Heart Disease Prediction using Data Mining Technique

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Abstract: ECG is the most common and basic test to run on patients to check any kind of anomalies in the heart. In the ECG result 10 to 20 minutes long continuous data of a patient's heart is down sampled and printed as a 1D graph. We have develop a program which will take the continuous dataset from the ECG machine and analyses the data and extracts various features of the ECG wave. At first we decompose the data using Wavelet decomposition. Then the data is reconstructed in 4 levels which removes the noise from the signal. In the same time we detect major components of the ECG wave which is P wave, QRS complex and T wave. An electrocardiogram (ECG) is an important diagnostic tool for the assessment of cardiac arrhythmias in clinical routine. In this process, we introduce the a deep learning based convolution neural network framework, which is previously trained on a general signal data set is transferred to carry out automatic ECG arrhythmia diagnostics by classifying patient ECG's into corresponding cardiac conditions. The Main focus of this process is to implement a simple, reliable and easily applicable deep learning technique for the classification of the selected two different cardiac categories conditions. The results demonstrated that the transferred deep learning classification cascaded with a conventional SVM were able to obtain very high performance rates. all this work has been performed by MATLAB simulation

Key words: SVM, NN, RF,KNN,CNN,ECG.

I INTRODUCTION

The rhythmic pumping system of the heart needs electricity to contract which is regulated by a specialized conduction pathway [8]. The conduction pathway consists of five essentials components i.e. the sino-atrial (SA) node, the atrio-ventricular (AV) node, the bundle of His and the Purkinje fibers which is shown in Fig. 1.4. The cardiac action potential (AP) is generated due to the brief change in membrane potential across the cell membrane of the heart is shown in Fig. 1.3. Voltage is generated due to the movement of charged ions through ionic channels that connects the inside and outside of the cell. The action potentials also vary within the heart because of the presence of different ion channels in various cells. The resting membrane potential of ventricular cells is around -90 millivolts. At rest state, the sodium (Na+) and chloride (Cl−) ions are found outside the cell, whereas the potassium (K+) ions found inside the cell [9]. The action potential starts with depolarization because of sodium channels opening that allow Na+ to flow into the cell. The depolarization begins after a brief delay, when K+ to leave the cell due to opening of potassium channels, creates a negative membrane potential. The calcium (Ca2+) ion found to be inside-outside of the cell to make sarcoplasmic reticulum (SR).

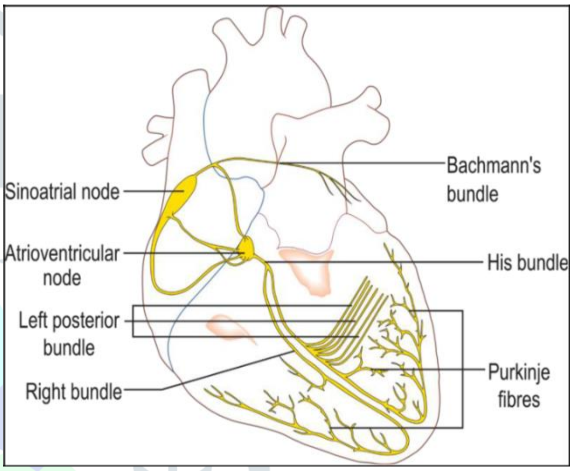


Fig. 1. Action potential of cardiac muscle ([Edited from [9]).

