

An Efficient Fingerprint Identification using Neural Network and BAT Algorithm

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Article Info

Article history:

Received Nov 15, 2017

Revised Dec 27, 2017

Accepted Jan 5, 2018

Keyword:

BAT algorithm

Classification

Histogram equalization

Hybridneural network

Median filter

ABSTRACT

The uniqueness, firmness, public recognition, and its minimum risk of intrusion made fingerprint is an expansively used personal authentication metrics. Fingerprint technology is a biometric technique used to distinguish persons based on their physical traits. Fingerprint based authentication schemes are becoming increasingly common and usage of these in fingerprint security schemes, made an objective to the attackers. The repute of the fingerprint image controls the sturdiness of a fingerprint authentication system. We intend for an effective method for fingerprint classification with the help of soft computing methods. The proposed classification scheme is classified into three phases. The first phase is preprocessing in which the fingerprint images are enhanced by employing median filters. After noise removal histogram equalization is achieved for augmenting the images. The second stage is the feature Extraction phase in which numerous image features such as Area, SURF, holo entropy, and SIFT features are extracted. The final phase is classification using hybrid Neural for classification of fingerprint as fake or original. The neural network is unified with BAT algorithm for optimizing the weight factor.

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1. INTRODUCTION

Multi-biometric recognition [1] and biometric template protection [2] are defined in this work to derive developments in the field of biometric recognition. The use of multi-biometric recognition improves the reliability and accuracy compared to the existing biometric system. An Automatic recognition system uses biometric indicator and it produces high error rates [3]. Biometric vendors are used the Multi-biometric system (e.g. fingerprint and finger vein by SAFRAN Morpho1) and it require large data sets (e.g. within the Aadhaar project [4] by the Unique Identification Authority of India (UIDAI)). The multi-biometric system provides multiple information about the same object and it the template of multi-biometric system requires more security. Missing of any information from biometric template delete the person identity and creates security problems. For instance permanency following from claiming subjects without assent [5], [6] alternately remaking from claiming unique biometric qualities (e. G. Fingerprints [7] alternately iris textures may turn into a sensible danger. That biometric format ought a chance to be secured by giving work to protection Also integument about saved biometric information. Format protections schemes give provable security alternately privacy, Furthermore useful recognition rates gotten are elusive, Indeed around little datasets.

Fingerprints are the unique characteristic of humanity. Fingerprint classification restores computational complexity by reducing the number of candidate campaigns to be preceded [8]. Fingerprint images are widely used in different systems, such as personal empathy, access control, Internet authentication and the generation of encryption keys due to their durability, uniqueness and distinctive character. The characteristic of the fingerprint system is affected by the image quality of the fingerprint [9]. The identification of fingerprints, however, is a computer-based challenge especially for databases. An operational indexing system provides a great help. Fingerprint classification classifies fingerprints into a set of predefined sets, and then makes the identical task possible [10].

Fingerprint classification is a granular level apportioning of a large fingerprint database, where the class of the input fingerprint is primarily persistent and therefore, a search is conducted inside the group of fingerprints suitable to the similar class as the input fingerprint [11]. The authentication process is secured by decreasing the number of comparisons that are essentially achieved. It is attained by isolating the fingerprint database into a number of classes. Fingerprint recognition is prerequisite to be associated only to the fingerprints in a single class of the database on the basis of its features. Fingerprint identification is broadly used due to ease in the characteristic acquisition; the ten fingers are accessible for collection and their usage and assortments of law implementation and immigration [12]. Fingerprint classification and acknowledgment schemes are inspiring missions for hackers as it includes unique identification technique, incorporating Data Mining methods such as Neural Networks and K Nearest Neighbor algorithms, the intelligence stage of the fingerprint identification is enhanced which safeguard accuracy and protected recognition [13].

The rest of the document is organized as follows: Section 2 defines a concise description of the latest research work; Section 3 refers to the processes that are part of our masterpiece method with surprising demonstrations and mathematical formulations. While Section 4 elucidates the results of the experimentation, Section 5 concludes the work.

2. RELATED WORK

Patil and Suralkar described a method of fingerprint classification scheme on the basis of ANN. Fingerprint identification scheme usages prior organization of fingerprint with minutiae feature [14]. In traditional methods performance of minutiae abstractions depend intensely on an augmentation algorithm. Thus several fingerprints are composed, taking a long time to match and authenticate a specified fingerprint. So as an alternative of classification with the minutiae [15] they projected a classification scheme that was on the basis of individual features such as the singular point. Singular point detection was very robust and reliable that overcomes the issue about rotation and translation.

Daramola et al. [16] projected a robust verification scheme on the basis of features abstracted from human fingerprints and a pattern classifier known as Support Vector Machine (SVM). Efficient fingerprint verification scheme was desired in numerous places for personal empathy to access physical facilities, data etc. Three group of features are attached together and passed to the classifier. The fused feature was utilized to train the scheme for operative verification of consumers fingerprint images.

Liu et al. [17] described a touch less multitier fingerprint capture scheme that acquires three dissimilar aspects of fingerprint images at the similar time. This gadget might have been planned Eventually Tom's perusing upgrading parameters in regards to those caught finger impression picture caliber and gadget measure. This machine was intended by optimizing parameters concerning the captured fingerprint image eminence and device size. A fingerprint mosaicking method was anticipated to splice together the captured images of a finger to form an image with a greater valuable print arena. Optimization design of their device was established by familiarizing the design process and associating with present touch less multitier fingerprint acquirement devices.

Latent prints are habitually improved from offense scenes and are connected with accessible databases of recognized fingerprints for recognizing criminals. However, current procedures to compare latent prints to great databases of exemplar (rolled or plain) prints are predisposed to errors. This recommended caution in creating conclusions about a suspect's identity on the basis of a latent fingerprint comparison. A cardinal of efforts accept been fabricated to statistically archetypal the account of a fingerprint appraisal in authoritative a actual accept/reject accommodation or its apocalyptic value. These methods, though, either accomplish unrealistic expectations about the archetypal or they abridgement simple clarification.

Nagar et al. [18] have contended that the posterior probability of two fingerprints fitting to dissimilar fingers provided their match score, mentioned to as the nonmatch probability (NMP), efficiently detentions any associating indication of the comparison. NMP was calculated by state-of-the-art matchers and was tranquil to understand. To integrate the effect of image quality, number of minutiae, and size of the

dormant on NMP value, they calculated the NMP vs. match score plots distinctly for image pairs (latent and exemplar prints) with dissimilar features.

Paulino et al. [19] projected a fingerprint matching algorithm that was particularly designed for matching latents. Recognizing suspects on the basis of impressions of fingers lifted from crime scenes was a routine process that is enormously significant to forensics and law implementation agencies. The projected algorithm utilizes a robust alignment algorithm to align fingerprints and trials similarities within fingerprints by taking into account both minutiae and orientation field data. To be consistent with the common practice in latent matching the orientation field was reassembled from minutiae. Subsequently, the projected algorithm depend only on manually marked minutiae, it could be effortlessly utilized in law enforcement solicitations.

