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AN IMPROVED BACK PROPAGATION TRAINING ALGORITHM USING EVOLUTIONARY ALGORITHM FOR ECG BEAT CLASSIFICATION

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ABSTRACT

Increased or slowing down of heartbeats causes irregular rhythms resulting in Cardiac Arrhythmia which are assessed by electrocardiograms (ECG). Various types of arrhythmia detected are relevant to heart disease diagnosis. Automatic arrhythmia ECG assessment is well researched area. This paper investigates ECG classification using soft computing techniques to classify arrhythmia type through the use of RR interval. Discrete Cosine Transform (DCT) is used to extract features from the time series ECG data using distance between RR waves. The extracted beat RR interval is used as a feature extracted in the frequency domain and classified using Multi-Layer Perceptron Neural Network (MLP –NN), and proposed Feed Forward Neural Network (FF NN) experiments were conducted through a MIT-BIH arrhythmia database. Genetic Algorithm (GA) with Artificial Neural Network (ANN) is proposed and considered for experiments.

Keywords: ECG, Arrhythmia classification, MIT-BIH ECG data, RR interval, Feed forward Neural Network, Multilayer Perceptron, Genetic Algorithm (GA) and Artificial Neural Network (ANN).

1. INTRODUCTION

Electrocardiogram (ECG) is the bioelectrical signals of the heart muscles activity; it is recorded in a graph which measures the heart's electrical voltage, called the electrocardiograph. This has an important role in diagnosing cardiovascular diseases. An ECG represents the heart beat's arterial depolarization/ventricular repolarization, and is obtained through many electrodes. P, Q, R, S, and T [1] revealed in Figure 1, are peaks and ECG waveforms.

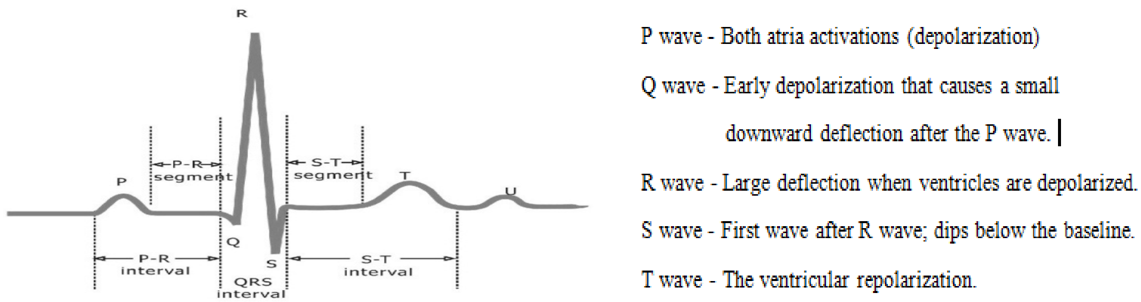

Fig.1. A sample ECG signal with P, Q, R, S and T.

Varied characteristics like PR, QRS, and ST intervals also diagnose cardiac arrhythmia [2]. The standard guidelines are shortlisted in [3] for heart rate variability measure categorization. A measure summary and models are presented in [4], and the examined physiological origins and heart rate mechanism seen in [5].

Cardiac Arrhythmia is due to irregular rhythms causing irregular heartbeats [6]. A slow or fast heartbeat causes irregular rhythm. Arrhythmia is indicative of serious heart problems but visual checks for arrhythmia are tedious and time consuming. This is the reason why automatic heart beat classification which expedites diagnosis benefits medical experts. Real time automatic arrhythmia detection/classification is critical in clinical cardiology. ECG arrhythmia diagnoses are improved through pattern classifier techniques. Every person has different ECG recordings due to noise and amplitude and so signals are pre-processed to ensure beat detection and feature extraction. Automatic arrhythmia ECG assessment is well researched as also cardiac rhythms and arrhythmia problems of automatic detection/classification. Heart Rate Variability (HRV) analysis measures heart rate variability signals considering variations of a time unit and heartbeats number, known as RR interval – the interval between consecutive R points of electrocardiogram's QRS complex. The position/magnitudes of PR interval/segments, ST interval, QRS interval [7, 8], and QT interval are used in heart disease diagnosis.

