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Spline Activated Neural Network for Classifying Cardiac Arrhythmia

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Abstract: Electro Cardiogram's (ECG) biomedical signals characterizing cardiac anomalies are used for identifying cardiac arrhythmia. Irregular heartbeat B Arrhythmia B affects heart rate causing problems. Many methods, trying to simplify arrhythmia monitoring through automated detection were developed over the years. ECG classification for arrhythmia is investigated in this study based on soft computing techniques. RR interval are extracted from time series of the ECG and used as feature for arrhythmia classification. Frequency domain extracted features are classified using Radial Basis Function (RBF) and proposed Spline Activated B Feed Forward Neural Network (SA-FFNN). Experiments were conducted with the MIT-BIH arrhythmia database for evaluating the proposed methods.

Key words: ECG, arrhythmia classification, RR interval, feed forward neural network, multilayer perceptron

INTRODUCTION

Arrhythmia is diagnosed through an ECG procedure as abrupt/abnormal ECG beats represent arrhythmia. Diagnosis is based on long term data through an ECG recorder like the Holter recorder. Also, as remote and mobile healthcare systems using ECG recorders are increasing, it highlights the importance of an automatic arrhythmia classification algorithm. Studies on arrhythmia classification exist with the algorithm being composed of pre-processing, feature extraction and classification stages. ECG is a much researched biomedical signal characterizing cardiac anomalies (Algazi and Meurin, 2000). Normal heartbeat is made up of waves based on the heart's mechanical actions. P-wave signifies auricular depolarization and complex QRS represents ventricular depolarization before mechanical contraction. The R wave has great amplitude as ventricle mass is more than that of auricles. T-wave represents ventricular repolarization in Fig. 1 (Singh and Tiwari, 2006). Usually, cardiac anomaly traces appear in one/more ECG wave related parameters. ECG signal dependencies are classified into two types: dependencies in one ECG cycle and across ECG cycles. Dependencies are also called intrabeat and interbeat dependencies, respectively (Bilgin *et al*., 2003). Efficient compression exploits both dependencies to achieve maximum data compression. Wave frequencies present heartbeat rate based variations. Such rhythm change is called arrhythmia. ECG signal frequency band is around 60 Hz for a normal person increasing to 130 Hz for an abnormal patient. ECG allows cardiac diseases detection/analysis.

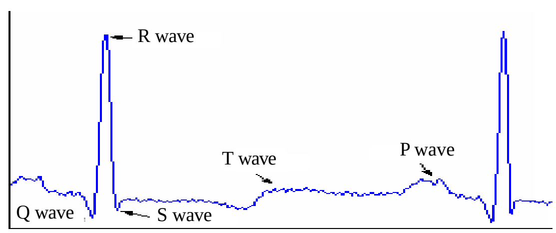

Fig. 1: Waves of ECG

Table 1 gives heart membrane actions for normal cases and associated waves like temporal and frequencies characteristics (Ramli and Ahmad, 2003; Schuck and Wisbeck, 2003). Pre-processing removes noise and includes more processing for accurate feature extraction/classification. ECG noise components include baseline drift, power line interference and moving artifacts (Friesen *et al*., 1990). Many filtering method reports were published for removal of noise components while simultaneously preserving ECG morphology/processing. Feature extraction leads to feature vectors used for classification. Arrhythmia diagnosis classification is made through acquired feature vectors following feature extraction. Many automated arrhythmia detection methods were developed over decades to simplify monitoring (Raut and Dudul, 2008). The usual ECG pattern classification methods are Statistica approaches (Ge *et al*., 2002; Jiancbeng, 2004), fuzzy inference approaches (Ceylan and Ozbary, 2007), self-organizing map and neural network approaches (Jadhav *et al*., 2010; Atoui *et al*., 2004).