Sankaran, et al. [20] focused on automatically segmenting latent fingerprints to distinguish between ridge and non-ridge patterns. There were three real commitments about that method: (a) An machine Taking in calculation to joining five diverse Classes of features for programmed idle finger impression segmentation, (b) a feature selection procedure utilizing changed reduction plan for dissecting those impact of various classification offers for idle finger impression segmentation, Furthermore (c) a novel SIVV built metric will measure the impact of the segmentation algorithm without the prerequisite will perform those whole matching transform. Those picture might have been decorated under nearby patches What's more saliency based Characteristics alongside image, gradient, ridge, What's more personal satisfaction based features were concentrated. Characteristic Choice might have been performed should ponder the commitment of the Different classification features towards closer view edge example representational.

Aliakbarzadeh, et al. [21] indicated that the GC-FID chromatograms of saffron samples were baseline corrected and aligned using asymmetric least squares (AsLS) and correlation optimized warping (COW) methods, respectively. Then, those entirety advanced profiles from claiming preprocessed chromatograms were normalized will internal standard, mean-centered, pareto-scaled Also At last demonstrated finally perusing PLS-DA to arrange saffron specimens as stated by their development regions. Afterwards, execution of distinctive variable determination techniques (i.e., rPLS, VIP, SR, sMC and loading weights) for picking the the vast majority vital variables (i.e., maintenance occasion when points) for GC-FID fingerprints, were compared As far as the model's interpretability Also unoriginality.

Raid Al-Nima, S. S. Dlay et al [22] proposed human authentication method in which Finger Texture (FT) patterns was used to make it efficient. To differentiate the fingers from the hand images, a robust and automatic finger extraction method was used. Enhanced Local Line Binary Pattern (ELLBP) was used to extract new features. The information embedded within the poorly imaged regions of the FTs a method is suggested to salvage missing feature elements. Classification was done by performing Probabilistic Neural Network (PNN).

Raid Al-Nima, S. S. Dlay et al [23] defined an approach which authenticates based on their finger textures. Finger Texture (FT) features of the four finger images (index, middle, ring and little) are extracted from a low resolution contactless hand image. To enhance the FTs, new Image Feature Enhancement (IFE) was used method to enhance the FTs. The resulting feature image is segmented and a Probabilistic Neural Network (PNN) is employed to classify intelligently for recognition.

Fingerprint matching is a critical issue to recognizing fingerprints What's more assumes a way part in the fingerprint distinguishment systems. However, performing fingerprint ID number in an expansive database might a chance to be an wasteful errand because of those absence of versatility Also secondary registering times from claiming fingerprint matching calculations. Fingerprint indexing may be an magic system to programmed fingerprint ID number frameworks which permit us to decrease the number of candidates, the look space, and the occurrences of false acknowledgement clinched alongside substantial databases. Javad Khodadoust and Ali Mohammad Khodadoust, [24] proposed an efficient indexing algorithm using minutia pairs and convex core point which employed k-means clustering and candidate list reduction criteria to increase the recognition performance. Their proposal could successfully reduce the search space and number of candidates for fingerprint matching, and thus achieved higher matching scores and considerably improved the system repossession performance.

3. NEURAL NETWORK AND BAT ALGORITHM BASED FINGERPRINT CLASSIFICATION

Fingerprint image classification has become an interesting topic in recent years because of the unique nature of fingerprints in the authentication process. The fingerprint authentication is regarded as one of the most secure ways of protecting the user information's due to its uniqueness and durability. Due to the widespread usage, there also exists some disadvantage like creating fake fingerprints in order to access the information. Hence the classification of fingerprint has become a much needed process while using fingerprint as an authentication technique. We have designed an efficient technique for fingerprint classification using soft computing techniques. The proposed classification system can be divided into three

stages. The first stage is the preprocessing stage where the fingerprint images are subjected to noise removal using the median filter. After noise removal histogram equalization is performed for enhancing the images. The second stage is the feature extraction stage. Here various image features like Area, holo entropy, SURF and SIFT features are extracted. The final stage in the proposed system is classification. We have utilized hybrid neural network for classification of fingerprint as fake or original.

3.1. Problem definition and Objectives

Fingerprint technology is a biometric method that is used to recognize persons on the basis of their physical traits. Fingerprint based authentication systems are becoming increasingly common these days. However, due to the excessive use of fingerprint security systems, they have become a target of attacks. The reputation of the fingerprint image regulates the durability of a fingerprint authentication scheme. We have designed an efficient technique for fingerprint classification using soft computing techniques.

Objectives:

- To protect biometric template with high security.
- To avoid cross-comparison of biometric templates in databases.
- To establish soft biometrics idea.
- To provide revocability to biometric templates.
- To impart revocability to biometric templates.
- To permit diversity to biometric templates.
- To make sure that the authorized user is recognized perfectly.

3.2. Fingerprint Classification

The neural network is incorporated with BAT algorithm for optimizing the weight factor. The flow diagram of our proposed system is shown in Figure 1.

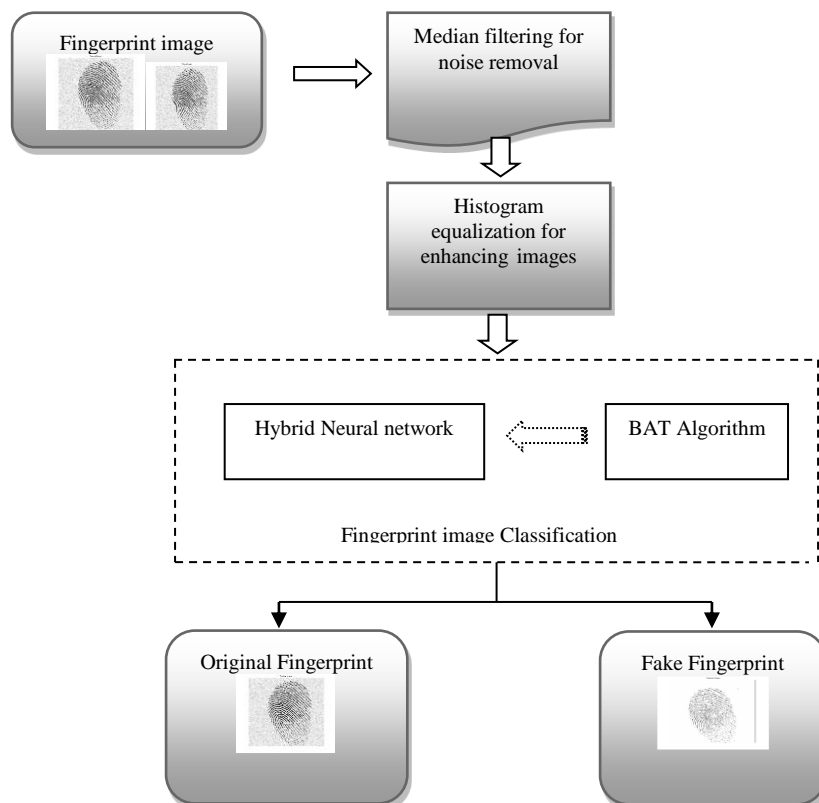


Figure 1. Flow diagram for proposed method

3.3. Noise Removal using Median Filter

Noise removal is a significant stage in image processing. In our projected technique we apply a median filter for the noise removal. The median filter is frequently employed to overcast worth images due to

its belongings of control protective flattening. In the median filtering operation, the pixel values in the vicinity window are graded according to intensity, and the median value turn out to be the output for the pixel under evaluation. The succeeding stages were accustomed to eliminate the noise from images,

