Optimized Multi-Model Biometric Based Human Authentication using Deep Neural Network

Rinky Ahuja, Latika Duhan

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Abstract*: *Biometrics provides greater security and usability than conventional personal authentication methods. Fingerprints, facial identification systems and voice recognition systems are the features that biometric systems can use. To improve biometric authentication, the proposed method considered that the input image is iris and fingerprint; at first, pre-processing is performed through histogram equalization for all image inputs to enhance the image quality. Then the extraction process of the feature will be performed. The suggested method uses modified Local Binary Pattern (MLBP), GLCM with orientation transformation, and DWT features next to the extracted features to be combined for feature extraction. Then the optimum function is found with the Rider Optimization Algorithm (ROA) for all MLBP, GLCM and DWT. Eventually, the approach suggested is accepted. Deep Neural Network (DNN) performs the proposed authentication process. A DNN is a multi-layered artificial neural network between the layers of input and output. The DNN finds the right mathematical manipulation to turn the input into the output, whether it is an acknowledged image or not. Suggested process quality is measured in terms of reliability recognition. In the MATLAB platform, the suggested approach is implemented.

KEYWORDS: Biometric Authentication, Multimodal, Feature Extraction, Classification, Rider Optimization Algorithm (ROA).

I. INTRODUCTION:

Biometrics is the science and innovation of estimating and breaking down natural human body information, removing from the information obtained a list of capabilities, and contrasting this with the layout set out in the database [1]. Biometric refers to the distinction between an individual based on their physiological or social attributes. It includes unique marking, hand geometry, palm printing, acknowledgement of voice, face and iris, and so on [2]. Biometric analysts investigate the use of auxiliary attributes such as scars, impressions, tattoos, and stature and body shape related to essential highlights such as the face [3] to improve human recognition. In one of the two following modes, a standard biometric system functions to be precise, enlisting and testing mode. The framework enrolls a client in the enlistment mode by placing their biometric information in the database as reference information (or layout). The reference data is then coordinated against the biometric information provided by the client during confirmation mode [4] who asserted a personality. Hand vein based confirmation is rising as a promising segment in biometric network [5]. The issue of dependable verification is of expanding significance in current society. Organizations, organizations and people frequently wish to limit access to sensible or physical assets to those with significant benefits [6].

Biometric information usually shows three attributes in the use of innovations in biometric authentication (BA): huge quantities of people, small example size and high dimensionality. One of BA's major research disorders is the single example issue of acknowledgement of biometrics [7]. Two major uses of biometric frameworks are Authentication or Verification and Identification, depending on the selected biometric attribute. This enlisted biometric value could be an individual's physiological or social attribute that meets the needs of comprehensiveness, individuality, eternal quality and collectability [8]. The ear is an interesting human element. In fact, in some respects, even the ears of "indistinguishable twins" contrast. In wrongdoing research centers there are people who expect the qualities of the human outside ear to be one of a kind for each person and perpetual during the lifetime of an adult. Throughout the years, proposals have been made in the infrequent writing that human ear shapes and attributes are generally extraordinary and may actually vary adequately with the ultimate goal of separating all people's ears [9]. Unimodal biometric frameworks need to tackle a variety of issues, such as uproar in data, intra-class varieties and restricted degrees of opportunity, incompleteness, parody assaults, and inappropriate blunder rates [10].

Multimodal biometrics has recently risen as the cyanosis of interest among enthusiastic specialists due to the inconceivable quality efficiency in the field of biometric discovery frameworks [11]. An innovative biometric multidisciplinary system is well equipped to address the deficiencies of unimodal biometric frameworks by combining data from the appropriate biometric sources [12]. The tale frameworks are capable of handling the specific issues that are begging to be addressed by equipping the coordinating personality with different bits of verification [13]. In connection with the single biometric confirmation systems, the driving brag multimodal techniques increase those of the previous ones outflanking. To tell the truth, multimodal biometrics are well equipped with the ability to join a few single biometric checking procedures, hosting the benefits of all classes of single biometrics to enhance the effectiveness of achieving the framework and pursue another vivacious strategy[14]. Recently, in tweaking the biometric accuracy, the multimodal biometrics has risen as a crucial exam wonder. For example, various biometric characteristics might detected by distinct sensors and a dining

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***** Correspondence Author
Rinky Ahuja, PhD Scholar, Ansal University
Latika Duhan, Professor, Ansal University

practice of biometric procedures may be conducted to yield information gathering and additional unique communication methods may be intended to attain individual match scores [15]. Today, the innovation in multimodal biometrics using different classes of biometric information has become a charming methodology widely used with the ultimate goal of individual validation and control [16].

II. CONTRIBUTION OF WORK:

- A novel study is proposed by choosing the best features to build the multimodal biometric authentication method.
- The proposed method is applied in three ways: pre-processing, extraction of features, selection, and classification.
- Different types of features, namely Modified LBP, DWT features, and GLCM features are extracted in this paper.
- Rider Optimization Algorithm (ROA) is used to choose optimum functions.
- Deep Neural Network (DNN) uses to create high-security for the purpose of classification of recognizing images.

The rest of the paper as follows; the literature survey is presented in Section 2 and section 3 presents the proposed framework for biometric authentication. The results of the experiments are analyzed in section 4 and the final part is presented in conclusion.

III. LITERATURE SURVEY:

Unimodal biometric techniques face a host of safety challenges, sometimes offering unwanted error rates. By setting up multimodal biometric systems, a large majority of the corresponding deficiencies can be overwhelmed. The quintessence of multimodal biometrics involves the integration of multiple biometric modalities into a single detection technique to increase detection accuracy. By integrating divergent biometric sources, they are well-downed with the ability to furnish superior detection accuracy and population coverage. In the coming sections, some of the modern techniques in this regard are being discussed in depth.

Wanget.al Desong. [17] Dexterely structured a creative DRM framework confirmation plan for remote clients subject to multimodal biometrics, such as unique brand and face highlights, checking and watermarking, and keen cards, which included two different validation stages, such as customer server checking and server validation. Their creative strategy was intensified for database verification and the comprehensive rendition of the ElGamal signature technique, the safety of which depended on the distinct issue of the logarithm, which was not yet made. From now on, their novel approach had the option of unerringly enforcing the rights of the board of computerized material through methods for the misconceived consumer to be monitored.

Md. Md. Maruf Monwar and others. 18] Magnificently propelled a productive combination plot mixing deftly the information offered by the numerous regional authorities as per the combination strategy of the rank-level combination. The imaginative role level mixture approach verification of character and function with a view to consolidating the findings obtained by the diverse biometric matchers. Methods for the highest position, Borda check, and calculated relapse strategies coordinated the positions of individual matchers. The appealing results delineated how the combination of individual modalities was capable of enhancing the absolute effectiveness of the biometric system, irrespective of the nature of the information.

