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Training Feed-Forward Artificial Neural Network using Enhancement Bat Algorithm for classification of fingerprint image

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Abstract

The Artificial Neural Network (ANN) contributes to important advantages in biometrics such as fingerprints, facial recognition, and others. Fingerprint recognition is one of the most reliable and popular biometric methods used for personal identification. It plays a very important role in forensic and civilian applications. ANN plays an important role through the application of neural networks, such as pattern recognition, classification, and others. However, much effort nowadays is focused on the development of neural networks. In this study, a new variant of the BAT algorithm is proposed, called the Enhancement Bat Algorithm (EBat). The proposed approach modifies the BAT standard by enhancing exploitation capabilities and avoiding escapes from local minimums. The ANN training process is a complex continuous improvement task. This paper aims to demonstrate a detailed comparative performance analysis of training the Forward Neural Network (FFNN) from the proposed technique (EBANN) over other decent gradient algorithms and population-based approaches on the fingerprint datasets taken from the FVC 2002 database. As our approach was done in three stages, the next step is to improve the fingerprint images using a preprocessing process using HOQ. The next stage is to extract features. The extraction of invariant features is the core of recognition systems. This work proposes a novel feature extractor-fusion scheme using two powerful feature descriptors known as Gabor Filters (GFs) and Histogram of Oriented Gradient (HOG). which do not need much preprocessing and multiple stages of improvement and can be combined with other metrics easily: After extracting features from both, the two filters are dimensioned reduced by the LDA algorithm, and then the features between the two filters are combined by concatenation. The combination of the two methods leads to a significant increase in the recognition of fingerprint images, better than the use of filters separately. The last step is to use FFANN with a better bat algorithm to classify the data.

KEYWORD: Artificial Neural Network, fingerprint, Gabor filter, HOG, feed forward ANN, BAT algorithm, training of neural network, metaheuristic.

1- Introduction

Due to its immutability and rareness, fingerprints are far and wide applied in many personal identification or authentication systems[1]. It uses personal computers, phones, and internet applications to deal with intelligent applications over the internet, such as E-banking, in which the customers conduct transactions electronically via the internet [2]. The ridge structures offer both global and local information [3]. An algorithm's performance is highly dependent on the quality of the input fingerprint pictures. A large proportion of fingerprint images obtained are of low-quality. In low-quality fingerprint pictures, the features that make up the local area aren't always clearly defined, so they can't be recognized properly [4].This causes following issues: (i)a considerable number of false minutiae may be produced, (ii) a large proportion of real minutiae may be disregarded, and (iii) major mistakes in minutiae localization (position and orientation) may be introduced. To guarantee that the minutiae extraction method's performance is resilient in terms of fingerprint image quality, an enhancement technique that can increase the clarity of the ridge structures is required Low quality.

They use directly the fingerprint images or features extracted from the image for matching, hence their name image based methods or non-minutiae based [5].

many of preprocessing stages are inefficient for small-scale fingerprint recognition systems [6], and the result is highly dependent on the accuracy of each preprocessing step. Also, it requires more computing effort and has a lower recognition rate. In contrast to minutiae-based techniques, non-minutiae overcome their disadvantages. In addition to the minutiae, it also takes into account local orientation and periodicity, as well as ridge shape and texture information. Binarization and thinning as well as post-minutiae processing may be abandoned in favor of extracting more discriminating information.

Recognition systems are based on the extraction of invariant features. This article offers a unique feature extraction approach based on two strong feature descriptors: Gabor Filters (GFs) and the Histogram of Oriented Gradients (HOG).

Among non-minutiae-based descriptors, Gabor feature-based descriptors have a relatively high matching accuracy due to their use of a bank of Gabor filters to capture both local and global information in a fingerprint [7].

Dalal & Triggs [8] suggested the HOG as an image descriptor for localizing pedestrians in complex images, and it has gained increasing popularity. This descriptor aims to characterize a picture using a series of local histograms that count the number of instances of gradient orientation in each image cell.

The combination of the two approaches results in a considerable boost in fingerprint image recognition, outperforming the usage of filters independently. To assess the suggested strategy, it was applied using the FVC2002 database [9]. To classify fingerprint images, we proposed in this paper the use of an improved artificial neural network by training weights by metaheuristic algorithms, in contrast to the traditional algorithm used to train an artificial neural network by using a gradient decent backpropagation algorithm. Blindly and does not ensure access to the best solution and traps you in the local minimum [10].To overcome this problem, the bat algorithm Which was used as an alternative to back-propagation. Contrasting the literature that used metaheuristic algorithms such as genetic algorithm, PSO algorithm, bat algorithm and others as hybrid algorithms with back-propagation algorithm to overcome the local minimum [11].

Xin-She Yang [12] proposed the bat algorithm, a nature-inspired algorithm that is a member of the swarm intelligent (SI) family. The bat algorithm is based on the echolocation of microbats and utilizes the echo of bats to locate food. Yang concentrated on three rules for the bat's implementation: To begin with, all bats utilize echolocation to determine the distance to a certain site. Second, bats fly randomly at a given frequency and at a fixed velocity toward a predetermined place, but the volume and wavelength may vary. Thus, bats modify their wavelengths.

The bat algorithm has lots of advantages, one of which is the ability to create incredibly fast convergence at an extremely important step by moving from exploration to exploitation. As a result, it's a good algorithm for services like categorization. However, if we let the algorithm go straight to the exploitation step, it could get stuck at a certain point [13].

As a result, we propose a method for improving local search capacity and overcoming the challenges of exploitation and exploration capabilities of the traditional Bat algorithm, which will prevent trapping in local optima. To address this problem, this work proposes the enhancement bat algorithm (EBA), which improves bats' exploitation skills and allows them to escape local minima. In this work, a change is made with the goal of improving the exploration and exploitation skills of the bat algorithm in order to increase its performance.

The remaining sections of the paper are organized as follows. The second section is related to work. In the third section, the proposed methodology that is covered includes image processing, Artificial Neural Network Classification of Fingerprints, the bat algorithm, and proposed enhancement of the bat-inspired algorithm. Section four: Results and discussion. This proves the efficiency of the proposed algorithm. A brief conclusion of the study is given in the last section.

2- Related work

Ganesh.Awasthi[14] Fingerprint identification is one of the most common biometric systems that exist. The proposed system of fingerprint recognition using neural networks is based on minutiae-based. The process consists of fingerprint acquisition, testing the fingerprint preprocessing, feature extraction, and training the neural network. It used some of the datasets from FVC2002 and FVC2004. In the preprocessing phase, many approaches are used to enhance the image, using Banalization, Thinning, and Histogram Equalization. For feature extraction, we used The Crossing Number (CN) method, which performs minutiae extraction, which extracts the ridge endings and bifurcations from the binary image. The Back Propagation algorithm trains the multi-layer of perception (MLP). The proposed system achieved the performance for fingerprint recognition system rate precisely by using a neural network of 91.10%, FAR 1.24%, and FRR 8.09%.

