A Fuzzy based Classification Approach for Efficient Fake and Real Fingerprint Classification with Intelligent Feature Selection

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Abstract: - Fake and real fingerprint classification has become an attractive research area in the last decade. A number of research works have been carried out to classify fake and real fingerprints. But, most of the existing techniques did not utilize swarm intelligence techniques in their fingerprint classification system. Swarm intelligence has been widely used in various applications due to its robustness and potential in solving a complex optimization problem. This paper aims to develop a new and efficient fingerprint classification approach which overcomes the limitations of the existing classification approaches based on swarm intelligence and fuzzy based neural network techniques. The proposed classification methodology comprises of four steps, namely image preprocessing, feature extraction, feature selection and classification. This work uses efficient min-max normalization and median filtering for preprocessing, and multiple static features are extracted from Gabor filtering. Then, from the multiple static features obtained from 2D Gabor filtering, best features are selected using Artificial Bee Colony (ABC) optimization based on certain fitness values. This optimization based feature selection selects only the optimal set of features which is used for classification. This would lessen the complexity and the time taken by the classifier. This approach uses Fuzzy Feed Forward Neural Network (FFFNN) for classification and its performance is compared with the SVM classifier. The performance and evaluations is performed for real and fake fingerprint images obtained from LivDet2015 database. It shows that proposed work provides better results in terms of sensitivity, specificity, and precision and classification accuracy.

Key-Words: - Fake and real Fingerprint classification, multiple static features, normalization, median filtering, Gabor filtering, Artificial Bee Colony (ABC) optimization, Fuzzy Feed Forward Neural network (FFFNN)

1 Introduction

As Biometric systems have been widely used in various applications such as access control, law enforcement systems and border management systems for human identification based on biological traits such as face, fingerprints, iris, etc. Nowadays, a wide variety of approaches have been developed in order to fulfill the growing demand for security. Among all the biometric traits aside, fingerprints are being extensively used in various applications. They are highly distinguished and unique, even for identical twins, and are publicly accepted as reliable traits. The ridges and valleys are the main reason for the distinguishing shapes of the fingerprint. The singular regions namely loop and delta produced by the ridges is the main factor used in fingerprint classification. The ridges would also represent the global attributes of the fingerprint through their unique orientation and frequency. Although the fingerprint based biometric systems produce significant results, they are still susceptible to the indirect attacks or the direct attacks at the sensor level.

Recent investigations and observations have [1],[2] showed that biometric systems are being subjected to various threats. The main issue and the challenge is to classify whether the biometric fingerprint is real or fake. In fact, it is difficult to make a fake fingerprint image having the same or better image quality than that of the original. In general, the classification of fake fingerprint image has become an active research area. K.Thaiyalnayaki et.al [3] detected the liveness of a fingerprint by computing the standard deviation of the fingerprint image through the wavelet transform. The benefit of this approach is that it is the speed and ease of use. This work has contributed an essential technique that can detect the liveness by observing the image quality. The fingerprint dummies can be fabricated through typical materials like gelatin, silicone or latex. These fake fingerprints are created by the intruders to get falsely accepted by the biometric system.

The transformed fingerprints are fabricated with the goal of being falsely rejected by the biometric system. Thus, fingerprint classification has been an attractive research area in the last decade. Generally, classification techniques consist of four steps, namely preprocessing, feature extraction, feature selection and classification. Image preprocessing becomes one of the essential steps in biometric systems to eliminate noise from fingerprint images and fake images. Li Wang and Nandita Bhattacharjee proposed an adaptive image preprocessing technique based on their noise level and contrast stretching capability through their power-law transformation and Gabor filter [4]. However, none of the above approaches utilize a normalization approach to eliminate noise in the images.

In this paper, a Min-max normalization and median filtering approaches are used as image preprocessing steps to eliminate noises from fake and real fingerprint images. The static technique is useful in extracting features, but the major limitation of this approach is that it makes a decision based on only a single image [5]. This would result in the degradation of the classification performance. In order to overcome these issues, this work extracts multiple statistical features such as power spectrum, directional contrast, ridge thickness, ridge signal, and first order histogram, of the fingerprint images using Gabor filtering methods. After efficient multiple statistical features are extracted, Artificial Bee colony (ABC) optimization technique is used which selects the best features of the extracted features and then classification takes through Fuzzy Feed forward Neural Network (FFFNN) classifier which classifies the real and fake fingerprint.

Thus, this research works mostly focuses on developing an efficient fingerprint classification approach with lesser complexity and higher accuracy when compared with the existing techniques.

2 Related Work

A number of existing approaches can be partitioned into hardware-based and software-based approaches [5]. Hardware based approaches focus on detecting the fake fingerprint through additional hardware tools and ability to measure physiological signs. The software-based systems are observed to be inexpensive and less conspicuous. These approaches use feature vectors obtained from one or multiple impressions (static measures) or multiple frames (dynamic measures) of the same finger to distinguish real and fake fingers [6].

Wavelet-based techniques were initially used in fake fingerprint detection [7] ,[8] but recently new approaches based on the wavelet transform of the ridge signal extracted along the ridge mask is presented which can detect the perspiration event using only a single image. Statistical features are extracted for multiresolution scales to distinguish between real and fake fingers. Based on these features, separation (real/fake) is performed using classification trees and neural networks. Results of test this method on the different dataset of fingerprint images show that can get approximately 90.9-100% classification of fake and original fingerprints [9]. In [10] introduced a new approach for discriminating fake fingers from real ones, based on the study of the distortion effects in fingerprint matching process. The user is required to move the finger while pressing it against the scanner surface, thus deliberately exaggerating the skin distortion. New techniques for extracting, encoding and comparing skin distortion information are formally defined and measured over a test set of real and fake fingers.

As mentioned [2], live and fake fingerprints are visually different. For example, fake fingerprint images look darker and have less contrast than their corresponding live fingerprints. Therefore, to analyze the visual differences between live and fake images used the seven first-order histogram features that were suggested [2].Fake fingerprints are used in the attempts to get falsely accepted by the biometric system. The fingerprint dummies are fabricated using typical materials like gelatin, silicone or latex. The weakness of the fingerprint based biometric systems regarding this problem was highlighted in [11] after these studies, liveness detection technologies were introduced based on skin odor [12], optical properties [13], Optical Coherence Tomography (OCT) technology [14]. Other properties were also used like thermal properties, which are not very reliable due to the temperature variations in operating environments and also the possibility to heat the finger artificially, electrical or biomedical properties which also have limitations.

A new method based on the distribution of minutiae and the orientation field was proposed in [15]. The minutiae are almost uniformly spread in the natural fingerprint area while in the altered fingerprint area (along the scars) they appear in an excessive number, many of them being spurious. The method was tested at finger level and at subject level, on a real altered fingerprints database (obtained from governmental agencies) and compared with the finger print image criterion [16]. It was proven that fingerprint quality estimation methods are not sufficient to detect fingerprints alteration.

3 Proposed Fingerprint Classification Methodology

This paper proposes an efficient fingerprint classification method to classify the fingerprint images as fake and real fingerprint image in an efficient manner. This work initially removes irrelevant noise from original and fake fingerprint image samples to increase both classification accuracy and interpretability of the digital data during the image pre-processing stage. In this work, normalization method is used as preprocessing step to perform image contrast enhancement and median filtering methods are used to remove the noises from samples. Then, multiple static features extraction are performed for single images which uses Gabor filtering method and thus fulfilling user requirements such as expediency, time complexity and accuracy. From the extracted features, best features are obtained from the Artificial Bee Colony (ABC) optimization algorithm based on the fitness function and then it uses a FFFNN as a classifier. These four steps are explained in detail in the following sections. The entire architecture of the proposed fingerprint Classification method is shown in Fig.1.