In median filtering, the adjacent pixels are graded in line with illumination and the average value turn out to be the new central pixel value. Median filter ensures the brilliant work of rejecting particular forms of noise, in the actual, “shot” or impulse noise in which some individual pixels have higher values. The common countenance for the median filter is assumed as per Equation (1),

$$O_{mf}(x_1, x_2, \dots, x_m) = \min\left(\sum_{l=1}^m \|x_1 - x_l\|, \dots, \sum_{l=1}^m \|x_m - x_l\|\right) \quad (1)$$

Where,

O_{mf} - Median Filtered output

x_1, x_2, \dots, x_m - Number of pixels under evaluation

m - Number of pixels

Here, m represents the total number of pixels in the image and x_1, x_2, \dots, x_m represents the pixels from first to m . With Equation (1), the median filtering is executed to eliminate the noise from the developed image. Once the noise removal stage is completed, the next stage is image enhancement where we utilize histogram equalization for enhancing the image.

3.4. Image Enhancement using Histogram Equalization

The histogram equalization represents a computer image processing method effectively employed to enhance the contrast in images. Let the original input be I and the equalized image of the histogram be I_h . The underlying motive behind the novel technique is involved in creating an enriched image, equipped with enhanced visual excellence far superior to I . However, it is easy to design a renovation function which is well-g geared to automatically realize the relative mapping impact, only in accordance with the data existing in the histogram of the input image.

Each bin representing the constraint of HE of a histogram in a gray scale image indicates the number of pixels with the identical gray value in the image. The probability distribution function (pdf) of input image and improved image are labeled as PD_I , and PD_{I_x} and related cumulative distribution functions (cdf) are CD_I , and CD_{I_x} correspondingly. Further the intensity of the original input image is defined as g and the adapted intensity of the output image as g_0 . As the output probability distribution function has to homogenous, i.e. $PD_{op} = \frac{1}{I_L}$, where I_L represents the number of intensity levels. The superlative output cumulative distribution functions is illustrated by means of the following Equation (2).

$$CD_{op}(g) = \sum_{r=0}^{g_0} \frac{g_0 + 1}{G_L} \text{ For } g_0 = 0, 1, 2, \dots, G_L - 1 \quad (2)$$

As $CD_I(g) = CD_{op}(g)$ subsequent to the histogram equalization, it is possible to attain the output intensity by means of the above Equation (2). Here, G_L specifies the gray level image intensities in the range of 0–255. In this regard, the flat, bell-shaped, and curved histograms constitute certain preferred histogram shapes for the image tiles. It incredibly improves the contrast of images by appropriately varying the intensity values, to usher in the output image whose histogram harmonizes with a homogeneous histogram. The transformation X for minimization is represented by means of the following Equation (3).

$$|CD_I(X(r)) - CD_r| \quad (3)$$

where CD_I the cumulative histogram of X , and CD_r represents the cumulative total of histograms for all intensities r . This minimization is subjected to various parameters such as that X has to be monotonic in nature and $CD_I X(r)$ must not exceed CD_I by more than 50% of the distance between the histogram counts at g . With an eye on cutting back the flaws in Equation (3) and adapting X as a monotonic function, a homogeneous HE input is furnished to Equation (3). The corresponding transformation is efficiently employed to map the gray levels in X to their new values with superior monotonic function.

3.5. Feature Extraction

Once the image is enhanced to improve the quality, the image is subjected to feature extraction where different extensive features like Area, holo entropy, SURF and SIFT features are extracted. The features extraction is a main stage in image processing as it provides the parameters for evaluating the image for classification purpose. Each feature extracted are explained below,

3.5.1. Area

The area is extracted in order to find out the exact position of the fingerprint in the image. The area is estimated using the expression given below,

$$\text{Area, } A = h * w \quad (4)$$

Where,

h - indicates the image height.

w - denotes the image width.

3.5.2. Holo Entropy

Holo entropy is an arithmetical measure of unpredictability that can be used to distinguish the texture of the input image. The holo entropy basically depends on the histogram value in the image.

The holo entropy can be measured in terms of summation of entropies on all the attributes in the particular section of image.

The holo entropy is defined as the ration of sum of entropy to that of total correlation which can also be represented in terms of summation of entropies which is given as per Equation (5) below,

$$X_H(I_m) = \sum_{k=1}^N X(p_k) \quad (5)$$

Where,

$X_H(I_m)$ - Holo entropy for the image I_m

$X(p_k)$ - Entropy of the image pixel.

3.5.3. SIFT and SURF Feature

3.5.3.1. SIFT Feature

The scale invariant feature transform (SIFT) is a powerful feature that is used in image retrieval process. The approach is performed by detecting the scale space extrema in the image where we identify the locations and scales in the image. The scale space of an image $Z(m,n)$ is represented by a function

$F_s(a,b,\rho)$ which is given by,

$$F_s(m,n,\lambda) = G_f(m,n,\lambda) * Z(m,n) \quad (6)$$

where,

$G_f(m,n,\lambda)$ - Gaussian function which is given by

$$G_f(m, n, \lambda) = \frac{1}{2\pi\lambda^2} e^{-\frac{(m^2+n^2)}{2\lambda^2}} \quad (7)$$

The sift feature vector are thus calculated using the above expression and these feature values are then used for further processing.

3.5.3.2 SURF Feature

The proposed facial recognition technique uses a robust feature extraction method (SURF) to extract the characteristics of the training and test image. The extraction method SURF is a method of extraction of insignificant scaling and rotational properties, which is faster than the commonly used extraction method. Transformation of invariant characteristic of the scale. SURF focuses on the invariant detectors on the scale and on the rotation in the plane and the descriptors of an image. The essential image is calculated from the image and calculates the sum of the pixel intensities in the integrated image using the following equation below,

$$h_\xi(p, q) = \sum_{a=0}^{a \leq p} \sum_{b=0}^{b \leq q} h(a, b) \quad (8)$$

The hessian matrix is used for determining the intensity point in SURF feature extraction. The matrix is calculated using the expression below,

$$H_m(g, \phi) = \begin{bmatrix} I_{g,g}(g, \phi) & I_{g,h}(g, \phi) \\ I_{g,h}(g, \phi) & I_{h,h}(g, \phi) \end{bmatrix} \quad (9)$$

Where $I_{g,g}(g, \phi)$ to $I_{h,h}(g, \phi)$ - Convolution of the Gaussian second order derivative.

The locations in the image where the determinant of Hessian matrix is maximum are detected. Pixel intensities are high where the determinant of Hessian matrix is maximum, so determinant of Hessian matrix gives the maximum intensity points in an image. The features of these maximum intensity points are extracted to implement the proposed Fingerprint image classification.

