Alexandria Engineering Journal (2019) 58, 103–114

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Alexandria Engineering Journal

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ORIGINAL ARTICLE

Entropy based Local Binary Pattern (ELBP) feature extraction technique of multimodal biometrics as defence mechanism for cloud storage

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Received 16 July 2018; accepted 11 December 2018
Available online 24 December 2018

KEYWORDS

Cloud Computing (CC) environment;
Biometric modalities;
Authentication;
Feature extraction;
Entropy based Local Binary Pattern (ELBP)

Abstract Cloud Computing (CC) is a technology that is growing by leaps and bounds and has attracted wide spectrum of users. The extensive usage of cloud technology is influenced by multiple factors like ease of use, pay-per usage strategy, easy access, cost-effectiveness etc. Though it is a widely used technology, challenges exist in the form of security threats. There are a variety of services that are offered by cloud. These include Software as a Service (SaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). Storage is one of the key service offerings under IaaS. To provide a secure digital platform for users to work with, this research work proposes a novel security architecture for secured storage in cloud that provides a robust authentication by employing multiple biometric modalities from users and allow/deny access accordingly. The crux of better authentication relies on the way the features are extracted from multiple biometric sensors and matched with registered users. For this purpose, a novel feature extraction technique is proposed in this research work. Entropy Based Local Binary Pattern (ELBP) is a new texture-based feature extraction technique proposed to describe the entropy information into Local Binary Pattern histogram in one-dimensional space. ELBP feature extraction technique needs no quantization. Biometric images exhibit higher uniqueness and hence incorporating entropy values into local regions add higher information content to these images, thus leading to better feature extraction. The experiments are performed on biometric images from Chinese Academy of Science, Institute of Automation (CASIA) Iris, Face and Fingerprint databases and the results show that the proposed ELBP feature extraction achieves substantial improvement, in terms of various classification metrics like accuracy, precision, recall etc. in comparison with the conventional rotation invariant LBP methods. The Receiver Operating Characteristics Curve (ROC) also bears testimony to the performance of the authentication system.

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Peer review under responsibility of Faculty of Engineering, Alexandria University.

https://doi.org/10.1016/j.aej.2018.12.008
1110-0168

1. Introduction

Biometrics system is the technology of using humans' physical as well as behavioural characters for identifying individuals. These characteristics remain unique and distinguishable. Biometric data are acquired from users and are stored during registration phase. At the time of authentication, the traits from users are compared against the registered templates. Multi-biometric system acquires multiple traits from single user (e.g., fingerprint, and iris and face) for verifying and authenticating a user [1]. This is done predominantly to enhance the security by ensuring that the person trying to gain access is genuine. There are many methods that are existing for identification of users based on their biometric traits and each of these generate varied operational characteristic.

When compared to password-based authentication methods, biometric-based authentication systems have better security, but still suffers from major challenges like performance in terms of error rate. It becomes difficult to strike a balance between false negative and false positive rates [2]. Other challenges include increased false negative rates when the genuine users are unable to provide with registered traits due to injury, aging and similar factors. In such cases, multiple modality usage comes as a solution since the authentication system does not solely rely on one single modality. This significantly decreases the false negative rates, there by resulting in better performance.

Multiple modalities increase the level of security since more than one traits are obtained from the same user and evaluated before allowing requested access [3,34].

To improve the identification performance, an optimal feature extraction method is developed. Feature extraction could reduce dimensions of obtained image and get the most important features accurately. The feature extraction technique should be employed in such a way that essential features are precisely extracted so that the case of accepting genuine users and rejecting imposters are high. Depending on the kind of modality considered, different feature extraction techniques can be applied. For example, an automatic and robust fingerprint feature extraction method is used to identify fingers from hand images [4].

One of the active research area in the field of computer vision and pattern recognition is texture analysis. Texture analysis involves few basic steps like image classification on the basis of content of texture; image segmentation into portions of textures of homogenous nature; texture synthesis; and extracting shape information from cues of textures [5]. Of these basic steps, classification of images based on texture has wide range of applications, like fabric classification [6], crops classification [7], medical image analysis [8] and face recognition [9].

Early texture classification methods focused on image texture's statistical analysis. These include methods like wavelet transform and wavelet frames [10], co-occurrence matrix method [11] and filtering approaches [12], like Gabor filtering. These methods exhibit good results for classification as long as the training as well as testing samples have same orientations. But this may not be possible all the time with real-time textures, resulting in poor performance. This resulted in the need for a texture-based classification method that is rotation invariant. Many research studies [13–15] on face feature recognition have proved that using LBP for face provides not only good recognition rate but also does it at higher speed. LBP method is robust for face recognition methods that perform well in conditions with different facial expressions, varied illumination conditions, age factors affecting face samples and rotation of image conditions. LBP, first developed for image processing [16–17], has gained increasing popularity in the last decade due to its effectiveness and simplicity. For the undertaken task, it eliminates the need for spectral denoising, impulsive noise removal, and contour tracing. The LBP operator is robust, effective, and computationally simple, resulting in a significant reduction in computational costs over the aforementioned methods.

Many research works have included multiple modalities as means of authentication for securing digital environment. Sree Vidya et al. [18] proposed a multiple finger based biometric authentication mechanism where any three fingers of user's choice are captured and random numbers are assigned to each finger during registration. During authentication, access is allowed only when both finger prints and assigned passwords match, resulting in a tight authentication framework.

Biometric Authentication Mechanism (BAM) is a cloud-based healthcare management system that ensures the security of sensitive medical data stored in cloud. Access to such data is enabled through a biometric signature-based authentication which relies on behavioural traits [19]. Biometric systems with multiple modalities are more resistant to spoofing attacks when compared to unimodal biometric systems. This is because multi-modalities combine more than one trait for authenticating, making it complex for an intruder to spoof all modalities concurrently.

Most common cases of authentication systems face challenges in terms of either genuine user is denied access, a case of false negative or imposters are provided with access, which is a case of false positive. Though both these contribute to poor performance, the latter is a case of breach of security, which is not a desirable scenario in an authentication system.

To avoid the above-mentioned issues, in this research, a novel security authentication framework for cloud users is proposed. This system authenticates users based on their biological traits that are totally unique to individual users. It also uses more than one biometric trait viz., fingerprint, Iris and face, thus making it complex for a hacker to imitate all the three traits simultaneously. This work aims at bringing down the false negative and false positive rates and increasing the true positive and true negative values. The feature extraction technique uses a new and robust method for extracting the essential features. It uses Entropy based Local Binary Pattern (ELBP) technique which is rotation and illuminance invariant and exhibits lower rates of misclassification of objects.