3.1. Min-max normalization for contrast Enhancement

In image processing, normalization is a process that adjusts the series of pixel intensity values, particularly when the contrast level of the images is low due to clarity. In this work, a Min –Max normalization method that adjusts the range of pixel intensity values for better clearness is used. It carries out a linear transformation function of the original input image. It is measured that min_A, max_A are the minimum and maximum range of pixel intensity values in the input image range (min_A, max_A), into a new image range v' in the range (new_min_A, new_max_A), by calculating,

$$v' = \frac{v - min_A}{max_A - min_A} \tag{1}$$

Min-max normalization method should maintain the same pixel intensity values for original images.If the intensity values of original input image values (A) are changed, it will be encountered as out of range error for future prediction of normalization process. Thus, if the intensity range of the given image is between 30 and 150 and the required image intensity range is between 0and 255, the normalization process starts with subtracting 30 from each given image of pixel intensity, making the range between 0 and 120. The intensity values of images ranges is multiplied by 255/120, creation of the range 0 to 255.

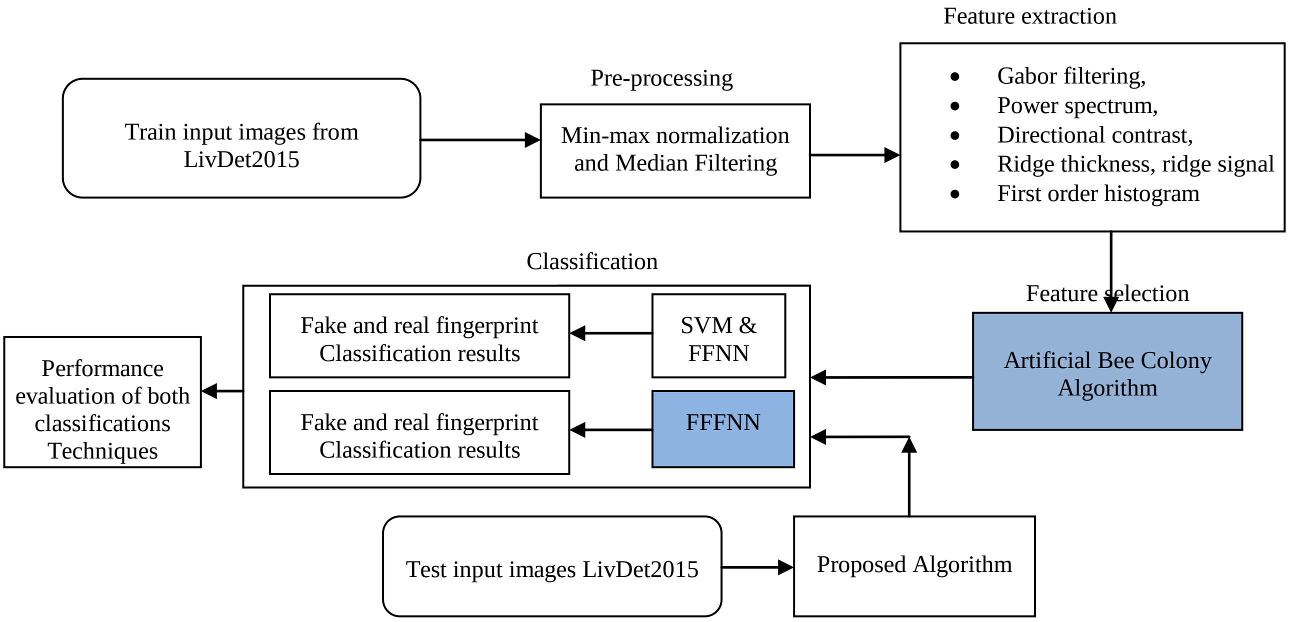

Fig.1 Proposed Fake and Real Fingerprint Classification Methodology

3.2. Median filtering method for noise removal

Median filter is one of the commonly used non linear filtering methods and it is used to reduce noise from image samples. Such noise reduction technique is a classic pre-processing step to enhance the results of processing. It is widely used in various digital image processing applications. The sliding median filter of a pre-specified image window with size $\mathrm{W} \times \mathrm{W}$centered at image pixels $\mathrm{i} = (\mathrm{i}_1, \mathrm{i}_2)$ progress consistently over the noisy image, g and selects median $\mu$of the pixels within a specified range of pixels for spatial domain $\Omega_{\mathrm{i}}^{\mathrm{W}}$approximately ito have g(i) and noisy image g(i) is replaced by μ. For the set of pixels within a square window $\mathrm{W_D} \times \mathrm{W_D}$, centered at $\mathrm{i} = (\mathrm{i}_1, \mathrm{i}_2)$and defined specified range of pixels for spatial domain $\Omega_{\mathrm{i}}^{\mathrm{W}}$approximately by equation, the median,μof the pixels in spatial domain $\Omega_{\mathrm{i}}^{\mathrm{W}}$ is

$$\mathrm{u}(\mathrm{i}) = \mu_{\mathrm{i}} = \mathrm{median}\left\{\frac{\mathrm{g}(\mathrm{j})}{\mathrm{j}} \in \Omega_{\mathrm{i}}^{\mathrm{W}}\right\} \quad (2)$$

Thus, the output of the median filter is defined as θ which produces lesser error rate results with the entire pixels in the local neighborhood defined by the mask. The output of the median filter at spatial location i can also be specified as $\mathrm{u}(\mathrm{i}) = \mu_{\mathrm{i}} = \underset{\theta}{\mathrm{argmin}} \sum_{\mathrm{r} \in \Omega^{\mathrm{W}}} |\mathrm{g}(\mathrm{r}) - \theta|$.

Fig.2 Input image samples

Fig.2 shows the input image sample in which the first row shows two real input image samples and second row shows the input image samples of two fake images obtained from LivDet2015 database.

Fig.3 Gaussian Noise Incorporated Image

Fig.3 shows the image samples after the Gaussian noise are added to images samples for both real and fake fingerprint images samples.

3.3. Gabor filtering for multiple static feature extraction

In order to improve fingerprint classification performance, it is not sufficient to extract single static features from images. Since the characteristics of input fingerprint samples vary according to the type of sensor and characteristics of fake and synthetically generated image samples which are based on conditions such as user skin, working surroundings, fabrication materials, etc.. In order to obtain better classification performance, it is desirable to extract specific static features. A Gabor filter-based multiple static feature extraction is proposed in this section. In this work, certain important multiple static features such as power spectrum, histogram, directional contrast, ridge thickness, and ridge signal are extracted from each and every fingerprint image and it provides the best description of the visual substance of fingerprint images. Based on this motivation, two-dimensional Gabor filtering is being selected for feature extraction in this approach. Thus, a bidimensional Gabor filter represents a complex sine wave plane of specific frequency and ridge orientation levels, it is transformed by a Gaussian envelope. It achieves an optimal resolution in both spatial and frequency domains.

$$G_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) = exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right). \cos(2\pi f_i x_{\theta_k} + \varphi) \quad (3)$$