Subba Reddy[15] In this study, a method is proposed to manage the improvement of fingerprint images. The proposed methodology passes through three stages. The first stage is that the fingerprint images are subjected to a noise reduction process by using a wave Atom transform. Then the image is improved using a morphological process, such as in order to improve the classification rate. In the last stage, it classifies the fingerprint images through the adaptive genetic artificial neural network. This method was applied to the fvc2000 database, and when the data was divided by 70% training and 30% testing, the result was for a set of parameters such as accuracy 94.82, precision 94.53, sensitive 98.5, specificity 92, F-measure 95.32.

Amrit Pal Singh Bhogal[16] The author created a non-neural threshold between true and fake values for the different non-reference image quality metrics (NR-IQM)". Following that, in the second step, we utilized the quality scores for leave-one-out cross-validation to get a precise claim regarding the classification capability of NR-IQM". To categorize data, we employed the k-nearest neighbors (kNN) algorithm". This technique facilitated the testing of all potential IQM combinations in a straightforward manner". Finally, the classification accuracy for distinguishing genuine from false photos is computed"." the suggested NR-IQM with KNN achieves performance measures such as precision 92.50, sensitivity 92.58, specificity 95.63, accuracy 93.07, and F-measure 90.20 for 70% training and 30% testing percentages.

V. H. Mahale[17] The proposed systemfor fingerprint identification is a pre-processing step for picture improvement, binarization, and thinning. The next step is Feature Extraction, which extracts features from the thinned image using minutiae extractor techniques to extract ridge termination and ridge bifurcation. The next step is matching (Identification) which involves comparing two minutiae points using the minutiae matcher technique, which makes use of similarity and distance measurements. The algorithm is validated using the FVC2000 and FVC2002 databases. The recognition system is evaluated using two factors: FAR and FRR. The FAR value in this system is 0.0154, and the FRR value is 0.0137, with an accuracy of 98.5 percent.

Jagadeeswar Reddy [2]:A team of researchers has projected a fingerprint matching algorithm. It takes into account the effect of image quality, number of minutiae, and size of the print on an individual person's prints as well as other factors. for images processing using Median filtering for noise removal, Histogram equalization for enhancing images. where using Area, holo entropy, SURF, and SIFT features are extracted in the extract feature phase. for classification fingerprint using a Hybrid neural network with bat algorithm. The ANN has four input units, n hidden units, and one output unit.

The bat algorithm is a metaheuristic algorithm, excited by the behavior of echolocation of micro bats. It is used to optimize the weight of hidden layer neurons with a backpropagation neural network to avoid local minimum. the dataset used fvc2000 and was the result 96% for ratio 70 training and 30 testing.

Table(1) explain the methodology and accuracy for The mentioned literature

Number Of Re.	**year**	**authors**	**Data set**	**Image processing methods**	**Matching process**	**Performa-nce modules**
[14]	2020	Ganesh.Awasthi et al	Some Fvc2000 And Fvc2002	Banalization, Thinning and, Histogram Equalization To enhancement image and Crossing Number (CN) to extract features minutia as a ridge endings and bifurcations	Multi-layer of perceptin (MLP)	**91.10%**
[15]	2018	Subba Reddy Borra et al.	Fvc2000	a wave Atom transform to denoised process and a morphological	adaptive genetic artificial neural network (GANN)	**94.82%**
[2]	2018	Jagadeeswar Reddy	Fvc2002	Median filtering for noise removal, Histogram equalization for enhancing images Area, holo entropy, SURF and SIFT features are extracted	Backpropaga-tion with bat algorithm	**97%**
[16]	2017	Amrit Pal Singh Bhogal et al.	Fvc2000	In preprocessing phase use non-reference image quality measures (NR-IQM) And using quality scores in feature extraction	k-nearest neighbors (kNN) classification	**accuracy 93.07 %**
[17]	2016	V. H. Mahal et al.	Some of Fvc2000 And Fvc2002	banalization, thinning to enhancement image and minutiae extractor methods to extract ridge ending and ridge bifurcation from thinning	using minutiae matcher method in which similarity and distance measure	**Accuracy 98.5%**

3- Proposed methodology

On the fingerprint datasets selected from the FVC 2002 database, the research seeks to present a comprehensive comparative performance analysis of training the Forward Neural Network (FFNN) from the suggested method (FFNN-BAT) over existing reasonable gradient algorithms and population-based techniques. Because our strategy was developed in three stages: The next step is to use a pre-processing method using HOQ to enhance the fingerprint pictures. The next step is to extract features from whole fingerprint photos using two of the most often used filters for extracting features from fingerprints, which do not need much pre-processing or many stages of enhancement and can easily be integrated with other metrics: After collecting features from both filters, the LDA method is used to dimension them down, and then the features from both filters are concatenated. The last step is to classify the data using a feed-forward artificial neural network algorithm and bat algorithm. The figure (1) shows whole propose methodology.

