HyBr: An Optimized Feature Selection Method for Feature Level Fusion in Multimodal Biometrics using Iris and Fingerprint

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Abstract: The demand of biometric system for security purposes is rise in these days. So, there is a need of efficient biometric system which helps to secure systems as required. Now days, multimodal biometrics systems are used for the same purpose. In multimodal biometric systems feature level fusion is one of the best fusion method which works at earlier level where features are extracted. The main issue of these systems is that the extracted features are more in number and fusion of these features is too difficult. To heal this challenge in this work, a hybrid feature selection method is proposed where firefly and intelligent water drop algorithm is used. This hybrid approach helps to improve the efficiency of the system as well speed up the process with optimized features. Overall 4% accuracy is improved by this proposed modal in terms of recognition accuracy.

1. Introduction

With the advancement in the technology, biometrics is also used to provide highly reliable security systems. These systems help to improve the identification rate in the traditional security system and gave a new platform to the security and identification. Unimodal biometrics systems uses only one trait for identification or recognition purposes which might not be as much secure because forgery attacks also increase with the development of technology. So, this will lead to generate a multimodal biometrics system which uses more than one biometric trait and achieve higher level of security [3]. The biometric traits are either physiological or behavioural traits of individuals used for security purposes.

Biometric Systems are also help to provide non-repudiation which ensures authentication. Non-repudiation is the assurance that no one can later deny what they have sent earlier. This authentication provides security at the level that (i) only authenticated users will access all the resources and (ii) no forgeries attacks will be there.

In the current security systems, multimodal systems are preferred because of its increased level of protection. Multimodal biometrics systems are the biometric system where two or more modalities are fused at different levels. There are mainly three level of fusion these are: (a) Fusion at Feature Level, (b) Fusion at Score Level and (c) Fusion at Decision Level. Research is being done on these different levels of fusion using different modalities and it is observed that the performance of feature level fusion is good in all aspects whether it is security or recognition rate [8]. Various methods for normalization and fusion are used at different fusion levels. Some of these are discussed in table 1:

Table 1: Fusion Levels and Methods Performance

Title	Year	Modalities	Level of Fusion	Method for fusion	Accuracy
Multimodal face and finger veins biometric authentication [1]	2010	face and finger veins	score fusion	weighted fuzzy fusion	95%
Face and speech based multimodal biometric authentication [2]	2010	face and speech	score level data fusion	expectation maximization(EM) and Figuieredo-Jain algorithms	96%
Feature level fusion of palmprint and palm vein for personal authentication based on Entropy technique [3]	2014	palmprint and palm vein	feature level fusion	Entropy technique	99%
Feature level fusion of face and fingerprint Biometrics [4]	2007	face and fingerprints	feature level fusion	min- max normalization	98%

Proposed Multimodal palm-veins- face biometric Authentication [6]	2011	palm vein and face	feature level fusion	Sum fusion	98.3%
Score level fusion of fingerprint and finger vein Recognition [7]	2012	fingerprint and finger vein	score level fusion	Weighted sum	98.74%
Multimodal Biometrics using feature fusion [9]	2009	fingerprint and palm print	feature level fusion	min-min approximation.	98%
Robust multi-biometric recognition using face and ear images [10]	2007	face and ear	decision level	majority vote rule	96%
Reliability- Based decision fusion in multimodal biometric verification systems [11]	2013	face and speech	decision level fusion	margin-derived confidence measures	87%
Feature level fusion of palm and face for secure recognition [12]	2008	face and palm print	feature level fusion	min- max normalization	95%

Table 1 shows that feature level fusion performs better than other fusion levels because features are actual representation of information. So, this level of fusion may be used in future to derive a new and better security system based on biometrics [13]. The next sections will provide different feature selection methods and also an optimized method used in proposed work and based on that the performance of the multimodal system.

2. Feature Extraction and Selection Methods

In the field of biometrics, features play a very important part. Features provide relevant information or data to solve any problem or to make computations easy. Features may be any kind of the following: (a) edges, (b) key points, (c) shape and many more. A number of methods are used for feature extraction in the field of biometrics according to trait used. Some of the feature extraction methods for iris and fingerprint are listed in Table 2.

Table 2: Feature Extraction Methods for Iris and Fingerprint

Sr. No.	Methods for Iris Feature Extraction	Methods for Fingerprint Feature Extraction
1	2D Gabor wavelets [14]	adaptive pore model for fingerprint pore extraction [22]
2	1D Log-Gabor wavelets [16]	minutiae extraction [23]
3	2D Log-Gabor wavelets [17]	ridge directions at each point [24]
4	Edges and Shape Features [15]	combining pores and ridges with minutiae [25]
5	binarized multi-scale Taylor expansion [18]	edges extracted using Marr-Hilderith operator [26]
6	patch-based-zero crossing [19]	edge detection operators [27]
7	ROI Features [13]	Spaced Frequency Transformation Algorithm (SFTA) [28]
8	drawing concentric circle on the Iris image and extracting the intensity information at various points [20]	Texture Features [31]
9	Extracting the statistical features [21].	Fingerprint Indexing [29]
10	Texture Feature [12]	scale-invariant key points [30]

As extracted features are sometimes more in number then this will increase storage requirement as well as matching of the data becomes difficult. Therefore, feature selection should be used for higher recognition rate. Feature selection is similar to attribute or variable selection where relevant features of any image are selected using some computation methods. In biometrics, feature selection is also used for the simplification of the models, to shorten training time and to enhance the generalization.