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Table 1: Characteristics of a normal arrhythmia

Mechanical actions	Associated wave	Duration (msec)	Amplitude (mV)	Wave frequency (Hz)
Auricular depolarization	P wave	80-120	≤0.3 mV	10
Depolarization of the ventricle	QRS complex	85-120	Q<0-S>0	20-50
Repolarization of the ventricles	T-wave	200	0.2 mV	5

Artificial Neural Network (ANN) with universal approximation is used for classification. ANN Radial Basis Functions algorithms are also used for classification (Pang, 2005; Blu and Unser, 2002; Yu and Chen, 2007). The difference is that RBFs are local models and not MLPs. In RBF structure, training is split into three independent stages to reduce complexity and to ensure practical online usage.

RR-intervals are the intervals between successive QRS detection points. Poor signal quality and errors in automatically generated QRS detections, RR-interval sequences from both sets of QRS detection times have physiologically unreasonable times (De Chazal *et al*., 2003). A preprocessing step before extracting ECG features is o performed to calculate a corrected RR-interval sequence where intervals were physiologically reasonable. ECG ensures an accurate means to identify cardiac arrhythmia (bad rhythm). This diagnosis is easy when we understand the heart's electrophysiology including normal conduction pathways (Babikier *et al*., 2011).

Cardiac arrhythmias are divided into many categories according to arrhythmia's mechanism of origin: escape, irregular rhythm, premature and tauchy-arrhythmias. Many features extraction based techniques were proposed to classify cardiac arrhythmias. Generally classification can be divided into three groups of systems, systems recording signals and performing classification off-line, systems performing remote real-time classification and systems providing local real-time classification. The last one is differentiated considering their mobility levels. Classification performance is dependent on classifier and features. Improved ECG signal processing benefits feature extraction. This study suggests an ECG processing methods analysis for each arrhythmia classification algorithm: pre-processing, feature extraction and classification for the development of a Robust algorithm. This study uses DCT to pre-process data to locate RR interval used as features. A proposed spline activated feed forward neural network and RBF are classifiers.

Literature review: A new cardiac arrhythmia disease classification method described by Jadhav *et al*. (2011) implements Modular Neural Network (MNN) framework to categorize arrhythmia into normal/abnormal classes. Experiments were undertaken on a UCI arrhythmia dataset. The proposed NN Model was developed from one to three varying hidden layers and trained on data set partitions with varied percentage. The study emphasizes creation of a confident arrhythmia classification outcome applicable to diagnostic decision support systems. GreyART, an adaptive resonance NN theory based on grey relational grade similarity measure for ECG beat classification was proposed by Wen *et al*. (2007). A FPG-based ECG signal classification based on block-based NN and a parallel GA was proposed by Jewajinda and Chongstitvatana (2010). A new Arrhythmia Classification algorithm consisting of fast learning speed and extremely accuracy using Principal Component Analysis (PCA), Extreme Learning Machine (ELM) and Morphology Filtering was proposed by Kim *et al*. (2009) which categorized six heartbeat types.

A dynamic model based on three coupled ordinary differential equations capable of generating realistic synthetic Electrocardiogram (ECG) signals was introduced by McSharry *et al*. (2003). The operator can specify the heart rate's mean and standard deviations, the PQRST cycle's morphology and the RR tachogram's power spectrum. Much beat to beat variation in morphology and human ECG timing including QT dispersion and R-peak amplitude modulation resulted. This model can assess biomedical signal processing techniques to compute clinical statistics from ECGs. Various techniques/ transformations proposed in literature earlier to extract features from ECG signals were discussed by Karpagachelvi *et al*. (2010). It also provided a comparative study of methods proposed by researchers to extract ECG signal features. The P-QRS-T segment's amplitudes and intervals value determine functioning of the human heart. The proposed schemes were based on Fuzzy Logic Methods, Artificial Neural Networks (ANN), Genetic Algorithm (GA), Support Vector Machines (SVM) and Signal Analysis techniques. All techniques have advantages and limitations.

