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An ECG classification using DNN classifier with modified pigeon inspired optimizer

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Abstract
Arrhythmia is a form of heart disease in which the regularity of the pulse is changed.ECG data may be analyzed to detect heart-related illnesses or arrhythmias. This paper presents a wrapper feature selection strategy that employs a Pigeon-inspired optimizer(PIO). The modified Pigeon Inspired Optimizer (MPIO) is used to optimize ECG features and the Deep Neural Network (DNN) to classify the ECG signals. In MPIO, the new blood pigeons were introduced to improve the accuracy of the algorithm. Morphological features, wavelet transform coefficients, and R-R interval dynamic features are extracted for classification of ECG signals. After feature extraction, MPIO is used for feature optimization because optimizing the feature plays a key role in developing the model of machine learning, and irrelevant data features degrade model accuracy and enhance model training time. Using optimised features, the DNN classifier is utilised to classify ECG data. The proposed method achieves 99.10% accuracy, 98.90% specificity, and 98.50% sensitivity. Additionally, when compared with other state-of-the-art methodologies, our method of feature selection also exhibited better outcomes.

Keywords Deep neural network · Heartbeat classification · PIO · Wavelet transform

1 Introduction

In the last decades, the death rate of humans due to heart diseases is growing very fast. In today's fast life man does not pay attention to his cardiac health. sudden cardiac arrest has been raising a large percentage of mortality of health patients. Two types of heart diseases: one is life-threatening, and the other one is non-life-threatening. Irregularity in heartbeat caused arrhythmia, which is related to heart disease. This can be minimized by using modern cardiovascular disease diagnosis tools, which are based on compute simulation and

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analysis of the biological signal. A signal is said to be biological if it is extracted from a living organism. A life threat can cause a heart attack and sudden death.

ECG is the electrical representative of heart function. P, Q, R, S, T is the name of different peaks of the ECG signal. The QRS complex of ECG is another useful pattern [27], which provides more relevant information about heart activity [19]. Usually, this PQRST wave repeats 72 times in a minute so that this signal is called periodic. Arrhythmia can be of two types: (i) catastrophic arrhythmia, i.e., bradycardia, fibrillation, skipped beat, etc., and (ii) premonitory arrhythmia, i.e., Pre Ventricular Contraction (PVC), R on T, bigeminy, and Trigemini interpolated PVC, etc. In Bradycardia arrhythmia the heart rate is reduced and the width of the P wave is increased with a normal PQ interval. It is identified if the RR interval is increased beyond 1.5 seconds. to detect bradycardia only ECG rhythm is required. In tachycardia, the heart rate is very fast up to 120 beats per min with the normal shape of ECG. Ventricular fibrillation is essentially an electrical activity that is fragmented. it can be detected by wide R wave up to 1.6 second and bizarre and wide QRS complex. In Premature Ventricular contraction(PVC) the QRS complex is premature with full adjustor pause and the T wave is in the reverse direction. Bigeminy occurs when PVC beats are paired with normal beats. In Trigeminy the normal beats follow two premature beats with full adjustor pause.

Arrhythmia monitoring has been used for the coronary care unit. In digital computer monitoring which is also known distributed approach, a small computer unit is used to monitor the rhythms of the heartbeat.It will alarm the nursing staff if the heart rate sample is high and row when ventricular extra rhythm occurs above monitoring rate. This data can be displayed to central display and stored for future reference. Another approach utilizes computers for monitoring of patients simultaneously up to 16 beds. The ECG is displayed on a video screen where clinical persons can see various rhythm distributions. But there is a problem with reliability and accuracy with such a system because the ECG waveform that is collected by ECG electrodes from the heart effected by chest shape and body fat and other factors. Also, there are chances of pseudo arrhythmia which lead to misinterpretation of external artifacts recorded on ECG. To detect arrhythmia various techniques has been developed in last two decades [2–4]. Various signal processing techniques are widely used to analyze the different type of arrhythmia. Only one ECG beat or a long length ECG may require to detect the arrhythmia.

This study attempts to summarise the major contributions of this work as follows:

- For arrhythmia identification, several feature descriptors were explored. Morphological feature, wavelet coefficient feature, and RR interval-based feature are utilized to extract the features.
- Based on Pigeon Inspired Optimizer (PIO), an efficient feature selection method termed MPIO is developed and DNN is used as a classifier.
- Finally, suggested technique is employed on the ECG database to assess its consistency and compare the results with existing metaheuristics. The reliability of the proposed classification is checked by accuracy, specificity, and sensitivity.

The rest of this paper is structured as follows. The literature study of Section 2 explores the previous research. Section 3 covers the MIT-BIH arrhythmia database, feature extraction techniques, the PIO, MPIO methodology, and the DNN classifier. Section 4 begins with an in-depth exploration of the experimental findings and comparisons with other well-known metaheuristic algorithms. Section 5 ends this paper with a conclusion. The block diagram of proposed work is shown in Fig. 1.