Feature selection methods are combination of a search technique to generate a new subset of the features [32]. There are three main methods for feature selection is: (a) Wrappers, (b) Filters and (c) Embedded methods.

(i) Wrapper — A predictive model is used by Wrapper methods for score feature subsets. Every subset is used to train a model, which is tested on a hold-out set. A score for a subset is calculated by counting the number of mistakes made on that hold-out set. These are computationally intensive, but provide the best performing feature set.

(ii) Filters — Proxy measure is used by Filter methods to score a feature subset. This measure is selected because of fast computations, but it captures useful feature set. These methods are usually less computationally intensive than wrappers, but they produce a feature set which is not tuned to a specific type of predictive model. This means a feature set from a filter is more general than a wrapper, and gave lower prediction performance.

(iii) Embedded — Embedded methods are a catch-all group of techniques which perform feature selection as part of the model construction process.

Different Soft Computing methods for feature selection are comes under Wrapper Method. These optimization methods are soft computing algorithms developed for finding the best from given inputs. Different researchers worked on these methods for efficient results.

Table 3: Feature Selection Methods based on Soft Computing

Technique	**Technique**
Wrapper	1. Ants colony [42]
	2. Genetic Algorithm [38]
	3. Tabu Search + PSO [41]

3. HyBr based Multimodal Biometrics Setup

The proposed work is to enhance the multimodal biometric systems in terms of accuracy and lead to high recognition rate. In this feature selection algorithm based on hybrid optimization is proposed. The process is start with data acquisition, normalization, feature extraction, feature selection, fusion and matching process. Every phase of this system plays an important role in recognition process.

If multimodal is used, the first issue is to select an appropriate modality for system which adds up chances of accurately recognition. Iris and Fingerprint modalities are used in this work. Both these modalities have higher accuracy, reliability and simplicity as compare with other biometric traits. These traits are used since many years and research proves that very less false matches are there when these modalities are used. Iris pattern is unique to each individual and remains constant throughout the lifetime of a person and fingerprint is basically composed of ridges and valleys that are on the surface of the finger.

The initial phase of the recognition system is training phase where after sample collections different processes are used and then database will be prepare using final output further this data is used for matching purposes. Various steps are involved in the process of training these are:

3.1 Database Acquisition: In this phase, database is either acquires using sensors or sample may also be collected from standard libraries. Here in this work, database is collected from two libraries one is CASIA and other is IITD (IIT Delhi). Dataset contains 200 samples where 2 samples are collected from 100 persons for both iris and fingerprint.

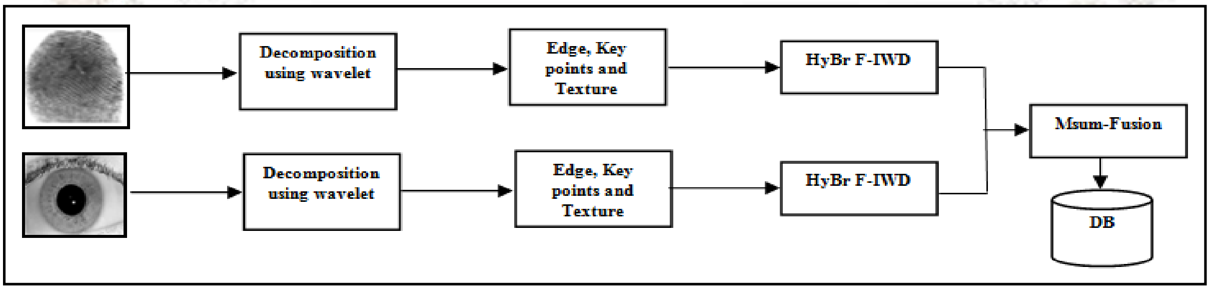


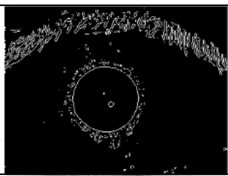
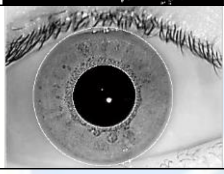
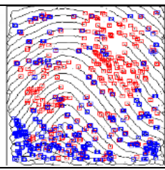
Fig 2: Training Phase

3.2 Decomposition using Wavelet: Wavelet transforms are multi-resolution image decomposition tool that provide a variety of channels representing the image feature by different frequency sub-bands. 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. The image is divided by vertical and horizontal lines and represents the first-order of DWT, and the image can be separated with four parts those are LL1,LH1, HL1 and HH1 [i]. Kekre proposed an algorithm to generate wavelet transform using DCT and Walsh based orthogonal transforms. Being a combination of two transforms, it combines good properties of both the component transforms. On the other hand being a wavelet transform it also provides advantages of wavelet transform. If we have two transform matrices A and B of sizes m x m and n x n respectively, then a hybrid wavelet transform matrix of size mn x mn is generated using the algorithm where A and B as component transform matrices. By varying sizes of these transform matrices; contribution of global and local properties of transform matrix can be varied.

