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# Designing Efficient Feature Space Reduction Schemes for Multi-Algorithmic Iris Recognition System based on Feature Level Fusion of Texture and Phase Features

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*Abstract*: ***Iris recognition system has gained prominent focus because of its uniqueness, stability over time. But the recognition level of single biometric based recognition systems is greatly affected by environmental conditions, physiological deficiency. Multi-biometric systems diminish this problem with the fusion of features collected from various traits or samples of the same trait, a single trait by employing multiple algorithms or multiple instances. To gain the advantages of multi-biometric systems in iris recognition, a Multi-algorithmic iris recognition system has been proposed where Texture features from iris are extracted by using 2D-Log Gabor filter and Phase features are extracted by Haar Wavelet; And these features can be integrated at various levels like Decision, Rank, Score, feature, and pixel. Even though the feature level fusion contains rich information about biometric samples when compared to remaining fusion levels; it involves mapping complexity, high dimensional feature space. To gain advantage of feature level fusion in iris recognition and to overcome the problem of resulted high dimensional feature space, Genetic Algorithm (GA) based reduction scheme, Principal Component Analysis (PCA) reduction strategy and a hybrid reduction scheme which is a combination of PCA and GA have been applied to reduce the resulted feature space. The performance of these reduction strategies have evaluated on CASIA iris database, IIT Delhi iris database using Machine Learning approaches. The results have shown that the feature space has dramatically reduced while keeping recognition accuracy and also revealed that space and time requirements have significantly decreased after employing feature reduction schemes.***

***Keywords : Feature Level Fusion, Genetic Algorithm, Iris recognition, Multi-Algorithmic biometric system, Principal Component Analysis.***

## I. INTRODUCTION

The fastest advancements in information systems and security threats are driving towards highly robust and accurate person authentication. Biometrics are playing a significant role in person authentication [1]. Iris based authentication is the most reliable biometric based recognition because iris texture contains a unique pattern which leads to low error rate and high recognition rate when compared to all other biometric traits [2,3,4]. The research in the area of the iris recognition has dramatically increased. Many researchers had developed iris recognition techniques and proposed various methodologies. Daugman first developed iris recognition system based on iris localization and removal of eyelids by means of integro-differential operator [20]. In [16], Boles suggested translation, rotation, and scaling invariant iris recognition algorithm. Wildes [4] located iris by combining edge detection approach with Hough Transform. [22] presented a different method for iris localization and pattern matching. A cluster based iris localization method has proposed for recognizing non-cooperative iris [23].

But unimodal biometric systems are facing problems like spoof attacks, intra-class variations [5]. Multimodal systems address some of these problems [5]; which are an integration of shreds of evidence collected from multiple samples or multiple instances or various sensors or multiple algorithms or multiple traits. A robust iris recognition system can be developed as a multimodal system which is a multi-algorithmic system where multiple algorithms are applied to extract different features from iris image; the biometric data obtained through these algorithms will be combined to classify genuine and imposter claims. The pieces of evidence in multibiometric systems can be integrated at various stages like pixel level, feature level, score level, and decision level. Among these levels of integration of cues at feature level fusion gives a rich quality of information about biometric sample when compared to remaining levels; which greatly affects the recognition rate [5].

Bastys, Kranauskas, and Kruger have proposed iris recognition system where score level fusion of shreds of evidence collected from iris using phase-based, local extremum has compared with individual ones; this combination has given better results than iris recognition without integration [6]. The Haar wavelet features and Gabor features were integrated at score level in [7] and shown a better result than unimodal systems. This work addresses feature level fusion for iris recognition by considering two different multi-algorithmic systems. But this level of fusion faces two problems, as stated earlier.

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First, the feature spaces which are to be integrated may be in different domains; they are not compatible with integration. Second, the fusion of two different feature spaces will generate new high dimension feature space, which leads to the curse of dimensionality. The two different feature spaces can be brought into the same space and made compatible for integration by applying normalization techniques; which is a solution for the first problem in feature level fusion.

