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Detection of Bundle Branch Block using Adaptive Bacterial Foraging Optimization and Neural Network

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Abstract The medical practitioners analyze the electrical activity of the human heart so as to predict various ailments by studying the data collected from the Electrocardiogram (ECG). A Bundle Branch Block (BBB) is a type of heart disease which occurs when there is an obstruction along the pathway of an electrical impulse. This abnormality makes the heart beat irregular as there is an obstruction in the branches of heart, this results in pulses to travel slower than the usual. Our current study involved is to diagnose this heart problem using Adaptive Bacterial Foraging Optimization (ABFO) Algorithm. The Data collected from MIT/BIH arrhythmia BBB database applied to an ABFO Algorithm for obtaining best(important) feature from each ECG beat. These features later fed to Levenberg Marquardt Neural Network (LMNN) based classifier. The results show the proposed classification using ABFO is better than some recent algorithms reported in the literature.

1. Introduction

Globally heart diseases are the most prevalent cause for human mortality. Every year, 9.4 million deaths are attributed to high Blood Pressure (BP) including 51% deaths due to strokes and 45% deaths due to the coronary heart diseases. Most cardiac diseases are due to risk factors, such as unbalanced diet, high blood pressure, tobacco usage, obesity, diabetes and physical inactivity.

BBB developed when there was a block along the conduction path of electrical pulses in the heart. BBB makes it difficult for the heart to pump blood effectively through the heart circulatory system because the impulse deviates from the preferred path. This delay may be observed through the changes in the ECG. There are two types of BBB : Left Bundle Branch Block (LBBB) and Right Bundle Branch Block

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(RBBB). ECG changes in Left Bundle Branch Block (LBBB) are

- Increased QRS complex duration (>0.12 s).
- Increased Q wave amplitude.
- Abnormal T wave.
- ECG changes in Right Bundle Branch Block (RBBB):
- Increased QRS complex duration (>0.12 s).
- RSR' format
- T wave inversion

as depicted in Figs. 1–3. ECG is the cost effective tool for analyzing the cardiac abnormalities. The diagnosis of the heart diseases by the physicians done by following a standard rule set (changes). In this project, our aim was to automate the above procedure so that it leads to correct diagnosis of the ailment of BBB. Good performance depends on the efficient and accurate detection of ECG features. Here in this paper ABFO technique used as the feature extraction (optimization) technique.

In recent years, many models are developed based on the evolutionary behaviors of living beings and have been applied for solving the practical real world issues. Among them, Bacterial Foraging Optimization (BFO) [27–29] may be a population based search optimization technique. Bacterial forage activity of *Escherichia coli (E. coli)* bacteria is used extensively as a model to solve many engineering applications. In Recent years, BFO has been applied with success to some engineering concepts such as, harmonic estimation [5], optimum management [7], reduction machine learning and transmission loss [6,25,26,34] and so on.

A scientific analysis of the simulated chemotaxis by the classical gradient descent search algorithm is explained in [9,10]. The analysis shows that varying the chemotaxis step-size can lead to better convergence as compared to a fixed step-size. The adaptation schemes, proposed for automatic adjustment of the step-size, are simple and do not impose any additional burden on the BFO algorithm regarding an excess number of functions. Several researchers have investigated the adaptation of step size in both deterministic and stochastic gradient descent optimization algorithms [11–16]

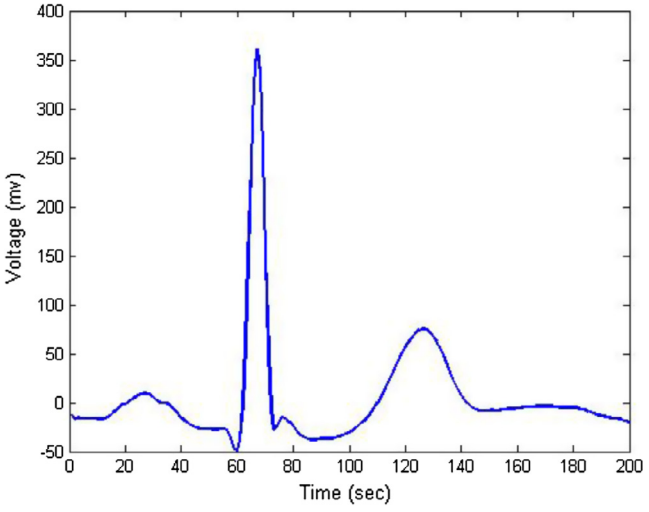

Figure 1 Normal beat.