An ECG signal processing method with Quad Level Vector (QLV) for ECG Holter System was proposed by Kim *et al*. (2010) which consists of compression and classification flows. The QLV was proposed for both flows to achieve improved performance with low-computation complexity. Performance was evaluated using MIT-Boston's Beth Israel Hospital Arrhythmia Database and Noise Robust test was performed to learn the algorithm's reliability. The proposed compression technique reduced overall processing cost by 45.3%.

A new approach to classify heartbeat based on combining morphological and dynamic features was proposed by Ye *et al*. (2012). Wavelet transform and Independent Component Analysis (ICA) were applied by to each heartbeat separately for morphological features extraction. Additionally, dynamic features were provided by RR interval information computation. The new method was validated on the baseline MIT-BIH arrhythmia database yielding an overall accuracy (percentage of heartbeats correctly classified) of 99.3% in "class-oriented" evaluation and 86.4% accuracy in "subject-oriented" evaluation which compared favorably with state of the art results for automatic heartbeat classification.

A generic and patient-specific classification system for robust and accurate ECG heartbeat patterns detection was presented by Ince *et al*. (2009) which utilized morphological wavelet transform features, projected on a lower dimensional feature space using PCA and ECG data's temporal features. Classification experiments on a benchmark database proved the new system achieved better results than most state of the art algorithms in detecting Ventricular Ectopic Beats (VEBs) and Supra-VEBs (SVEBs). The proposed system was highly generic due to its parameter-invariant nature and thus was applicable to any ECG dataset.

Three active learning strategies for ECG signals classification was presented by Pasolli and Melgani (2010). Starting from small/suboptimal training sets, these strategies selected additional beat samples from large unlabeled data sets. To illustrate the proposed method's performance an experimental study based on simulated data and real ECG signals from the MIT-BIH arrhythmia database was conducted. The results revealed that the new strategies were capable of choosing samples significant for classification.

SVMs were used to classify heartbeat time series by Kampouraki *et al*. (2009). Statistical methods and signal analysis techniques extracted signal features. SVM classifier was compared favorably to other NN based classification approaches through performance of leave-one-out cross validation. SVM performance regarding other state-of-the-art classifiers is confirmed by signals classification with very low signal to noise ratio.

A wearable module and NN based activity classification algorithm for energy expenditure estimation was presented by Lin *et al*. (2012) which consists of procedures for data collection, preprocessing, activity classification, feature selection and EER models construction using NN. Experimental results successfully validated the wearable sensor module's effectiveness and its NN based activity classification algorithm for energy expenditure estimation. Additionally, the results proved the superior performance of GRNN compared to RBFN.

A method for automatic heartbeats classification in ECG signals was proposed by De Lannoy *et al*. (2012). As this task has specific characteristics like time dependences between observations and strong class unbalance, a specific classifier was suggested and evaluated on MIT arrhythmia database's real ECG signals. This was a weighted variant of conditional random fields classifier. Experiments revealed that the new method outperformed earlier heartbeat classification methods, especially for pathological heartbeats.

A new algorithm for ECG signal compression based on local extreme extraction, adaptive hysteretic filtering and Lempel-Ziv-Welch (LZW) coding was presented by Fira and Goras (2008). The algorithm was verified using eight most frequent normal and pathological cardiac beats types and a Multi-Layer Perceptron (MLP) NN trained with original cardiac patterns and tested on reconstructed ones. The possibility of using PCA for cardiac pattern classification was also investigated. A new compression measure called idquoquality score, rdquo which considers reconstruction errors and compression ratio was proposed.

A simple ECG feature models based heart beat classifier selected to improve generalization capability was studied and validated by Llamedo and Martinez (2011). Classification and generalization were studied using available databases like MIT-BIH Arrhythmia, MIT-BIH Supraventricular Arrhythmia and St. Petersburg Institute of Cardiological Technics (INCART) databases. A Floating Feature Selection algorithm obtained best performing and generalizing models in training and validation sets for various search configurations. The best model comprehended eight features trained in a MIT-BIH Arrhythmia partition and evaluated in a completely disjoint partition of same database. Results were: 93% global accuracy; 95%, for normal beats and sensitivity (S), 98% positive predictive value (P+) for supraventricular beats, S 11%, P+ 39% and for ventricular beats S 81%, P+ 87%. To test generalization capability, performance was evaluated in INCART with results comparable to that from the test set. This classifier model has reduced features performing better than state of the art methods. Results suggest better generalization capability.