Where $x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$, $y_{\theta_k} = y\cos\theta_k - x\sin\theta_k$,$f_i$ present the central frequency of the sine wave at an angle θ_k with the x-axis ,σ_x, σ_y represent the standard deviations of ridges together with the axes x and y match to image size .Set the phsae $\varphi = \frac{\pi}{2}$ And compute each and every ridge orientation as $\theta_k = \frac{k\pi}{n}$ where $k = \{1, \ldots \ldots n\}$.Thus, certain proper variance values are considered which are a set of radial frequencies of the ridges in the image and a sequence of orientations. Consequently, the filter's parameters are considered as$\sigma_x = 29_y = 1$. $f_i \in \{0.75, 1.5\}$is represented as the frequency differentiation of the features and n=5, $\theta_k \in \{\frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}, \pi\}$[17]. t is applied to fingerprint images.. The resulted Gabor filter is then grouped into a three-dimensional feature vector. If I characterizes such a fingerprint image, then a $[X \times Y]$ size is included, and its feature extraction can be specified as follows:

$$V(I)[x,y,z] = V_{\theta(z),f(z),\sigma_x,\sigma_y}(I)[x,y] \tag{4}$$

Where $x \in [1, X]$, $y \in [1, Y]$ and

$$\_(z) = \begin{cases} \theta_z, & z \in [1,n] \\ \theta_{z-n}, & z \in [n+1, 2n] \end{cases}, f(z) = \begin{cases} f_1 z \in [1,n] \\ f_2\ , z \in [n+1, 2n] \end{cases} \tag{5}$$

And

$$V_{\theta(z),f(z),\sigma_x,\sigma_y,}(I)[x,y] = I(x,y) \otimes G_{\theta(z),f(z),\sigma_x,\sigma_y}(x,y) \tag{6}$$

An efficient 2D Gabor filtering method can be performed using the Fast Fourier Transform; consequently it is equivalent with the following relation

$$\mathrm{V}_{\theta(z),f(z),\sigma_x,\sigma_y,}(\mathrm{I}) = \mathrm{FFT}^{-1}\left[\mathrm{FFT}(\mathrm{I}).\,\mathrm{FFT}\left(\mathrm{G}_{\theta(z),f(z),\sigma_x,\sigma_y}\right)\right] \tag{7}$$

After the features are extracted, these features are given to the feature selection algorithm in order to select the best features. This work uses ABC algorithm for best feature selection.

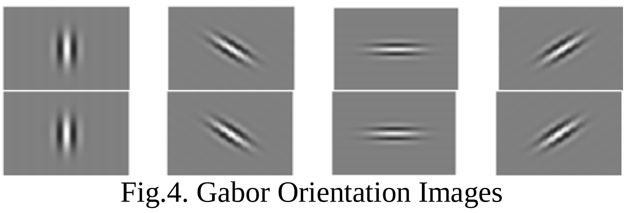

Fig.4. Gabor Orientation Images

Fig.4 shows the feature extraction results of real and fake fingerprint image samples with Gabor orientation.

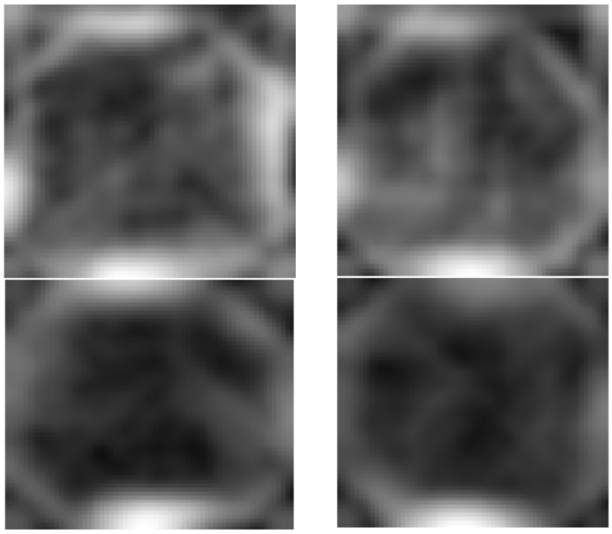

Fig.5. Gabor Images

Fig.5 shows the Gabor images for real and fake fingerprint images after the Gabor filtering is applied.

3.4. Artificial Bee Colony (ABC) optimization for multiple static feature selection

One of most important swarm-based optimization algorithms are Artificial Bee Colony (ABC). ABC has been successfully used for feature selection optimization [18] as it is easy to develop and solve many optimization problems with only a few controls of parameters [19]. ABC suggests the intellectual searching behavior of a honey bee swarm. In ABC, the dependency of artificial bees contains three major groups of bees namely employed bees, onlookers and scouts. As an initial step, initial populations of size SN is randomly generated, where SN (total number of input fingerprint samples with feature extracted results) denotes the size of the population. Each feature selection, solution $\mathrm{x_i}, (\mathrm{i} = 1,2, \ldots .\mathrm{SN})$ is a D-dimensional vector. Here, D is the number of optimized parameters. After initialization of features, each population has a number of features positions which is subjected to a maximum number of cycles, $\mathrm{C} = 1, 2, \ldots, \mathrm{MCN}$, to complete feature selection search processes of the bees.

In ABC optimization, employed bees visit the food source position considered as features and gathers information about multiple static features to improve quality of classification results. Employed bees have memory, so they know the places they have visited before and the quality of features there have selected. Employed bees perform the local investigation of best feature selection and try to exploit the neighboring locations of features such as power spectrum, directional contrast, ridge thickness, ridge signal, and first-order histogram, food source and search the best places of features food source in the nearby areas of the present value. The bees waiting in the nest area to choose important feature are termed as onlooker bees. The decision of feature selection is made on information about multiple static features given by employing bees. Onlooker bees perform the global investigation for discovering new multiple static feature selection results and update global optimum multiple static feature selection results. Scout bees randomly search for each multiple static feature selection. Scout bees discover the new features selection areas which are not focused by the employed bees, these bees are completely random in nature and their operation of search. Scout bees avoid the search process to get attentive in local minima. These three steps are continued until a termination criterion is satisfied.

The position of each multiple static feature solution represents a probable solution to the best feature selection and the nectar amount of a feature solution corresponds to the quality of best multiple static features that associates with each one of the features.

$$\mathrm{fit_i} = \frac{1}{1 + \mathrm{fit_i}} \tag{8}$$

The fitness of each of multiple static features is assigned randomly depends on the importance of the multiple static feature. The importance of every multiple static features is separately estimated using the following conditions. The fitness of each static feature value is described in table 1. The power spectrum values depend on ridge-ridge distance level. The histogram features are selected based on entropy measures. If the corresponding image feature is greater than the entropy value, then the feature is elected else removed. The ridge thickness estimates based on gray level values of every block in a way on usual to the ridge orientation. When ridge thickness gray level values reach the threshold value then it is selected, else it is not selected. The individual fitness condition for each static feature is mentioned in table 1.

Table.1. Fitness condition for static features

Features	Fitness condition
Power spectrum	Ridge-to-ridge distance (500 dot/in)
Histogram and Contrast	Entropy
Ridge thickness, and Ridge signal	Best gray level values

An artificial onlooker bee selects best static features rely on the probability value associated with that feature spacep_i, calculated by the following expression,

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{9}$$

wherefit_irepresents the fitness value of the feature solution i in the location and SN is the number of extracted features results for images, which is equivalent to the number of employed bees.

