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Experimental Analysis of Face and Iris Biometric Traits Based on the Fusion Approach

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Abstract

Objectives : To develop an efficient algorithm for face and iris multimodal traits on ORL and CASIA dataset and to increase the performance rate and decrease the error rate of the model. The main goal is to increase the performance rate and decrease the error rate of the model. **Methods:** The proposed algorithm utilizes a fusion of face and iris modalities using Stationary Wavelet Transform (SWT) and Local Binary Pattern (LBP) techniques. The Principal Component Analysis (PCA) is applied to reduce the dimensionality of each sample, improving efficiency while preserving the most relevant information. The relevant characteristics from both face and iris modalities are fused to create a comprehensive pattern for an individual. **Findings:** The obtained features are compared with the features of the database images using a Euclidean Distance classifier. The performance of the proposed model is evaluated using the ORL and CASIA iris datasets. The accuracy achieved by the proposed algorithm is 99.42%, demonstrating robustness. **Novelty:** The algorithm introduces feature-level fusion, combining the characteristics of both face and iris modalities. The model encompasses the training and recognition phases within a biometric system. During the training phase, the biometric modality is captured and processed using the fusion of SWT+LBP+PCA techniques to form a template for each user. These templates are later stored in the database for recognition purposes.

Keywords: Biometrics; Trait; Face; Iris; Multimodal; Stationary Wavelet Transform

1 Introduction

Biometric recognition systems have gained significant importance in recent years, with increasing demands for reliable and authenticated identification. These systems find applications in both private and government sectors[1]. Traditional biometric systems typically rely on a single characteristic of an individual, which can be affected by noise during the image acquisition process. To address these limitations, multimodal biometric systems have been developed. Figure 1 illustrates a multimodal biometric system.

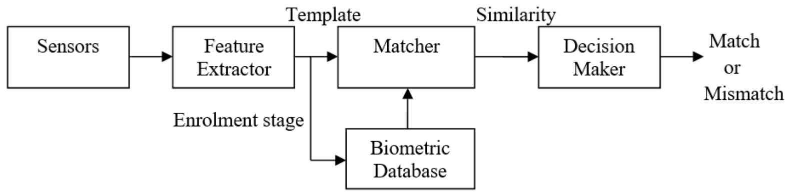


Fig 1. Biometric recognition system

The multimodal biometric system combines multiple biometric traits, such as face and iris, to enhance the accuracy and reliability of the recognition process. By utilizing multiple modalities, the system can overcome the limitations associated with single characteristic-based systems, such as susceptibility to noise or variations in individual traits. The integration of different biometric modalities in a multimodal system offers several advantages. Firstly, it increases the discriminatory power of the system by considering multiple traits simultaneously. This leads to improved recognition performance and reduced error rates. Secondly, multimodal systems enhance the security level by utilizing multiple independent sources of information for identification. This makes it more challenging for unauthorized individuals to manipulate or impersonate the system. Multimodal biometric systems have emerged as a solution to address the limitations of traditional single characteristic-based systems. By combining multiple biometric traits, these systems provide improved accuracy, reliability, and security for biometric recognition applications in various sectors. The Fusion levels in Multimodal Biometric Systems are shown in Figure 2[(2)].

