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# A Genetic Algorithm Based Multi-modal Biometric Recognition System Using Iris and Fingerprint

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## Abstract:

In today's sensitive era, an accurate personal authentication has become a major challenge in wide category of application domains. Currently, most of the biometric systems employed are based on single biometric trait which is named as uni-biometric systems. In spite of extensive advances in recent years, still there are confronts in person authentication using single biometric trait such as spoof attack, intra-user variations and susceptibility, noisy data and unacceptable error rates.Multi-modal biometric systems can address these issues with the integration of evidences from multiple biometric traits. The integration of evidences can be done at various levels like pixel, feature or score, etc. Even though feature level integration results a high quality feature space for better recognition it contains complex feature space mapping and high dimensional resultant feature space. To get the advantage of multi-modal biometrics system with feature level fusion, this paper proposes a Genetic Algorithm (GA) based feature selection and normalization address the issues in feature level integration of iris features with fingerprint features. The performance of the GA based feature selection is compared against Principal Component Analysis (PCA) based feature space reduction on CASIA, IITD and FVC databases using Machine Learning algorithms. The results shown that the feature space after feature level fusion of iris and fingerprint features have been greatly reduced with GA compared to PCA with good recognition accuracy.

**Keywords:** Genetic Algorithm, Feature selection, Feature Level Fusion, Iris, Fingerprint, Multi-modal biometric systems.

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## 1. Introduction:

In this modern society, a diverse range of systems need reliable person authentication mechanisms to authorize or decide the uniqueness of persons seeking their facilities. The purpose of such mechanisms is to ensure that the offered facilities are accessed by a genuine user, and not anybody else. Examples of such systems include secure access to mobiles, laptops, computers, buildings, ATMs, and systems in a military environment. In the absence of robust authentication mechanisms, these systems are susceptible to the tricks of an impostor.In this context, Biometrics is playing a significant role in person authentication because of its properties like cannot be stolen, forgotten [1]. Among various biometric traits, iris and fingerprint most widely used trustworthy person authentication systems in various security applications [2,3].Among various biometric traits, Fingerprint and Iris has gained more focus [2] because it is perfect across each individual, each finger and iris of the same person even in twins also [4] and its characteristics are persevered (not changed) over time [5].

Though, the performance of unimodal biometric system is affected by noise,sample size, and spoofing attacks [6], multibiometric biometric systems can conquera number of these problems by combining the features from a single trait or morethan one biometric trait. The majority of users, however, find the multibiometric

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method unacceptable since it requires adding more resources of all kinds to biometric systems [7]. When compared to multimodal systems based on different biometric traits, such as systems with multiple features from a single fingerprint [8], systems with multiple classifiers [9], systems with various impressions of the single finger [7], and systems including multiple fingers [10], the majority of researchers in the literature have shown that systems with a single biometric trait, one feature, and only one classifier or matcher produced poor performance. Multimodal systems can improve biometric recognition's performance.

In multimodal biometric systems, the evidences can beintegrated at various levels: fusion at sensor level, feature level, score level, anddecision level [11]. The recognition performance is impacted by the post-mapped methods score level and decision level, which require less information regarding biometric trait [11]. One of the pre-mapped solutions is sensor level fusion, which takes into account noise in the photos and results in poor recognition [11]. On the other hand, feature level fusion uses discernible qualitative information [11] about biometric traits and improves recognition rate. However, this fusion strategy has two major issues as well, just like earlier strategies.Two issues are the first, compatibility [12] of two distinct feature spaces, which [11] can be resolved most effectively by normalization; the second, high dimensional feature space [13], which unquestionably raises the demands on memory and computational resources and, in the end, necessitates the complex design of a classifier to operate on fused feature space [14]. Either feature transformation or feature selection can be used to solve this issue.

The process of selecting a subset of features that are significant for a dependable and robust feature space categorization is known as feature selection. This procedure promises to increase classification (recognition) performance by removing duplicated, noisy, and irrelevant characteristics [15]. The act of translating an original feature vector space into a new feature space that is more reflective of the data is known as feature transformation.

Despite the fact that numerous techniques, including Kernel-based PCA (KPCA) [17], Independent Component Analysis (ICA) [17], Linear Discriminant Analysis (LDA) [16, 17], and Principal Component Analysis (PCA) [16, 17], have been used in literature to reduce the amount of data in a variety of large-scale data sets. Using an objective function as a basis for optimization, feature selection techniques identify the minimum number of characteristics that are necessary. Many popular feature selection techniques have been used in the literature as effective feature selection mechanisms, including General Sequential Forward Selection (GSFS), Sequential Forward Selection (SFS), Artificial Neural Networks (ANN), Sequential Backward Selection (SBS), Sequential Forward Floating Selection (SFFS), and Sequential Backward Floating Selection (SBFS) [18, 19, 20].

Because of the need for a high identification rate and the space and time complexity of the data, dimensionality problems are common in the field of biometric data even though they can be solved in a variety of ways.

**Problem Deduction**

It is evident from the review above that only research has been done on score level fusion based multimodal iris recognition. Furthermore, it is well known that feature level fusion yields richer biometric inputs than score level fusion, which is not fully explored in the case of multimodal biometric recognition due to a significant issue known as high dimension feature space. The literature has demonstrated that feature selection techniques or data transformation methods like PCA can both shrink the feature space. Even though there is a large range of feature space reduction techniques available, choosing one necessitates having a clearer

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understanding of which aspects in the fused feature space should be prioritized. If any optimization strategies may be used to lower the feature space and raise the recognition system's performance levels, more clarification and research are needed.