2. Related work

Lee et al. [20] discussed about Orientated Local Histogram Equalization (OLHE) where the edge orientations are exploited compensating illumination. This edge orientation is useful for recognition of facial features. Face recognition mechanism included three contributions. Encoding of edge orientations, better contour preserving capability and better performance even under high illumination conditions. The work presented that LBP is a special case of OLHE, and it outperforms LBP for face recognition. The results also showed that the computational complexity of OLHE is less in comparison to their previous studies.

Lin et al. [21] presented a method for retrieval of images followed by classification using Adaptive Local Binary Patterns (ALBP). ALBP is texture-based feature extraction technique. Adaptive local binary pattern histogram (ALBPH) and gradient for adaptive local binary patterns (GALBP) are proposed based on texture features. These features describe the relationship among the pixels in local neighbourhood. ALBPH like LBP finds the distribution of texture image by calculating the difference between the central pixel and pixel values of its associated neighbour values. In the GALBP, the gradient for each pixel is calculated and the total of these gradients is used as an image feature.

Abhishree et al. [22] presented Anisotropic Diffusion (AD) and Gabor filter methods. AD is used for pre-processing and Gabor filter is used for extraction of features. This process is focused to improve the face recognition performance. Gabor filter captures the facial features and by using Particle Swarm Optimization (PSO) technique, important features are selected. It also reduces the number of irrelevant features which increases the time recognition of face.

Zhang et al. [23] introduced the use of Artificial Fish Swarm Algorithm (AFSA). This was used as a tool that could concurrently set up a Neural Network (NN), with parameter adjustments, and reduce feature under consideration. These reduced features and the hidden units are used to represent the artificial fishes in the process of optimization. Nosaka et al. [24] presented an image feature that was based on spatial co-occurrence of micro patterns. Here, Local Binary Pattern represents each of the micro patterns. The Local Binary Pattern of each of the micro patterns in the image are finally combined into one single histogram.

Kambi Beli and Guo [25] introduced a new work to address issues associated with face recognition like facial expressions, illumination etc. They employed a two-step procedure for better recognition. The first step includes usage of LBP for extracting face features. The second step includes k-Nearest Neighbour (KNN) algorithm for classification of images. This yielded good results in terms of similarity measures of face features.

Guo et al. [26] came up with a novel texture descriptor, LBP variance (LBPV). The aim of the work was to bring in the local contrast information of the given image to an LBP histogram of single dimension. LBPV needs no quantization and training. This work also used distance measurement as matching scheme that reduce the dimensions of features resulting in a lesser computation time.

Yuan [27] proposed a local binary pattern that is invariant to both rotation as well as scaling. This was achieved by using circular shift sub-uniform and scale space and high order directional derivatives altogether. Different order derivatives yield various codes. These codes lead to the generation of various histograms for an image. These histograms after multiplying by weights are concatenated. This helps in complete utilization of information of derivates of different orders.

Tran et al. [28] presented a novel approach, which involves two phases namely extraction of features, followed by classification. For the purpose of feature extraction, Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) are used. Post feature extraction, classification algorithm is employed for classifying features that operates based on similarity of selected features, thus improving recognition rate. The first phase of recognition involves segmenting face image into smaller parts and applying LBP and LTP to obtain feature vector. The second phase involved selection of face features that exhibit higher similarity with that of trained images, resulting in classification of faces.

Though there are multiple extensions that have been made to LBP, there is still scope for improvisation and this research work is one such contribution and cater to better recognition rate. In this work the Entropy based Local Binary Pattern (ELBP) is proposed to represent features with high information gain in the LBP style. Unlike conventional way of computing a total histogram, this proposed ELBP computes the entropy of local regions of the image's sampling pixels. These are then accumulated into the Local Binary Pattern bin.

3. Proposed entropy based Local Binary Pattern (ELBP) feature extraction

In this research, a novel security architecture for storage in cloud computing is proposed. Cloud service providers let users store and retrieve data from cloud. In order to ensure strong authentication, proposed technique involves acquiring multiple biometric traits from users viz. fingerprint, iris and face; extracting essential features and matching with the database for determining if it is a genuine user or an imposter. A new feature extraction technique, Entropy based Local Binary Pattern (ELBP) is proposed in this research work. Once the features are extracted, matching is done using Multiclass Support Vector Machine (MSVM) for the purpose of decision making as to allow or deny access. The overall block diagram of the proposed defence system is illustrated in Fig. 1.

The steps involved in this architecture are as follows:

1. Histogram equalization
2. Feature Extraction -ELBP
3. Multimodal authentication – MSVM

3.1. Histogram equalization

One of the most widely used methods for pre-processing of images is histogram equalization. Pre-processing is done for betterment of the acquired images from different sensors. Since multi-modal biometric images are acquired from users, these images, if enhanced, aid in better extraction of features. The equalization technique transforms the image histogram into a histogram which is constant for all brightness values, thus enhancing the image. This would represent a brightness distribution where all the values have equal probability. Histogram equalization is given by the following equation:

$$P(i) = \frac{n_i}{N} \tag{1}$$

where$i \in 0, 1 \cdots .k-1$ grey level, n is individual pixel and N is the pixel's count in the image. The transformation function is given by:

$$I_{out} = \sum_{i=0}^{k-1} \frac{n_i}{N} = \sum_{i=0}^{k-1} p(i) \tag{2}$$

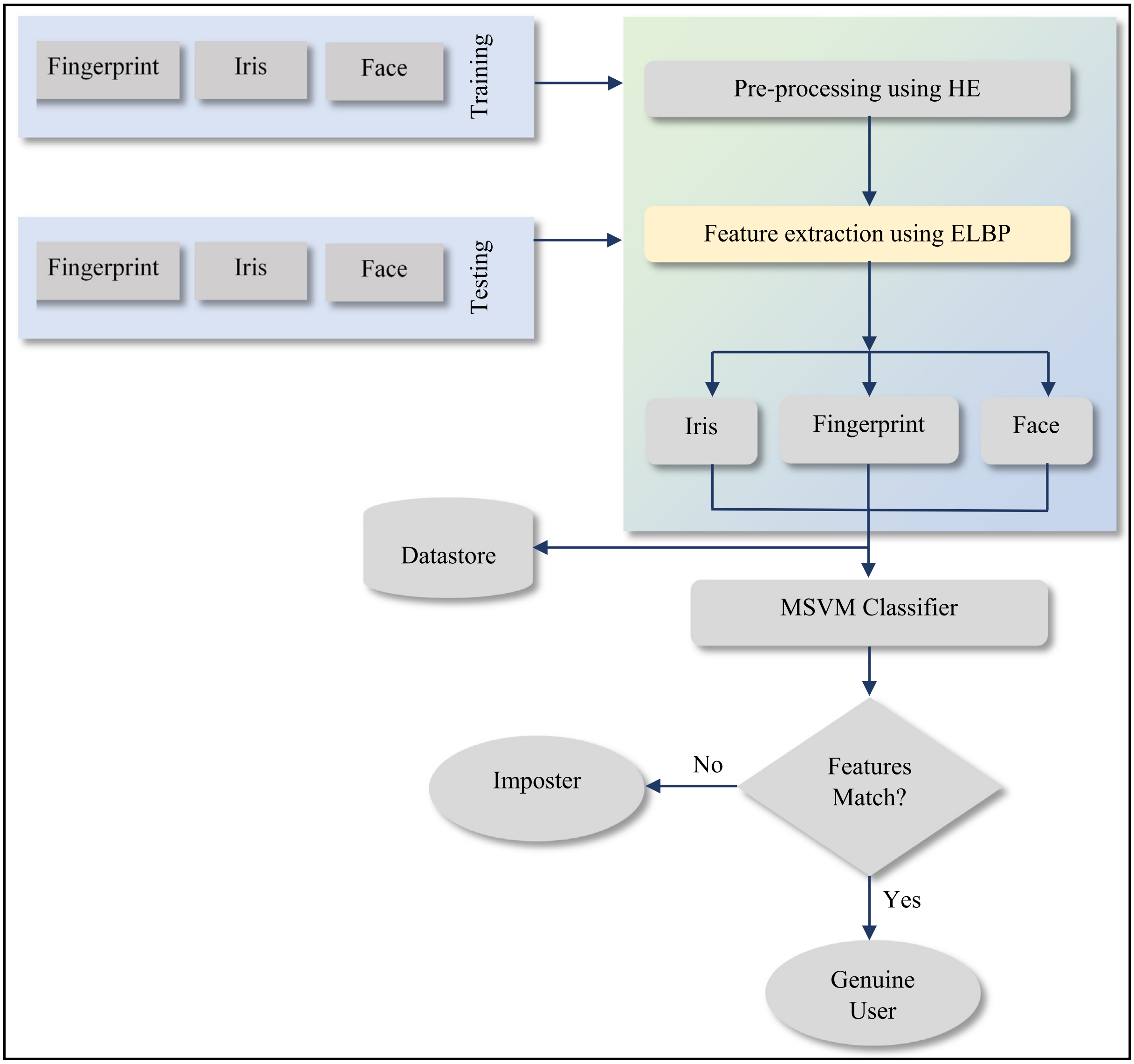


Fig. 1 Overall block diagram of Multimodal Biometrics As Defence Mechanism For Cloud Storage.

Eq. (2) maps the intensity values of pixels from the range [0–255] to [0–1] domain. I_{out} is the output image after preprocessing step by using histogram equalization method [29–30].

3.2. Feature extraction

Feature extraction refers to the process of mapping an image from n-dimensional space to lower dimensions by applying some function on to the original image. These smaller dimensions aid in better and faster classification. There are a number of ways of feature extraction; extraction based on shape, texture, edges etc. Texture based extraction has applications in many fields that include machine vision, medical image analysis and visual inspection. Effective extraction of features forms the basis for all texture related problems. Of the various texture-based feature extraction techniques, the most widely applied descriptor is Local Binary Pattern (LBP). Thus, LBP is the most powerful tool in the field of texture analysis [31]. In the recent years, a variant of LBP, called LBP Variance (LBPV) [26] is used for feature extraction.

3.2.1. Local Binary Pattern (LBP)

Local Binary Pattern proposed by Ojala et al. in 1996 [31], is a texture-based feature extraction technique that has wide applications in biometric image classification. The captured digital image is segmented into smaller portions from which the features are extracted. The LBP operator works by thresholding the neighbourhood of each central pixel and this results in a binary number. The LBP operator is defined as in equation (3)

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \tag{3}$$

where there are P neighbours, with radius of neighbourhood R,x_c, y_c are co-ordinates of pixel at the center of the local region, and g_p, g_c are gray internsity values of neighbouring pixel and sampling center pixel and s(x) is defined as

$$s(x) = \begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases} \tag{4}$$

Local Binary Patterns are obtained by sampling in a circular fashion around the central pixel. The operator uses either uniform patterns or non-uniform patterns. For a uniform pattern, the number of bitwise transitions is no more than two. For example, 00000110 is a uniform pattern where the transitions are 2. In the case of pattern 10101100, the number of transitions is 6, and hence falls under the category of non-uniform patterns. The pattern of LBP code for each of the pixel in the segmented images are collated into a histogram. Classification is carried out by calculating histogram similarities.

3.2.2. LBP variance (LBPV)

Local spatial pattern and contrast of neighbourhood pixels are the two information used by $LBP_{P,R}/VAR_{P,R}$. These are complementary information and such a usage makes it very robust [26]. Unlike $LBP_{P,R}$, $\mathrm{VAR_{P,R}}$ has continuous values and necessitates for a quantization process. Quantization is done by using all images of training samples to calculate feature distributions, resulting in a total distribution. From this, threshold values are calculated to obtain N bins from the calculated total distribution, with each bin having equal number of values. This results in higher quantization resolution. The VAR of the test images are then quantized using the threshold values.

Though high-resolution quantization values are obtained, there are some major drawbacks. Some of these are as follows: a mandatory training stage is required to obtain the threshold values; since the employed method deals with texture classes, the contrast values vary with classes, and training samples influence quantization to a greater extent. Decision on number of bins is critical, since too many can lead to large number of classes and too few provides less discriminative information. Finding the optimal number of bins is a difficult task.

David et al. [26], proposed a LPBV descriptor that tries to overcome the above-mentioned problems of $LBP_{P,R}/VAR_{P,R}$ descriptor. This is a joint method of using Local Binary Pattern and contrast distribution. In this method, every LBP pattern is assigned the same weight 1. Then the values of variance are used as adaptive weights to adjust the distribution of contrast in histogram calculation. The use of variance as adaptive weights is attributed to the fact that high frequency regions of texture have higher variance values and hence the discrimination of images is also higher.