The European database for evaluation of automatic detection of ST segment was used by Lee *et al*. (2013) which comprises many steps: ECG signal loading, signal preprocessing, QRS complex and R-peak, ST segment detection and other relation parameter measurements. The application displays analysis results. The ECG signal analysis provides clinical information for heart disease diagnosis. ECG signal includes P, QRS complex and

T-wave. The waves correspond to fields induced by the cardiac surface's specific electric phenomenon. Of them, ischemia detection is achieved by analyzing the ST segment. Ischemia is a widely prevalent and most serious heart disease.

MATERIALS AND METHODS

This study uses RR interval for arrhythmia identification. The RR peaks are detected as follows:

- The moving average of the signal is computed using a number of records
- New signals obtained by deducting the moving average from the original signal
- Peak of the signal R is found
- Peaks of P, Q, S and T are found by relative position

The peak amplitude is measured from k line. The k line is given by:

$$k = \max(\theta_i,\ i = 1, 2, ..., 11) + c \tag{1}$$

Where:

θ_i = The greatest amplitude, type of heartbeat

c = A constant

Figure 2 shows the RR measured using MATLAB. Arrhythmia beat by beat classification is through a set of rules on RR-interval signal. Rules are provided by medical experts based on clinical procedures to detect arrhythmic events from RR-intervals (Tsipouras *et al*., 2005). Rules are used for classification of middle RR interval of a 3 RR-interval sliding window. Classification concerns second beat of middle RR-interval. Beats are classified in four categories:

- Normal sinus beats (N) and three arrhythmic ones
- Premature Ventricular Contractions (PVC)
- Ventricular Flutter/Fibrillation (VF)
- The 28 beat block (BII)

It is assumed that a beat not from one of the above arrhythmic categories is classified as normal. The algorithm starts with window 'i' comprising of RR1i, RR2i and RR3i intervals. The middle RR-interval (RR2i) is a priori normal and classified in category 1. MIT-BIH Arrhythmia database was the first available standard test material to evaluate arrhythmia detectors and was used for that purpose and also for cardiac dynamics basic research at about 500 sites globally from 1980. It took 5 years to complete the MIT-BIH Arrhythmia database (Moody and Mark, 2001). Tools used to create the database were primitive by current standards. ECG recordings were made using Del Mar Avionics Model 445 two-channel reel to reel Holter recorders and analog signals recreated for digitization used a Del Mar Avionics Model 660 playback unit. More than half MIT-BIH Arrhythmia Database is available via PhysioNet) (PhysioNet, 2010), enabling students and others to use a major portion of such data for cost free studies. ECG datasets signals for training/testing are collected from MIT-BIH arrhythmia database (http://www.physionet.org/physiobank/database/mitdb). Selected arrhythmias include Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB) and Normal. Each ECG beat used is a matrix (275×1) for a ECG lead. Each ECG signal has five clear points (P, Q, R, S and T) for EC interpretation as shown in Fig. 3.

Time series signals are converted into basis frequency components by Discrete Cosine Transform (DCT). Pre-processed data locates RR interval using Fast DCT. The FDCT (Che *et al*., 2011) of a list of n = real numbers s(x), x = 0, 1, ..., n-1 is given by:

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

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

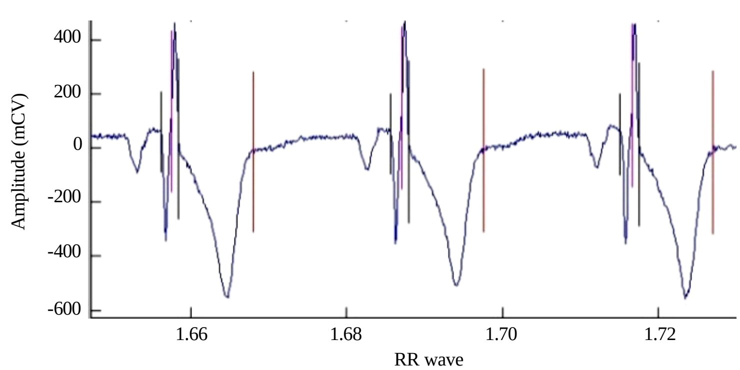
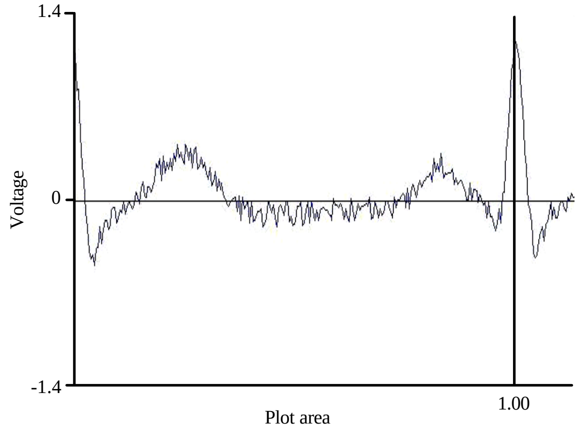


Fig. 2: RR wave shown in MATLAB



Time	Voltage
0.0	1.09800797
0.00390625	1.11745230
0.0078125	0.83489689
0.01171875	0.84014583
0.015625	0.49422203
0.01953125	0.26478166
0.0234375	0.14535142
0.02734375	-0.0790567
0.03125	-0.2095075
0.03515625	-0.3787657
0.0390625	-0.4355313
0.04296875	-0.4089855
0.046875	-0.4830247
0.05078125	-0.3606808
0.0546875	-0.3570710
0.05859375	-0.1963949
0.0625	-0.3250939

Fig. 3: Sample of ECG signal with P, Q, R, S and T peaks

The constant factors are chosen so that the basis vectors are orthogonal and normalized. The Inverse Discrete Cosine Transform (IDCT) is defined as:

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

Existing system

Feed-forward Neural Networks (FNN): ANN is biologically inspired classification algorithms having an input node layer, one or more hidden layers and an output layer. Each layer node has a corresponding node in next layer, creating a stacking effect (Haykin, 2001). ANNs are versatile tools widely used to tackle issues. Feed-forward Neural Networks (FNN) are popular among ANNs. These networks solve complex problems through modeling complex input-output relationships. The Back-Propagation algorithm is the workhorse for design of special class of layered feed-forward networks known as Multilayer Perceptrons (MLP). A popular layered feed-forward network is Radial-Basis Function (RBF) network with important universal approximation properties.

RBF networks are different from multilayer perceptrons in fundamental respects (Ileana *et al*., 2004). While RBF networks are local approximators, multilayer perceptrons are global approximators:

- RBF networks have one hidden layer while multilayer perceptrons have many hidden layers
- The RBF network's output layer is linear while in a multilayer perceptron, it is linear/non-linear
- The RBF network's hidden layer activation function computes Euclidean distance between input signal vector and the network's parameter vector whereas a MLP's activation function computes inner product between input signal vector and pertinent synaptic weight vector

The feed-forward structure design leads to the minimizing generalization error of learning time and of network dimension implies establishment of layer number, neuron number in every layer and interconnections between neurons. For now, there are no formal methods as an optimal choice for NN's dimensions. The number of layers choice is made knowing that a two layer network (one hidden layer) approximates most non-linear functions demanded by practice. A three layer network (two hidden layers) approximates any non-linear function. Hence, it ensures that a three layer network is enough for any problem (Ahmed and Natarajan, 1983). In reality use of large number of hidden layers is useful if each layer's neurons number is too big in a three layer approach.