Once the features are extracted, these feature vector values $[A, X_H, F_s, h_\xi]$ are applied to the classifier for classification of images which is explained in below section.

3.6. Fingerprint Classification Using Hybrid Neural Network

The Hybrid Neural Network is used to discover the unique classification of fingerprints and is prepared using the values of the components extracted from each image. The Hybrid Neural Network is well trained by extorted characteristics. The Hybrid Neural Network has four input units, n hidden units, and one output unit. Here n represents the number of hidden layer neurons. In our proposed method, the number of hidden neurons will be approx. 20. The contribution of the neural system is the element vector we have extricated from the images. The system is prepared under an extensive arrangement of various images from info database so as to empower them to successfully order the correct unique finger print image in the testing stage. The Hybrid Neural Network works making utilization of two stages, one is the training phase and the other is the testing phase.

a. Learning Algorithm – Back Propagation Algorithm

The Back Propagation Algorithm is efficiently exploited as the Learning algorithm in the Feed Forward Neural System. The Back Propagation Algorithm essentially signifies a managed Learning policy and supplementary it distinguishes the collapse of delta regulation. For the principle of execution compilation, it necessitates of a dataset of the fundamental efficiency for diverse inputs. Typically, the Back Propagation Algorithm is the ultimate one for the Feed-Forward Networks and the Learning algorithm necessitate that the service principle engaged by means of neurons must be varied [25].

b. Back propagation Algorithm Steps for FFBNN

The weight for the neurons of hidden layer and the output layer are premeditated erratically decides the heaviness. Though, the input layer acquires the steady weight.

The predictable Bias task and the establishment task are estimated through Equations (10) and (11) for the FFBNN.

The Back Propagation fault is estimated for each one node and subsequently, the weights are restructured as per the subsequent Equation (11).

$$w_{(n')} = w_{(n')} + \Delta w_{(n')} \tag{10}$$

The weight $\Delta w_{(n')}$ is adapted as per Equation (11) shown below.

$$\Delta w_{(n')} = \delta \cdot X_{(n')} \cdot E^{(BP)} \tag{11}$$

Where,

δ - Learning Rate, which is habitually in the range of 0.2 to 0.5.

$E^{(BP)}$ - BP Error.

The process is constant by the aid of steps signify in Equations (10) and (11), till the BP fault is condensed to the least i.e. $E^{(BP)} < 0.1$.

On accomplishing the least value, the FFBNN become known suitably appropriate for the transmission segment.

Accordingly, the FFBNN classifier is successfully practiced and the organization standards are experienced through utilizing the characteristic. The categorization of fault is implemented which categorize the complete fault engender from the classifier.

The Hybrid Neural Network works by using two stages, one is the training phase and the other is the testing phase.

3.6.1. Training Phase

In the training phase, the input image is extracted from features and this feature vector is provided as the input to the neural network. Initially, the nodes receive random weights. As the output is already known in the training phase, the output obtained from the neural network is compared with the original and the weights vary to reduce the error. This process is carried out for large data in order to produce a stable system with assigned weights in the nodes. In our methodology we use a multilayer feed forward neural network. The structure is represented in Figure 2.

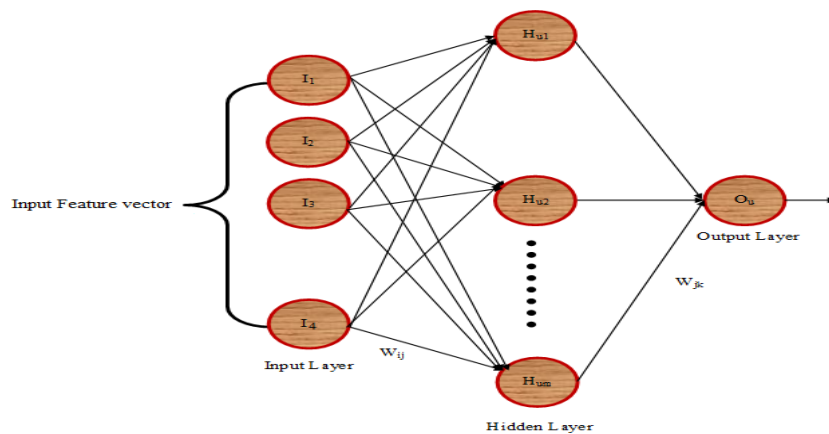


Figure 2. Structure of artificial neural network

3.6.2. Testing Phase

In the test phase, the input image is fed to the trained neural network that has particular weights in the nodes and the output is calculated to classify the images according to the trained data set. In the ordinary neural network, the process will stop after the test. In the proposed modified neural network, for the test process, we have incorporated the optimization algorithm to optimize the weight used for the tests. In our proposed method, the weights are optimized with the help of the BAT Algorithm. By incorporating the optimization process, the accuracy of the classification will be improved there by providing a better classification of the images. The structure of the artificial neural network is illustrated in Figure 2.

3.6.3. Bat Algorithm for Optimizing Weights in ANN

The bat algorithm is a metaheuristic algorithm, excited by the behavior of echolocation of microbats [26-34]. The bat algorithm (BA) is used to optimize the weight of hidden layer neurons in the neural network.

The BA that exploits this echolocation function depends on some of the important parameters, such as frequency, velocity, pulse rate and loudness. The BA changes to the optimal solution when updating the current position with the velocity of the most suitable solutions. Now, the pulse emission rate, as well as the loudness, is also efficient in each iteration. In the demand to achieve the BA some of the expectations were predefined depending on the characteristic characteristics of the bats.

Assumption:

Several of the assumptions must be made within the Bat (BA) Algorithm. Expectations are irregular here,

- a. All bats are able to distinguish between background and Prey.
- b. All bats use echolocation property to detect distance.
- c. All bats fly unsystematically with velocity v_i in position x_i and releases pulses of sound with frequency f_i , fluctuating wavelength λ and loudness l_i .
- d. Frequency (or) wavelength varies established in the vicinity of the target particle.
- e. Furthermore, the pulse emission rate can also be varied between the range of 0 and 1 based on the target location.
- f. Loudness l_i congregates among the maximum loudness l_{\max} to constant minimum loudness l_{\min}

The following flow illustration for the bat algorithm used to optimize the whole value is assumed by the Figure 3.

