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ECG Beat Classification by Radial Basis Function Neural Networks Classifier based on PSO, GSA and Hybrid PSOGSA Techniques

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Electrocardiogram (ECG) is the electrical recording of the cardiac activity and its analysis provides an effective way in order to identify the various cardiac diseases. Thus the classification of ECG signal is a significant task which aids in the diagnosis. In this paper, an optimized Radial Basis Function Neural Networks (RBFNN) has been proposed to classify six types (Premature Ventricular Contraction (PVC), Normal Beat (N), Atrial Premature Beat (A), Fusion of Ventricular and Normal Beat (F), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f)) of electrocardiogram (ECG) signal. The ECG heart beat signals are acquired using wearable telemonitoring device and preprocessed to remove noise present in the ECG signals. Once the noise has been removed from the ECG signals, RR Intervals and morphological features are extracted which are then fed into the classifier for classification among six types of beats. Here, the proposed classifier uses Gravitational Search Algorithm (GSA) and hybrid PSOGSA algorithm to search for the best value of the Radial Basis Function Neural Networks (RBFNN) parameters. The performance of the proposed approach is analyzed using existing RBFNN-PSO in terms of accuracy and sensitivity

Key words: Electrocardiogram (ECG), Heart beat classification, Radial Basis Function Neural Networks, Gravitational Search Algorithm (GSA), Particle Swarm Optimization (PSO).

The Electrocardiogram (ECG) is the widely utilized bioelectric signal that gives the physicians the most accurate data, concerning the cardiac activity of the patients. A significant process in diagnosing arrhythmia is classification [1] of heart beats using ECG signals. Thus continuous recording of ECG signals is essential for diagnosing cardiac condition [2]. This is achieved by using the Holter recorder and ambulatory heart activity recording system. But the diagnosis is carried out off-line depending on a transient pattern. As the number of beats to evaluate is more, this task becomes tedious and time consuming. Thus an automated classification of ECG signals is imperative. The electrocardiogram (ECG) is a non-intrusive monitoring and diagnostic tool that records the heart beat activity at the body surface. It provides exceptionally accurate status of the cardiovascular system.

The QRS complex, the P wave and the T wave are three typical features of the waveform which are effortlessly recognized. These waves are related with the activation of the ventricles, activation of the atria and re-polarization of the ventricles [3]. A patient may have diverse ECG waveforms and in a single ECG distinctive sorts of beats may introduce that are dissimilar to one another. The beats may be Premature Ventricular

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Contraction (PVC), Normal Beat (N), Atrial Premature Beat (A), Fusion of Ventricular and Normal Beat (F), Right Bundle Branch Block Beat (R), Fusion of Paced and Normal Beat (f) and so on.

In this paper, an automatic classification of heart beat into Premature Ventricular Contraction (PVC), Normal Beat (N), Atrial Premature Beat (A), Fusion of Ventricular and Normal Beat (F), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f) based on ECG signals has been presented. The ECG heartbeat signals are acquired using wearable telemonitoring device and preprocessed to remove noise present in the ECG signals. Once the noise has been removed from the ECG signals, RR Intervals and morphological features such as QRS complex features and T wave features are extracted from these signals which are then fed into the optimized RBFNN classifier for classification among six types of signals.

The rest of the paper is structured as follows: section II presents various techniques that have been used by several researchers to classify the ECG signals, section III presents the proposed methodology for classifying the ECG signals into six different types and results are discussed in section IV. Finally section V concludes the paper.

Related Work

The difficulty of continuous monitoring of cardiac function which needs a long time recording of (Electrocardiogram) ECG signals [4]. Since it needs to monitor huge number of beats, the inter-patient heart beat classification is a big issue for physicians. So, the objective of this paper is to classify the relevant feature sets of ECG signal from the heart beats. This classification is performed by Support Vector Machine (SVM) which takes the input ECG signals, assign some weights to each signal based on its features and differentiate each signal. Thus the classification done using SVM shows better results than the inter-patient classification models that are used previously with an average accuracy of 83.0%.

