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# Swarm Intelligence Approaches for Score Level Fusion in Multimodal Biometric Authentication in Airport Security System

**[1] Dr. B. Karthikeyan, [2] Ms. S. Aswini, [3] Dr. B. Narasimhan**

[1]*Assistant Professor, Department of IT and DCFS, Nehru Arts and Science College, Coimbatore - 641105*

[2]*Assistant Professor, Department of IT, Kongunadu Arts and Science College, Coimbatore - 641029*

[3]*Assistant Professor (SG), Department of Computer Science, Nehru Arts and Science College, Coimbatore - 641105*

***Abstract:-*** Multimodal biometric system arise for overcoming the restrictions of unimodal biometrics systems like non-universality, noisy data, spoofs, intra- and inter-class variabilities and so on. In this research the modalities of finger print and iris are used as an Mutlimodal. Matching score level fusion is typically favoured since matching scores are available with ease and comprise enough data for distinguishing between genuine and fraudulent cases. For a particular number of biometrics systems, matching scores may be generated for a predetermined number of users with no knowledge of the underlying features extraction and matching algorithms of all biometrics systems. Hence, combination of data comprised in the matching scores appears both feasible and practicable. In this research work, similarity scores are considered wherein matching scores are used for creating fused templates from the feature of both finger print and Iris for identifying or verifying an individual's identity. For creating a template we propose an Swarm-Intelligene (SI) based algorithm Artificial Bee Colony (ABC) with Artificial-Neural-Network (ANN) as an hybrid model (ABC-ANN). The ANN refer to parallel distribution processors created by processing neurons features that possess natural propensity for storage of experiential expertise and ensuring that it is accessible for usage. The designs of ANNs owe their inspiration to the anatomy of the brain which is a real world model of error-tolerant parallel processing that is both rapid and powerful. ABC algorithm presumes the presence of a set of operations which resemble certain features of the activity of honey bees. Fitness values to create a strong biometric template refer to food source quality which is strongly linked to food location. The procedure mimics bees' search for precious food source giving rise to an analogous procedure for discovering optimum solutions. The database templates and input data are compared by error rates such as FRR, FAR, Accuracy-Rate, and Storage Space Complexity parameters. The FAR, FRR, Accuracy, and Storage Space Complexity are compared with various threshold levels. It had obtained minimal FRR, FAR and Storage Space Complexity for the proposed ABC-ANN in experimental analysis and a higher Accuracy-Rate while comparing it with the existing Gabor-HOG, AOFIS and ACNN method.

***Keywords****: Multimodal-Biometrics, FingerPrint, Iris, Artificial Bee Colony, Neural Network*

## 1. Introduction

Biometrics authentication systems authenticate an individual's claimed identity through behavioural singularities such as signature or voice or even physical singularitiessuch as face, iris or fingerprint [1]. Multimodal biometric system arise for overcoming the restrictions of unimodal biometrics systems like non-universality, noisy data, spoofs, intra- and inter-class variabilities and so on. Multimodal biometric system may be built through usage of more than one physiological or behavioural characteristic for the purpose of recognition or authentication [2]. These kinds of systems are primary built for securityreasons in several fields such as crime research, online commerce or even military applications [3].

The usage of biometrics for access control in restricted architectures has been exhaustively studied in the last half century. Biometrics involves the measurement of unique physiological or behavioural features of an individual as a way or recognizing or authenticating their identity [4]. Typical physiological biometric traits are finger prints, hand geometry, iris, facial features and so on. Behavioural biometric traits are signature, voice, keystroke patterns, gait and so on. Multimodal biometric system built through the usage of fingerprint and Iris requires the user to have physical contact with the capturing device [5].

Score level fusion is the fusion at the matching score level. Various matching scores obtained by several classifiers or from various biometrics may be merged at this level. Fusionin this level may be considered in two approaches: i) It may be considered as a classification issue where feature vector is obtained using matching scores output by individual matchers which are then sorted as either accepted or rejected and ii) It may be considered as an information combination issue where individual matching scores are merged to create one scalar score which is used for making final decision [6].

Multimodal biometric system incorporates data from several biometrics sources for compensating the restrictions in performance of all individual biometrics systems. Matching score level fusion is typically favoured since matching scores are available with ease and comprise enough data for distinguishing between genuine and fraudulent cases. For a particular number of biometrics systems, matching scores may be generated for a predetermined number of users with no knowledge of the underlying features extraction and matching algorithms of all biometrics systems. Hence, combination of data comprised in the matching scores appears both feasible and practicable. In the current work, similarity scores are considered [7].

Typical techniques of classifier fusion at decision levels utilize estimation of average errors of all unimodal classifiers, generally on the basis of resampling of training data. Average modality error data may be employed to weight the unimodal classifier at the time offusion [8]. The shortcoming of this method is that it does not consider the fact that individual decisions rely on the acquisition conditions of the information given to the expert and on the discriminative power of the classifiers. If there are two modalities, the method is similar to the systemic usage of decisions of the more correct modality and thereby, defines the objective of fusion. Signal quality and fraud/client score distributions are used in training weights for classifier combinations of multimodal biometric verification [9].

**Fusion in Multimodal Biometrics:** Biometric systems comprise four significant modules. Sensor module obtains the biometric information from the user; feature extraction module processes the obtained biometric information and extracts features set for representing it; matching module compares the extracted features set with stored templates through usage of classifier or matching algorithm for generating matching score; and decision module wherein matching scores are used for identifying or verifying an individual's identity [10].

The research's problem statement deals with the optimization in the multimodal biometric fusion process. Optimization is a general issue faced in almost all engineering disciplines. Optimization implies the discovery of best possible solution for a fusing process to generate a strong biometric template. The various kinds of optimization issues range widely and are numerous and so techniques for resolving these issues are actively researched.Optimization algorithms are either deterministic or stochastic in nature. The former's attempts to resolve optimization issues need great amounts of computation efforts that fail when problem size becomes larger.

To overcome this problem we found the solution on bio-inspired algorithms. This is the reason for which bio-inspired stochastic optimization algorithms are employed as the operationally effective alternate to the deterministic method. Metaheuristics have their basis in the iterative enhancement of either population of solutions like in Evolutionary Algorithm (EA) or a single solution like in Traditional System (TS) these can utilize randomization and local searches for solving given optimization issues.

The main contribution of this research works is to employ the Swarm-Intelligence (SI)algorithm relied on bio-inspiring process for fusing the individual scores of the Fingerprint and Iris modalities to create a strong template for authentication process. Generally the SI refers to a recent and rising paradigm in bio-inspired computing for the implementation of adaptive systems. In this regard, it is an expansion of Evolutionary Computation (EC). Although EC has its basis in genetic adaptation of organisms, SI has its basis in collective social behaviour of species. Swarm intelligence is defined as the collective intelligence of sets of basic agents which mimic the activity of real world animal swarms, as a problem solving tool. The term 'swarm' comes from the irregular motion of particles in the problem space. SI is formulated along with EC. Trajectory tracking algorithms owe their inspiration tothe group behaviour of animals that display decentralized and self-organizing foraging activity. In this research work, Artificial Bee Colony (ABC) based Neural-Networks are implemented for fusing purpose.

