Multimodal Biometric Recognition Using Score Level Fusion

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Abstract

Multi-classifiers based score level fusion of multimodal biometric recognition and its implementation in remote biometric authentication is proposed here. In the proposed method, processing is initially performed, then classified and later fused. The method is executed through the usage of MATLAB and FAR, FRR and accuracy are used as evaluation measures. The proposed method is contrasted with other state-of-the-art methods. The methods used for the comparison are ABC-NN, Fuzzy, Bayesian, ABC-NN+ Bayesian, Bayesian + Fuzzy and ABC-NN +Fuzzy methods. For detailed analyses, various fusions of modalities are taken like fingerprint-face and the fused fingerprint-face. Outcomes reveal that the proposed method achieves improved accuracy value and ROC curve.

KeyWords: Face, Fingerprint, Score level, Fuzzy

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Introduction

Multimodal biometric systems offer identification and security applications in the recent few decades. In this regard, they are being adapted to several fields of application. A few of these multimodal systems are essentially human-computer dialog based interaction systems where the users interact with the system through voice, vision or other pointing devices for completing a particular job. Multimodal biometric systems are capable of using more than one physical or behavioral feature for enrolling, verifying or identifying an individual

Biometric systems are typically pattern recognition systems in which systems measure and analyze the human body. Physical features like fingerprint, retina of the eye, iris, vocal pattern, facial features, and hand measurements are used for authentication purpose. Unimodal biometric systems possess various restrictions like lack of uniqueness, extreme spoofing rates, extreme error rates, lack of universality and noisy data. For instance, in facial recognition, there is an influence of position, emotion and quantity of ambient light.

It has been made apparent for almost all experts that around 2% of the population does not possess a clear finger print and thereby are not capable of being enrolled in a finger print biometrics system. In current, the usage of several biometric features is the best alternate for alleviating this particular drawback. The usage of multiple biometric indicators for the identification of people is called as multimodal biometrics and has been revealed to improve accuracy and population coverage while reducing threats of spoof attacks. The significant component in multimodal biometrics is the fusion level of the several biometric modalities

Literature Survey

Meraoumia et al., [1] incorporated fingerprint as well as Finger- Knuckle Prints (FKP) for constructing effective multi-modal biometrics systems on the basis of matching score levels as well as image-level fusions. In the current work, the investigators utilized MinimumAverage Correlation Energy (MACE) as well as Unconstrained MACE (UMACE) filters along with two correlation plane performance metrics, max peak value as well as peak-to-side lobe ratios, for determining efficacy of the technique.

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Biggio et al., [2] experimented on various datasets with actual spoof assaults linked to multi-modal authentication systems on the basis of facial features as well as fingerprints. Helder Matos et al., [3] have proposed an approach to identify finger valley and tips by determining the skeleton of the hand, from hand images acquired using a scanner without pegs from 46 individuals. The performance result of 8.7% FAR is reported. The database size is too small for evaluation purpose. Rong-Xiang Hua et al. [4] have designed an image acquisition set up for capturing hand images from 200 users using a digital camera. The image acquisition setup consists of a peg free platform on which the users have to position their hand facing the camera. A recognition method based on shape representation, namely shape contexts and inner-distance shape contexts which is proposed by the authors can handle different hand poses.

Park et al., [5] suggested a novel multi-modal biometrics recognition system using fingerprints as well as finger veins. The suggested gadget captures both features concurrently and the device is also minute in size and may be adopted onto mobile devices as well. Fingerprints are recognized through minutia points of ridge areas while finger veins were identified through Local Binary Patterns (LBP) with appearance data of finger region. Gnanasivam&Muttan et al., [6] utilized ear as well as fingerprints for identifying people. A new method of Edge Interaction Point‘s Detection (EIPD) was utilized for determining ear attributes. Bu et al., [7] suggested a new multi-modal biometrics on the basis of several hand attributes, that is palm print, palm veins, palm dorsal veins, finger veins as well as hand geometries. Luo et al., [8] suggested a personal identification model that fused palm print as well as palm vein pattern. Particular devices were designed to possess Near-Infra-Red (NIR) cameras as well as NIR illumination sources, such that palm prints as well as palm vein data may be obtained in one image concurrently. Osslan Osiris et al., [9] have proposed a verification system based on hand geometry features extracted from hand images acquired using a scanner from 120 individuals. The preprocessed hand image is transformed to wavelet domain and 31 geometrical features are computed to identify users. The nearest neighbor algorithm is applied for classification of the hand image as a genuine or an impostor. Ashok Rao et al. [10] proposed a hand vein biometric for both condition of unimodal as well as multimodal with palmprint. Chetty & Lipton., [11] suggested new local features analyses as well as features level fusion method for detection of tampering as well as forgery for face biometrics based online access control settings. Kanade et al., [12] suggested multi-modal biometric systems based cryptographic key regeneration strategy that joined data from irises as well as faces for obtaining long cryptographic keys possessing great entropies

Chetty et al., [13] suggested a new fusion protocol on the basis of fuzzy fusions of face as well as voice attributes for ascertaining liveness in protected identities authentication systems on the basis of facial as well as vocal biometric features. Goh Kah et al., [14] have identified valley points between adjacent fingers and fingertip points to extract the largest rectangle area lying inside the contour of the finger which is considered as IKP ROI. Finite radon transform which is defined as the summation of image pixel values along a set of lines is applied on IKP to find the ridgelet coefficients. Computed coefficients are used to find energy measures, which are considered as IKP features.

Bahareh Aghili et al., [15] Recognition system based on geometrical features of fingers is proposed. Twenty four geometrical features extracted from four fingers are used as features. Anil Jain et al., [16] explored multimodal biometric recognition using fusion of face, fingerprint and hand geometry at score level fusion. Xuebin et al., [17] suggested multi-modal biometrics verification methods on the basis of pixel-level fusions for improving recognition rate of unimodal biometrics as well as for resolving minute sample recognition issue. The investigators utilized two types of biometric methods, palm print as well as face identification. Raghavendra et al., [18] suggested an effective features level fusion strategy which was employed on face as well as palm print scans. The suggested technique was contrasted with AdaBoost and it was proved that the suggested technique outperformed on all accounts. Alsulaiman et al., [19] performed studies for exploring usage of GEP in discovering analytic functions which can act as classifiers in high dimensional haptic features spaces.