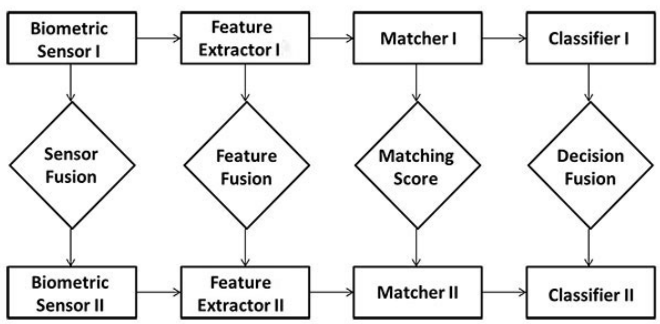


Fig 2. Fusion levels in Multimodal Biometric Systems

In this research work, feature level fusion is employed[(3)]. The training and recognition phases are conducted within the biometric system. During the training phase, the biometric modality (e.g., face or iris) is captured and processed using specific algorithms to create a template for each user. These templates are then stored in the database for later use. In the recognition phase, new samples are captured from the individual being identified. These samples undergo processing like the training phase, extracting relevant features. The obtained features are then compared with the templates stored in the dataset. This comparison is typically performed using matching algorithms or distance metrics[(4)]. Based on the comparison results, the system determines whether the samples match any of the stored templates or not. If a match is found, the individual's identity is verified or recognized. Otherwise, if there is no match, the samples are considered as not matched[(5)].

Overall, the research work contributes to the development of an efficient recognition model by applying preprocessing, feature extraction using SWT and LBP, feature-level fusion, dimensionality reduction using PCA, and classification using the Euclidean distance. These contributions collectively enhance the accuracy and performance of the recognition system. The overview of various research related to multimodal biometric systems for face and iris recognition is addressed. These works cover different aspects such as feature extraction techniques, fusion methods (score level or feature level), evaluation datasets, and performance evaluation.[(1)] describes a multimodal biometric system for face and iris recognition using PCA, LDA, LBP, and Transformation-based score fusion. The system is evaluated on the ORL face and CASIA iris datasets.[(6)] presents a hybrid level fusion approach using the 2D-log Gabor filter on face and iris samples. The templates are created based on feature vectors, and the system is evaluated on the CASIA dataset.[7] focuses on score normalization techniques for genuine and non-genuine scores to improve recognition performance. The confidence from matched scores is captured using mean-to-maximum and mean-to-minimum of genuine and non-genuine scores, respectively.[8] provides an overview of different approaches and state-of-the-art methods for multimodal biometric traits. It discusses working models and databases used, along with the limitations of existing models.[9] conducts experiments on a multimodal biometric system using face, fingerprint, and hand-geometry traits. The different score fusion techniques such as min-max and z-score normalization are used on a database of 100 users.[2] combines fingerprint and iris traits for recognition, evaluated on the CASIA-Iris V1 and FVC 2000 fingerprint databases.[3] presents multimodal face and iris recognition with score-level fusion using wavelet denoising. The system is evaluated on the FERET and CASIA datasets.[4] utilizes face-iris combination for recognition with feature-level fusion using 2D Log-Gabor filter and SSA with WT. ORL and FERET datasets for face, and CASIAv3.0 for iris, are used.[5] performs both matching score and feature-level fusion for recognition using CASIA and IITD databases. PSO and BSA are used for feature selection.[10] addresses face-iris recognition with feature-level fusion using 2D Gabor filter bank, PCA for dimensionality reduction, and SVM for classification.[11] discusses threshold-optimized decisions for fusion of features generated through feature extraction, followed by classification of samples.[12] implements weighted score-level fusion for face and iris recognition, using Doughman and PCA for feature extraction, and weighted fusion for identification and recognition.[13] extracts features using DCT and PCA for face and iris traits, performs feature-level fusion, and uses Genetic algorithm for feature selection. SVM is employed as the classifier.[14] developed an algorithm that utilizes Discrete Wavelet Transform (DWT) for feature extraction in analyzing face and iris data features. The extracted features are used to form feature vectors, which are then employed to classify the patient samples. The algorithm also incorporates Metaheuristic Genetic Algorithm (MGA) to optimize the classifiers.[15], both matching score and feature level fusions are employed for recognition. Real-time datasets are used to evaluate the model, indicating its applicability in practical scenarios.[16] explores various approaches, including Histogram-based Thresholding (HT), Fourier Transform (FT), Radon Transform (RT), and Wavelet Transform (WT), for feature extraction. Feature vectors are formed based on these approaches, and the importance of Information Processing (IP) and classifications is emphasized to address different score level and feature level fusion mechanisms.[17] different feature extraction techniques are addressed, with a particular focus on applying DWT on the samples to extract four different sub-bands: LL, LH, HL, and HH. The fusion is performed at the score level during the classification phase.