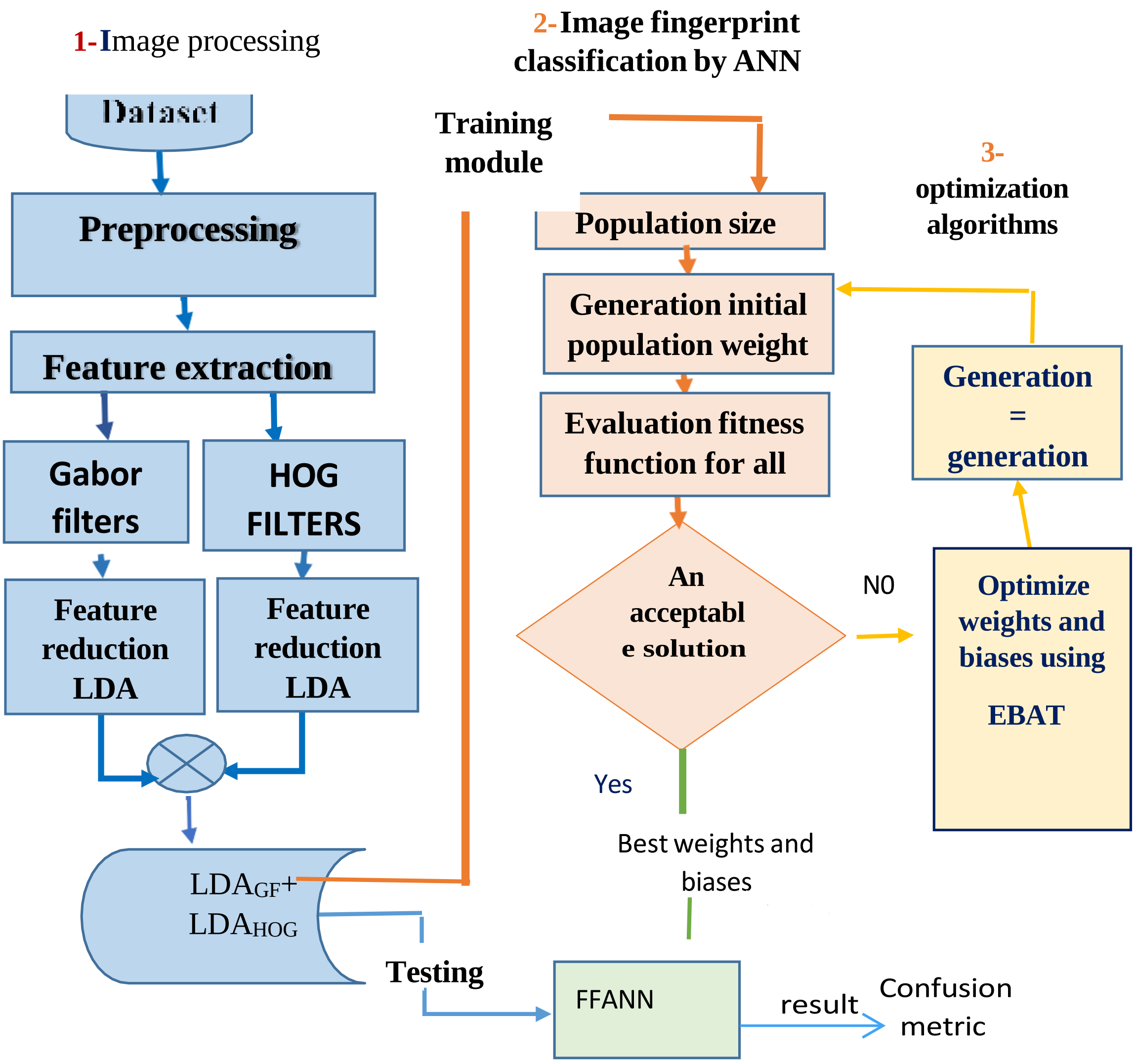

Figure (1) proposal methodology

3.1 Preprocessing of Fingerprints using HOQ

This step will enhance the contrast of the fingerprint pictures so that the next phase of fingerprint matching can provide clear details. The contrast of the Fingerprint is increased by the histogram equalization technique [18]. Histogram Equalization (HOQ) is used to boost the contrast of fingerprint images. This is performed by identifying pixel intensity values spanning from 0 to 255 that occur on a regular basis. This method of fingerprint pre-processing adds to better results.

3.2 Feature extraction of fingerprint

After the image is optimized to increase its quality, it undergoes feature extraction. Due to poor image quality and different input conditions, it is difficult to accurately determine fingerprint-based minutes, which may result in lower matching accuracy [19]. However, the advantages of a strategy that is not built on details outweigh its disadvantages. It takes advantage of fingerprint edge pattern elements beyond the characteristics of fine detail, such as local orientation, frequency, ridge shape, and texture information [20]. It can extract more discriminating data and skip preprocessing steps like binarization and thinning, as well as post-minutiae processing.

The feature extraction stage of image processing is critical because it creates the parameters required for image analysis for classification purposes [21]. At this stage, we propose to combine two of the most common descriptors in feature extraction from fingerprints to obtain a high-accuracy description of the image when it is matched.

3.2.1 Descriptor based on Gabor filters In this stage, we extracted Gabor features using the Gabor filter. In image processing applications such as fingerprint identification optical character recognition [22], and iris recognition [23], the Gabor extent is very useful. The Gabor filter's most important property is its stability in rotation, gradient, and translation [24]. Gabor filter is used to extract the characteristics from the whole fingerprint image. Relationships between activations for an Objects in a picture may be distinguished by their precise spatial placement. The Gabor-based filter is moved around.

straight from a grayscale picture in a 2D spatial range We will discuss this in more detail in the paragraph that follows. Explain the ideas behind the implemented Gabor filter and its bank.

Gabor filter bank:

Gabor's filter bank is regarded as one of the greatest methods in the world for eliciting the qualities of grizzly pictures [25]. They are also a strong mechanism against Gaussian function rotation. They are similar to the qualities of the human visual system, especially in terms of frequency ( )and orientation submission. They are also ideal for texture submission, as seen in

$$W_{\omega.\theta}\ \ (C.U)=\frac{1}{2\pi\sigma^2}=\exp\left(-\frac{c^2+u^2}{2\pi\sigma^2}\right)\exp(f\omega x') \tag{1}$$

$$C' = c\cos\theta + u\sin\theta\,.\,u' = -\sin\theta + u\cos\theta \tag{2}$$

where (c, u) represents the spatial domain pixel location, ω is the center angular frequency of a sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian function, and σ represents the sharpness of the Gaussian function in both the c and u directions. The Gabor filter recognizes several pattern problems. In our test, we order $\sigma \approx \pi/\omega$ to describe the link between ω and σ, so that we may use the Gabor filter to elicit features of finger pictures. It may have 5 frequencies and 8 orientations at times. Figure (2) illustrates a Gabor filter bank with 5 distinct levels and 8 different orientations. Give the Gabor filter bank 5 frequencies m=1,2, ...,5) and 8 orientations (n=1,2, ,8) in the following equation:

$$\omega_m = \frac{\pi}{2} * \sqrt{2}^{-(m-1)} \tag{3}$$

$$\theta_n = \frac{\pi}{8}(n-1) \tag{4}$$

Convolution of the input image I (c, u) with the Gabor filter, Ψω, θ(x, y), yields the following Gabor feature representation:

$$G_{m.n}(c.u)=I(c.u)*\Psi\omega_{\mu}.\,\theta_n(c.u) \tag{5}$$

They convert longitudinally along the direction of the sinusoid at this stage, but their size changes slowly and their Gm,n (c, u) values vary little with displacement [26].