In order to generate a candidate feature selection position from the earlier feature selection result, ABC uses a following equation (8) and update it location,

$$v_{ij} = \chi_{ij} + \phi_{\mathrm{ij}}\left(\chi_{ij} - \chi_{k\mathrm{j}}\right) \tag{10}$$

Where k and j are randomly selected feature samples $\mathrm{k} \in \{1, 2, \ldots, \mathrm{SN}\}$&$\mathrm{j} \in \{1, 2, \ldots, \mathrm{D}\}$. $\phi_{\mathrm{ij}} \in [-1,1]$, it is used to control the production of nearest optimal feature selection sources approximately x_{ij} and represents the evaluation of two optimal feature selection locations visible to a bee. As it is observed from the equation (8), the differentiation among two different features extracted image samples of $\chi_{i,j}$ and $\chi_{k,j}$ decreases, the rest of the feature selection position χ_{ij} decreases. So that the optimum features selection solution in the searching process, the step length adaptation is reduced. From this result, the parameter value of χ_{ij} exceeds its threshold value, the result of feature selection is acceptable else it is not acceptable as best features, it is also replaced with a new feature selection results by the scouts bees, this operation can be defined in equation (9). In ABC, these static feature selection operations are replicated by producing a new feature selection position of randomly selected static features and changing it with the discarded one. In ABC, if a current feature selection position does not improve the result within a pre - specified number of iterations, then the current features selection position is assumed to be neglected.

In equation (10) the $\phi_{\mathrm{ij}} \in [-1,1]$ becomes randomly generated random value it decrease the result of the feature selection ,in order to overcome these problem here introduce the Gaussian distribution function with zero mean and standard deviation value of the current features samples , it is represented in the form of

$$v_{ij} = \chi_{ij} + G(0, \sigma^2) \tag{11}$$

Where $G(0, \sigma^2)$ represents the Gaussian distribution with zero mean and standard deviation of the current feature samples.

$$\chi_i^j = \chi_{min}^j + rand(0,1)(\chi_{max}^j - \chi_{min}^j) \quad (12)$$

Then, feature selection samples position v_{ij} is estimated then its performance is compared with that each one of the previous features selection results. If the new feature selection result is better than old selected feature results, it is replaced with the old feature selection results in the memory. Or else, an old feature selection is kept as same. In other words, a greedy selection system works for the selection of feature operation between new selected features and subset features.

ABC algorithm employs four different selection processes:

(1) A global probabilistic selection process for each multiple static features such as power spectrum, directional contrast, ridge thickness, ridge signal, and first-order histogram, in which the probability value is calculated by equation (7) used by the onlooker bees for discovering promising multiple static features regions,

(2) A local probabilistic multiple static feature selection process for fake and real fingerprint images is carried out in a region by the employed bees and the onlooker bees depending on the visual information of features and is named as greedy selection, if quality feature selection results are not achieved, bee disregarded the current feature selection results and memorizes the candidate source produced by the equation (8)

(3) Bees keep the current multiple feature selection results.

(4) Multiple static features are randomly selected and it is done through scout bees as defined in equation (9).

All the above mentioned steps majorly depend on three parameters which restrict the operation of multiple static feature selection: The number of food sources which is equal to the number of image samples from feature extraction results(SN),maximum and minimum number of iterations to complete multiple feature selection process(MNC).

Algorithm 1: Artificial Bee Colony (ABC) optimization for multiple statistical feature selection

1. Initialize the population of solutions $x_i, i = 1, \dots\dots. SN$,each population as a number of features $x_1 = \{$Power spectrum, directional contrast, ridge thickness, ridge signal, and first -order histogram$\}$
2. Evaluate the population with features
3. Set cycle = 1
4. Repeat
5. Produce new feature selection solutions v_i for the employed bees (features) by using (8) and evaluate them best feature
6. Apply the greedy selection process for the employed bees are considered as features
7. Calculate the probability values P_i by (9)
8. Produce the new feature solutions v_i for the onlookers from the solutions X_i selected depending on P_i and evaluate them
9. Apply the greedy selection process for the onlookers are considered as features
10. Determine the abandoned feature solution for the scout, if exists, and replace it with a new randomly produced solution χ_i^j by (12)
11. Memorize the best solution achieved so far
12. cycle $=$ cycle $+ 1$
13. until cycle $=$ MCN

For those selected features from ABC then perform classification methods to classify feature samples results into fake and real images. Fuzzy Feed Forward Neural Network is used for classification and it makes decision either fake or real image.

3.5. Fuzzy Feed Forward Neural network for classification

In this work, the multilayer FFFNN method is used to classify fake and real fingerprint images from selected features results. Multilayer feed forward neural network can represent a very broad set of nonlinear functions to classify fake and real fingerprint images for selected multiple static features from the ABC optimization algorithm. FFFNN starts through input layer multiple static features selected results from ABC for fake and real fingerprint image samples. The input multiple static features from ABC for fake and real fingerprint images are connected to the hidden layer. In ANN system the networks are known as feed forward, since input layer from one multiple static features neurons feed forward into another next layer of neurons. Typically, all the input samples with features selected results of all nodes are entirely connected to hidden nodes and outputs real, fake fingerprint classification results.

So, it is very positive to solve the difficulty of classification results for those selected features. To perform activation function first we need to assign weight values between connected nodes in FFFNN of input multiple static selected features. Assigning weight values randomly do not give an exact result for classification. In order to overcome these problems, in this work, a special weight has been used for both hidden layer and output layer process. The weight value w_0 that feeds into every selected multiple static features node at the hidden layer and a special weight (called z_0) that feeds into every node at the output layer to classify results such as fake and real fingerprint class names. These types of special weights are known as bias. Initially, every one of the weight values of nodes are set to zero or small number of values. The training of ABC features selected results samples on the network will adjust these weights using the Back propagation algorithm so that the output fake and real fingerprint generated by the network matches the correct fake, real fingerprint classification results. Every input from selected multiple static features are connected to hidden layer and in the output classification layer performs classification through its weight value from input node to classify results (fake or real fingerprint images). Each layer of FFFNN working principles varies according to conditions and their own characteristics. The complete processing of each layer is discussed in the following section.

Input units: The input units are considered as important selected features results from ABC. The results from input units (feature selection results in ABC) unit is labeled x_j , for $j \in [1, d]$, where d input units. There is also a special type of input labels named as x_0, which always has the value of 1. It is used to provide bias values to the hidden nodes.

Hidden units: The connections coming out of input selected static features results have weight values connected with them. A weight going to hidden unit z_h from important selected features unit x_j would be labeled w_{hj} .The special form of input node with static features, x_0, is connected to hidden nodes in the network along with weight value w_{h0}. In the training of important multiple selected features from ABC, these base weight values are not considered and the remaining weight of nodes is updated through the BP algorithm. Already know that the weight value of the specialized input node is always one. Each hidden node calculates the weighted sum of its fake and real fingerprint samples for selected features from ABC and applies a thresholding function to determine the fake and real fingerprint output of the hidden node z_h, it is defined in equation (13) as:

$$\sum_{j=1}^{d} w_{hj} x_j \tag{13}$$

The activation function of input selected features nodes with threshold values, it is in the form of equation (13):

$$sigmoid(a) = \frac{1}{1+e^{-a}} \tag{14}$$

At the hidden node, apply the equation (13) to the weighted sum of the selected features input to the hidden node, so get the output (fake and real fingerprint images) classification results from hidden node z_h is:

$$z_h = sigmoid\left(\sum_{j=0}^{d} w_{hj} x_j\right) = \frac{1}{1+e^{-\sum_{j=0}^{d} w_{hj} x_j}} \tag{15}$$