The remainder of this article is categorize as following: Section 2 discusses recent biometrics efforts by various authors, Section 3 discusses the methodology of both proposed and existing approaches, Section 4 compares the outcomes of both proposed and existing approaches with discussions, and Section 5 finally concludes up the article.

## 2. Related Works

The researchers of [11] presented "Hand Movement Orientation and Grasp (HMOG)",a lot of conduct features to consistently validate cell phone clients. HMOG features inconspicuously catch unpretentious small scale development and direction elements coming about because of how a client handles, holds, and taps on the cell phone. They assessed authentication and "Biometric Key Age (BKG)" execution of HMOG features on informationgathered from 100 subjects composing on a virtual console. Their outcomes recommend this is because of the capacity of HMOG features to catch particular body developments brought about by strolling, notwithstanding the hand-development elements from taps.

The researchers of [12] proposed an Ocular biometrics alludes to the utilization of features of the eye for individual acknowledgment. For example, the exceptional and stable surface of the iris has been perceived as a ground-breaking visual biometric trademark. In thisinvestigation, the creators propose to improve biometric authentication with a multimodal visual biometric framework dependent on the iris design and the three-dimensional state of the cornea. They show how the cornea can be utilized as a biometric quality for individual acknowledgment and afterward, they propose an intra-visual fusion with iris features to improve the general execution of the framework.

The researchers of [13] propose a user-centric biometric authentication scheme (PassBio) that empowers end-clients to scramble their very own templates with proposed light-weighted encryption conspire. During authentication, every one of the templates remain encoded to such an extent that the server will never observe them legitimately. Be that as it may, the server can decide if the separation of two scrambled templates is inside a pre- characterized limit. Their security examination demonstrates that no basic data of the templates can be uncovered under both latent and dynamic assaults.

The researchers of [14] presents an understood wearable gadget client authentication component utilizing blends of three sorts of coarse-grain minute-level biometrics: behavioral (step counts), physiological (heart rate), and hybrid (calorie burn and metabolic equivalent of task). From their investigation of more than 400 Fitbit clients from a 17-month long wellbeing study, they can validate subjects with normal exactness estimations of around .93 (stationary) and .90 (non-inactive) with equivalent blunder paces of .05 utilizing parallel SVM classifiers. Their discoveries likewise demonstrate that the hybrid biometrics perform superior to anything different biometrics and conduct biometrics don't have a noteworthy effect, not with standing during non-inactive periods.

## 3. Methodologies

Multimodal biometric recognition systems are more dependable because there are several, non-dependent sets of information available. They aim at the alleviation of the drawbacks of several unimodal biometric systems through the integration of information given by several biometric features. In this research work, a fused Fingerprint-Iris recognitionsystem is presented that is capable of overcoming several implicit problems in unimodal biometric systems. The system further offers anti-spoofing features by ensuring that it is hard for intruders to spoof several biometric features at the same time.

### 3.1 ACNN (EXISTING MODEL)

Combining Finger Print and Iris variables, the existing research presents an ACNN based multi-modality authentication technology. This framework's fundamental architecture is shown in Figure 1. In beginning, images of a specific individual's finger print and iris are collected from databases. Next, employing RT for finger prints and DRS for Iris, features are derived from the modality. Finally, the multi-modality systems, which consist of fusedACNN for finger print and iris classification are employed to build the template for identification [15].

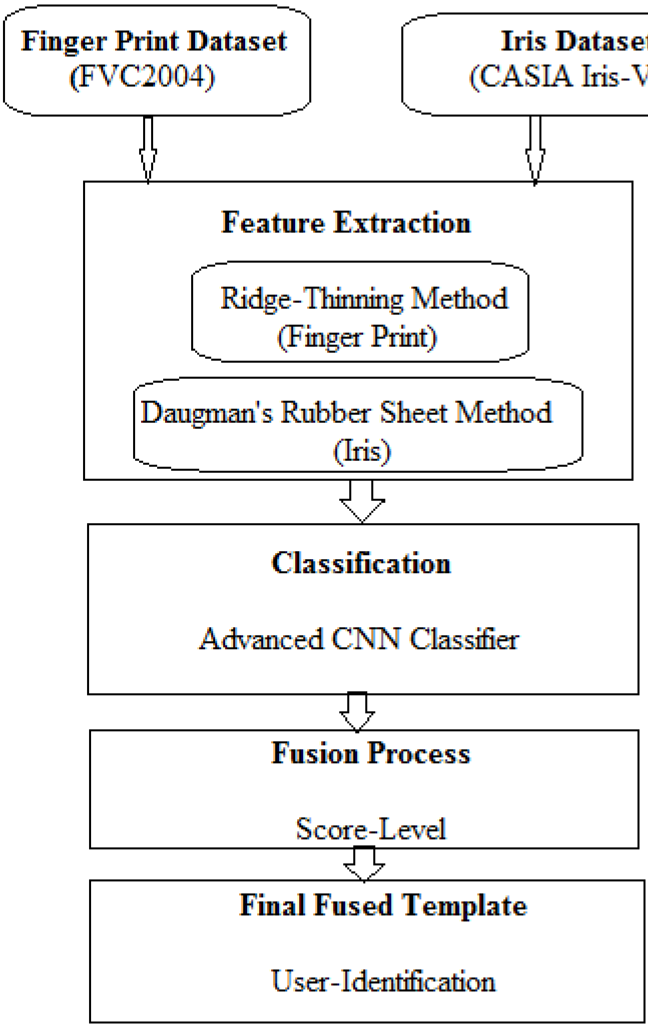


**Figure 1: ACNN Overall Structure**

The research framework in our earlier research [15] was employed to produce this proposed multi-modality authentication technology combining the two features from fingerprint and iris. It starts by testing and training the framework for each feature individually to ensure that each uni-modal system is accurate before merging them into a multi-modality framework. For classifying, the ACNN approach was employed. The correlation scores of the two characteristics, finger print, and iris, were merged using score-level fusing. Two datasets have been chosen for early tests on finger print and iris uni-modal modeling, correspondingly, in required to training and evaluate the framework. Due to the obvious significant benefit here between ease of combining the characteristics' data and greater information richness, score-level fusing has been selected. Furthermore, integrating the scores produced by the several CNN approaches is a very simple process.