Arrhythmia is determined mainly by a QRS complex wave. QRS waveform detection, feature selection and heartbeat classification form part of ECG signal analysis. Various studies have analyzed ECG signals for cardiac arrhythmia, with those based on QRS pattern, automatic detection of discerning arrhythmia using Hidden Markov models [9], wavelet transform [10], Hermite function [11] and Neural networks [12, 13]. Feature selection is required for efficient automatic ECG classification. Features are selected from the time or frequency domains and wavelet transforms are used to denoise ECG signals [14, 15]. Wavelet transforms decompose ECG signal into differing components of various scales with phase information being maintained by transforms linear operations. Wavelet functions that suggest symmetry/compactness reveal that ECG signals can achieve great accuracy.

This paper proposes arrhythmia ECG signals classification and the proposed method is evaluated using MIT-BIH physiobank arrhythmia database [16]. RR intervals are used as features which are extracted using Discrete Cosine Transform (DCT). The extracted features are classified using RBF, MLP, feed forward neural networks. The paper is organized as follows: section I includes the introduction, section II details about related works, section III discusses materials and methods followed in the paper, section IV reveals the experimental setup with the final section V presenting results/conclusions.

2. RELATED WORK

Kim, et al., [17] suggested the ECG holter system which is a ECG signal processing technique with a three-step compression and classification flow with a quad level vector (QLV). The proposed holter system attained highly improved performance with low-computation complexity when processing ECGs for both compression and classification flows. To lower processing costs while maintaining signal quality, a Unit block- size optimization, adaptive threshold adjustment, and 4-bit-wise Huffman coding methods were utilized. Heartbeat segmentation and R-peak detection schemes classified the algorithm and its reliability is achieved through a noise robust test leading to an average compression ratio of 16.9:1 with 0.641% percentage root mean square difference value and encoding rate is 6.4 kbps. Accuracy performance of the R-peak detection is 100% without noise and the accuracy obtained was 95.63% for 10 dB SNR noise.

Wen et al., [18] suggested an adaptive resonance NN GreyART theory based on grey relational grade similarity measure for classifying ECG beats which in turn was further divided into two phases. The first was the offline learning phase where an optimal value for a vigilance threshold and corresponding cluster centers from learning results were determined. The results were initial settings of an online examining phase where all ECG beats which passed the vigilance test were classified in real time. For beats which failed the vigilance test, the online classifier generated new clusters reporting the templates for further investigation. Inan et al., 19] suggested a classification approach for the beats of a large dataset by training a neural network (NN) classifier through use of wavelet and timing features. Experiments revealed that a dyadic wavelet transform fourth scale with a quadratic spline wavelet combined with a pre/post RR-interval ratio was highly effective to distinguish normal and premature ventricular contraction (PVC) from various beats.

Shivajirao et al., [20] suggested another procedure for classification of cardiac arrhythmia disease. The proposed method implemented modular neural network (MNN) framework categorizing arrhythmia as normal and abnormal classes. Experiments were also undertaken with a dataset of UCI Arrhythmia. The proposed neural network model was developed from 1-3 varying number of hidden layers which were also trained in partitioning data sets with differing training percentages. The study emphasised generation of a most confident arrhythmia classification outcome with the capability to be applied in diagnostic decision support systems. The results revealed more than 82.22% testing classification accuracy. Jiang, et al., [21] presented a personalized ECG heartbeat pattern classification based on block-based NNs having a 2-D array of modular component NNs with flexible structures and internal configurations which was later implemented. Local gradient-based search and evolutionary operators with adaptively changing rates was used, and network structure/connection weights were optimized depending on the earlier evolution period's effectiveness. Melgani, et al.,[22] investigated SVM classifiers generalization capability in ECG beat classification, improving further the classification system based on particle swarm optimization (PSO). For this SVM classifier design was optimized by attempting to find best parameters value to tune its function and locating the best features subset which fed the classifier.