The histogram of LBPV histogram is given by the following equations.

$$LBPV_{P,R}(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} w(LBP_{P,R}(i,j),k), k \in [0,K] \tag{5}$$

$$w(LBP_{P,R}((i,j),k)) = \begin{cases} VAR_{P,R}(i,j), & LBP_{P,R}(i,j) = k \\ 0, & otherwise \end{cases} \tag{6}$$

3.2.2.1. Rotation invariant variance measures (VAR). The measure of local variance rotation invariance is defined as [26]

$$VAR_{P,R} = \frac{1}{P} \sum_{p=0}^{P-1} (g_p - u)^2 \tag{7}$$

where $u = \frac{1}{P}\sum_{p=0}^{P-1} g_p$. When the two complementary information, viz., $\mathrm{LBP_{P,R}/VAR_{P,R}S}$ are jointly distributed, image's local texture is better characterized when compared to sole usage of $LBP_{P,R}$. While Ojala et al. [31] proposed distribution of $LBP^{riu2}_{P,R}$ and $VAR_{P,R}$ jointly, other non-uniform patterns, like $LBP^{u2}_{P,R}$, can also be used with $\mathrm{VAR_{P,R}}$. Nevertheless, $LBP^{u2}_{P,R}$ has higher dimensions and is not rotation invariant. In general, the same values for P and R are used for $LBP^{riu2}_{P,R}$ and $VAR_{P,R}$.

In a coordinate system, considering that LBP and VAR belong to two orthogonal axes, then LBPV can be an integral projection [32] along the axis of VAR. This represents a simplified 2D LBP/VAR distribution. Since $LBPV^{u2}_{P,R}\left(LBPV^{riu2}_{P,R}\right)$ is a simplified descriptor of $LBPV^{u2}_{P,R}/VAR_{P,R}\left(LBP^{riu2}_{P,R}/VAR_{P,R}\right)$, its feature size becomes smaller than that of $LBP^{u2}_{P,R}/VAR_{P,R}\left(\frac{LBP^{riu2}_{P,R}}{VAR_{P,R}}\right)$ and is the similar to that of $LBP^{u2}_{P,R}\left(LBP^{riu2}_{P,R}\right)$.

3.2.3. Proposed methodology - Entropy based Local Binary Pattern (ELBP)

In this research, Entropy based LBP (ELBP) is proposed to improve the performance of feature extraction technique. ELBP is based on the LBPV proposed by David et al. [26]. The proposed work computes information content of each neighbourhood pixel and, thus the calculated entropy contributes as an adaptive weight to gauge the information gained from each neighbouring pixel. The formulation of LBPV was mentioned in Eq. (6).

Though LBPV technique does not rely heavily on training samples and needs no quantization, the LBPV feature extraction just considers the image's uniform binary patterns. Those patterns that represent the image's non-uniform patterns are not considered. Hence, the features of LBPV are the histograms representing uniform patterns in an image's texture. Patterns' information on spatial distribution is not considered, which plays a key role in classifying textures. Hence, in the proposed work, non-uniform patterns are also considered which result in better classification. Therefore, the research work proposes a new entropy-based rotation invariant method that comes as an extension to the conventional LBPV approach. By adopting such an approach, the high information content present in biometric images' textures are brought out. The images under consideration are biometric images from which features are extracted based on texture. In original Local Binary Pattern, non-uniform patterns were not considered since these patterns increased the computational complexity of feature extraction. When applying ELBP feature extraction onto biometric images, the images are comparatively small and hence do not increase the complexity of computing non-uniform patterns. Consideration of non-uniform patterns for biometric images add more significance in extraction features as biometric images are highly unique and differ greatly from one user to another.

Entropy of the local absolute difference is utilized to make the matching more robust against local spatial structural changes. Entropy is a measure of the expected information content or uncertainty of a probability distribution.

Application of entropy to feature extraction reveals lot of information about the features under consideration. This is because of the fact that lower the probability, higher the information gain. Let X_i denote a pixel and p_i denote the probability of occurrence of that pixel X_i. Let n be the number of such pixels in a given image. Hence, the pixels $X_1, \ldots, X_n$ with $p_1, \ldots, p_n$ as probabilities, add up to 1. Those pixels whose probability of occurrence is lesser, provide more information since probability of occurrence and information content are inversely proportional. Thus, entropy h, a measure of information is a decreasing function of probability p_i. Claude Shannon proposed a log function $h(p_i)$ to define information and is given by the following equation.

$$h\left(g_{p_i}\right) = \log_2 \frac{1}{P(g_{p_i})} \tag{8}$$

where (g_{p_i}) deotes the probability of sampling pixel. It is a decreasing function from infinity to 0. The value of $P(g_{p_i})$ ranges between 0 and 1. This function shows that lower the probability of a pixel to exist, higher the amount of information, showing that the pixel exists. This is more relevant in a biometric image, since lower the probability, more unique the extracted feature is. From these n information values h (g_{p_i}), the expected information content entropy H, is formulated by measuring the information value and associated probabilities.

$$H = -\sum_{i=1}^{n} P(g_{p_i})\log_2 P(g_{p_i}) \tag{9}$$

Given a discrete random variable R with probabilities $P = (P_1, \ldots, P_n)$, the Shannon entropy can be defined as

$$H\left(g_p\right) = -k\sum_{i=1}^{n} P(g_{p_i}) lnP(g_{p_i}) \tag{10}$$

where k depends on the unit used and is usually set to unity.

3.2.3.1. Rotation invariant entropy measures (ENTRI). The measure of local entropy's rotation invariance can be defined as follows.

$$ENTRI_{P,R} = \frac{1}{P}\sum_{p=0}^{P-1}\left(g_p - H\left(g_p\right)\right)^2 \tag{11}$$

Therefore, entropy is the average amount of information in a certain pixel. Thus, the ELBP is used to produce complete representation of features from the images.

$$ELBP_{P,R}(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} w(LBP_{P,R}(i,j),k), k \in [0, K] \tag{12}$$

$$w(LBP_{P,R}((i,j),k)) = \begin{cases} ENTRI_{P,R}(i,j), & LBP_{P,R}(i,j) = k \\ 0, & otherwise \end{cases} \tag{13}$$

where, P is the neighbourhood size with radius R. Depiction of the proposed ELBP is shown in Fig. 2.

Features extracted using ELBP operator from multimodal biometric traits is shown in Fig. 3.

