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A Neural Network based Cardiac Arrhythmia Diagnosis system from Dynamic Features of Electrocardiogram Signal

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Abstract

Objectives: Cardiac arrhythmia is a type of disorder where the heartbeat is irregular, too slow, or too fast. As a result of heart diseases, there is an increase in death yearly. The early detection of cardiac diseases is important for preventing the deaths due to the cardiac diseases. **Methods**: The Electrocardiogram (ECG) is used to record the electrical activity of the heart for physician to diagnose the heart diseases. In this study, we propose a cardiac diagnosis system for diagnosing cardiac arrhythmia disease. It will be most helpful for the patients who undergone a heart surgery for continuous monitoring of post-surgical status. **Findings**: The major objective of this paper is to implement an effective algorithm to discriminate between the normal and diseased persons. The Monitoring process includes the following tasks, such as preprocessing and feature extraction by Pan Tompkin's algorithm and the features are classified using neural network and support vector machine. The performance of the classifiers was evaluated using the parameters such as sensitivity, specificity and accuracy. The Accuracy of the neural network algorithm is 88.54% and the accuracy of the Support Vector Machine is 84.37%. **Application/Improvements:** The Neural network classifier shows better performance compared to support vector machine. In future the classifier is trained using the best set of features using feature selection techniques.

Keywords: Cardiac Arrhythmia, Electrocardiogram, Neural Network, Pan Tompkins QRS Detection, Support Vector Machine

1. Introduction

According to the World Health Organization (WHO), Cardio Vascular Diseases are the number one cause of death. Around 17.7 million people were died due to Cardio Vascular Diseases in 2015 that represents 31% of global deaths. People with heart disease or who are at high risk of heart diseases due to the existence of the risk factors such as diabetes, hypertension and hyperlipidaemia requires timely detection to save their lives[1]. The early diagnosis of cardiovascular diseases plays an important place for preventing the deaths due to cardiovascular diseases. Especially the rural people lack in early detection due to the unawareness about the symptoms of heart diseases and poor facilities in rural areas. The vast majority of People – 95% now own a mobile phone. There are 77% of persons have smart phones, and among that just 35% have ownership in the Pew Research Center's ownership survey conducted in 2011[2].

The rapid growth of technology and the high-speed internet has direct to a huge growth in the number of smart phone consumers in India. Approximately 291.6

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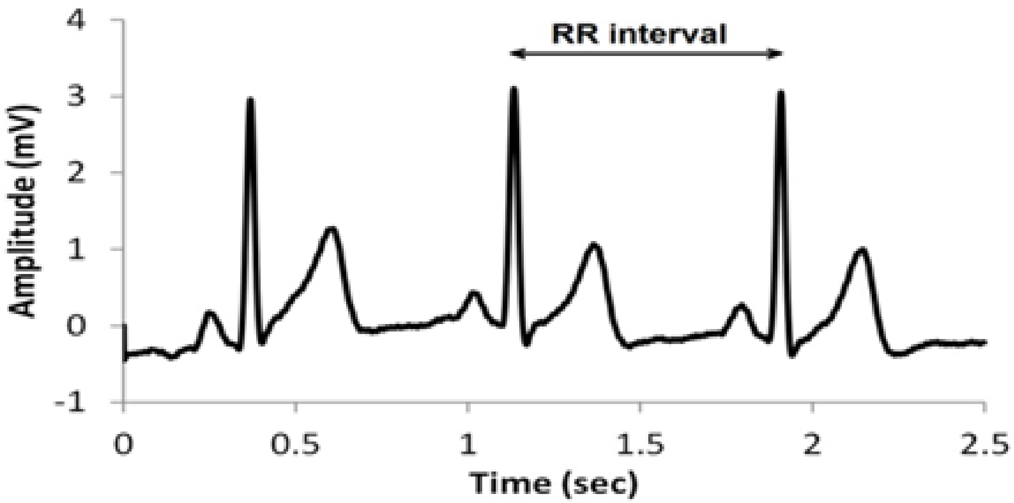

Figure 1. RR interval.

million smart phone users are in India at the end of 2017. The number of smart phone users in India is expected to reach 337 million by the end of the year 2018. The ECG signals are denoised and RR intervals are extracted for the diagnosis of heart diseases. RR interval is the interval between one peak of the ECG signal and the succeeding peak of the ECG signal. The RR interval is shown in the Figure 1. Dynamic features are extracted from RR interval.