Wu et al., [20] suggested a new biometric cryptographic model on the basis of city block distances. Real valued biometric features vectors are initially quantized and later coded into binary strings so that city block distances between two features vector are translated into Hamming distances between two binary strings. Jian-Gang Wang et al., [21] have presented an acquisition

setup that acquires the palm print and palm vein images of an individual using two cameras. Nageshkumar et al., [22] have proposed a multimodal biometric system based on face and palm print. U. Jayaraman et al. [23] have proposed an indexing approach using a Kd-tree. Their work is based on feature level fusion which uses the multidimensional feature vector of Iris, Face, Ear, and Signature modalities. Chen & Chandran et al., [24] described a novel technique that utilized entropy-based features extraction procedure along with Reed-Solomon error correcting codes which can formulate deterministic bit-sequences from outputs of iterative one-way transforms. The method was valuated through three-dimensional face information and is revealed to dependably yield keys of adequate length for 128-bit AES. Wang &Plataniotis., [25] suggested a technique for dynamic generation of cryptographic keys through face biometric signals. The suggested method has its basis in two-dimensional quantization of distance vectors between biometric features as well as pairs of arbitrary vectors. Miguel Gaurav Jaswal. [26] proposed a multimodal system based on the hand geometry, palm print and finger print modalities. Different set of rules for feature, score and decision level fusion are proposed. Zheng et al., [27] suggested a lattice mapping based fuzzy commitment technique for generating cryptographic keys from biometric information.

C. Poon et al,. [28] have captured hand images from 170 individuals using a CCD camera without any pegs for hand placement. Valley points between fingers are used as reference points to align the hand image such that the palm region will have minimal rotation and translation errors. Li et al., [29] Gabor transform is used to extract line features from all fingers except the thumb. A hierarchical classification approach is proposed using location and line features of second knuckle print. Location feature is used for coarse level classification, and line features to find the identity of the test image.

Experiments conducted on 720 hand images acquired from 72 users report a Rank (1) identification accuracy of 68.8%. Wu et al., [30] have proposed an approach for classifying palm prints extracted from hand image captured from camera into six categories based on the number of the principal lines present, and their intersections.

Proposed Methodology

Biometric modalities used in the current study are fingerprints and face. Features extraction is carried out through Ridge thinning algorithms (for fingerprints) and Local Gabor XOR Patterns (face). The scores for all modalities are calculated through comparison of test image attributes to those in the dataset on the basis of Euclidean distances. Score level fusion is performed through usage of three groups of classifiers in the study. Classifiers used are fuzzy classifiers, Naïve Bayes classifiers and ABC-NN. The simulation is done using MATLAB while FAR, FRR and accuracy are used as the evaluation measures. The suggested method is compared with other state-of-the-art methods and is analyzed. Evaluations are performed on the basis of accuracy values and ROC curves.

In the current study, score level fusion is performed with three groups of classifiers which are fuzzy rule classifiers, lazy classifiers (Naïve Bayes) and learning classifiers (ABC-NN). The three possesses their own benefits as well shortcoming and so the hybridization of the three leads to the overall enhancements through the rectification of their shortcomings by other algorithms and retaining their benefits. The fused outcome is used for biometric authentication. The proposed method comprises of two modules which are processing, classifier and combination modules.

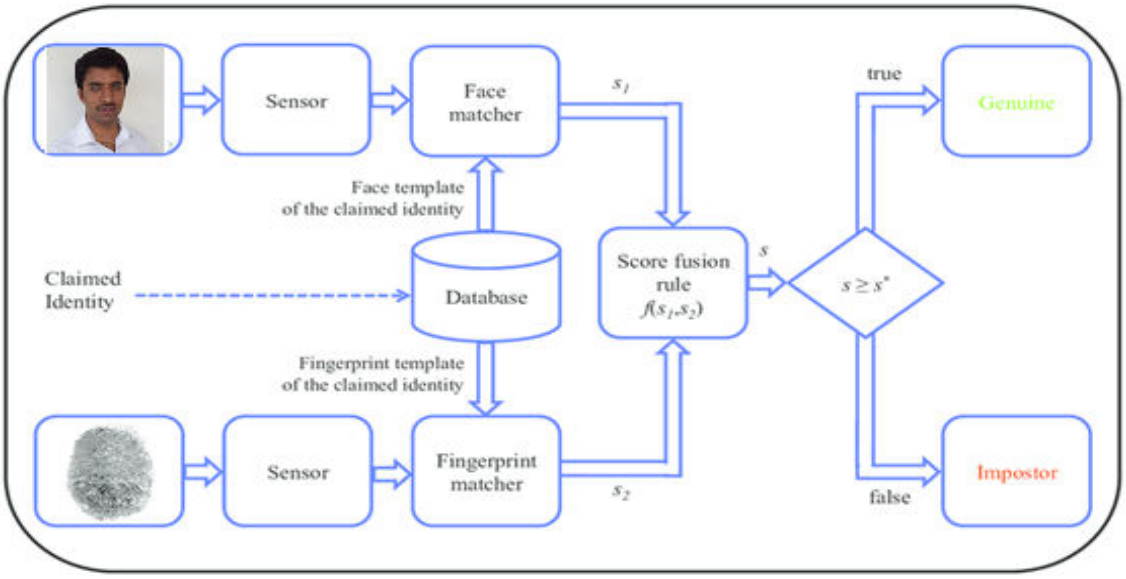

Figure 1: The proposed method comprises of two modules which are Processing, classifier and combination modules

3.1 Feature Extraction for Multimodal Biometrics

Multimodal biometric recognition systems are more dependable because there are several, non-dependent sets of information available. They aim at the alleviation of the drawbacks of several uni-modal biometric systems through the integration of information given by several biometric features. In the current study, a fused face-fingerprint recognition system is presented that is capable of overcoming several implicit problems in uni-modal biometric systems. The system further offers anti-spoofing features by ensuring that it is hard for intruders to spoof several biometric features at the same time.

3.1.1 Feature Extraction of Fingerprints

A good fingerprint representation should have the following two properties: saliency and suitability. Saliency means that a representation should contain distinctive information about the fingerprint. Suitability means that the representation can be easily extracted, stored in a compact fashion, and be useful for matching.

Feature extraction is done in order to reduce the work to be done on large data. If it tries to match the data, the process becomes very tiring so certain features are taken from the actual data. Hence, this process is called as feature extraction. It describes a large set of data accurately. Fingerprint is a well-established forensic technique with automated fingerprints systems. Since fingerprint is unique for each person it is a very good trait for person identification. No two persons will have the same print and this adds to the advantage of taking fingerprint into consideration. Figure 2 shows the fingerprint sample images.