In order to tackle these issues, this work has explored Genetic Algorithm as feature selection technique to minimize fused feature space. Boll's research has demonstrated that, regardless of the methodology, subset-based outcomes yield superior performance [21]. In this case, high dimension feature space in biometric feature level fusion has been solved using GA. To determine which approach—transformation or feature selection—isbetter; PCA has been used for feature reduction and contrasted with feature selection technique.

In order to minimize the data following feature level fusion in multimodal systems, this paper examined the aforementioned reduction methodologies. As mentioned earlier, tests utilizing fingerprint and iris have been conducted on six distinct multi-modal biometric recognition systems. The CASIA iris database, the IIT Delhi iris database, the CASIA fingerprint database, and the FVC fingerprint database have all been used in these experiments.

**Organization**

The format of this paper is as follows: Section 2 describes the unimodal iris system using three distinct feature extraction algorithms. A unimodal fingerprint system based on two distinct feature extraction algorithms based on thinning techniques is shown in Section 3.In section 4, feature level fusion in six multi-modal systems is explained. Details of the PCA data transformation approach are presented in Section 5. The suggested GA algorithm used as a feature selection technique is presented in Section 6. In Section 7, an analysis of the experimental results is presented. Section 8 finally provides a conclusion.

## 2. Unimodal iris systems:

This section discusses three distinct feature extraction strategies for unimodal iris recognition systems, as illustrated in Fig. 1. The following steps make up the general iris system: iris image preprocessing, which entails extraction of the iris from the eye image by localization, normalization, and then feature extraction,matching.

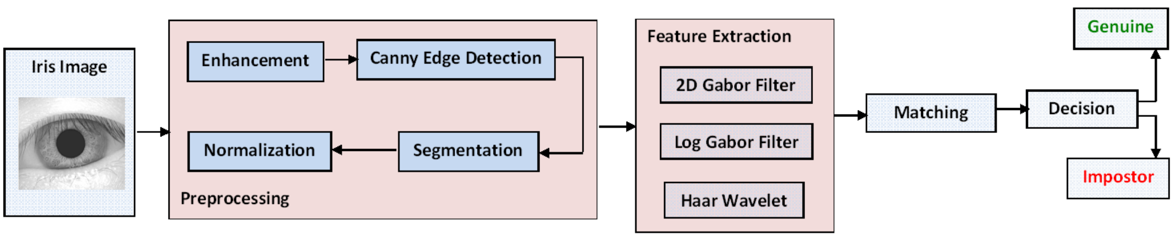


**Fig 1: Unimodal Iris Recognition System**

**Preprocessing**

The technique of removing the iris image from an eye image so that it can be used for feature extraction is known as iris preprocessing. The two key phases in this process are called localization, which separates the iris image from the eye image, and normalization, which transforms the segmented iris into a fixed dimension representation. Many methods can be used to perform localization, such as the integro-differential operator-based Daugman's [23] technique, the edge detection-tailed Hough transform approach of Wildes [22], the

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extraction of the iris by Boles [24] by locating the outer boundary, the extraction of features by using the pupil as a reference point, and the extraction of the iris [25 based on pixel intensity projections, thresholding, and circular Hough transform. This technique uses clever edge detection with the Hough transform applied to extract the iris. The Canny Edge detection technique has been extensively used in a wide variety of edge detection applications. The following procedures are involved in the canny edge detector: smoothing, gradient discovery, non-max suppression, and edge tracking using hysteresis. The radius and center pixel coordinates of the pupil and iris boundaries were then computed using the circular Hough transform.The following equation has been used to calculate radius center pixel values

$$a^2 + b^2 - r^2 = 0 \quad (1)$$

The maximum point resembles to the radius 'r'; the centre coordinates (a, b) of the circle are given by the edge points in the Hough space.The segmented iris has then been normalized using Daugman's rubber sheet model [3]. This involves remapping every pixel in the iris image into polar coordinates of the form (r, θ); r is represented as 20 pixels, and θ is the angle between [0,2π], which has been taken as 240 in this work.

## Feature Extraction

Many different methods for extracting features from a normalized iris image have been documented in the literature [26]. Phase and texture-based techniques, zero-crossing representation, keypoint descriptors, and intensity variation analysis are a few of the several iris feature extractors [26]. A high recognition rate and reduced computational complexity have been achieved with feature extraction based on Haar Wavelets [25, 27]. The use of Gabor filters to extract iris features has significantly improved recognition accuracy [3, 27, 28]. These benefits allow phase features to be derived from the iris's Haar Wavelet decomposition, and texture characteristics to be extracted from the iris using the 2D-Gabor and 2D-Log Gabor filters.

### A. Haar Wavelets

Phase characteristics from the iris have been extracted using the Haar wavelet transform [29]. Using a five level decomposition, the iris feature pattern was reduced to a single vector by taking approximation coefficients into account; this vector is referred to as the feature vector [25].

### B. 2D - Gabor Filter

The literature shows Gabor based feature extraction has extensively applied in various application of pattern recognition. Unstable contrast and brightness of images are better handled by the Gabor function and gives the location of time frequency exactly [30]. Because of these advantages, the following Gabor filter bank has applied to iris texture extraction [30, 31].

$$g(a,b;\theta,\varphi,\sigma,\gamma,\lambda) = exp\left(\frac{a^2+\gamma^2 b^2}{2\sigma^2}\right) + \ exp\left(i\left(2\pi\frac{a}{\lambda} + \ \varphi\right)\right)(2)$$

Where,

$$a = a\cos\theta + b\sin\theta$$

$$b = \ -a\sin\theta + b\cos\theta$$

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θsignifies the orientation of the normal to parallel stripes of a Gabor function, φ is the phase offset, λ specifies the sinusoidal factor wavelength, σ is the standard deviation of the Gaussian envelope and γ is the spatial aspect ratio [30].