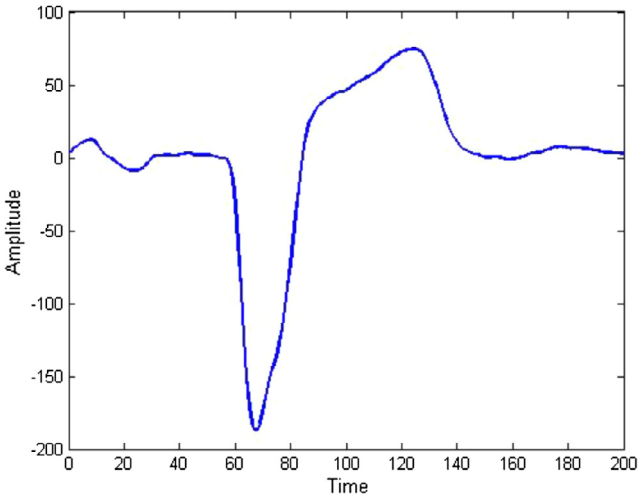

Figure 2 Left Bundle Branch Block.

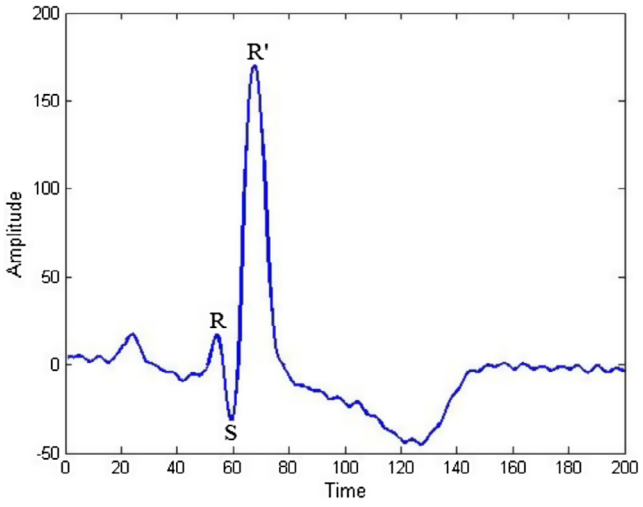

Figure 3 Right Bundle Branch Block.

in the context of training neural networks. Unlike the works cited in [11–16] adaptation schemes implemented in this paper for the chemotaxis step-size are not based on complex calculus techniques, such as Hessian matrix evaluation [17,18]. They are solely based on the fitness information of individual avoiding any oscillatory behavior around the optimum and accelerate the convergence of the bacterium toward an optimum.

The proposed ABFO compared with the Genetic Algorithm (GA) [20,21,4,19] which is a traditional algorithm for optimization of ECG features on the following performance measures such as convergence speed, and the accuracy in the final output. Bacterial foraging feature classification using neural network fuzzy learning implemented in [8].

The layout of the paper organized as follows. In Section 2, we outline the Preprocessing ECG such as Data collection, Noise removal and Segmentation of ECG into beats. In Section 3, we explained the Algorithm of classical BFO and modification to the BFO algorithm. Section 4 provides a classification of ABFO features. Section 5 contains results and Sections6 and 7 provide discussion and conclusions. The classification flow diagram shown in Fig. 4.

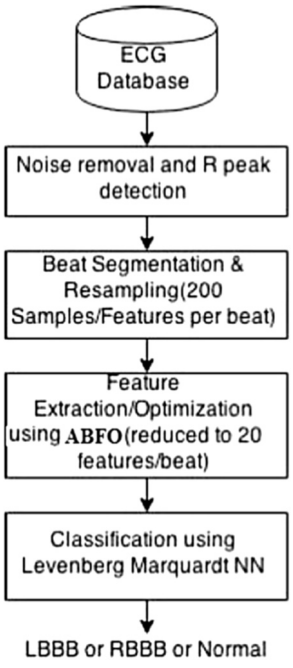

Figure 4 ECG classification flow diagram.