Step 1: Input micro-bats (B_i) population is randomly generated. According to our proposed approach, the weights of neurons are considered as the micro-bats. Each micro-bat has the velocity vector (v_i) and position vector (x_i), which is described by the following Equation (12). Initially, the values of these credentials are assigned randomly to a particular range.

$$B_i = \begin{bmatrix} (v_{11}, x_{11})^{b1} & (v_{12}, x_{12})^{b2} & \dots & (v_{1n}, x_{1n})^{bn} \\ (v_{21}, x_{22})^{b2} & (v_{22}, x_{22})^{b2} & \dots & (v_{2n}, x_{2n})^{bn} \\ \vdots & \vdots & & \vdots \\ (v_{m1}, x_{m1})^{b1} & (v_{m2}, x_{m2})^{b2} & \dots & (v_{mn}, x_{mn})^{bn} \end{bmatrix} \quad (12)$$

Step 2: To allocate the echolocation parameters, the micro-bat populations are included with the echolocation parameters like frequency (f_i), pulse rate (pr_i), and the loudness parameters (l_i). These parameters are non-negative real values with the following ranges.

$$f_{\min} \leq f_i \leq f_{\max}, \quad pr_{\min} \leq pr_i \leq pr_{\max}, \quad l_{\min} \leq l_i \leq l_{\max} \quad (13)$$

Here, we allocate the frequency range $f_{\min} = 0$ and $f_{\max} = 1$, the pulse rate minimum value $pr_{\min} = 0.5$ is and the loudness maximum value is $l_{\max} = 1$. The remaining values are determined by the subsequent Equation (14).

$$l_{\min} = \frac{1}{\sqrt{n_{\text{sec}}}} \quad (14)$$

$$pr_{\max} = 1 - \frac{1}{n_d} \leq 1 \quad (15)$$

Where, n_{sec} is the number of sections in the discrete set used for sizing the design variable and n_{sec} is the number of discrete design variables.

Step 3: Calculate the objective function of the initial populations; the required fitness function is described by the following Equation (16).

$$F_i = \min MSE \quad (16)$$

According to Equation (16), the frequency of each class label is used to define fitness value for each microbat. The fitness function of the micro bats is determined based on the mean square error (MSE). When the obtained MSE of a micro bat is found low, then the micro bat is ranked as a best micro bat.

Step 4: Store the current population and augment the iteration count as $t+1$, i.e., iteration $t = t+1$.

Step 5: The current population of rules is randomly updated based on the frequency and the velocity. Initially, the frequency can be evaluated, which is described by the following Equation (17).

$$f_i^t = f_{\min} + (f_{\max} - f_{\min})u_i \quad (17)$$

Where, u_i is the random number of values, which is selected from 0 to 1, then the frequency is applied to the velocity equation, which can be described by the following Equation (18).

$$v_i^t = \text{round} [v_i^{t-1} + (x_i^{t-1} - x_{\psi})f_i^t] \quad (18)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (19)$$

Where, v_i^t and v_i^{t-1} are the velocity vectors of the micro-bats at the time steps t and, x_i^t and x_i^{t-1} are the position vectors of the micro-bats at time steps t and, x_{ψ} is the current global best solution. Here after performing the local search in the randomly selected population, this is described by the following Equation (20). A solution is selected among current best solutions and then random walk is introduced to obtain new solution

$$x_{\text{new}} = x_{\text{old}} + \xi_{i,j} l_{\text{avg}}^t \quad (20)$$

Where, $\xi_{i,j}$ is a random number between -1 and 1 , l_{avg}^t is the average value of loudness at time step.

Step 6: Find the fitness of the new micro-bats population using the Equation (16). After evaluation, the micro-bats echolocation parameters are updated for better moving of the micro-bats, which can be described by the following Equation (21).

$$l_i^{t+1} = a.l_i^t \quad \text{and} \quad pr_i^{t+1} = pr_{\max} [1 - \exp(-\gamma)] \quad (21)$$

Where, l_i^{t+1} and l_i^t are the updated and previous values of the loudness pr_i^{t+1} is the pulse rate of the micro-bats in the time step, a and γ are the adaptation parameters of the loudness and pulse rate.

Step 7: To find the best micro-bats, which satisfies the objective function.

Step 8: The steps 4 to 7 is continued until the termination criteria are attained.

Here the input will be the weights of Neuron, based on the fitness; the optimal weights of a neuron are selected. The optimal weights will help the ANN to classify the fingerprints more accurately. The fitness

of BA algorithm is the minimization of MSE. For a neural network, we have to minimize the error, to get the accurate classification.

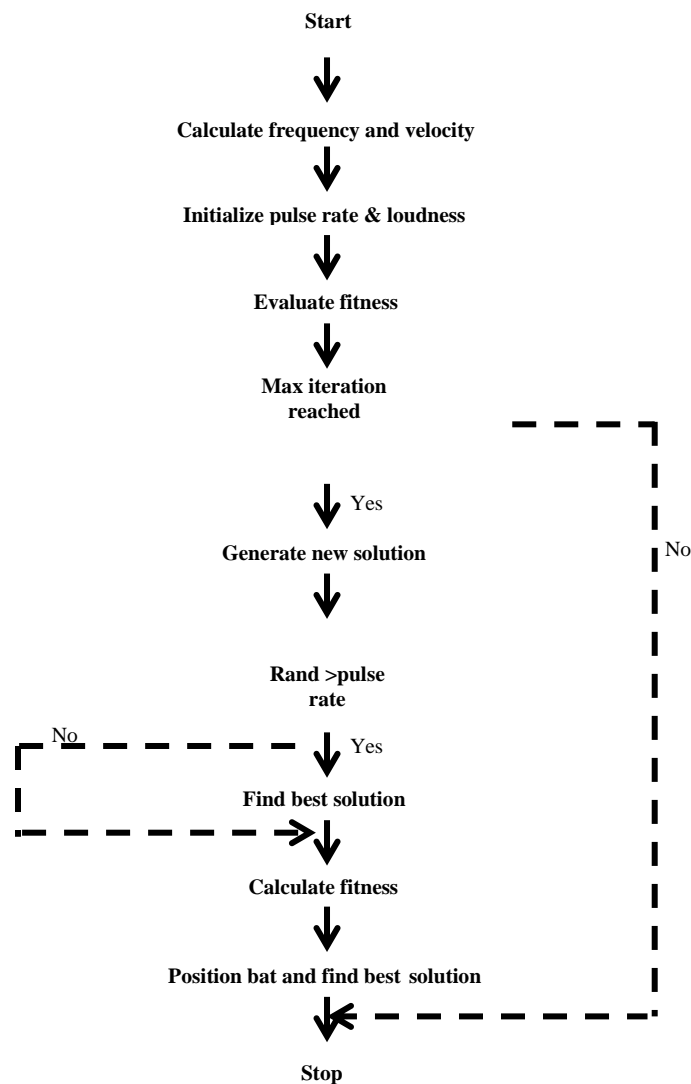


Figure 3. Bat Algorithm

By utilizing the BAT algorithm as shown above, the weights are assigned to the NN which makes the classification of images more accurate and improved. The Hybrid Neural Network delivers better accuracy in terms of classifying the exact image because of incorporating the optimization process. Various input images are applied to our proposed system and using the extensive features extracted for each image, the classification is done with the aid of proposed Hybrid Neural Network and the results with improved classification accuracy are evaluated

4. RESULTS AND DISCUSSION

4.1. Database Description

The experiment is done in MATLAB (2015a) by applying the proposed approach and Image Processing Toolbox was used to produce the improved finger print image. The propped approach is validated using FVC2000 dataset. The original and fake fingerprint images are collected through Fingerprint Verification Competition or FVC2000 [30] and the samples are drawn from SFinGE. Different sensors are

applied on FVC2000 to collect four databases from FVC2000 database. Low cost Optical sensor was used to collect images for DB1. Low cost Capacitive Optical sensor used to collect images for DB2. DB3 is collated using a fairly sizeable quality of optical sensors. At final, databases DB4 is synthetically generated using SFinGE. Here the total number of images used is nearly 300. In this, we have taken 90-10 ratio for training and testing. The results will be analyzed by varying the training and testing ratio such as 80-20 and 70-30. The data base specifications are given in Table 1 and the sample images are shown from Figure 3 to Figure10.