Arrhythmia is an abnormal electrical activity, that the heart beat may be too slow or too fast. It leads to two major problems. They are the heart pumps too quick and ventricles filled with inadequate blood. There are different types of arrhythmias. Some of them are Normal sinus Rhythm, Atrial Fibrillation, Ventricular Fibrillation and Supraventricular tachycardia[3]. The data are collected from the Physionet database. The feature extraction process is done by the discrete wavelet transform. The extracted features are selected by using principal component analysis and then classified using support vector machine. A rising interest in body wearable sensors has recently emerged as powerful tools for healthcare applications and different devices are currently available commercially for different purposes including personal healthcare, activity awareness and fitness. IoT plays an important role in health care by sending patient's physical signs[4] such as blood pressure, ECG, SpO2, heart rate, blood fat and blood glucose to the remote monitoring system.

According to the Statistics Portal, the number of IoT healthcare units was expected to increase through the years. It was at 11.1 million units in 2017, and it was expected to reach 25.8 million units by 2025. Internet of Things (IoT) grows as a prevailing domain in which embedded devices and sensors can connect and exchange information over the Internet[5]. The deep neural network was proposed for the classifying coronary artery disease dataset[6]. CAD data set collected from UC Irvine Machine Learning Repository. The deep neural network constructed by combining a stacked auto encoder networks with soft max classifier. Auto encoder is the feed forward neural network which has one input layer and one output layer. The number of neurons in output layer and input layer are equal. Soft max classifier is used to classify the learned features. The method was tested in Cleveland, Hungarian, Long Beach and Switzerland data from the UCI repository.

The IoT devices, sensors and mobile devices are widely used healthcare sector for remote access of medical help via the medical Internet of Things (mIoT)[7]. Wearable sensors and mobile devices used widely in the healthcare. It is helpful in symptom tracking, and collaborative disease management. The feed-forward multilayer perceptron and support vector machine (SVM) was used for the diagnosis of cardiac disease[8]. He used the data from UC Irvine machine learning repository. He used 13 attributes (Age, Sex, Chest Pain Type, Resting blood pressure, Cholesterol and blood sugar etc.,) to train the classifier. The author compared the performance measures of the Support Vector Machine and the neural network. Among these SVM outperforms and gave an accuracy rate of 87.5%.

An artificial neural networks-based (ANNs) diagnosis model was proposed for coronary heart disease (CHD) using a compound of conventional and genetic factors of the disease[9]. A diagnosis system was proposed for diagnosis of coronary heart disease with neural network using Feature correlation analysis (NN-FCA)[10]. The Korea National Health and Nutrition Examination Survey (Knhanes) dataset was used for evaluating the performance of the system.

A computer aided system was proposed to diagnose heart diseases[11]. She used many classifiers such as Naïve Bayesian, Decision Trees, Logistic, Random Forest, and Support Vector Machine for various datasets. Among this Support Vector Machine provide better accuracy compared to other classifiers. A classification model was proposed that detects the wide range of Arrhythmias from electrocardiogram recorded with wearable monitor[12]. He used convolution neural network to train the input data, and then the network matches the sequence of ECG samples to a sequence of rhythm classes. The paper aims to use the machine learning algorithms in health care for early diagnosis of heart diseases.

2. Material and Methodology

2.1 System Architecture

The architecture of the system is organized as two layers: the training layer and the testing layer. The Figure 2 shows the system architecture. The training layer is responsible for building a model for classification process. The ECG data was collected from Physio Bank ATM. Matlab Processing includes preprocessing of the signal and extracting the features from ECG signal. The Pan Tompkin's QRS detection algorithm[13] was used for extracting the features. The RR interval is extracted from the R-Peak and then Dynamic features were calculated from RR interval. The Dynamic features are applied to the neural network. A feed forward multilayer perceptron was used for training the network.