2. Preprocessing of ECG data

2.1. Data acquisition

The data for the classification were collected from the MIT–BIH Arrhythmia Database [30], which consist of 5 normal, 3 LBBB and 3 RBBB patients data at 360 Hz sampling rate of one-hour duration. The total number of beats in each class is as shown in Table 1.

2.2. Noise removal and beat segmentation

To remove the baseline wander present in the signal Sgolay FIR smoothing filter was used as shown in Fig. 5. RR interval is the distance between two R peaks. 1/3 of the RR interval samples to the left of R peak and 2/3 of the RR interval samples to the right of R peak were considered as one beat. Different patients have different RR intervals. Each ECG beat was re-sampled to 200 samples so that it is easy to process them.

1/3 of RR interval: (R peak): 2/3 of RR interval.

3. Bacterial foraging optimization

The bacterial foraging activity of *E. coli* bacteria [24] is used as the inspiration for extracting (optimizing) the features of ECG. Feature selection may be an international optimization problem in machine learning. It reduces the number of features, which are redundant and noisy leading to acceptable accuracy.

The Bacterial Foraging Optimization (BFO) projected by Passino [2,3] in 2002 relies on the selection that tends to get rid of an organism with low search methods. Several generations with poor foraging methods have been eliminated, whereas only the organisms with good search strategy are surviving since they are the fittest. The BFO formulates the search

Table 1 MIT–BIH record numbers.

Record	NB	LBBB	RBBB
100	2237	0	0
01	1858	0	0
103	2080	0	0
106	1505	0	0
109	0	2490	0
111	0	2121	0
118	0	0	2164
123	1513	0	0
124	0	0	1529
207	0	1457	85
Total	3778	6068	9193

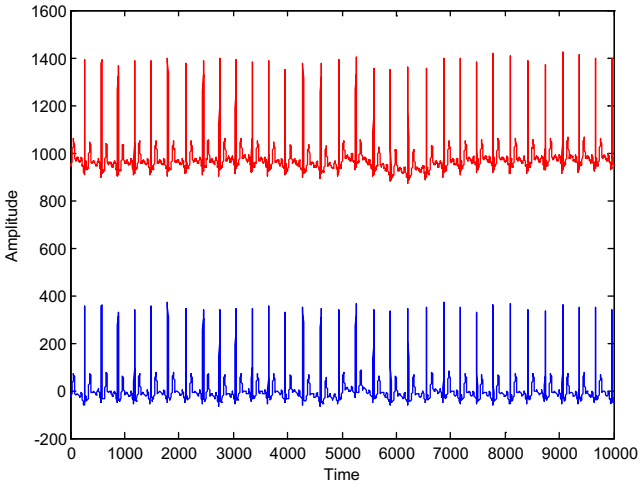

Figure 5 ECG baseline wander removal, up signal: original signal, down signal: baseline wander re-moved signal.

behavior as exhibited by *E. coli* to solve the optimization problem. Certain real-world optimization problems [33], BFO have been reportedly outperformed several powerful optimization algorithms regarding final accuracy.

Bacteria move into a random direction to search for favorable direction of increasing nutrients. Hence this optimization technique is useful when the gradient of the cost function is not known. BFO is good because of its less mathematical complexity. The BFO is a non-gradient optimization problem inspired by the search mechanism used by *E. coli* microorganism, as it maximizes its energy intake per unit time spent in search. The three operating steps in bacteria per area unit are

(a) Chemotaxis
(b) Swarming
(c) Reproduction

(a) *Chemotaxis:* The movement of *E. coli* bacterium can be explained via two steps, Swimming and Tumbling, through the flagella. Basically, the *E. coli* bacteria will move in 2 alternative ways. It will swim for an amount of time within the same direction, or it will tumble (change direction). It will alternate between these 2

modes of operation for its entire life period. Suppose $x(i)$ represents ith bacteria and C is the size of the step taken in the random direction specified by the run length, in the process of chemotaxis $x(i+1)$ of the bacteria could also be given by

$$x(i+1) = x(i) + C(i)\frac{Del(i)}{Del(i)Del^T(i)} \quad (1)$$

where '*Del*' indicates a vector in the random direction whose elements lie in −1 to 1. The simulated chemotactic movement of *E. coli* bacterium may be viewed as a random hill climbing.