Table 1. The four FVC2000 databases

| Database names | Sensor type | Image Size |
|----------------|------------------------------------|------------|
| DB1 | Low-cost Optical | 388 X 300 |
| DB2 | Low-cost Capacitive Optical sensor | 256 X 364 |
| DB3 | Optical sensor | 448 X 478 |
| DB4 | Synthetic generator | 240X 320 |



Figure 3. DB1 sample images; each row shows different images of fingerprints of the same finger



Figure 4. Fingerprint images of DB1; all samples are from different fingers and are prepared by quality (top left: high quality, bottom right: low quality)

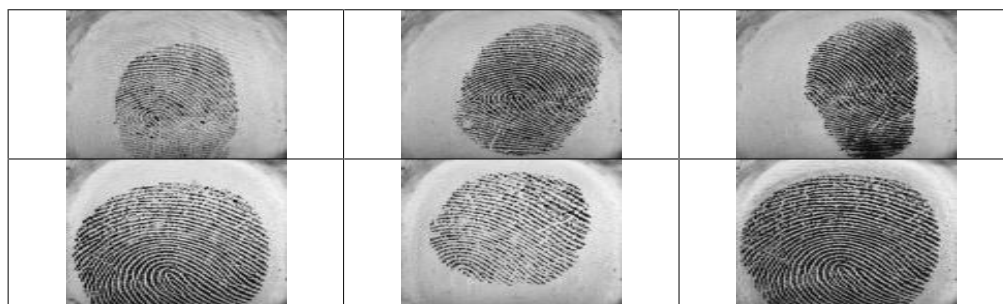


Figure 5. DB2 sample fingerprint images; each row shows different images of fingerprints of the same finger



Figure 6. DB2 fingerprint images; all samples are from different fingers and are prepared by quality (top left: high quality, bottom right: low quality)

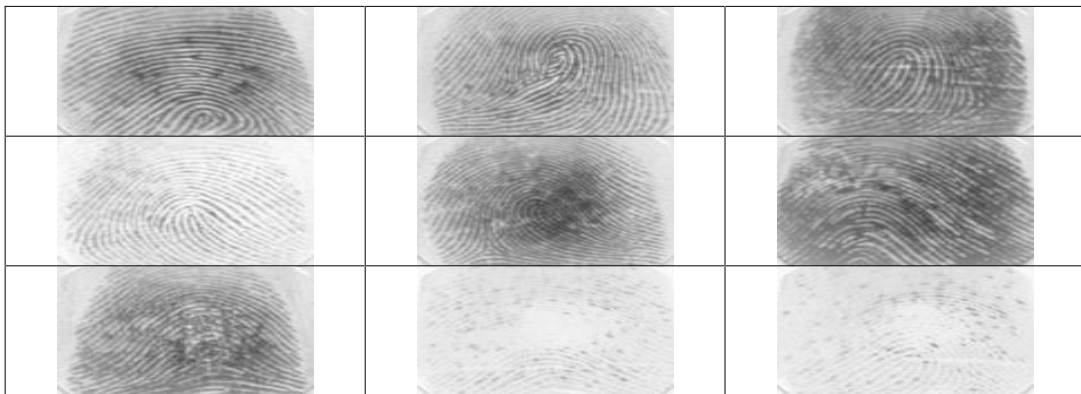


Figure 7. Fingerprint images of DB3; each row shows different images of fingerprints of the same finger

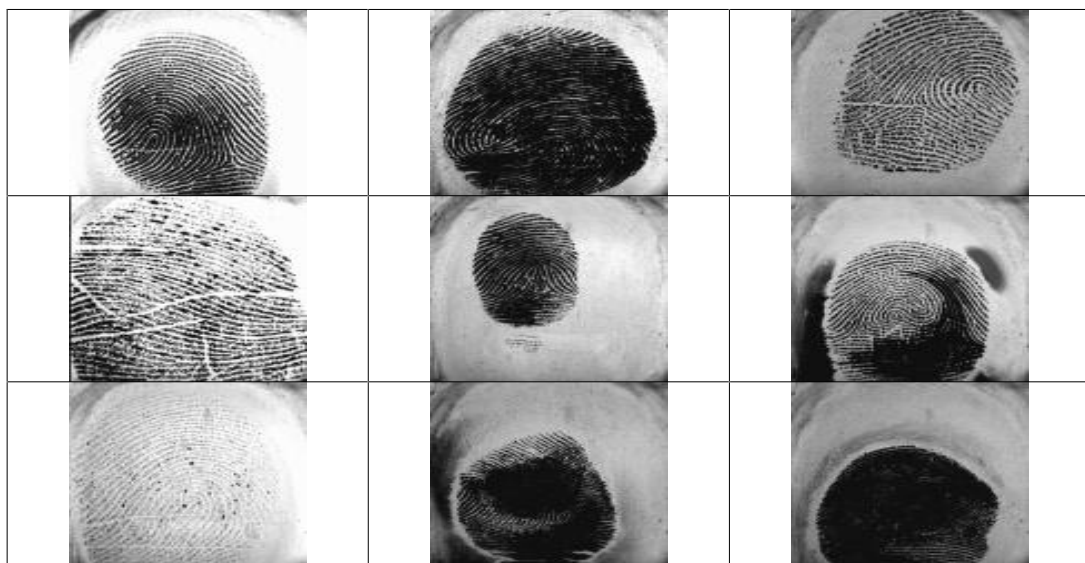


Figure 8. Fingerprint images of DB3; all samples are from different fingers and are ordered by quality (Top left: high quality, bottom right: low quality)

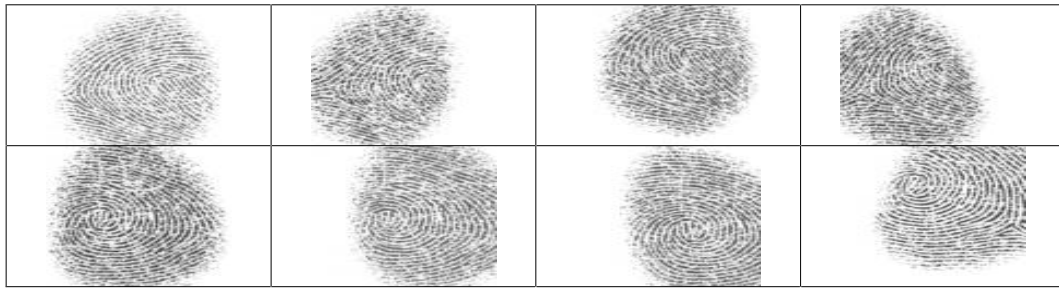


Figure 9. DB4 sample images; each row shows different images of fingerprints of the same finger