The heart rate variability feature of different combinations results in four varieties of cardiac rhythms namely supraventricular arrhythmia, normal, congestive heart failure and any arrhythmia [5]. To make this classification automated, various schemes are available which may be used based on the application. These schemes are inspected using random forest classifier. It results in the linear and non-linear features with the combination of frequency and time domain. The assessment of these features shows that the linear features lead the most weight in all four classifications. The classification accuracy is 93%. In future work, the non-linear features also gain better results which is used along with time and frequency domain.

The Fuzzy Neuro Learning Vector Quantization (FLVQ) algorithm [6] is implemented which solve the disadvantages of other classification model such that it classifies the unknown beats in the entire classification model. The objective is to find the arrhythmia types in a computerized way which can be able to classify the unknown beats from the ECG signal. This classification consists of three step procedure namely data preprocessing which allows the data to be prepared initially, removal of noise from the data and cut the ECG signal into beat by beat using pivot R peak. The second and third procedure are feature extraction and selection in which wavelet algorithm is used. The classification of ECG signals is done using the FLVQ and Back-propagation algorithm which has two phases. The first phase is to classify the trained category beats whereas the second phase is to classify the unknown category beat. Even though back-propagation provides better results than the FLVQ, it shows poor results in classifying unknown category beats and the method obtained a classification accuracy of 95.5%.

The concept of artificial neural network and data mining techniques are used for analyzing and classifying ECG signals [7].The activity of the human heart is monitored by the electronic simulators inside the heart, which are gathered by the ECG acquisition devices through sensor devices attached to the human body. Due to the small deviation in ECG signal leading to severe cardiac disaster, the representation of both the time and frequency domain is concentrated. The signals from the ECG are taken as input of equal length, which will be preprocessed to remove the noise and sent for feature extraction. The extracted signals are given to the already trained neural network for classification using data mining techniques. After the classification, the results are compared. In the future work, classification of all types of heart beats will be implemented and 82.22% is classification accuracy.

There are several methods available for the identification of types of ECG signal, but there is still some knowledge able and excellent method is needed for better accuracy in the signals. Hence in [8], a Quantum Neural Network (QNN) based classifier and rough sets for the classification of ECG signals into normal and abnormal classes is proposed. The input signals are taken from the database which is useful and widely used database. The feature parameter is extracted from the normalized ECG signal using wavelet transform. To maintain the rough sets efficiently, the redundant attributes and the unwanted data are removed from the signal by Quantum Neural Network (QNN). The experimental result shows that the RS-QNN is superior to all the conventional methods in performance wise and the classification accuracy is 91.7%.

The assessment of ECG signal compression performance by comparing the original and reconstructed signal is carried out in [9]. Compression of ECG signal takes place by using the set partitioning in hierarchical trees (SPIHT) and beat reordering techniques. The SPIHT takes care of redundancy between the adjacent beats and samples; whereas beat reordering is used to arrange the beat order in the form of 2-D ECG array. Again the above steps are performed in reverse to get the reconstructed signal. The classification of signal is done with two methods, namely, sleep stage classification and arrhythmia classification. Both produces more or less the same result.

The feature extraction of ECG signal plays a vital role in identifying the cardiac diseases. This feature extraction from the signal measures the amplitude and the interval between every beat frame. In [10], a discussion of a technique is held based on Support Vector Machine (SVM), Fuzzy logic methods, Genetic Algorithm and some other techniques. Previously deployed feature extraction techniques and the proposed algorithms for ECG feature extraction are discussed with the advantages and disadvantages. The future work mainly deals with the fast and accurate feature extraction algorithm for analyzing ECG with 95.9% accuracy.

The problem of classifying the ECG signals is a complex pattern recognition tasks. The proposed scheme includes the integrated features of Principal Component Analysis (PCA), Fuzzy C-Means Algorithm (FCM), and Neural Network concepts for the ECG beat classification [11]. PCM is used to separate the ECG signals into a weighted sum of beats that are mutually independent. FCM is used to cluster the similar signals into a training pattern for data reduction. For Neural Network, Back-propagation NN is used as a classifier. The paper compares the performance of all these three techniques and their combinations. Finally it concludes that the FCM-PCA-NN method performs much faster and better than all other techniques discussed.