Radial Basis Function (RBF): NN's have many neurons/computational unit layers all interconnected. Inputs fed on input layer are propagated through hidden layers to get an output. The latter is calculated through use of weights, bias and activation function (Lippmann, 1987). The NN is trained between outputs and desired output which is the error. The following algorithms calculated various parameters in NN training. The input for a neuron is given:

$$s_k = \sum_j w_{jk} y_j + \theta_k \qquad (4)$$

Where:

S_k = The total or effective input for a unit k
w_{jk} = The weight of the connection
y_j = Current activation
θ_k = The bias

The function A_f takes input and gets new activation value according to Eq. 5:

$$y_k(t) = A_f(y_k(t-1) \times s_k(t-1)) \qquad (5)$$

Radial Basis Function (RBF) is a NN variant, better at interpolation and cluster modeling. RBF is embedded in a two layer neural network with radial activated function implemented in hidden layer (Broomhead and Lowe, 1988). Network outputs to inputs are fit to optimize network parameters during training which in turn is evaluated using cost function and assumed to be square error. Gaussian activation function is used in pattern classification given by Wang and Jia (2004):

$$\phi_j(X)=\exp\left[-(X-\mu_j)^T\sum_j^{-1}(X-\mu_j)\right] \tag{6}$$

Where:

j	=	1, 2, ..., L
X	=	The input feature vector
L	=	The number of hidden units
μ_j and Σ_j	=	The means and the covariance matrix of the jth Gaussian function

The output layer implements a weighted sum of hidden-units and modified as:

$$\psi_k(X)=\sum_{j=1}^{L}\lambda_{jk}\phi_j(X) \tag{7}$$

for k = 1, 2, ..., M. RBF classifier's every hidden-layer node represents a class and constructs a hypersurface for it. These hypersurfaces are viewed as discriminant functions with each hidden layer node producing a high value for the class it represents and low value for other classes. A Gaussian RBF is a good choice for hidden layers as it is a good similarity function (Bishop, 1995):

$$\Phi(\bar{x})=\exp\left(\frac{-\|x_i-\mu_k\|^2}{2h\sigma_k^2}\right) \tag{8}$$

Proposed system

Spline Activated Feed Forward Neural Network (SA-FFNN): The spline-based NN is built using Generalized Sigmoidal (GS) neuron with adaptive parametric spline activation function (Guarnieri *et al*., 1995) which is easy to adapt and implement. It retains sigmoid's squashing property and smoothing characteristics. MLP constructed with spline activation functions are universal approximators with lowered structural complexity. Spline activation function (Vecci *et al*., 1998) reproduces total cubic spline shape along directions specified by w_j, where j = 1, 2, ..., n and defined by:

$$\varphi\left(w_j x\right)\sum_{i=1}^{N}c_i\left|w_j x-\alpha_{ij}\right|^3 \tag{9}$$

f(x) can be written as:

$$f(x)=\sum_{j=1}^{n}\mu_j\phi_j(w_j x) \tag{10}$$

where, μ_j and w_j use back propagation, thereby locating an optimal set of parameters and coordinates. Spline tracts are described by combining coefficients. Local spline basis functions controlled by 4 coefficients represent activation function. Catmull-Rom cubic spline is used and its ith tract is expressed as:

$$F_i(u)=\begin{bmatrix}F_{x,i}(u)\\F_{y,i}(u)\end{bmatrix}=\frac{1}{2}\begin{bmatrix}u^3 & u^2 & u & 1\end{bmatrix} \tag{11}$$

CART is classification process using historical data to construct decision trees. Based on available dataset information, a classification/regression tree is constructed. Such a tree is used for classification of new observations. It searches for all possible variables and possible values to find best split-the question that splits data into two parts with maximum homogeneity. The process is repeated for every resulting data fragments.