The proposed model addresses the limitations over the existing models, such as high error rates and lack of robustness, by proposing a fusion technique at the feature level. Specifically, the fusion of Stationary Wavelet Transform (SWT), Local Binary Pattern (LBP), and Principal Component Analysis (PCA) is introduced to enhance the performance of the model. The paper is organized as follows: Section 1deals with the introduction of multimodal biometric system. Section 2 provides a detailed explanation of the proposed model, which includes the fusion of SWT, LBP, and PCA techniques at the feature level. The algorithms and methodologies used in the fusion process are likely described here. Section 3 discusses the evaluation parameters used to assess the performance of the proposed model. These parameters might include accuracy, precision, recall, F1 score, and other relevant metrics. The obtained results are analyzed and presented, highlighting the improvements achieved by the proposed model compared to existing approaches. The paper concludes by summarizing the contributions and findings of the proposed model. The advantages of the fusion technique and its impact on improving performance and robustness are likely emphasized. Additionally, potential areas for future research or further improvements may be mentioned.

2 Methodology

The main contribution of the research work is to preprocess the image samples obtained through face and iris datasets before applying to recognition model. Next, the SWT and LBP are used to extract the features of face and iris samples and later fusion at the feature level is performed. The PCA is applied on the samples to reduce the dimensionality of the images. The Euclidean distance is used as classifier to match the trained and testing images. Figure 3 shows the proposed model.

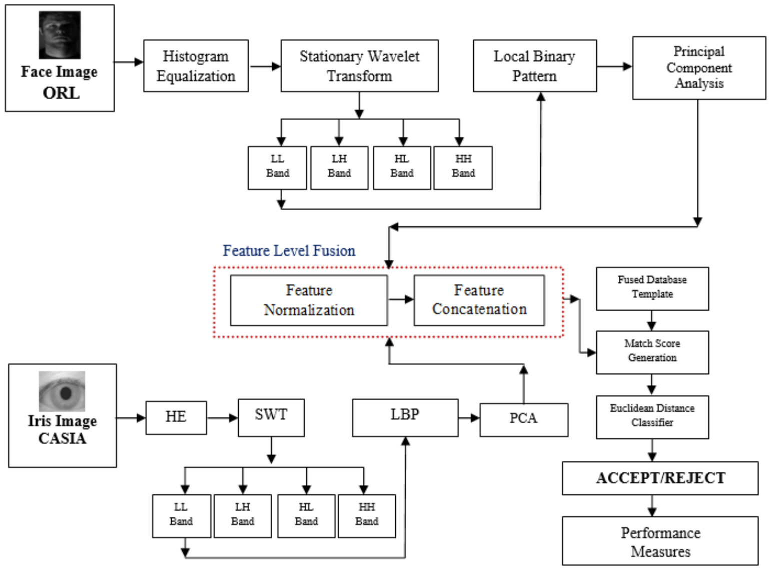
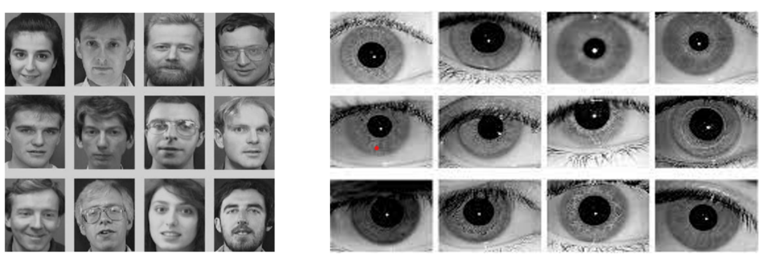


Fig 3. Proposed Methodology

2.1 Dataset[16,17]

The face images having 400 samples with 40 distinct patterns are presented in the ORL database. The samples are captured with the different times, for different emotions of face. The size of each sample of the dataset is 92x112 pixels. The samples of ORL dataset are shown in Figure 4 a.



