calculated by:

$$\text{FAR} = \{(\text{Number of Features Accepted}) / (\text{Number of Features Tested})\} \times 100 \quad (7)$$

FRR is calculated by:

$$\text{FRR} = \{(\text{Number of Original Features Rejected}) / (\text{Number of Original Features Tested})\} \times 100 \quad (8)$$

The final decision for authentication is taken based on the comparison of the decision threshold and the generated score. The decision threshold is adjusted according to the application. High-security applications require low FAR, while low-security applications require high FAR. EER (Equal Error Rate) is the value at which FAR = FRR.

Figure 9 shows the FAR calculation for different classifiers. FAR is 0.32% in the case of neuro-fuzzy classifiers, which is least among all the classifiers due to which it is depicted that compared to other classification techniques, PCA using a neuro-fuzzy classifier accepts only the genuine users. This also implies that the classifier will train the multimodal framework at an effective rate, and the number of genuine users will be authenticated only. A neuro-fuzzy classifier along with PCA is also tested based on FRR and EER rate. Figure 10 shows the FRR calculation of all the classifiers, and the EER rate calculation is shown in Figure 11.

FRR for PCA using a neuro-fuzzy classifier is computed to be 0.88, which is the highest as compared to other classifiers. This indicates that the proposed classifier will reject unauthorized biometric access at a higher rate compared to other classifiers, which will increase the security of the overall system.

Equal Error Rate (EER) is the final threshold value on which FAR is equal to FRR. The lower value of EER makes the system more effective. EER is the intersection point of FAR and FRR. The lower value of EER makes the system more accurate. The ideal value of 0% EER is impossible to achieve in a biometric system. For the proposed PCA-based neuro-fuzzy classifier, an EER value of 0.2 is reached, which increases the effectiveness and accuracy of the system.

From Figures 9–11, it is concluded that the proposed neuro-fuzzy classifier has the best outcome in terms of FAR, FRR and EER. The classifier is also compared for accuracy in comparison to all the other classifiers. Figure 12 shows the accuracy comparison of all the classifiers.

The comparative analysis of different classifiers is performed in Table 2, and the output is predicted in the form of FAR, FRR, EER, and accuracy. The overall accuracy of the proposed neuro-fuzzy classifier using a PCA-based approach is found to be 98%, which is the highest among all the classifiers.

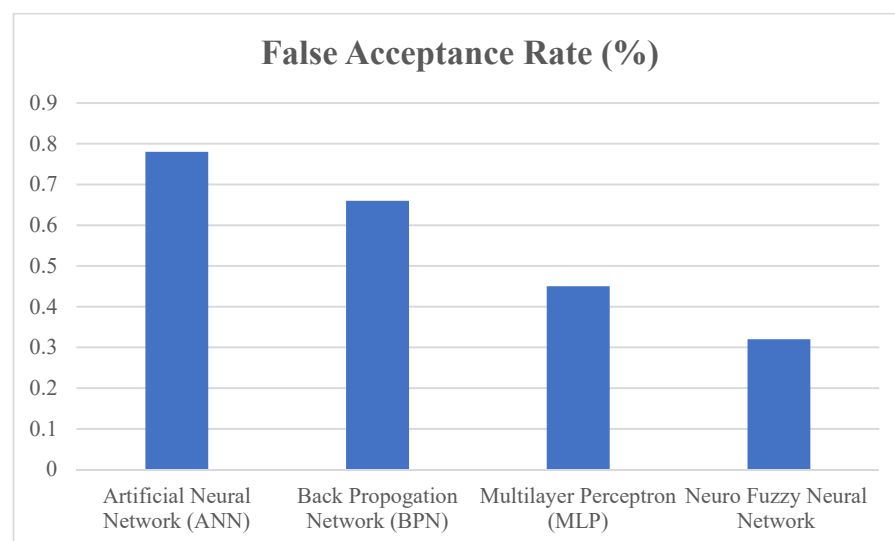


Figure 9. FAR calculation for various classifiers.