Khoureich Ka [23] proposed a patient-specific ECG beat classification founded on waveform similarity and RR interval. A patients ECG beats database is created for it. Wavelet transform based techniques were used to denoise the ECG signal in this procedure which also used a java implementation to lower noise due to the baseline wander cancellation and high oscillation noise. Extracted RR intervals are used as features and classification is through neural network/fuzzy logic. The results showed high classification beat accuracy. Jiapu Pan and Willis J. Tompkins developed a Z-80 microprocessor based real-time QRS detection algorithm [24]. Denoising experiments were conducted on ECG signals using a bandpass filter built to cascade high and low pass filers. The fiducial points were located through detection of the highest squared slope during ECG wave's high spectral energy. These observations led to many fiducial points than actual QRS complexes. When no QRS complex candidates were located a search back algorithm was applied. The experiment proved its performance by an average of 99.325% when tested and compared with a MIT-BIH open-source arrhythmia database.

Sufi, et al., [25] presented a method that executed real-time cardiovascular disease (CVD) classification which automatically informed emergency personnel/hospital through SMS/MMS/e-mail when a CVD affected patient had a life-threatening cardiac abnormality. Though initially, the new procedure used data mining techniques including attribute selection (that selects few features alone from a compressed ECG) and expectation maximization (EM)-based clustering it had some constraints when used in data mining techniques in hospital servers. Experiments revealed that cardiac abnormalities including ventricular flutter/fibrillation, premature ventricular contraction and atrial fibrillation were detected successfully with 97% accuracy on 50 MIT-BIH ECG entries. Pasolli, et al., [26] proposed three active learning strategies for ECG signal classification based on support vector machine (SVM) classification, margin sampling; posterior probability and query by committee principles. Every proposed strategy revealed high performance as regards stability and accuracy in connection with a total random selection strategy. A comparison between strategies proved that that based on MS principle chose the most informative sample quickly. Active learning method showed improved performance compared to the "full" classifier by decreasing mis-labelling. The strategies results exhibited an ability to choose useful samples useful for a classification process (i.e.,) classification accuracy improved through reduction of the number of labelled samples.

Faezipour, et al.,[27] presented a repetition-detection concept in a patient-adaptive cardiac profiling system. A well-organized wavelet-based beat-detection mechanism extracted fiducial ECG points accurately followed by a new local ECG beat classifier being applied to profile a patient's normal cardiac behaviour. Based on a person's physical conditions/environment, ECG morphologies differed with time for every person and also from person to person. This system provides for an automatic early warning for an individual's abnormal cardiac behaviour. Experiments on the MIT-BIH arrhythmia database revealed that the proposed system could detect beats with 99.59% accuracy. Abnormalities were detected with a high classification accuracy of 97.42%.

Kumar and Kumaraswamy [28] investigated soft computing techniques for ECG classification based on the type of arrhythmia using RR interval. Features were extracted from the time series ECG data using Discrete Cosine Transform (DCT) and the distance between RR waves were computed. The extracted RR interval of the beat was used as feature. Features extracted in the frequency domain were classified using Classification and Regression Tree (CART), Radial Basis Function (RBF), Multi-Layer

Perceptron Neural Network (MLP-NN), and proposed Feed Forward Neural Network (FF-NN). Experiments were conducted using MIT-BIH arrhythmia database. Das and Ari [29] used S-transform to extract the eight features which were appended with four temporal features. The performances of two approaches were compared to classify the five classes of ECG beats which was recommended by AAMI EC57 1998 standard (Association for the Advancement of Medical Instrumentation). Performance was evaluated on several normal and abnormal ECG signals of the MIT-BIH arrhythmia database using two techniques such as temporal and S-transform with NN classifier (TST-NN) and other Wavelet Transform with NN classifier (WT-NN). The experimental results demonstrate that the TST-NN technique shows better performance compared to the WT-NN technique.