In this work, a wavelet transform matrix is generated using two different orthogonal transform matrices of different sizes. Based on the size of component transform, numbers of rows in the resultant hybrid wavelet transform matrix contributing to global and local properties of transformed image vary. In the proposed method, hybrid wavelet transform is generated from DCT as global component combined with Walsh with size combinations (64, 4), (32, 8), (16, 16), (8, 32) and (4, 64) for both. For these sizes, DCT is computed as second component transform that its local component is computed.

3.3 Feature Extraction: In recognition systems, feature extraction plays a very important role to achieve good accuracy. Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. In proposed system texture features, key point features and edge features are extracted. The combination of these features gives the entire information about the images. An example is shown in table 4.

Table 4: Extracted Features

Features	Iris	Fingerprint
Edge		
Key-points		
Texture	**Coarseness:** 47.8697 **Contrast:** 48.7723 **Directionality:** 0.55187 **Entropy:** 7.3025 **Homogeneity:** 0.031167 **Energy:** 1.5665e-005	**Coarseness:** 48.6166 **Contrast:** 66.1937 **Directionality:** 0.062914 **Entropy:** 5.5267 **Homogeneity:** 0.090372 **Energy:** 3.7441e-005

The texture details obtained for the sample after decomposition is shown in Table 5. The last column in Table 4 is the average of LL5, LH5, HH5 and HL5 for level 5. These average values are used as input to a feature classifier network is used for further purposes. From Table 5 we compute that Coarseness and Homogeneity is better at HH-band, Contrast is better at LH-band, whereas Directionality, Energy and Entropy is better at HL-band in case of Iris Features and Coarseness, directionality, Entropy and Contrast is better at LH-band, Homogeneity is better at LH-band, whereas Energy is better at LL-band in case of Fingerprint Features.

Table 5: Texture Features in detail

Iris Features after Decomposition					
At Level 5	**LL5**	**LH5**	**HL5**	**HH5**	**Avg_Iris**
Coarseness	47.8697	46.7362	47.7382	48.3726	47.679175
Contrast	48.7723	49.3725	48.9362	48.2628	48.83595
Directionality	0.55187	0.54372	0.55462	0.49833	0.537135
Entropy	7.3025	7.9262	8.3726	7.9373	7.88465
Homogeneity	0.031167	0.043729	0.035268	0.046282	0.0391115
Energy	1.5665e-005	1.0162e-005	2.2811e-005	1.0295e-005	1.473E-05
Fingerprint Features after Decomposition					
At Level 5	**LL5**	**LH5**	**HL5**	**HH5**	**Avg_Fingerprint**
Coarseness	48.6166	49.8362	49.2625	48.2872	49.000625
Contrast	66.1937	67.2625	66.8297	66.9282	66.803525
Directionality	0.062914	0.065282	0.064262	0.063829	0.0640718
Entropy	5.5267	5.9272	5.8276	5.8392	5.780175
Homogeneity	0.090372	0.092725	0.096254	0.092578	0.0929823
Energy	3.7441e-005	3.5361e-005	2.98275e-005	3.6241e-005	3.472E-05

3.4 Feature Selection: When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features. Determining a subset of the initial features is called *feature selection*. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Optimization algorithms are used for selection of the best features from a large set of features. So in this work, a Hybrid optimization algorithm is used for feature selection purpose. *HyBr F-IWD* is a combination of firefly and intelligent water drop algorithms. Both are nature inspired algorithms and works efficiently with each other to provide superior results. Hybrid Algorithm is already explained in the above section. All the extracted features are input for this hybrid algorithm and produces results as some specific selected features on the basis of their intelligence.

In this work, a hybrid method is proposed for feature selection which is a combination of intelligent water drop and firefly algorithm. Both algorithms are nature inspired algorithms. As optimization is a best tool for decision making systems and for analyzing physical systems. These methods help to find a best solution among the given set of solutions. These algorithms follow some simple steps which include (a) Objective Function Evaluation, (b) optimization engine, (c) Process repetition, and (d) Stop Criterion. The basic information about the firefly and IWD is as given below.

Firefly Algorithm: Fireflies are one of the families of insects that live in tropical environment and produce-cold light chemically which may be yellow, green and pale-red [42]. Firefly algorithm is based on the flashing patterns and behaviour of fireflies. The function of these flashes is to communicate with mating partners and for protective warning mechanism. All the fireflies have a unique pattern. The Female fireflies respond to a male's unique pattern of flashing. With the increasing distance, light becomes weaker and weaker because of absorption by air. There are three main rules followed by firefly algorithm:

- One firefly attracts other so that all fireflies are unisex.
- Brightness is proportional to attractiveness and decreases with increasing distance.
- To determine the brightness of the firefly, objective function is used.