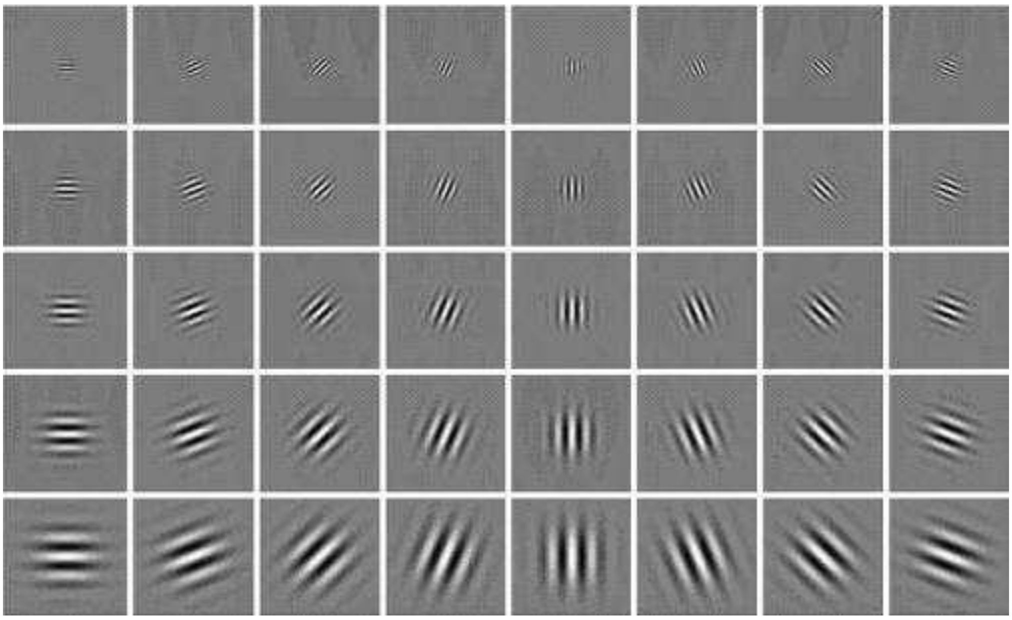

Figure 2: Real-parts-of-the-Gabor-filters-at-5-scales-and-8-orientations

3.2.2 Descriptor based on HOG

Dalal and Triggs (2005) created HOG for the purpose of human detection, and it has since become one of the most popular and effective feature descriptors in pattern recognition. HOG is a gradient-based descriptor that is more efficient when used to describe a fingerprint picture. The HOG feature descriptor is a straightforward and efficient approach for extracting features. Due to the simplicity of the calculations, it is a faster and more efficient feature descriptor than SIFT and LBP [27]. Additionally, it has been shown that HOG features are an effective descriptor for detection. It is mostly used in image processing [28] and computer vision[29] for pattern discovery. The form and appearance of the picture may be described using HOG..

After extracting and select the features, apply concatenation feature vectors values [LDA_{GF}+ LDA_{HOG}] to the classifier for image classification, as described in the section below.

3.3 Artificial Neural Network Classification of Fingerprints

The artificial Neural Network is used to determine the unique categorization of fingerprints [30] . It is constructed utilizing the values of the image's components. By exploiting characteristics, the Artificial Neural Network is well-trained. There are 19 input units, n hidden units, and 10 output units in the feed forward Artificial Neural Network. Here, n is the number of neurons in the hidden layer. The number of hidden neurons in our suggested technique will be 25. The neural system contributes the element vector extracted from the images. The system is constructed using a comprehensive arrangement of various images from the information database in order to enable it to correctly identify each individual's unique fingerprint image.

a. Learning Algorithm – Back Propagation Algorithm

Backpropagation (backward propagation) is a mathematical technique used in data mining [31] and machine learning [32] to increase the accuracy of predictions. Backpropagation is a technique for computing derivatives, it is a learning method that is used in artificial neural networks to calculate a gradient descent with regard to weights [33]. The desired outputs are compared to the realized outputs of the system, and then the systems are tuned by modifying the connection weights to minimize the difference between the two. The method derives its name from the fact that the weights are modified in reverse order, from output to input. In most cases, the Back Propagation Algorithm is the ultimate one for Feed-Forward Networks.

b. Back propagation Algorithm Steps for FFBNN

The weights assigned to the neurons in the hidden layer and output layer are predetermined sporadically, which determines the heaviness. However, the input layer gets a constant weight. The predicted bias and setup tasks are computed for the FFBNN using Equations (6) and (7). Each node's Back Propagation defect is calculated, and then the weights are reorganized according to the following Equation (7).

$$w_{(n')} = w_{(n')} + \Delta w_{(n')} \qquad (6)$$

The weight $\Delta w_{(n')}$ is adapted as per Equation (7) shown below

$$\Delta w_{(n')} = \delta \cdot X_{(n')} \cdot E^{(BP)} \qquad (7)$$

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

$$E^{(BP)} - \text{BP Error.} \qquad (8)$$

The procedure is constant with the assistance of the stages indicated in Equations (6) and (7) until the BP fault is minimized, i.e. $E^{(BP)}<0.1$.

The main disadvantage of Backpropagation [10].

.Backpropagation is an optimization feed forward neural network. It avoids the need for long training sessions to find an acceptable weight solution because of the well-known difficulties inherent in gradient descent optimization, such as small error gradients and memory usage.

.Weights and biases in initialization have a substantial influence on backpropagation. A poor choice can result in stagnation at local minima, resulting in a suboptimal solution. there is no guarantee to find the global solution of a problem

So we optimization feed forward neural network by using meta - heuristic algorithm [34] instance the backpropagation algorithm

3.3.3 Bat Algorithm for Optimizing Weights in ANN

The bat algorithm is a meta - heuristic algorithm that was inspired by micro bat echolocation behavior [35]. In a feed-forward neural network, the bat algorithm (BAT) is used to optimize the weight and bais of hidden layer neurons.

The BAT that uses this echolocation function is determined by a lot of important factors, including frequency, velocity, pulse rate, and loudness. When updating the current location with the velocity of the most appropriate options, the BAT switches to the ideal solution. In each repetition, the pulse emission rate, as well as the loudness, is now efficient. Some of the expectations for achieving the BAT were predetermined based on the bats' distinct characteristics [2]. Figure 3 shows the main components of BAT algorithm.

Step 1: A random population of input microbats B_I is formed. The weights of neurons are referred to as micro-bats in our suggested technique. Each micro-bat has a velocity vector (V_I)and a location vector (X_I), which are given by the equation below (9). At first, these credentials' values are given randomly to a specified range.

$$B_i = \begin{bmatrix} (v_{11}.x_{11})^{b1} & (v_{12}.x_{12})^{b2} & \dots & (v_{1n}.x_{1n})^{bn} \\ (v_{21}.x_{22})^{b2} & (v_{22}.x_{22})^{b2} & \dots & (v_{2n}.x_{2n})^{bn} \\ \vdots & \vdots & & \vdots \\ (v_{m1}.x_{m1})^{b1} & (v_{m2}.x_{m2})^{b2} & \dots & (v_{mn}.x_{mn})^{bn} \end{bmatrix} \quad (9)$$

Step 2 :Echolocation characteristics including frequency (f_i) , pulse rate (pr_i)and loudness (l_i) are assigned to the micro-bat populations in step 2 of the process. Non-negative real numbers with the following ranges are included in these parameters.

$$f_{min} \le f_i \le f_{max}.pr_{min} \le pr_i \le pr_{max}.l_{min} \le l_i \le l_{max} \quad (10)$$

The frequency range is set to $f_{\min} = 0$ to $f_{max} = 1$, the pulse rate is set to $pr_{\min} = 0.5$, and the loudness is set to $l_{\max} = 1$. The succeeding Equation (11) determines the remaining values .

$$l_{min} = \frac{1}{\sqrt{n_{\text{sec}}}} \quad (11)$$

$$pr_{max} = 1 - \frac{1}{n_d} \le 1 \quad (12)$$

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

Step 3: Calculate the starting populations' goal function; the requisite fitness function is defined by the following Equation (13).

$$F_i = minMSE \quad (13)$$

Equation (13) specifies the fitness value for each microbat based on the frequency of each class label. The mean square error is used to calculate the fitness function of the micro bats (MSE). When a micro bat's MSE is discovered to be low, the micro bat is classified as a top micro bat.