Mingxing He et al. [19] were instrumental in researching the exhibition of whole rule-based score level combination and support vector machines (SVM) -based score level combination. In their examination, they talked about three biometric qualities like the unique finger impression, face, and finger vein. The brilliant results of different tests performed on four unique multimodal databases showed that the as recreation of the novel methodology in total principle based combination and SVM-based combination brought about stunning degrees of precision.

Hong Huang et al.[20] displayed an adjusted complex learning procedure, called the Nearby Uncorrelated Fisher Discriminant Investigation (ULFDA), which was committed to ear recognition. The basic thought process of their novel method was to consider a sub-complex component in such a way that the inside-complex dispersion is impressively reduced and inter-complex dissipation was extended extraordinarily simultaneously in the embedding space by using the novel disparity subordinate goal improvement function viable. In addition, they had the option to retain an acceptable parameter to motivate the measurably unrelated extricated highlights. The shimmering end results of the new strategy delineated without any confusion that it was well-equipped to achieve the perfect and lossless discriminative information and, moreover, to ensure that all the extricated highlights are measurably removed.

Li Yuan et al. [21] fantastically propelled a 2D ear-recognition method subject to neighborhood information coordination to handle the ear-recognition under fractional impediment effectively. The enthusiastic test after-effects on the USTB ear dataset and UND data set underlined how the arrangement of trifling number of sub-windows promoted powerful representation of the ear's largest position, and the multi-classifier template suggested its guts by performing superlative recognition force as opposed to using the entire picture for recognition.

Tak-Shing Chan and Ajay Kumar charismatically suggested a novel technique for simple personal identification with the aid of gray-level ear images. Using 2-D quadrature filtering (both monogenic and quaternionic), the groundbreaking technique has proven capable of collecting vigorous phase information. The deployment of the quadrature filters was prompted by their innate ability to collectively locate phase information in the segmented ear images. The enchanting test results with 2-D quadrature filters have emerged as incredibly exciting, showing the substantial increase in efficiency compared to the time-tested phase encoding using 1-D quadrature filters.

IV. PROPOSED METHODOLOGY:

An efficient fusion technique for integrating information from the single modality systems essentially needs the Multimodal biometric system. Biometrics offers greater security as well as comfort than traditional methods of personal authentication. Properties that can be used by biometric systems include iris and fingerprints. To improve biometric authentication, the proposed method, which is considered as input image, is iris and fingerprint.

The objective of the proposed work is to implement a new modality, considering the deep neural network for effective training and testing positions in iris and fingerprint classification. The proposed method of recognition classifies images in a pre-processing manner as recognized and unrecognized, and is a feature extraction process. These procedures have been effectively implemented with the help of different techniques and optimization methods. The proposed multimodal biometric system is graphically represented as follows;

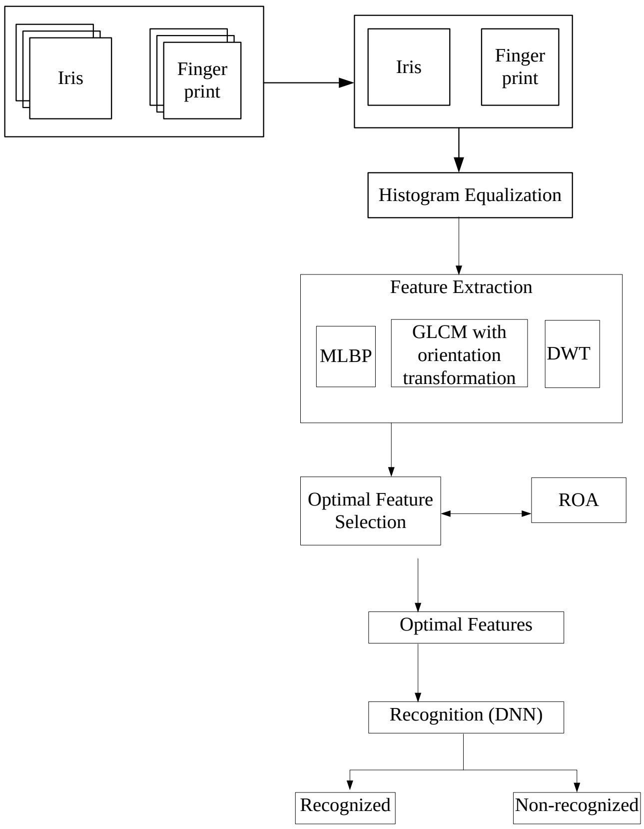


Figure 1: A schematic diagram of the proposed biometric multimodal crypto system

Figure 1 provides an overview of the model being proposed. Initially, the technique of histogram equalization is used in the pre-processing module to improve the contrast enhancement of images. Using the modified Local Binary Pattern (MLPP) feature, GLCM features, DWT features and GLCM with extracted orientation change features, a collection of these images in the extraction process. Next, the extracted features are combined with the optimal level of fusion of features. With the help of the Rider Optimization Algorithm (ROA), feature values are optimally selected. ROA-based select the optimal features and then combine the selected features. DN then found the correct mathematical method to transform the input into output, whether or not it is known. The following sections explain the techniques and procedures used in this system.

3.1 Pre-processing:

In the stage of pre-processing, the input images (iris and fingerprint) are first initialized. Here, the input iris image and fingerprint images are pre-processed. Pre-processing makes the image fit for further enhance the image quality histogram equalization is used. Fingerprint image enhancement is used to make the image better to facilitate more functions. Since fingerprint images obtained from the camera or other sensors are not guaranteed to be of the best quality, image enhancement should be carried out. In this work, the image enhancement using histogram equalization the process involved in histogram equalization is explained as follows;

3.1.1 Histogram Equalization (HE) based contrast enhancement:

First, all the input image is pre-processed by the histogram equation. Image enhancement basically improves digital image quality. Image histograms can be useful for improving image enhancement. The histogram behind the image processing is the function that shows the events of each extreme value of the image, and the histogram equation is the technique that increases the dynamic range of an image's histogram.

HE is used to enhance the variability of the extracted area after selecting a portion of the images. Usually, the histogram equation is accomplished by continuously redistributing them in the image pixel gray conditions spatial domain. In more boring or spectacular movies, this is generally done to improve image quality and performance for recognition. The numerical description of the histogram equation is as follows;

$$HE(e) = round\left(\frac{cdf(e) - cdf_{\min}}{(W \times HE) - cdf_{\min}} \times (G-1)\right) \quad (1)$$

Where;

HE (e) → the value of histogram, Cdf → cumulative distribution function,

$cdf_{\min}$ → minimum non zero value of cdf, W → width, H → Height,

G → number of grey levels.