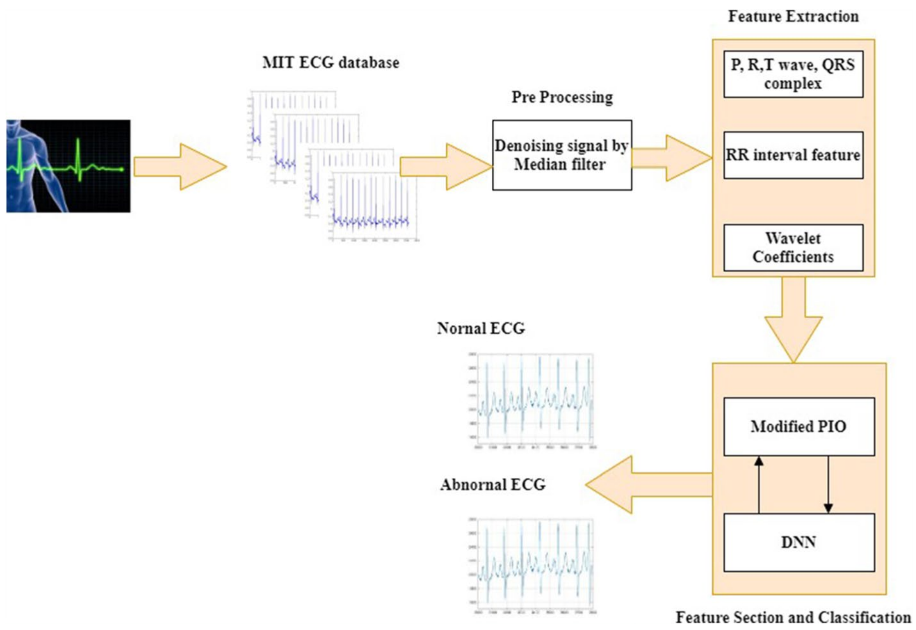

Fig. 1 Block diagram of proposed work

2 Literature review

Numerous research have shown the effectiveness of machine learning technology in developing classification models [36] such as DNN, Multilayer perception network (MLP) [12], Probabilistic Neural Network (PNN)[11] and the Support Vector Machine (SVM) [20], Hybrid with other methods for ECG classification. Metaheuristic methods such as Ant Colony Optimization algorithm (ACO) [16], Artificial Bee Colony (ABC) [23] and Whale Optimization Algorithm [33] (WOA) have been developed for addressing optimization issues. The ECG signal classification issues have received significant support for metaheuristic methods, Li et al. [29] introduced a technique to extract ECG signals from a nonlinear function. The methodology combines the estimated entropy of the wavelet packets with the wavelet packets themselves. The ECG signal classification approach described by Celin and Vasanth [7] used various classification models, artificial neural networks (ANN), and SVM. Choi et al. [9] developed a machine learning algorithm that utilizes fuzzy vectors in which local data receives more weight than other data and training data are assessed for membership in a fuzzy vector. Kora et al. [25] showed the Bundle branch block model may be detected based on the behaviour of fireflies and, perhaps, other firefly sensors coupled with PSO. Mar et al. [32] developed the sequential search floating method forward coupled with MLP for a complete ECG arrhythmia classification feature. Jiang et al. [22] suggested a new multi-module neural network method to address the imbalance issue in the ECG heartbeat categorization reported an ECG multiresolution transformer QRS complex feature model that classifies four kinds of ECG beats.

The biometric method focusing on Convolution neural networks(CNN) for ECG classification is described by Labati et al. Yildirim [45] proposed a new technique, based on wavelet sequences, incorporating two-dimensional architecture, for improving long-lasting short-term memory (LSTM) networks for deeper multidirectional network measurements. Several types of rhythms derived from the MIT-BIH dataset were tested. In order to build a model with an automated functional learning framework and effective optimisation technique, Wang et al.[44] developed a global classification scheme called the recurrent global neural network. Elif Ubeyli [43] proposed a recurrent neural network (RNN) which is trained with the Levenberg Marquardt algorithm to classification ECG beats. Mehmet Korurelc *et al.*[26] introduced a method with particle swarm optimization (PSO) and RBFNN. PSO is used for feature optimization and these optimized features are applied to the RBFNN classifier. Khosravy et al.[24] presented a one-step ECG baseline morphological estimate utilising PSO for parameter definition. For the identification and classification of rhythmic signals, the combined linear and non-linear ECG characteristics are utilized by the SVM-based and radial function-based methods proposed by Elhaj et al.[18]. Baloglu et al.[5] developed a deep learning algorithm to identify myocardial infarction on a standard 12-lead ECG. The trials on the public ECG physio bank are for training purposes only. Deng et al. [13] developed a dynamic ECG identification framework for human identification and categorization of cardiovascular illnesses. Shu lih oh et al.[37] designed a automated system for diagnosis of arrhythmia. Convolution neural networks and LSTM are used to classify the ECG signals.

The DNN model for the ECG classification was presented by Sannino and De Pietro [39] in the same area. Another profound method built upon a one-dimensional residual convolution network is given with the deep heart disease classification ResNet by Li et al. [31]. Diker et al. [15] suggested a model that ECG's sign categorization be enhanced with greater precision using the differential evolution (DE) algorithm. In combination with discrete wavelet transformation (DWT), PCA and PSO, Ince et al. [21] presented the classification model for categorizing five groups of ECG heartbeat. Genetic (GA) and background-propagation neural categorization systems have been utilized by Li et al. [30] to divide the six ECG heartbeat types.

An ECG arrhythmia classification method using DNN-MPIO is suggested for better feature selection to enhance the classification accuracy.

3 Material and method

3.1 Database

The arrhythmia database was taken from the Massachusetts Institute of Technology Beth Israel hospital (MIT-BIH) [35]. There were 48 records in that database. The resolution of the signal was 11bit, and the sampling rate was 360Hz. The duration of each signal was 30 minutes after segmentation. In order to be consistent with previous comparable studies, this data set was separated into DS1 (training set) and DS2 (testing set) [1]. The two sets combined all of the MIT-BIH recordings as follows:

DS1:[101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203,205, 207, 208, 209, 215, 220, 223, 230]

DS2: [100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213,214, 219, 221, 222, 228, 231, 232, 233, 234]

This dataset is quite imbalanced, as nearly 90% of the samples are in normal group, while only 15% are in any other group (Abnormal). To take a fair comparison between our results and those from previous studies, the inter-patient partitioning methodology is used. We collected a total of 100911 items from the entire database. Out of 100911 beats, 89695 normal beats and 11216 +abnormal beats were found. Due to this imbalance dataset a bias towards minorities, thus the algorithm produces a classifier that says everything is the majority class. To overcome these issues, we opted to use just 4000 items, with 2000 are the normal beats class (N) and 2000 are the abnormal beats class (A), which are chosen randomly amongst all participants.This dataset is classified into two categories: the training and testing environment, in compliance with other related works [39].

The training and testing data sets are detailed in the Table 1. The classifier is trained by training data set while the testing data set is used to assess the classifier's output.

3.2 Preprocessing

Preprocessing is used to eliminate the noise from the ECG signal. When the ECG signal is acquired from the human body, it is the combination of ECG signal and noise. Power line interference and baseline wander the significant artifacts in signal [8]. Previously different filter methods are used to remove these artifacts. To remove baseline wander artefacts, two window size median filters of 600 ms and 200 ms are employed [42]. When an n-length median filter is applied to ECG signal X, the median filter's output is shown by equation:

$$Y(i) = \begin{cases} X\left(i - \frac{n-1}{2}\right) : X\left(i + \frac{n-1}{2}\right), & n \quad odd \\ X\left(i - \frac{n}{2}\right), X\left(i - \frac{n}{2}\right) + 1, ...X\left(i + \frac{n}{2} - 1\right). & n \quad even \end{cases} \tag{1}$$

MATLAB function medfilt1 was used to design median filter [28]. Power line interference arises as a result of the power supply, introducing noise at the 50/60 Hz frequency. A 35Hz Low Pass Filter (LPF) was employed to remove the noise. Figure 2 depicts the original signal as well as the filtered signal, which is the result of the median filter and low pass filter.