MATERIALS AND METHODS

The block diagram of the proposed heartbeat classification system is shown in figure 1. The proposed approach comprises of the following stages (i) preprocessing (ii) feature extraction and (iii) classification. In preprocessing stage, the noises contained in the ECG signals are removed using quadratic filter and R peak is detected. Then RR interval features and morphological features are extracted which are then fed into RBFNN classifier evolved using GSA and Hybrid PSOGSA optimization techniques that classifies the signal into Premature Ventricular Contraction (PVC), Normal Beat (N), Atrial Premature Beat (A), Fusion of Ventricular and Normal Beat (F), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f).

In this paper, wearable telemonitoring device has been used which incorporates a sensor, processing and communication units in a single chip confined in the patient's body to acquire ECG signal. The sensor collects ECG signals and transmits it to the processing unit for processing and detecting abnormality. The sensor continuously obtains the ECG signal from the electrodes. Since the ECG signals are generally 1mV peak-to-peak, amplification of 300 is vital to extract this signal and is filtered with 0.5 Hz cut-off frequency high pass filter and 100?Hz cut-off frequency low pass filter. A right back driver is utilized to minimize the common mode noise. It introduces the common mode signal into the patient body to cancel them. The ECG signal is then passed to the processing unit for further analysis and digitization.

Preprocessing

The ECG signal contains several types of noises like baseline wander, electromyography noise (EMG), electrode motion artifacts, power-line interface and so on. These noises change the parameters of the ECG signal such as P, Q, R, S and T waves. Thus, it is essential to denoise the ECG signals polluted with various types of noises so that significant information present in the ECG waveform would not be lost. Thus, in this study a quadratic filter (QF) proposed by [12] is utilized to eradicate noise contained in the ECG signal. The QF is a derivative of second order volterra filter. The linear phased quadratic filter is developed using two Gaussian filters which is expressed as

$$G(c_{1k}, c_{2l}) = \frac{G_1(c_{1k}, c_{2l}) + G_1(c_{1k}, c_{2l})}{\max\{G_1 + G_1\}} \quad ...(1)$$

Where

$$G_i(c_{1k}, c_{2l}) = \exp\{-[X(c_{1k} - c_{1i})^2 + Y(c_{1k} - c_{1i})(c_{2k} - c_{2i}) + Z(c_{2k} - c_{2i})^2]\} \quad ...(2)$$

for i=1,2 and

$$X = \left(\frac{\cos\theta}{\beta_x}\right)^2 + \left(\frac{\sin\theta}{\beta_y}\right)^2 \quad ...(3)$$

$$Y = -\frac{\sin 2\theta}{\beta_x^2} + \frac{\sin 2\theta}{\beta_y^2} \quad ...(4)$$

$$Z = \left(\frac{\sin\theta}{\beta_x}\right)^2 + \left(\frac{\cos\theta}{\beta_y}\right)^2 \quad ...(5)$$

The coefficient (c_1k,c_2l) is Gaussian filter centers, ?x& ?y represent the width of the pass band filter along two directions and ? indicates rotation angle. The goal is to estimate quadratic filter coefficients (f(n1, n2)) from the frequency response expressed as

$$F\left(e^{j\,c1k}, e^{j\,c2l}\right) = G(c_{1k}, c_{2l})\, e^{j\varphi\,(c_{1k}, c_{2l})} \quad ...(6)$$

Here G(c_1k,c_2l) indicates the preferred magnitude response depending on the Gaussian filter and ?(c_(1k,) c_2l) indicates the phase response. Once the coefficients f(n1,n2) are acquired, the output signal is generated by employing the coefficients to the ECG signal which is given as

$$y(k) = \sum_{n_1=0}^{p-1} \sum_{n_2=0}^{p-1} f(n_1, n_2)(k - n_1)(k - n_2) \quad ...(7)$$

Once the noise has been suppressed from the signal, baseline correction is performed by employing morphological operations [13]. In this study, morphological operations such as opening and closing have been selected to perform correction.