(a) (b)

Fig 4. ORL face and CASIA Iris samples

The CASIA[17] iris dataset has 756 samples of iris from 108 eyes of an individual. Each individual sample having the size of 320x280 captured in two sessions, available in BMP format. The sample of the dataset is shown in Figure 4 b.

2.2 Preprocessing

The face and iris images of the ORL and CASIA are fetched to carry out the preprocessing step. The images are cropped and resized to 128x128 to maintain uniformity throughout the experiments. The Histogram Equalization is applied on the samples to enhance the quality. The preprocessing process for face and iris samples is shown in Figure 5.

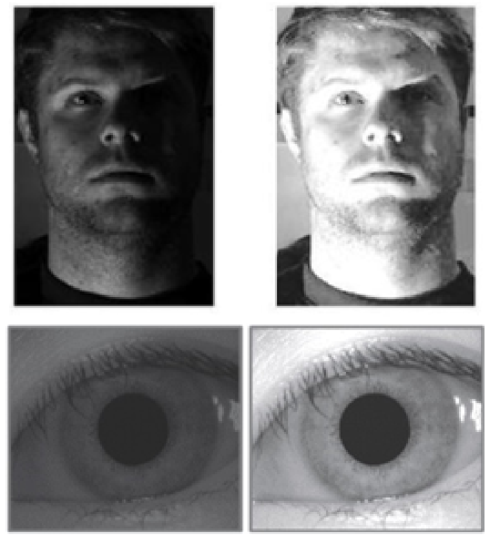


Fig 5. Preprocessing process

2.3 Iris Extraction

The circular icon of the eye, where the part 'iris' located in between pupil and sclera. To extract the iris region from the CASIA image, few of the portions related to pupil is neglected. The iris template is formed using the concatenation of right and left region (having 40 pixel) of the pupil. The template of iris is shown in Figure 6.

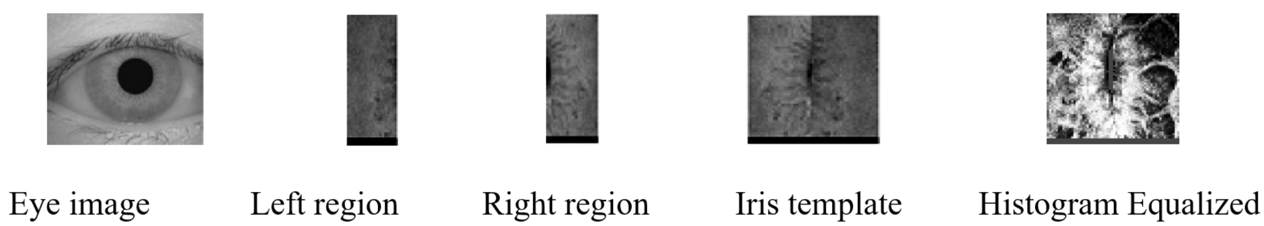


Fig 6. Formation of iris template

2.4 Feature extraction

Feature extraction is an important task, that can be done before the classification phase. In this stage, the significant and relevant features of the image samples are extracted to result with maximum matching score. In this paper, Stationary Wavelet Transform (SWT) is applied on the face and iris samples to extract the useful information of both the samples. The SWT is decomposed into four sub bands which includes LL, LH, HL and HH sub bands. The maximum representative and relevant information are relied on LL sub band. So, neglecting the higher sub bands (LH, HL and HH) the Local Binary Pattern (LBP) is applied on LL sub band to extract the more significant coding of the process. Later, the Principal Component Analysis (PCA) is applied on the LBP features to reduce the dimensionality throughout the experimentation. Finally, the feature level fusion is performed by adopting the features normalization and concatenation. The process of SWT, LBP and PCA is explained in detail.