The testing layer involves the real-time ECG signal. Here the signal was preprocessed and the RR intervals were calculated from R-Peak which is extracted with Pan Tompkin's algorithm. Then the Dynamic features from RR intervals were sent to the trained neural network system and support vector machine for diagnosis. The performance of these classifiers was analyzed. The diagnosis result was sent to the Doctor as well as the patient's caretaker.

2.2 Database

The ECG signal for training the classifier was collected from Physio Bank ATM. Physio Bank is the large storage of physiologic signals. ECG signal was downloaded as a mat file from MIT-BIH Normal Sinus Rhythm Database (nsrdb) and MIT-BIH Supraventricular Arrhythmia Database (svdb). MIT-BIH Normal Sinus Rhythm Database (nsrdb) includes 18 ECG recordings and MIT-BIH Supraventricular Arrhythmia Database (svdb) contains 78 ECG recordings.

2.3 Pan Tompkin's Algorithm

The Figure 3 represents the work flow of the Pan Tompkins algorithm. Pan Tompkin's QRS detection algorithm involves the following steps.

The first step is band pass filter. It is used to emphasize signal characteristics while suppressing irrelevant information.

a. The band pass filter diminishes the muscle noise, baseline wander noise, and the T-wave interference. A band pass filtering is completed by merging low and high pass filters.
    - The low pass filter with cut off frequency 11 Hz and the gain is 36.