3.3 Feature extraction

In this work, morphological features, wavelet coefficients and RR interval based features are extracted. Morphological characteristics of the signal were extracted using WFDB (wave database toolbox) available in MATLAB [41]. The ecgpuwave() function applied to the signal and exact position of P, R, and T waves. Segmentation of the ECG data is done into single after finding the P and T peaks. In every beat, 50 samples are collected that were evenly dispersed from P peak to T peak. The QRS complex was detected using Pan and Tompkins algorithm. [38] Fig. 3.

Wavelet transforms represent the signal in the time and frequency domain both. The ECG signal is decomposed into three level using Daubechies wavelet (Db-3).

Table 1 Data set details

	Training set	Testing set	Complete set
Normal Beats	1200	800	2000
Abnormal Beats	1200	800	2000
Total	2400(60%)	1600(40%)	4000

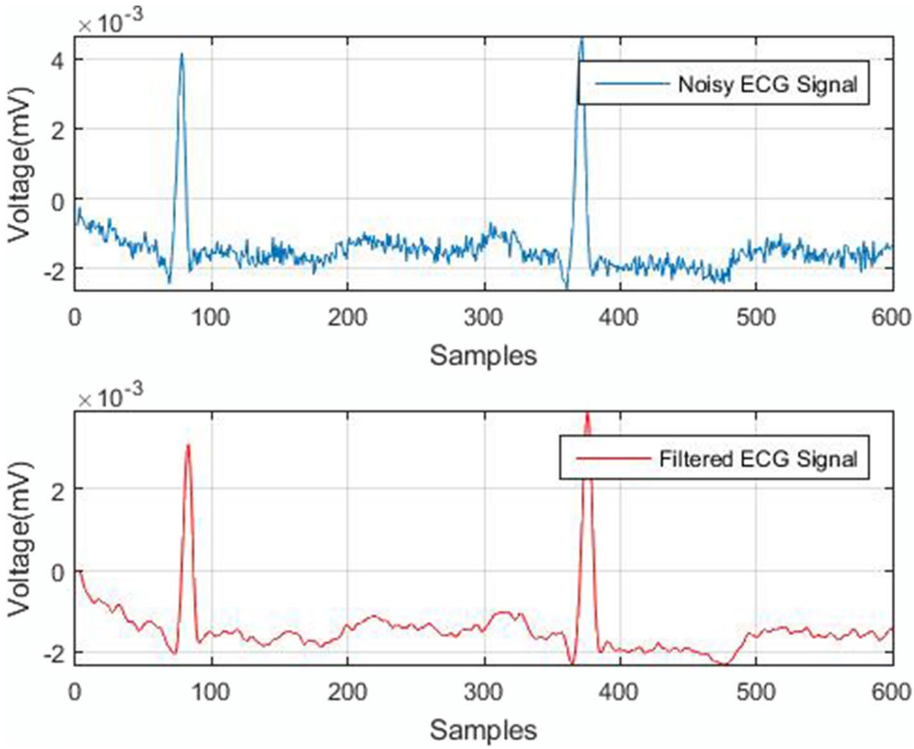

Fig. 2 Raw signal and filtered output of ECG signal

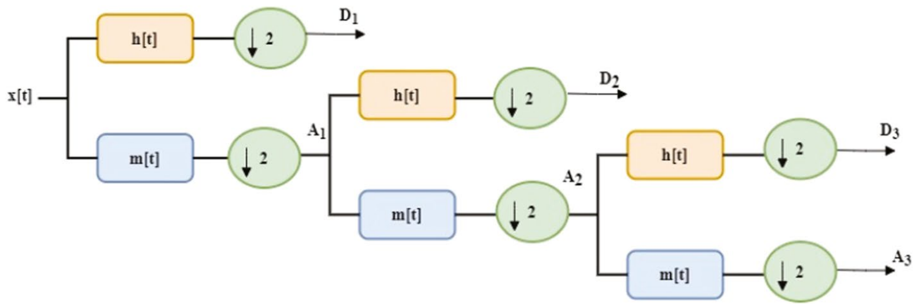

Fig. 3 Decomposition of Discrete wavelet transform implementation (DWT)

All wavelet transforms have a low pass filter m that satisfies the quadrature mirror filter requirement:

$$M(z)M(z^{-1}) = M(-z)M(-z^{-1}) = 1 \tag{2}$$

M(z) is the z transform of the filter m. This filter's complementary high pass filter can be written as

$$H(z) = zM(-z^{-1}) \tag{3}$$

the sequence of filter is calculated as

$$M_{i+1}(z) = M(z^{2^i})M_i(z), \tag{4}$$

$$H_{i+1}(z) = H\left(z^{2^i}\right)H_i(z) \;\; i = 0, 1, 2 \ldots I - 1 \tag{5}$$

with initial condition $M_0(z) = 1$. In the time domain, it is expressed as a two-scale relationship.

$$\begin{aligned} M_{i+1}(k) &= [M]_{\uparrow 2} iM_i(k), \\ H_{i+1}(k) &= [H]_{\uparrow 2} iH_i(k) \end{aligned} \tag{6}$$

where $[.]_{\uparrow 2}$ denotes a factor of n up sampling and k denotes uniformly sampled discrete time. The normalized wavelet $p_{i,j}(k)$ and scale basic functions $q_{i,j}(k)$ can be defined as

$$\begin{aligned} p_{i,j}(k) &= 2^{i/2} m_i(k - 2^i l), \\ q_{i,j}(k) &= 2^{i/2} h_i(k - 2^i l), \end{aligned} \tag{7}$$

where $2^{i/2}$ represents an inner product normalisation, i represents a scale parameter, and l represents a translation parameter. The DWT decomposition can be explained as

$$\begin{aligned} A_{(i)}(l) &= x(k)p_{i,j}(k), \\ D_{(i)}(l) &= x(k)q_{i,j}(k) \end{aligned} \tag{8}$$

where $A_{(i)}(l)$ is the approximation coefficients and $D_{(i)}(l)$ is the detail coefficients. The four features related to R-R interval are used.

The distance between the two R peaks was the R-R interval. These four features are

(i) **Previous R-R**: The interval between the previous peak and current peak.
(ii) **Post R-R**: The interval between the current R peak and the next R peak.
(iii) **local R-R**: The average of ten R-R intervals.
(iv) **Global R-R**: The average R-R interval over the last 10 minutes.