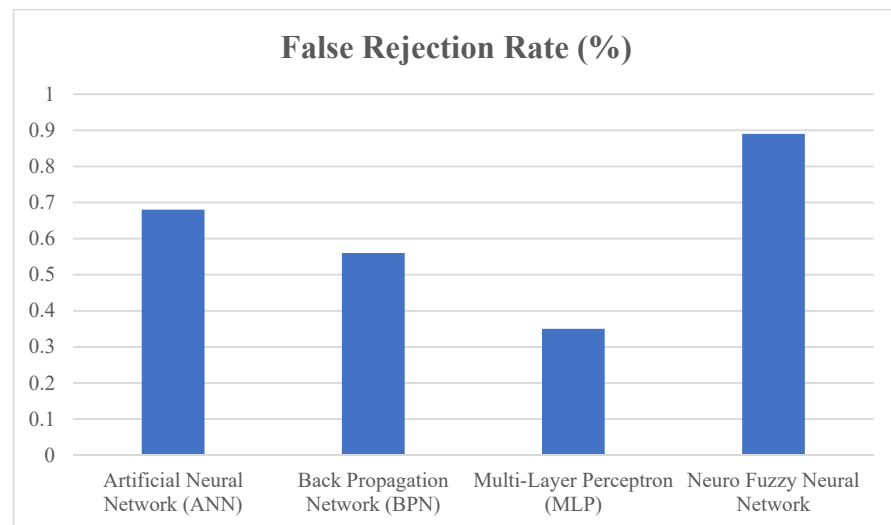


Figure 10. FRR calculation for different classifiers.

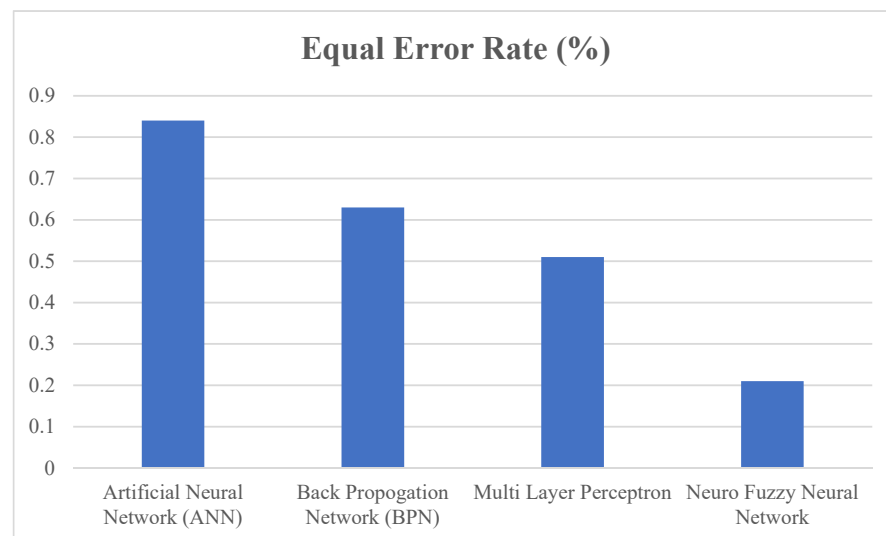


Figure 11. EER calculation for different classifiers.