**C.2D-Log Gabor Filter**

Because of time/space and frequency invariance, symmetry on the log frequency axis, Log-Gabor filter has systematically investigated and applied for texture based feature extraction [32]. The Log Gabor filter has applied by using the following formula [31]:

$$G(\rho,\theta,a,b) = \exp\left(\frac{-1}{2}\left(\frac{\rho-\rho b}{\sigma a}\right)^2\right) + exp\left(\frac{-1}{2}\left(\frac{\theta-\theta_{ab}}{\sigma\theta}\right)^2\right) \quad (3)$$

In which (ρ, θ) are the log-polar coordinates, a and bgivesorientation and scale, the pair (ρk, $\theta_{pk}$) corresponds to the frequency center of the filters, and ($\sigma_\rho$ ,$\sigma_\theta$) is the angular and radial bandwidths.

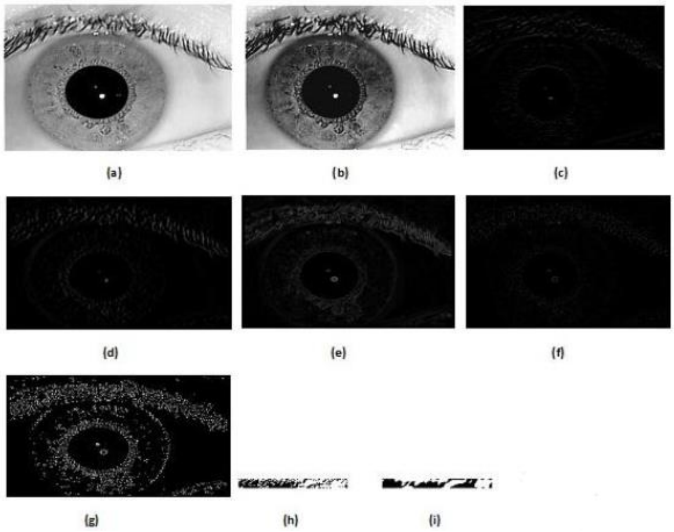


**Fig 2 (a) Iris Image (b) Enhanced Iris Image (c) X-Derivative of IrisImage (d) Y-Derivative of Iris Image (e) Gradient Image (f) Image AfterNon-Maximum Suppression (g) Post – Hysteresis of Iris Image (h)2D-GaborFeatures (i) 2D-LogGabor Features**

**Matching**

Since the feature space is continuous, Euclidean distance has been used for matching. The feature vectors that are claimed and those that are enrolled are measured in distance. To identify a real person from an imposter, this value is compared to a threshold that is specific to the user [30]. To determine whether the provided template is authentic or a fake, machine learning techniques such as Naïve Bayes, SMO, C4.5, and Random Forest classification algorithms have been used.

## 3. UnimodalFingerprint systems:

This section discusses three distinct feature extraction strategies for unimodalfingerprint recognition systems, as illustrated in Fig.3. The following steps make up the general fingerprint system: fingerprint image preprocessing, which entails segmentation, normalization& filtering, thinning and then Minutiae feature extraction,matching.

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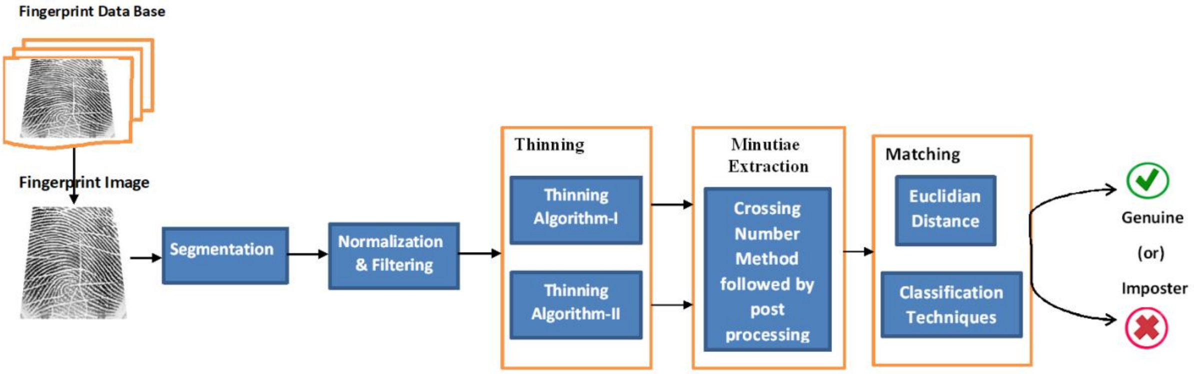


**Fig 3: UnimodalFingerprint Recognition System**

The fingerprint in non-ideal surroundings has isolated areas and fingerprint line misconnections from noise and disturbances, which have an impact on the fine details that need to be extracted. To reduce noise and enhance image quality, the fingerprint image must be preprocessed to remove undesired areas. Preprocessing typically consists of the following: region mask, binarization, thinning, segmentation, filtering and ridge frequency, normalizing, and image orientation [33]. Here, the fingerprint picture has been preprocessed using segmentation based on morphological processing [34], normalization, orientation, filtering and ridge frequency, region mask, and finally thinning.

**Normalization**

Variations in gray level values may occur in the image produced by the fingerprint image acquisition procedure along ridges and valleys. This could occur if the finger makes incorrect contact with the sensor. Consequently, by controlling the range of gray level values, the normalizing step is necessary to remove the effects of these variations. This procedure uses a given mean and variance to normalize a finger image. Let the intensity values of the supplied finger image and the normalized image at pixel (p, q) be represented by $I_m$ (p, q) and $N_m$(p, q). The following equation is used to obtain the normalized image.

$$N_m = \begin{cases} M_0 + \sqrt{\frac{V_0(I_m(p,q)-M)^2}{V}} & if\ I_m(p,q) > M \\ M_0 - \sqrt{\frac{V_0(I_m(p,q)-M)^2}{V}} & otherwise \end{cases} \quad (4)$$

In Eq. 4 *M* and *V* are the estimated mean and variance of *Im*(p, *q*), respectively, and $M_0$and $V_0$are the desired mean and variance values, respectively.