3.4 Feature selection

All the features extracted from the ECG signals may not be useful for the detection of Arrhythmia because it may increase the execution time and complexity of the detection system. To get a high detection rate and minimal false alarms, a subset of these traits should be selected. In addition, the feature selection procedure is vital to decrease the number of functions needed to develop the detection system for arrhythmias. In this work, a metaheuristic is suggested for managing the selection process on the basis of a Pigeon Inspired Optimizer (PIO).

3.4.1 Pigeon Inspired Optimizer (PIO)

Pigeon Inspired is the innovative methodology developed for optimizing the functionality [17] Pigeon has a special ability to reach home using earth magnetic field and landmarks around their way. In the first and second world wars the German, French, U.S. and British armed forces employed pigeons for war to transmit communications. Pigeon skills in the form of equations can be stated. Two major map and compass operators and landmark operators employed pigeon homeowners talents. Pigeons use the earth's magnetic field to change their orientation, as well as the sun's altitude as a compass for changing direction.

Mathematically the position of pigeon X_k and velocity V_k of the pigeon can be expressed for every iteration

$$V_k(n+1) = V_k(n)e^{-Rn} + rand(X_g - X_k(n)) \tag{9}$$

$$X_k(n+1) = X_k(n) + V_k(n+1) \tag{10}$$

Where R defines the map and compass factor and rand defines random numbers with rang 0 to 1. Global best solution is X_g. $X_k(n)$ is the current position of the pigeon at iteration n. $V_k(n)$ is the velocity of the pigeon at iteration n. In Fig. 4 Pigeons are able to alter locations according to the optimum global pigeon position using map and compass operating. The best pigeon, in this case, is a black pigeon and others follow it as like (9). part one of this equation is shown the current direction of the pigeon in Fig. 4 the gray colour arrow shows it. Part two shows the direction of the best pigeon and in Fig. 4 the black colour arrow shows it. Pigeon adjusts their position using these two equations.

In landmark operator (Fig. 5) the number of pigeons is half after every iteration. The fitness value of all pigeons is used to arrange pigeon position. After every iteration, the number of pigeons is updated as

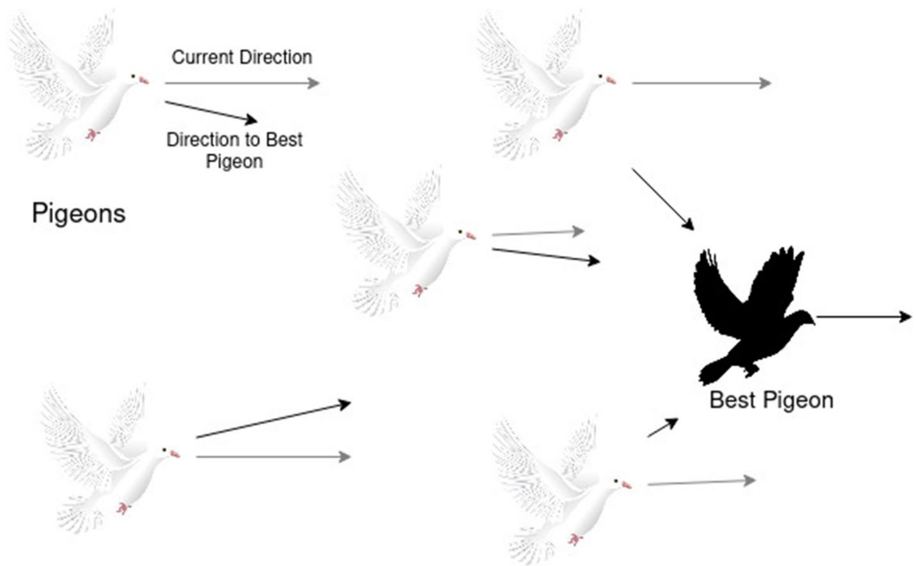

Fig. 4 White pigeon adjust their position according to black (best) pigeone

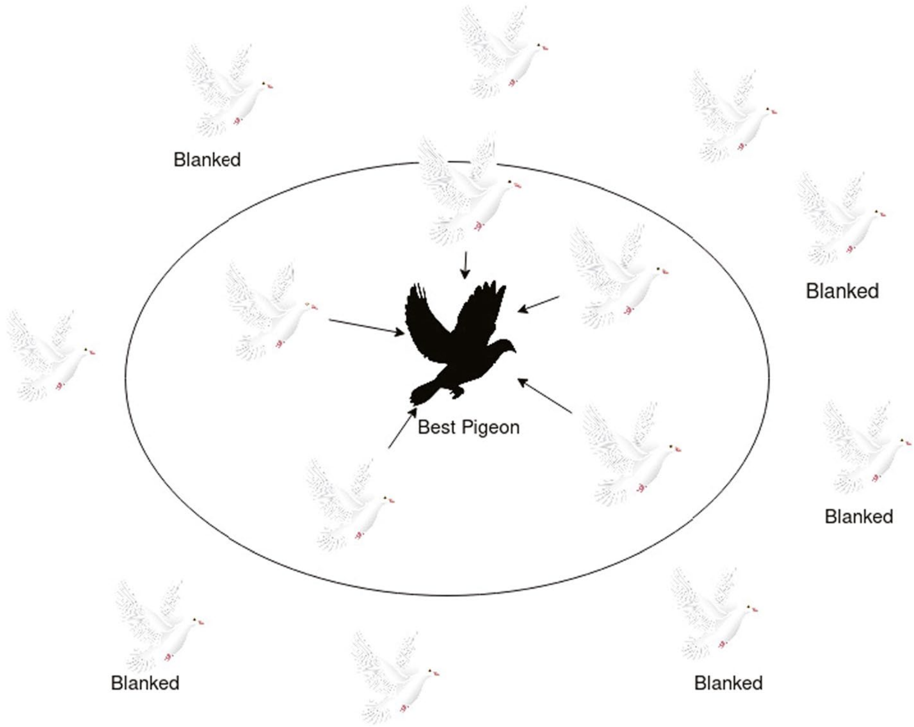

Fig. 5 Landmark operator model

$$N_p(n+1) = \frac{N_p(n)}{2} \tag{11}$$

The number of pigeons in iteration n is denoted by Np. In the (11), we can see that only half of the pigeons are considered evaluating the desired position of the centered pigeon. The desired position of the pigeon is calculated by

$$X_c(n+1) = \frac{\sum X_k(n+1).Fitness(X_K(n+1))}{N_p \sum Fitness(X_k(n+1))} \tag{12}$$

X_c is the desired destination.