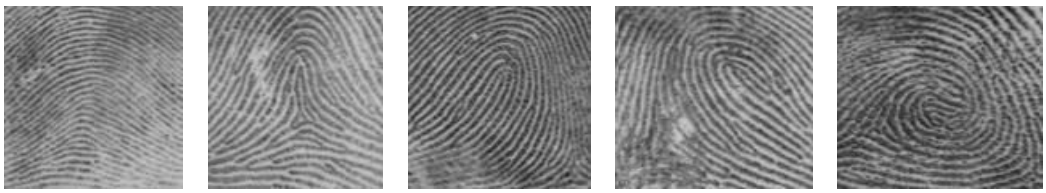

Figure 2: Fingerprint Sample Images

The fingerprint has various patterns, the pattern varies in each finger. The various patterns are arch, loop and whorl. Arch is a pattern where the ridges rise in the center and exit on both the sides. Loop forms loops where the lines enter the finger on a side and the line after forming a circle exit through

the same side. Whorl is formation of circles from a centre point and continues to spread around without any exit points. Even though the patterns are different, they cannot be considered as patterns though similar for people. The features are called as minutiae. It consists ofTerminations - It is the termination point of the line.
Bifurcations - It is the point where the ridges split into two ridges like a branch.

3.1.2 Histogram Equalization

The image during the scanning process is usually of low contrast and it improves the global contrast. This gives a better detail of the picture and also gives a clear bone structure of the picture. There are various techniques available to enhance the contrast but the histogram is the best way to depict the contrast values and equalize it. Histogram equalization defines a mapping of gray levels p into gray levels q such that the distribution of gray level q is uniform. This mapping stretches contrast (expands the range of gray levels) for gray levels near the histogram maxima. Since the contrast is expanded for most of the image pixels, the transformation improves the detectability of many image features. The probability density function of a pixel intensity level rk is given by equation (3.1):

$$\boldsymbol{P_r(r_k)} = \frac{\boldsymbol{n_k}}{\boldsymbol{n}} \text{..(3.1)}$$

where, 0<rk<1, k = 0, 1, 2..... 255, nk is the number of pixels at intensity level rk and n is the total number of pixels. The histogram is derived by plotting Pr (rk) versus rk. A new intensity sk of level k is defined as equation (3.2):

$$\boldsymbol{S_k} = \sum_{\boldsymbol{j=0}}^{\boldsymbol{k}} \frac{\boldsymbol{n_j}}{\boldsymbol{n}} = \sum_{\boldsymbol{j=0}}^{\boldsymbol{k}} \boldsymbol{P_r(r_j)} \text{..(3.2)}$$

After this process, the contrast is improved followed by the next step.

3.1.3 Binarization

This step is done to change the image into a 1-bit image where only 1's and 0's are the values in the particular matrix of the picture. The black takes the values 0 and white takes the value 1. Based on the intensities the values are assigned accordingly. A locally adaptive Binarization is performed to binarize the image where depending on the intensity the value is assigned either as 1 or as 0 in equation (3.3).

$$\mu_{mn} = \frac{1}{AB} \sum_{j=nB}^{(n+1)B-1} \sum_{i=mA}^{(m+1)A-1} G_s(i,j) \text{..(3.3)}$$

where is the mean region (m*n)th sub image of size (A×B) μ_{mn}
G_s(i, j)- Original image

The pixel wise binarized image is given in equation (3.4):

$$Inew(n1,n2) = \begin{cases} 1 & if\, I_{old(n1,n2)} \geq \mu_{mn} \\ 0 & else \end{cases} \text{..(3.4)}$$

3.1.4 Thinning

The images do not contain much information because the ridges obtained are not very clear. Therefore, thinning process is done in order to provide more information and make the lines much more clear. The width of the fingerprint does not give any useful information therefore; thinning process is done in order to reduce connected patterns to a desired pixel by maintaining the basic structure of the fingerprint. It should also be noted that the algorithm is resistant to noise and produces a skeleton that falls approximately on the medial axis of the pattern.

3.1.5 Minutiae Extraction

The fingerprint gray-scale image to be converted into a binary image. The binary images are usually submitted to a thinning stage which allows for the ridge line thickness to be reduced to one pixel, resulting in a skeleton image.
A simple image allows the detection of pixels that corresponds to minutiae. The minutiae consist of the ridges which are terminations and bifurcations. In order to find the location of the terminations and bifurcations, a 3□3 window is used. If the central pixel value is 1 and has only one 1-value neighbour, then the central pixel is a termination. If the central pixel value is 1 and it has three 1-value neighbours, then the central pixel is a bifurcation. If the central pixel value is 1 and it has two 1-value neighbours, then the central pixel is just a usual pixel (neither a termination nor a bifurcation).
After the extraction, the following steps are done in order to avoid the unnecessary data that have been extracted to get the appropriate data.

3.1.6 Removal of Spurious Minutiae

Not all the minutiae that have been extracted are considered as features. Minutiae that are close to each other are ignored i.e. if there are many minutiae, close to each other from the centre minutiae are ignored and the minutiae beyond that distance are considered. A particular distance is considered and between two minutiae the distance value is calculated and the value is compared with the reference value that has been fixed previously. If the distance obtained is lesser the particular

point is ignored but if the distance is greater than the minutiae is considered.

3.1.7 Region of Interest (RoI)

While scanning the image the image is cut at the edges and those points are also considered to be the termination points and therefore, an error might occur. Therefore, a particular area of interest is considered for the points. Minutiae present at the edges of the images are not actually real minutiae which may happen due to the error of capturing an image. So a region of interest is considered and only the minutiae in that area are considered. After performing these particular steps, the features are extracted and they are stored in the form of a template.

After all these steps, the features of the fingerprint are obtained. These features give better information about the image.

3.2 Feature Extraction of Face

The facial image is partitioned into multiple small blocks and the pixel values in each block are formed into vector. Subsequently, the vector is applied to Local Gabor XOR Pattern (LGXP), which provides the feature vector. Figure 3 shows the face sample images.

Figure 3: Face Sample Images

In LGXP, it makes use of the phase information of each pixel followed by processing the same and plotting histograms in response to the analysis made on each pixel. Here, the basic idea is to alleviate the sensitivity of Gabor phase to the varying positions. At first, in a LGXP descriptor phases are quantized into different ranges. The number of phase ranges is made such a way that to make the patterns robust to the variations of Gabor phase, hence cannot be too high. After the quantization process, each of the phase value is quantized into the quantized level values. Subsequently, LGXP operator is applied to the quantized phases of the central pixel and each of its neighbors. The XOR operator is used and the values are calculated accordingly.

In the example (Figure 4), (a) is the matrix showing the initial phase of the pixels after passing through the Gabor filter, (b) is the matrix obtained after the quantization and (c) is the matrix obtained after the XOR comparison with the center quantized value.