**Segmentation**

A fingerprint image often includes the region of interest (ROI) known as the foreground, which is composed of ridges, bifurcations, and valleys; additionally, it may include a background, a rectangular bounding box, and distorted portions of a pattern known as the background. To avoid extracting fine details from the noisy region, the fingerprint's ROI is divided from the backdrop. Segmentation is the process of removing ROI from an image. Several methods can be used to accomplish this procedure, such as segmentation based on statistical features and orientation field, segmentation based on ridge orientation and frequency features, and ROI extraction from fingerprints using a neural network-based method. A morphological processing segmentation [34] has been performed here to obtain ROI from fingerprint.

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The ridges should be found once ROI has been excised. This image of a finger has first been normalized. The consistent direction of ridgelines, bifurcations, and valley lines in an ideal fingerprint image makes it simple to identify minute characteristics. However, in the actual world, there are a number of factors—such as cuts on the skin, noise in sensors, low image quality, skin moisture, and inadequate finger-sensor contact—that make it difficult to extract minute details. Normalization of the image is necessary to prevent the extraction of erroneous minutiae features and the loss of important minutiae points, which enhances the clarity of the image. The mean and standard deviation are used to create the normalized image. Nowadays, 1-D masking is used to find ridges based on ridge orientation.

**Thinning**

By removing unnecessary edge pixels while preserving the connectivity of the original ridge patterns, the technique known as "thinning" reduces the width of ridgelines to one pixel. This morphological process serves skeletonization purposes primarily. The process of thinning yields a thinned image, also known as a skeleton image, which is a line drawing representation of a pattern [2]. The preprocessing module's thinning process makes higher-level analysis and recognition easier for a variety of applications, including optical character recognition, fingerprint analysis, and picture comprehension.Here thinning has been achieved by using two different algorithms separately; Zhang Suen thinning algorithm, Sentiford Thinning algorithm.Zhang Suen thinning algorithm [35] is a parallel and fast thinning algorithm with two sub iterations. Stentiford thinning algorithm [36] is an iterative skeletonization approach based onmask concept.

**Minutiae Extraction**

The accurate extraction of minutiae features determines the consistency of thefingerprint recognition. The CN approach is widely applied for extraction minutiaepoints from fingerprint. In [37], Rutovitz's defined crossing number of apixel as

$$CN = 0.5 \sum_{i=1}^{8} |P_i - P_{i+1}|$$

| | | |
|---|---|---|
| $P_4$ | $P_3$ | $P_2$ |
| $P_5$ | $P$ | $P_1$ |
| $P_6$ | $P_7$ | $P_8$ |

Where $P_i$is the neighborhood binary pixel value of $P$ with $P_i$= (0 or 1) and $P_1 = P_9$.

| CN | Property |
|---|---|
| 0 | Isolated Point |
| 1 | Ending Point |
| 2 | Connective Point |
| 3 | Bifurcation Point |
| 4 | Crossing Point |

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

Bifurcation Point (CN=3)

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 1 |

Ridge Ending Point (CN=2)

**Fig 4: Crossing Number Properties**

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As illustrated in Figure 4, the features of CN are utilized to identify even the smallest points from the thinned image. When examining a 3x3 window on a thinned image, a pixel is identified as a bifurcation point if its central pixel value is 1 and all three of its neighboring pixels have the same value. Ridge ending is indicated if every neighboring pixel has a value of 1 and the central pixel has a value of 1. Truth and false minutiae points are derived from the preprocessed obtained fingerprint, despite this. And the postprocessing procedure eliminates these erroneous points.

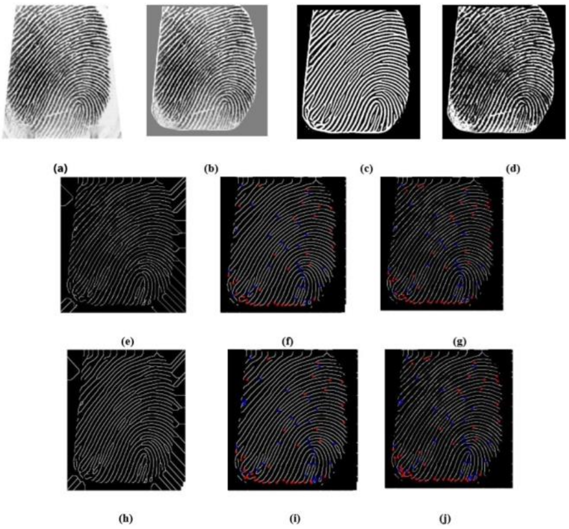


**Fig5: (a) Input Image (b) Segmented Image (c) Normalized Image (d) Binary Image (e) Thinned Image1 (f) Minutiae extraction1 (g) Post processing1 (h) Thinned Image2 (i) Minutiae extraction2 (j) Post processing2**

**Post-processing**

Both true and false minutiae points are included in the minutiae features that were taken from the preprocessed binary fingerprint picture. Post-processing is utilized in order to get the actual minute details. This technique looks at the neighborhood surrounding the point and validates the tiny points in the thinned image. The distance between the termination and bifurcation sites is determined using the Euclidian distance method. False minutiae points will cause the fingerprint matching's FAR and FRR to rise. The algorithm is used for bifurcation points and ridge endpoints in order to eliminate these erroneous minutiae points.