Intelligent Water Drop (IWD) Algorithm: This algorithm is designed to take the important properties of the natural water drops that flow in the beds of rivers [43]. In this algorithm, it is assumed that IWD has an amount of soil (S_{IWD}) and current velocity (V_{IWD}). There are some rules followed by IWD algorithm:

- The environment is assumed to be discrete and composed of N nodes
- Each IWD need t move from one node to another
- Two nodes are linked by an arc which holds an amount of soil which is increased or decreased based on the activities

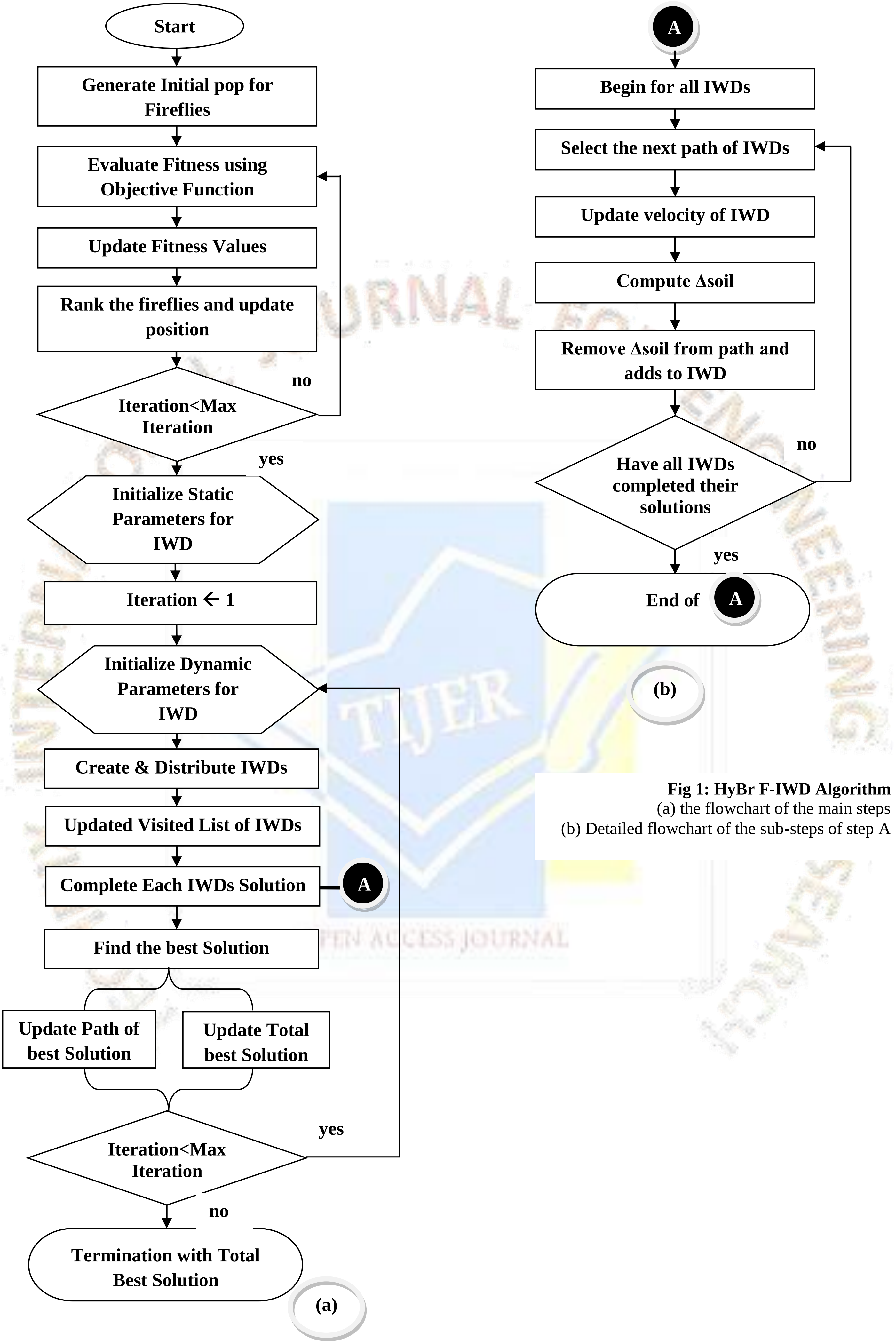


Fig 1: HyBr F-IWD Algorithm
(a) the flowchart of the main steps
(b) Detailed flowchart of the sub-steps of step A

HyBr F-IWD Algorithm: This algorithm is a combination of the firefly and IWD algorithm as shown in fig 1. In this firstly inputs are given to fireflies and then outputs of firefly are inured to IWD which will then yield a final best solution. Both algorithms are nature inspired algorithms so it is easy to make hybrid of it.