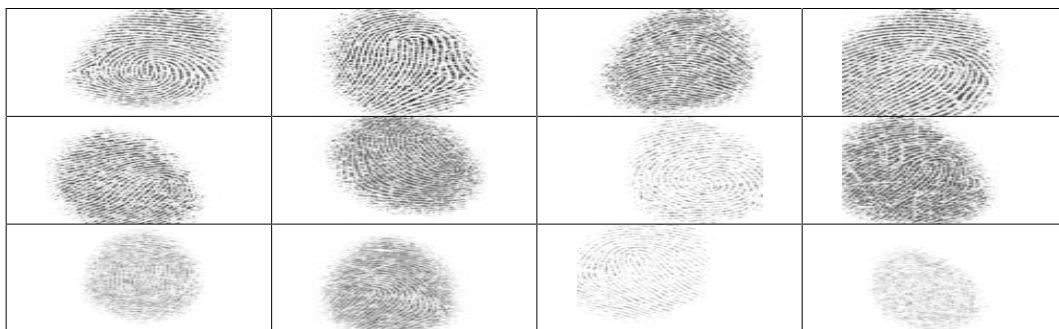


Figure 10. DB4 images; all samples are from different fingers and are ordered by quality (top left: high quality, bottom right: low quality)

| S.No | Input images | Enhanced image | Classified Results |
|------|--------------|----------------|--------------------|
| 1. | | | |
| 2. | | | |
| 3. | | | |
| 4. | | | |
| 5. | | | |

Figure 11. Processed output of fingerprint image classification

Figure 11 show the specified the processed output for the input fingerprint images.

As publicized in above figure, the input image is substance to noise reduction and then improved by the Histogram equalization technique. The improved images are then classified on the basis of the input query image using Hybrid Neural Network. The categorized images are then stowed for empathy. The presentations of proposed technique in organization of exact images are then assessed and are associated with that of available neural network.

4.2. Performance Evaluation

The performance of the proposed approach is validated by using metrics namely Precision, sensitivity, specificity, accuracy and F-Measure. These metrics are assessed for different training testing percentages and are tabularized. Similar metrics for the existing methods are also evaluated and tabulated for comparing with proposed method. In our proposed scheme we have utilized neural network which is one of the existing method for classification. The performance metrics are defined in Table 2. Table 3 show the Performance assessment of Proposed Method (NN+BAT)

Table 2. Performance metrics

| | |
|--------------------|---|
| True Positive(tp) | The number of images recognized as correct, which are actually correct |
| False Positive(fp) | The number of images recognized as correct, which are actually out of classification or wrong. |
| True Negative(tn) | The number of images recognized as wrong or out of classification , which are actually wrong or out of classification |
| False Negative(fn) | The number of images recognized as wrong or out of classification, which are actually correct. |
| Precision | $\frac{tp}{tp + fp}$ |
| Recall/sensitivity | $\frac{tp}{tp + fn}$ |
| Specificity | $\frac{tn}{tn + fp}$ |
| Accuracy | $\frac{tp + tn}{tp + tn + fp + fn}$ |
| F-Measure | $2 * \left(\frac{recall * precision}{recall + precision} \right)$ |

- Precision shows the class agreement of the data labels with the positive labels given by the classifier.
- Sensitivity shows the effectiveness of a classifier to identify the positive labels.
- Specificity shows how effectively a classifier identifies the negative labels.
- Accuracy shows the overall effectiveness of a classifier.
- F-measure shows the relation between data's positive labels and those given by a classifier.

Table 3. Performance assessment of Proposed Method (NN+BAT)

| Training –Testing Percentage | 90-10 | 80-20 | 70-30 |
|------------------------------|----------|----------|----------|
| Accuracy | 0.987513 | 0.978514 | 0.958265 |
| Sensitivity | 0.98479 | 0.986572 | 0.995466 |
| Specificity | 0.95625 | 0.87964 | 0.987463 |
| Precision | 0.9756 | 0.9652 | 0.9453 |
| F-Measure | 0.9375 | 0.9084 | 0.9532 |

The Figure 12 shows the metrics values like Precision, sensitivity, specificity, accuracy and F-Measure accomplished by the anticipated methods for various training and testing quantities.

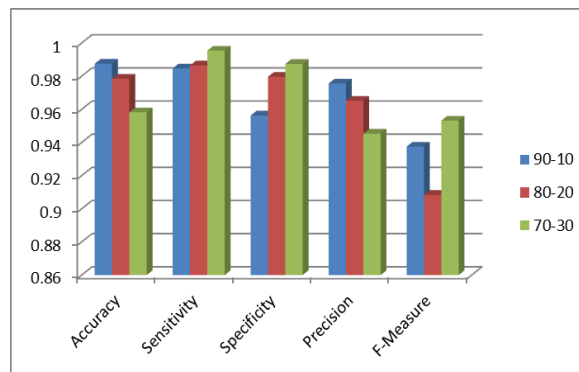


Figure 12. Evaluation of Performance Metris for different training and testing ratios

The Table 4 specified below exemplifies the metrics values like Precision, sensitivity, specificity, accuracy and F-Measure accomplished by the anticipated and predominant methods. From the values accomplished it is apparent that our anticipated system has outdone the existing method

Table 4. Performance assessment of proposed and prevailing methods

| Training – Testing Percentage | Proposed Method (NN+BAT) | | | Neural Network with PSO algorithm | | | Neural network Without Optimization | | |
|-------------------------------|--------------------------|----------|----------|-----------------------------------|--------|---------|-------------------------------------|----------|----------|
| | 90-10 | 80-20 | 70-30 | 90-10 | 80-20 | 70-30 | 90-10 | 80-20 | 70-30 |
| Accuracy | 0.987513 | 0.978514 | 0.958265 | 0.9738 | 0.9684 | 0.9465 | 0.9625 | 0.958962 | 0.930789 |
| Sensitivity | 0.98479 | 0.986572 | 0.995466 | 0.98 | 0.9532 | 0.94566 | 0.975 | 0.92479 | 0.925896 |
| Specificity | 0.95625 | 0.87964 | 0.987463 | 0.9 | 0.8054 | 0.96462 | 0.75 | 0.75478 | 0.9563 |
| Precision | 0.9756 | 0.9652 | 0.9453 | 0.9723 | 0.9525 | 0.9385 | 0.9638 | 0.935 | 0.925 |
| F-Measure | 0.9375 | 0.9084 | 0.9532 | 0.9274 | 0.9045 | 0.9325 | 0.9075 | 0.8875 | 0.9025 |

Hence the above performance evaluation shows Precision, sensitivity, specificity, accuracy and F-Measure over Neural network without optimisation , Neural network with PSO algorithm and Neural Network with BAT algorithm. Therefore it is proved that our proposed NN with BAT algorithm working efficiently comparing to the existing methodolgies mentioned above. The below Figure 13 shows the comparison of all the above paramters for proposed and exisitng methods.

In [35] order to improve the limitations of existing fingerprint image enhancement methods an efficient technique is proposed for image processing with low image quality fingerprint images. The methodology is divided into three modules. In the first module, the fingerprint image is subjected to denoising process where Wave atom transform is utilized. After the completion of this process the image enhancement is performed with the help of optimization algorithm. In ths approach, a Modified cuckoo search (MCS) algorithm is used as an optimizer. This helps to come across for the best gray level distribution that maximizes the objective function.