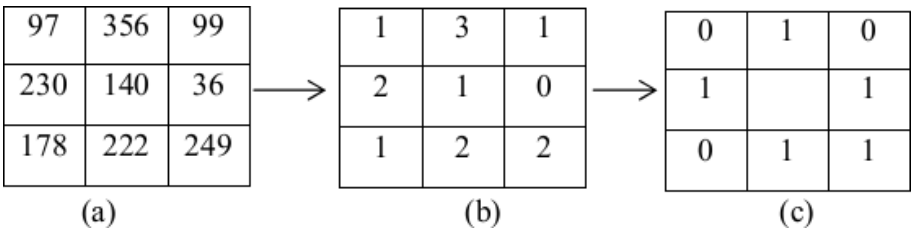

Figure 4: Example of LGXP method where the phase is quantized into 4 ranges

3.2.1 Score Level Fusion

In this work, a few parameters like mean, standard deviation and correlation are found out to find the target value in the testing phase. The mean values of ABC-NN classifier, Fuzzy classifier, Naïve Bayes classifier and Target output are considered as A, F, B and T which are represented by μ_A, , and

.These are defined by the following equations (5.1) – (5.4):

$$\boldsymbol{\mu_A} = \frac{\mathbf{1}}{\boldsymbol{N_t}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{Nt}} \boldsymbol{d_{i,1}} \text{..(5.1)}$$

$$\boldsymbol{\mu_F} = \frac{\mathbf{1}}{\boldsymbol{N_t}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{Nt}} \boldsymbol{d_{i,2}} \text{..(5.2)}$$

μ_B μ_T μ_F

$$\boldsymbol{\mu_B} = \frac{\mathbf{1}}{\boldsymbol{N_t}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{Nt}} \boldsymbol{d_{i,3}} \text{..(5.3)}$$

$$\boldsymbol{\mu_T} = \frac{\mathbf{1}}{\boldsymbol{N_t}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{Nt}} \boldsymbol{t_{i,\theta}} \text{..(5.4)}$$

The standard deviation value of A, F, B and T are represented

by , and are defined by the following equations (5.5) – (5.8):

$$\sigma_A = \sqrt{\frac{1}{N_t} \sum_{i=1}^{Nt} \left(d_{i,1} - \mu_A\right)} \text{..(5.5)}$$

$$\sigma_F = \sqrt{\frac{1}{N_t} \sum_{i=1}^{Nt} \left(d_{i,2} - \mu_F\right)} \text{..(5.6)}$$

$$\sigma_B = \sqrt{\frac{1}{N_t} \sum_{i=1}^{Nt} \left(d_{i,3} - \mu_B\right)} \text{..(5.7)}$$

$$\sigma_T = \sqrt{\frac{1}{N_t} \sum_{i=1}^{Nt} \left(t_i - \mu_T\right)} \text{..(5.8)}$$

In classifier modules, three distinct classifiers are employed for producing their own output on the basis of fusion of input scores. The classifiers used are ABC-NN, fuzzy rule classifiers and Naive Bayes classifiers.

ABC-NN: In this method, ABC is used for training the neural networks. NNs are used in several applications in fields like industry, commerce, scientific research and even in the military. Artificial Neural Networks (ANN) map input to output spaces is carried out randomly on complicated non-linear decision bounds. For classification tasks, ANN is required to be trained so that the network can yield anticipated inputs-outputs mapping.[31] The primary infrastructure of ANN is the multi-layer feed forward network (MLP) that uses back propagation algorithm. However, training speed is generally slower and issues like forced local minimum, overfitting and weight interference ([32], [33]) are present. Hence, these may be effectively decreased through the usage of ABC as a training algorithm.

Artificial Bee Colony Algorithm is an optimization method that offers a population-based search process where individual population known as food positions are modified by artificial bees and the objective of the bees is the discovery of food sources with great nectar quantity and in the end, that with the greatest nectar quantity.

In Fuzzy Rule Classifiers, the scores calculated for all modalities are inputted to fuzzy rule classifiers for obtaining final authentication outputs. Here, scores are first transformed to fuzzy linguistic format (Angelov& Zhou [34]). The fuzzy classifiers convert

the score into high, low and medium and utilize triangular membership functions that are given in equation (5.9):

$$fuzzy_{value(Fv_i:y_1,y_2,y_3)} = \begin{cases} 0 \quad , if Fv_i < y_1, Fv_i > y_3 \\ \frac{Fv_i - y_1}{y_2 - y_1} \quad , if y_1 \le Fv_i \le y_2 \\ \frac{Fv_i - y_1}{y_3 - y_1} \quad , if y_1 \le Fv_i \le y_3 \end{cases} \text{..(5.9)}$$

Where y denotes fuzzy parameter values. Fuzzy classifiers work on the basis of the defined rule. In general, if-then rules are used in fuzzy classifiers. For instance, a rule may be: IF (score 1 is less) AND (score 2 is less) AND (score 3 is less), THEN (allow biometric authentication). After rule matching, decisions are transformed back to crisp values with the assistance of de- fuzzifiers. Crisp values denote if the classifier can detect the input as either authenticated or not.

Naive Bayes classifiers refer to basic probabilistic classifiers on the basis of application of Bayes' theorem with naïve independence assumption. A better phrase for the base probability model is 'independent feature model'. Naïve Bayes classifiers assume that the presence or absence of certain features are not related to the presence/absence of any other attribute, if a particular class parameter is specified. Three scores are individually considered without featuring the remaining scores.

In combination modules, the outcomes obtained by all classifiers are fused through the usage of the proposed fusion method for forming the final outcome for biometric recognition. The module comprises of two phases, one being the training phase while the other is a testing phase. In the former, real outputs may be achieved through all known classifiers. In the latter, final outputs may be yielded by the usage of the suggested fusion method. The proposed method makes use of the correlation between classifier output and real

output in the training stage and fuses them in the testing stage for producing the desired outputs.

Let training images in consideration be denoted by D = {D1, D2, D3,.....,DNt} where Nt represents the total quantity of images obtained for training. Let dij represent the classification values by the corresponding classifier as denoted in Table 1. Where dij 0 or 1, 0 i Nt, 0 j 3

Table 1: Table showing classification values from classifiers and target value

Training Data (D)	ABC-NN (A)	Fuzzy Classifier (F)	Naives Bayes (B)	Target (T)
D1	d1,1	d1,2	d1,3	t1
D2	d2,1	d2,2	d2,3	t2
D3	d3,1	d3,2	d3,3	t3
....	....	....	....	....
DNt	dNt,1	dNt,2	dNt,3	tNt

From the Table 5.1, values under ABC-NN (which is denoted by $A = \{d_{i,1}\}\, for\ 0 < i < Nt$) produce the classified output for the input image by using ABC-NN classifier. Likewise, the values under Fuzzy Classifiers (that are given by $F=\{d_{i,2}\}\, for\ 0 < i < Nt$)) and Naïve Bayes (that are given by $B = \{d_{i,3}\}\, for\ 0 < i < Nt$)) produce the classified output for the input image by using fuzzy classifier and Naïve Bayes classifier correspondingly. The values under target $T = \{t_i\}\, for\ 0 < i < Nt$) produce the target output for the input image.