The rest of pigeons positions are updated by

$$X_k(n+1) = X_k(n) + randX_c(n+1) - X_k(n) \tag{13}$$

The fitness function is used to evaluate the solutions. The fitness function demonstrates the solution quality. Here the fitness function value is the accuracy of the classifier defined as

$$Fitness\,value = fmax(acc) \tag{14}$$

The solutions are represented in binary form shows in Fig. 6. In this form, the population size of the solution is 100. The length of the solution is the total extracted features. Binary no. 1 shows that a feature is selected in solution and 0 number shows rejected features.

Fig. 6 Structure of solution

f1	f2	f3	f4	f5	f6		fn
1	0	1	1	0	1	....	1

f1	f2	f3	f4	f5	f6		fn
1	1	0	1	1	1	....	0

3.4.2 Modified PIO

In PIO position of pigeons is updated after every iteration and also updated fitness value of pigeons. Modified PIO adds a new blood pigeon in the swarm. Each pigeon represents one solution. Each solution has its fitness by (14). This method was invented by looking at the increased chances of generating many answers through replication and maybe the fitness of pigeons is very less. New entrances to the pigeon can only be implemented in map and compass operators. A judge will have to be brought in to take the imitation pigeon's position as the new higher fitness value pigeon. If the fitness value of the new solution(pigeon) is better than the exiting solution then replace that solution with the new one. This will allow you to explore more efficiently.

To generate a new solution, select solutions from the existing population, Which is done by the concept of Genetic algorithm. Roulette wheel selection is used to select solutions. After the selection of solution double point crossover is used to generate a new solution. In double point crossover randomly two crossover points are taken from the parent solution. This solution may be repeated after some time because just taken the two different parts of the two solutions without doing any modification. So for some modification on the new solution, the Gaussian function is used. After this fitness has been determined, it will be ready to be used. If the new solution yields a higher fitness value, then replace the existing answer with it. In this way, it's possible to get closer to an optimal solution.

3.5 Classification

Classification divides input signals into two classes: normal and abnormal class. Here DNN is used to classify given ECG signals.

3.5.1 Deep Neural Network (DNN)

DNN is the imitation of human brain functioning. After getting optimal features from the optimization algorithm, it applies to DNN for classification. Using the DNN signal classify into two classes: normal and abnormal. DNN has two stages of working one is pre-training, and the second one is a fine-tuning of the system.

Now, the process was initialized by the weights of each layer randomly by treating all pairs of a layer as Restricted Boltzmann Machine(RBM). RBM consists of a visible layer with Bernoulli or Gaussian distribution and a hidden layer with Bernoulli distribution.

The energy function for given RBM is defined as

$$E(v,h) = -\sum_{x} a_x v_x - \sum_{y} b_y h_y - \sum_{x}\sum_{y} v_x w_{x,y} h_y \tag{15}$$

Where w_{xy} defines the weight of connection between hidden unit h_y and visible unit v_x. a and b is the bias term. The probability distribution over hidden layer and visible unit in terms of energy function is defined as

$$P(v,h) = exp(-E(v,h)/Z \tag{16}$$

Where Z is a partition function which is the summation of all $exp(-E(v,h)$ over all feasible configurations in between hidden, and visible layers.

The probability assigned to a visible unit v is

$$P(v) = \sum_h exp(-E(v,h)/Z \tag{17}$$

Provided the hidden unit activation, the visible unit activation is conditionally autonomous, and vice versa. As a result, the conditional probabilities can be written as follows:

$$P(v_x = 1/h) = \sigma(a_x + \sum h_y w_{x,y}) \tag{18}$$

and

$$P(h_y = 1/v) = \sigma(b_y + \sum v_x w_{x,y}) \tag{19}$$

Where σ is the logistic sigmodal function. $\sigma = \frac{1}{1+e^{-x}}$.

The above description is for only one hidden and one visible layer. The same theory is used for multi-layer generation neural networks. Here RBM is used for pretraining of the neural network to initialize the weights. To make the fine-tuning of the network backpropagation algorithm is applied.

The Fig. 7 diagram represents a DNN with layered RBMs. There are Gaussian visible nodes and Bernoulli hidden nodes in the RBM at the bottom layer. For the remaining RBMs, both the visible and hidden layers exhibit Bernoulli distributions. Pre-trained weights (W1, W2, and W3) were utilized during fine-tuning to determine the starting weights, and weights between the top two layers (W4) were started using small random values. Therefore, after every epoch, 30% of the training set was utilized to compute the accuracy of the network. This is useful in preventing overfitting by using early stopping. A pre-training phase may be required to offer network regularisation, and an early pausing approach is recommended to assist in training model overfitting. DNN has a 0.001 learning rate , 0.5 momentum and 100 maximum number of iterations(epoch).

4 Result & discussion

The proposed method is implemented on a computer with i5 CPUs and four gigabytes of RAM using the working stage of MATLAB 2015a. The raw ECG signals are influenced by several artifacts types so that for further processing it is required to eliminate the artifacts. The median filter and 35Hz low pass filter are used for the pre-processing of the ECG signal.

To evaluate the efficiency of the classifier, major indices are used: accuracy (Acc), precision(Pre), sensitivity (Se) and specificity (Sp). These can be defined as