2.5 Stationary Wavelet Transform (SWT)

The face and iris samples are through the filter to record the significant information along with the detailed information. Due to the characteristics of NO decimation, the coefficients remain the same in every sub band. Further, the response of low pass and high pass are given as an input to LPF and HPF to generate the approximation band (LL) and detailed bands (LH, HL, HH).

The decomposition of SWT is shown in Figure 7. The sub bands of SWT for ORL face and CASIA Iris data samples are shown in Figure 8 and Figure 9 respectively.

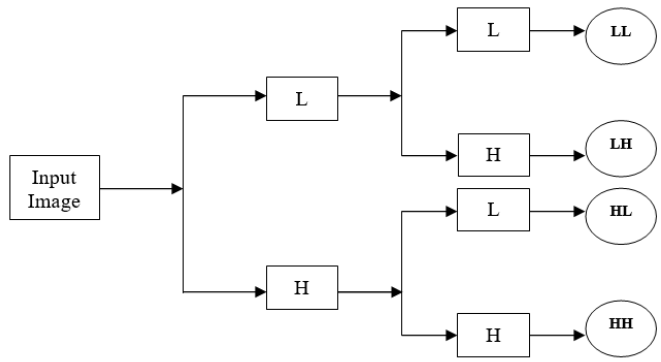


Fig 7. SWT Decomposition

Original Image LL Sub band LH Sub band HL Sub band HH Sub band

Fig 8. SWT four subband images

From the Figures 8 and 9, it is observed that, the approximation band (LL sub band) of face and iris samples are composed of significant information. The approximation band (LL sub band) contains the same significant coefficients of the original ORL and CASIA image. The horizontal, vertical, and diagonal details are represented as LH, HL and HH respectively.

Approximation Band (LL Sub band) Horizontal Band (LH Sub band) Vertical Band (HL Sub band) Diagonal Band (HH Sub band)

Fig 9. SWT four sub band images

2.6 Local Binary Pattern

Local Binary Pattern will handle many occlusions and problems existing from handle illumination changes and used in many issues includes such as image/facial and motion analysis. The procedure for extracting the LBP features are as follows:

- Creation of tiny cells with the provision of radius and number of neighbors.
- Thresholding with the consider of pixel existing in central position and its neighbor pixels. Binary number will be the outcome for thresholding and intern the same will be converting into decimal numbers.

- Each of the LBP will be store in 'count' and later, calculate the histogram for the frequency of each 'count'.
- Concatenation of the histograms to compute the feature vector is performed.

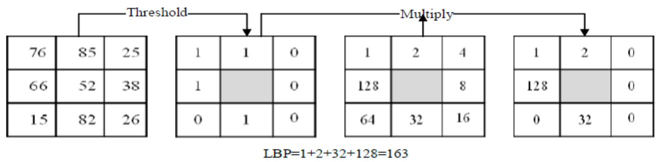


Fig 10. Local Binary Pattern Process

The process of LBP is shown in Figure 10. The input patterns having threshold and weight is addressed, a radius of 1 with 8 neighbors surrounding the center pixel is considered in the LBP process. The LBP equation is stated in equation 1.

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} S\left(f(x,y)\right) f\left(x_p, y_p\right) 2^p \tag{1}$$

Here, P and R represents neighborhood and radius of neighbors around the pixels.

2.7 Primary component Analysis (PCA)

The PCA is applied on the LL sub band of SWT to reduce the dimensionality of the samples. The computations of the Eigen vectors and corresponding Eigen values are made to identify the strength of the variations in the image data.

2.8 Feature Level Fusion

The features produced by the hybrid model based on SWT, LBP and PCA are fused and combined to generate the features consisting of 43 features. Using these feature vectors, the fusion is performed and results in the generation of match scores.

2.9 Euclidean Distance

Based on the matching scores, the ED is used as a classifier to match the data of trained and testing sample. The result of ED may be recognized as Genuine or Imposter. Finally, the performance of the proposed model is measured and compared with the different state-of-the-art multimodal face and iris methods.