Pseudo Code:

```
Begin
Generate Initial Population of Fireflies fi (i=1,2,3….)
Formulate the light intensity L so that L is directly proportional to objective function O(x).
While (k< MaxGeneration)
For i=1:m (all fireflies)
For j=1:m (all fireflies)
If ( Li > Lj ), vary attractiveness with distance and move firefly I towards j;
Evaluate new solution and updated light intensity
End of if
End of for
End of for
Rank fireflies and find the current best;
End while
Post processing results
 Static parameter initialization using these results
             Problem representation in the form of a graph
             Setting values for static parameters
Dynamic parameter initialization: soil and velocity of IWDs
Distribution of IWDs on the problem's graph
Solution construction by IWDs along with soil and velocity updating
             Local soil updating on the graph
              Soil and velocity updating on the IWDs
Local search over each IWD's solution (optional)
 Global soil updating
Total-best solution updating
Process repeated till termination condition is satisfied
End
```

3.5 Feature Level Fusion: Feature selection produced a set of features for both iris and fingerprint. Fusion of these features is done using msum algorithm. The fused Feature vector is computed by calculating mean value after adding the feature vector for modalities involved. Then these fused features are saved into database.

MSUM Method for Feature Level Fusion

a) The feature vectors of both the modalities samples are brought to same dimension. For this:
   - The extra 0 bits are padded to the lower dimensional sample (here signature sample has lower dimensional value than speech signal sample).

b) The sum of feature vectors of both the modalities is computed.
   - The sum of two m × n matrices **A** and **B**, denoted by **A** + **B**, is again an m × n matrix computed by adding corresponding elements:

$$A + B = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \dots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \dots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix}$$
$$= \begin{bmatrix} a_{11}+b_{11} & a_{12}+b_{12} & \dots & a_{1n}+b_{1n} \\ a_{21}+b_{21} & a_{22}+b_{22} & \dots & a_{2n}+b_{2n} \\ \vdots & \vdots & \dots & \vdots \\ a_{m1}+b_{m1} & a_{m2}+b_{m2} & \dots & a_{mn}+b_{mn} \end{bmatrix}$$

c) The mean of computed sum of feature vectors is done.
   - x_{ij} is the i^{th} independently drawn observation (i=1,.......,N) on the j^{th} random variable (j=1,...,K). These observations can be arranged into N column vectors, each with K entries, with the K ×1 column vector giving the i^{th} observations of all variables being denoted $x_{i,}$ (i=1,...,N).
   - The **sample mean vector** $\bar{x}$ is a column vector whose j^{th} element $\bar{x_j}$ is the average value of the N observations of the j^{th} variable:

$$\bar{x_j} = \frac{1}{N}\sum_{i=1}^{N} x_{ij}\,, j = 1, \dots \dots \dots, K.$$

   - Thus, the sample mean vector contains the average of the observations for each variable, and is written:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Testing phase involves the twenty percent of original data and some forged samples for recognition purpose. The initial steps involved in this phase are similar to training phase but in this phase fused vector is not saved anywhere instead of that fused features are matched with the training data set and accordingly obtain a decision.

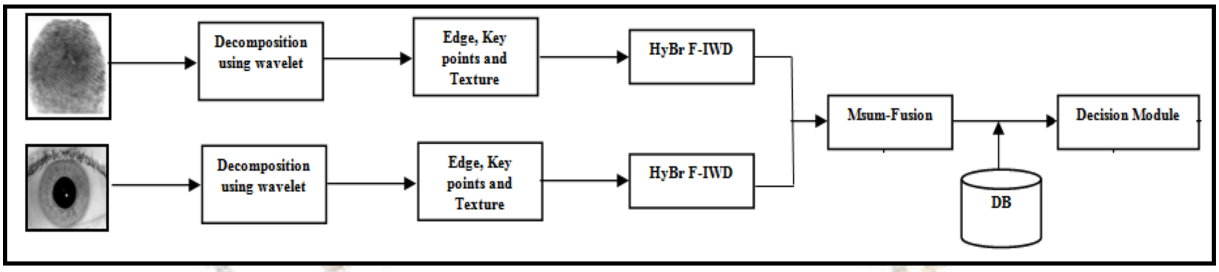


Fig 3: Testing Phase

4. Experiment Analysis

To analyze the performance of this proposed system a dozen of experiments are performed and different parameters are calculated. In this work, two data sets CASIA and IITD used for both fingerprint and iris samples. Experiments are performed on both the data sets individually as well as combined. Different statistical measures are used to analyze the performance of this proposed system.