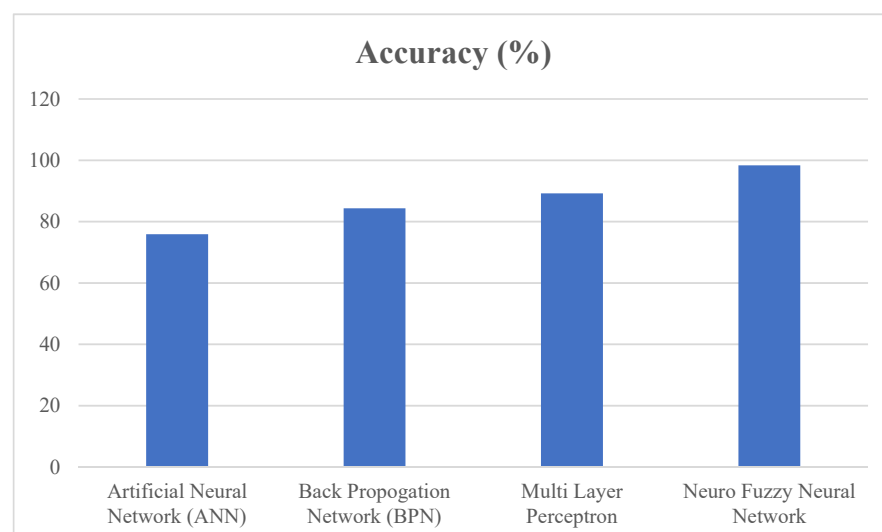
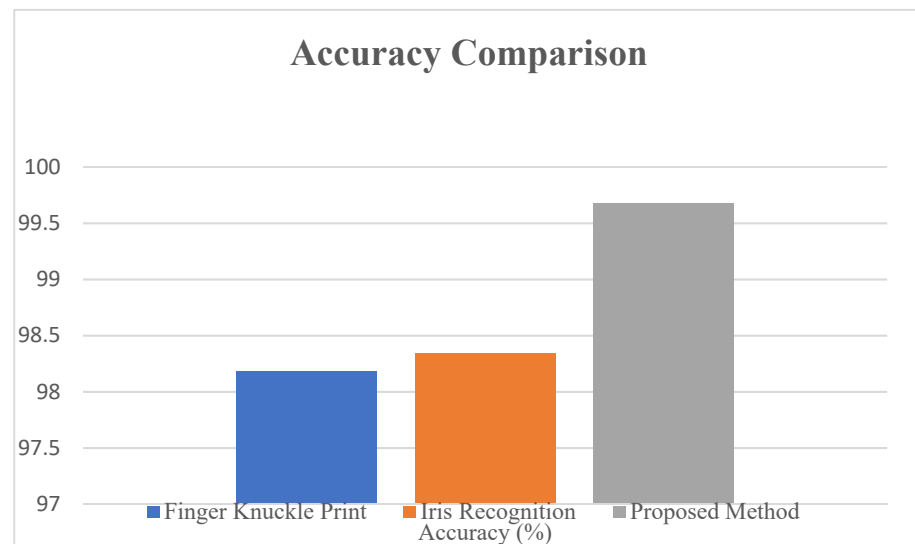


Figure 12. Accuracy comparison of different classifiers.

Table 2. Comparative analysis of different classifiers.

Classifier	False Acceptance Rate (FAR) (%)	False Rejection Rate (FRR) (%)	Equal Error Rate (EER) (%)	Accuracy (%)
Artificial Neural Network (ANN)	0.79	0.69	0.83	78
Back Propagation Network (BPN)	0.65	0.56	0.63	84
Multi-Layer Perceptron (MLP)	0.45	0.34	0.51	88
Neuro-Fuzzy Neural Network	0.32	0.88	0.21	98

It is visible from Figure 12 that the neuro-fuzzy neural network classifier, along with the principal component analysis, is best suitable for processing compared to other classifiers. Both the individual traits, FKP and iris, are tested for accuracy and performance using the Poly-U and CASIA dataset, and the respective plot is plotted. Figure 13 shows the accuracy analysis of both the biometric traits and their fusion. Performance analysis is performed by plotting the ROC curve of the individual biometric traits and their fusion.

**Figure 13.** Accuracy comparison of FKP, iris, and proposed method.

The accuracy of the biometric system can be computed by:

$$\text{Accuracy} = 100 - \left\{ \frac{\text{FAR} + \text{FRR}}{2} \right\} \quad (9)$$

The proposed PCA using a neuro-fuzzy classifier, when compared with FKP and iris recognition methodologies, results in 99.68% accuracy, which is better than an individual biometric trait.

ROC Curve is the best mechanism for the performance evaluation of biometric systems. A ROC plot is drawn in order to predict the performance of single biometrics and the proposed method in Figure 14. After the plot is drawn, it is clearly visible that the proposed methodology is certainly better than the unimodal characteristics for authentication of human.