The second problem can be solved by employing dimensionality reduction techniques or feature selection approaches. The literature has investigated a wide range of reduction and selection approaches in various fields. Data transformation based reduction approaches like PCA and Independent Component Analysis (ICA) has applied in [8]. The features collected from face and hand have integrated at feature level; then SFFS has been used to select optimum features [9]. PCA has thoroughly investigated as reduction approach at feature level fusion of palmprint evidences and face evidences [10, 11]. The researchers have extensively studied, and motivating work has performed on feature selection approaches after feature level fusion [9,12,13,14].

This paper aimed to gain the advantages of feature level fusion in multi-algorithmic iris recognition system and to investigate whether data transformation technique PCA or Optimization technique Genetic Algorithm (GA) will produce good amount of reduction with prominent recognition accuracy. The proposed system architecture has shown in Fig1. The claimed eye image has been preprocessed to get fixed dimension iris image by performing localization using canny edge detection and Hough transform followed by Daugman's rubber sheet model for normalization. Then three different algorithms based on 2D-Gabor filter, Haar Wavelet, and 2D-Log Gabor filter have been applied to extract features from normalized iris. The extracted feature vectors have integrated at feature level. Then three feature reduction approaches called PCA, GA, and Hybrid approach, which is the application of PCA followed by GA have applied. The reduced feature vector has been matched with the stored iris template database using either Euclidean distance based matching or classification based matching to identify genuine or imposter claim.

This paper has planned as follows: section 2 gives how preprocessing of eye image has been carried to get normalized iris image. Different feature extraction algorithms applied to the normalized iris image has presented in section3. The integration of different feature spaces obtained in section3 has explained in section4. How the feature space has reduced by applying different reduction strategies has been presented in section5. The Experimental setup, results, and analysis have discussed in section6. The work has concluded in section7.

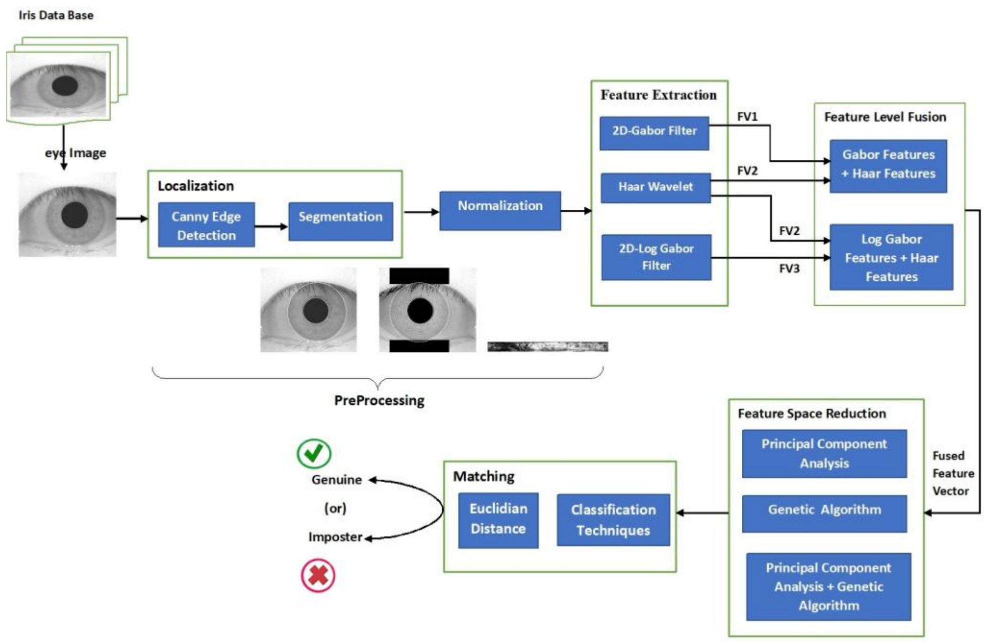


**Fig1: Proposed System architecture**

## II. PREPROCESSING

Iris preprocessing is a process of extracting iris image from eye image which is suitable for feature extraction. This process involves two significant steps called localization, where iris image is segmented from eye image and normalization where the segmented iris is converted to fixed dimension representation. Localization can be performed by various approaches like Daugman's [15] technique based on integro-differential operator, Wildes [4] approach based on edge detection tailed by Hough transform, Boles[16] extracted iris by locating outer boundary, pupil using edge detection and extracted features by considering pupil as reference point, [17] extracted iris based on pixel intensity projections, thresholding, circular Hough transform. In this work, the iris has extracted by applying canny edge detection tailed by Hough transform. Canny Edge detection approach has thoroughly applied in extensive range of applications for edge detection. The canny edge detector involves the following steps: smoothing, finding the gradient, non-max suppression, edge tracking by hysteresis.