(b) *Swarming:* In *E. coli* bacteria group behavior is observed as in several species, where complex and stable spatiotemporal groups are formed in a semisolid nutrient medium. The *E. coli* bacteria form themselves like a traveling ring and moving down toward the nutrient food. The cells in the *E. coli*, excited by a high level of succinate, release an attractant aspartate, which helps them to arrange into groups and thus move as coaxial patterns of swarms with high density. The cell to cell fitness of each bacterium calculated by the following objective function.

$$f(x) = \sum_{i=1}^{d}\left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right] \quad (2)$$

where d is the dimension and x_i is the ith bacterium.

(c) *Reproduction:* The unhealthy bacteria finally die while the remaining healthy bacteria (those yielding a higher value of the cost function) asexually split into 2 bacteria, then placed in the same location, and kept the swarm size constant.

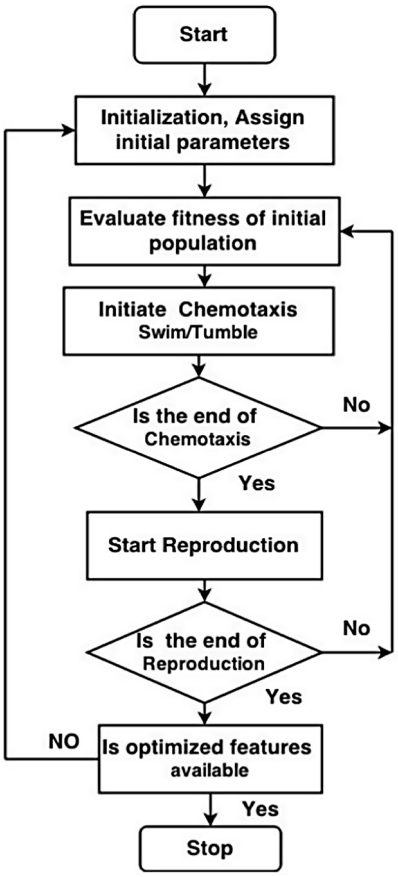

Figure 6 BFO flow chart.

3.1. Algorithm for BFO

The complete pseudo-code for feature optimization using BFO given below, and the flow chart for the BFO algorithm is shown in Fig. 6.

Step 1 Set the BFO parameters.
N: Number of bacteria in the population.
Nc: Count of Chemotaxis steps.
Nre: Total reproductive steps.
n: Dimension of the problem.
Ned: Total number of elimination dispersal events.
Ped: Probability of elimination dispersal.
C(*i*): Step-size taken by tumble.
Step 2 Begin Elimination dispersal loop.
Step 3 For every reproduction step perform the following.
Step 4 For every chemotaxis step perform the following.
(i) Calculate the fitness function (*J*) of the initial population using the Eq. (2).
(ii) Set *J* last = *J* Hold this value.
(iii) Tumble: create a random vector delta from −1 to 1.
(iv) Move: Let the bacterium move to a position with step size *C*(*i*) using the Eq. (1) called Tumble.
(v) Again Swim
(a) $m = 0$.
(b) While $m < Ns$ (if have not climbed too long).
(c) $m = m + 1$.
(d) If $J(i) > J$ last (if doing well).
(e) Again move the bacteria using Eq. (1). Use this J to calculate the new J as in point (iv). Let J last = $J(i)$.
(f) Else, let $m = Ns$; the end of the while statement.
(g) Go to the next bacteria i.e. go to (i) to calculate the next bacteria.

