© May 2018 | IJIRT | Volume 4 Issue 12 | ISSN: 2349-6002

Classifier Based Detection of Myocardial Infarction and Atrial Fibrillation on ECG Signals

Dhanya V K[1], Chinchu S[2]

[1]*M .Tech student, Sree Buddha College of Engineering, Elavumthitta, Kerala, India*

[2]*Assistant Professor, Department of Electronics and Communication Engineering, Sree Buddha College of Engineering, Elavumthitta, Kerala, India*

***Abstract*- Myocardial Infarction (MI) and Atrial Fibrillation (AF) are serious heart diseases. The number of patients related to the heart failure due to MI and AF is increasing day by day. Early detection of MI and AF may reduce the risk of death due to the heart failure. In this, a novel technique is proposed for the detection of Atrial fibrillation and Myocardial infarction from electrocardiogram (ECG). In myocardial infarction inversion of T-wave, changes occurring on ST elevation, hypercute T-waves or pathological Q-wave are the pathological characteristics seen in the ECG signals. Wavelet decomposition of the ECG signals segments the components at different sub bands for feature extraction. In this work, entropy and covariance values are used for diagnostic features. Probabilistic Neural Network (PNN) is used as a classifier to detect the MI. In atrial fibrillation, the irregularity in the R-R intervals and the absence of P-wave are the characteristics seen in ECG signals. For the detection of AF use the algorithm that follows the parametric statistic such as RMSSD, SE, and non-parametric statistic is TPR. Then check the result of RMSSD, TPR and SE of every beat, whether it crosses the threshold level or not. If all these parameters will cross the threshold level then the beat affected by AF. The accuracy, the sensitivity and the specificity values higher compared to other methods.**

***Index Terms*- AF, MI, Probabilistic neural network classifier, RMSSD,SE,TPR.**

I. INTRODUCTION

Heart is the most important and imperative organ of human body. Major causes of threat to life are the diseases associated with heart. According to World Health Organization (WHO) CVD is the major disease, which cause many people to die every year. 9.4 million deaths occur in each year, in this 45% deaths occur due to the coronary heart disease. Myocardial Infarction (MI) and Atrial Fibrillation (AF) are two critical and common heart diseases[5]. MI is defined as the shortage of blood flow to the location of heart which will cause damage to the heart muscles on that area. AF is the uncoordinated atrial activity due to the structural changes and disrupted electrical pathways in the heart. If these diseases are not detected in time, the activity and the structure of the heart gets deteriorated quickly. An estimated 0.9 million Americans experience different kinds of MI or AF in each year. So, if the MI and AF is detected early then it could reduce the cost of treatment, rate of hospitalization and other risk factor associating with it. With the help of ECG, the presence of MI and AF can be detected.

The early detection gives the information about heart abnormalities and increase life of human. ECG signal is mainly used to measure the regularity and irregularity of beat, rate of heartbeats also it measure the size and position of chambers. ECG signal is mainly into two phases, that is depolarization and repolarization of the heart muscle fibers. These two phase consist of P-waves, QRS-complexes and T-waves and this will provided the fundamental information about the electrical activities of the heart. ECG signal is analyzed based on the accurate and the reliable detection of the QRS complex, also the T and P waves in the ECG. During ECG signal analysis, QRS complex detection is the most important task. A more detailed examination of ECG signal is possible once the QRS complex have been detected and it also including ST segment and the heart rate occurred.

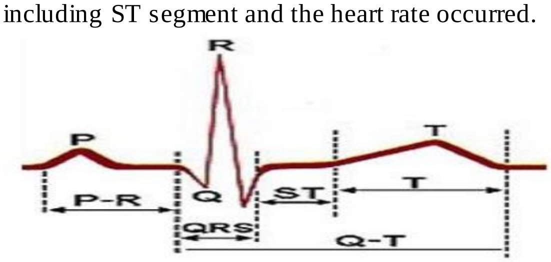

Fig.1. Normal ECG signal with PQRST peaks.

The ECG wave with lead visualize the heart at a unique angle, it helps to localized a abnormal condition occur in a heartbeat signal. With the help of ECG signal, the presence of MI and AF can be detected. The myocardial infarction is the blockage of one of the coronary arteries present in the human heart. These are the different conditions which alters covariance structure of the corresponding matrices at different scales[3]. MI detection methods are, detect ST-segment Elevation, time-domain method analysis, the wavelet-transform based method to extract on ECG signal features and the other method is neural network method.