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## 3.2 ABC-ANN (PROPOSED MODEL)

### 3.2.1 Feature Extraction of Fingerprints

Feature extraction is done in order to reduce the work to be done on large data. If it tries to match the data, the process becomes very tiring so certain features are taken from the actual data. Hence, this process is called as feature extraction. It describes a large set of data accurately. Fingerprint is a well-established forensic technique with automated fingerprints systems. Since fingerprint is unique for each person it is a very good trait for person identification. No two persons will have the same print and this adds to the advantage of taking fingerprint into consideration. Figure 2 shows the fingerprint sample images.

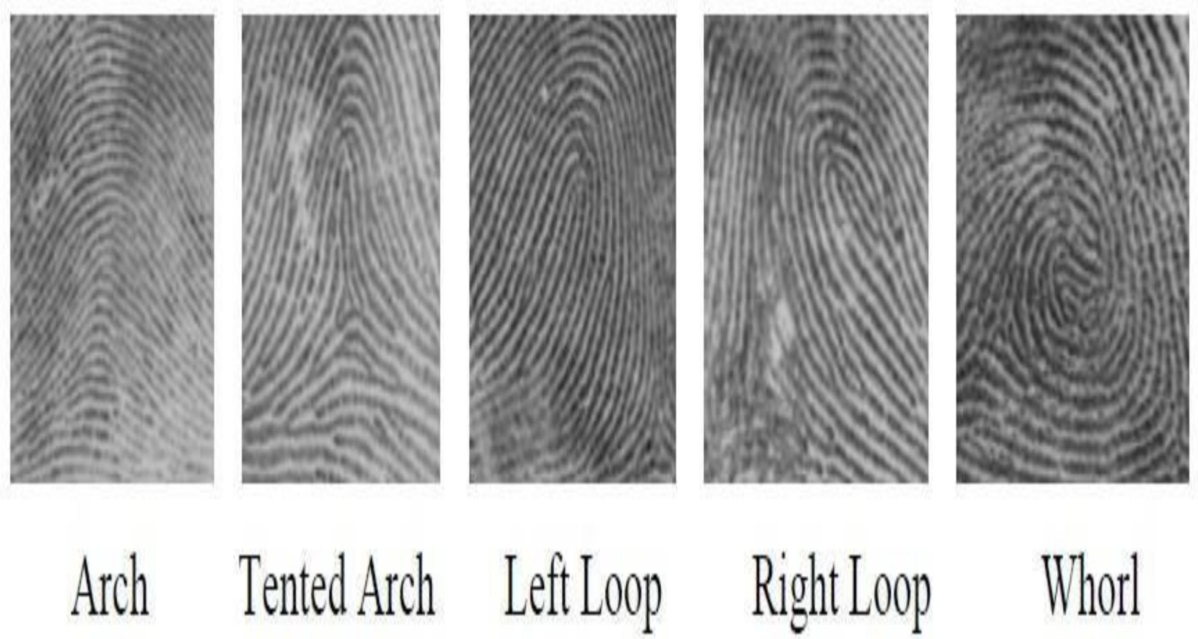


**Figure 2: Fingerprint Sample Images**

The fingerprint has various patterns, the pattern varies in each finger. The various patterns are arch, loop and whorl. Arch is a pattern where the ridges rise in the centre and exiton both the sides. Loop forms loops where the lines enter the finger on a side and the lineafter forming a circle exit through the same side. Whorl is formation of circles from a centre point and continues to spread around without any exit points. Even though the patterns are different, they cannot be considered as patterns though similar for people. The features are called as minutiae. It consists of i) Terminations - It is the termination point of the line, ii) Bifurcations - It is the point where the ridges split into two ridges like a branch.

### (i) Minutiae Extraction

Most of the automatic systems for fingerprint comparison are based on minutiae matching and hence, reliable minutiae extraction is an extremely important task and a substantial amount of research has been devoted to this topic. Most of the proposed methods require the fingerprint gray-scale image to be converted into a binary image. Some binarization processes greatly benefit from an a priori enhancement. On the other hand, some enhancement algorithms directly produce a binary output, and therefore, the distinction between enhancement and binarization is sometimes faded. The binary images are usually submitted to a thinning stage which allows for the ridge line thickness to be reduced to one pixel, resulting in a skeleton image. A simple image allows the detection of pixels that corresponds to minutiae. The minutiae consist of the ridges which are terminations and bifurcations. In order to find the location of the terminations and bifurcations, a 3*3 window is used. If the central pixel value is 1 and has only one 1-value neighbour, then the central pixel is a termination. If the central pixel value is 1 and it has three 1-value neighbours, then the central pixel is a bifurcation. If the central pixel value is 1 and it has two 1-

value neighbours, then the central pixel is just a usual pixel (neither a termination nor a bifurcation). After the extraction, the following steps are done in order to avoid the unnecessary data that have been extracted to get the appropriate data.

### (ii) Region of Interest (RoI)

While scanning the image the image is cut at the edges and those points are also considered to be the termination points and therefore, an error might occur. Therefore, a particular area of interest is considered for the points. Minutiae present at the edges of the images are not actually real minutiae which may happen due to the error of capturing an image. So a RoI is considered and only the minutiae in that area are considered. After performing these particular steps, the features are extracted and they are stored in the form of a template. After all these steps, the features of the fingerprint are obtained.

### 3.2.2 Feature Extraction of Iris

The Iris is the coloured part of the eye. The iris pattern varies from person to person and the most important is that the iris pattern is unique for the same person from the left eyeto the right eye. Therefore, the chances of finding two individuals with the identical iris pattern are almost zero. The human eye is one of the most remarkable sensory systems.

Leonardo da Vinci was acutely aware of its prime significance. Human beings gather most of the information about the external environment through their eyes and thus, rely on sight more than on any other sense, with the eye being the most sensitive organ it has. Besides its consideration as a window to the soul, the eye can indeed serve as a window to the identity ofan individual. It offers unique features for the application of identification technology. Both the highly detailed texture of the iris and the fundus blood vessel pattern are unique to every person by providing suitable traits for biometric recognition. There are many features that canbe considered while considering the eyes but it concentrate on the iris as it is highly unique for all people and also different from one eye to another. Figure 3 shows the iris sample image.