## 4.Integration of Feature Vectors

This section presents the integration of iris features with Fingerprint features. The Haar wavelet decomposition of 20×240 iris image has produced 1×114 Haar feature vector. And Gabor features (2D-LogGabor or 2D-Gabor) of iris image contains 12 different images G of size 20×240 each. By Horizontal and vertical downsampling it has been brought to an image GF of size 20×240. Then it has been converted to a vector of 1× 4800. Gabor values and Haar values are ranges in different scales when compared to fingerprint minutiae features. Because of different domain ranges, to avoid driving of one set of values in classifier normalization has been applied to bring into the same domain. Haar features and Gabor features of iris, fingerprint minutiae features are normalized to [0, 1]. These features are concatenated to generate the integrated template. Then these vectors concatenated to form single feature vector. The integrated feature vector size varies from 4912 to 4852 based on fingerprint databases. Here, six multi-modal (MM) systems based on fingerprint and iris are designed namely

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**MM_Finger_Iris_sys1 –** which is a multi-modal system developed based on integration of Log-Gabor features of iris with minutiae features extracted from thinned fingerprint image obtained from Zhang Suen thinning algorithm.

**MM_Finger_Iris_sys2 –** which is a multi-modal system developed based on integration of Log-Gabor features of iris with minutiae features extracted from thinned fingerprint image obtained from Stentiford thinning algorithm.

**MM_Finger_Iris_sys3 –** which is a multi-modal system developed based on integration of Gabor features of iris with minutiae features extracted from thinned fingerprint image obtained from Zhang Suen thinning algorithm.

**MM_Finger_Iris_sys4 –** which is a multi-modal system developed based on integration of Gabor features of iris with minutiae features extracted from thinned fingerprint image obtained from Stentiford thinning algorithm.

**MM_Finger_Iris_sys5 –** which is a multi-modal system developed based on integration of Haar features of iris with minutiae features extracted from thinned fingerprint image obtained from Zhang Suen thinning algorithm.

**MM_Finger_Iris_sys6 –** which is a multi-modal system developed based on integration of Haar features of iris with minutiae features extracted from thinned fingerprint image obtained from Stentiford thinning algorithm.

## 5. Features Space Reduction Using PCA

PCA is primarily a dimensionality reduction and subspace projection approach that can be applied to image compression and recognition issues. PCA has mostly been used in biometrics to extract features from the face [16, 38, 41], palmprint [39], and footprint [40]. In order to reduce the dimensionality of different biometric features, such as fingerprints, faces, and signatures, separately before classification, PCA and LDA have been used in conjunction in [42]. PCA has been used to decrease the dimension vector in order to improve image recognition [43]. PCA is a widely used approach for identifying patterns in high dimension data [44]. Following feature level fusion, PCA has been used as a dimensionality reduction technique in three different multi-biometric systems that use eye, palm, and finger prints [30].

A linear data reduction technique called principal component analysis (PCA) projects data into a new space where it is represented by the directions of maximum variability. PCA converts the original picture data into a collection of principle components (PCs) that are perpendicular to one another and in decreasing order of variance among the image data.

PCA measures the degree of variation in the feature vectors of iris and fingerprint images in various orientations [30]. Let T be the training dataset consisting of p one-dimensional iris and fingerprint templates with dimensions of 1 x q. The data set T of size p×q is reduced via the PCA algorithm to the data set T' of size p×k, where k≤q. The following equation is solved by the function eigen() in this algorithm to determine the eigen vectors and eigen values:

$$[cov - \lambda I]e = 0 \tag{5}$$

cov is the covariance matrix in this case. The eigen vectors (e1, e2, e3,...,eq) are given by the identity matrix I, the eigen value λ, and the eigen vector e. The eigen vectors e1, e2, e3,...eq are sorted by the Sort() function in decreasing order of their associated eigen values $\lambda_1, \lambda_2, \ldots, \lambda_q$.

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## 6. Genetic Algorithm based Feature Selection

An optimization method called the genetic algorithm effectively locates the global optimum solution over a wide range of spaces [63]. It is a potent stochastic algorithm that mimics Darwin's survival-of-the-fittest theory and was inspired by the biological gene mechanism [64–66]. GA begins with a fixed size population of chromosomes generated at random, and the fitness of each is determined. To get the population to the best possible convergence, a number of iterative processes including selection, crossover, and mutation are carried out. The fingerprint was subjected to GA for line detection [64], face detection [67], iris image reconstruction [68], and iris recognition [69] weight learning. Walker-assisted gait was studied using GA-based feature selection [70].

GA randomly initializes a population of chromosomes for an optimization problem of n dimensions, assigning a random bit string gene to each chromosome in n-dimensional space as a potential solution. Fitness function is used to assess each chromosome's fitness. Then, chromosomes are identified via a selection mechanism based on their fitness values. Crossover and mutation operations are used to create the population's next generation. Iteratively performing selection, crossover, and mutation processes continues until an ideal solution is reached or a predetermined number of generations are reached.

The proposed GA represents chromosome as a binary vector on n genes shown in Fig 6, where n is the number of features in the biometric fused feature vector. The value of each gene is “0‟ represents the non-selected feature, “1‟ depicts the selected feature. The initial population of $N_c$ chromosomes is randomly generated by using the following function:

$$Ch_{ij} = \begin{cases} 1 & if\ rand > R \\ 0 & otherwise \end{cases} \tag{6}$$

‘rand‟ denotes a random number between [0,1] and R represents a constant between 0 and 1; it was assigned a value of 0.5.

| | | | |
|---|---|---|---|
| **Ch1,1** | **Ch1,2** | .................... | **Chi,n** |

**Fig 6 Representation of Chromosome**

**Fitness Function**

In order for GA to choose a subset of traits and produce viable progeny from the present generation, the fitness function is a key motivator. The features subset's performance is assessed by this fitness value. Every chromosome's fitness is determined using the C4.5 machine learning technique. After identifying the chosen characteristics in the provided chromosome, a new biometric dataset is created using the chosen features from the provided biometric dataset. By utilizing the C4.5 algorithm on a fresh biometric dataset, the accuracy of classification or recognition is achieved, denoted by α. The current chromosome's fitness role is described as follows:

$$fit = \alpha + \beta + \gamma \tag{7}$$

In biometric data, α represents accuracy based on chosen features, β indicates how selected features affect biometric recognition, and γ indicates how non-selected features affect recognition.