3.3. Multimodal authentication system with MSVM

Support Vector Machine is a classification algorithm of supervised machine learning. It has gained much popularity in the recent past for the wide variety of applications it has. It plays a key role in solving a spectrum of classification problems. Once the features are extracted from users, the next step is to ascertain whether the user is a genuine user or an imposter. This can be effectively done by means of SVM. The classification problem is peculiar in the current scenario since three modalities are involved and result of classification of all three modalities should belong to a single user class label. Hence in this research, a multi-class SVM is employed. Multiclass SVM and SVM differs in the way the classification problem is dealt with. When the classification problem is binary with two classes, SVM is employed and when there are multiple classes involved in a classification problem, then an MSVM is used. Partial ranking formulation of multiclass SVMs [33] is briefed in the following section.

3.3.1. Partial ranking

An MSVM has M classes and each of these include binary classifiers that can be trained to separate one class from the other. To perform, a multi-class classification, a function 'f' needs to be defined. This function 'f' has features $p \in P$ that are to be mapped to a set of class labels which are discrete. Let the discrete class labels be $q \in Q$. A discriminant function $S(p,q) \in R$ is a function which can evaluate the correctness of mappings between the feature p and class label q.

$$f(p) = arg \max_{q \in Q} S(p,q) \tag{14}$$

The discriminant function S is defined as in Eq. (15)

$$S(p,q) = \langle w, \phi(p,q)\rangle \tag{15}$$

where $\phi(p,q)$ maps the feature-label pair (p, q) into an appropriate feature space. The function ϕ is based on joint kernel functional specification and is defined as follows:

$$K\left(p,q,\bar{p},\bar{q}\right) = \left\langle \phi(p,q), \phi\left(\bar{p},\bar{q}\right)\right\rangle \tag{16}$$

Let the training features be $p_1, p_2 \ldots p_n \in P$ and their class labels be $q_1, q_2 \ldots q_n \in Q$. The key idea is to find a correct association that has a score of mapping between features and class labels $S(p_i, q_i)$ higher than score of incorrect association, $S(p_i, q), q \neq q_i$. Such a scoring results in carrying out a partial order relationship between elements of P and Q. Thus, partial ranking is given by constraints as in Eq. (17)

$$\forall i = 1, \cdots n, \forall q \neq q_i \quad \langle w, \delta\phi_i(q_i, q)\rangle \geq 1 \tag{17}$$

$\delta\phi_i(q_i, q)$ is defined as in Eq. (18)

$$\delta\phi_i(q_i, q) = \phi_i(p_i, q) - \phi_i\left(p_i, \bar{q}\right) \tag{18}$$

ξ_i is the slack variable that is introduced to account for any constraint violation. It also accounts for optimizing the slack and weight vector w. The slack variable is given in Eq. (19)

$$\min_w \frac{1}{2}\langle w, w\rangle + C\sum_{i=1}^{n}\xi_i \tag{19}$$

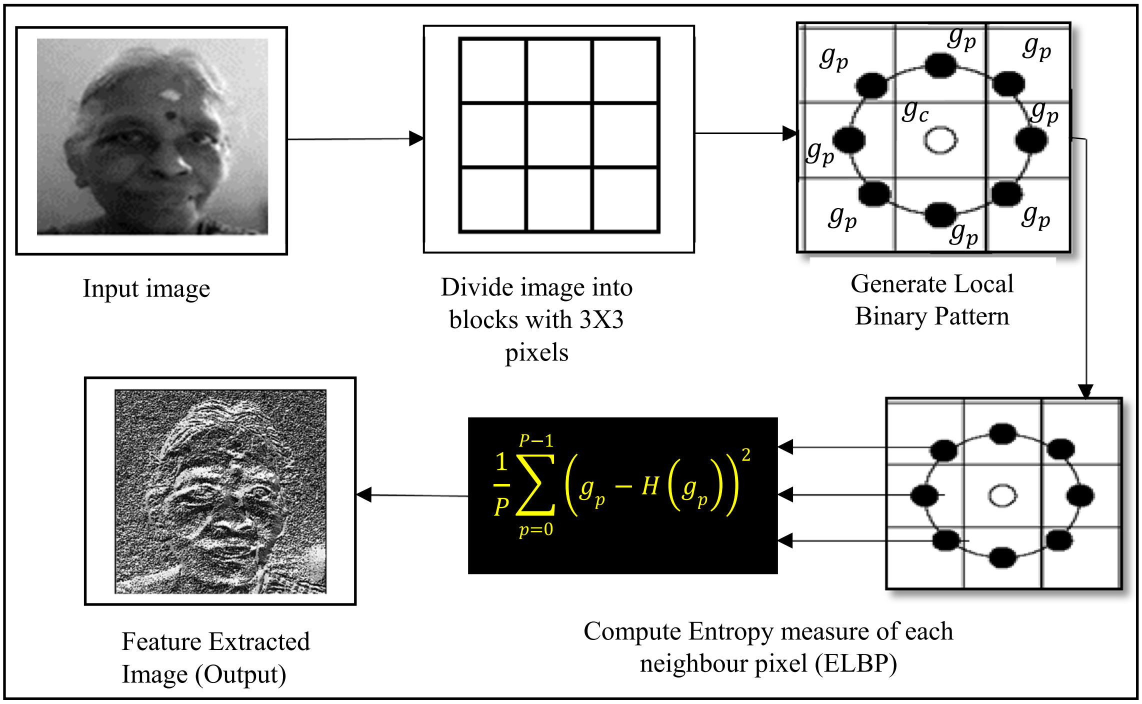


Fig. 2 ELBP Depiction.

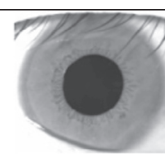
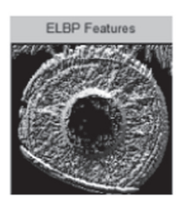
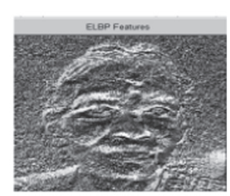
Type of trait	**Fingerprint**	**Iris**	**Face**
Original Image			
Feature Extracted image using ELBP			

Fig. 3 Feature Extraction using ELBP from multiple modalities.

$$subject\ \ to \begin{cases} \forall i \xi_i \geq 0 \\ \forall i \forall q \neq q_i \langle w, \delta\phi_i(q_i, q) \rangle \geq 1 - \xi_i \end{cases} \tag{20}$$

Thus, by applying ELBP to biometric images, texture features are extracted from three varied modalities and are tested against the trained samples. Thumb rule of 80–20 ratio was applied to training and testing samples. The datasets for face, Iris and fingerprint are obtained from CASIA Biometric Ideal Test Database. The results of classifier are checked whether all the three modalities belong to the same user or not. The users are labelled as authorized if and only if all three modalities, classified by MSVM map to class labels belonging to the same user.