bundle of His into the ventricles. The bundle of HIS then divides into right and left bundle branches that stimulate the right and left ventricles. The pacemaking signal stimulates the right and left atrium to contract first, and then the right and left ventricles to allow the process of blood flow throughout the body The SA node also called natural pacemaker of the heart. It is a specialized tissue located in the atria and under normal condition of the heart generates an electrical stimulus of 60 to 100 times per minute at a regular interval of time. Each generated stimulus spreads rapidly through both atria in the form of a wave of contraction that passes through the myocardial cells. The electrical impulse travels from the SA node to the atrioventricular (AV) node, then impulses are slowed down for a very short period. The electrical stimulus travels in the conduction pathways to ventricles, which cause to contract and pumps out the blood. The two atrial chambers of the heart are stimulated first, then two ventricular chambers to contracts over a short period of time. The stimulus current travels in conduction pathway via the The electrocardiogram (ECG) is a key diagnostic tool used to assess the health conditions of the heart. It records the electrical activity of heart during different phases of the cardiac cycle. The heart triggers tiny electrical impulses at SA node and spread through the conduction system of the heart to contract rhythmically. These impulses can be recorded by the ECG machine by placing the surface electrodes over the skin of different part of the body. The tracings of the heart's electrical activity are called ECG waveform and the dips and spikes will show the conditions of the heart as shown in Fig.1.5. The ECG waveform is a series of positive and negative waves produced due to different deflection in each portion of heartbeat typical ECG tracing consists of P-wave, a QRS complex, and T-wave in each cardiac cycle. The ECG detects the transfer of ions through the myocardium, which changes in each heartbeat. The is electric line is the baseline voltage of ECG which is traced following the T-wave and preceding the next P-wave. The upper chambers of heart make the first wave called P-wave. The P-wave is first to be generated due to contraction of the upper chamber of the heart followed by a flat line due to electrical impulse goes to the lower chambers. The contraction of ventricles makes the QRS complex and final T-wave produced for resting state of the ventricles [10]. The repetitive cycle of the electrical activity of heart is represented by the P-QRS-T sequences. The normal value of the different waveform of ECG is presented in the Table 1.1 [11].

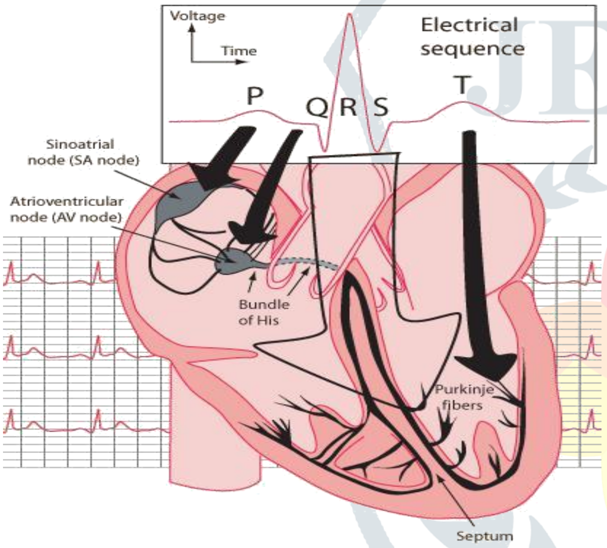


Fig.2 Generation of normal ECG signal ([Edited from [10])

II RELATED WORK

Several surveys have come up with the result that heart diseases are among the top five reasons of deaths worldwide. Conventional diagnosis of heart diseases relying on symptoms and standard tests like the ECG highly depends upon the experience of the physician and the fluctuations in the test data. Errors arising out of any of the above factors may have serious repercussions. In this, we present a technique in which consists of data pre-processing using the wavelet transform, classifying using the Euclidean Distance Classifier. Elimination of noise from ECG signals in pre-processing stage. Detection of precise R-peaks and QRS complex using different transform techniques such as wavelet, Hilbert and EMD in healthy and arrhythmia conditions. Extraction of both time and transform domain features (e.g. temporal features, heartbeat interval features and ECG morphology) from QRS complex and ECG waveforms. Selection and ranking of features to improve the classification accuracy in further tasks. Automated classification of arrhythmia beats using suitable machine learning techniques. Comparative performance analysis with published results in terms of sensitivity, specificity, positive predictive (Pp) and accuracy through arrhythmia beat classification. The main purpose of this work is to predict the ECG signal using an efficient classification method. To improve the accuracy of the classification and to reduce the miss class.