Carvalho et al., [30] reviewed the possible application of ANNs to the problem of Ventricular Activity (VA) cancellation. The system proposed consists of estimating a non-linear time-varying transfer function between two ECG channels using a Time Delay Neural Network (TDNN). Three different TDNN topologies (purely feed-forward, simple recurrent, and fully recurrent) were implemented and tested using record 108 of the MIT-BIH DB. In order to evaluate these networks, two performance measures were introduced in this work, namely VA energy change and Signal to Noise Ratio (SNR) improvement. Preliminary results using VA energy change and SNR improvement indicators showed that the simple recurrent topology presents the best performance. Ogawa et al., [31] presented an intelligent diagnosis system for ECG intensity images using ANN. Features were extracted from many preprocess such as Wavelet Decomposition (WD), Edge Detection (ED), Gray Level Histogram (GLH), Fast Fourier transform (FFT), and Mean-Variance (M-V). The ANN supervised feed-forward back propagation using adaptive learning rate with momentum term algorithm used as a classifier. The input data to the classifier has been very large so, ECG images data were grouped in batches that introduced to ANN classifier. An expert system for ECG diagnosis was introduced that was more suitable preprocess for the used 63 ECG intensity images, and simplest ANN architecture classifier, depending on the higher accuracy of the classifier related to the extracted input features.

Basu et al., [32] used the artificial neural network method for electrocardiogram (ECG) pattern recognition. Four types of ECG patterns were chosen from the MIT-BIH database to be recognized, including normal sinus rhythm, premature ventricular contraction, atrial premature beat and left bundle branch block beat. ECG morphology and R-R interval features were performed as the characteristic representation of the original ECG signals to be fed into the neural network models. Three types of artificial neural network models, SOM, BP and LVQ networks were separately trained and tested for ECG pattern recognition and the experimental results of the different models have been compared. The SOM network exhibited the best performance and reached an overall accuracy of 95.5%, and the BP and LVQ network reached 92.5% and 91.5%.

3. MATERIALS AND METHODS

3.1. MIT-BIH Arrhythmia Database

For training and testing of ECG datasets signals for evaluating the proposed method is taken from Massachusetts Institute of Technology/Beth Israel Hospital (MIT-BIH) arrhythmia database [16]. Selected Cardiac Arrhythmias for classification include LBBB (Left Bundle Branch Block), RBBB (Right Bundle Branch Block) and normal. Each ECG beat used is a matrix (275x1) for one ECG lead with every ECG signal having five distinct points (P, Q, R, S and T) used for ECG interpretation.

3.2. RR Interval

RR interval is used for classification as it has a major role in arrhythmia identification. Peaks amplitude is measured from the k line which is given by:

$$k = Max(\theta_i, i = 1, 2, .., 11) + c \quad (1)$$

where θ is the greatest amplitude, i type of heartbeat, and c is a constant. Figure 2 shows the RR measured using Matlab.