4. Results and discussion

The results of the proposed research are based on five classification parameters namely, Accuracy, Precision, Recall, F-measure and Specificity. For all these parameters, the scores of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) are used. TP is correct identification of an authorized user as authorized, FN is incorrect identification of authorized user as unauthorized, TN is right identification of unauthorized user as unauthorized and FP is wrong identification of unauthorized user as authorized user. The context of TP, TN, FP and FN is showed in table 1 below.

Table 1 Context of TP, FN, FP and TN.

	Allow Access	Deny Access
Authorized user	True positive (TP)	False Negative (FN)
Un-authorized user	False Positive (FP)	True Negative (TN)

The proposed algorithm's experimental setup includes Intel (R) Core (TM) i3-7100U processor with 4 GB RAM with 64-bit OS, x-64 based processor. The proposed ELBP technique for feature extraction is compared with two feature extraction techniques viz., Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV). Since the images are biometric images that exhibit high uniqueness, computing entropy for local regions result in better feature extraction, thus aiding in classification.

Chinese Academy of Science, Institute of Automation (CASIA) is a repository that holds biometric images with different traits (http://biometrics.idealtest.org/). These traits include face, signature, iris, palmprint, fingerprint, handwriting etc. The proposed research work is experimented on three databases, CASIA Fingerprint database, CASIA Iris database and CASIA Face database. The fingerprint database holds a total of 500 classes with 400 samples in each of the class. The Iris database includes 756 images that are obtained from 108 eyes with 7 images per eye. 1000 classes with 4 images in each class are included in face database.

The results show that the proposed Entropy based Local Binary Pattern (ELBP) feature extraction technique outperforms the existing Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV) feature extraction techniques.

The results of experiments conducted on various metrics and on different databases are sketched below.

4.1. Accuracy

Accuracy measure of ELBP is compared with two other techniques on three databases. It is the proportion of true results to the total number of data. Accuracy is given by the following equation.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{21}$$

Accuracy is a parameter which shows the correctness of classification of data samples. Higher the true positive and true negative values and lower the false positive and false negative values, higher the accuracy. The features extracted using ELBP, when classified using classifier algorithm, exhibits lower false positive and false negative rates. Accuracy for the proposed ELBP method is higher when compared to other techniques for all the three databases and is shown in Fig. 4.

4.2. Precision

Precision denotes the Positive Predictive Value and is given by:

$$Precision = \frac{TP}{TP + FP} \tag{22}$$

False positive is a case where unauthorized user is falsely classified as an authorized user. Higher false positive rates pose threat to the authentication system since it is a case of breach of security. Hence false positive rates should be as low as possible. Since, precision value is inversely proportional to false positive values, higher precision value indicates lower false positive rates. Fig. 5 indicates higher precision value for the proposed ELBP technique. Precision values on three databases for the proposed method is higher as compared to the methods.

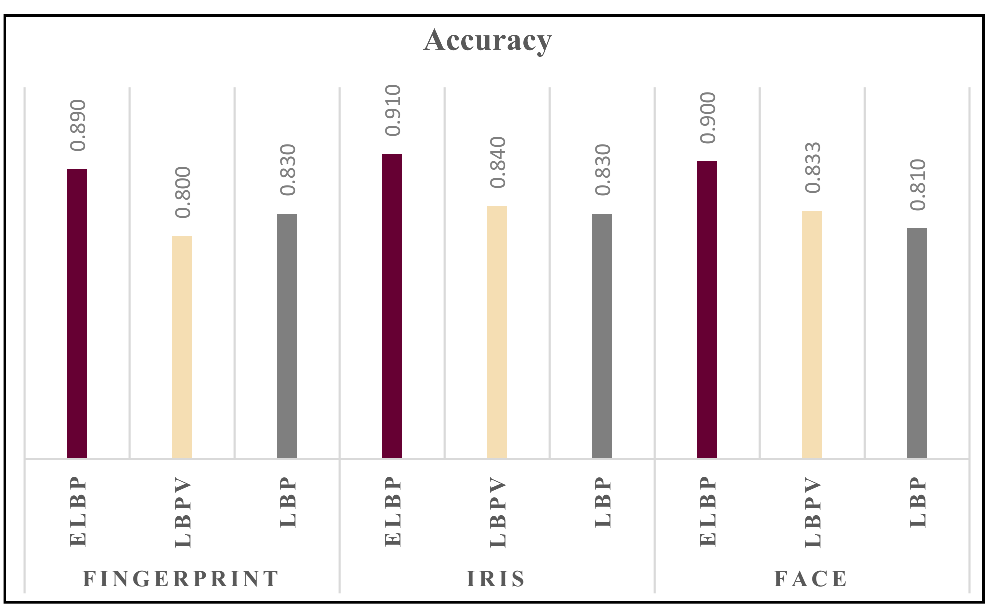


Fig. 4 Performance comparison of Accuracy on Fingerprint, Iris and Face Databases.

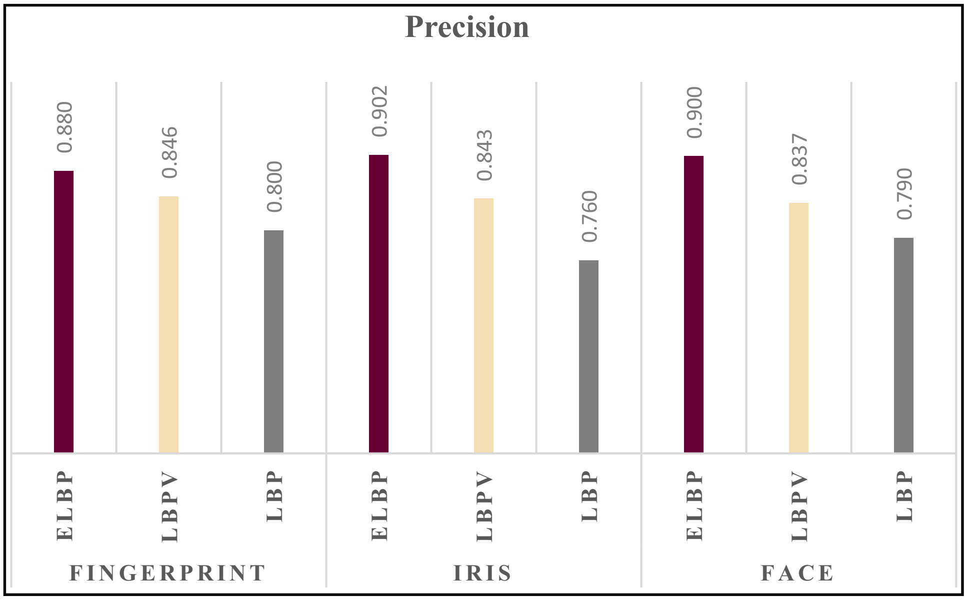


Fig. 5 Performance comparison of Precision on Fingerprint, Iris and Face Databases.