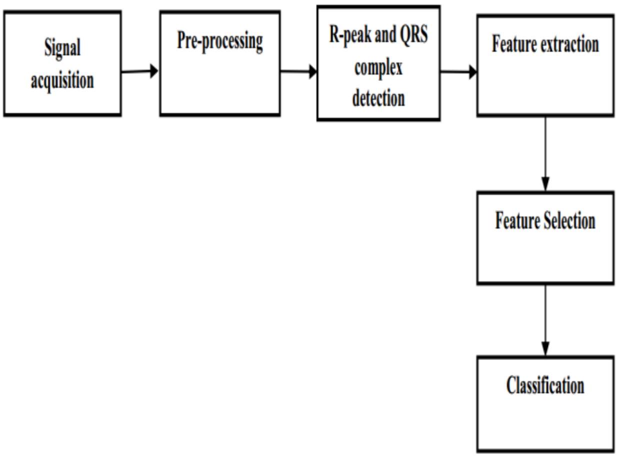


Fig. 3 proposed Block Diagram

III PROPOSED APPROACH

In this process, we propose a deep arrhythmia-diagnosis method, base on four classification model, to automatically detect the abnormality of the heartbeats using the ECG signals. This classification model mainly consists of four convolution layers: two BLSTM layers and two fully connected layers. The datasets of RR intervals (called set A) and heartbeat sequences (P-QRS-T waves, called set B) are fed into the above-mentioned model. Most importantly, our proposed approach achieved favorable performances with an accuracy of 99.94% and 98.63% in the training and validation set of set A, respectively. In the testing set (unseen data sets), we obtained an accuracy of 96.59%, a sensitivity of 99.93%, and a specificity of 97.03%.The main advantage of the multi SVM compared to other classifiers is mainly on the reduction of the cross validation and post optimization functions.SVM produces better classification results comparing to other classifiers mainly due to the global optimization functions included.SVM has shown a good concert in classification

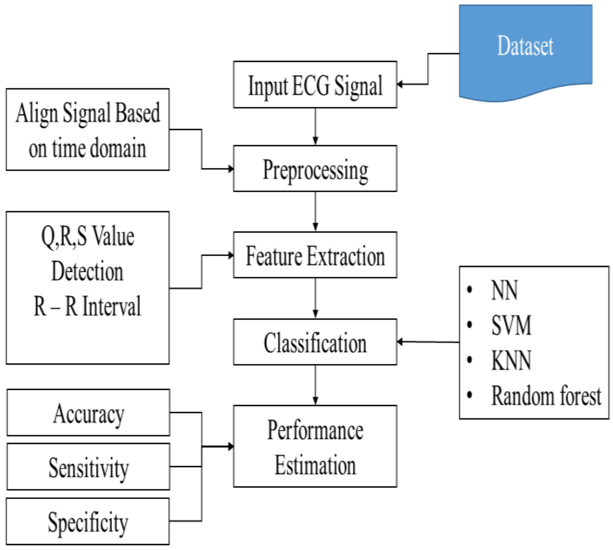


Fig. 4 Flow Diagram

Table :1 Different Attributes

S.No	Attribute
1	Age
2	Blood pressure (SI)
3	Urea
4	Sex
5	Blood pressure(DI)
6	Creatin
7	Bilirubin
8	PR (Per Rectum)
9	SGPT (Pyruvic)
10	Sugar
11	SGOT (Serum glutamic oxaloacetic transaminase
12	Sodium
13	HB(Hemoglobin
14	Family history
15	Stress level
16	Pottasium
17	Height
18	Smoker(yes/no)
19	Weight
20	Sedentary lifestyle

PREPROCESSING: Pre-processing means "preparation" of the sample/image to introduce it to an algorithm for specified task: tracking targets, recognition, feature extraction, etc.Data pre-processing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and/or lacking in certain behaviours or trends, and is likely to contain many errors. Data pre-processing is a proven method of resolving such issues. We can convert our data files(.xlsx) into .mat files and align the data. The purpose of optimization is to achieve the “best” design relative to a set of prioritized criteria or constraints. Selecting the suiting features are important to the mode land considerably influence the results. Quality and quantity of the features have great impact on whether the model is good or not. In order to improve the prediction model, different Data pre-processing techniques were applied Data integration is to combine data from multiple sources into a coherent store. In integration processing, the redundant data problem always occur, since the same real world entity, attribute values from different sources have different names, or one attribute may be a derived attribute in another table. Therefore, researchers should carefully identifyreal world entities from multiple data sources by using correlation analysis. Otherwise, careful integration of the data from multiple sources may help to reduce/avoid redundancies and inconsistencies and improve mining speed and quality [9].