RESULTS AND DISCUSSION

An energy extraction measure using discrete cosine transform was used and RR interval extracted and used as a feature in this study. The extracted beats include 68 instances of left bunch bundle block, 30 instances of right bunch bundle block and 56 normal instances. The proposed SA-FF neural network was tested using 10 fold validation Classification And Regression Tree (CART), Radial Basis Function (RBF) and Multilayer Perceptron (MLP). The classification accuracy is given in Table 2 and Fig. 4. Table 3, Fig. 5 and 6 show the precision and recall of the classification methods used.

For automated ECG Arrhythmia Classification System precision and recall play a crucial role in finding true positives and the proposed system improved both prevision and recall. It is observed that though the average precision of the proposed SA-FNN is higher, it

Table 2: Classification accuracy

Type of accuracy	RBF	SA-FFNN
Correctly classified instances	137 (89.54%)	139 (90.85%)
Incorrectly classified instances	16 (10.46%)	14 (9.15%)

Table 3: Precision and recall

	RBF		SA-FFNN	
Types of instances	Precision	Recall	Precision	Recall
Left bundle bunch block	0.861	0.912	0.888	0.914
Left bundle bunch block	0.902	1.000	0.967	1.000
Normal Instances	0.967	0.821	0.902	0.852

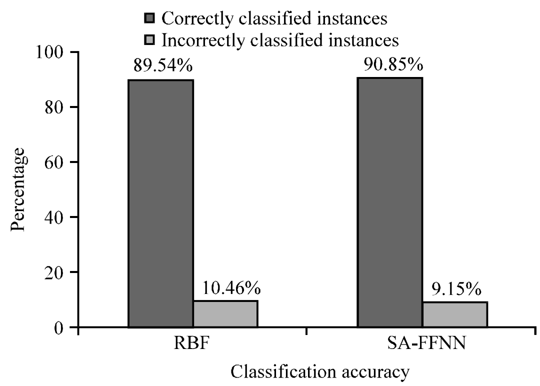


Fig. 4: Classification accuracy of various methods

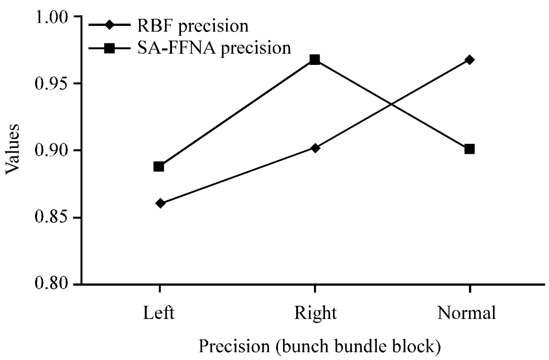


Fig. 5: Precision for various classification methods

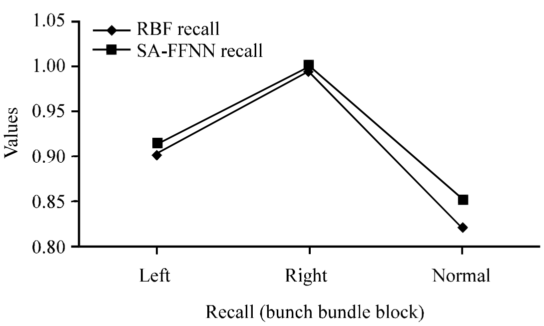


Fig. 6: Classification accuracy of various methods

has lower precision for classifying normal instances. The proposed method improves the recall by 0.22-3.78% when compared to RBF.

CONCLUSION

Diagnosis systems are the base for several research domains in cardiology. Traditional classification methods include limitations in applications with neuronal techniques being considered promising algorithms to offset this. This study suggests an ECG Arrhythmia Classification System using DCT for feature extraction in frequency domain. An improved feed forward NN based on spline activation function was suggested. The proposed Spline Activated Feed Forward NN (SA-FFNN) improves classification accuracy by 1.31% when compared to RBF. Further work is needed in the field of NN to improve classification accuracy.

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