$$S_e = (TP/TP + FN))X100 \tag{20}$$

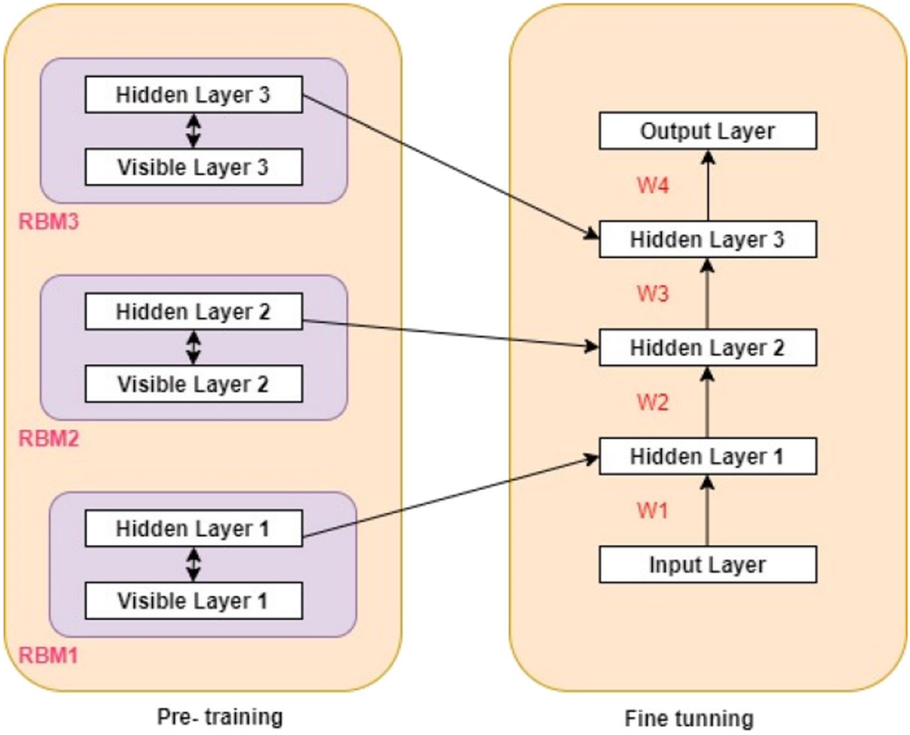

Fig. 7 Structure of DNN network

$$S_p = (TN/(TN + FP)X100 \tag{21}$$

$$Pre = (TP/(TP + FP))X100 \tag{22}$$

$$Acc = ((TP + TN)/(TP + TN + FP + FN))X100 \tag{23}$$

TP (true positive) defines that normal class is classified as a normal class and TN (True negative) defines that abnormal class is classified abnormal. FP (false positive) defines that abnormal class is classified as a normal class and TN (true negative) defines that normal class is classified as an abnormal class.

The ability of the DNN network to classify signals is depends upon the hidden layers, therefore, the number of hidden layers are varied from 1 to 5 during the training of DNN and found that the maximum accuracy is achieved for 3 hidden layers. This can also be verified from the Fig. 8(a). Similarly the number of hidden nodes during DNN training is also varied from 1 to 250 and found that when the number of hidden nodes was equal to 100, the highest performance was achieved. Which is shown in Fig. 8(a)(b). Therefore, for better classification or for better future predictions, the DNN classifiers, should have 3 hidden layers and each layer should have 100 nodes.

Feature distribution is shown in Fig. 9 in the bar chart. A detailed look at the suggested methodology reveals that it plays a key role in determining the ECG signal state. Notably, the rate of chosen features for R-R is 50% (2 out of 4); wavelet features are 43% (10 out of

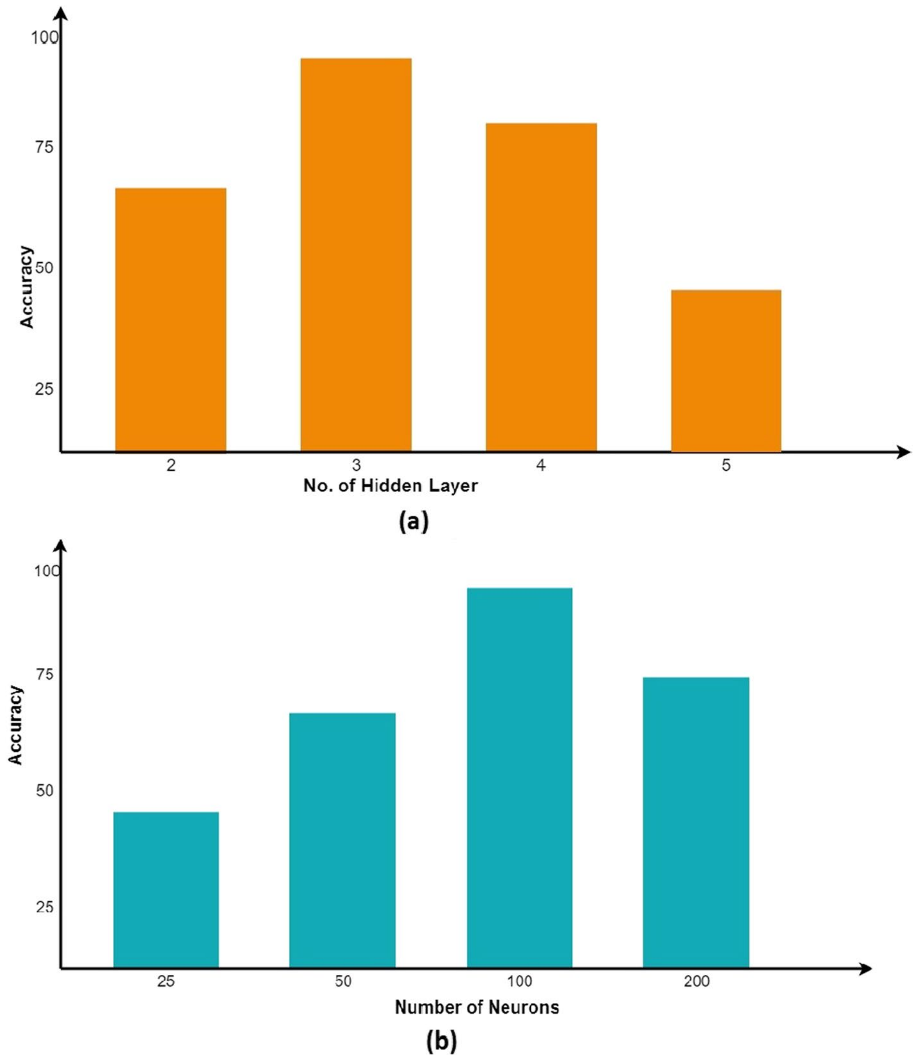

Fig. 8 (a) Variation of hidden layer in DNN network (b) Variation of nodes in hidden layer

23), and morphological features is 63%. (5 from 8). The total number of extracted features from all 35 features is 17, which means that the suggested DNN-MPIO decreased the size of the features by 52%. In other words, just 48% of all features were utilized to construct the classification model.

Figure 10 shows the comparison between PIO and modified PIO optimization algorithm. The fitness value of modified PIO is gradually increased and getting saturated after 80 iterations. The graph shows proposed algorithm provides the best fitness value of the solution comparative to the PIO algorithm.

Figure 11 depicts the confusion matrix for the entire data set and the training dataset. In the complete dataset, 1985 normal samples and 1979 abnormal samples are properly predicted, whereas 15 normal samples and 21 abnormal samples are incorrectly predicted.