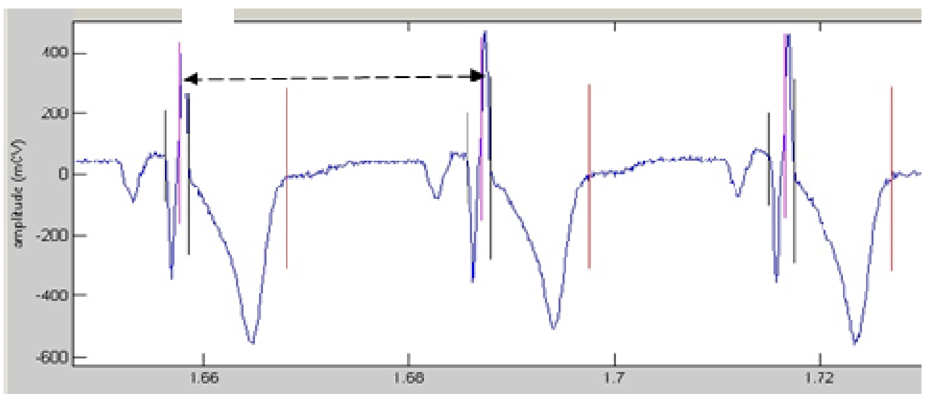

Fig.2. RR wave shown in Matlab

3.3 Discrete Cosine Transform (DCT)

Features are extracted from time series ECG data using Discrete Cosine Transform (DCT) while distance between RR wave computed. Discrete Cosine Transform (DCT) translates time series signal into basic frequency components. Also fast DCT is used to pre-process data to locate RR interval. The FDCT [33] is of a list of n real numbers s(x), x = 0, ..., n-1, is the list of length n given by:

$$S(u) = \sqrt{2/n}\,C(u)\sum_{x=0}^{n-1} s(x)\cos\frac{(2x+1)u\pi}{2n} \quad (2)$$

where $C(u) = 2^{-1/2}$ for u=0 or otherwise $C(u) = 1$

Constant factors are chosen to ensure that basis vectors are orthogonal and normalized. The inverse cosine transform (IDCT):

$$S(x) = \sqrt{2/n}\sum_{x=0}^{n-1} C(u)\,s(u)\cos\frac{(2x+1)u\pi}{2n} \quad (3)$$

3.4 Neural Network

Neural network models are divided into feed-forward neural networks and recurrent neural networks based on network signal transmission. Feed-Forward Neural Network (FNN), and Multi-Layer Perceptron (MLPs) (so called as it has many hidden layers) are most widely applied for its distinction as a universal function approximator [34]. Curve fitting, pattern classification and nonlinear system identification are some FNN applications. FNN are supervised, trained with a popular algorithm called error back-propagation algorithm. The learning of FNN is composed of two runs in Standard Back-Propagation (SBP) algorithm [35]. The input signal passes through the network in a forward direction, on a layer-by-layer basis with fixed weights in the forward run. In a backward run, error signal is propagated backward. Weights are adjusted on an error-correction rule. Though successful in various applications, SBP's major drawbacks include slow learning speed and parameter sensitivity. Many iterations are needed to train small networks even for minor problems. The proposed Feed Forward Neural Network has an additional weight support from input to output layer as revealed in Figure 3.

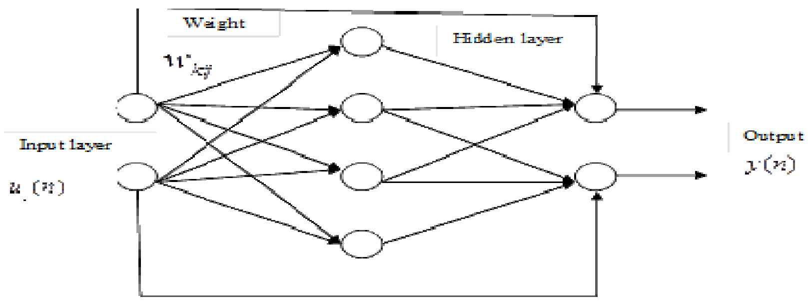

Fig. 3. The proposed modified Neural Network model

The parameters used in the proposed neural network and the MLP network are shown in table 1.

Table 1. Parameters used for the neural network

Parameters	Value
Number of neurons in input layer	60
Number of neurons in output layer	3
Number of hidden layer	1
Number of neurons in hidden layer	20
Transfer function of context unit	Sigmoid
Learning rule	Back propagation
Number of epochs for termination	500
Learning rate	0.1
Momentum	0.5

3.5 Genetic Algorithm (GA) with Artificial Neural Network (ANN)

GA is combined with ANN to optimize the parameters of an NN. GAs is used to search for the weights of the network and to search for appropriate learning parameters, or to reduce the size of the training set by selecting the most relevant features. Also it is used to design the structure of network. The number of input variable determines the size of NN. To give better performance and for avoiding over fitting problem, the number of input variable must be considered as less. In NN, there are several approaches like "forward", "backward" and "stepwise". The Genetic Algorithm optimizes the inputs from a larger pool of variables, attempts to generate appropriate network architecture for a given data set. The standard individual representation for attribute selection consists simply of a string of *N* bits, where *N* is the number of original attributes and the *i*-th bit, i=1,…,N, can take the value 1 or 0, indicating whether or not, respectively, the *i*-th attribute is selected.