A few variables such as mean, standard deviation and correlation are determined for finding target values during the testing stage. After obtaining mean and standard deviation, it is required to found the correlation between classifier output and target output. X, Y and Z denote the correlation values between ABC-NN, fuzzy classifiers and Naïve Bayes classifier with the target outputs. These are expressed by the following equation (5.10):

$$X = Corr(A,T) = \frac{E[(A-\mu_A)(T-\mu_T)]}{\sigma_A \sigma_T}$$

$$Y = Corr(F,T) = \frac{E[(F-\mu_F)(T-\mu_T)]}{\sigma_F \sigma_T}$$

$$Z = Corr(B,T) = \frac{E[(B-\mu_B)(T-\mu_T)]}{\sigma_B \sigma_T} \text{..(5.10)}$$

In the testing stage, test images are inputted and respective outputs are discovered. Let test images be expressed by Dk while related classifier output by ABC-NN, fuzzy classifiers and Naïve Bayes classifiers be given by $d_{k,1}$, $d_{k,2}$ and $d_{k,3}$ .The final classified output of the proposed method is denoted as T^ and is given by equation (5.13):

$$\widehat{T_k} = X * \left(\frac{d_{k,1}}{3}\right) + Y * \left(\frac{d_{k,2}}{3}\right) + Z * \left(\frac{d_{k,2}}{3}\right)$$

The final classified output is normalized (denoted by $\widehat{T_{Nk}}$) by appending one and the value is in the range, $\widehat{T_{Nk}}$ [1, 2] in equation (5.14).

$$\widehat{T_{Nk}} = \widehat{T_k} + 1 \text{ ..(5.14)}$$

The classification for matching and non-matching is performed with the usage of threshold set (that is denoted by th). Classification is performed so that in (5.15):

$if\left(\widehat{T_{NK}} < th\right)$, DK considered match

$if\left(\widehat{T_{NK}} \geq th\right)$, DK considered non − match ..(5.15)

Therefore, biometric recognition is carried out and recognition is obtained.

3.1.2 Biometric Authentication

The proposed method may be expanded for remote biometric authentication. For this application, features of particular quantity of individuals (denoted by Na {Na1, Na2 ,..., Nanp }) are stored in the dataset. Here, np refers to the total quantity of individuals in consideration. The users are asked to choose one individual from the set and let the chosen individual be denoted by Nak.

After the individual is chosen, related features are extracted from the samples. Extracted features are encrypted by equation (5.16):

$E = x^{fyr}$..(5.16)

Let, E represents the encrypted value, f denotes the extricated features, numbers are represented as x & y while r represents an arbitrary number. Consequently, in the dataset, decryption is performed for obtaining the original image using equation (5.17):

$$D = \frac{\log\left(\frac{E}{y^r}\right)}{\log(x)} \text{..(5.17)}$$

Consequently, distance (dis) is computed between decrypted image and all the images in the dataset. Authentication has it basis in the threshold set (thr) and the computed distance. When distance is lesser than threshold, users are authenticated. This is expressed by (5.18):

if (dis thr), the user is authenticated else if (dis thr), authentication failed(5.18)

Results And Discussion

The proposed multi classifier based score fusion for multimodal biometric recognition using hybridization technique. The simulation results obtained for six hundred samples from ninety persons where each person has five fingerprint and face samples. For this algorithm, FAR, FRR, ROC and Accuracy performance metrics are evaluated and these metrics help to evaluate the system performance and also in comparative analysis as follows:

4.1 False Acceptance Rate (FAR)

It is a ratio of number of false acceptance and a number of total imposter attempts. It is indirectly proportional to the number of total imposter attempts in equation (5.19).

$$FAR = \frac{No of false acceptance}{No of total imposter attempts} ..(5.19)$$

4.2 False Rejection Rate (FRR)

It is a ratio of number of false rejection and a number of total authentic attempts. It is indirectly proportional to the number of total authentic attempts in equation (5.20).

$$FRR = \frac{No of false rejection}{No of total authentic attempts} ..(5.20)$$

The accuracy measurement of the system is calculated using following formula (5.21):

$$Accuracy = 1 - \left(\frac{FAR+FRR}{2}\right) ..(5.21)$$

The Total Error Rate (TER) is calculated using the formula (5.22)

$$TER = FAR + FRR ..(5.22)$$

Simulation Results

The simulation results obtained for the proposed technique is shown in Figure 5. Totally six hundred samples from ninety persons, where each person has five fingerprint and face samples are collected from FVC 2002 fingerprint database and Georgia tech face database respectively.