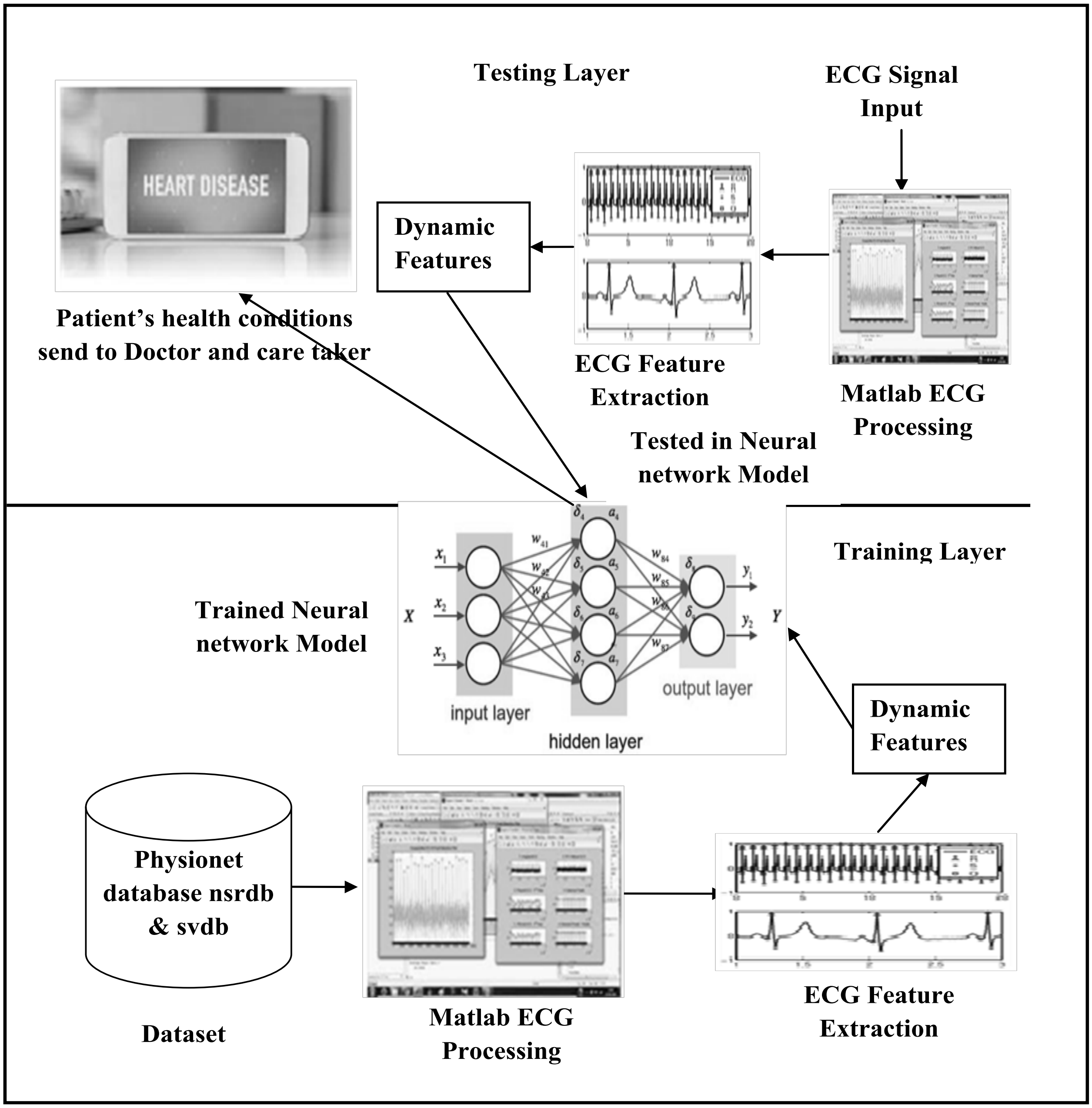

Figure 2. System architecture.

- The high pass filter with cut off frequency 5 Hz and the gain is 32.

b. After filtering, the next step is the differentiation which is used to provide the QRS complex slope information.

c. When the differentiation is completed, the signal is squared to point by point. This step creates all points as positive and performs enlargement of output.