For $h \in [1, H]$, where H is the total number of hidden nodes to perform classification operation. Now the output of classification result for each multiple static feature selection samples results from ABC is represented as,

$$o = \sum_{h=0}^{H} v_{ih}\, z_h \tag{16}$$

To differentiate each input node, weight values are assigned to output results y_i of unit i. This is the problem of discriminating between two classes such as fake and real fingerprint images. Since one node can output either a fake or a real, can have one class correspond to a fake output, and the other class corresponds to an output of real. Consequently, apply the sigmoid function to get an output classification result unit, y:

$$y = sigmoid(o) = sigmoid\left(\sum_{h=0}^{H} v_h\, z_h\right) = \frac{1}{1+e^{-\sum_{h=0}^{H} v_h z_h}} \tag{17}$$

Training your neural network to produce the correct outputs for given inputs selected features from ABC an iterative process, in which you continually present the network with an example, compare the output on this classification (fake and real fingerprint images) results with required correct output, and weight values of hidden nodes and output nodes are updated continuously to reduce error in equation (21,22). FFFNN results correct classification such as fake and real fingerprint images through BP learning process and weight updation among nodes in the network. The general procedure of backpropogation algorithm is to use momentum function from equation (22,23) to update weight values of input units to reduce error value of classification (fake and real fingerprint) between node output and target output results

.Calculating the weight updates for given a single instance (x^t, r^t) where x^t the input training samples with selected features from ABC, r^t is the target output either fake or real image classification result, and y^t is the correct classification result from network. Here, the t superscript means that the current running feature selection network is training on. It uses positive learning methods to update weight values.

Classification for 2 classes fake and real fingerprint weight updates for this case are:

$$\Delta v_h = \eta(r^t - y^t)z_h^t \quad (18)$$

$$\Delta w_{hj} = \eta(r^t - y^t)v_h z_h^t(1 - z_h^t)x_j^t \quad (19)$$

Classification for K > 2 classes, weight updates for this case is:

$$\Delta v_{ih} = \eta\left(r_i^t - y_i^t\right)z_h^t \quad (20)$$

$$\Delta w_{hj} = \eta\left(\sum_{i=1}^{K}\left(r_i^t - y_i^t\right)v_{ih}\right)z_h^t (1 - z_h^t)x_j^t \quad (21)$$

Measure the result of the classification and how well the algorithm works by testing the FFFNN and calculate the error for one output node results for fake and real fingerprint classification for one completion of the training process epoch as follows

$$E(W, V|\chi) = \frac{1}{2}\sum_{(x^t,r^t)\chi}(r_i^t - y_i^t)^2 \quad (22)$$

One easy way to speed the learning process of the fake and fingerprint image classification is to use momentum. Momentum constant values take into description of earlier weight values while consideration of current weight values. So, must need to save the weight of earlier one training process for each time step. Then, on the next process of weight updating, this earlier update information is used. It is observed that the weight updates of earlier one were as follows:

$$v_{ih} = v_{ih} + \Delta v_{ih} \quad (23)$$

$$w_{hj} = w_{hj} + \Delta w_{hj} \quad (24)$$

Now the updated equation after constant momentum parameters as ,

$$v_{ih}^t = v_{ih}^t + \Delta v_{ih}^t + \alpha\Delta v_{ih}^{t-1} \quad (25)$$

$$w_{hj}^t = w_{hj}^t + \Delta w_{hj}^t + \alpha\Delta w_{hj}^{t-1} \quad (26)$$

In equation (3.26) still the weight value updation based on the constant moment parameters not achieve higher classification results, it reduces the performance for detection rate of fake fingerprint images, In order to solve the weight updation problem and new calculation of the weight values introduce the fuzzy membership function to calculate the weight values to each selected multiple static features samples from ABC.

A membership function provides a measure of the degree of similarity of a weight element to a fuzzy set .Membership functions can take any form, but there are some common examples that appear in pattern.

$$\mu_A(w) = \begin{cases} 0 & if\ w \le a \\ \frac{w-a}{b-a} & if\ a \le w \le b \\ \frac{c-w}{c-b} & if\ b \le w \le c \\ o & if\ w \ge c \end{cases} \quad (27)$$

Where $a \in (0 - 0.3), b \in (0.3 - 0.7)\ and\ c \in (0.7 - 1)$. In this work, the superscript t refers to the current image samples with the feature selection results for fake and real fingerprint images and $t - 1$ refers to the previous training example by the Fuzzy Feed Forward neural network So, with α constant momentum parameter a adjusts new weight values to improve classification accuracy. Here, α is a constant called momentum, with$0 \le \alpha < 1$. The typical structure of FFFNN was shown in Fig.6.

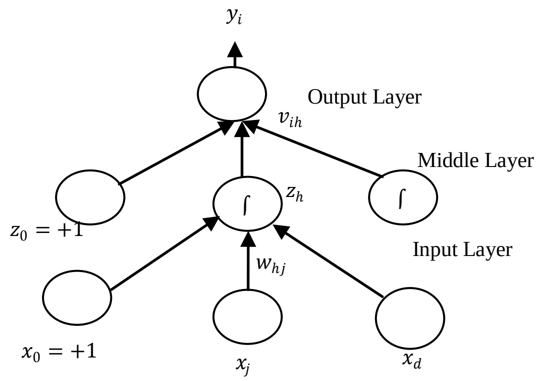

Fig.6 Typical structure of a multilayer Fuzzy feed forward artificial neural network

After completion of the training process for multiple static feature selection results, then the accuracy of classification result is evaluated, so testing samples are given as input to image preprocessing step, then all the steps of the proposed system are followed for testing fingerprint samples. The results are compared based on the parameters like sensitivity, specificity, and precision and classification accuracy.

4 Experimental results

In this section, the classification results of proposed FFFNN, existing FFNN and SVM classification methods are compared. The real fingerprint images and fake fingerprint images obtained from LivDet2015 database. From this LivDet2015 database, five different databases were collected. Each and every database samples are different from each other since each optical sensor works in a different manner. LivDet2015 competition is open to all academic and industrial institutions which have a solution for software-based fingerprint vitality detection problem. It comprises five datasets such as Crossmatch, Digital_Persona,Green_bit, Hiscan and Timeseries of real and fake fingerprints captured each of them with a different optical sensor:

CrossMatch Verifier 300CL (500 dpi). This dataset comprises 992 real and 1510 fake images. Fake fingers were generated with gummy fingers of body double (494), Ecoflex (498), and playdoh (481).

Digital_Persona. This dataset comprises 1000 real and 1000 fake images. The fake images were generated with gummy fingers made of Ecoflex_050 (250), gelatine (250), Latex (250) and WoodGlue (250).

Green_bit. This dataset comprises 1000 real and 1000 fake images. The fake images were generated with gummy fingers made of Ecoflex_050 (250), gelatine (250), Latex (250) and WoodGlue (250).

Hiscan. This dataset comprises 1000 real and 1000 fake images. The fake images were generated with gummy fingers made of Ecoflex_050 (250), gelatine (250), Latex (250) and WoodGlue (250).

Timeseries. This dataset comprises 4400 real and 4495 fake images. The fake images were generated with gummy fingers made of body double (1481), Ecoflex_050 (1529) and playdoh (1485).

In order to evaluate the performance of SVM and FFNN and FFFNN, certain parameters are defined below which plays a major role in the classification results.