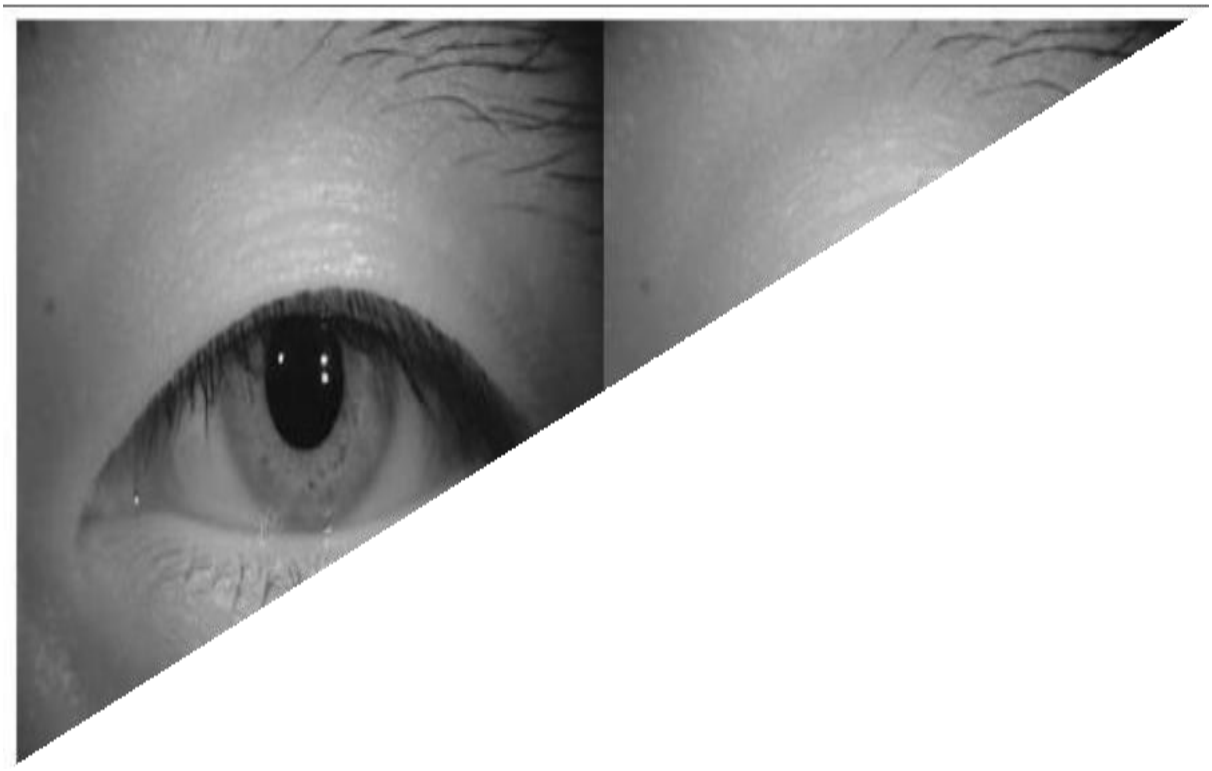

**Figure 3: Iris Sample Images**

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**(i) Iris Segmentation**

The first stage of iris feature extraction is to isolate the actual iris region in a digital eye image. The iris region can be approximated by two circles: one for the iris/scleraboundary and another, interior to the first, for the iris/pupil boundary. The eyelids andeyelashes normally occlude the upper and lower parts of the iris region. In addition, specular reflections can occur within the iris region corrupting the iris pattern. A technique is required to isolate and exclude these artefacts by locating the circular iris region. During segmentation the iris regions are segmented into two circles which are the cornea/sclera outline and the other is the pupil outline. A very good quality of the image is required in order to recognize the features correctly. Canny edge detection is done first to generate the edge and then using the circular Hough transform to detect the iris and pupil boundaries along with the radius, centre coordinates are found. The circular Hough transform is performed only on the iris for more accuracy instead of the whole eye. As a result of performing the circular Houghtransform, six parameters are stored: radius and centre coordinates for both circles.

## 3.3 Artificial Bee Colony-Artificial Neural Networks (ABC-ANN)

Artificial Neural Networks (ANN) refer to parallel distribution processors created by processing neurons that possess natural propensity for storage of experiential expertise and ensuring that it is accessible for usage. Primary advantages of ANN are non-linearity and adaptation which conventional model-fitting methods do not have. The reasons for using ANN as modeling tool are as follows:

i) ANN is able to detect and extract non-linear relations and interactions amongst predictorparameters

ii) ANN's inferred patterns and related estimates of precision are not reliant on assumptionsregarding any parameter distributions

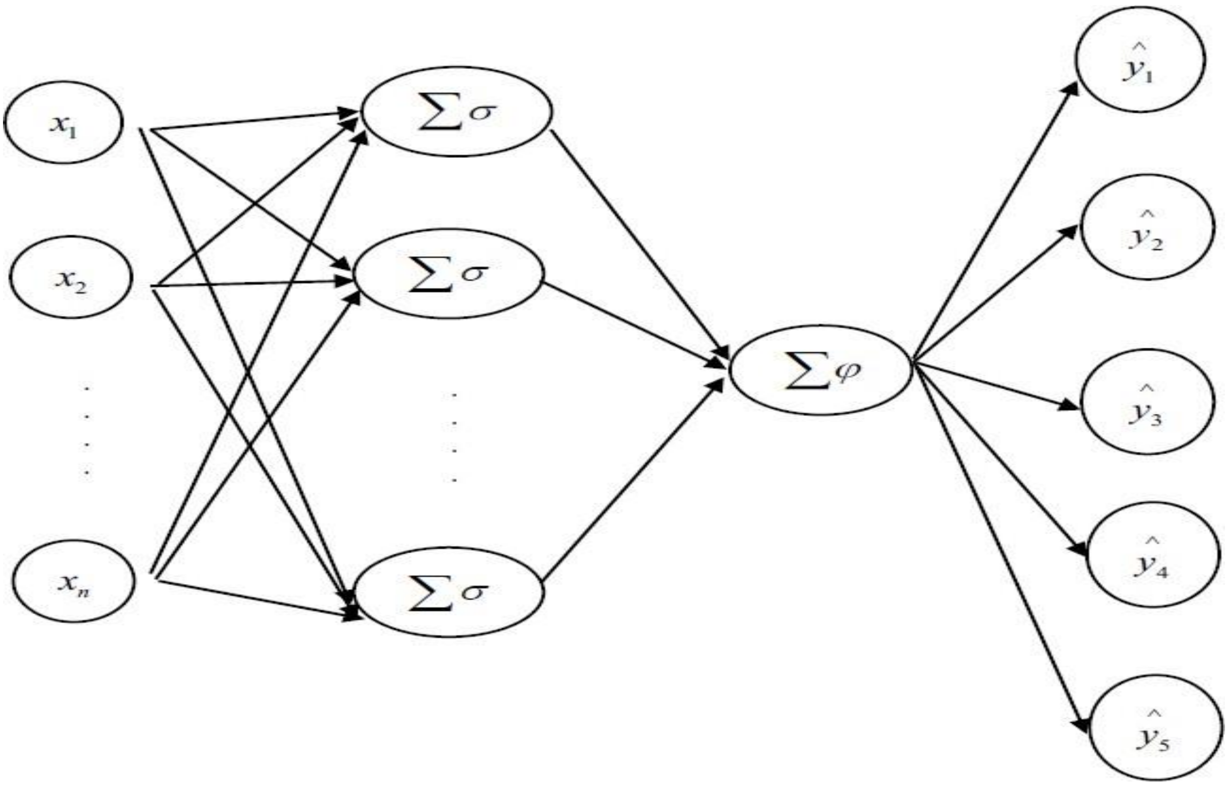


**Figure 4: ANN with one hidden layer and five output neurons**

The designs of ANNs owe their inspiration to the anatomy of the brain which is a real world model of error-tolerant parallel processing that is both rapid and powerful. ANN is generally accepted as a three-layer forward network with an identity transfer function in the middle layer neurons which are capable of approximating all continuous functions randomly as long as there are sufficient middle-layer neurons.