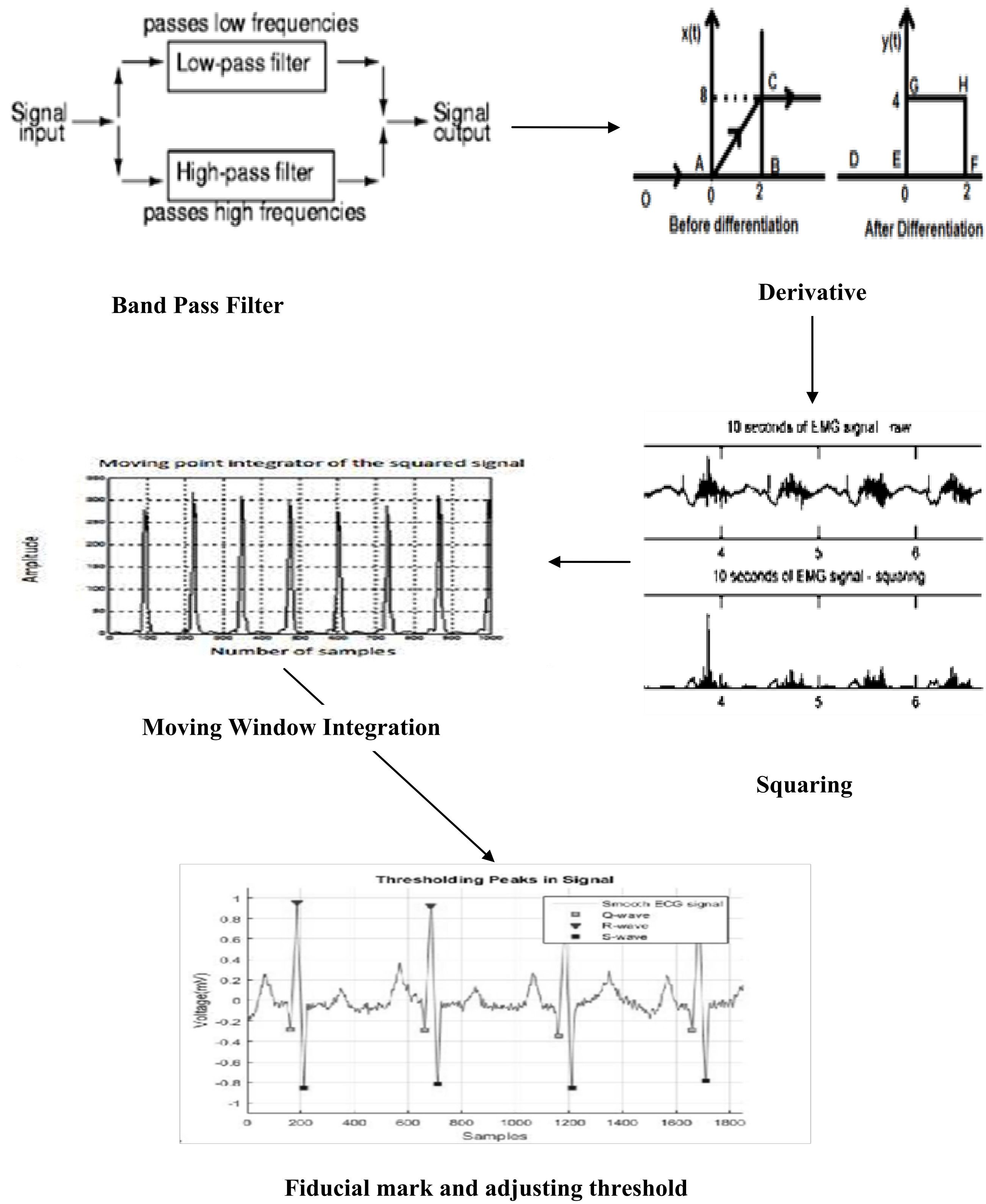

Figure 3. Work flow of the Pan Tompkins algorithm.

d. To acquire waveform feature information in addi tion to the slope of the R wave, moving-window integration is used.

e. A fiducially mark of the QRS complex can be obtained from the increasing edge according to the preferred waveform feature to be spotted such as the maximal slope or the peak of the R wave.

f. The thresholds are automatically altered to float over the noise.

g. The R Peaks are marked in the original signal.

2.4 Classification

2.4.1 Neural Network System

The Dynamic features are applied as an input. The data are trained by feed-forward neural network using tool in MATLB. The trainlm is used as the training function which updates weight and bias values. The adoption learning function learngdm, the gradient descent with momentum weight and bias learning function is used for classification. And the tansig transfer functions compute a layer's output. The Figure 4 shows the mean squared error for the training of the classifier.

2.4.2 Support Vector Machine

The support vector machine trained the data through classification learner app in MATLAB. The app starts a new session with input and target data and 10 fold cross-validations. In this paper, we have applied all SVMs such as linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian, Medium Gaussian and Coarse Gaussian SVM. Among these the medium Gaussian SVM gives better results.

3. Results and Discussion

The ECG signal dataset collected from Physionet ATM database. Here we have chosen two databases. They are MIT-BIH Normal Sinus Rhythm database (nsrdb) and MIT-BIH Supraventricular tachycardia database (svdb). Totally we have 96 records, having 18 normal persons and 78 persons affected by supra ventricular tachycardia. The Signal was processed by Pan Tompkin's QRS detection algorithm and the RR intervals are marked. Then

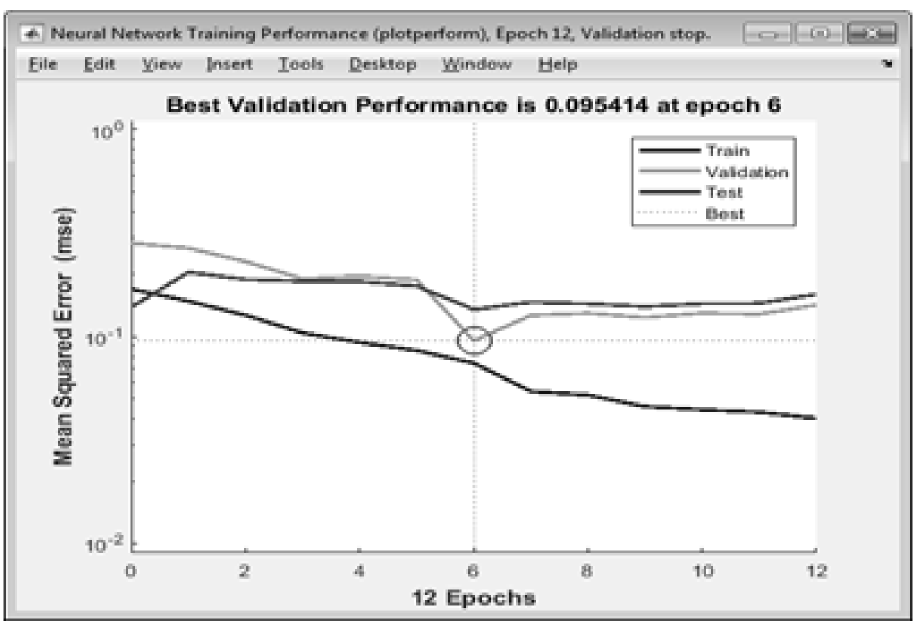

Figure 4. Mean squared error.