False Acceptance Rate: It is the probability that the system inaccurately matches the input pattern to a non-matching template in the database list. It measures the percent of invalid inputs which are incorrectly accepted. In this work, performance has been tested by extracting features individually and combined. This will show that the FAR is least in the case of combined optimized feature where feature selection is also performed after merging all the features as shown in fig. 4. This figure shows that false acceptance rate is improved by 66% from edge features whereas 21% from key-points and 45% from texture features. On an average improvement is 44%.

$$FAR = \frac{Number\ of\ Samples\ that\ Falsely\ accepted}{Total\ Number\ of\ Samples - Number\ of\ Samples\ that\ Falsely\ accepted} x\ 100 \qquad (i)$$

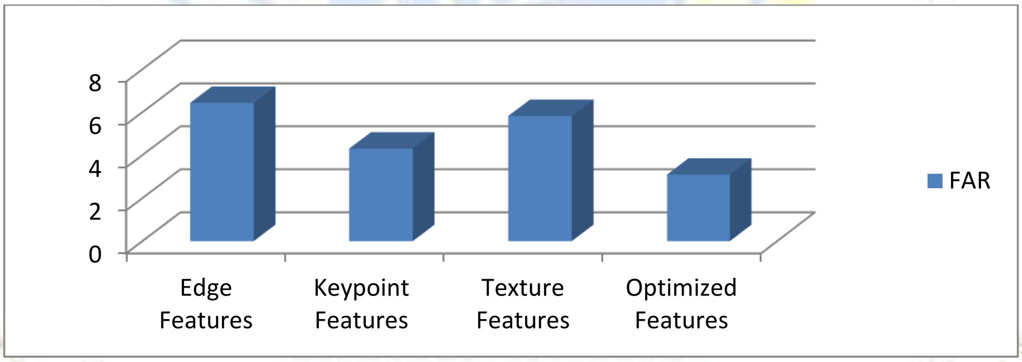


Fig 4: FAR for Different features

The other fig 5 shows the FAR calculated for individual data set of CASIA, IITD and combined data set of both. This figure shows that false acceptance rate is varying with respect to database. Here, the samples of IITD datasets are more falsely accepted if compared with CASIA and when performance of these two datasets are analyzed using 200 samples where 100 samples are taken from each dataset, then it perform averagely fine and better than IITD.

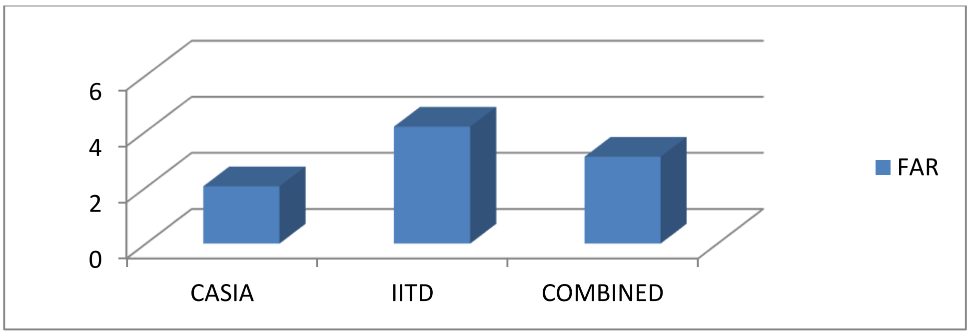


Fig 5. FAR for Different Datasets

False Rejection Rate: The probability that the system fails to audit a match between the matching template in the database list and input pattern. It computes the percent of valid inputs which are incorrectly rejected. In this work, performance has been tested by extracting features individually and combined. This will show that the FRR is least in the case of combined optimized feature where feature selection is also performed after merging all the features as shown in fig. 6. This figure shows that false acceptance rate is improved by 51% from edge features whereas 28% from key-points and 47% from texture features. On an average improvement is 42%.

$$FRR = \frac{Number\ of\ Samples\ that\ Falsely\ rejected}{Total\ Number\ of\ Samples - Number\ of\ Samples\ that\ Falsely\ rejected} x\ 100 \qquad (ii)$$

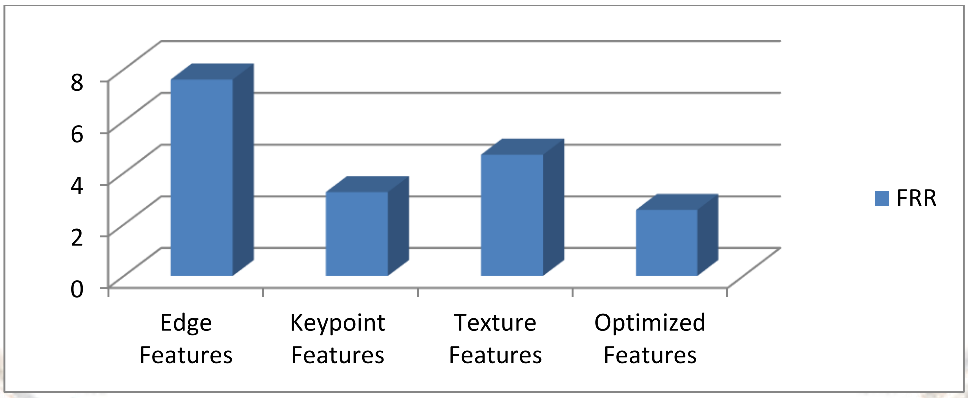


Fig 6: FRR for Different features

The other fig 7 shows the FRR calculated for individual data set of CASIA, IITD and combined data set of both. This figure shows that false rejection rate is varying with respect to database. Here, the samples of IITD datasets are more falsely rejected if compared with CASIA and when performance of these two datasets are analyzed using 200 samples where 100 samples are taken from each dataset, then it perform averagely fine and better than IITD.