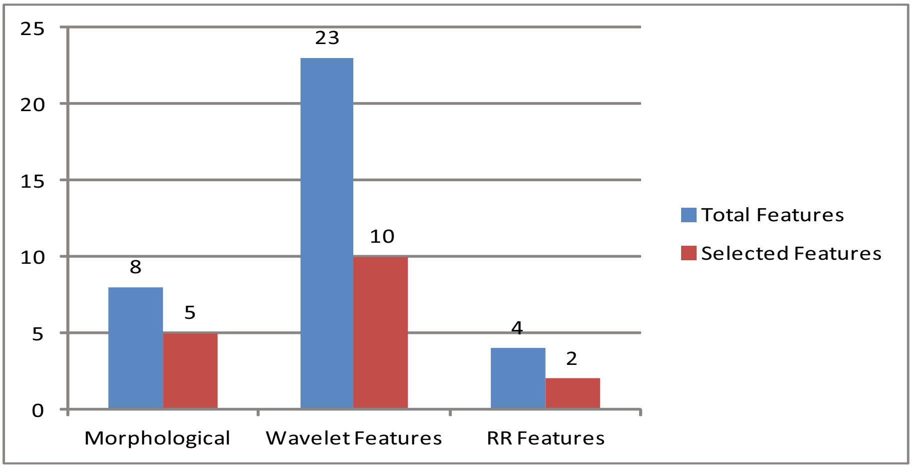

Fig. 9 The distribution of features derived by applying the best chosen features from DNN-MPIO

In the testing dataset, Only 16 out of 1600 items were incorrectly predicted. This is a very small value, indicating that the classifier's accuracy is excellent.

Figure 12 represents the outcome of a DNN classifier with various feature refinements. When all retrieved features were given straight to the DNN classifier, it obtained 97% accuracy. When the PIO method is applied to features for optimization, it achieves 98.45% accuracy. This demonstrates that our proposed method, which achieves 99.1% accuracy, is better and provides the best features for the DNN classifier.

The results from the different datasets are shown in Table 2, which shows the overall performance of the proposed DNN-MPIO, based on accuracy, sensitivity, specificity, and precision. The accuracy of the testing dataset is 99.01%, while the accuracy of the full

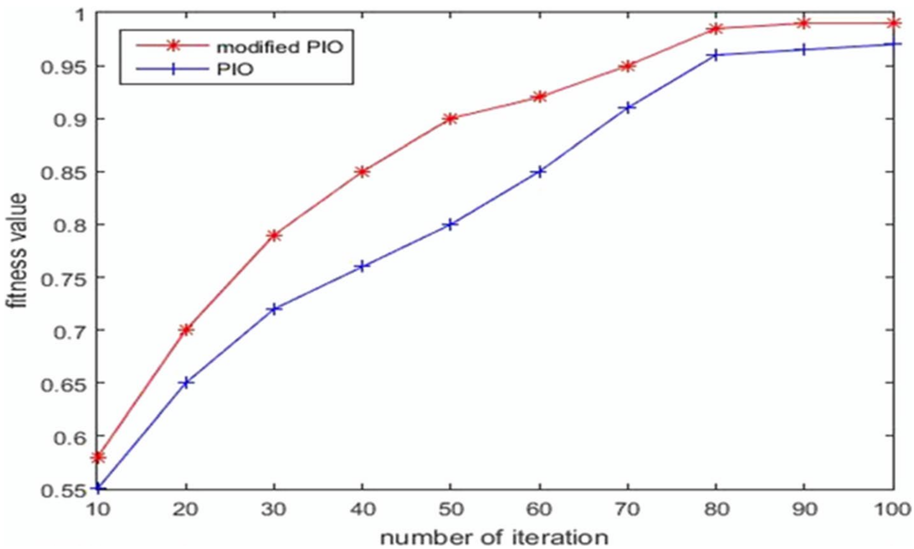

Fig. 10 Fitness value curve

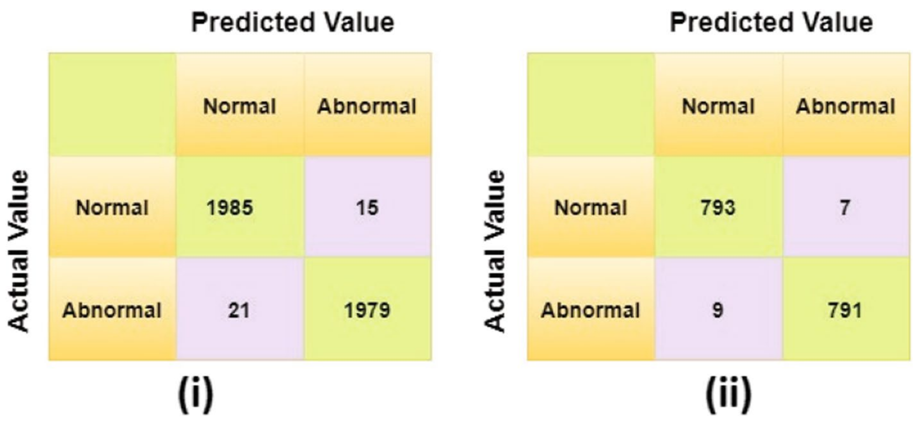

Fig. 11 Confusion matrix (i) Complete dataset (ii) Testing dataset

dataset is 99.1%. The precision of the testing dataset is 99.25%, whereas the entire dataset has a precision of 99.125%.

Table 3 shows the learning and classification time of different methods.The DNN with all features takes 121.25 sec for training while using PIO optimization algorithm the learning time goes to reduced 54.75sec.The learning time for our proposed method is 21.23sec and classification time is 0.4977sec, which is sufficiently effective to diagnose a wide variety of cardiovascular ECG signals in real time.It shows that the learning time of classifier is reduced by 61% when we use MPIO instead of PIO algorithm.This result is average of 10 experiments.