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Then circular Hough transform has applied to compute radius and center pixel coordinates of pupil and iris boundaries. The following equation has been used to calculate radius center pixel values

$$p^2 + q^2 - r^2 = 0 \quad (1)$$

The maximum point resembles to the radius 'r'; the centre coordinates (p, q) of the circle are given by the edge points in the Hough space.

Then Daugman's rubber sheet model has applied to normalize the segmented iris [3]. This is a process of remapping each pixel of iris image into polar coordinates of the form (r, θ); where θ is the angle between [0,2π] which has taken as 240 in this work, r has considered as 20 pixels.

## III. FEATURE EXTRACTION

The literature shows a wide variety of feature extraction approaches from a normalized iris image [18]. Various types of feature extractors from iris are Phase and Texture Based methods, Zero-crossing Representation, Keypoint Descriptors, Intensity Variation Analysis [18]. Haar Wavelet based feature extraction has produced a good recognition rate with less computation complexity [17,19]. Gabor filters for iris feature extraction has given prominent recognition accuracy [20,3,19,21]. Because of these advantages, phase features are extracted from Haar Wavelet decomposition of iris and texture features are extracted from iris by applying 2D-Gabor filter and also by applying 2D-Log Gabor filter.

### A. Haar Wavelets

Haar wavelet transform has applied to extract phase features from iris [22]. Five level decomposition has employed, and the iris feature pattern has characterized to a single vector by considering approximation coefficients; that vector is named as feature vector [23]. It has obtained by applying the following steps on the normalized iris:

(i) Gaussian Low Pass Filter (LPF) for smoothing and Gaussian High Pass Filters (HPF) for sharpening has applied on row blocks of normalized iris.
(ii) Even indexed columns have considered after downsampling columns by 2.
(iii) Now, Gaussian LPF and Gaussian HPF have applied on column blocks.
(iv) Even indexed rows have considered after downsampling rows by 2.
(v) Rows and Columns of filter entries have convolved.
(vi) Approximation matrix coefficient and Detail matrix coefficient in term of Low to Low (LL), Low to High (LH), High to Low(HL) and High to High(HH) have stored. Decomposed level1 image has obtained.
(vii) Decompose image for Level2, level3, level4, level5 by repeatedly applying steps from (i) to (vi). Feature vector has obtained from these decompositions.

### 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 [24, 26]. Because of these advantages, the following Gabor filter bank has applied to iris texture extraction [24, 25].

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

Where,

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

θ signifies 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 [24].

### 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 [27]. The Log Gabor filter has applied by using the following formula [25,26]:

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

In which (ρ, θ) are the log-polar coordinates, a and b gives orientation and scale, the pair (ρk, θpk) corresponds to the frequency center of the filters, and (σρ , σθ) is the angular and radial bandwidths.

## IV. INTEGRATION OF FEATURE SPACES

This section explains how the different features collected from the iris image by applying two distinct feature extraction approaches have been integrated at feature level. The texture features extracted from iris by using 2D-Gabor filter, or 2D-Log Gabor filter are not compatible with the phase features extracted from iris by applying Haar Wavelets. The texture analysis of 20×240 iris image obtained by using either 2D-Gabor filter or 2D-Log Gabor filter produces 12 different images of size 20×240 each; this texture has brought to a single image of size 20×240 by applying horizontal and vertical downsampling. Further, it converted into a row feature vector of size 4800. The phase features extracted from Haar Wavelet decomposition produced a row feature vector of size 114. To combine these two different feature space, min-max normalization has applied for both texture features and phase features. Now the feature vectors are concatenated to produces integrated feature space.

## V. FEATURE SPACE REDUCTION

5. Feature Space Reduction

The integration of multiple feature vectors at feature level fusion is causing the dimensionality problem. This problem can be solved by applying feature reduction approaches like any data transformation methods like PCA, feature selection approaches like traditional feature selection methods or optimization approaches. This work has investigated a data transformation technique called PCA, and an evolutionary algorithm called GA and a hybrid approach which is a combination of strategies PCA, GA where reduction has carried with PCA followed by GA.