Step 4: Save the current population and augment by t+1 to get the iteration count, i.e., iteration t = t+1.

Step 5: Based on the frequency and velocity, the current population of rules is randomly modified.

To begin, the frequency may be calculated using the following Equation (14).

$$f_i^t = f_{min} + (f_{max} - f_{min})u_i \quad (14)$$

The frequency is applied to the velocity equation, which can be expressed by the following Equation, where u_i is the random number of values taken from 0 to 1. (15).

$$v_i^t = \text{round}\,[v_i^{t-1} + (x_i^{t-1} - x_\Psi)f_i^t] \quad (15)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (16)$$

Where v_i^t and tv_i^{t-1} represent the velocity vectors of the micro-bats at time steps t, x_i^t andx_i^{t-1} represent the position vectors of the micro-bats at time steps t, and x_Ψ is the current global best solution. This is defined by the following Equation(17) after doing the local search in the randomly chosen population. A solution is chosen from the current set of best solutions, and then a random walk is used to generate a new solution.

$$x_{new} = x_{old} + \xi_{i.j} l^t_{\text{avg}} \quad (17)$$

Where $\xi_{i.j}$ is a random integer between -1 and 1, and l^t_{avg} is the time step's average value of loudness.

Step 6: Using Equation(13), determine the fitness of the new micro-bat population. Following assessment, the echolocation parameters of micro-bats are modified to better their movement, as represented by the following Equation (18).

$l_i^{t+1} = a \cdot l_i^t$ and $pr_i^{t+1} = pr_{max}[1 - \exp(-\gamma t)]$ (18)

Where l_i^{t+1} and l_i^t are the updated and prior loudness levels, respectively. pr_i^{t+1} is the pulse rate of the micro-bats during the time step, while a and γ are the loudness and pulse rate adaptation parameters.

Step 7: Identify the optimal micro-bats that satisfy the goal function.

Step 8: Repeat steps 4–7 until the termination requirements are met.

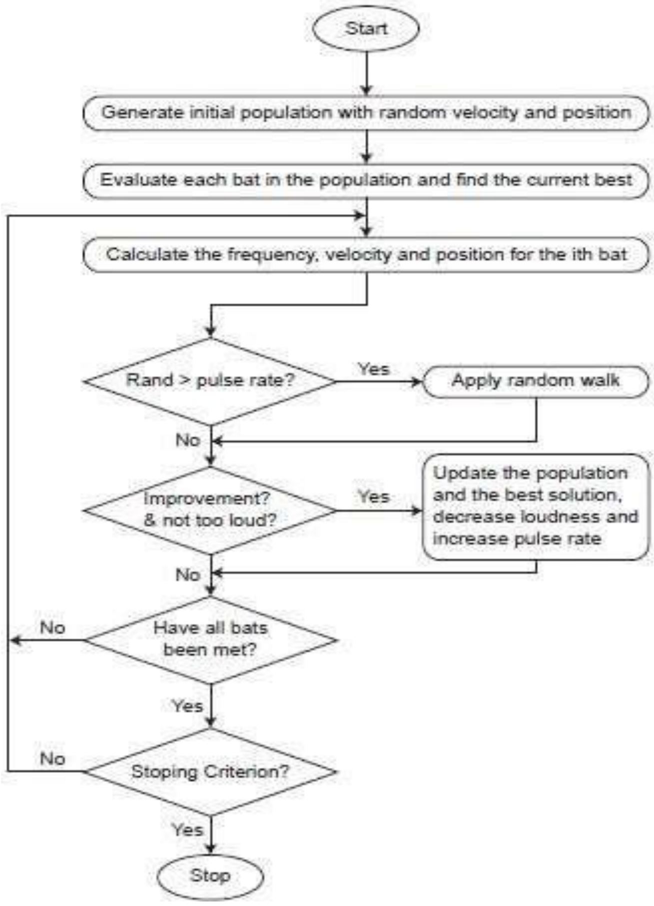

Figure 3: the main components of BAT algorithm

3.3.4 Enhancement Bat Algorithm

That makes it an effective algorithm for services much like classifications. Nevertheless, when we permit the algorithm to switch to exploitation stage much too immediately, it may result in stagnation after certain first stage [2].

EBAT is inspired by the principle of life restoration. Technically, the life of a bat is ended when the bats do not have a power for find new solution. It is developed the mechanism of bat by increase the diversity and replace the population if and only if the bats still in stagnation after n iterations. In fact, high diversity in population methodologies are proposed with the aim to promote diversity in the next generations[36] . Therefore, the exploration of a new solution has increased by high diversity Moreover, EBAT like other EAs consists of four stages: initialization, population distribution, updating population, and termination.

So that we suggest an approach to enhance the local search capability and overcome the issues of exploitation and exploration capabilities of conventional Bat algorithm will avoid to trap in local optima. To reduce this issue, in this paper, proposed enhancement bat algorithm (EBA), which improve the exploitation ability of bats and escaping from local minima.

In order to reduce the probability of stagnation in the search process, the proposed algorithm kill all bats if the bat not have contributed best solution and move the search operation toward another best solution. Equation (19) illustrates the constraint to re-generate bats in new generation.

$$\boldsymbol{\sigma} > \textbf{Round}\,(\boldsymbol{O}_{max} - (\frac{iter}{max_{iter}})^2 \times (\boldsymbol{O}_{max} - \boldsymbol{O}_{min}))) \qquad (19)$$

Where σ: set by user , Iter : is current iteration , max_{ite} is max iteration

$O_{max}.O_{min}$ is constant coefficient to control on the restart operation

Enhancement Bat Algorithm (EBA)

Input : Bat parameters:

Population size (P_z) , Problem dimensions (m) , Omax , Omin, $F_{max}.F_{min}$

Output: $Best_{cost}.\ Best_{weight}$

Begin {
σ ← *0* //set zero to **σ** because no a stagnation in begging
P ← Population initialization ($P_z.U.L.m$)
V_i←0, F_i←0 ,set initialize $A.r$
While $iter<max\_iteration$ and not satisfy the termination criteria do {
For each $X \in P$ **do**{
$F_i \leftarrow F_{min}+(F_{max}-F_{min})\beta$
$V_i^{iter} \leftarrow V_i^{iter-1}+(X_i^{iter-1} - G_{\text{best}}) * F_i$
$X_i^{iter} \leftarrow X_i^{iter-1} + V_i^{iter}$
If random > r_i, **then {**
$X_i^{iter} = X_i^{iter} + \varepsilon * \mathrm{A}$
}//EndIf
cost$_{\text{pos}}$← accuracy of (X_i^{iter})
If cost$_{\text{pos}}$ > cost$_{\text{pos}-1}$**then {**
$\sigma \leftarrow 0$
Else
$\sigma \leftarrow \sigma + 1$
}//EndIf
If σ > Round $((O_{max} - (\frac{iter}{max\ iter})^2 \times (O_{max} - O_{min})))$ **then {**
$X_i^{iter} \leftarrow$ Population initialization
}//EndIf
If cost$_{\text{pos}}$ > $Best_{cost}$ **then {**
$Best_{cost} \leftarrow$ cost$_{\text{pos}}$
$G_{\text{best}} \leftarrow X_i^{iter}$
$A_i^{iter} \leftarrow \alpha * A_i^{iter-1}$
$r_i^{iter} \leftarrow r_i^{iter-1} * (1 - e^{-\gamma t})$
}//EndIf
}// EndForEach
}// **EndWhile**
Return $Best_{cost}.\ G_{\text{best}}$
//End Algorithm

Algorithm () : Population initialization
Input: Omin, Omax , vector size (V) , population size (P_z)
Output: X (initial population)
1. **Begin** {
2. Population ← [] # population stored as a list
3. **For** i **in range(**P_z**) do**
4. pos = [uniform(O_{min}, O_{max}) for _ in range(V)] // new candidate solution (bat)
5. X [i] ← pos
6. }// EndFor
7. **Return** X
8. **} //End Algorithm**

Using the comprehensive features extracted from each image, the classification is performed using the proposed forward neural network, with the results showing improved classification accuracy.

where that 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 EBat algorithm is the minimization of MSE. For a neural network, we have to minimize the error, and avoid the stagnation to arrive for the near optimal or best solution to get the accurate classification.

4. Results and discussion

4.1. Database Description

The experiment was conducted in MATLAB (2020a) using the suggested technique, and an optimal fingerprint picture was created using the Image Processing Toolbox. The technique used in this study was verified using the FVC2002 dataset [2]. The Fingerprint Verification Contest, or FVC2002, is used to gather fingerprint pictures, and samples are obtained from SFinGev2.51. Numerous sensors are attached to FVC2002 in order to gather data from four databases inside the FVC2002 database. The photos for DB1 were collected using a low-cost optical sensor. A low-cost capacitive optical sensor was utilized to gather images for the DB2. DB3 is constructed using relatively high-quality optical sensors. Finally, DB4 databases are created industrially utilizing SFinGe v2.51. The total number of photos utilized in this instance is 320. We used a 70-30 ratio for training in this. Calculate the frequency and velocity Begin by measuring your pulse rate and loudness. Assess fitness Develop a novel solution Determine the optimal solution Calculate the greatest level of fitness attained Rand > Pulse frequency Position the bat and search for the finest options.

4.2 image processing

the input fingerprint images improved by the Histogram equalization technique to contrast enhancement. then feature extraction by using Gabor filter and reduction dimension by use the LDA and concatenation with histogram of gradient after reduction dimension by LDA.

We extract feature from image by Gabor filter with LDA about 9 feature represent as vector for each fingerprint image. also extract by HOG after reduction about 10 feature for each fingerprint image form all database fvc2002. this vectors Gabor-LDA+HOG-LDA concatenation together that equal 19 features for each image to represent an input for feedforward artificial neural network with EBat algorithm to classification images and comparison with the Original Bat algorithm, Backpropagation Artificial Neural Network and Genetic Algorithm.

4.3 Performance Evaluation

The suggested approach's performance is evaluated using many measures, including precision, recall, accuracy, worst, and F-score. These stats are tabulated for various training testing percentages. Similar metrics are also examined and calculated for current techniques in order to compare them to the proposed approach. In our suggested methodology, we used a neural network, which is a well-known classification technique. Table (2) Set of used parameters in the experiment for performance analysis of the proposed algorithm and Table (3) summarizes the performance evaluation of the proposed method (FFNN+EBAT).

Table (2) Set of used parameters in the experiment for performance analysis of the proposed algorithm

Metaheuristic	Parameter	Value
Artificial Neural Network	epochs = 50	50
	number of input neurons	19
	number of hidden layer	1
	number of hidden neurons	17
	number of out neurons	10
	random range	[-0,5,0,5]
	learning_rate	0.01
	momentum_rate	0.9
	activation faction	Sigmoid
Genetic algorithm	population_size	100
	Selection- method	elites
	elite_proportion	0.05
	Crossover -method	Single point
	Tournament-proportion	0.07
	Crossover rate	0.90
	Mutation rate	0.05
BAT	population_size	100
	Loudness	0.95
	Pulse rate	0.5
	Random walk	[-1,1]
	Frequency minimum	0
	Frequency maximum	2
	Alpha	0.9
	gama	0.9
EBAT	Loudness	0.95
	Pulse rate	0.5
	Omin	5
	Omax	10

Table 3. Evaluation of the Proposed Method's Performance (FFNN+EBAT)

Training –Testing	**90-10**	**80-20**	**70-30**
Accuracy	97.875	98.4375	98.958
worst	94.75	96.87	97.916
Best	97.875	98.4375	98.958
Precision	97.656	98.6328	99.074
F-score	97.264	98.5350	99.016

The figure (4) illustrates the precision, sensitivity, specificity, accuracy, and F-Measure values attained by the predicted approaches for a variety of training and testing variables.

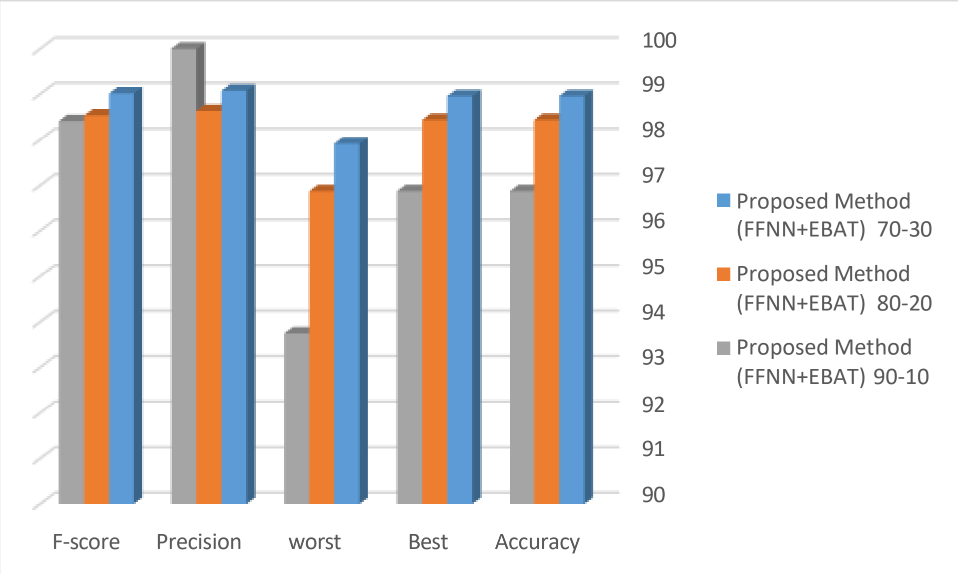

Figure 4:Proposed Performance (FFNN+EBAT) for different training and testing ratios

The following Table (4) illustrates the Best, precision, Recall, worst, accuracy, and F-score values obtained using the predicted and prevalent approaches. From the results obtained, it is clear that our expected system outperformed the old technique.