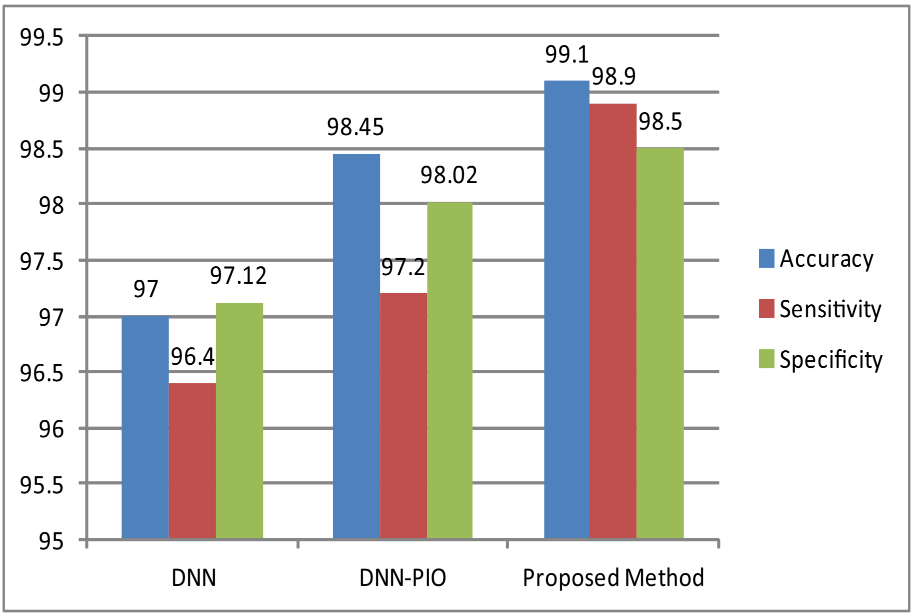

Fig. 12 Comparisons with all features and optimized features

Table 2 Performance of Proposed method

	Training dataset	Testing dataset	Complete dataset
Accuracy	100	99.01	99.1
Sensitivity	100	99.20	98.9
Specificity	100	98.90	98.5
Precision	100	99.125	99.25

Table 4 shows that the comparison of the different previous classifiers with the proposed method in terms of accuracy, sensitivity, and specificity. All the methods used MIT-BIH public database. The numbers of classes for these methods are different so that every class has different accuracy. Here we take the average of these accuracies for comparison.

M. Korurelc et al. presented a method using PSO-RBFNN, achieved 99.10% accuracy and 96.25% sensitivity. Daamouche et al. [10] proposed combining the polyphase representation of wavelets and the PSO for feature extraction. SVM is employed as a classifier, and 91.75% accuracy is achieved. Shadmand et al.[40] used a classifier based on a Block-based Neural Network (BBNN). The PSO algorithm is used to optimize the network structure and weights. This technique has a 73% accuracy rate. Diker et al. [14] introduced a two-class classifier using statistical and morphological features. The hybrid classifier ANN and k-NN was used and 80.60% accuracy was achieved. Hongqiang Li et al. created a Genetic Algorithm - Back propagation Neural Network (GA-BPNN) algorithm that obtained 97.78% accuracy. The GA algorithm is utilised for feature optimization, while the BPNN algorithm is used for ECG classification. Bhagyalakshmi et al. [6] suggested an efficient approach named the Genetic Bat Optimization Algorithm for training the Support Vector Neural Network (GB-SVNN) for arrhythmia classification. For extracting wavelet features and other texture data from the ECG signal, a multi-resolution wavelet-based method and Gabor filters are utilized and obtained 96.96% accuracy. Sannio et al. [39] developed a DNN for automated ECG signal recognition. The system has seven secret layers, each of 5, 10, 30, 50, 30, 10, and 5 neurons. The accuracy of the suggested system was 99.68 %. Monderjar-Guerra et al. [34] used SVM for classifier and achieved 94.45% accuracy. Li et al. [31] suggested a deep learning approach for classifying cardiac arrhythmia with ResNet (deep residual network). Using a 31-layer 1D residual convolutional neural network, they generated an accuracy of 99.06%. Comparative findings are displayed in Table 4, where authors compare features, feature selection, used classifier, and classification outcomes. According to other research, DNN-MPIO is superior in accuracy to other competitors by 99.10%. DNN-MPIO outperforms all other methods in the total classification of the measurement criteria. The recommended optimization technique, MPIO, decreases the dimensions of feature vectors, increasing computing speed and efficiency.

Table 3 Learning time and classification time

Method	Learning time(sec)	Classification time(sec)
DNN	121.25	0.9254
DNN-PIO	54.78	0.6245
Proposed Method	21.23	0.4977

Table 4 Comparison between other methods an proposed method

Author	Year	Class	Features	Method	Results
M. Korurek et al.[26]	2010	6	Morphological	PSO-RBNN	Acc:96.25% Se:99.104%
A. Daamouche et al.[10]	2012	6	Wavelet	SVM	Acc:91.75% Se:96.14% Sp:89.14%
S. Shadmand et al. [40]	2016	5	Hermit function coefficient, temporal	PSO-block based NN	Acc:73% Se:98.9% Sp:97.7%
Diker et al.[14]	2017	2	Statistical, Morphological	ANN,k-NN	Acc:80.60% Se:86.58% ,Sp:64.7%
H.Li et al.[30]	2017	6	Wavelet Coefficients	GA-BPNN	Acc:97.78%, Se:97.78%, Sp:97.81%
Bhagyalakshmi et.al[6]	2018	2	Wavelet,Gabor	GB-SVNN	Acc: 96.96% Se: 99%
Sannino et al. [39]	2018	2	Morphological, RR interval	DNN	Acc:99.48% Se:99.83% Sp:99.68%
Monderjar-Guerra et.al[34]	2019	4	RR, wavelet,LBP,HOS	SVM	Acc:94.45% Se:70.30%
Li et al.[31]	2020	4	End-to-end	31-layer deep ResNet	Acc:99.06% Se:93.21%
Proposed method	2020	2	Morphological,wavelet,RR interval	DNN-MPIO	Acc:99.1% Se:98.9% Sp:98.5%

5 Conclusion

An electrocardiogram is used by cardiologists to assist in the development of better heart treatments. It improves and protects the health and well-being of thousands of individuals. The ECG is important for diagnosis since it observes the electrical activity of the heart during a certain time period. In this article, the authors introduced an effective technique known as DNN-MPIO, which makes it possible to automatically classify the ECG signals using MPIO and DNN. The MPIO method is used to identify the key features of classification models and improve their accuracy. The MPIO method optimizes the extracted features up to 48%, which improves signal classification. Using three steps for the classification of ECG signals automatically, the suggested method utilizes a module for preprocessing, a module for feature extraction, and a module for classification optimization. In the experimental findings, the DNN-MPIO classification method demonstrated that it was more effective than the other competitor methods and get 99.10% accuracy. The proposed method also compare to the previous PIO method and unoptimized features with the DNN classifier. Therefore, the method used by the researchers has shown good utility for health professionals who want to identify disorders of the heart using the ECG signal.

Future work may include using other machine learning-based techniques like the convolutional neural network to detect arrhythmias and irregular heartbeats and also to classify the multi-class ECG signals related to arrhythmias.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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