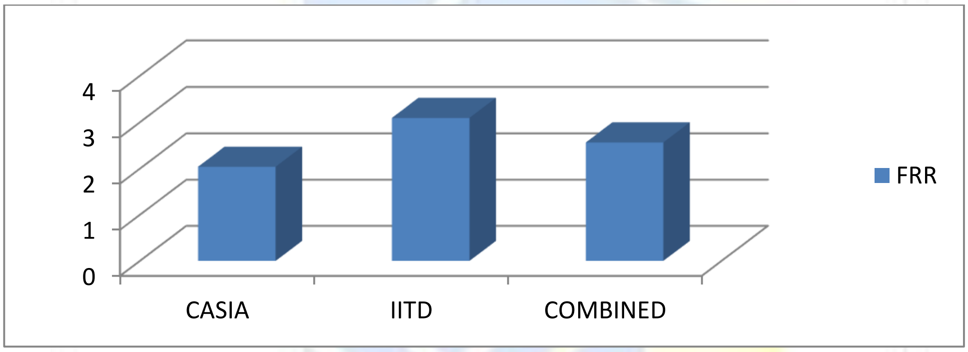


Fig 7: FAR for Different Datasets

Accuracy: The correctness of the system is measured by calculating its accuracy. Accuracy plays a very important role to test a method so that the feasibility of the system is been checked. This proposed work shows that the accuracy is higher in the case of combined optimized feature where feature selection is also performed after merging all the features as shown in fig. 8. This figure shows that accuracy is improved by 9% from edge features whereas 2% from key-points and 3% from texture features. On an average improvement is 4%.

$$\boldsymbol{Recognition\ Accuracy = 100 - \frac{(FAR + FRR)}{2}} \qquad \text{(iii)}$$

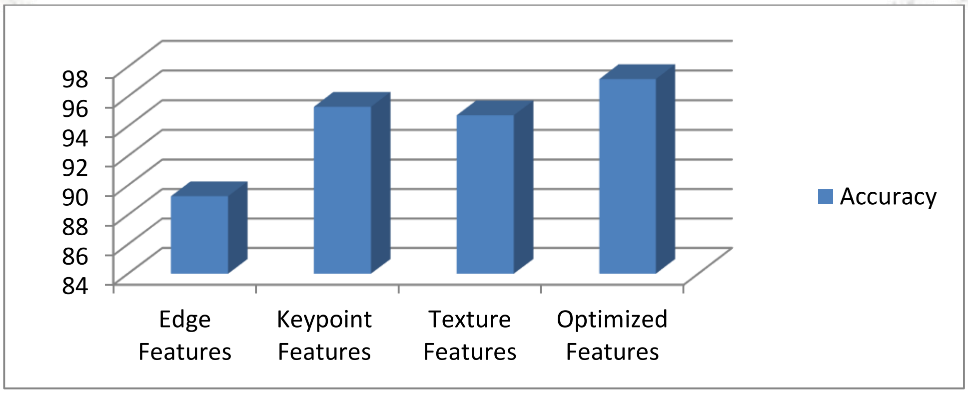


Fig 8: Accuracy for Different features

The other fig 9 shows the accuracy calculated for individual data set of CASIA, IITD and combined data set of both. This figure shows that accuracy is varying with respect to database. In this the accuracy of IITD datasets is poor than CASIA and when performance of these two datasets are analyzed using 200 samples where 100 samples are taken from each dataset, then it perform averagely fine and better than IITD.

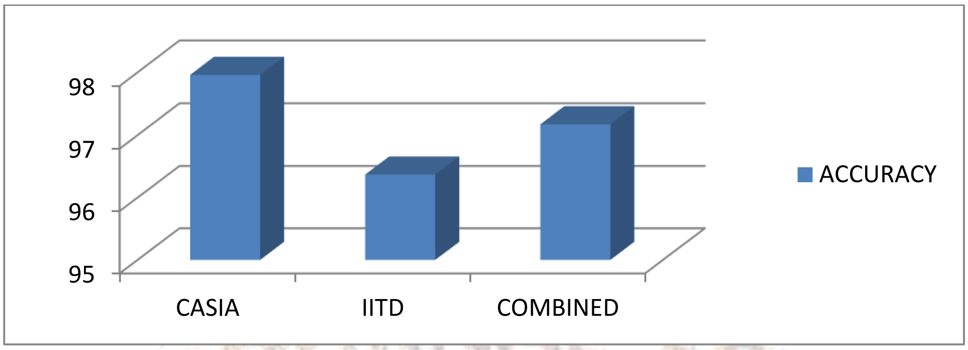


Fig 9: Accuracy for Different Datasets

To analyze the performance of this proposed system Confusion Matrix is used. Confusion matrix is a table which is used to describe the performance of any new recognition system on a set of test data for which the true values are known. There are two possible predicted classes: "yes" and "no". If we were predicting the existence of a sample means that the sample is matched/existed in the database or not. This proposed system is tested on a dataset of 200 samples. Out to 200 cases, this system predicted “yes” 181 times and no “19” times. In reality there are 180 original samples and 20 forged samples.