Step 5 End of Chemotaxis loop? If NO, repeat Step 4.
Step 6 Begin Reproduction loop.
(i) Calculate the health of each bacterium by finding the maximum cost value of each bacterium.
(ii) The bacteria with the lowest *J* health values die and the remaining bacteria with the best values are split into two bacteria thus making the population of bacteria constant.

3.2. Adaptive BFO: Our contribution

BFO with fixed step size *C*(*i*) suffers from two main problems [1]:

- If step-size is very large, then the precision gets down although the bacterium reaches the vicinity of optimum point rapidly. It moves around the maximum for the remaining chemo-taxis steps.
- If the step-size is small, then it takes many chemotaxis steps to reach out to the optimal point.

So the converging rate decreases. It may not reach optimum point using a small number of iterations. Hence for increasing convergence speed and decreasing the error in the final out the step-size plays a major role. So it is required to adjust the step-size depending on the distance between the bacteria from the optimal point. If the variation is very high, then the step-size is to be increased and if the deviation is small indicating that the bacterium is near to the optimal point, then the step-size must be reduced. Here, the principle of adaptive delta modulation is used to control the step-size. In adaptive delta modulation, the error between the actual signal and the predicted value of the signal is integrated and then the output of the integrator is given as the input to the voltage controlled oscillator (VCO) that adjusts the step-size. The procedure for Adaptive step-size shown in Fig. 7.

- X: The parameter to be optimized.
- $E(j)$: Deviation from the desired value.
- $C(i, j)$: Step size to be modified in each chemotaxis step depending on the deviations in the previous steps.

Here we have taken the deviation in the last chemotaxis step and is multiplied with the previous step-size. The multiplier increases or reduces the step-size accordingly. X for the next step, is obtained by adding the step size to the previous value.

3.3. Implementation for ECG feature extraction

In the year 2002 Passino designed BFO algorithm to reduce the size of population by mimicking the behavioral model (foraging strategy) of *E. coli* bacteria present in our inter-stain. The matrix below shows that there are N bacteria each having six features. By using ABFO algorithm [31,32,35] the size of features can be reduced by taking the features with good fitness strategy only.

$$\text{Data} = \begin{pmatrix} \text{Bacterium 1} & f1 & f2 & f3 & f4 & f5 & f6 \\ - & f1 & f2 & f3 & f4 & f5 & f6 \\ - & f1 & f2 & f3 & f4 & f5 & f6 \\ - & f1 & f2 & f3 & f4 & f5 & f6 \\ \text{Bacterium } N & f1 & f2 & f3 & f4 & f5 & f6 \end{pmatrix}$$

where $f1$, $f2$, $f3$, $f4$, and $f5$ are the features of each bacterium.

In this study, the ABFO algorithm is used for reducing the features (not for reducing the bacterium population). So we have taken the transpose of the above data so that the rows of the matrix represent features.

$$\text{Data}^T = \begin{pmatrix} \text{Bacterium 1} & - & - & - & \text{Bacterium } N \\ f1 & f1 & f1 & f1 & f1 \\ f2 & f2 & f2 & f2 & f2 \\ f3 & f3 & f3 & f3 & f3 \\ f4 & f4 & f4 & f4 & f4 \\ f5 & f5 & f5 & f5 & f5 \\ f6 & f6 & f6 & f6 & f6 \end{pmatrix}$$

Here our aim is to reduce features (rows) to keep the size of population same as above. After applying the ABFO algorithm, the features are reduced as shown in the matrix below:

$$\text{Data}^T = \begin{pmatrix} \text{Bacterium 1} & - & - & - & \text{Bacterium } N \\ f2 & f2 & f2 & f2 & f2 \\ f1 & f1 & f1 & f1 & f1 \\ f3 & f3 & f3 & f3 & f3 \end{pmatrix}$$

The features with the lowest health values die and the remaining features are placed in the descending order of their cost value (health status). Again find the transpose of the above matrix as

$$\text{Data}^T = \begin{pmatrix} \text{Bacterium 1} & f2 & f1 & f3 \\ - & f2 & f1 & f3 \\ - & f2 & f1 & f3 \\ - & f2 & f1 & f3 \\ \text{Bacterium } N & f2 & f1 & f3 \end{pmatrix}$$

ECG beat features optimized to 20 features. The ABFO gives optimized features (best features) for the classification. ECG beat features before optimization = [1 2 3 . . . 200]. The optimized ECG features (20 features) using ABFO algorithm are [67 68 66 69 65 70 71 64 72 63 73 62 74 61 60 75 59 76 58 77].