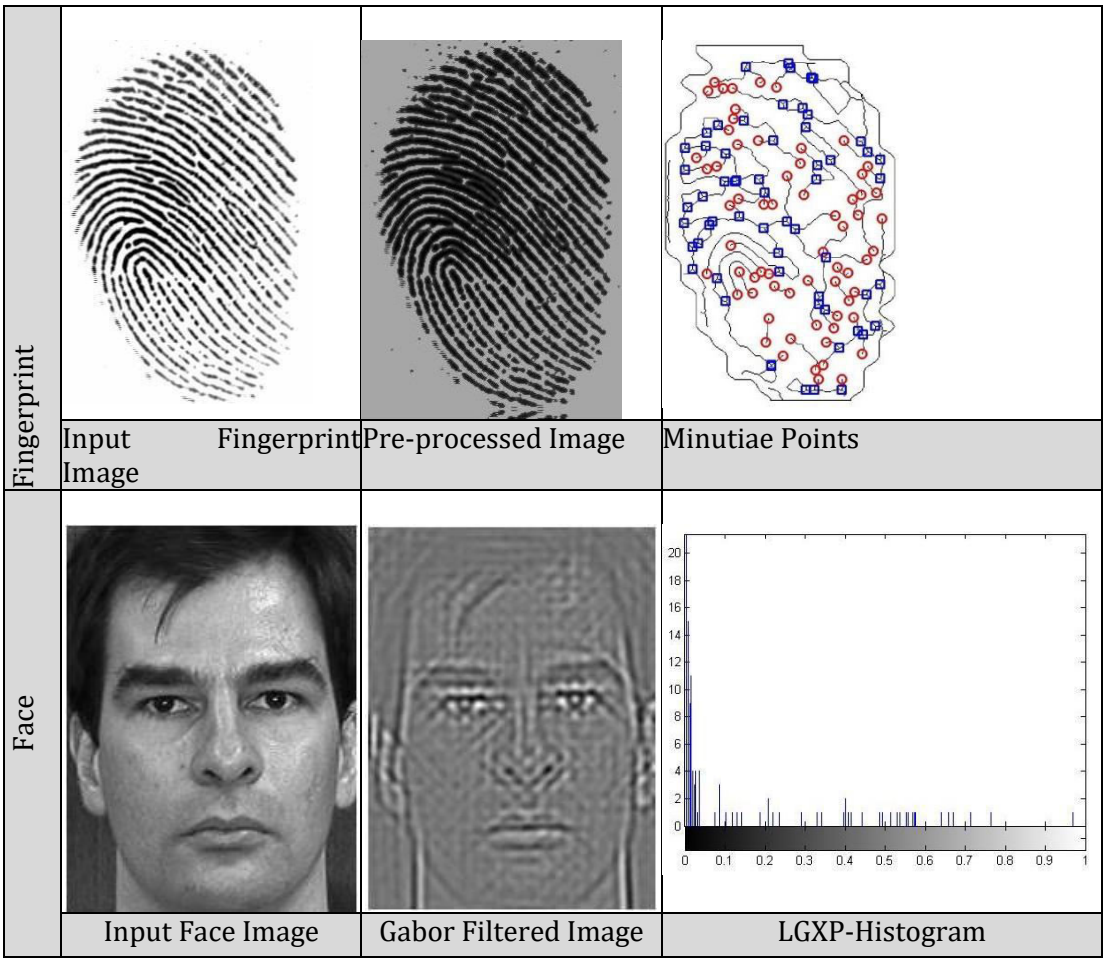

Figure 5: Simulation Results

Comparative Performance Analysis

The performance of the proposed technique is evaluated with the help of evaluation metrics in this section. FAR, FRR, ROC, training accuracy and testing accuracy are taken as the evaluation metrics. The proposed technique (ABC-NN+ Bayesian+ Fuzzy) is compared with other techniques such as ABC-NN, Fuzzy, Bayesian, ABC-NN+ Bayesian,
Bayesian + Fuzzy and ABC-NN +Fuzzy techniques which are used for classifications.

Far

In this section, it analyses the performance of the technique with FAR. Tables 2 shows the FAR values obtained for Fingerprint-Face samples respectively.

Table 2: FAR values for Fingerprint- Face samples

	Threshold										
Classifiers	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ABC-NN	0	0.051	0.128	0.359	0.564	0.718	0.923	0.974	1	1	1
Bayesian	0	0.564	0.564	0.564	0.564	0.564	0.564	0.564	0.564	0.564	1
Fuzzy	0	0.000	0.026	0.077	0.103	0.179	0.308	0.487	0.513	0.872	1
ABC-NN + Bayesian	0	0.385	0.564	0.564	0.564	0.564	0.564	0.564	0.615	0.949	1
Bayesian + Fuzzy	0	0.026	0.154	0.410	0.564	0.564	0.564	0.590	0.590	0.667	1
ABC-NN + Fuzzy	0	0	0.026	0.077	0.103	0.179	0.282	0.513	0.513	0.846	1
ABC-NN+ Bayesian +Fuzzy	0	0.026	0.077	0.282	0.462	0.564	0.564	0.590	0.590	0.667	1

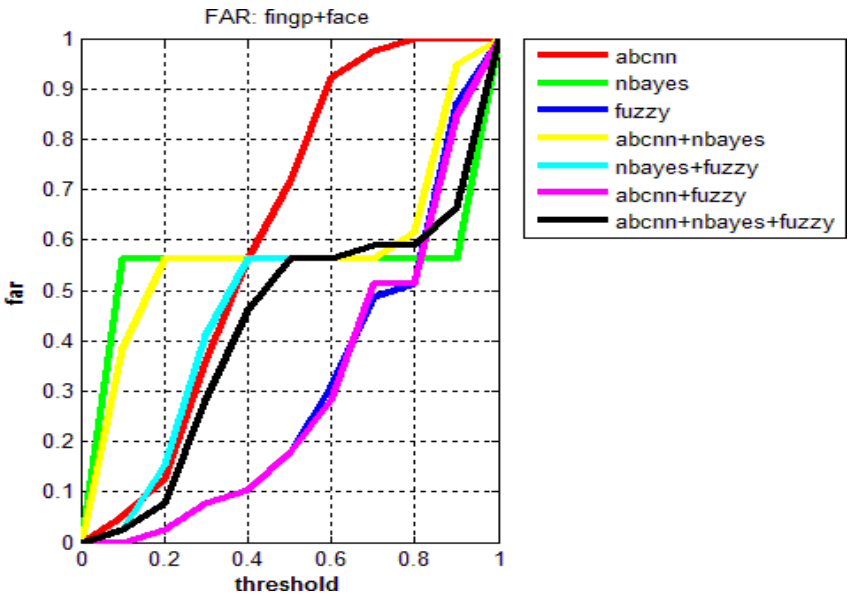

Figure 6: FAR graph for Fingerprint-Face samples

Figure 6 shows the graphical representation of the results obtained. From Figure 6 it can be observed that the FAR for fingerprint-face at threshold of 0.5, multimodal technique using a combination of ABCNN + Bayesian + Fuzzy improved the performance by 48.28% when compared to ABCNN technique. Similarly the proposed technique showed an improvement of 58.82 % compared to Fuzzy, 66.67% compare to ABCNN+Fuzzy. However no significant changes were observed when

compared to ABCNN+Bayesian and Bayesian+Fuzzy based techniques. At higher threshold of 0.8, there were significant improvement in FAR for fingerprint-face of the proposed ABCNN+Bayesian+Fuzzy based technique improved its performance by 51.16% compared to ABCNN technique. In the same way, proposed technique showed an improvement of 4.44% compared to Bayesian and 13.95% compared to Fuzzy. Compared to combination techniques of ABCNN+Bayesian and ABCNN+Fuzzy, the proposed technique showed an improvement of 4.26% and 13.95% respectively.

b)FRR

In this section, it analyse the performance of the technique with the help of FRR. Tables 3 shows the FRR values obtained for Fingerprint-Face respectively.