### A. Principal Component Analysis

PCA is a dimensionality reduction approach based on subspace projection and widely applied for image compression and recognition problems [38]. PCA has been used for extracting features from palmprint [33], face [28,11,29], and applied as reduction strategy in various biometric recognition like face, signature, fingerprint, palm print before matching [30,31,24]. PCA is a linear data reduction technique and projects the original data into new dimensional space with maximum variability. The projected data is a collection of principal components which represents new dimensions of the data. The following steps have been applied to perform PCA based reduction:

i) For each feature of the iris data set, Mean has calculated.
ii) Mean subtracted iris dataset has computed.
iii) The covariance matrix of the mean subtracted data has computed, then computed eigen values and eigen vectors.
iv) According to eigen values, the eigen vectors sorted in decreasing order of their eigen values.
v) Required principal components have extracted.
vi) The reduced data set has been produced by projecting the mean-shifted images into the eigenspace based on principal components.

### B. Genetic Algorithm based Feature Space Reduction

Genetic Algorithm is a population based optimization approach which mimics the evolution of man [32,33], which consists of fitness, reproduction, and the mathematical operations called mutation, crossover [34]. The collection of chromosomes called population represents potential solutions. For selecting optimum features from fused feature space, a binary representation of the chromosomes has taken. The size of the chromosomes is the same as the number of dimensions in the fused feature space. And 1 in chromosome represents the selected feature, and 0 represents a non-selected feature. Initially, chromosomes have randomly initialized, and then the evolution process continues as generations. In each generation, a selection method has been applied on population, and then fitness of the selected chromosomes will be calculated. Based on these fitness values, some of the chromosomes will be chosen for the new population, and on remaining chromosomes, crossover and/or mutation operation will be applied to generate new chromosomes for new population. This process will be continued for the maximum number of iterations. After these iterations, the chromosome with the best fitness value will produce an optimal solution for the problem [34, 35].

$$fit(C_i) = RR + n_{selected} * \left(\frac{N_{DB}}{n}\right) \quad (4)$$

Where nselected is the number of selected features in the given chromosome Ci. NDB represents the total number of iris samples in dataset and n represents the number of dimensions or features in the dataset. By applying the Roulette Wheel selection method and then using single point crossover, mutation operations new population has generated. The following steps have applied for selecting optimum features based on GA.

**Algorithm GA**
**Input:**
Nc: Number of chromosomes in generation
fit: Fitness function
n: Number of dimensions or features
max_iter: Maximum number of generations
**output:** The selected features are that whose position in the best chromosome is 1.
**Procedure:**
Step1: Randomly generated population of the size Nc; where each chromosome of the size n.
Step2: Calculated fitness of each chromosome using the fitness function fit described in equation (4).
Step3: Roulette Wheel selection has applied and selected chromosomes with least fitness value from the population.
Step4: Single point Cross over has been applied on selected chromosomes and generated new chromosomes. And then bit string mutation has been used on newly created chromosomes.
Step5: New population has generated by replacing the chromosomes selected in step3 by the new chromosomes generated in step4.
Step6: Repeat the steps from 2 to 5 for max_iter times.
Step7: Select the best chromosome with the highest fitness value and which represents the solution

### C. Hybrid Approach for Feature Space Reduction

This work also aimed to investigate a combination of data transformation technique and optimization techniques as feature space reduction strategy; Where initially PCA has been applied to reduce the fused feature space in multi-algorithmic systems and then for that PCA reduced feature space GA has been used for further reduction. This approach has dramatically reduced the feature space.

## VI. EXPERIMENTAL RESULTS AND ANALYSIS

This section describes the experimental environment in which the proposed systems have tested evaluated. The experiments are performed on two different databases, namely CASIA Version1.0 [36] iris database and Indian Institute of Technology Delhi (IITD) iris database version1.0 [37]. CASIA database consists of 756 iris images collected from 108 individual persons. For each person, 7 images have captured in two different sessions. From this database, 6 samples have been selected from each individual person to evaluate the proposed system. The IITD database contains 2240 iris images collected from 224 different persons. From each user, 5 samples from the left eye and 5 samples from the right have captured. Since each eye of the same person contains utterly different pattern from another eye of the same person, here the samples from each eye has been considered as samples individual subjects; 448 subjects have selected, and from each subject 3 samples were chosen for the evaluation process. The experiments were carried on a system with i7 processor CPU @1.8GHz;16 GB RAM and implemented with Matlab 9.5.