4.1. Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio (PSNR) is an important metric to measure image quality after and before preprocessing methods is applied.

$$\mathrm{PSNR} = 10\ \log_{10}\left(\frac{\mathrm{R}^2}{\mathrm{MSE}}\right) \qquad (28)$$

The MSE represents the increasing squared error between the filtered image and original images before filtering, normalization

$$\mathrm{MSE} = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \qquad (29)$$

Where M and N represents the total number of rows and columns in the current image samples, respectively. In the previous equation, R is the maximum changeability in the input image data type.

Table.2. PSNR and MSE value comparison

Preprocessing schemes	Noise $\sigma = 10$		Noise $\sigma = 20$	
	PSNR	MSE	PSNR	MSE
Min max normalization	53.4	1.5	34.3	1.9
Median filtering	58.6	0.8	35.6	1.73

From Table 2 it is observed that PSNR and MSE values after normalization and after median filtering with different Gaussian noise levels are added. In this work, the quality of the fingerprint and fake image sample using PSNR ratio parameter is evaluated using preprocessing step.

Table.3.Performance and time comparison results of the classification methods

No of features	Total no of the features	Feature from ABC
	300	100
No of iterations	FFNN	FFFNN
	10	14
Time comparison	2.4958181818 18182e+000	3.1442000000 00000e+000

From Table 3 it is observed that feature selection results of the proposed ABC is significant which in turn improves the classification accuracy as it selects 100 features from 300 features. The number of iterations taken by FFNN is 10 where as the proposed FFFNN approach takes 14 iterations to complete the process. Time taken by the proposed FFFNN technique is slightly higher than the FFNN technique. Even though the time taken is slightly higher, the impact of accuracy is observed to be significant as shown in the following evaluations.

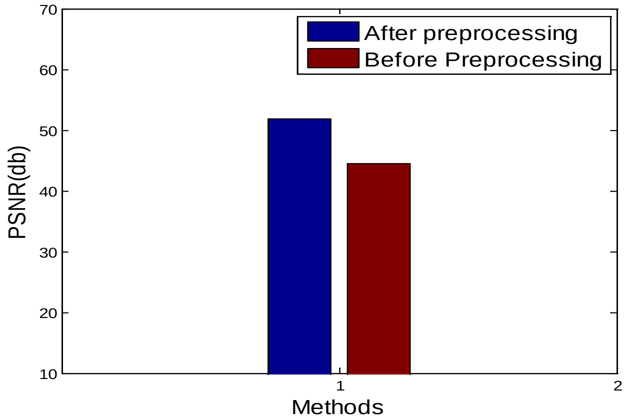

Fig.7.PSNR for before and after preprocessing methods

Fig.7 shows the performance comparison results of PSNR before and after preprocessing technique is applied. It is clearly observed from the figure that PSNR value is high after the preprocessing method is applied.

Fig.8 shows that PSNR results of two preprocessing approaches. It is observed from the figure that the median filtering approach obtained higher PSNR value for Gaussian noise $\sigma = 10$ when compared.

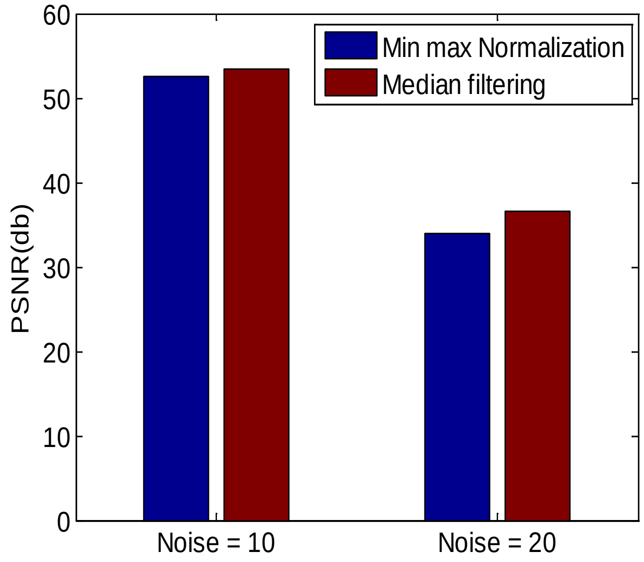

Fig.8.PSNR for preprocessing methods

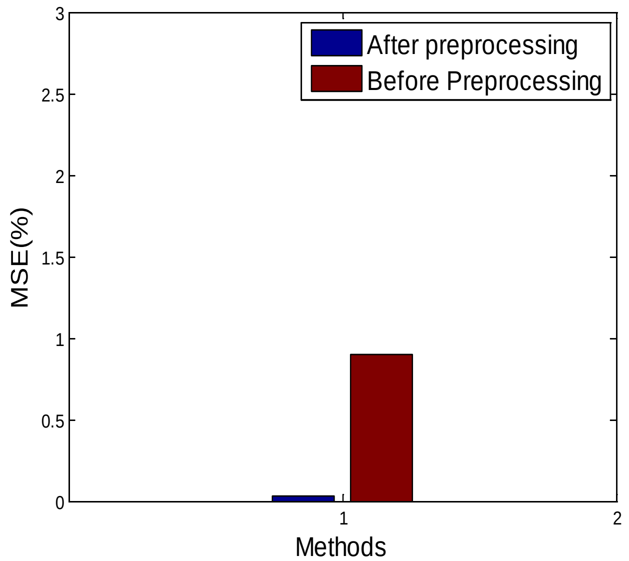

Fig.9. MSE for before and after preprocessing methods

Fig.9 shows the performance comparison MSE results before and after preprocessing. It shows that MSE value is lesser after the preprocessing method is applied.

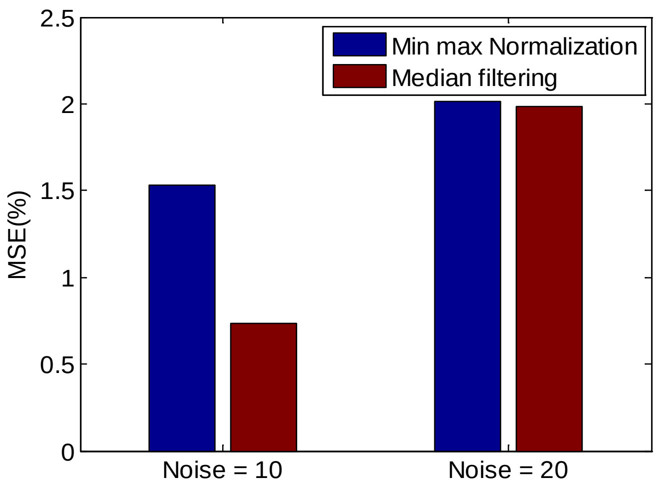

Fig.10. MSE for preprocessing methods

Fig.10 shows the performance comparison of the min max normalization and median filtering methods with different levels of Gaussian noise σ=10&20. The performance of the median filtering approach is observed to be significant with lesser MSE. The MSE results for $\sigma = 10$ is lesser when compared with $\sigma = 20$.