3.2 Feature Extraction:

To improve image quality during the pre-processing cycle and changes images to modify they further. In this, several interface methods are used to separate the set of images into the extraction process of features. Another feature set is created at the extraction level of the feature from a combination of different feature set methods. The extraction method is clearly seen as follows,

At this point, iris and fingerprint images are effectively extracted from the shapes and texture properties. Grayscale images are provided as input to the extraction process of the feature. The Iris shape and fingerprint images using local binary pattern (MLPP), GLCM, DWT, and GLCM with a change of orientation (by changing the orientation value) with features. Then, the extracted features are combined with the desired level of fusion of features. With the aid of the Rider Optimization Algorithm (ROA), function values are optimally selected.

3.2.1 Modified Local Binary Pattern (MLBP):

The iris and the fingerprint system and its characteristics were defined using a revised local binary process (LPP). These analyzed system features can be used as system classification input and then effectively classify the system based on the characteristics of the statistical system. By comparing the pixel of an object that is mathematically depicted as follows, an LPP code is measured;

$$LBP_{Px,Rd} = \sum_{Px=0}^{Px=1} R(G_{Px} - G_C)2^P, R(x) = \begin{cases} 1, u \geq 0 \\ 0 u < 0 \end{cases}$$

(2)

Where;

$G_C \rightarrow$ grey level value of the center pixel

$G_{Px} \rightarrow$ Neighboring pixels of the centre

P → total number of neighboring pixels

R → radius of the neighborhood

The LPP method is calculated for each pixel of an image and a histogram is generated to represent the iris and fingerprint layout, which is mathematically represented as follows;

$$HG(z) = \sum_{u=1}^{U} \sum_{v=1}^{V} k(LBP_{Px,RD}(u,v), z \in [0, z] \quad (3)$$

$$k(m,n) = \begin{cases} 1, & m = n \\ 0, & otherwise \end{cases} \quad (4)$$

Where; k→ maximal LBP pattern value

Modified Local Binary Pattern steps are represented as the following Table:1,

Table 1: ***MLBP Steps***

Step1: Divide the image into frames (3 * 3). Step2: Apply MLBP_M (Magnitude) and MLBP_C (Contrast) on every block. Step3: Compute the histograms for both MLBP_M and MLBP_C. Step4: Calculate the maximum occurring pattern from MLBP_C Step5: Calculate variance and standard deviation from the histograms. Step 6: Multiply the variance and maximum occurrence to create the image feature. Step7: Input the feature into DNN classifier for texture classification.

In MLBP M, by evaluating the initial pixel value, it measures the form instead of comparing the pixel value to the other. So the image now has two formats, one by comparing the center pixel with the other by analyzing the original pixel value. Histograms for both MLBP C and MLBP M are now created separately.

3.2.2 Grey Level co-occurrence Matrix (GLCM):

Feature extraction methods have been used in GLCM systems. GLCM functions describe the structure of an image by calculating how often the pixel is aligned with the specified values. Structural feature counts use the GLCM object to provide the degree of radical variation in the pixel of interest. The GLCM is continuously represented as a matrix in which the number of rows and columns is the number of gray positions in the figure, G. The Matrix element $p(x, y \mid d_1, d_2)$ symbolizes the equivalent segregated by a pixel distance (d1 and d2). The GLCMs are capable of collecting appropriate statistics from them through the grey co-props feature, which provides the specifics of an image's texture that can be classified as follows.

a. Energy
b. Entropy
c. Cluster shade
d. Homogeneity
e. Maximum probability

Energy:- The angular second moment, also called uniformity or power, represents the number of squares of inputs in the GLCM. This is called the sustainability model. The limit of energy is known as[0.1]. The energy value for the static image is taken together. The energy estimation formula will be presented as follows.

$$Energy = \sum_{x,y} p(x,y)^2 \quad (5)$$

Where, $p(x, y)$ is the pixel value at the point x, y of the texture image of size ($M \times N$)

Entropy: - Entropy provides a helping hand to refer to the system image and to determine the distribution shift in one area of the image. The associated parameter effectively evaluates the disorders of an image. Although the picture does not seem to be the same in text, many GLCM elements have very low values, which reveal the fact that the entropy is unnecessarily large. Entropy is estimated according to the following equation

$$Ent = \sum_{x,y} p(x,y) \log(p(x,y)) \quad (6)$$

Cluster Shade:

$$CS = \sum_{x,y} ((x - \alpha_x) + (y - \alpha_y))^3 T(x,y) \quad (7)$$

Homogeneity:- The homogeneity of the non-zero entries in the GLCM is uniformly evaluated. If the differences in the gray values are high, then the low GLCM integrity is low, thereby facilitating a better GLCM difference. Integrity is within the range of [0, 1]. If the image is moderately variable, the integrity is high, and if the image is unchanged, the homogeneity is equal to one.

$$Homogeneity = \sum_{x,y} \frac{P(x,y)}{[1+(x-y)^2]} \quad (8)$$

Maximum probability:

$$Max\ probability = \max(p(x,y)) \quad (9)$$

3.3 Discrete Wavelet Transform (DWT):

In this case, the pre-processed images are decomposed into time-frequency representations using DWT. The feature extraction in bandwidth transformation was performed in the following two steps. (1) Pre-processed images are distorted with respect to individual frequency sub-bands. (2) Split images in discrete frequency subgroups are evaluated using multiple resolutions.

For the preprocessed images $w(t)$ the wavelet transform with the wavelet function $\phi q, r(t)$ is given as (3):

$$D(q,r) = \int_{-\infty}^{\infty} w(t).\phi q, r(t)dt \quad (3)$$

DWT is used to extract properties from pre-processed images at various scales by continuous high-pass and low-pass filtration. Bandwidth coefficients are a series of approximations and detail coefficients. To perform the filtration process we take a two-dimensional haar-wavelet transformation; this is because it reduces the computation time and also extracts more features. Assume, t as input image ψ_t as the haar-wavelet transform q_t is given as

$$q_t = H_t \psi_t \quad (4)$$

In this wavelet, each stage consists of two digital filters and two down samplers by 2 to produce the digitized image. The first filter, H [t] is a discrete mother wavelet, which is a high-pass filter, and the second, L [t] is low-pass filter. Sample outputs under the first high-pass filters as well as low-pass filters provide the description, D1 and approximate A1. In the first approximation, A1 decomposes again and this process continues.