There are three components to the fitness function fit. The first component, α, quantifies the degree to which the underlying distribution of biometric images can accurately identify the biometric image. The weight

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of a subset of features relative to all features in the collection of biometric images is determined in the second section. This may be assessed as

$$\beta = n_{selected} * \left(\frac{N_{DB}}{n}\right) \qquad (8)$$

Here, $n_{selected}$ is the cardinality of selected features, n represents the total number of features, $N_{DB}$ denotes the total number of biometric images in the given dataset.

The third part reflects the impact of other non-selected features or weight factor of other features not present in chromosome on recognition. This is calculated as

$$\gamma = n_{non-selected} * \left(\frac{N}{n}\right) \qquad (9)$$

Where $n_{non-selected}$ is the cardinality of non-selected features of the chromosome, n denotes the total number of features, N represents the number of trained biometric images. The three parts of the function look for optimum features in the biometric feature space with a complete description of each biometric, and this function also shows that the calculations are performed based on trained data without the usage of test data.

**Genetic Operations**

Finding the best chromosomes in the current population is known as the selection operation. Declaring high-performing chromosomes in the population with the hope that they will pass on likelihood information to future generations through their progeny is the primary goal of selection. The selection process has a big influence on convergence, hence in order to prevent early convergence, population diversity should be maintained. Other genetic operations should be balanced with this. Because roulette wheel selection is a simple and effective selection method, it was used in our research.

A crossover is another genetic surgery that involves selecting two parent chromosomes and transferring their information to create new children. The main goal of this procedure is to create a child with the intention of having healthy progeny. In a crossover operation, the information exchange procedure enables GA to explore the search space. An application for the exploration of the integrated search space is single point crossover.

The process of randomly choosing a gene's position on a binary chromosome and flipping it is known as a mutation. By preserving population chromosomal variety and dispersing genetic information, this process keeps the GA from reaching a local optimum. A bit-string mutation was used, causing the value of a randomly chosen gene to flip.

## 7. Experimental Results

This section includes the experimental information, such as the evaluation environment, databases used to compare performances, and the kind of matching process or classifiers used to distinguish between a real and a fake.

**Databases and Matching Evaluation process**

The tests make use of two distinct fingerprint databases: the Fingerprint Image Database (CASIA Version 1.0 [85]), which contains the left and right hand fingerprint pictures of one hundred distinct individuals. Four samples are taken from each of the person's four fingers on each hand. Since each finger on an individual is unique, two fingers from each hand—two on the left and two on the right—are taken into consideration for studies. A total of 400 individuals are chosen, with four samples chosen and tested for each subject. Ten distinct human fingerprint pictures are chosen for the trials from the FVC 2004 DB1_B fingerprint database. Six samples are selected from the fingers of each unique person.

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Two separate iris databases were used for the experiment. The first is the 756 iris images from 108 different eyes in the CASIA Version 1.0 [78] Iris image database. Seven photos are taken of each individual eye over the course of two sessions, with three iris samples taken in the first session and four samples in the second. Six samples were selected from each individual eye in this database. The second is the iris image database version 1.0 from the Indian Institute of Technology, Delhi (IITD) [79]. There are 2240 photos in the database from 224 distinct users. Ten samples of each user's eyes are taken, five from the left eye and the remaining five from the right. Because each user's eye is entirely distinct from the other, we regarded a single user's left and right eyes as two separate users in our experiment. Then, a total of 448 distinct subjects are selected, with three samples selected for each subject.

In building our multi-modal biometric databases, each virtual person has been constructed by considering one biometric trait from one database and another trait from different database.As an illustration, during the construction of a multimodal database utilizing fingerprint and iris data, each virtual individual was created by selecting one individual's fingerprint samples from the Fingerprint CASIA DB and one individual's iris samples from the iris CASIA DB. Another database has been produced for the same multimodal systems. In this database, each virtual person is created by combining fingerprint samples from the Fingerprint FVC DB with iris samples from the iris IITD DB. The aforementioned procedure yields diverse multi-modal biometric databases.

All of the methods were run on a PC equipped with an i7 processor running at 1.8 GHz 2.00 GHz, 16 GB of RAM, and Windows 10 for the experiments.In order to determine the most effective and reliable reduction method, two reduction strategies are evaluated on the aforementioned multi-modal systems. They are PCA and GA, as was previously mentioned. The efficiency of these two strategies can be determined by calculating the functionality of the suggested systems. In this case, we use a combination of techniques, including a Euclidean distance measure and a measure based on supervised algorithms, to determine the true and false positive rates. The proposed systems are implemented using four distinct supervised algorithms: the C4.5 decision tree algorithm, the Random Forest algorithm, the SMO algorithm, and the Naive Bayes algorithm.

**Result Analysis**

Here, we show and talk about the outcomes of deploying various fingerprint and iris-based multimodal systems with and without reduction techniques. The primary goals of these calculations are recognition rates, computation times for processing datasets, and feature space reductions brought about by feature level fusion.