n=200	Predicted: No	Predicted: Yes	
Actual: No	TN=14	FP=6	20
Actual: Yes	FN=5	TP=175	180
	19	181	

Fig 10: Confusion Matrix

The above confusion matrix contains different factors. These are:

- True positives (TP): These are cases in which predicted value is yes means existed in database, and in reality samples are original.
- True negatives (TN): These are the cases where predicted value is no, and the samples are forged in reality.
- False positives (FP): These are cases in which predicted value is yes, but the samples are not actually original. This is also called as "Type I error."
- False negatives (FN): These are the cases where predicted value is no, but in reality samples are original. This is also known as "Type II error."

Figure 11 shows the performance of the proposed system on the basis of different parameters which is calculated using above defined confusion matrix. **True Positive Rate** is when the samples are actually yes and system predicted it yes. **False Positive Rate** is when the samples are actually no and system predicted it yes. **Specificity** is when the samples are actually no and system predicted it no. **Precision** is when the system predicted it yes and it is correct and **Prevalence** is how often the yes condition actually occurs in the system.

Table 6: Performance Factors based on Confusion Matrix

Performance Factor	Formula Used	Calculations
True Positive Rate	TP/actual yes	175/180
False Positive Rate	FP/actual no	6/20
Specificity	TN/actual no	14/20
Precision	TP/predicted yes	175/181
Prevalence	actual yes/total	180/200

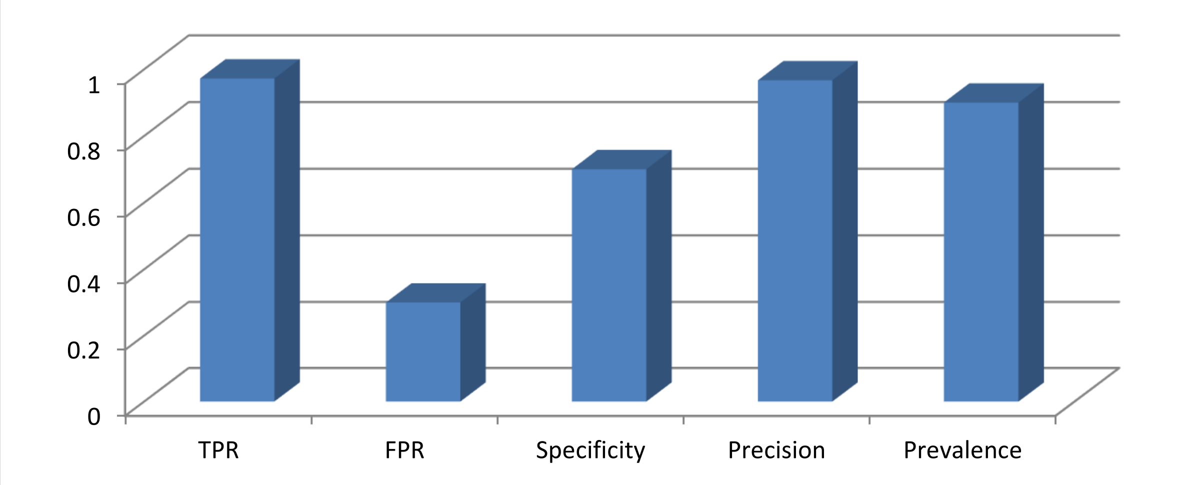


Fig 11: Performance Factors

5. Conclusion

This work is to enhance the multimodal biometric system where iris and fingerprint modalities are used. In this work, edge, keypoint and texture features were extracted for both iris & fingerprint and then combined these features. To reduce the number of features hybrid optimization algorithm is used where firefly and intelligent water drop algorithm is used. These selected features are fused using msum algorithm. Firstly training dataset is prepared and saved into database. Then testing set is used to analyze the performance of this modal where difference performance matrices are used. The results also show that the false acceptance rate is improved by 66% from edge features whereas 21% from key-points and 45% from texture features. On an average improvement is 44% in FAR whereas false acceptance rate is improved by 51% from edge features whereas 28% from key-points and 47% from texture features. On an average improvement is 42% in FRR. This proposed setup also achieves 9% accuracy improved from edge features whereas 2% from key-points and 3% from texture features. On an average improvement is 4% in accuracy. This means the performance of the proposed system is 97% in terms of recognition accuracy. In future, this work will be extended by adding more data sets and testing on different setups with different traits to enhance the performance of biometric based security systems.

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