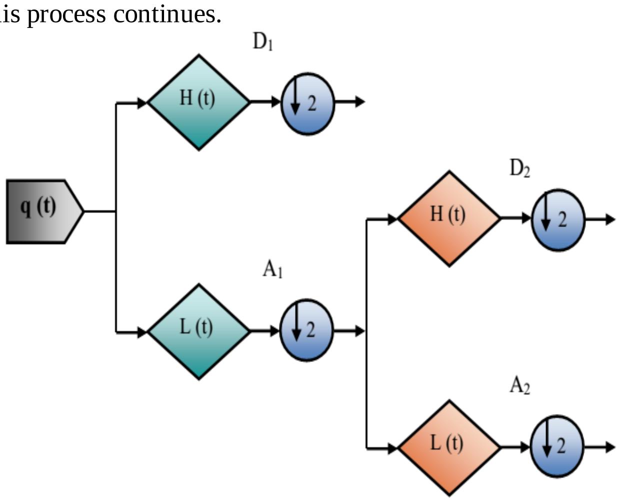


Figure 2: DWT decomposition

Where, H as well as L denotes the high and low pass filters, respectively, ↓ 2 represents the sub-sample. The mean of the detail coefficients is calculated by taking average of the detail coefficient.

$$d[a_t] = \sum a_t \quad (5)$$

Where, Δ_{a_t} represents the mean value for the approximate coefficient; the standard deviation of the detail coefficients from the mean value is measured by taking the square root of the mean value.

$$\sigma_{a_t} = \sqrt{d[a_t] - (d[a_t])^2} \quad (6)$$

Where, σ_{a_t} is the standard deviation for the approximation coefficient. After this, combine all the above features. Here, the key features are optimally selected with the help of Rider Optimization Algorithm (ROA). The ride optimization algorithm is used for selection purpose and its description is represented as follows;

3.4 Selecting optimal features using Rider Optimization Algorithm (ROA):

With the support of the Rider Optimization Algorithm (ROA), features are enhanced in this. Inspired by riders on their way to their destination, the suggested ROA is. The number of teams listed is four, where each group chooses the number of riders equal to the total number of riders. To order to achieve the goal, each team follows different strategies. On this basis, optimal features are chosen. As discussed in the following sections, this chapter describes ROA's methodological technique by constructing a well-structured mathematical model. ROA consists of four classes that are the algorithm's key words that are described as follows.

- Bypass rider
- Follower
- Over taker
- Attacker

Bypass rider: Bypass Rider is the rider of first group, who crosses the path of the front and hits the target. This indicates that the bypass rider does not follow the lead rider, he is riding in the lead position.

Follower: As a follower, he is depended on or follows the lead rider on most axes.

Over taker: This ride type follows its own position to reach the destination according to the location near the front ride.

Attacker: An aggressive player is an attacker who uses maximum speed to take the position of the driver to hit the target stage. The proposed ROA is outlined in this chapter, inspired by riders driving to the destination place. The choice of optimal conditions is dependent on subsequent processing steps. The measures in the proposed cycle of optimization are explained as follows:

Step 1: Initialization

To develop an optimal co-efficient ROA will be used. Solution creation i.e., initialization is an important step of optimization algorithm that helps to identify the optimal solution quickly. In this, the input images (iris and fingerprint) are first initialized which is represented as I (ir, f) and the preprocessed images are represented as PI = {p (ir), p (f)}. Based on MLBP, DWT and GLCM with orientation transformation (by changing the orientation value) here, the orientation values are represented as OV= {0, 45, 90, 135}. ROA is used to select the optimal coefficient. After initialize solution, the obtained solution is given for the next step i.e. fitness evaluation.

Step 2: Fitness calculation

After the solution initialization, find the fitness for initial solution and opposite solution. At every iteration, Assess the fitness function based on the equation and after that choose the best one. Here, the fitness is assessed based on accuracy. The fitness is mathematically given in equation (7).

$$Fitness = Max\ (accuracy) Fitness = Max\ (accuracy) \qquad (7)$$

$$Accuracy = \frac{TN + TP}{(TN + TP + FN + FP)} \qquad (8)$$

After fitness calculation, the obtained solution is given for the next step i.e. updation solution.

Step 3: ROA based updation solution

After the fitness assessment, we update the solution based on the Rider Optimization Algorithm (ROA). Using the equation (9, 10, 11), the mathematically classified solution can be updated as follows,

The position update of this set is given randomly, as expressed in the following equation, as the bypass rider bypasses the common path without following the leading riders:

$$X_{t+1}^{B}(i,j) = \delta[X_t(\eta,j) * \beta(j) + X_t(\zeta,j) * [1-\beta(j)]] \qquad (9)$$

Update process of the followers are mathematically represented as follow:

$$X_{t+1}^{F}(i,k) = X^{L}(L,k) + [\cos(T_{i,k}^{t}) * X^{L}(L,K) * d_i^t] \qquad (10)$$

Update process of the Overtaker is represented as follows:

$$X_{t+1}^{O}(i,k) = X_t(i,k) + [D_t^I(i) * X^L(L,K)] \qquad (11)$$

Update process of the attacker is represented as follows:

$$X_{t+1}^{A}(i,j) = X^{L}(L,j) + [\cos(T_{i,j}^{t}) * X^{L}(L,j)] + d_i^t \qquad (12)$$

Step 3: Stopping Criterion Phase

Until the greatest cycle achieves this procedure is duplicated. The enhanced result will be reviewed for to decide of biometric pictures. We halted the entire procedure by setting a most extreme cycle. The calculation suspends its execution just if a most outrageous number of cycle is cultivated and the arrangement which is holding the best wellness worth is picked. At the point when the best wellness is practiced by strategies for ROA, chose highlight is given to characterization which is spoken to as pursues:

3.5 Deep Neural Network (DNN):

DNN is one of the successful techniques for characterization. All things considered, DNN isn't fitting for order of gigantic sum informational collections in light of the fact that the unpredictability of DNN is amazingly dependent on the information size. In the wake of choosing ideal highlights from removed pictures (iris, unique finger impression), the pictures is utilized for anticipating the strange and ordinary pictures utilizing DNN. A falsified model of the neural system is called DNN with the different layers of the shrouded units and yields. It also includes both pre-preparation (use of deep-seated generative conviction system or DBN) and tweaking stages in its learning parameter.

3.5.1 Pre-training stage

The DBN model enables the system to deliver unmistakable enactments based on the states of its veiled units that reflect the conviction of the system. Here, to work out the above problem, we executed the RBM.