4.2. Sensitivity

Sensitivity evaluates the percentage of actual positive which are fake and real fingerprint subjects class. It is observed that the classified percentage of real and fake fingerprint results for the proposed approach is higher. The sensitivity is defined as below:

$$Sensitivity = \frac{T_p}{T_p + F_n} \tag{30}$$

Where T_p is defined as positive results against both fake and real fingerprint images

F_p is defined as negative results against both fake and real fingerprint images

T_n is defined as negative results without both fake and real fingerprint images

F_p is defined as positive results without both fake and real fingerprint images

Fig.11 shows the sensitivity results for proposed Fuzzy Feed Forward Neural Network (FFFNNN) ,feed forward Neural network (FFNN) and Support Vector Machine (SVM) classification methods. The performance is evaluated based on the influence of the feature selection method. The sensitivity results obtained with feature selection approach and without feature selection approach is clearly shown in the figure. It is observed that the proposed FFFNN have higher sensitivity results than FFNN, SVM methods with ABC based feature selection.

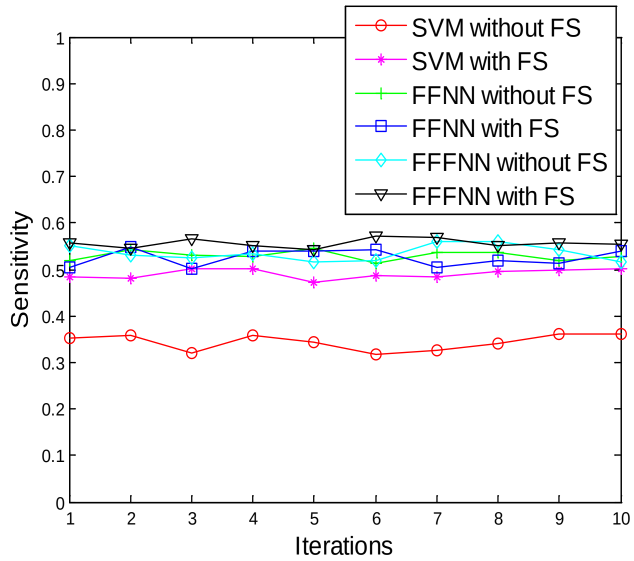

Fig.11. Sensitivity for classification

4.3. Specificity

Specificity evaluates the percentage of actual negatives which are related to negative subjects class that is fake image is classified as real fingerprint images and real images are classified as fake images.

$$Specificity = \frac{T_n}{T_n + F_p} \tag{31}$$

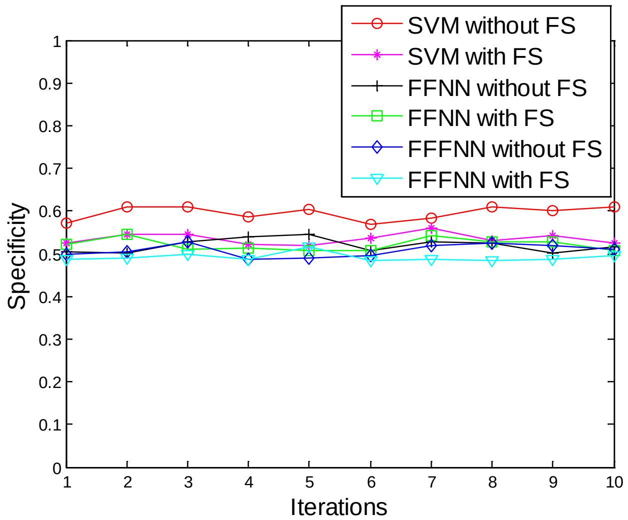

Fig.12.Specificity for classification

Fig.12 shows specificity results of proposed classification methods with and without ABC feature selection. The proposed FFFNN classification approach with ABC feature selection is observed to have lesser specificity results and it can be compared with FFNN and SVM classification methods.

4.4. Precision

Precision is defined as the proportion of the true positives against both true positives and false positives results for fake and real fingerprint images. It is defined as follows:

$$Precision = \frac{T_p}{T_p + F_p} \tag{32}$$

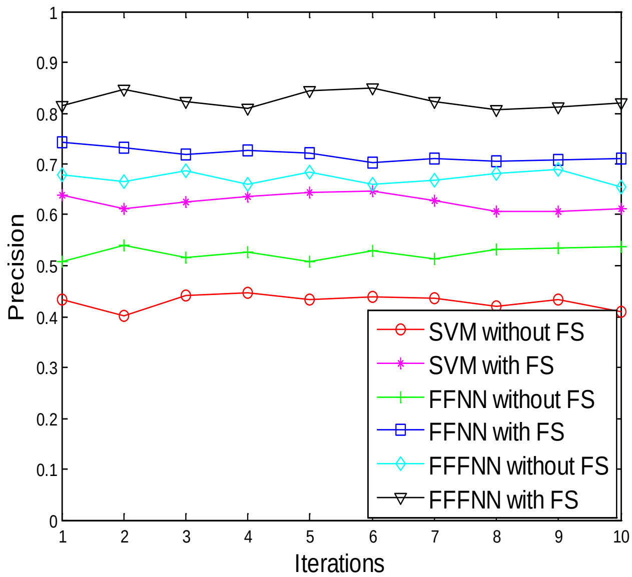

Fig.13. Precision for classification

Fig.13 shows the precision results of FFFNN, FFNN and SVM methods with and without ABC feature selection. It is observed that the proposed FFFNN with ABC feature selection have higher precision accuracy than classification methods FFNN, SVM without feature selection. The importance of the feature selection approach is clearly seen in the figure.

4.5. Classification Accuracy

Accuracy is defined as the overall correctness of the model and is calculated as the sum of actual classification parameters $(\mathrm{T_p} + \mathrm{T_n})$ separated by the total number of classification parameters $(\mathrm{T_p} + \mathrm{T_n} + \mathrm{F_p} + \mathrm{F_n})$

$$\mathrm{Accuracy} = \frac{\mathrm{T_p} + \mathrm{T_n}}{\mathrm{T_p} + \mathrm{T_n} + \mathrm{F_p} + \mathrm{F_n}} \tag{33}$$

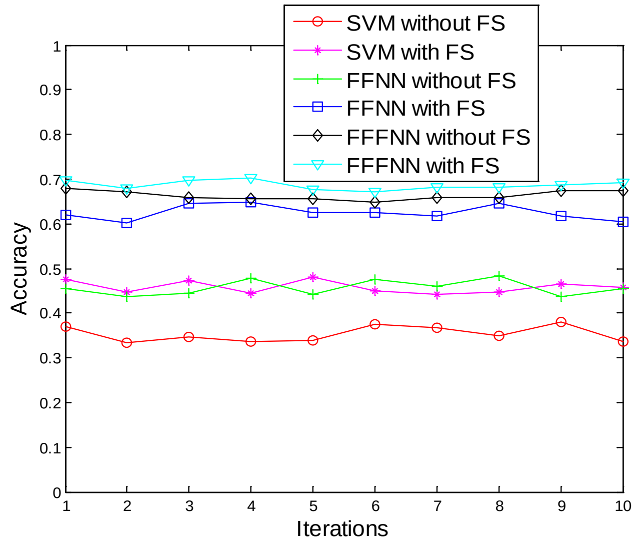

Fig.14. Classification accuracy

Fig.14 evaluates the classification results of FFFNN, FFNN and SVM classification methods. The classification result is evaluated with and without feature selection and it is observed that the proposed FFFNN with ABC feature selection approach has higher accuracy results than classification method without feature selection. This significant performance of the proposed FFFNN approach is mainly due to continuous updation of weight values according to gradient momentum function in FFFNN, it reduces error values in FFFNN. Moreover, the result also shows the importance of the ABC feature selection algorithm in classification.