4.3. Recall

Recall is also known as Sensitivity and is as defined as follows.

$$Recall\ \ or\ \ Sensitivity = \frac{TP}{TP + FN} \tag{23}$$

Recall values are significantly high when false negative rates are low. Unlike false positive rates, false negative rates do not contribute to the breach of security. But higher false negative rates may affect the performance of the authentication system since genuine users are falsely rejected. In Fig. 6, the recall value of ELBP is a clear indicator of lower false negative rates. Higher values of recall on three different databases indicate that the proposed method outperforms exiting conventional feature extraction techniques.

4.4. Specificity

Specificity is a measure that indicates that true negative cases are rightly rejected. The performance chart below in Fig. 7 indicates that the specificity is high for the proposed ELBP technique. This is attributed to the performance of authentication system that is intolerant to unauthorized users claiming as authorized. Specificity metric is defined as follows.

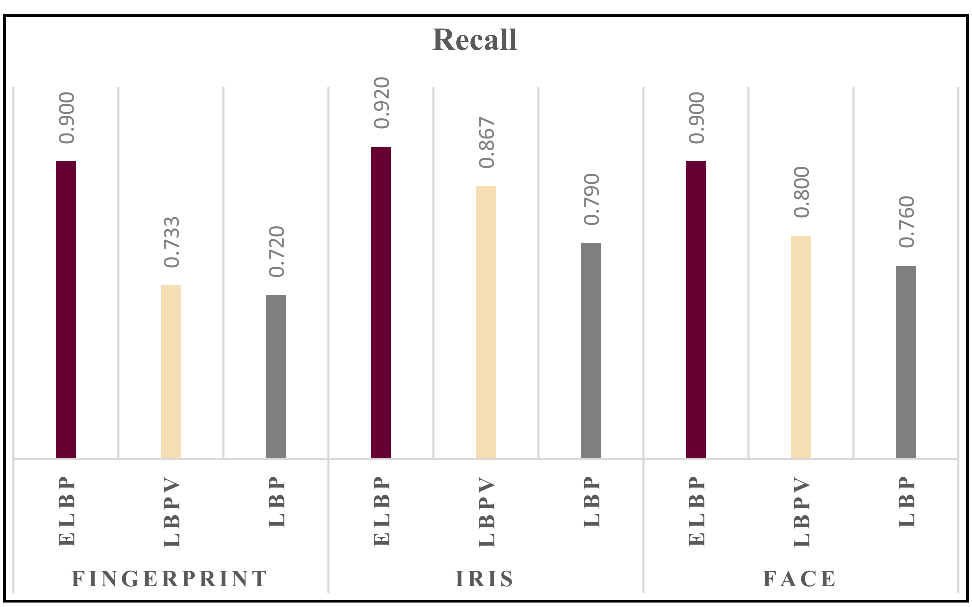


Fig. 6 Performance comparison of Recall on Fingerprint, Iris and Face Databases.

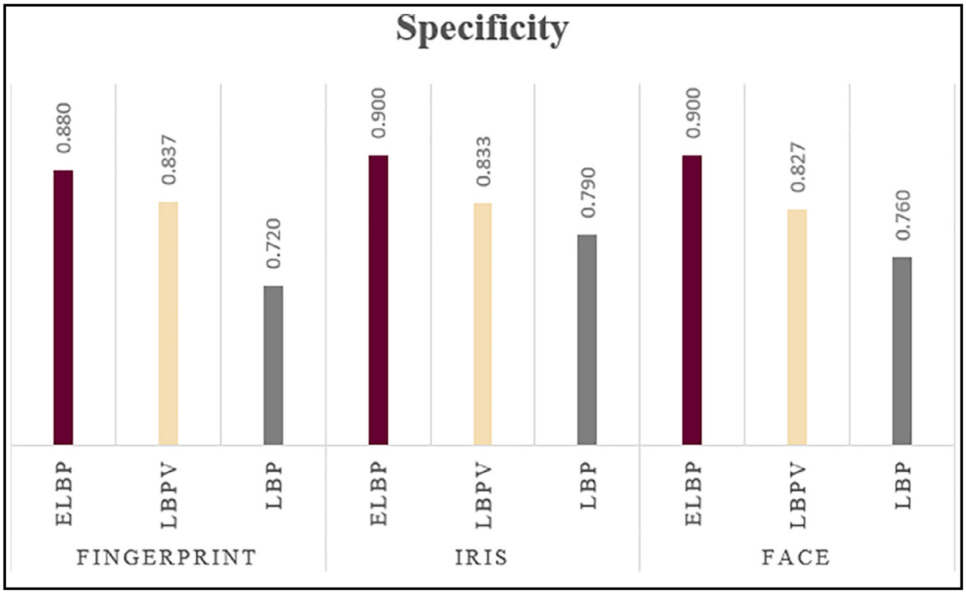


Fig. 7 Performance comparison of Specificity on Fingerprint, Iris and Face Databases.

$$Specificity = \frac{TN}{TN + FP} \tag{24}$$

Fig. 7 shows that the proposed ELBP method has higher values of specificity on all the three databases as compared to LBP and LBPV technique.

4.5. F-Measure

F-measure is a metric that shows how precisely the classifier performs and how robust it is. It is the harmonic mean of precision and recall values. The F-measure value is given by the following equation.

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{25}$$

Fig. 8 illustrates comparative values of three techniques on three different databases. The results show that the proposed ELBP method has higher F-Measure value than LBP and LBPV methods. Thus, the results from above figures indicate that the proposed method performs better than other techniques.