Restricted Boltzmann Machine: A RBM is a restrictive type of arbitrary Markov field that has one layer of stochastic concealed units (normally Bernoulli) and one layer of (commonly Bernoulli or Gaussian) stochastic observable or discernible units. Figure 3 shows the DNN structure that the number of input neurons representing the appropriate features selected and different hidden layers is used in DNN, and then the output layer marked the object as recognized or unrecognized.

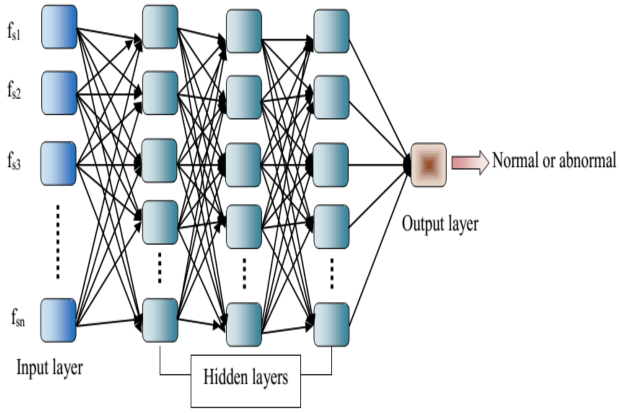


Figure 3: DNN structure

Step 1: Primarily, we are initialized the visible units' that means the selected features f_{si} to the training vector.

$$E(x,y) = -\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij} f_{si} y_j - \sum_{i=1}^{I} \alpha_i f_{si} - \sum_{j=1}^{J} \beta_j y_j \qquad (14)$$

Where, Q_{ij} is represented the symmetric interaction term between the visible unit f_{si} and the hidden unit y_j, α, β is the bias term, I, J is the number of visible and hidden units. The derivative of a training vector's log probability about a weight is erratically easy. There are no direct influences between the hidden units in an RBM; it is enormously easy to get an impartial sample of $(f_{si}, y_j)_{data}$

$$\rho(y_j = 1 \mid f_{si}) = \zeta\left(\sum_{i=1}^{I} Q_{ij} f_{si} + \alpha_j\right) \qquad (15)$$

Where $\zeta(x)$ is the logistic sigmoid function $\frac{1}{(1+\exp(x))}$, f_{si}, h_j is the unbiased sample.

Step 2: In the visible and hidden units given, we update the hidden and visible units in parallel. This shows the way to a much uncomplicated learning rule to perform the stochastic steepest ascent in the log probability of the training data.

$$W_{ij} = \theta\left(f_{si} y_j\right)_{data} \left(f_{si} y_j\right)_{reconstruction} \tag{16}$$

Where, W_{ij} is represented the modified weight of the changed weight in the hidden layer; when the RBM is equipped, a dissimilar RBM may be "stacked" to form a multilayer template on top of it. As input to the novel RBM, the closing layer of the already-trained layers is engaged. The deep network weights accomplished are involved in the initiation of a fine-tuning process.

3.5.2 Fine tuning phase

The step of fine tuning is simply the ordinary algorithm of propagation of the back. A layer of output is intended at the top of the DNN to categorize the system performance. The training data collection is also qualified until the optimal weight or high performance is grasped. The major advantage of the DNN classifier is that the classifier automatically takes the object and used it for further processing during classification the chances of losing any objects in this case.

DNN output (optimal solution): Our DNN's main contribution is to evaluate the minimum error variable. The learning dataset is also talented until the optimized weight or total accuracy is reached. Finally, by analyzing the input dataset, the images are labeled in the test stage based on the optimal weight (w) in the output layer. It discovers recognized and unrecognized images based on optimal features from the DNN strategy review. The summary of our research is shown in table 2 below.

Table 2: *Training and testing process*

Input: Dataset (Iris and Fingerprint)
Preprocessing: Remove noises of database (histogram equalization)
Feature extraction: Extracting features from MLBP, DWT and GLCM with orientation transformation (0, 45, 90, 135)
Feature selection: Selecting optimal features (ROA)
Classifier: DNN
Testing Process
Input: Trained databases
Classifier: Proposed classifier model
Output: Recognized and Non-recognized images

4. RESULTS AND DISCUSSIONS:

This section evaluates and analyzes the proposed technique for generating iris and human authentication based on fingerprints using deep neural network for optimized multi-model biometrics. MATLAB implements the proposed methodology on a computer with 6 GB RAM and 2.6 GHz Intel i-7 processor. Measure and analyze the technique's accuracy and efficiency and collect the iris and fingerprint images from the dataset.

4.1 EVALUATION METRICS:

The efficiency of the proposed method is evaluated by means of computing certain performance measures.
TP: True positive TN: True Negative.
FP: False positive FN: False Negative
The system performance is tested by applying the assessment metrics such as Sensitivity, Specificity and Accuracy which are demonstrated in below.

Sensitivity: The ratio of a number of true positives to the sum of true positive and false negative is called as sensitivity.

$$Sensitivity = \frac{No.of\,(TP)}{No.of\,(TP) + No.of\,(FN)} \times 100 \tag{17}$$

Specificity: Specificity is the ratio of a number of true negative to the sum of true negative and false positive.

$$Specificity = \frac{No.of\,(TN)}{No.of\,(TN) + No.of\,(FP)} \times 100 \tag{18}$$

Accuracy: Accuracy is calculated by the measures of sensitivity and specificity. It is denoted as follows,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{19}$$

4.2 DATABASE DESCRIPTION:

Finger print: In this, fingerprints are randomly chosen by the data base after collecting the fingerprints the images are pre-processed. Here, some sample images are specified which is given as follows.

Figure 4: sample images of fingerprint

Iris: In this, iris images are randomly chosen by the data base the collected images are pre-processed. Here, some sample images are specified which is given as follows.

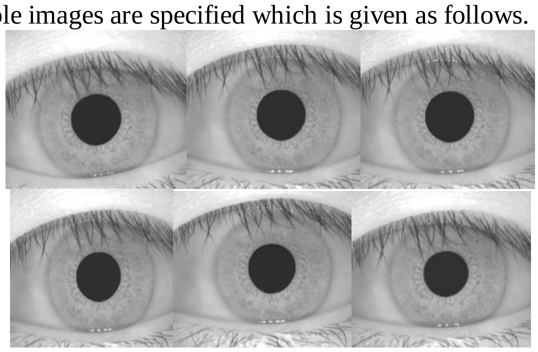


Figure 5: sample images of iris

Table 3: Input and Pre-processed Fingerprint Images

	1	2	3	4
Input Image				
Pre-processed Image				

In this, five input images are chosen by the database and the 5 images are pre-processed. The above table specifies the input and its pre-processed fingerprint image. Pre-processing is done by histogram equalization for all input image.