Figure 4 shows a three-layer forward network with inputs "x1, x2,.. xn" and outputs "y^1, y^2 ,....., y^5". All arrows symbolize variables in the network. Networks are split into layers. Input layers comprise data which input to the network. Later, hidden layers are followed that comprise any quantity of neurons or hidden neurons placed parallelly. Most significantly, quantity of hidden neurons is chosen through trial and error technique. All neurons carry out weighted summations of inputs that then pass non-linear activation functions r, additionally known as neuron functions. The functionality of hidden neurons is given in a mathematical form by Equation (1):

$$\sigma\left(\sum_{j=1}^{n} w_j x_j + b_j\right)$$

Eq 1

where the weights and bias "{wj,bj}" are symbolized with arrows feeding into the neuron. Network outputs are formed by other weighted summations of outputs of neurons in the hidden layer. Summations on outputs are known as output layers. In Figure 4, five output neurons in the output layer are present. In typical, the number of output neurons is equal tothe number of outputs of the approximation issue. The outputs of the networks are given in Equation (2):

$$\hat{y}_k(\theta) = \varphi_k(\theta, \mathrm{x}) = \sum_{i=1}^{nh} w_i^2 . \sigma\left(\sum_{j=1}^{n} w_{ij}^1 x_j + b_i^1\right) + b_k^2$$

Eq 2

where n refers to the number of inputs, "nh" refers to the number of hidden neurons, "i" refers to the index with a link "wij" from input "j" to hidden neuron "i, $bi^1$" refers to the bias of hidden neuron "i", while "$b^2$" refers to the bias of output neuron "k (k = 1……5)".The parameters "{$wij^1$, $bi^1$, $w^2$, $b^2$}" refer to the variables of the network model which are denoted in a collective manner by the variable vector "Θ". In general, the neural network models are denoted by "φk(Θ, x)". In the training procedure, the variables are altered in an incremental manner until training data fulfills anticipated mapping where "y^ (Θ)" matches anticipated output "y" as nearly as possible till a maximal quantity of iterations.

ABC algorithm presumes the presence of a set of operations which resemble certain features of the activity of honey bees. For example, all solutions in search spaces include k

variable set denoting food source locations. Fitness values refer to food source quality which is strongly linked to food location. The procedure mimics bees' search for precious food source giving rise to an analogous procedure for discovering optimum solutions.

Minimum model for honey bee colonies comprises of three classes: employed, onlooker and scout bees. The employed honey bee handles the investigation of food sources and share the data with onlookers. They, in turn, make decisions regarding the selection of food sources through examination of the data given to them. Food sources possessing greater quality are more likely to be chosen by the onlookers than those with lesser quality. The employed bees whose food sources are rejected as having lesser quality are changed to scout bees who arbitrarily set out for discovering new food sources. Hence, exploitation is brought about by employed and the onlookers where exploration is brought about by the scouts. Similar to other metaheuristic methods, ABC algorithm is an iterative procedure. It begins with a population of arbitrarily created solutions or food sources. The three operations given below are employed till terminating criteria is fulfilled:

- Send forth employed bees.
- Choose optimal food sources by onlooker bees.
- Determine scout bees.

***Initializing the population:*** The algorithm begins through the initialization of "Np" food sources. All food sources are D-dimensional vectors comprising variable values for optimization that are arbitrarily and uniformly distributed between pre-specified lower initial variable bound "$x_j^{low}$" and the upper initial variable bound "$x_j^{high}$" given in Equation (3).

$$x_{j,i} = x_j^{low} + rand(0,1) \cdot \left(x^{high}\right.$$
$$j = 1, 2, \ldots D$$

Eq 3

with j and i being the variable and individual indexes correspondingly. Therefore, "xj,i" refers to the "$j^{th}$" variable of the "$i^{th}$" individual.

***Send employed bees:*** The quantity of employed bees is the same as the quantity of food sources. In this step, all employed bees generate novel food sources in the neighborhood of the current position as given in Equation (4).

$$\left.\begin{array}{l} v_{j,i} = x_{j,i} + \phi_{j,i}\ (x_{j,i} - x_{j,k}); \\ k \in \{1, 2, \ldots N_p\};\ j \in \{1, 2, \ldots, D\} \end{array}\right\}$$

Eq 4

"$x_{j,i}$" refers to an arbitrarily selected "j" variable of the "$i^{th}$" individual while "k" refersto an "$N_p$" food source, fulfilling the criterion "$i \neq k$". If a particular variable of the potential solution $v_i$ exceeds the pre-specified bounds, the variable is to be modified for fitting into the correct range. Scale factor "$\phi_{j,i}$" refers to an arbitrary number within the range [-1, 1]. When novel solutions are created, fitness values denoting profitability related to certain is computed. Fitness values for minimization problems may be designated to all solutions "$v_i$" through given in Equation (5):

$$fit_i = \begin{cases} \dfrac{1}{1+J_i} & if\ J_i \geq 0 \\ 1 + abs(J_i) & if\ J_i < 0 \end{cases}$$

Eq 5

where "$J_i$" refers to the objective function which is to be made minimum. Greedy selection procedure is therefore employed between "$v_i$" and "$x_i$". If nectar quantity of "$v_i$" is greater, solution "$x_i$" is substituted with "$v_i$" else, "$x_i$" remains.

***Select the food sources by the onlooker bees:*** All onlookers choose one of the suggested food sources, on the basis of their fitness values which have been described by the employed bees. The likelihood that a food source will be chosen is got from the Equation (6):

$$\text{Prob}_i = \frac{fit_i}{\sum_{i=1}^{N_p} fit_i} \quad \text{Eq 6}$$

where "$fit_i$" refers to the fitness value of food source "i", that is associated with the objective function value "($J_i$)" relating to the food source "i". The likelihood of a food source being chosen by onlookers rises with a raise in fitness values of food sources. Once food sources are chosen, onlookers go to the chosen food source and choose a fresh potential food source position in the neighborhood of the chosen food source. The fresh potential food source may be denoted and computed by "$v_{j,i}$". If the nectar quantity is greater than that of thenew solution, the position is held, else the last solution remains.