After the noise removal and baseline correction have been done, R peaks are identified using double difference [14] algorithm from the ECG signal data. The peak detection is performed because it is essential to extract vital features from the ECG waveform which is utilized in the next step of ECG signal interpretation. Since the ECG data are dynamic in nature, it is vital to normalize them before extracting significant features from it. Normalization calibrates the signal to have zero mean and a standard deviation of one.

Feature Extraction

Extracting various features is significant in automatic classification of ECG heartbeat signals. The word "feature"refers to the characteristics of the ECG waveform. A feature vector must minimize the original waveform into a lower dimension that contains significant information from the original waveform. In this study, two types of features such as temporal and morphological features are extracted from a single cardiac ECG cycle.

Temporal features: RR interval features are extracted to retrieve the dynamic information about the cardiac beat. Four RR interval features namely previous RR (RRpre), post RR (RRpos), average RR (RRavg) and local RR (RRloc) are utilized. The RRpre is the interval between the current and the previous R peak. The RRpos is the interval between current and the next R peak. The RRloc is estimated by taking average of all the RR intervals within the previous 10 sec period and RRavg is computed by taking the mean of the RR intervals.

Morphological features :Here, two kinds of morphological features are extracted from every heartbeat signal. Nine QRS complex features and nine T wave features are extracted using linear interpolation approach as shown in Figure 2. These features are extracted from the chosen heart beat after detecting the fiducial point (FP). The FP indicates the R peak. A stable sampling rate is utilized for morphological feature extraction and the sampling windows are found after identifying FP. Here two sampling windows are considered: (i) a window between -80 to + 100 ms that covers the QRS morphological features and (ii) a window between +150 to +420ms that contains morphological features of T wave. A sampling rate of 60 Hz is applied to the window comprising QRS morphological Features that result in nine features and a rate of 20 Hz is applied to the window containing T wave features which results in nine features.

Classification

In this study, a Radial Bias Function Neural Network (RBFNN) has been utilized to classify the ECG heartbeat signals into PVC, N, A,F, R and f.RBNN is a feed forward neural network comprising an input, hidden and an output layer as shown in figure 3. Each input layer is connected to the hidden layer which is described by its center

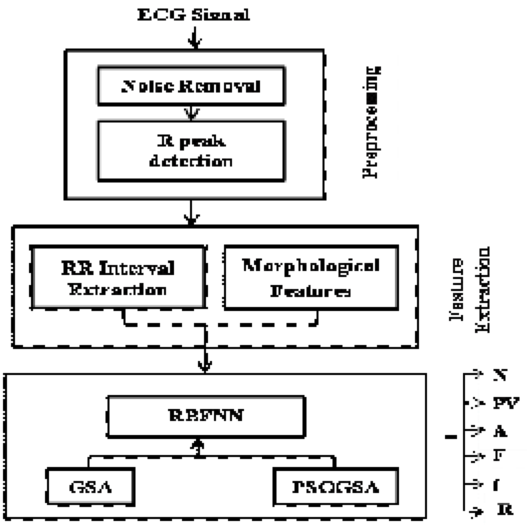

Fig. 1. Schematic Representation of the Proposed Approach

(a vector having dimensions equal to the number of input features). The hidden node is local tuned processor that utilizes activation function to calculate a grade for the match between the input feature vector and its center. The hidden layer is connected to the output layer that performs of the weighted sum of the hidden layer outputs which is given as

$$y = \sum_{i=1}^{n} w_i \cdot f_i(x) \qquad ...(8)$$

Here, $f_i(.)$ indicates the i^{th} hidden node's radial basis function, wire presents the weight of the i^{th} node and n is the total number of hidden nodes. There are several kinds of radial basis function. Generally a Gaussian function is employed which is expressed as,

$$f_i(x) = e^{\left[\frac{||x-c_i||^2}{2\sigma_i^2}\right]} \qquad ...(9)$$

Here, Ã and c indicates the width and the center (feature vector) of the hidden nodes respectively. Determining the width and the center of the hidden node is vital as it impacts the RBFNN performance. In this study, Gravitational Search Algorithm (GSA) and hybrid PSOGSA has been employed to determine the center and the width of