Table 4: Input and Pre-processed Iris Images

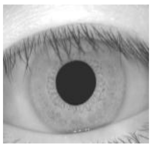
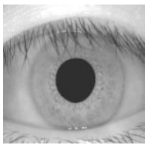
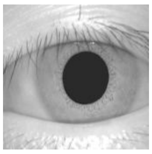
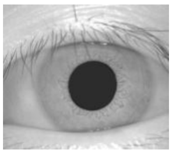
	1	2	3	4
Input Image				
Pre-processed Image				

Table 4 specifies the input and pre-processed iris images. The database contains more number of images but here, only five iris images are chosen by the database and those 5 iris images are pre-processed. The above table specifies the input and its pre-processed iris image. Pre-processing is done by histogram equalization for all input image.

4.2.1 FEATURE RESULTS:

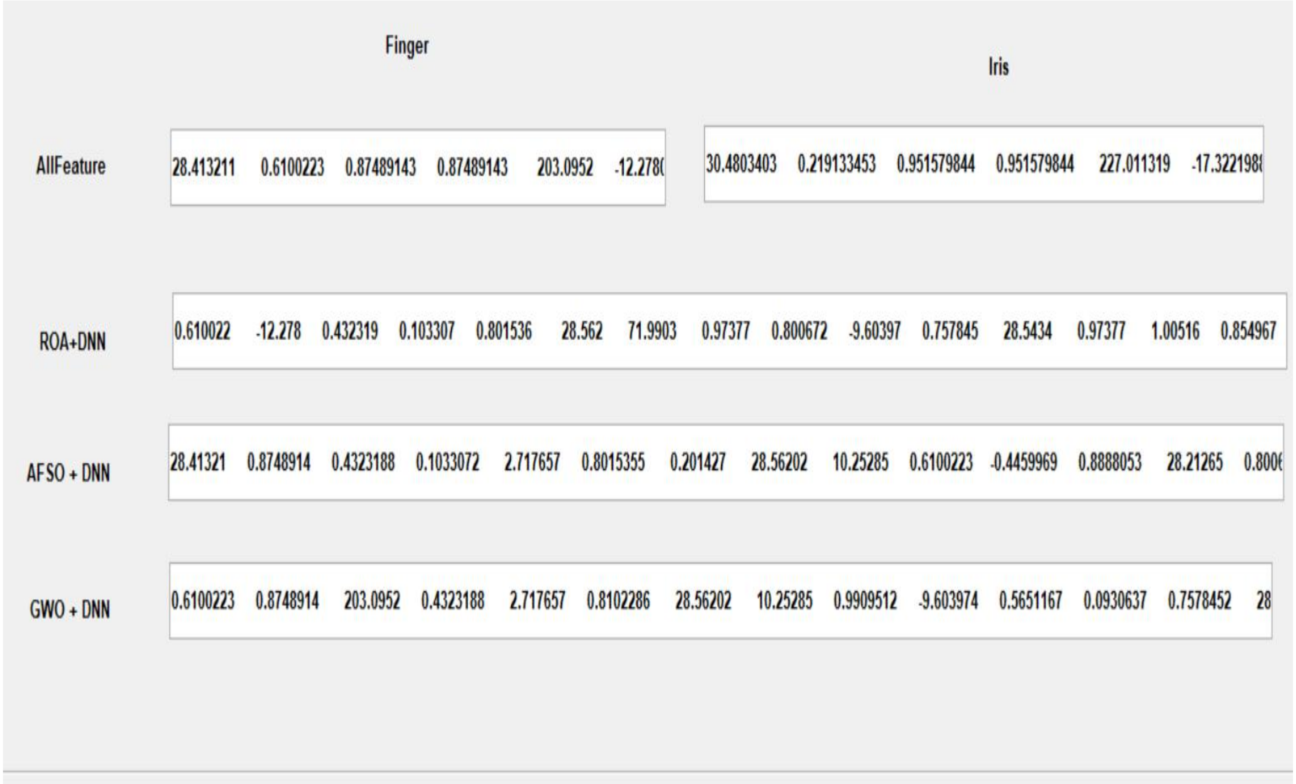
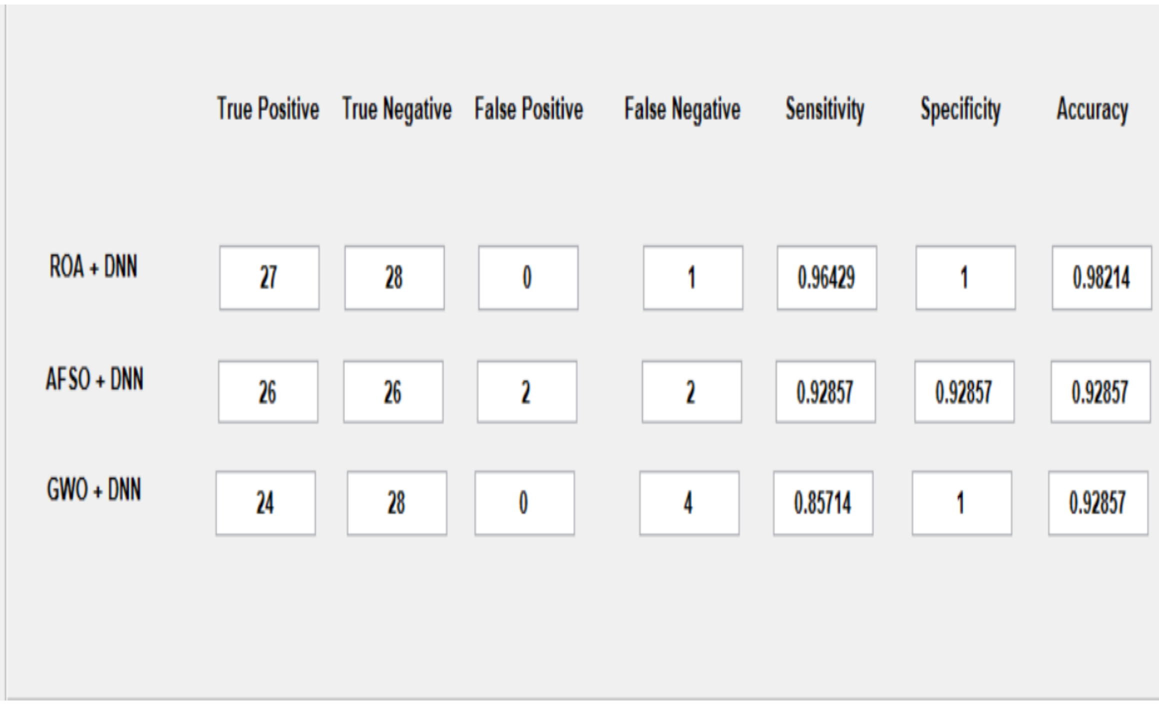


Figure 6: sample feature results

The above figure specifies the feature results of both finger and iris. In this, iris as well as fingerprint-based human authentication using deep neural network for optimized multi-model biometric is evaluated and analyzed.