Table 1. Statistical parameters of dynamic features

Features	Statistical parameters											
	Normal Sinus Rhythm						Supraventricular tachycardia					
	Mean	Median	Standard deviation	Min	Max	Variance	Mean	Median	Standard deviation	Min	Max	Variance
SDNN	18786	18006	5969	7864	27651	35623186	17976	18231	3217	6458	25097	10350927
SDANN	11436	11192	3504	4073.5	17173	12280495	11113	10873	2483	3156	16959	6167474
RMSSD	28241	30922	7417	11866	40420	55006604	27456	27043	5552	10292	41284	30821983
NNx	179.78	186.5	17.71	148	209	313.4771	77.038	77.25	4.564	56.5	87.8	20.83123
PNNx	96.996	98.396	2.544	91.848	99.479	6.470127	183.19	184	11.47	132	203	131.456
Mean HR	76.178	76.85	5.367	68.4	87.2	28.80889	97.258	97.492	1.789	89.03	99.492	3.2008

the Dynamic features[14,15] were calculated from the RR interval. The features are standard deviation of normal to normal interval (SDNN), standard deviation of average of normal to normal interval (SDANN), square root of the mean of the sum of the squares of differences between adjacent NN intervals (RMSSD), The number of pairs of successive NNs that differ by more than x ms (NNx), Percentage of differences between adjacent NN intervals that are > x ms (PNNx), mean Heart Rate bpm (mean HR). The Table 1 represents the statistical parameters of the features of normal and supraventricular tachycardia patients. The parameters described are mean, median, standard deviation, min, max and variance.

3.1 Performance Evaluation

The performance of the classifier is evaluated using sensitivity, specificity and accuracy. Sensitivity is the measure of ratio of actual affected persons identified correctly. Specificity is the measure of ratio of normal people identified properly. The accuracy of the classifier is described as that how correctly the classifier identifies the cardiac arrhythmia disease. These measures can be obtained using the following parameters such as a person having cardiac arrhythmia disease diagnosed positive refers to True Positive (TP). If the person does not have cardiac arrhythmia disease diagnosed as normal refers to True Negative (TN). If some person having cardiac arrhythmia disease diagnosed normal refers to False Negative (FN). A person does not have cardiac arrhythmia disease diagnosed positive refers to False Positive (FP).

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (1)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Table 2. Confusion matrix of the classifiers

		Neural Network		Support Vector Machine	
		Predicted		Predicted	
		Yes	No	Yes	No
Actual	yes	TP =77	FN=1	TP =78	FN=0
	no	FP=10	TN=8	FP=15	TN=3

Table 3. The performance measure of the classifiers

Sl.No	Performance measures	Neural Network	Gaussian SVM
1.	Sensitivity	98.71%	**100%**
2.	Specificity	**44.44%**	16.66%
3.	Accuracy	**88.54%**	84.37%

The Table 2 refers the confusion matrix for the two classifiers used and Table 3 represents the performance measures of the classifiers used in this work.

The analysis of performance measure express the neural network classifier outperforms than the support vector machine. The classification accuracy of the neural network is higher than the SVM classifier. Even though the sensitivity of the SVM is high, its specificity is too low. That it misclassifies the normal person as cardiac disease persons.

4. Conclusion

In a medical field correctness in the diagnosis is an important constraint. The misdiagnosis leads to severe crisis. To reduce the misdiagnosis, we implement a cardiac monitoring system for the diagnosis of cardiac arrhythmia disease. Here we have compared two classifiers for diagnosis. From the results, it is identified that the neural network gives better accuracy for the classification of cardiac arrhythmia disease. It gives the accuracy of 88.54%. The cardiac arrhythmia monitoring system is suitable for diagnosis of cardiac arrhythmia diseases accurately and in time.

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