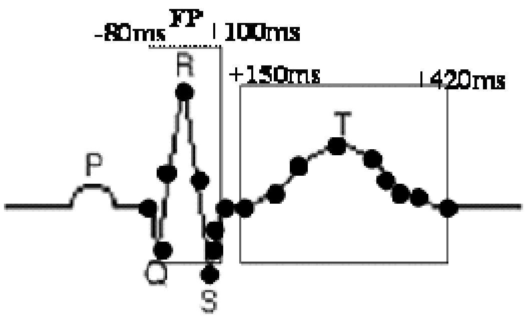

Fig. 2. ECG Morphological Feature Extraction

Table 1. Test Data

Beat Type	Number of beats
Normal Beat (N)	130
Atrial Premature Beat (A)	180
Premature Ventricular Contraction (PVC)	150
Right Bundle Branch Block Beat ®	140
Fusion of Ventricular and Normal Beat (F)	150
Fusion of Paced and Normal Beat (f)	100

Table 2. Overall Sensitivity and Accuracy

Classifier	Sensitivity (%)	Accuracy (%)
RBFNN-PSO	89.33	90.17
RBFNN-GSA	94.04	94.55
RBFNN-PSOGSA	96.72	96.97

the RBFNN network.

Gravitational Search Algorithm (GSA)

GSA is a population based heuristic technique where the individuals of the population correspond to an agent (features). In this study the center and the neuron bandwidth are considered as agents in the search space. The agents of the system match up with various solutions (classes). The agent is characterized by their position and the mass value. The algorithm searches for the RBFNN Structure with best fitness value. The GSA steps involved to evolve RBFNN are illustrated in figure 4. GSA provides the solution for an optimization problem with n agents and d dimensions (number of features) is considered. An agent can be stated as

$X = \{x_i^1, x_i^2, \ldots\ x_i^n\}$ for i=1,2,..n (10)

The energy between the feature (agent) i and j during the time t and at n dimension is estimated by using eqn (11):

$$F_{ij}^n = G(t)\frac{m_i(t)\cdot m_j(t)}{d_{ij}(t)+\varepsilon}\times\left(x_j^n(t)-x_i^n(t)\right),\ t=0,1,\ldots M \quad ...(11)$$

Here, $m_i(t)$ is the mass of the i^{th} agent during the time interval , G(t) is the gravitational constant, this value decreases throughout the search process, d_{ij} represents the distance between the i^{th} and j^{th}agent, M is the number of iterations and µ is a constant. The total force imposed on an agent is given by the equation

$$F_i^n = \sum_{j=1, j\neq i}^{N} rnum_j F_{ij}^n \quad ...(12)$$

Here, $rnum$ is the random number between [0,1] and the mass (mi(t)) of the agent is estimated using

$$M_i(t) = \frac{ft_i(t) - wor_i(t)}{bst_i(t) - wor_i(t)} \quad ...(13)$$

$$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^{N} M_j(t)} \quad ...(14)$$

Here $ft_i(t)$ represents the fitness value of the i^{th} agent, $wor_i(t)$ represents the worst fitness value and $bst_i(t)$ indicates the best fitness value. The acceleration of the agent with n dimensions and at time t is given as

$$a_i^n = \frac{F_i^n(t)}{m_i(t)} \quad ...(15)$$

The consecutive velocity of the agent is then found by adding current velocity to the acceleration as