DATA EXTRACTION: Data extraction means to analyze and scrutinize the data to retrieve relevant information from different data sources in a specific pattern. Here, the attributes are dentified for classifying process

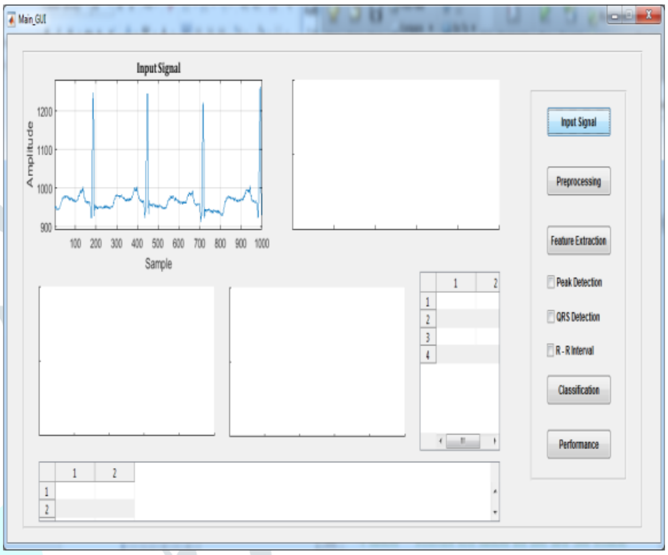


Fig. 5. Architecture Diagram

RECONSTRUCT SIGNAL: Extract the Coefficients after the transform while plotting the coefficients we observed that the frequency bands are separated and ca1, ca2, ca3 and ca4 are cleaner signal. But they will have less number of samples than the actual Signal due to down sampling. We can see that first signal resembles to the actual signal but has exactly one forth number of samples because the signal was decomposed in 4 levels. 2nd level has exactly half number of samples that of 1st level, 3rd level has exactly half number of samples than the 2nd level. Because the number of samples is reduced, such signals are also called down-sampled signal. It is clear that 2nd level decomposed data is noise free. Therefore we consider this signal as ideal ECG signal from which QRS must be detected. But the first R is located in 3rd level decomposition signal at approximately 40th sample whereas the same is located in the original signal at 260th location. Therefore once R peak is detected in 3rd level reconstructed signal, it must be cross validated in the actual signal.