The GA-NN algorithm is presented below:

1. To determine the symptoms
2. To initialize count=0, fitness=0, number of cycles
3. Generate the Initial Population. The chromosome of an individual can be formulated as a sequence of consecutive genes, each one coding an input.
4. To design suitable network that is with input layer, hidden layer and output layer
5. Assign weights for each link
6. Train the network using Back Propagation algorithm
7. To find cumulative error and the fitness value. The genotypes are evaluated based on the fitness function.
8. If (previous fitness<current fitness value) Then store the current features
9. count = count +1
10. **Selection:** Two parents can be selected by using the roulette wheel mechanism
11. **Genetic Operations:** Crossover, Mutation and
12. Reproduction to generate new features set (Apply new weights to each link)
13. If (number of cycles <= count) go to 4
14. Finally to train the network with the selected features study the performance with test data [36].

4. RESULTS AND DISCUSSION

4.1 With 153 instances of extracted beats

This study used an energy extraction method using DCT for feature extraction. An extracted RR interval was used as feature and 153 instances of extracted beats with 68 instances of left bunch bundle block, 29 instances of right bunch bundle block and 56 normal instances were evaluated. Radial Basis Function (RBF), MLP were used for classifying the features and compared with the proposed FNN and FNN with GA. Table 2 summarizes the results of classification accuracy, Root mean squared error (RMSE), precision and recall for various techniques.

Table 2. Summary of results

Classification Method	Classification Accuracy in %	RMSE	Precision	Recall
RBF	89.5425	0.2511	0.896	0.895
MLP	88.2353	0.2679	0.882	0.882
Proposed FNN	92.8105	0.2084	0.929	0.928
Proposed FNN with GA	94.1176	0.1943	0.951	0.953