$$v_i^n(t+1) = rnum_i^n v_i^n(t) + a_i^n(t) \quad ...(16)$$

The present position of the agent is then obtained using

$$x_i^n(t+1) = x_i^n(t) + v_i^n(t+1) \quad ...(17)$$

Hybrid PSOGSA

The hybrid PSOGSA integrates certain features of PSO (Particle Swarm Optimization)[15] into GSA that is exploitation ability (gbest) with exploration ability of GSA. Initially all the agents are initialized. The agents that are close to the optimal solution moves gradually thereby guaranteeing the exploitation phase of the algorithm. Once the agents are initialized, the gravitational constant, gravitational and resultant force between the agents are computed using eq (11) and (12) respectively. In each iteration of the search process best solution obtained so far should be updated. The acceleration of the agents are then estimated. Finally, the velocity and the position of the agents are updated until the termination condition is met. The hybrid PSOGSA steps involved in evolving RBFNN are illustrated in Figure 5.

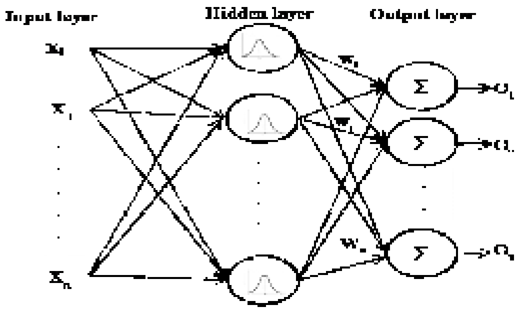

Fig. 3. Typical RBFNN Structure

RESULTS AND DISCUSSION

To evaluate the performance of the proposed algorithm, experiments are conducted by obtaining the ECG signal from five different persons. The performance of the proposed algorithm is compared with the PSO algorithm. Each recording of the ECG signal took about 30 minutes. Table 1 shows the test data utilized in this study. The accurate classification is measured by using

1: Initialize the number of agents

2: Evaluate G(t), best fit, worst fit and mass of the agents using the following equations

$$G(t) = G_0 e^{-\frac{\tau t}{M}}$$

Here, G_0 and □ are initialized previously and the value decreases with time to regulate the accuracy of the searching process and M is the number of iterations.

$bst(i) = \min_{i\in\{1,2,..N\}} ft_i(t),\ wor_i(t) = \max_{i\in\{1,2,..N\}} ft_i(t)$

$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^{N} M_j(t)}$ where $M_i(t) = \frac{ft_i(t) - wor_i(t)}{bst_i(t) - wor_i(t)}$

3: Calculate the total force

$F_i^n = \sum_{j=1, j\neq i}^{N} rnum_j F_{ij}^n$ and F_{ij}^n is given by $F_{ij}^n = G(t)\frac{m_i(t)\cdot m_j(t)}{d_{ij}(t)+\varepsilon} \times \left(x_j^n(t) - x_i^n(t)\right)$

4: Calculate acceleration

$$a_i^n = \frac{F_i^n(t)}{m_i(t)}$$

5: Update velocity and position using

$$v_i^n(t+1) = rnum_i^n v_i^n(t) + a_i^n(t)$$
$$x_i^n(t+1) = x_i^n(t) + v_i^n(t+1)$$

6: Repeat steps 2 to 5 until termination condition is met

Fig. 4. Evolution of RBFNN using GSA

1: Initialize the number of agents

2: Evaluate G(t), best fit, worst fit and mass of the agents using the following equations

$$G(t) = G_0 e^{-\frac{\tau t}{M}}$$

Here, G_0 and □ are initialized previously and the value decreases with time to regulate the accuracy of the searching process and M is the number of iterations.

$bst(i) = \min_{i\in\{1,2,..N\}} ft_i(t),\ wor_i(t) = \max_{i\in\{1,2,..N\}} ft_i(t)$

$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^{N} M_j(t)}$ where $M_i(t) = \frac{ft_i(t) - wor_i(t)}{bst_i(t) - wor_i(t)}$

3: Calculate the total force

$F_i^n = \sum_{j=1, j\neq i}^{N} rnum_j F_{ij}^n$ and F_{ij}^n is given by $F_{ij}^n = G(t)\frac{m_i(t)\cdot m_j(t)}{d_{ij}(t)+\varepsilon} \times \left(x_j^n(t) - x_i^n(t)\right)$

4: Calculate acceleration

$$a_i^n = \frac{F_i^n(t)}{m_i(t)}$$

5: Update velocity and position using

$$v_i^n(t+1) = w \cdot rnum \cdot v_i^n(t) + a_i^n(t) \cdot rnum \cdot b_1' + b_2' \cdot rnum \cdot (gbst - X_i(t))$$
$$x_i^n(t+1) = x_i^n(t) + v_i^n(t+1)$$

Where b_1' and b_2' are weight factors.