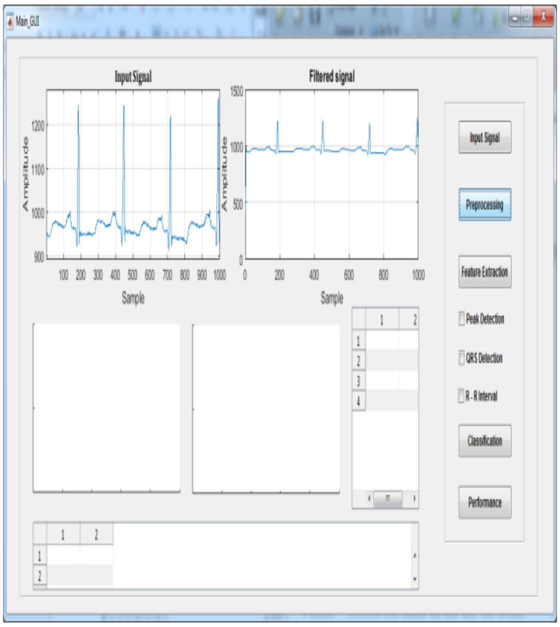


Fig. 6 Architecture Diagram

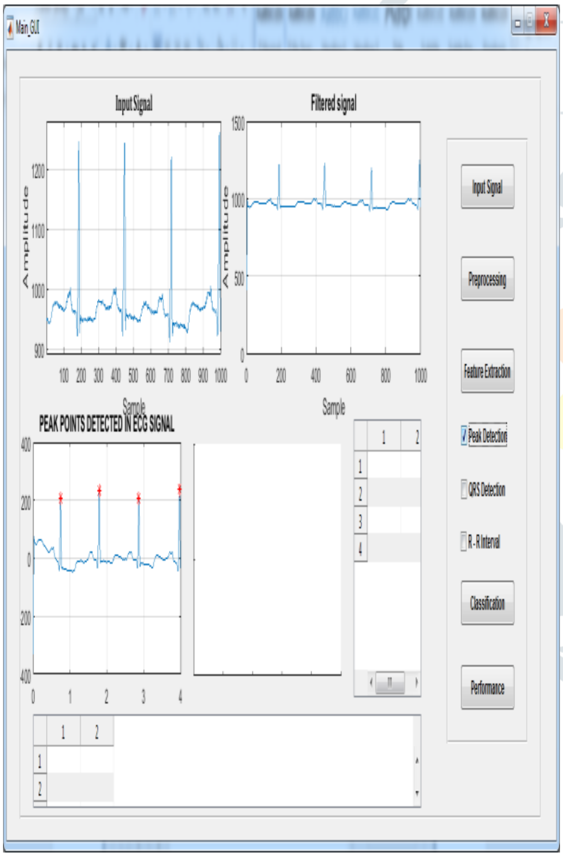


Figure 7 Reconstructed Signal

[c,l]=wavedec(s,4,'db4');

ca1=appcoef(c,l,'db4',1);

ca2=appcoef(c,l,'db4',2);

ca3=appcoef(c,l,'db4',3);

ca4=appcoef(c,l,'db4',4);

QT Interval Measured from beginning of QRS to end of T wave in the frontal plane

Normal: heart rate dependent (corrected QT = QT_c = measured QT, sq-root RR in seconds; upper limit for QT_c = 0.44 sec)

Long QT Syndrome: "LQTS" (based on upper limits for heart rate; $QT_c \geq 0.47$ sec for males and ≥ 0.48 sec in females is diagnostic for hereditary LQTS in absence of other causes of increased QT)This abnormality may have important clinical implications since it usually indicates a state of increased vulnerability to malignant ventricular arrhythmias, syncope, and sudden death. The prototype arrhythmia of the Long QT Interval Syndromes (LQTS), a polymorphic ventricular tachycardia characterized by varying QRS morphology and amplitude around the is electric baseline. Causes of LQTS include the following:

- Drugs (many antiarrhythmics, tricyclics, phenothiazines, and others)
- Electrolyte abnormalities (↓K^+, ↓Ca^{++}, ↓Mg^{++})
- NS disease (especially subarrachnoid hemorrhage, stroke, trauma)
- Hereditary LQTS (e.g., Romano-Ward Syndrome)
- Coronary Heart Disease (some post-MI patients)

No disease/ Healthy Heart

For a healthy heart the primary condition is:

ST Deviation/100 <

And for a perfect heart condition which is very rare includes these conditions:

- PR Interval: 0.12 - 0.20s
- QRS Duration: 0.06 - 0.10s
- Heart Rate: 60 - 90 bpm

4.1.3 QRS Duration

Duration of QRS complex in frontal plane

Normal: 0.06 - 0.10s
Prolonged QRS Duration:

QRS duration > 0.10s:

- QRS duration 0.10 - 0.12s
- Incomplete *right* or *left* bundle branch block
- Nonspecific intraventricular conduction delay (IVCD)
- Some cases of left *anterior* or *posterior* fascicular block

QRS duration ≥ 0.12s:

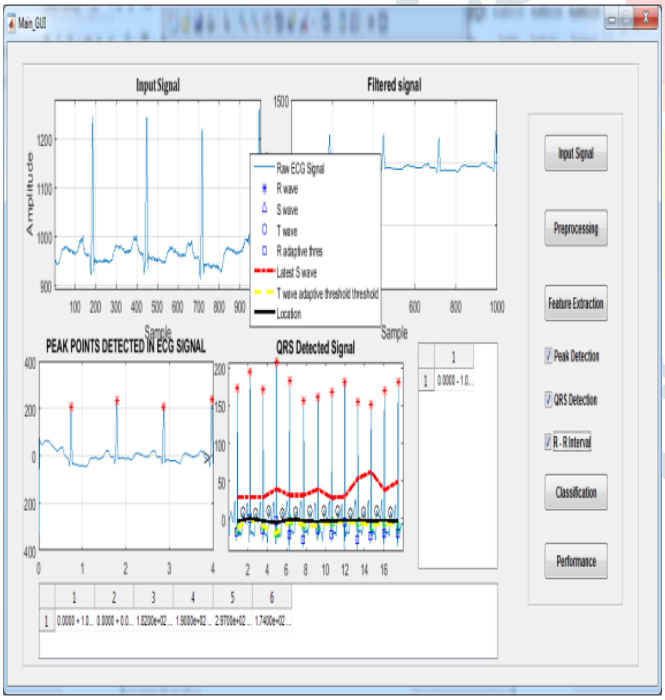
Complete RBBB or LBBB

Nonspecific IVCD
Ectopic rhythms originating in the ventricles (e.g., ventricular tachycardia, pacemaker rhythm)
Q-R-S Detection: The QRS complex is a combination of three of the graphic deflection seen on a typical ECG. This study proposes a real-time QRS detection and R point recognition method with low computational complexity while maintaining a high accuracy. The enhancement of QRS segments and restraining of P and T waves are carried out by the proposed ECG signal transformation, which also leads to the elimination of baseline wandering. In this study, the QRS fiducially point is determined based on the detected crests and troughs of the transformed signal. Subsequently, the R point can be recognized based on four QRS waveform templates and preliminary heart rhythm classification can be also achieved at the same time.QRS complex consists of Q,

R and S waves. R wave has the greatest amplitude, therefore after applying wavelet transformation, a first R peak detection is performed. Afterwards, Q and S waves are detected by simple methods of local minimum / maximum.. In cases where QRS complex has a concave shape, R wave detection is done by searching values that are less than a predetermined threshold.

RR interval: the RR interval is the time between the R peak of a heartbeat with respect to another heartbeat, which could be its predecessor or successor. With exception of patients that utilize a pacemaker, the variations perceived in the width of the RR interval are correlated with the variations in the morphology of the curve, frequently provoked by arrhythmias . Thus, the features in the RR interval have a great capacity to discriminate the types of heartbeats and some authors have based their methods only on using the RR interval features [67–69]. Variations of this feature are used to reduce noise interference and are very common, e.g., the average of the RR interval in a patient for a certain time interval

RR-interval significantly improves the classification results. Only normalized RR-intervals are used in that work and the results are comparable to the state-of-the-art methods even under the inter-patient paradigm..the efficiency of normalized RR-intervals by means of feature selection techniques Features extracted from the domain of time/frequency together with the features of the RR interval appear as part of the methods that produced the highest accuracies



	1
1	0.0000 - 1.0...

	1	2	3	4	5	6
1	0.0000 + 1.0...	0.0000 + 0.0...	1.8200e+02 ...	1.9000e+02 ...	2.9700e+02 ...	1.7400e+02 ...