Two Multi-algorithmic iris systems have been implemented. They are

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1. LH - Multi-algorithmic system where features extracted from iris image by applying 2D-Log Gabor filter and Haar Wavelets have been integrated at feature level.
2. GH - Multi-algorithmic system where features extracted from iris image by applying 2D-Gabor filter and Haar wavelets have combined at feature level.

Because feature level fusion generates high dimension feature space, to overcome this problem different feature space reduction approaches have been implemented and tested on two systems LH and GH. The results obtained after reduction and before reduction have compared. The comparisons have carried on the following systems:

(i) A multi-algorithmic system with feature level fusion without any feature space reduction approach;
(ii) A multi-algorithmic system with feature level fusion and then PCA as feature space reduction approach;
(iii) A multi-algorithmic system with feature level fusion and then GA as feature space reduction approach;
(iv) A multi-algorithmic system with feature level fusion and then a hybrid approach which is the application of PCA as a reduction strategy and then again GA for further feature space reduction.

**Table1: Recognition Accuracy and Computation time for processing dataset with Euclidian distance based matching for three multi-algorithmic systems with different reduction strategies**

| Approach | Recognition Accuracy (%) | | Computation Time in seconds | |
|---|---|---|---|---|
| | CASIA DB | IITD DB | CASIA DB | IITD DB |
| Feature Level Fusion-LH | 79.02 | 79.8 | 1294 | 1601 |
| Feature Level Fusion-GH | 79.4 | 80.4 | 1293 | 1602 |
| Feature Level Fusion-LH with PCA | 81.3 | 82.4 | 182 | 240 |
| Feature Level Fusion-GH with PCA | 82.2 | 83.1 | 118 | 156 |
| **Feature Level Fusion-LH with GA** | **85.2** | **86.7** | **554** | **771** |
| **Feature Level Fusion-GH with GA** | **86.1** | **86.9** | **532** | **782** |
| **Feature Level Fusion-LH with PCA+GA** | **82.02** | **82.8** | **127** | **150** |
| **Feature Level Fusion-GH with PCA+GA** | **82.9** | **83.5** | **112** | **132** |

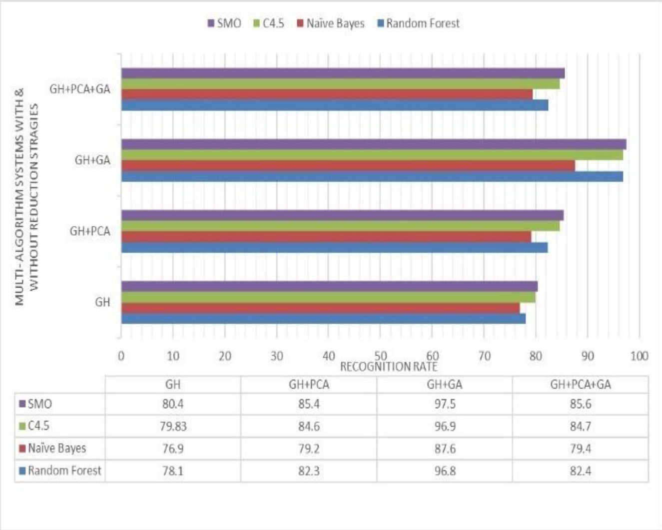
Table1 presents the recognition accuracy and the time taken for the reduction of feature space for two different multi-algorithmic systems LH and GH with different reduction strategies. These results have taken at FAR =0.01% for the two databases — the results have shown that any reduction approach is giving an improvement in the recognition rate. And the hybrid reduction approach, which is PCA in combination with GA, has given maximum feature space reduction when compared remaining reduction approaches. But, along with the amount of reduction recognition rate must be acceptable. Because of this reason, GA based reduction approach is given both adequate reductions in feature space and recognition rate. From these results, the application of GA has increased the recognition accuracy even after application PCA also when compared to only PCA as reduction approach.