4.2.2 CLASSIFICATION:



	True Positive	True Negative	False Positive	False Negative	Sensitivity	Specificity	Accuracy
ROA + DNN	27	28	0	1	0.96429	1	0.98214
AFSO + DNN	26	26	2	2	0.92857	0.92857	0.92857
GWO + DNN	24	28	0	4	0.85714	1	0.92857

Figure 7: classification results

4.2.3 GUI COMPARISION:

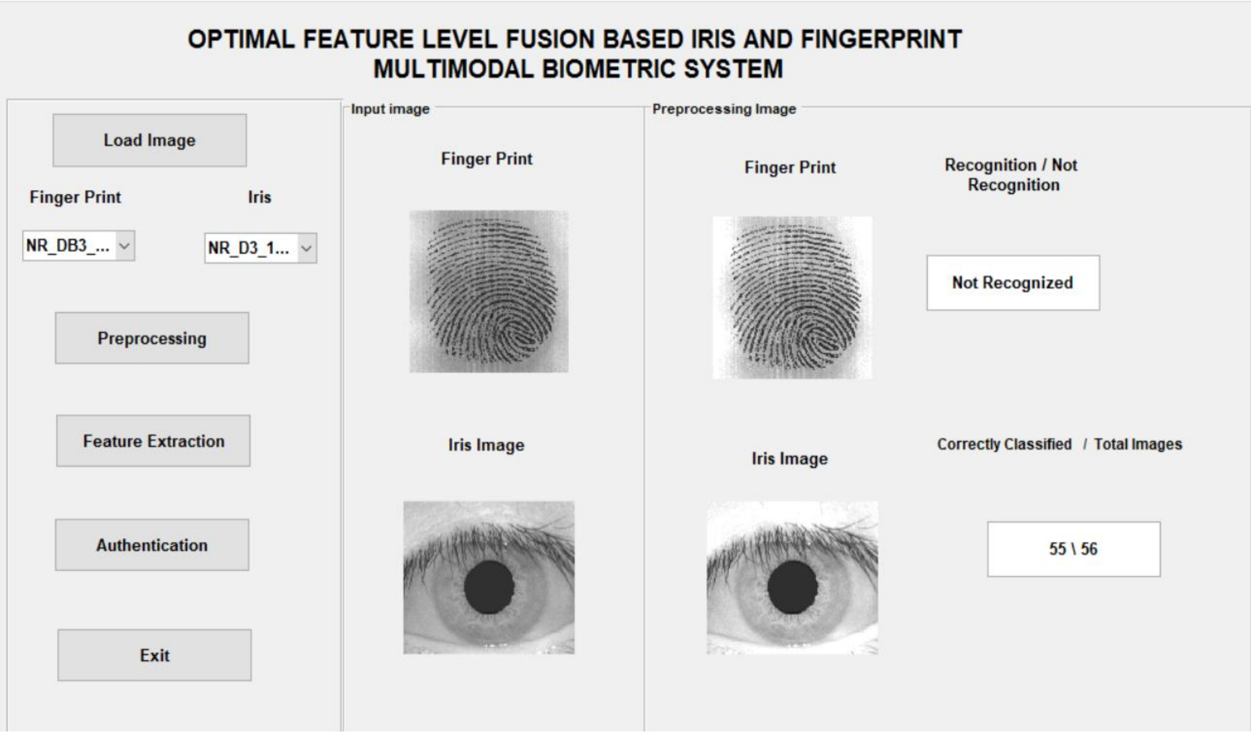


Figure 8: GUI Representation

4.3 COMPARATIVE ANALYSIS:

To test the performance of our proposed ROA and DNN this can be exact to verify the effectiveness of all of the compared algorithms. Not all of the features are generally used for classification purposes. To achieve good classification results, optimal features should be selected. To select the optimal features Rider optimization algorithm (ROA) is used which will find the optimal global best solution with enhanced classification accuracy. DNN is perfectly suited for classification in our research. DNN is used to predict and identify the cycle of authentication and finds the right mathematical method to transform the input into the output, whether it is a linear relationship or a non-linear relationship.

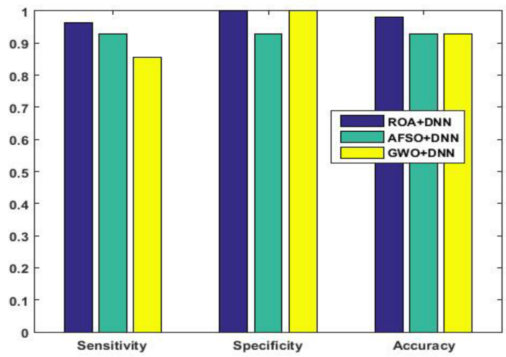


Figure 9: Comparative Analysis of Classify Measure

In this, all the proposed and existing optimization techniques are compared with deep neural network (DNN). The above figure shows the Sensitivity, Specificity and Accuracy of the proposed approaches. When analyzing the above figure the proposed ROA + DNN achieve higher outcomes. From the above figure, clearly understand our proposed approach achieves the better results compare to existing AFSO and GWO approaches.

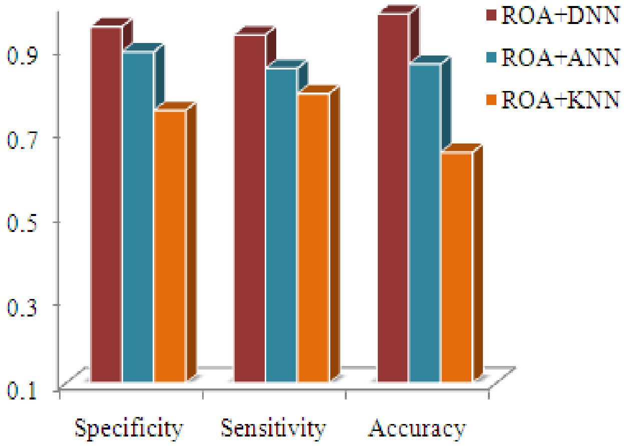


Figure 10: comparative analysis of performance measure

In this, all the proposed and existing optimization techniques are compared with DNN, ANN as well as KNN. The above figure shows the Sensitivity, Specificity and Accuracy of the proposed approaches. When analyzing the above figure the proposed ROA + DNN achieve higher outcomes. From the above figure, clearly understand our proposed approach achieves the better results compare to existing AFSO+ANN and GWO+KNN approaches.