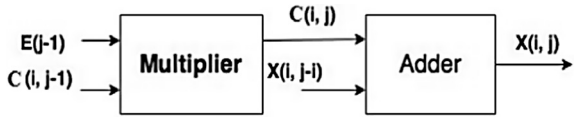

Figure 7 Adaptive step-size process.

4. Classification by Back Propagation Neural Network

Back Propagation Neural Network (BPNN) [23] is widely used in the machine learning applications. BPNN structure made up of interconnected layers: The input layer, hidden layers (one or more) and output layer. The input to the input layer is fed by the external source. The internal link between input and output layers is provided by the hidden layer. The output results of the Neural Network can be taken from the output layer as shown in Fig. 8.

4.1. Levenberg–Marquardt Neural Network (LMNN)

In this work for the detection of BBB, back propagation Levenberg–Marquardt Neural Network (LMNN) was used. This NN provides rapid execution of the network to be trained. To test the performance of this algorithm, Scalar Conjugate Gradient (SCG) NN and LMNN were used. The LMNN algorithm is a robust, and very simple method for approximating a function [36]. The LMNN [22] gives a numerical solution for minimizing a nonlinear function, over a space of parameters. The LMNN is an alternative to the Gauss–Newton technique for minimizing a function. SCG NN

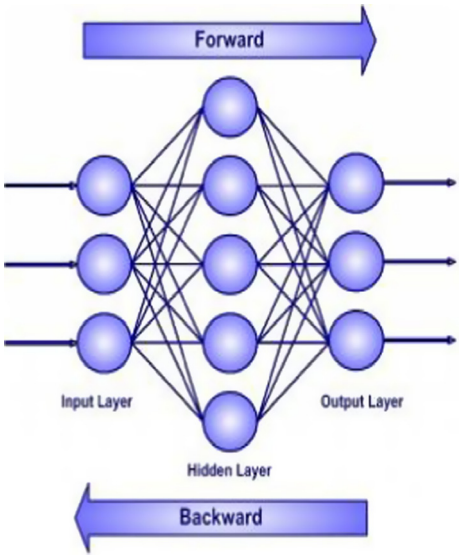

Figure 8 Feed forward back propagation NN.

method provides conjugate directions of search instead of performing linear search. The network training and testing are performed using 12,692 and 6347 ECG beats correspondingly by setting the total number of iterations to 1000 and mean square error less than 0.001 with the minimum time requirement.

5. Results

The performance of ABFO is compared with Genetic Algorithm (GA), and BFO Optimization techniques and the results are shown in Table 2. The ABFO and GA features are classified using SCG NN, LM NN as in Table 3:

- Count of Normal beats used for classification – 9193.
- Count of RBBB beats used for classification – 3778.
- Count of LBBB beats used for classification – 6068.
- Total number of beats used for classification – 19,039.
- Count of correctly classified beats – 18,800.
- Total misclassified beats – 239.

For measuring accuracy two parameters sensitivity (Sen) and specificity (Spe) are calculated using the following equations:

$$\text{Specificity} = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \quad (3)$$

Table 2 Accuracy comparison of GA, BFO and ABFO with LM NN classifier.

Classifier	Sen (%)	Spe (%)	Accuracy (%)
GA + LM NN	98.5	98.2	97.1
BFO + LM NN	96.5	96.2	96.1
ABFO + LM NN	98.5	98.9	98.74

Table 3 Accuracy Comparison of GA, BFO and ABFO with SCG NN classifier.