***Determine the scout bees:*** If food source i is not capable of being enhanced further through a pre-specified trial number called "***limit***", food source is regarded as abandoned and therelated employed bee is changed to a scout. Scouts explore search space with no prior data, i.e., novel solution is created arbitrarily as denoted by "$x_{j,\,i}$". For Verification, if potential solutions have arrived at the pre-specified limit, counter "$A_i$" is designated to all food sources. Counters are incremented subsequently to a failure of a bee operation for improving the fitness of food source. The ABC based ANN is shown in Figure 5.

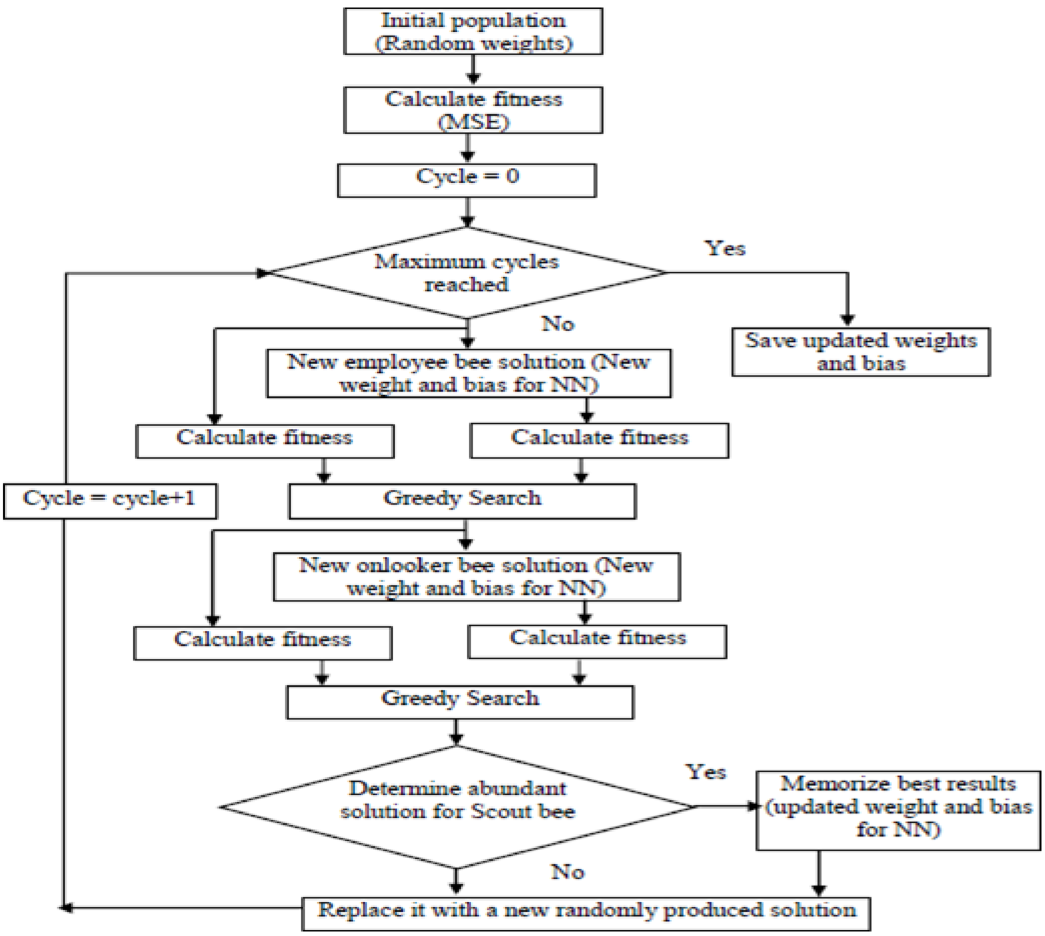


**Figure 5: The flow diagram of the ABC based ANN**

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***ABC based ANN is developed by the steps given below:***

1. Set up population through arbitrary distribution. Let it be denoted as "$pop_{in}$" possessing population size of "$N_{ps}$"solutions. Let the solutions be represented by D-dimensional vectors expressed as "$sol^j$",where "$1 \leq j \leq N$". Here, "D" refers to the number of optimization variables involved. This is the initial weight and bias for the NN training.

2. Test the population with the use of fitness function that is the Minimum "Mean Squared Error (MSE)".

3. For all iteration cycles, continue the following steps (4-12).

4. Position is updated through:

Eq 7

where, "$npos_{j,k}$", refers to the novel position, "$opos_{j,k}$", refers to the old position, "$r_{j,k}$" represents an arbitrary number between [−1, 1]. This is the new weights and bias for the Neural Network.

5. Calculate the fitness for the new solution for employee bee.

6. Use greedy search between "$npos_{j,k}$" and for "$opos_{j,k}$" employee bee.

7. Calculate the probability value for the solution through:

$$\Pr_j = \frac{Fit_j}{\sum_{k=1}^{N_{ps}} Fit_k} \qquad \text{Eq 8}$$

Here, "$Fit_j$" refers to the fitness value for the solution "j". The value is computed for the onlooker bee.

8. Compute the updated position for the onlooker bee through:

$$npos_{j,k} = opos_{j,k} + r_{j,k}(sol_{j,k} - sol_{i,k}),\ i \neq j \qquad \text{Eq 9}$$

This is the new weights and bias for the Neural Network.

9. Calculate the fitness for the updated positions for onlooker bee through MSE.

10. Utilize greedy search between "$npos_{j,k}$" and for "$opos_{j,k}$" onlookers.

11. Check for abandoned solution for scout. If there are scouts, then substitute it with novelarbitrary solution through:

$$opos_j^{\,k} = opos_{min}^{\,k} + rand(0,1)(opos_{max}^{\,k} - opos_{min}^{\,k}) \qquad \text{Eq 10}$$

12. Retain the best solution for the cycle and this forms the new weight and bias for the ANN.

13. Stop the cycle when cycle count crosses the maximal count. Save the updated weight andbias for the ANN and this mark the end of the training of ANN.

14. The test data (scores form two modalities) is provided to the trained ABC-ANN Networkfor producing the result.

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## 3.4 SCORE FUSION

Feature set consists of features from two modalities viz., fingerprint, and iris. Featuresfrom two modalities are matched individually and subsequently and fusion of scores iscarried out using neural network.