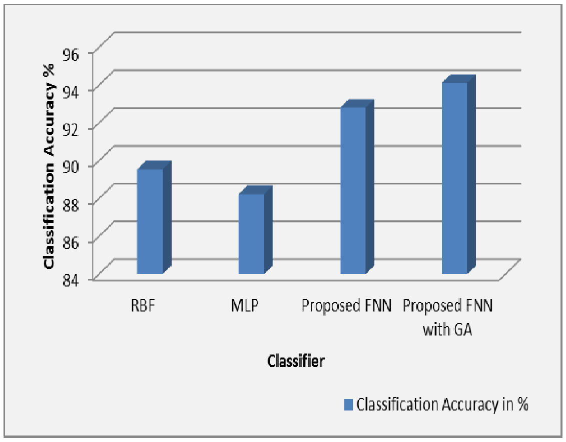

Fig. 4. Classification accuracy of various classification methods

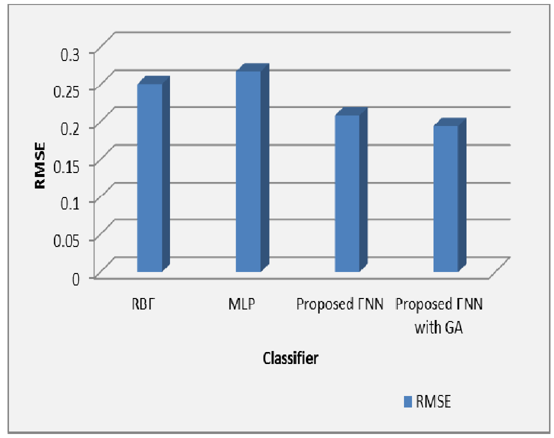

Fig. 5. Root mean squared error

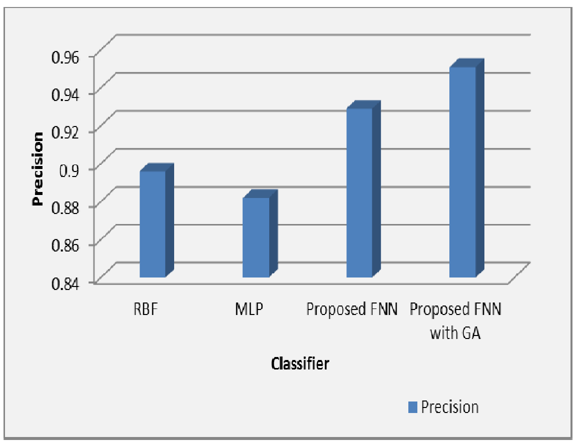

Fig. 6. Precision

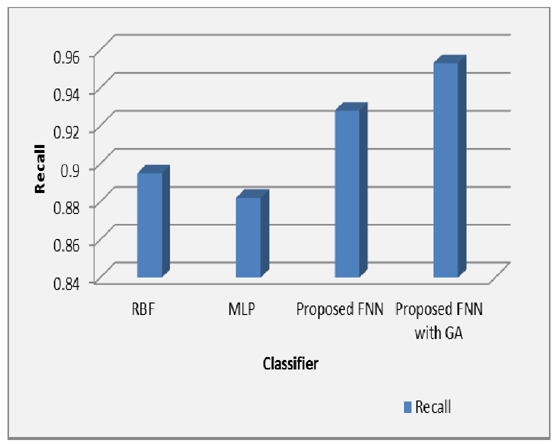

Fig. 7. Recall

Figure 4 shows that the proposed FFNN with GA optimization outperforms RBF and MLP neural network by 5.11% and 6.67% achieving accuracy of 94.12%, which is highly significant for medical data processing. The optimization improves the proposed FNN efficiency by 1.41%. The root mean squared error is seen in Figure 5.

Figure 5 shows that the proposed FFNN with GA optimization lowers the RMSE by 22.62% and 27.47% for RBF and MLP neural network respectively. The optimization lowers the RMSE by 6.77% for the proposed FNN. Figure 6 and 7 shows the average precision and recall achieved for various classifiers. The proposed FNN with GA achieves higher precision and recall when compared to other classifiers.

4.2 Data set with 13300 beats of 20 recordings

In the second experiment 13300 beats were taken from 20 recordings. Four additional Markers including sex, Age, Family History and smoker / non-smoker were considered for the classification problem. The results obtained are tabulated in table 3.

Table 3. Classification accuracy high data set

Classification Method	Classification Accuracy in %	Precision	Recall
RBF	84.69	0.8071	0.7977
MLP	85.94	0.8266	0.8030
Proposed FNN	86.05	0.8264	0.8032
Proposed FNN with GA	87.55	0.8499	0.8115