Table (4) compares the performance of suggested and established approaches

Training – Testing	ProposedMethod (FFNN+EBAT)	(FFNN+BAT)	Artificialneural network and genetic algorithm	Backpropagation Neural network
Accuracy	98.958	97.916	96.875	85.416
best	98.958	97.916	96.875	85.416
worst	97.916	96.875	94.791	53.125
Precision	99.074	98.239	97.326	88.531
Recall	98.958	97.983	96.875	85.416
F1-scor	99.016	98.0776	97.1001	86.946

Training and testing of 70%-30% from the data extracted using concatenation Gabor-LDA and HOG-LDA. As a result, the above performance evaluation illustrate Accuracy, best , worst , Precision , Recall , F1-scor over feed-forward artificial neural network with enhancement bat algorithm and compared with FFANN-BAT , FFANN-GA ,and BPANN . As a result, it is shown that our suggested FFNN with EBAT algorithm outperforms the previously discussed methods. The following Figure (5) compares all of the above-mentioned parameters for proposed and anther algorithm also above mentioned with 30-70 testing-training.

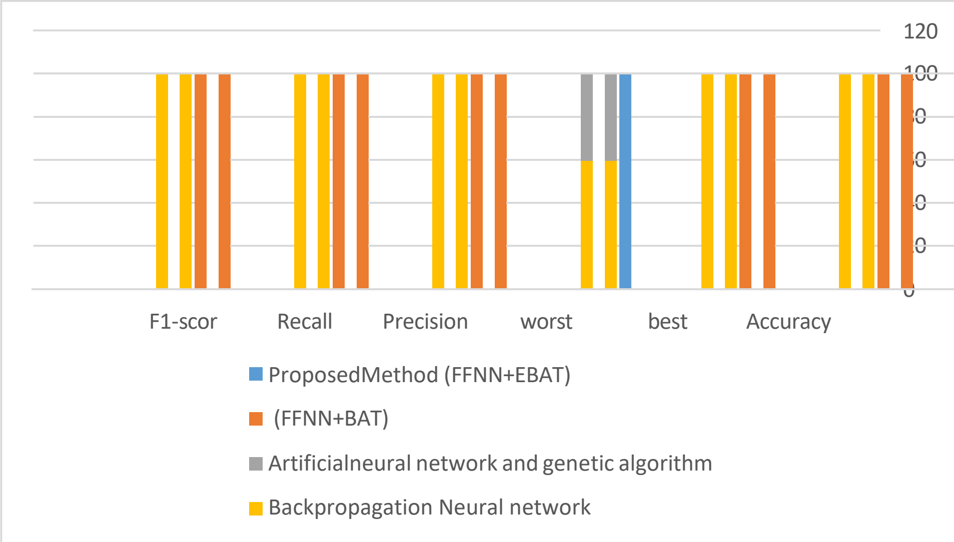

Figure (5) Graphical representation of Performance metrics for proposed and prevailing methods.

Table(5) specified below shows the values of metrics such as accuracy, sensitivity, specificity, accuracy and F-scaling achieved by the expected and dominant methods. All algorithms were tested with Gabor-HOG descriptors with 19 inputs, 10 outputs and one hidden layer with number of neuron approximate 25 and were trained and tested with different ratios 70-30, 80-20, 90-10, it is clear that our expected system has outperformed the learning method using feedback, as well as the meta-heuristic methods such as the bat algorithm and the genetic algorithm because the proposed algorithm was able to overcome the local minimum and jumping from it to approach the optimal solution or reach the best solution.

Table(5): shows the values of metrics with different training and testing ratios.

Algorithm	**Proposed Method (FFNN+EBAT)**			**(FFNN+BAT)**			**Artificialneural network and genetic algorithm**			**Backpropagation Neural network**		
Train-test / Performance	**90-10**	**80-20**	**70-30**	**90-10**	**80-20**	**70-30**	**90-10**	**80-20**	**70-30**	**90-10**	**80-20**	**70-30**
Accuracy	98.4375	98.958	98.958	93.75	96.875	97.916	90.625	95.313	96.875	96.875	81.25	85.416
best	96.87	97.916	98.958	93.75	96.875	97.916	90.625	95.313	96.875	96.875	81.25	85.416
worst	98.4375	98.958	97.916	90.62	95.31	96.875	84.37	92.18	94.791	43.75	45.31	53.125
Precision	98.6328	99.074	99.074	96.354	97.206	98.239	88.261	96.19	97.326	84.375	86.08	88.531
Recall	98.5350	99.016	98.958	93.75	96.875	97.983	90.625	95.313	96.875	81.25	84.73	85.416
F1-scor	98.4375	98.958	99.016	95.034	97.04	98.0776	89.427	95.753	97.1001	82.78	85.22	86.946