The Precision (P) and Recall (R) curve and the ROC curve are considered to plot the graphical representation of the proposed model. The PR talks about the precision and recall, whereas the TPR and FPR relation will be brought by plotting the ROC curve. Here, TPR and FPR are considered to know the images either genuine or imposter. By considering the low threshold, we can achieve more TP and FPR. The evaluation parameters are given in equation 2, 3, 4.

$$TPR = Recall = \frac{Tp}{Tp + FN} \tag{2}$$

$$FPR = \frac{Fp}{Fp + TN} \tag{3}$$

$$P = \frac{Tp}{Tp + Fp} \tag{4}$$

For desired face and iris sample, True positive (TP) is accepted (positive) and False Positive negative (FN) is rejected. Whereas, for Undesired face and iris sample, False positive (FP) is accepted (positive) and True negative (TN) is rejected. The proposed algorithm is tabulated in Table 1.

Table 1. Proposed algorithm

Input: Read the images from ORL and CASIA Dataset Output: Recognition of multimodalities
1. The images from the ORL and CASIA dataset is taken and resized to 128X128, followed by cropping the sample.
2. The HE is applied on both the samples to enhance the output image.
3. The SWT is applied on both the samples to extract the features. The SWT is decomposed to LL, LH, HL and HH sub bands.
4. Next, The LBP is applied on approximation band LL, to extract the significant local and statistical features. Later, the PCA is applied on the statistical features to reduce the dimensionality of the image. The LBP is calculated using equation 5.
$LBP\ (x_c,\ y_c) = \sum_{i=0}^{7} s\,(g_i - g_c)\,2^i$ (5)
Where x_c represents neighbors, y_c indicates the neighborhood radius, g_i and g_c indicates gray value of neighbors and central pixel respectively.
The mean of each vector is given in equation 6.
$X_m = \frac{1}{N}\sum_{k=1}^{N} Xk$ (6)
The Eigen Vectors and values are given in equation 7.
$(C - \lambda I]\,e = 0$ (7)
Where, 'λ' is Eigen value and e is Eigen vectors.
5. The feature level fusion is performed before the generation of match score. The fusion feature ξ in sum rule is given in equation 8.
$\xi = X_1 + Y_1 \ldots . X_d + Y_d$ (8)
6. The Euclidean distance is used to classify the samples of face and iris give in equation 9.
$d\ (p,\ q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$ (9)
Where, p = (p_1, p_2, p_3, ... p_n) is the known feature vector and q = (q_1, q_2, q_3, ...q_n) is test feature vector.
7. Performance of the proposed model is computed and evaluated.

3 Results and Discussion

In this research work, the ORL and CASIA datasets were used for experimentation. The ORL dataset consists of face samples, while the CASIA dataset contains iris images. The proposed model was implemented and simulated using MATLAB. The images from both datasets were combined into a single dataset with 168 folders, containing both face and iris samples. The model was then tested using different combinations of feature extraction techniques, including the state-of-the-art method (DWT+DCT+HT) and the proposed model (SWT+LBP+PCA+ED). The dataset consisted of 1600 image samples with varying matrix sizes. The experimental results showed that the fusion of SWT, LBP, and PCA performed better during the testing phase, particularly for a matrix size of 128. The receiver operating characteristic (ROC) curve of the existing DWT+DCT+HT multimodal method was shown in Figure 11. It was observed that as the threshold value increased, the false acceptance rate (FAR) decreased while the false rejection rate (FRR) increased. Additionally, the true success rate (TSR) was found to be 88.86% for a given threshold, with an error rate of 12.14%. The performance of the existing model can be improved by considering a hybrid model that combines SWT+LBP and PCA for feature extraction.