**Table2: Computation time for processing dataset with a related number of features for three multi-algorithmic systems with different reduction strategies**

| Approach | Number of features | | Computation time to process the data in seconds | |
|---|---|---|---|---|
| | CASIA DB | IITD DB | CASIA DB | IITD DB |
| Feature Level Fusion-LH | 4914 | 4914 | 918 | 1023 |
| Feature Level Fusion-GH | 4914 | 4914 | 919 | 1025 |
| Feature Level Fusion-LH with PCA | 194 | 179 | 107 | 122 |
| Feature Level Fusion-GH with PCA | 77 | 202 | 90 | 130 |
| **Feature Level Fusion-LH with GA** | **2438** | **2226** | **442** | **579** |
| **Feature Level Fusion-GH with GA** | **2475** | **2251** | **457** | **601** |
| **Feature Level Fusion-LH with PCA+GA** | **85** | **102** | **94** | **103** |
| **Feature Level Fusion-GH with PCA+GA** | **36** | **77** | **51** | **94** |

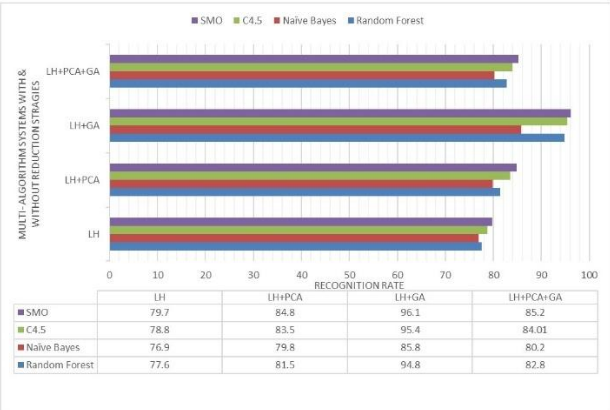
Table2 presents the details of the number of features in the dataset before and after employing various reduction approaches for the two multi-algorithmic systems, LH and GH. And also the computation time to perform classification based matching has been presented. In the amount of reduction perspective, PCA produced a significant reduction, which is more than 80% in both LH and GH system. GA has given a reasonable reduction of more than 51%, and the hybrid approach has provided the best reduction of more than 90% in both the systems LH, GH.

Figures from 3 to 6 gives the performance of the two systems, LH and GH with and without reduction approach on four different classification algorithms, namely SMO, C4.5, Naïve Bayes, and Random Forest. Fig3 presents classification accuracy of LH system on CASIA database; Fig4 gives classification performance of GH system on CASIA database with respect to Accuracy; Fig5 shows the classification accuracies for LH system on IITD database; Fig6 depicts GH system classification accuracies on IITD database. In both LH and GH multi-algorithmic iris systems GA based reduction has produced the best accuracies of 97.5%, 97.6% with SMO classifier. In two databases, for both LH and GH systems, SMO and C4.5 are giving best and very close classification accuracies. When compared to Euclidean distance based matching, classification based matching has produced the best accuracy results in both the multi-algorithmic systems LH and GH with and without reduction strategies. As already mentioned, the amount of reduction with reasonable recognition rate is acceptable. So, GA based reduction strategy has given noticeable results in terms of both the amount of reduction and recognition accuracy.



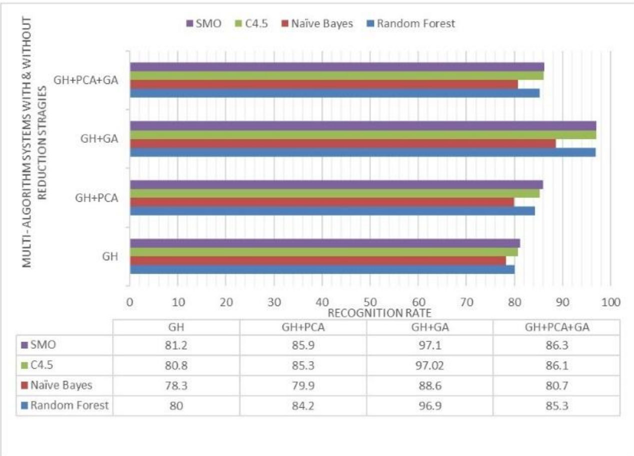

| | GH | GH+PCA | GH+GA | GH+PCA+GA |
|---|---|---|---|---|
| SMO | 80.4 | 85.4 | 97.5 | 85.6 |
| C4.5 | 79.83 | 84.6 | 96.9 | 84.7 |
| Naïve Bayes | 76.9 | 79.2 | 87.6 | 79.4 |
| Random Forest | 78.1 | 82.3 | 96.8 | 82.4 |