### (i) Extraction of two traits:

### (a) Fingerprint:

Each minutiae points extracted from a fingerprint image is denoted as (x,y) coordinates. In this regard, it stores those extracted minutiae points in two different vectors: vector "F1" comprises every "x" coordinate values and vector "F2" comprises every "y" co- ordinate values in Equation (11).

$$F_1 = [x_1\ x_2\ x_3\ \ldots\ x_n];\ \ F_2 = [y_1\ y_2\ y_3\ \ldots\ y_n];\ |F_1| \text{ and } |F_2| = n$$

Eq11

### (b) Iris:

The texture properties obtained from the log-Gabor filter are complex numbers "(a+ib)". Equivalent to fingerprint representation, it also stores the iris texture features in two various vectors: vector "I1" includes the real part of the complex numbers and vector "I2" includes the imaginary part of the complex numbers in Equation (12).

Eq12

The four vectors namely "F1, F2, I1 and I2" are fed as input to the fusion process. The multimodal biometric template is obtained from the output of the fusion process.

### (ii) Score Computation

Initially, the score is calculated for the two modalities individually and the fusion of the two scores is carried out with the different classifiers. The score for each individual feature is calculated as the Euclidean distance. Suppose, the feature be represented as "f =

{f1, f2,…, fn}" and the feature in the database be "f' = {f1', f2',..., fn'}", then Euclidean distance is given by Equation (13):

$$d = \sqrt{\sum_{i=1}^{n} (f_i' - f_i)^2}$$

Eq13

Similarly, the two feature scores (fingerprint,and iris) are computed using the Euclidean distance.

## 4. Results And Discussions

Tests were carried out on a series of image data of 50 participants for studies utilizing the proposed framework. These involve five fingerprint images from the fingerprint database FVC 2004 and five CASIA-Iris V2 iris image databases. The ErrorRates are termed as FAR and FRR. The FalseAcceptanceRate (FAR) is to validate the risk of an individual becoming misidentified as another user. The FalseRejectionRate (FRR) is to validate the possibility thata reported person is not detected by the method. According to the statistical analysis we have used the above experiments to determine the inter-class and intra-class thresholds to identify

the FAR and FRR. By varying the threshold values we can identify which method provides better efficiency. The performance of FAR was compared for both proposed and existing models with different threshold levels shown in Table 1 and Figure 6. The threshold level means about the quality of the images from 1.5 good quality to 5.5

bad quality. The results shows that phase 3 (ABC-ANN) produce lower FAR Rate when compare it with base paper (GABOR-HOG), phase 1 (AOFIS), phase 2 (ACNN).

**Table 1: FAR Comparision**

| THRESHOLD LEVEL | GABOR-HOG | AOFIS | ACNN | ABC-ANN |
|---|---|---|---|---|
| 1.5 | 0.4 | 0 | 0 | 0 |
| 2.5 | 0.7 | 0.1 | 0 | 0 |
| 3.5 | 1.3 | 0.3 | 0.1 | 0 |
| 4.5 | 2.7 | 0.6 | 0.3 | 0.1 |
| 5.5 | 3.9 | 0.9 | 0.5 | 0.3 |

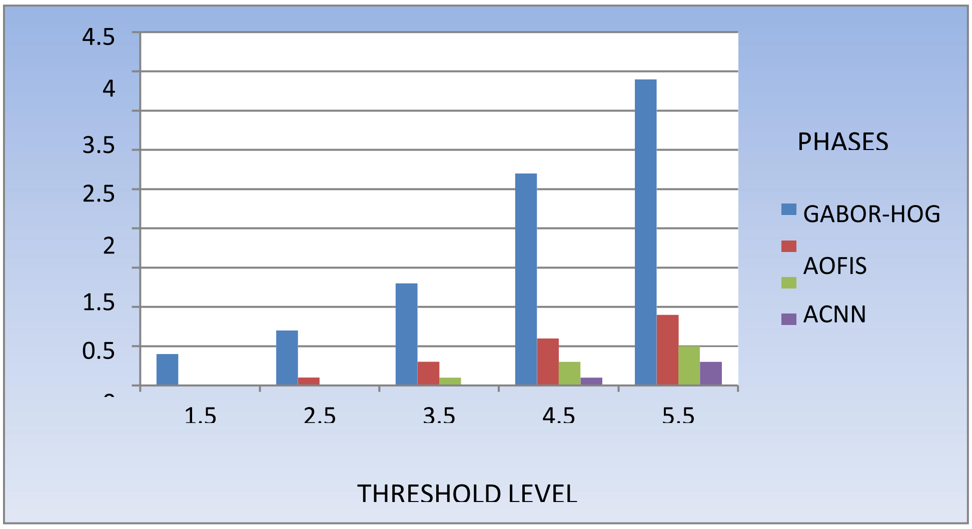


**Figure 6:FAR Comparison Graph**

The performance of FRR was compared for all phases and base paper models with different threshold levels shown in Table 2 and Figure 7. The threshold level means about thequality of the images from 1.0 good quality to 5.0 bad quality. The results shows that phase 3 (ABC-ANN) produce lower FRR Rate when compare it with base paper (GABOR-HOG), phase 1 (AOFIS), phase 2 (ACNN).

**Table 2: FRR Comparision**

| THRESHOLD LEVEL | GABOR-HOG | AOFIS | ACNN | ABC-ANN |
|---|---|---|---|---|
| 1.5 | 10 | 0 | 0 | 0 |
| 2.5 | 30 | 4 | 1 | 0 |
| 3.5 | 45 | 15 | 6 | 2 |
| 4.5 | 70 | 25 | 11 | 4 |
| 5.5 | 95 | 30 | 16 | 7 |

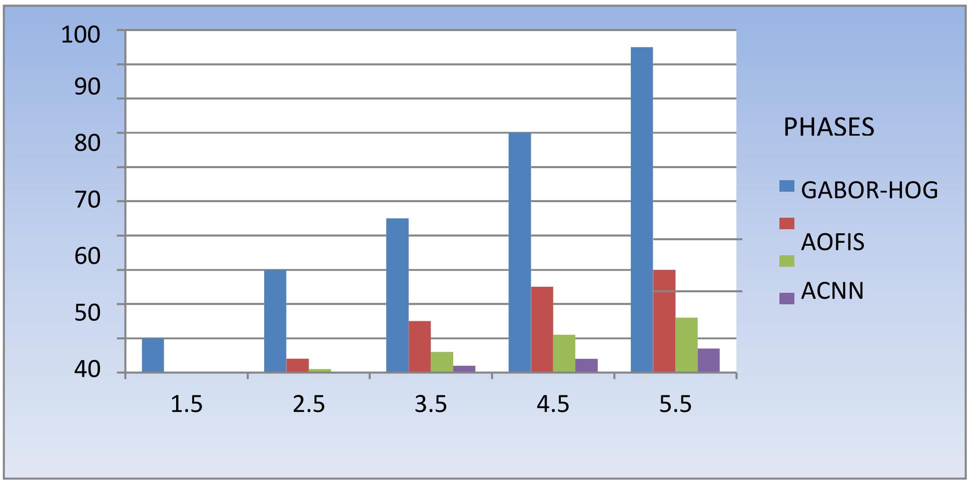


**Figure 7: FRR Comparison Graph**

Comparison of the Accuracy-Rate is done for each phases and basepaper models. Based on the findings, it concludes that the accuracy of the phase 3 method is higher than thatof the base paper, phase 1 and phase 2 methods. This study reveals that the phase 3 offers better performance following the results of multimodal systems applied with typical matches. The performance of Accuracy was compared for all phases with different threshold levels shown in Table 3 and Figure 8.