6: Repeat steps 2 to 5 until termination condition is met

Fig. 5. Evolution of RBFNN using hybrid PSOGSA Algorithm

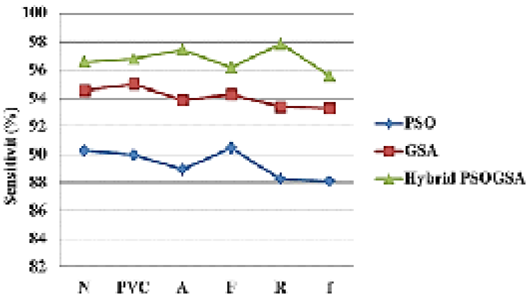

Fig. 6. Sensitivity of six heartbeat types

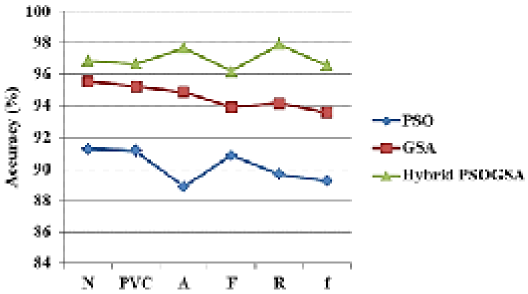

Fig. 7. Accuracy of six heartbeat types

four metrics: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). The accuracy and sensitivity of the classifier are calculated by utilizing these metrics.

Sensitivity and accuracy are defined as

$$sensitivity\ (s_e) = \frac{TP}{TP + FN} \quad ...(18)$$

$$Accuracy\ (A_c) = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(19)$$

Figure 6 and 7 shows the sensitivity and accuracy of the six heartbeat type's classified using PSO, GSA and hybrid PSOGSA algorithm respectively. From figure 6 it is obvious that the sensitivity of the hybrid PSOGSA is about 96.57%, 96%.78%, 97.45%, 96.15%, 97.85%, and 95.55 % for N, PVC, A, F, R and f respectively. Thus it is clear that the hybrid PSOGSA outperforms the GSA and PSO algorithm.

From figure 7 it is shown that the accuracy of the hybrid PSOGSA is about 96.87 %, 96.64 %, 97.68 %, 96.2 %, 97.91 % and 96.55 % for N, PVC, A, F, R and f respectively. Thus it is clear that the hybrid PSOGSA outperforms the GSA and PSO algorithm. Table 2 shows the overall sensitivity and accuracy of the proposed approach.

CONCLUSION

The Electrocardiogram (ECG) is the widely utilized bioelectric signal that gives the physicians the most accurate data concerning the cardiac activity of the patients. A significant process in diagnosing arrhythmia is classification of heart beats using ECG signals. Thus, in this paper an optimized Radial Basis Function Neural Networks (RBFNN) has been proposed to classify six types (Premature Ventricular Contraction (PVC), Normal Beat (N), Atrial Premature Beat (A), Fusion of Ventricular and Normal Beat (F), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f)) of electrocardiogram (ECG) signal. The proposed classifier uses Gravitational Search Algorithm (GSA) and hybrid PSOGSA algorithm to search for the best value of the RBFNN parameters. The performance of the proposed approach is analyzed in terms of sensitivity and accuracy and the results are compared with the existing RBFNN-PSO. The results show that the sensitivity and accuracy of the proposed GSA algorithm is about 94.04 % and 94.55 % and the sensitivity and accuracy of hybrid PSOGSA is about 96.725 % and 96.97 % respectively.

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