**Fig 3: Classification Performance of 2D-Gabor and Haar Wavelet based multi-algorithm systems with and without applying reduction strategies for CASIA DB**



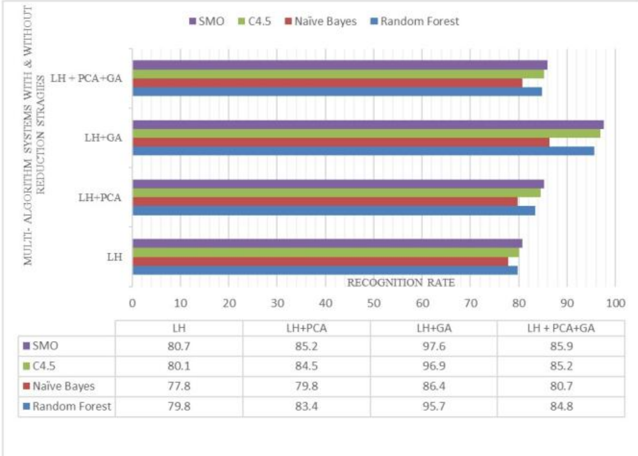

| | LH | LH+PCA | LH+GA | LH+PCA+GA |
|---|---|---|---|---|
| SMO | 79.7 | 84.8 | 96.1 | 85.2 |
| C4.5 | 78.8 | 83.5 | 95.4 | 84.01 |
| Naïve Bayes | 76.9 | 79.8 | 85.8 | 80.2 |
| Random Forest | 77.6 | 81.5 | 94.8 | 82.8 |

**Fig 4: Classification Performance of 2D-LogGabor and Haar Wavelet based multi-algorithm systems with and without using reduction strategies for CASIA DB**




| | GH | GH+PCA | GH+GA | GH+PCA+GA |
|---|---|---|---|---|
| SMO | 81.2 | 85.9 | 97.1 | 86.3 |
| C4.5 | 80.8 | 85.3 | 97.02 | 86.1 |
| Naïve Bayes | 78.3 | 79.9 | 88.6 | 80.7 |
| Random Forest | 80 | 84.2 | 96.9 | 85.3 |

**Fig 5: Classification Performance of 2D-Gabor and Haar Wavelet based multi-algorithm systems with and without applying reduction strategies for IITD DB**




| | LH | LH+PCA | LH+GA | LH + PCA+GA |
|---|---|---|---|---|
| SMO | 80.7 | 85.2 | 97.6 | 85.9 |
| C4.5 | 80.1 | 84.5 | 96.9 | 85.2 |
| Naïve Bayes | 77.8 | 79.8 | 86.4 | 80.7 |
| Random Forest | 79.8 | 83.4 | 95.7 | 84.8 |

**Fig 6: Classification Performance of 2D-LogGabor and Haar Wavelet based multi-algorithm systems with and without applying reduction strategies for IITD DB**

## VII. CONCLUSION

Multibiometric systems produce robust recognition systems based on feature level fusion with a solution to high dimensional feature space after fusion. This work has addressed this solution in terms of presenting different feature space reduction approaches after feature level fusion in multi-algorithmic iris recognition systems. This work investigated two different perspectives of feature reduction strategies called reduction using data transformation technique called PCA and reduction based on Evolutionary algorithm called GA. And it also investigated a hybrid approach which is application of both data transformation technique PCA and optimization techniques GA as feature space reduction approach. Among all reduction approaches at feature level fusion GA based reduction approach has produced noticeable results in terms of both the amount of reduction and recognition accuracy in both LH and GH multi-algorithmic iris systems. And Machine learning based matching has given the best recognition rate when compared to traditional Euclidean distance based matching. GA has given 97.2% of recognition accuracy.

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