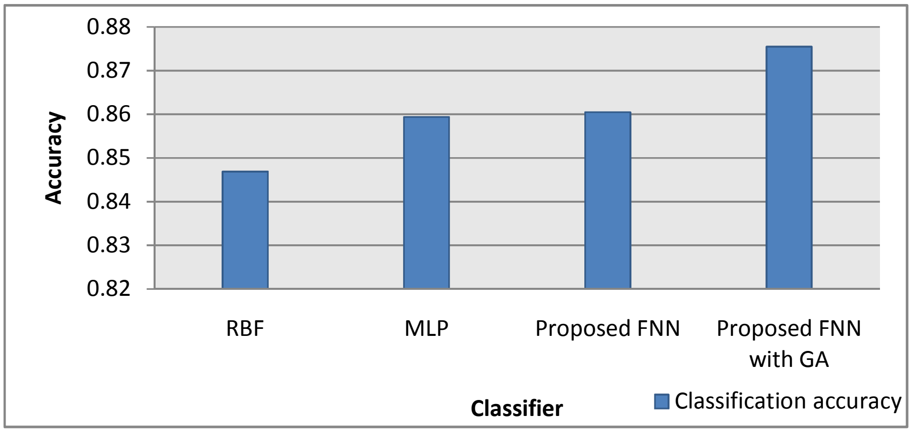

Fig. 8. Classification Accuracy

Figure 8 show that the proposed FFNN with GA optimization outperforms RBF and MLP neural network by 3.38% and 1.87% achieving accuracy of 87.55%, which is highly significant for medical data processing. The optimization improves the proposed FNN efficiency by 1.74%.

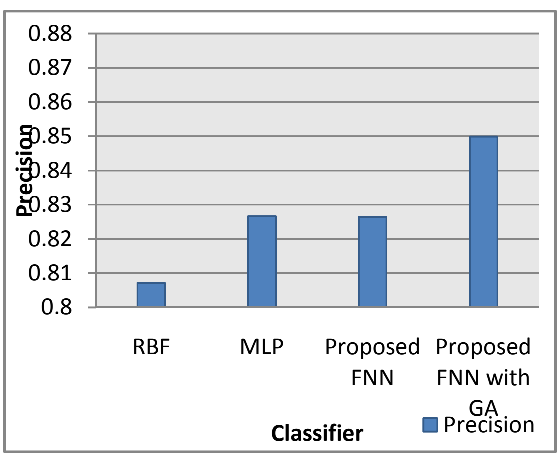

Fig. 9. Precision

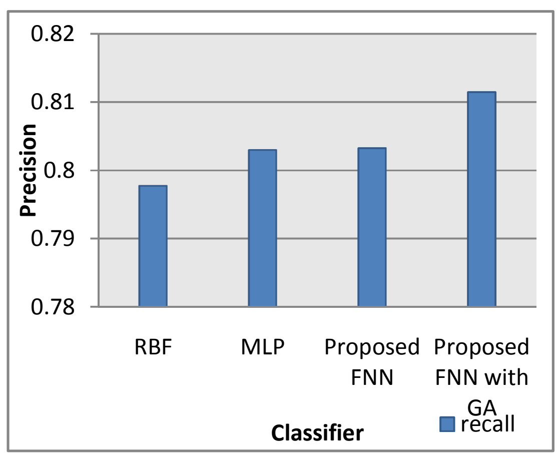

Fig. 10. Recall

Figure 9 show that the proposed FFNN with GA optimization outperforms RBF and MLP neural network by 5.3% and 2.81% achieving Precision of 0.8498, which is highly significant for medical data processing. The optimization improves the proposed FNN efficiency by 2.84%. Figure 10 show that the proposed FFNN with GA optimization outperforms RBF and MLP neural network by 1.72% and 1.05% achieving Recall of 0.8114, which is highly significant for medical data processing. The optimization improves the proposed FNN efficiency by 1.03%.

5. CONCLUSION

This paper proposed an ECG arrhythmia classification system using DCT for feature extraction in the frequency domain and a feed forward neural network that provided additional weights between input and output layers. Genetic Algorithm (GA) with Artificial Neural Network (ANN) was proposed. Classification accuracy is improved by 6.67% by proposed FNN with GA when compared to standard back propagation algorithm for MLP. The proposed method achieved a satisfactory level of classification accuracy of 94.12%. The proposed optimization also improves the precision and recall of the classifier. In the second experiment 13300 beats were taken from 20 recordings. Four additional Markers including sex, Age, Family History and smoker / non-smoker were considered for the classification problem. Proposed FFNN with GA optimization outperforms RBF and MLP neural network by 3.38% and 1.87% achieving accuracy of 87.55%, which is highly significant for medical data processing. The optimization improves the proposed FNN efficiency by 1.74%.

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