4.6. Receiver Operating Characteristics (ROC) curve

Receiver Operating Characteristics (ROC) charts quantify matching accuracy of biometric authentication systems by plotting True Positive Rates (TPR) or Sensitivity against False Positive Rates (FPR) or 1-Specificity.

Fig. 9 shows ROC curves drawn for different databases using proposed ELBP method. The figure shows that out of

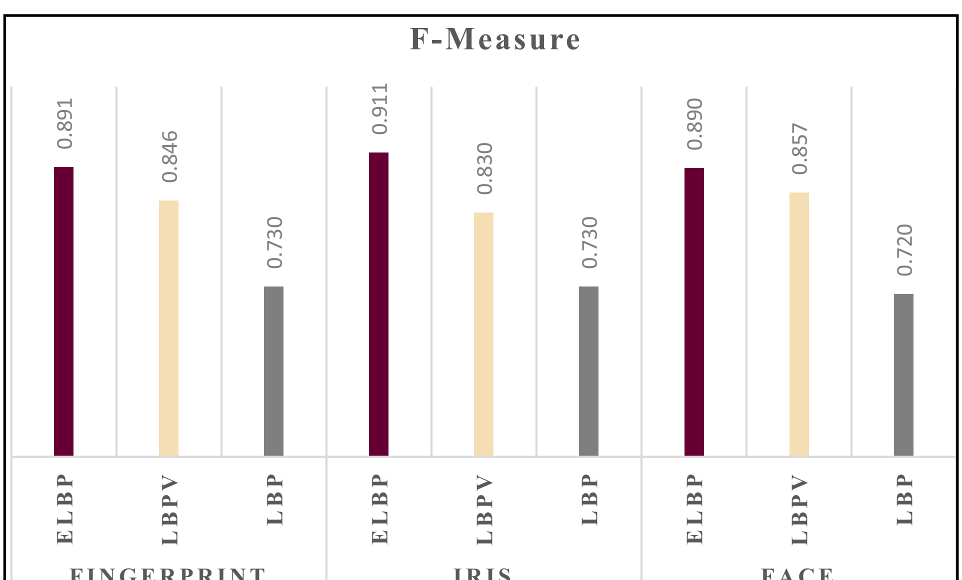


Fig. 8 Performance comparison of F-measure on Fingerprint, Iris and Face Databases.

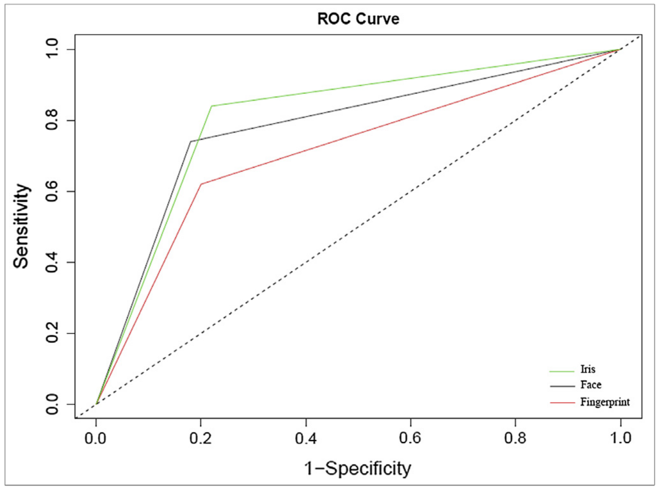


Fig. 9 Receiver Operating Characteristics (ROC) for multiple modalities from CASIA databases for the proposed ELBP method.

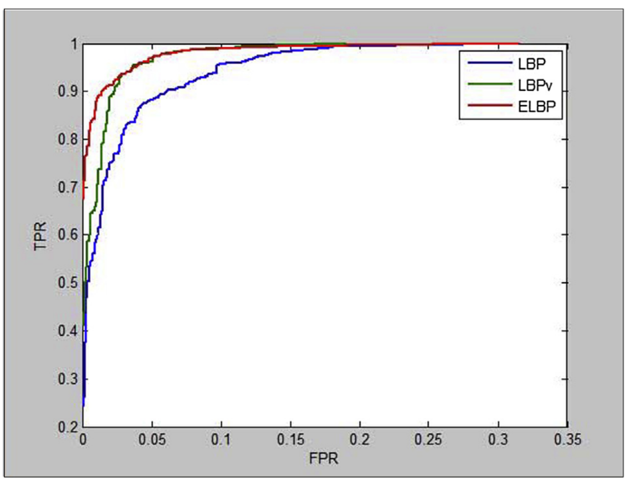


Fig. 10 Receiver Operating Characteristics (ROC) for proposed ELBP method and LBP and LBPV methods.

three modalities, Iris has highest accuracy as compared to other two modalities. Face features have better accuracy as compared to fingerprint features. The figure shows comparison of accuracy values among three modalities and it is evident that all three modalities exhibit good accuracy as the curve for all the three modalities are above Area Under Curve (AUC).

Fig. 10 shows the accuracy of the authentication system for the proposed ELBP method and other classical feature extraction techniques. The curve shows that the proposed ELBP technique has better performance in allowing access to authorized users and denying access to unauthorized users as compared to LBP and LBPV methods. Thus, ROC charts signify the accuracy of ELBP method among different databases for multiple modalities.

5. Conclusion and Future work

The main aim of the proposed research work is to tighten the security and transaction in cloud environment by developing a multi-modal authentication system so that the users of cloud can have a safe digital platform to work with. This works in advantage for both the service providers and users. The service providers can ensure safe storage of user's data in cloud and users can trust the system since only authorized user is allowed to access the data stored in cloud. Performance of this mechanism is attributed to the correct functioning of the authentication system. This is achieved by proposing entropy based local binary pattern ELBP, which extracts the essential features and benefits in better identification. ELBP is applied on all the three modalities that include fingerprint, face and iris. The proposed research work is evaluated based on the metrics of feature extraction like Accuracy, Precision, Recall, Specificity and F-Measure. Future work may involve extraction of features using ELBP within optimal time period. This may result in an effective feature extraction technique that extracts significant features within minimal time. Extraction time is important to be considered as one of the parameters since there are three modalities that are associated with a single user in this defence mechanism. As the number of cloud users increase for a particular service provider, the number of images becomes thrice as the number of users. Hence to make the system scalable, feature extraction time can be kept minimal and evaluated so that it can extract features at a fairly good rate even with the increase in number of users in cloud.

6. Additional information

Competing Interests: The authors declare that there are no competing interests and no conflict of interest.

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