Table 3: FRR values for Fingerprint- Face samples

Classifiers	Threshold										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ABC-NN	1	0.25	0.075	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0
Bayesian	1	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0
Fuzzy	1	0.675	0.4	0.15	0.75	0.025	0.025	0.025	0	0	0
ABC-NN + Bayesian	1	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0
Bayesian + Fuzzy	1	0.225	0.05	0.025	0.025	0.025	0.025	0.025	0.025	0	0
ABC-NN + Fuzzy	1	0.675	0.375	0.125	0.075	0.025	0.025	0.025	0.025	0.025	0
ABC-NN+ Bayesian +Fuzzy	1	0.325	0.075	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0

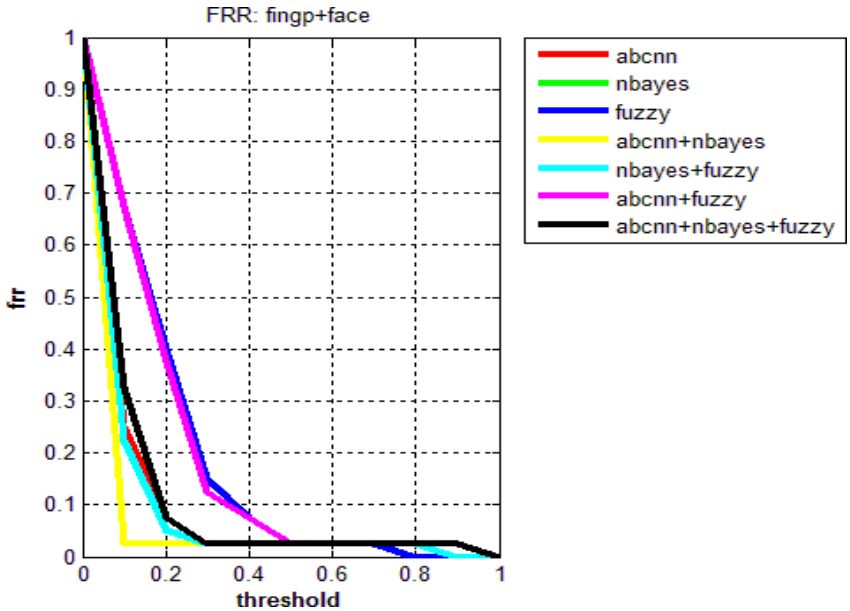

Figure 7: FRR graph for Fingerprint –Face samples

Table 7 gives the numerical results obtained through the experiments. Figure 7 shows the graphical representation of the results obtained. From Figure 7 it can be observed that the FRR for fingerprint-face at threshold of 0.5, multimodal technique using a combination of ABCNN + Bayesian + Fuzzy improved the performance by 26.09% when compared to ABCNN. Similarly the proposed technique showed an improvement of 171.43% compared to Bayesian, 70% compared to Fuzzy, 171.43% compared to ABCNN+Bayesian, 36.36% compared to Bayesian+Fuzzy and 70%

compared to ABCNN+Fuzzy. Compared to combination techniques of ABCNN+Fuzzy, the proposed technique showed an improvement of 133.33%. However no significant changes were observed when compared to ABCNN+Bayesian and Bayesian+Fuzzy based techniques.

c)ROC

In this section the ROC curve obtained for the technique for different modalities are given. Figures 8 shows the ROC graph obtained for Fingerprint-Face respectively.

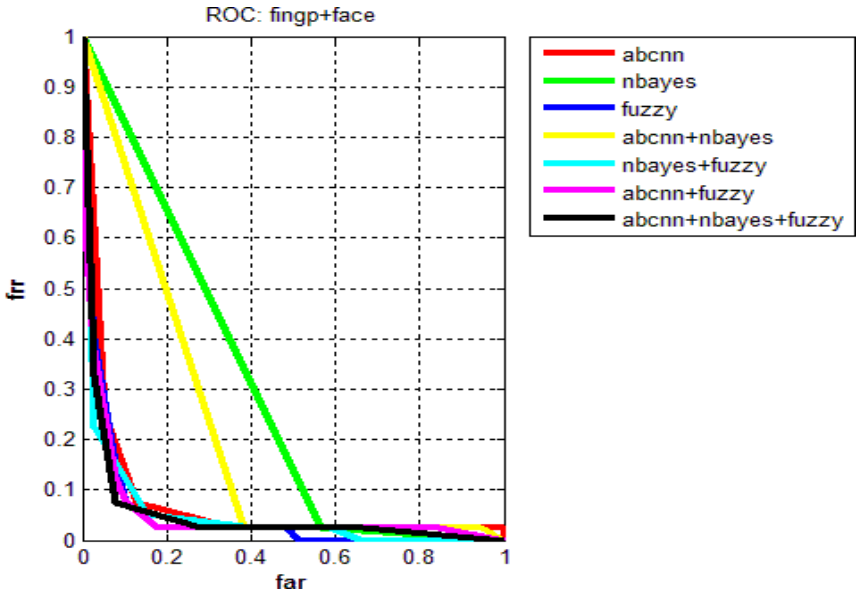

Figure 8: ROC graph for Fingerprint-Face samples

It is observed from Figure 8 that the ROC graph obtained for Fingerprint-Face of ABCNN + Bayesian + Fuzzy, ABCNN + Fuzzy and Bayesian + Fuzzy performs better than other combinations.

The proposed technique outperforms irrespective of the modality combination taken by having the lower ROC curve when compared with other techniques. It can also be observed that, the technique achieved best results when all the two modalities were fused.

Training Accuracy

In this section, it analyze the performance of the technique with the help of training accuracy. Tables 4 shows the Training Accuracy values obtained for Fingerprint-Face respectively.

Table 4: Training Accuracy values for Fingerprint- Face samples

	Threshold										
Classifiers	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ABC-NN	0.5	0.513	0.636	0.600	0.572	0.543	0.505	0.494	0.488	0.508	0.5
Bayesian	0.5	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.726	0.5
Fuzzy	0.5	0.513	0.535	0.696	0.724	0.673	0.616	0.532	0.502	0.502	0.5
ABC-NN + Bayesian	0.5	0.739	0.720	0.726	0.726	0.726	0.726	0.726	0.561	0.500	0.5
Bayesian + Fuzzy	0.5	0.513	0.727	0.739	0.726	0.726	0.720	0.662	0.542	0.502	0.5
ABC-NN + Fuzzy	0.5	0.513	0.531	0.696	0.703	0.678	0.619	0.511	0.502	0.502	0.5
ABC-NN+ Bayesian +Fuzzy	0.5	0.513	0.698	0.739	0.724	0.726	0.701	0.650	0.511	0.502	0.5