Classifier	Sen (%)	Spe (%)	Accuracy (%)
GA + SCG NN	98.2	97.2	97.9
BFO + SCG NN	96.5	95.5	95.6
ABFO + SCG NN	96.7	96.7	98.1

$$\text{Sensitivity} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FN)}} \quad (4)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \quad (5)$$

- TP (True Positive) = Correctly classified Normal beats.
- TN (True Negative) = Correctly classified Abnormal beats.
- FP (False Positive) = Count of Normal beats classified as Abnormal.
- FN (False Negative) = Count of Abnormal beats classified as Normal.

In the training, we applied multilayer NN, and checked the network performance and decided whether any changes to be made to the training process, or the data sets, the network architecture. First, check the training record, 'trainlm' Matlab function.

The property training indicates the iteration is up to the point, where the performance of the validation reached a minimum. The training continued for 16 iterations before the stop. The next step is validating the network, a plot of epochs versus Mean Squared Error (MSE), which shows the relationship between the number of epochs of the network to the MSE as shown in Fig. 9. If the training is perfect the network outputs and the targets are exactly equal, but that is rare in practice.

6. Discussion

The proposed ABFO is compared against other four BBB detection algorithms such as Wavelet Transform (WT), Continuous Wavelet Transform (CWT), Wavelet Transform and

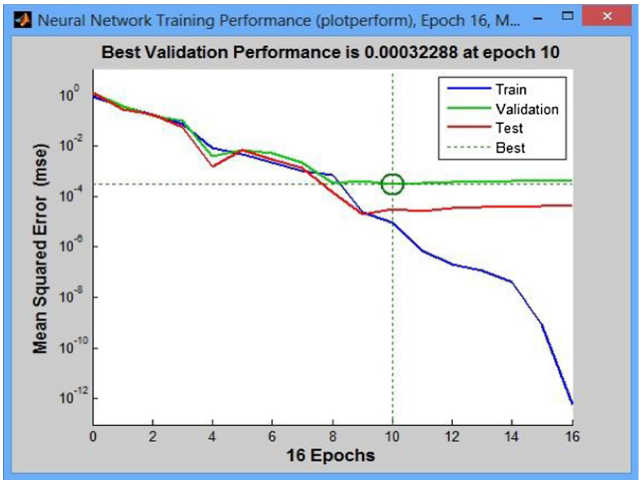

Figure 9 Neural network training performance plot.

Table 4 Comparative study for the detection of BBB.

Studies	Approach	Accuracy (%)
Yu et al. [37]	WT and PNN	98.39
Kutlu et al. [38]	CWT	97.3
Ceylan et al. [39]	WT	98.1
Kora et al. [36]	BFPSO	98.1
Proposed approach	ABFO	98.74

Probabilistic Neural Network (PNN) and Hybrid Bacterial Foraging and Particle Swarm Optimization (BFPSO) in terms of related features selected from the original database and classification accuracy obtained from different classifiers using Matlab software.

The work in [39] explores an experimental study of using WT for extracting relevant features and KNN based classifier for the detection of BBB. The work presented in [38] used morphological features for classification using SVM. The work proposed in [37] used Arrhythmia dataset from MIT/BIH repository and 20 morphological and wavelet features are extracted then PNN is used for supervised learning and classification. The work in [36] explores an experimental study of using Hybrid BFPSO for extracting relevant features and LMNN based classifier was used for the detection of BBB. From the experiments, it is concluded that the proposed ABFO with LMNN classifier outperformed other three algorithms with a selection of a minimal number of relevant features. This increases the classification accuracy as shown in Table 4. The ABFO employed to intelligently select the most relevant features that could increase the classification accuracy while ignoring noisy and redundant features.

7. Conclusion

In the present study we developed a simple computational model for the detection of BBB using the ABFO algorithm. It also projected that ABFO algorithm can be used for ECG feature extraction in (or "intending to") improving its convergence behavior and decreasing the error in the final output. The classical BFO algorithm was compared with the ABFO algorithm and the evolutionary based algorithm such as GA. In our study, we observed improved classification accuracy. The ABFO variants were shown to provide better results than their classical BFO for all the tested data. Thus, this ABFO optimization method that we applied may be useful for further such investigations.

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