To begin, we describe the outcomes of matching multimodal systems using Euclidean distance across all reduction strategies. Table2 illustrates the recognition rate corresponding to tried data reduction methodologies on six systems for two datasets. And with that in mind, we've set the FAR = 0.01% recognition rate. PCA requires less processing time than GA, yet it only achieves a slightly lower recognition rate across all six systems here. However, when comparing GA to PCA, GA produced a higher recognition rate. As was previously said, the results demonstrate that GA performs better on large-scale datasets.

**Table 1 Number Of Features Selected In Multi-Modal System Based On Fingerprint And Iris For Various DB's**

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| Multi-modal Systems | Without FS | PCA | GA |
|---|---|---|---|
| MM_Palm_Finger_Iris_sys1 | 14860 | 3219 | 3428 |
| MM_Palm_Finger_Iris_sys2 | 14860 | 3235 | 3531 |
| MM_Palm_Finger_Iris_sys3 | 10174 | 2344 | 2522 |
| MM_Palm_Finger_Iris_sys4 | 14860 | 3215 | 3561 |
| MM_Palm_Finger_Iris_sys5 | 14860 | 3231 | 3578 |
| MM_Palm_Finger_Iris_sys6 | 10174 | 2340 | 2523 |
| MM_Palm_Finger_Iris_sys7 | 14850 | 3214 | 3431 |
| MM_Palm_Finger_Iris_sys8 | 14850 | 3223 | 3523 |
| MM_Palm_Finger_Iris_sys9 | 10164 | 2334 | 2529 |
| MM_Palm_Finger_Iris_sys10 | 14850 | 3211 | 3565 |
| MM_Palm_Finger_Iris_sys11 | 14850 | 3218 | 3581 |
| MM_Palm_Finger_Iris_sys12 | 10164 | 2327 | 2533 |

Table 1 shows the number of reduced features in eigen space i.e. PCA, GA for multi-modal systems proposed in section 4 based on fingerprint and iris. Table 2 shows the performance attained using the Euclidean distance measure in PCA, GA. In any system feature space reduction with good recognition rate is highly required. It is clear from Table 1 and Table 2 that even though PCA is reducing the feature space better than GA algorithm it does not produce significant improvement in the recognition accuracy; which is attained highly in GA than rest of the approaches. Table 3 presents the accuracy of various proposed multi-modal systems using supervised learning classifiers. It is clear from Table 2 and Table 3 that the use of supervised classifiers produced prominent recognition rate compared to distance measure. For this reason, in our work, it is clear that the GA procedure allows significant improvement level of performance as the global scheme while reducing significantly the number of features, which shows that GA preserves the most discriminant features during the reduction process.

Table 3 presents results for six multi-modal systems using fingerprint and iris. These Based on the results presented in Table 3, in all multi-modal systems SMO and C4.5 classifiers produced merely very close and high recognition accuracy compared to the remaining two classifiers NB, RF. Among these classifiers NB has produced better results than distance measure but it poor among supervised classifiers because it is poor in handling continuous data. 93.5 % of accuracy obtained in MM_Finger_Iris_sys1 system by C4.5, 93.2% of recognition accuracy achieved by SMO in MM_Finger_Iris_sys2, C4.5 produced 93.5% accuracy for MM_Finger_Iris_sys3, 94.1% recognition rate attained in MM_Finger_Iris_sys4 using SMO, 94.1% of accuracy produced in MM_Finger_Iris_sys5 by C4.5, and 93.1% of recognition level achieved by C4.5 in MM_Finger_Iris_sys6. These results are obtained for multimodal database constructed using fingerprint CASIA DB and iris CASIA DB.

**Table 2 Recognition Accuracy using Euclidean Distance Measure In Multi-Modal Systems Based On Fingerprint And Iris For Various DB's**

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| Multi-modal Systems | Without FS | PCA | GA |
|---|---|---|---|
| MM_Palm_Finger_Iris_sys1 | 82.1 | 86.1 | 91.8 |
| MM_Palm_Finger_Iris_sys2 | 81.3 | 85.3 | 91.6 |
| MM_Palm_Finger_Iris_sys3 | 82.7 | 86.4 | 91.7 |
| MM_Palm_Finger_Iris_sys4 | 81.2 | 85.6 | 91.2 |
| MM_Palm_Finger_Iris_sys5 | 82.1 | 86.2 | 92.3 |
| MM_Palm_Finger_Iris_sys6 | 81.3 | 85.7 | 91.7 |
| MM_Palm_Finger_Iris_sys7 | 82.3 | 86.4 | 92.3 |
| MM_Palm_Finger_Iris_sys8 | 82.2 | 86.1 | 92.1 |
| MM_Palm_Finger_Iris_sys9 | 82.8 | 86.7 | 91.2 |
| MM_Palm_Finger_Iris_sys10 | 81.4 | 86.9 | 92.5 |
| MM_Palm_Finger_Iris_sys11 | 81.1 | 86.3 | 92.6 |
| MM_Palm_Finger_Iris_sys12 | 81.5 | 86.1 | 91.2 |

The results obtained for multimodal database constructed using fingerprint FVC DB and iris IITD DB are as follows: 93.6 % of accuracy obtained in MM_Finger_Iris_sys1 system by C4.5, 93.4% of recognition accuracy achieved by SMO in MM_Finger_Iris_sys2, C4.5 produced 93.4% accuracy for MM_Finger_Iris_sys3, 94.2% recognition rate attained in MM_Finger_Iris_sys4 using SMO, 94.2% of accuracy produced in MM_Finger_Iris_sys5 by C4.5, and 93.8% of recognition level achieved by SMO in MM_Finger_Iris_sys6.