Fig. 8 QRS signal

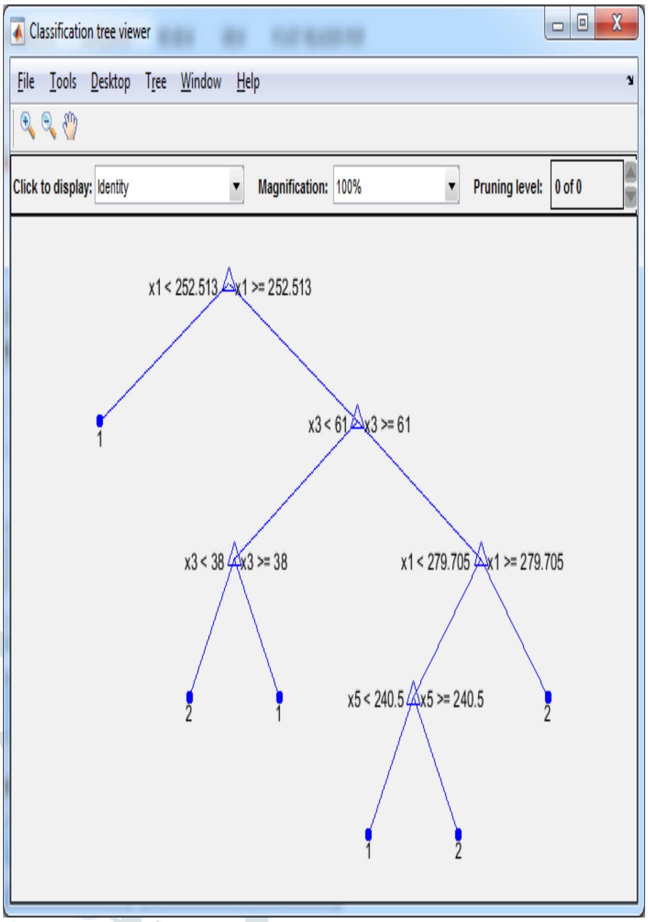
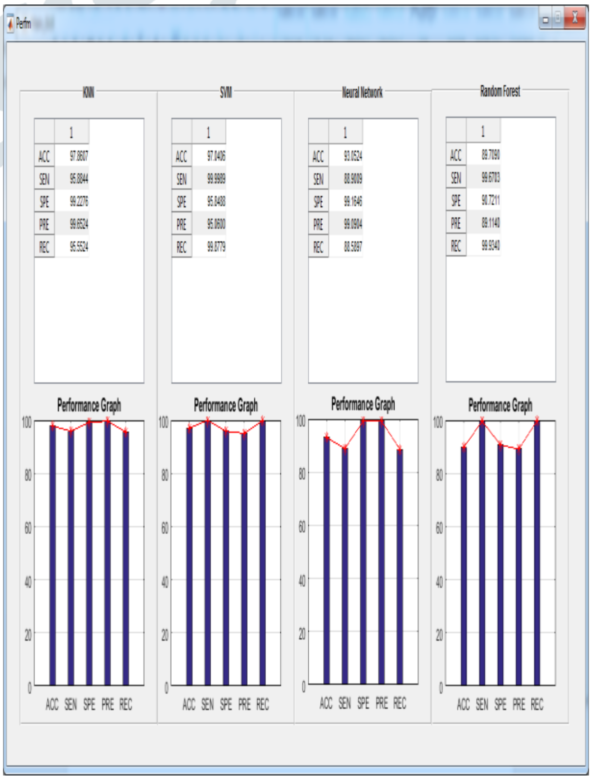


Fig. 9 RF Classifier tree



KNN

	1
ACC	97.8607
SEN	95.8844
SPE	99.2276
PRE	99.6524
REC	95.5524

SVM

	1
ACC	97.0406
SEN	99.9989
SPE	95.8488
PRE	95.0600
REC	99.8779

Neural Network

	1
ACC	93.0524
SEN	88.9009
SPE	99.1646
PRE	99.0904
REC	88.5897

Random Forest

	1
ACC	89.7090
SEN	99.6703
SPE	90.7211
PRE	89.1140
REC	99.9340

Fig. 10 classifier comparison graph

Table 2. Comparison Result

Classifier	Previous Work %	PROPOSED				
		Accuracy %	Sensitivity %	Specificity %	Precision %	Recall %
SVM	85.88	97.	99.9	95.8	95.0	99.8
KNN	83.2	97.8	95.8	99.2	99.65	95.5
NN	92.21	93.0	88.9	99.1	99.09	88.0
RF	85.88 %	89.7	99.6	90.7	89.11	99.9

IV CONCLUSION

A novel ECG beat classification algorithms are proposed and the signals are taken from the data base. Provide a brief survey on ECG classification. The examination of the ECG has been comprehensively used for diagnosing many cardiac diseases. Various techniques and transformations have been proposed earlier in literature for ECG signal. This proposed provides an over view of Noise removal, Waveform detection and classification of the Heart rate. This also revealed a comparative table evaluating the performance of different algorithms that were proposed earlier for ECG signal. And also provide the problem of the existing work and gives the direction for this also. We noticed that the most of the work for the removal of noise they used combination of filters. Most of the uses QRS complex for heart rate classification the medical profiles twenty attributes are extracted such as age, blood pressure and blood sugar etc. to predict the likelihood of patient getting heart diseases. These attributes are fed in to SVM, Random forest, KNN, and ANN classification Algorithms in which SVM gave the best result with the highest accuracy. Valid performance is achieved using SVM algorithm in diagnosing heart diseases and can be further improved by increasing the number of attributes.

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