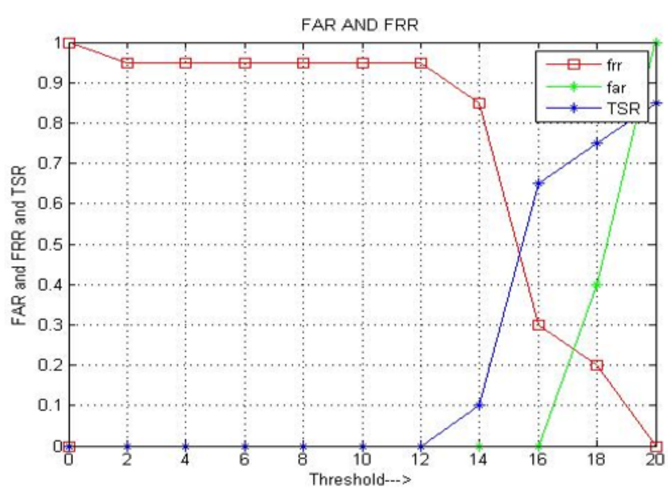


Fig 11. ROC for the proposed model

Figure 12 shows that the true success rate (TSR) for the given threshold is 99.42% with an error rate of 0.58%, it indicates that the proposed multimodal model achieved a high recognition accuracy, with a low percentage of errors. These results suggest that the proposed SWT+LBP and PCA multimodal model is effective in distinguishing between genuine and impostor samples, with a high level of recognition accuracy and a low error rate.

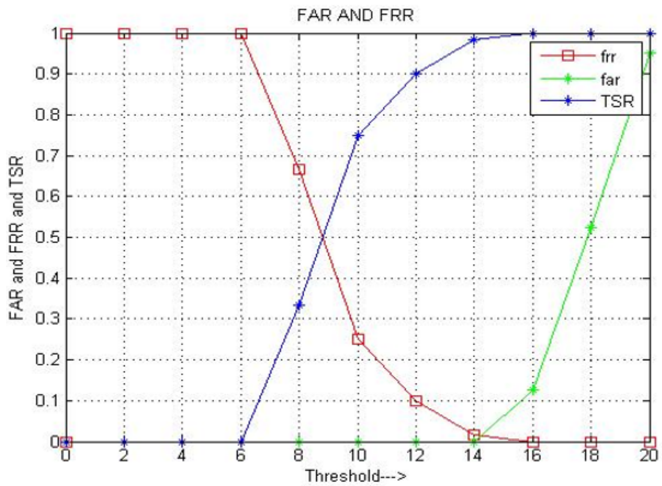


Fig 12. ROC for the proposed model

Based on the experimentation results, it is observed that the proposed model for face and iris multimodalities achieved an accuracy of 99.42%. This accuracy is claimed to be an improvement compared to different state-of-the-art methods, which is tabulated in Table 2.

Table 2. Comparison of proposed model with state-of-the-art methods

Authors	Method Descriptions	Matrix size	Face and Iris Recognition rate (%)
Bouzouina et al., [1]	DCT, Log-Gabor and Zernike moment, Genetic algorithm and SVM	128	96.72
B. Ammour et al., [9]	Log Gabor filter spectral regression kernel discriminant analysis and Euclidean	128	97.45%
B. Ammour et al., [4]	Singular Spectral Analysis and Normal Inverse Gaussian, Log-Gabor filter, and spectral regression kernel discriminant analysis and KNN	128	98.18
Proposed Model	**SWT+LBP+PCA+ED**	**128**	**99.42%**

4 Conclusion

In this research study, the model is tested using different combinations of feature extraction techniques. The testing phase is conducted on 1600 image samples with varying matrix sizes. The researchers find that the fusion of SWT, LBP, and PCA performs better for a matrix size of 128. The ORL dataset, consisting of face samples, and the CASIA dataset, comprising iris images, are used to conduct the experiments on the proposed model. The experimental results demonstrate a higher recognition rate of 99.42% for the proposed multimodal approach compared to various existing multimodal face and iris techniques. This suggests that the fusion of SWT, LBP, and PCA enhances the performance of the model in recognizing individuals based on their face and iris traits. In future, the model could be further developed by incorporating deep learning techniques. This could involve exploring multimodal traits beyond face and iris, such as ear, fingerprints, and other biometric characteristics.

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