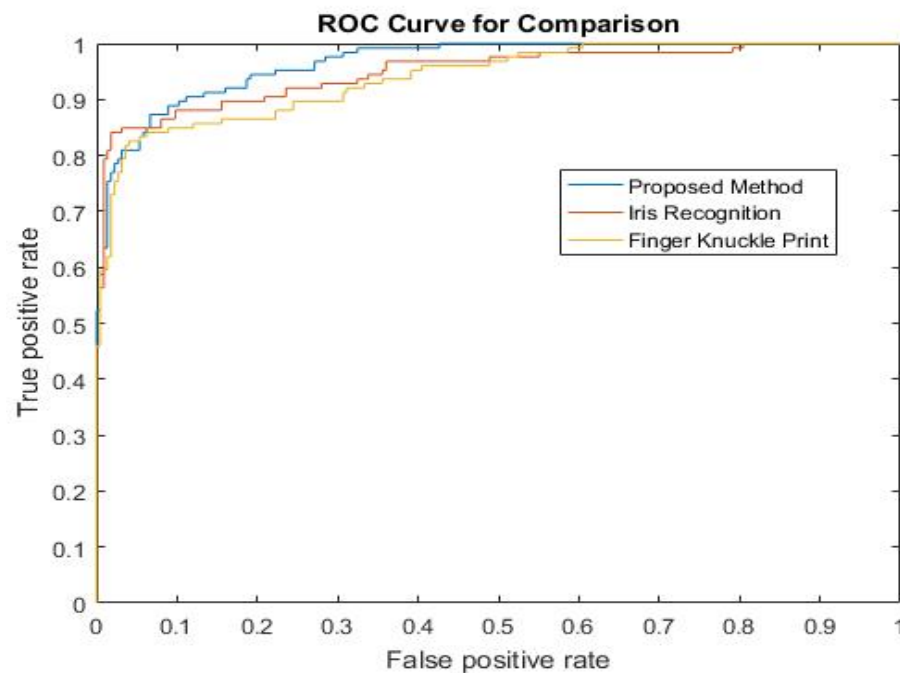


Figure 14. ROC curve for proposed method.

6. Conclusions

Biometric frameworks have been viewed as vulnerable to security attacks at various places. Issues connected with security in unimodal as well as multimodal biometric frameworks have been tended to in the work by giving various techniques. A biometric framework that coordinates various characteristics could defeat some restrictions. Thus, in this work, implementation is performed in multimodal biometric frameworks connected with its security and execution issues. Issue of heterogeneity of the biometric sources, combination intricacy, and relationship among the different biometric sources are major testing issues.

In this paper, a fusion of FKP and iris biometric modalities is proposed using a neuro-fuzzy classifier. In the proposed work, the features of FKP and iris are extracted with the help of SIFT and SURF methodologies. After feature extraction, the fusion of both the traits is performed, and authentication is performed. The proposed feature vectors are classified using a neuro-fuzzy classifier. The scheme is tested on two different open databases: Poly-U for FKP and CASIA for iris biometric traits in MATLAB 2016a. The comparative analysis of individual biometrics and the fused biometrics are performed on the parameters of accuracy and performance. The accuracy of the proposed method is obtained as 99.68%, which is far better as compared to the individual biometric. The current work depends on two modalities, specifically, the finger–knuckle print and iris; the framework might be additionally improved by including the number of biometrical characteristics or by combining new biometric attributes for any complex application. In fusion methodologies, FKP and iris can be melded with other fusion strategies apart from match score, and further various calculations for feature extraction may be utilized to increase the accuracy of the biometric framework.

The current work depends on two modalities specifically; finger knuckle print and iris; the framework might be additionally improved by adding the number of biometrical qualities or by swapping new biometric attributes for any modern application. In combination methodologies, FKP and iris can be melded with other combination procedures apart from at match score, and, furthermore, various calculations for feature extraction might utilize raising the vigor of the biometric framework.

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