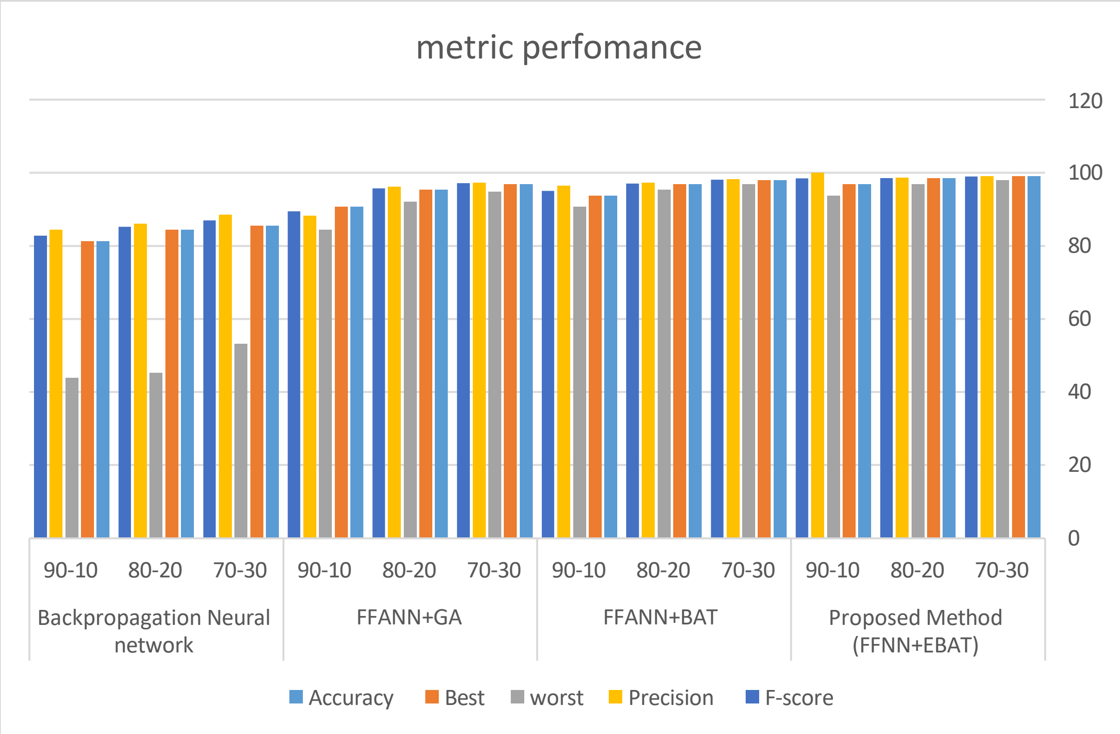

Figure (6): Evaluation of Performance Metris for different training and testing ratios

Table (6): Performance assessment of proposed and prevailing methods

Algorithm / Performance	Proposed Method (FFNN+EBAT)	BPANN-BAT	BPNN-PSO	Adaptive genetic algorithm with BPNN	Back propagation ANN without optimization
Accuracy	98.958	95.8265	94.65	94.82	93.075
Precision	99.074	94.53	9385	94.53	95.63
Recall	98.958	95.8265	93.25	94.82	93.075
F1-score	99.016	95.32	94.65	95.32	90.25

As a result of the aforementioned performance assessment, precision, Recall, accuracy, and F1-score are superior to Neural network without optimization, the Neural network with PSO algorithm, and the proposal feed-forward Artificial Neural network with EBAT method. As a result, it has been shown in table(6) that our suggested FFANN with EBAT algorithm better from hyper Backpropagation Artificial Neural Network with Bat algorithm hyper BP-Artificial Neural network with PSO and hyper BP-Artificial Neural network with Genetic algorithm because the ANN is dependent on gradient descent but proposal method can avoid on the problem of ANN by using the meta-heuristic instance of the backpropagation to training feed-forward ANN and proved the EBAT algorithm better from the original Bat algorithm and Genetic algorithm. Because it can able to be balanced between exploration and exploitation to overcome the state of stagnation and escape local minimum to arrive the best solution. The comparison of all of the above parameters for proposed and existing approaches is shown in the below Figures(7,8).

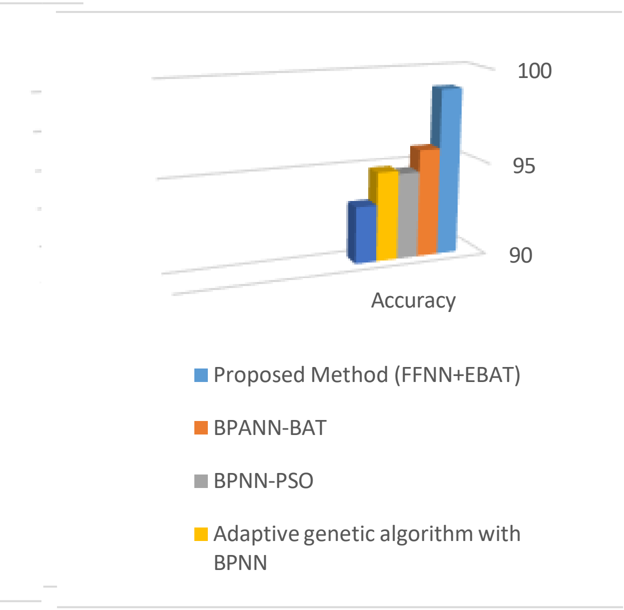

Figure (7): Graphical representation for Accuracy attained by proposed and availabl methods.

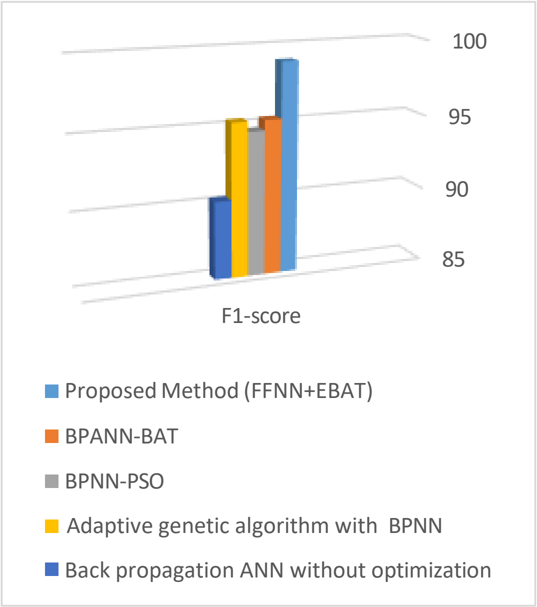

Figure (8): Graphical representation for F-Measure attained by proposed and availabl methods

5. Conclusion

The features extraction is the main stage in a fingerprint as it provides the parameters for evaluating the image for classification purposes. Matching accuracy depends on extracting features precisely and reliably. In this research, the concatenation method between Gabor filter and filter was used to get the best features for fingerprints from both filters after reducing their dimensions using the LDA algorithm. This feature vector (LDA GF+LDAHOG) is provided as the input to the ANN.

To classify the fingerprint images, we used a feed-forward artificial neural network and optimized the network weights by using metaheuristic algorithms instead of the backpropagation algorithm to get a more accurate and less complex neural network. To achieve this goal, we proposed an improved bat algorithm based on the original algorithm in order to improve the exploration and exploitation strategy of the algorithm in the community to promote balance and avoid escape from local minimums. The EBAT algorithm was compared with the original bat algorithm, the genetic algorithm, and BPANN algorithm, and the results of the proposed algorithm were superior to the above-mentioned algorithms. The proposed algorithm was also compared with the literature of methods that used the hybrid BPANN algorithm with Metaheuristic algorithms such as the GA, PSO algorithm, BA algorithm, and the proposed algorithm EBAT-FFANN achieved better accuracy than the hybrid algorithms and proven to be the best alternative to the traditional ANN training approach for solving classification problems. The proposed algorithm gave an accuracy of about 99% in training-testing 70-30. The proposed strategy maintains the diversity of the swarm and improves the local search capability. This shows that the proposed method has better convergence accuracy and can avoid premature convergence.

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