**Table 3: Accuracy Comparision**

| THRESHOLD LEVEL | GABOR-HOG | AOFIS | ACNN | ABC-ANN |
|---|---|---|---|---|
| 1.5 | 75 | 90 | 95 | 99 |
| 2.5 | 60 | 82 | 91 | 97 |
| 3.5 | 50 | 79 | 87 | 94 |
| 4.5 | 40 | 72 | 83 | 91 |
| 5.5 | 35 | 65 | 79 | 87 |

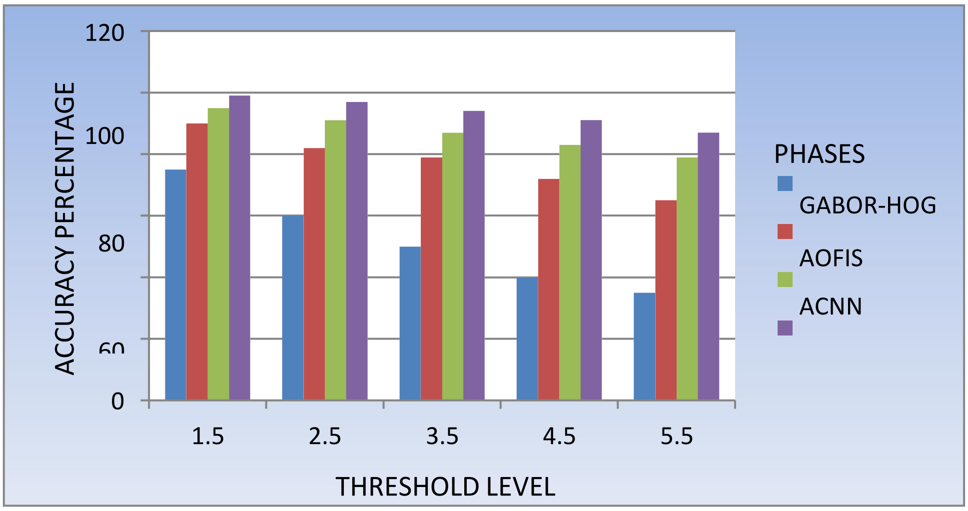


**Figure 8: Accuracy Comparison Graph**

The storage space complexity is evaluated as the amount of memory space is consumed to store the constructed template in the server. The space complexity is measuredin terms of KiloBytes (KB). The lower value of space complexity ensures better performance of the technique.

**Table 4: Storage Comparision**

| NUMBER OF USER DATA | GABOR-HOG | AOFIS | ACNN | ABC-ANN |
|---|---|---|---|---|
| 10 | 390 | 230 | 190 | 90 |
| 20 | 460 | 310 | 280 | 160 |
| 30 | 570 | 430 | 370 | 230 |
| 40 | 790 | 610 | 460 | 310 |
| 50 | 970 | 750 | 550 | 390 |

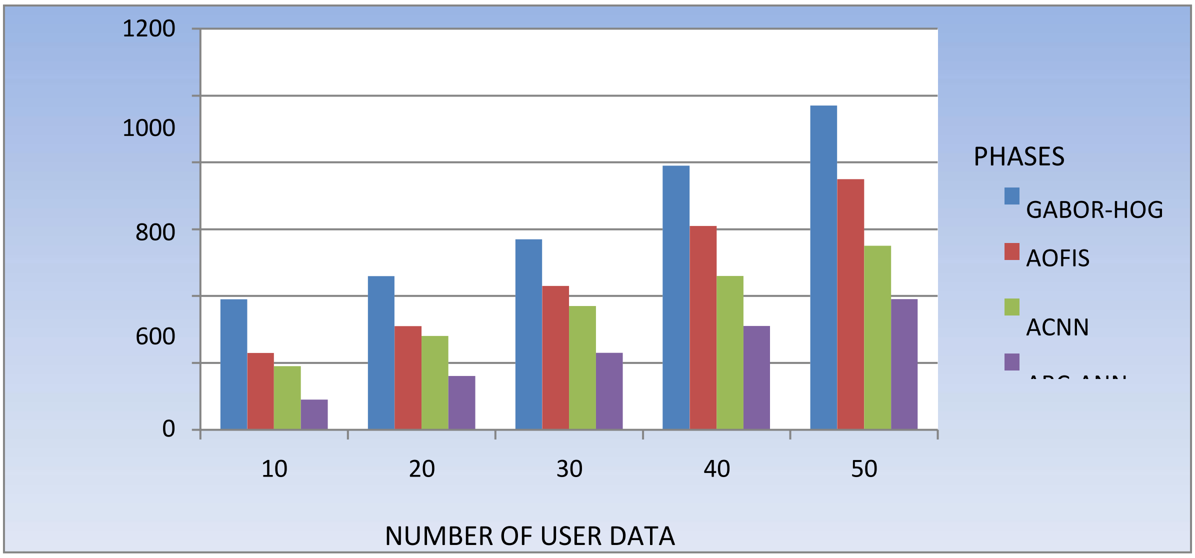


**Figure 9: Storage (Memory Size) Comparison Graph**

Table 4 and Figure 9 shows the experimental results of the storage space complexity based on the different number of biometric templates. The number of biometric template data is considered from the range of 10 to 50 which is taken as input while conducting the experiments. The performance of Space complexity gradually changes in the above methods with the respect to the number of biometric template data in the server. Here, the proposed model effectively minimizes the memory space than the existing models.

## 5. Conclusion

Multimodal biometrics is an active research area that offers more reliability andaccuracy. In the current study, multimodal biometric score fusion is carried out with the assistance of ANNs. The two features which are chosen for fusion are finger prints, and iris because of their efficacy and resilience to spoofing. The kind of fusion used in the system is score level fusion. Neural network classifier method is selected for exploiting excellent learning efficacy. The system carried out training of the neural networks through the usage ofrecently formulated evolutionary algorithm, the ABC algorithm. In the current work, neural network models are constructed which is optimized by ABC with adequate training procedurefor approximate gene expressions and also comparison is made on the training capability. Results show that the accuracy of the proposed model performs better by than the existing models.

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