In all multi-modal systems, the proposed GA attained highest recognition rate compared to existing approach PCA. The feature space reduction is high in PCA which nearly 90% but the recognition rate is very poor compared to proposed algorithm. GA reduces feature space to more than 80% with highly significant recognition rate of 94.2%. In any biometric authentication systems, along with space recognition rate is critical and main performance requirement. Due to this constraint GA has given best performance compared to PCA.

**Analysis of Computation Time:** All FS approaches PCA, GA used in experiments are applied to the same databases and experimented in the same environment. Among all even though the proposed algorithm GA takes more training time than remaining algorithms, produced minimum testing time. In biometric systems, training is carried only once at the time of enrollment and it will be done in offline. But, the testing is not like that. So, in these biometric systems, the testing time shows more impact and it is compared to training time. Since the proposed algorithm generate a minimum number of features compared to others it always takes less time to classify the test biometric template as genuine or imposter.

**Table 3 Recognition Accuracy using Various Classifiers in Multi-Modal System Based on Fingerprint and Iris for Various DB's**

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| Databases | Multi-modal Systems | Classifiers | Without FS | PCA | GA |
|---|---|---|---|---|---|
| CASIA DB | MM_Finger_Iris_sys1 | SMO | 84.5 | 85.3 | 93.4 |
| | | C4.5 | 84.2 | 85.1 | 93.5 |
| | | NB | 83.1 | 83.8 | 90.6 |
| | | RF | 84.01 | 84.9 | 92.1 |
| | MM_Finger_Iris_sys2 | SMO | 82.4 | 85.1 | 93.2 |
| | | C4.5 | 81.9 | 84.6 | 93.1 |
| | | NB | 81.3 | 82.8 | 91.2 |
| | | RF | 82.1 | 84.1 | 91.8 |
| | MM_Finger_Iris_sys3 | SMO | 85.3 | 86.7 | 93.4 |
| | | C4.5 | 85.1 | 87.1 | 93.5 |
| | | NB | 82.3 | 84.5 | 91.1 |
| | | RF | 84.5 | 85.6 | 92.6 |
| | MM_Finger_Iris_sys4 | SMO | 86.2 | 87.8 | 94.1 |
| | | C4.5 | 86.01 | 87.6 | 94.01 |
| | | NB | 81.3 | 83.9 | 90.2 |
| | | RF | 85.02 | 85.8 | 91.7 |
| | MM_Finger_Iris_sys5 | SMO | 85.3 | 87.3 | 93.9 |
| | | C4.5 | 85.4 | 87.1 | 94.1 |
| | | NB | 82.01 | 84.3 | 91.2 |
| | | RF | 84.6 | 85.5 | 92.3 |
| | MM_Finger_Iris_sys6 | SMO | 81.03 | 85.1 | 93.1 |
| | | C4.5 | 80.9 | 84.9 | 92.8 |
| | | NB | 80.1 | 82.9 | 90.7 |
| | | RF | 80.3 | 83.9 | 91.2 |
| FVC DB & IITD DB | MM_Finger_Iris_sys1 | SMO | 84.3 | 85.5 | 93.5 |
| | | C4.5 | 84.1 | 85.6 | 93.6 |
| | | NB | 83.2 | 83.7 | 90.5 |
| | | RF | 83.9 | 84.8 | 92.3 |
| | MM_Finger_Iris_sys2 | SMO | 82.3 | 85.4 | 93.4 |
| | | C4.5 | 82.5 | 85.3 | 93.3 |
| | | NB | 81.1 | 82.7 | 91.2 |
| | | RF | 82.3 | 84.4 | 91.9 |
| | MM_Finger_Iris_sys3 | SMO | 85.2 | 86.8 | 93.3 |
| | | C4.5 | 85.1 | 87.2 | 93.4 |
| | | NB | 82.2 | 84.2 | 91.03 |
| | | RF | 84.6 | 85.4 | 92.5 |
| | MM_Finger_Iris_sys4 | SMO | 86.3 | 87.7 | 94.2 |
| | | C4.5 | 86.1 | 87.8 | 94.1 |
| | | NB | 81.2 | 83.5 | 90.1 |
| | | RF | 85.2 | 85.7 | 91.6 |
| | MM_Finger_Iris_sys5 | SMO | 85.4 | 87.3 | 94.1 |
| | | C4.5 | 85.5 | 87.4 | 94.2 |
| | | NB | 82.1 | 84.1 | 91.1 |
| | | RF | 84.2 | 85.6 | 92.5 |
| | MM_Finger_Iris_sys6 | SMO | 81.3 | 85.3 | 93.8 |
| | | C4.5 | 81.1 | 85.2 | 93.7 |
| | | NB | 80.2 | 82.8 | 90.5 |
| | | RF | 80.4 | 83.6 | 91.7 |

## 8. Conclusion

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This study presented a method using GA to combine features from many biometric modalities in order to reduce the feature space. While principal component analysis (PCA) is useful for managing huge datasets, it is possible that important features would be missed every time it is done. This inspired us to develop GA, which efficiently deals with this issue by increasing the exploration of feature space using a proposed exponential function. The GA approach has been demonstrated to be more effective than PCA in dealing with feature space reduction in experiments involving fingerprint and iris benchmark datasets CASIA, IITD, and FVC.

In every case, including feature space reduction, recognition accuracy using a distance measure, and the performance of supervised classifiers, GA yielded impressively positive outcomes. In all of the multi-modal systems developed in section 4, GA has significantly enhanced recognition accuracy in comparison to the PCA technique.Using supervised classifiers, PCA achieves a maximum of 87.8% accuracy, whereas GA achieves 94.2% accuracy. The main benefit is that it would make it easier to find more distinguishing traits, which improves classification's accuracy. As can be seen from the results, supervised algorithms based matching is more accurate than matching based on Euclidean distance.

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