In [36] to enhance the restrictions of prevailing fingerprint image augmentation approaches authors projected an effectual method to pact with small quality fingerprint images. The projected methodology is alienated into three modules. Primarily, the fingerprint image is endangered to denoising procedure where Wave atom transform is used. Once this procedure is accomplished the image augmentation is achieved for improving the classification rate. The morphological operation is used in this projected technique inorder to augment the image. The morphological operators such as dilation and area opening are used here for

improvement. The final step in this is the ordering of fingerprint image. In this authors used Adaptive genetic neural network (AGNN) intended for classification of images.

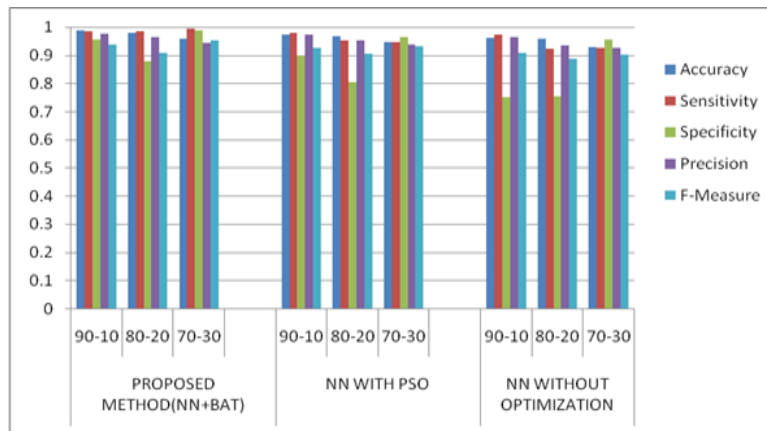


Figure. 13 Graphical representation of Performance metrics for proposed and prevailing methods

Table 5. Performance assessment of proposed and existing methods

| Training – Testing Percentage (%) | Proposed Method (NN+BAT) | | | Wave Atom Transformations+ AGNN Method | | | Wave Atom Transformations+ Modified cuckoo search (MCS) algorithm | | |
|-----------------------------------|--------------------------|----------|----------|--|----------|----------|---|--------|--------|
| | 90-10 | 80-20 | 70-30 | 90-10 | 80-20 | 70-30 | 90-10 | 80-20 | 70-30 |
| Accuracy | 0.987513 | 0.978514 | 0.958265 | 0.978125 | 0.964785 | 0.948265 | 0.9730 | 0.9545 | 0.9248 |
| Sensitivity | 0.98479 | 0.986572 | 0.995466 | 1 | 0.986572 | 0.985466 | 0.9435 | 0.9748 | 0.9785 |
| Specificity | 0.95625 | 0.87964 | 0.987463 | 0.95625 | 0.938796 | 0.925875 | 0.9435 | 0.9280 | 0.9175 |
| Precision | 0.9756 | 0.9652 | 0.9453 | 0.9756 | 0.9652 | 0.9453 | 0.9650 | 0.9450 | 0.9385 |
| F-Measure | 0.9375 | 0.9084 | 0.9532 | 0.9375 | 0.9084 | 0.9532 | 0.9250 | 0.90 | 0.9450 |

The proposed method uses the neural network and BAT algorithm in place of wave atom transformation to by minimizing the time improve the performance of detection by minimizing the detection time which is shown in Figure 15. Comparative analysis of performance metrics are shown in Table 5 and Figure 14.

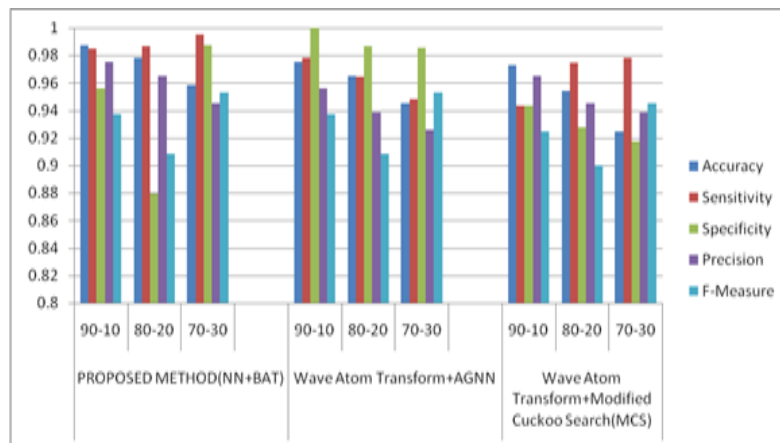


Figure14. Graphical representation of Performance metrics for proposed and existing methods

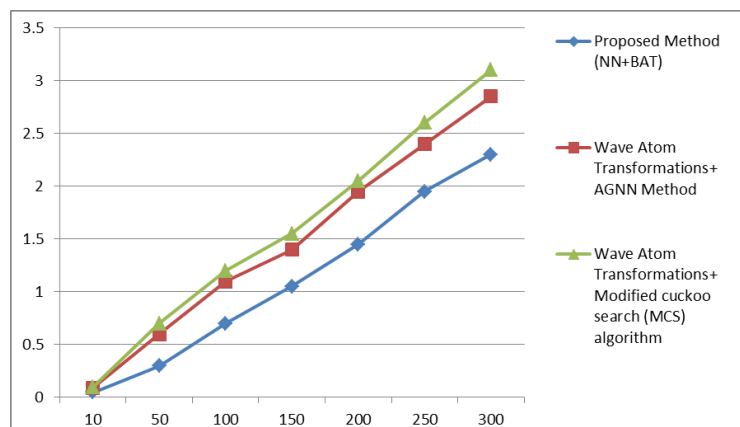


Figure 15. Detection time comparison of Proposed method with existing methods (X-Axis no.of images and Y-axis Detection time in Milli seconds)

5. CONCLUSION AND FEATURE WORK

In this effort, in order to overawe the fingerprint images classification issues in dissimilar available plan, an effective fingerprint image classification technique has been projected. The biometric fingerprint classification system is used in criminal identification and human authentication process in real time. In order to ensure the security and authorization, we need to identify the original fingerprint. For this purpose, we are developing a fingerprint classification system. The projected method uses median filter for noise removal, Histogram equalization for image augmentation and Hybrid neural network for image classification. The projected approach aided in classifying the images into original or fake meanwhile the images are improved and utilization of hybrid neural network. Numerous parameters such as accuracy, sensitivity, specificity, Precision and F-Measure are assessed by the projected method and are then associated with the available neural network. From the solution attained it is vibrant that our projected scheme of fingerprint image classification overtakes the available technique with improved classification accuracy. To improve the template security of biometric systems in future work are given below

To improve the performance of individual traits and to raise the performance of the overall system lot of matching algorithms are discussed. For real time application any kind of Biometric System can be used. It needs various sensors to capture the data and fetch the same process in the real time application for training and testing phase. There should not be noise, illumination changes and background variations in the captured data. The less memory consumption and computational effort can be improved in further proposed scheme.

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