4.6. Confidence interval test results

However, it is difficult to evaluate its performance, due to diverse databases and the evaluation method. It is also not easy to collect a test set that is sufficiently representative to cover all types of live and fake fingerprints from various environments. Therefore, it would be desirable if lower and upper bounds of the performance rate could be estimated. In this work adopted the bootstrap method which is a popular nonparametric statistical method to measure performance variations from a limited data set. For estimating the lower and upper bounds of the error rates, the following procedure was executed:

$$n = \frac{N}{1+N(e^2)} \quad (34)$$

where n is the determined sample size, N is the population size, and e is the level of precision. To satisfy the 95% confidence level, set e at 0.05. The FAR, FRR, of the proposed method were computed using the randomly selected test set.

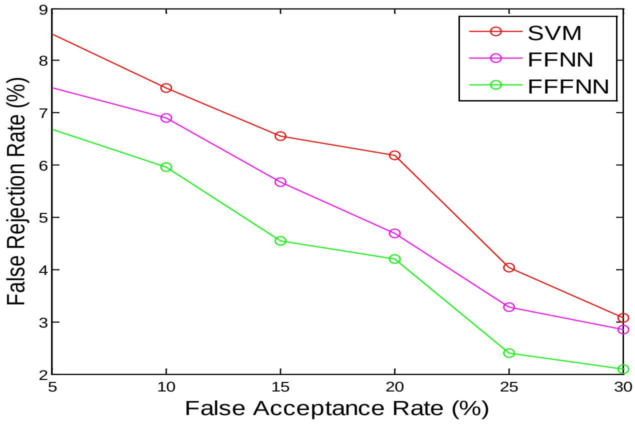

Fig.15. Performance evaluation of FAR vs. FRR for classification methods

The performance of the proposed FFFNN method was evaluated using the false-acceptance rate (FAR) and the false rejection rate (FRR) is shown in Fig.15. The FAR is the probability of accepting a fake fingerprint as a live one, and the FRR is the probability of rejecting a live fingerprint as a fake one .It shows that the FAR vs. FRR of the proposed FFFNN is less when compared to existing FFNN and SVM classification methods.

Table.4. Confusion matrix sample results

Predicated outcome for SVM with (original = 40, fake =20 images)		
Actual value	True positive (TP) = 23	False positive (FP) = 17
	False negative (FN) = 8	True negative (TN) = 12
Predicated outcome for FFNN with (original = 40, fake =20 images)		
Actual value	True positive (TP) = 26	False positive (FP) = 12
	False negative (FN) = 14	True negative (TN) = 8
Predicated outcome for FFFNN with (original = 40, fake =20 images)		
Actual value	True positive (TP) = 27	False positive (FP) = 16
	False negative (FN) = 13	True negative (TN) = 14

Table 4 shows the confusion matrix results of the methods based on FAR and FRR values. It is observed from the table that the True positive (TP) predicated outcome value of proposed FFFNN classifier is 27 which is higher than the other SVM and FFNN classifiers taken for consideration. It shows that the proposed FFFNN classifier correctly matches fake and real fingerprint images. Moreover, false negative results of the proposed FFFNN classifier are also less when compared to with existing SVM and FFNN classifiers. It is observed that, when FAR increases, FRR rate automatically decreases and via versa.

Confusion matrix sample results for proposed system in FAR and FRR.

False positive rate (α)=False acceptance rate = type I error = 1 − specificity = FP / (FP + TN)

False negative rate (β) = False rejection rate = type II error = 1 − sensitivity = FN / (TP + FN)

Which is also similar when the number of FAR increase the FRR rate is automatically decrease since false negative rate increases ,false positive rate automatically decreases.

There are certain important aspects to be taken into consideration while using fake fingerprint images. The main factor is that, the fake fingers should be able to interact with fingerprint recognition system. If the fake finger is of very low quality, it could be taken as a non matched finger and gets simply rejected. So, ensuring the image quality is very vital and this work utilizes Natural Image Quality Evaluator (NIQE) for quality assessment. Quality of the distorted image is expressed based on the multiple static feature selection models from the distorted image:

$$D(v_1, v_2, \Sigma_1, \Sigma_2) = \sqrt{\left((v_1 - v_2)^T \left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1} (v_1 - v_2)\right)} \quad (35)$$

v_1, v_2 be the mean value of input and distorted image, Σ_1, Σ_2 be the covariance matrix of input and distorted image. Each fingerprint image was assigned to one of five quality levels namely excellent, very good, good, fair, and bad according to the quality measure.

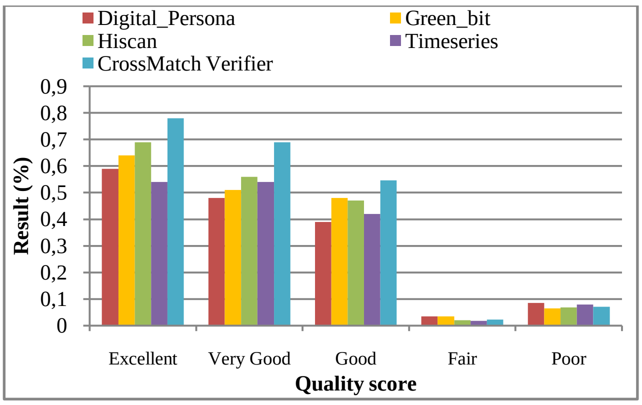

Fig.16. Fake fingerprint image

Fig.16 shows the NIQE quality-checking results for five different categories of fake fingerprint images samples from LivDet 2015 is taken into consideration. It is observed that most of the fake fingerprint images are of good quality and is applicable to be used in the evaluation.

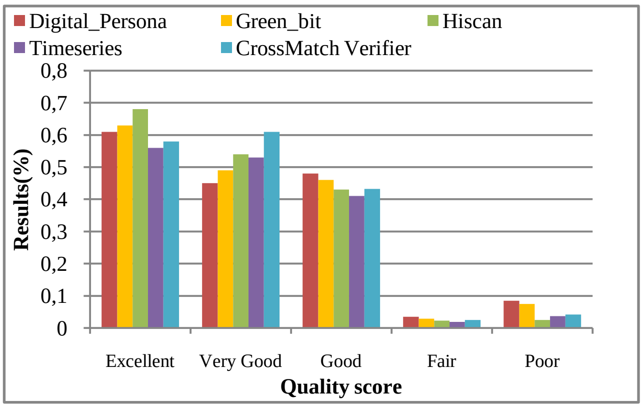

Fig.17. The results of the NIQE quality check on live fingerprint image

Fig. 17 shows the NIQE quality-checking results for five different categories of live fingerprint images samples from LivDet 2015 is taken into consideration. It is observed that most of the live fingerprint images are of good quality and is applicable to be used in the evaluation.

5 Conclusion

This paper presents a new approach to classify fake and real fingerprint images using efficient fuzzy based classifier and intelligent feature selection technique. Initially, the fingerprint images are preprocessed to enhance the image quality and clarity. In this research, normalization has been carried out for contrast enhancement and median filtering method is applied for removing the noise from finger print image. After the completion of the filtering method, multiple static features are extracted from fingerprints using 2D Gabor filtering method. The best optimized multiple static features are selected through ABC optimization algorithm to improve the classification performance of the Fuzzy Feed Forward Neural network (FFFNN). The performance of the proposed approach is evaluated for each fingerprint images through the parameters like sensitivity, specificity, and precision and classification accuracy. The results showed that the proposed FFFNN with ABC feature selection approach provides better classification accuracy than the conventional SVM and FFNN classifiers.

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