5. CONCLUSION:

This paper proposes the recognition of multimodal biometric images based on pre-processing, extraction of features, selection of features and recognition. These approaches are used by applying some features to MLBP, GLCM with orientation transformation and DWT and then recognition with DNN help. Here, the recognition process output is further discussed. The classifier's exhibitions for the techniques of recognition analysis were tested using different observable criteria such as tolerance, precision, and accuracy. The results of the test showed significant fluctuations in performance compared to existing strategies. The study result shows that the proposed method achieves optimum accuracy; it shows that the model being proposed understands the objects better than existing methods.

REFERENCE:

1. Nageshkumar. M, Mahesh.PK and M.N. Shanmukha Swamy, "An Efficient Secure Multimodal Biometric Fusion Using Palm print and Face Image," International Journal of Computer Science Issue, Vol. 1, pp. 49-53, Aug 2009.
2. Muhammad Khurram Khan and Jiashu Zhang, "Multimodal face and fingerprint biometrics authentication on space-limited tokens", Neuro Computing, Vol. 17, No. 12, pp. 3026 – 3031, 2008.
3. Arun Ross and Ayman Abaza, "Human Ear Recognition", IEEE Computer Magazine, Vol.44, No.11, pp. 718-737, 2011.
4. Abdallah Meraoumia, Meraoumia1, Salim Chitroub and Ahmed Bouridane, "Fusion of Finger-Knuckle-Print and Palm print for an Efficient Multi-biometric System of Person Recognition," In Proc. of the 2011 IEEE International Conference on Communications (ICC), Kyoto, pp. 1-5, Jun 2011.
5. Raghavendra.R, Mohammad Imran, Ashok Rao and Hemantha Kumar.G, "Multimodal Biometrics: Analysis of Handvein & Palmprint Combination Used for Person Verification", In proc. of Third IEEE International Conference on Emerging Trends in Engineering and Technology, pp. 526-530, 2010.
6. Carsten Maple and Vitaly Schetinin, "Using a Bayesian Averaging Model for Estimating the Reliability of Decisions in Multimodal Biometrics", In Proc. of the First IEEE International Conference on Availability, Reliability and Security, pp. 929-935, 2006.
7. Yong-Fang Yaoa, Xiao-Yuan Jing and Hau-San Wong, "Face and palm print feature level fusion for single sample biometrics recognition", Neuro Computing, Vol. 9, No. 8, 2007.
8. B.Prasanalakshmia , A.Kannammal, "Biometric Cryptosystem Involving Two Traits And Palm Vein As Key", In Proceedings of IEEE International Conference on Communication Technology and System Design, Vol. 30, 2012, pp. 303–310, 2011.
9. Md. Mahbubur Rahman, Md. Rashedul Islam, Nazmul Islam Bhuiyan, Bulbul Ahmed, Md. Aminul Islam,"Person Identification Using Ear Biometrics", International Journal of The Computer, the Internet and Management Vol. 15, No.2, pp. 1 - 8, 2007.
10. Arun Ross and Anil K. Jain, "Multimodal Biometrics: An Overview", In proc. of 12th European Signal Processing Conference (EUSIPCO), Vol. 14, No: 1, pp. 1221-1224, September 2004.
11. M.1. Ahmad, W.L. Woo and S.S. Dlay, "Multimodal Biometric Fusion at Feature Level: Face and Palm print", In proc. of the 7th International Symposium on Communication Systems Networks and Digital Signal Processing (CSNDSP), pp. 801 - 805, 2010.
12. Madasu Hanmandlu, Jyotsana Grover, Ankit Gureja and H.M. Gupta, "Score level fusion of multimodal biometrics using triangular norms", Pattern Recognition letters, Vol. 32, No. 14, pp. 1843–1850, 2011.
13. A.Jameer Basha, V.Palanisamy and T.Purusothaman,"Fast Multimodal Biometric Approach Using Dynamic Fingerprint Authentication and Enhanced Iris Features", In proc. of the IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2010, pp. 1-6, 2010.
14. JuCheng Yang, "Biometrics Verification Techniques Combing with Digital Signature for Multimodal Biometrics Payment System", In proc. of IEEE International Conference on Management of e-Commerce and e-Government, pp. 405 - 410, 2010.
15. S. K. Dahel and Q. Xiao, "Accuracy Performance Analysis of Multimodal Biometrics", In proc. of the IEEE Workshop on Information Assurance, pp.170 - 173, 2003.
16. Hyunsoek Choi and Miyoung Shin, "Learning Radial Basis Function Model with Matching Score Quality for Person Authentication in Multimodal Biometrics", In proc. of First Asian IEEE Conference on Intelligent Information and Database Systems, pp. 346-350, 2009.
17. Desong Wang, Jianping Li and Gokhan Memik, "Authentication Scheme of DRM System for Remote Users Based on Multimodal Biometrics, Watermarking and Smart Cards", In proc. of the WRI Global Congress on Intelligent Systems (GCIS '09), Vol.2, pp. 530-534, 2009.
18. Md. Maruf Monwar and Marina L. Gavrilova, "Multimodal Biometric System Using Rank-Level Fusion Approach", IEEE Transactions on Systems, Man and Cybernetics, Vol. 39, No. 4, pp. 867- 878, August 2009.
19. Mingxing He, Shi-Jinn Horng, Pingzhi Fan, Ray-Shine Run, Rong-Jian Chen, Jui-Lin Lai, Muhammad Khurram Khan and Kevin Octavius Sentosa, "Performance evaluation of score level fusion in multimodal biometric systems", Pattern Recognition, Vol. 43, No. 5, pp. 1789–1800, 2010.
20. Hong Huang, Jiamin Liu, Hailiang Feng and Tongdi He, "Ear recognition based on uncorrelated local fisher discriminant analysis", Neuro Computing, Vol.74, No. 17, pp. 3103–3113, 2011.
21. Li Yuan and Zhi chun Mu, "Ear recognition based on local information fusion", Pattern Recognition letters, Vol. 33, No. 2, pp.82-190, 2012.
22. Tak-Shing Chan and Ajay Kumar, "Reliable ear identification using 2-D quadrature filters", Pattern Recognition letters, Vol. 33, No.14, pp. 1870–1881, 2012.