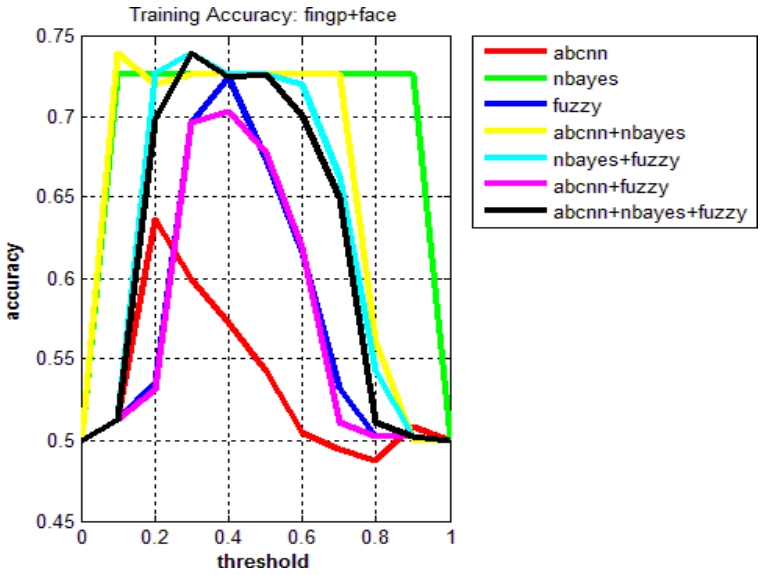

Figure 9: Training Accuracy graph for Fingerprint-Face samples

Figure 9 shows the graphical representation of the results obtained. From Figure 9 it can be observed that the training accuracy for fingerprint-face at threshold of 0.3, multimodal technique using a combination of ABCNN + Bayesian + Fuzzy improved the performance by 20.81% when compared to ABCNN technique.

d)Testing Accuracy

In this section, it analyze the performance of the technique with the help of testing accuracy. Tables 5 shows the Testing Accuracy values obtained for Fingerprint-Face respectively.

Table 5: Testing Accuracy values for Fingerprint- Face samples

Classifiers	Threshold										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ABC-NN	0.5	0.849	0.898	0.808	0.705	0.629	0.526	0.500	0.488	0.488	0.5
Bayesian	0.5	0.705	0.705	0.705	0.705	0.705	0.705	0.705	0.705	0.705	0.5
Fuzzy	0.5	0.663	0.787	0.887	0.911	0.898	0.834	0.744	0.744	0.564	0.5
ABC-NN + Bayesian	0.5	0.795	0.705	0.705	0.705	0.705	0.705	0.705	0.680	0.513	0.5
Bayesian + Fuzzy	0.5	0.875	0.898	0.782	0.705	0.705	0.705	0.693	0.693	0.667	0.5
ABC-NN + Fuzzy	0.5	0.663	0.800	0.899	0.911	0.898	0.846	0.731	0.731	0.564	0.5
ABC-NN+ Bayesian +Fuzzy	0.5	0.875	0.924	0.846	0.757	0.705	0.705	0.693	0.693	0.654	0.5

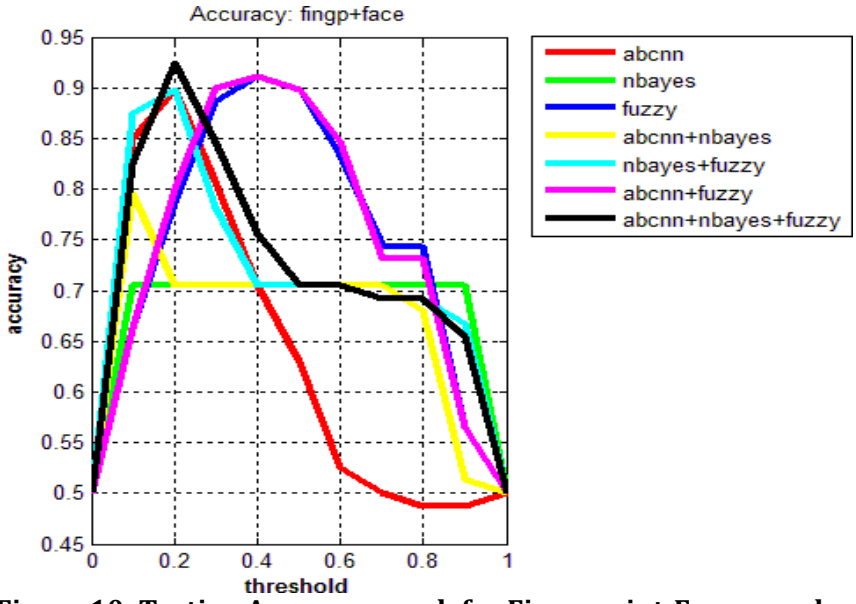

Figure 10: Testing Accuracy graph for Fingerprint-Face samples

Similarly the proposed technique showed an improvement of 2.07 % compared to Bayesian, 4.6% compared to Fuzzy, 2.07% compared to ABCNN+Bayesian, 2.07% compared to Bayesian+Fuzzy and 4.6% compared to ABCNN+Fuzzy. At higher threshold, there were significant improvement of the proposed ABCNN + Bayesian + Fuzzy technique compared to Bayesian and Fuzzy techniques in the order of 5.61% and 10.1% respectively. Compared to combination techniques of ABCNN+Bayesian, Bayesian+Fuzzy and ABCNN+Fuzzy the proposed technique showed an improvement of 5.61%, 1.9% and 3.87% respectively.

Table 10 gives the numerical results obtained through the experiments. Figure 10 shows the graphical representation of the results obtained. From Figure 10 it can be observed that the testing accuracy for fingerprint-face at threshold of 0.2, multimodal technique using a combination of ABCNN + Bayesian + Fuzzy improved the performance by 2.8% when compared to ABCNN technique. Similarly the proposed technique showed an improvement of 26.83 % compared to Bayesian, 15.99% compared to Fuzzy, 26.83% compared to ABCNN+Bayesian, 2.85% compared to Bayesian+Fuzzy and 14.43% compared to ABCNN+Fuzzy. When the threshold is set at 0.9, the testing accuracy for fingerprint-face of ABCNN+Bayesian+Fuzzy based technique improved its performance by 29.19% compared to ABCNN technique. At higher threshold, there were significant improvement of the proposed ABCNN + Bayesian + Fuzzy technique compared to Bayesian and Fuzzy techniques in the order of 7.54% and 14.79% respectively. Compared to combination techniques of ABCNN+Bayesian, Bayesian+Fuzzy and ABCNN+Fuzzy the proposed technique showed an improvement of 24.16%, 1.89% and 14.73% respectively.

By analyzing the performance of the proposed technique, it can be seen that the technique was able to achieve good performance.

6. Summary

Multi-classifiers based score level fusion of multimodal biometric recognition and their applications in remote biometric authentication are proposed here. In the proposed technique, feature extraction is initially performed, then classified and finally fused. The technique is executed using MATLAB and FAR, FRR and accuracy is used as evaluation measures. The proposed technique is compared with other state-of-the-art techniques. The techniques employed for the comparison are ABC-NN, Fuzzy, Bayesian, ABC-NN+ Bayesian, Bayesian + Fuzzy and ABC-NN +Fuzzy methods. For in-depth analysis, various combinations of fusions of modalities considered are fingerprint-face and the fused fingerprint-face. The proposed technique yielded a maximal accuracy of 95% and the noted values denote the efficacy of the proposed technique.

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