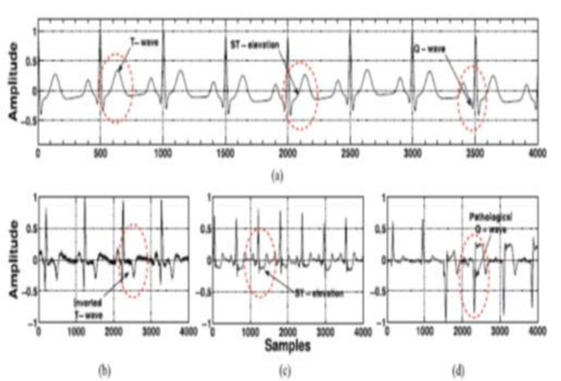

Fig.2. (a) ECG signal with abnormality, (b,c,d) Myocardial infracted wave with its abnormality detected wave

During AF, the heart rate become irregular becasuse of irregular electrical discharges is conducted from the atrium into the and, usually it will be rapidly beating and also the electrical Atrial Activity (AA) is disorganized[1]. Both of them can be easily detected by the analysis of an ECG signal. So for this, noticing the absence of the P-wave and irregular R-R intervals from the ECG signals. So, there are basically two methods for the detection of AF from the ECG signal. They are the RR Irregularity (RRI) and the AA. Any one of the two methods can be followed to detect the AF. The combination of the RR Irregularity and the AA can also be used to get enhanced detection performance. The RR irregularity is the most common method and very frequently used. This method is much easier because the R wave is the most prominent characteristics in the ECG signal, so it is relatively easy to detect. This paper, only consider the RR Irregularity to detect the AF from an ECG signal.

Fig.3. AF detected ECG signal

This paper is organized as follows. A brief description on materials and methods based on proposed framework is given in section II. In section III, obtained results are analyzed and consequent issues are discussed. Finally conclusions are described in section IV.

II.MATERIALS AND METHODS

A.Database

In this paper need to import ECG data for analysis for this use the Intracardiac Atrial Fibrillation database. This database consists of endocardial recordings, which is taken from the right atria of 8 patients in atrial fibrillation or flutter. A decapolar catheter is fixed in four separate regions of the human heart with 2-5-2mm spacing. The 5 bipolar signals were recorded along with 3 surface ECG leads from each region. Data was digitized at 1kHz. A set of four records for each of the eight patients is included in the database. The name of each record identifies each patient (iaf1, iaf2, ..., iaf8) and their placement of the catheter (svc, ivc, tva, afw). Each record consist of eight signals. Each of them is sampled at 1 kHz with 14-bit resolution; then the signal amplitudes are uncalibrated. The .qrs annotation files were produced using sqrs, and it have not been corrected.

B.Proposed algorithm

The proposed algorithm work-flows are described as:

Step 1: Import original ECG signal from Physionet

Step 2: Remove the baseline noise using fast Fourier transform.

Step 3: Remove the noisy by moving average filter

Step 4: Detect the peaks of R waves.

Step 5: Calculate the RR interval and plot the signal of RR interval against per beat.

Step 6: Calculate the RMSSD, SE and TPR for every beat from the signal of RR interval.

Step 7: Check if all the 3 parameters cross the threshold level or not. If the 3 parameters cross the threshold level then return 1 else 0, 1 represents AF and 0 represents

Step 8: Take the noise free signal from step 3 and find the discrete wavelet transform

Step 9: Extract the specific features entropy and covariance from the transformed signal

Step10 Train the neural network classifier with both Myocardial and and normal ECG signals

Step 11: Then test the input signal with the extracted features if its match with MI data means its 1 else 0

Step 12: Compare the results with the ground truth samples calculate the number of TP, TN, FP and FN.

Step 13: From the number of TP, TN, FP and FN calculate the sensitivity, specificity and accuracy.

C. Detection Methods

Atrial Fibrillation (AF) and Myocardial Infarction (MI) are two critical and common heart diseases. Cardiac arrhythmias are the serious heart related problems, AF is the important among them. AF can cause uncoordinated atrial activity due to the structural changes and disrupted electrical pathways in the heart. Recently different mathematical models and statistical models are used for early AF detection [12]. It already established that RR-intervals would be used for the detection method. The irregularity and variability is the main characteristics for AF [12]. Myocardial infarction is the main genesis of coronary artery disease (CAD), the inversion of the ST segment, QRS complex and PQ changes normally occur in a abnormal signal. Here PNN Classifier is used to detect the abnormal and normal case.

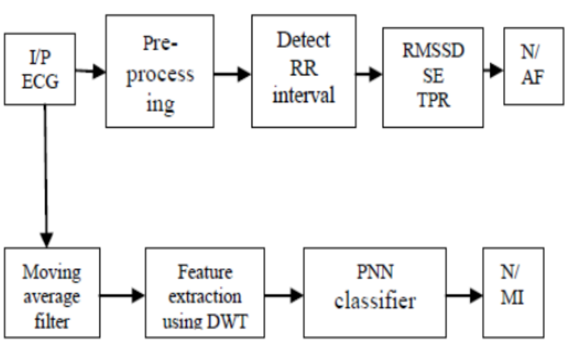

Fig.4. Block diagram of proposed system

D. AF detection method

In this paper, statistical analysis is used to distinguish between the degrees of variability in the signals. Three different statistical methods were followed throughout the thesis are root mean squares of successive differences (RMSSD), Shannon entropy (SE) and turning point ratio (TPR). RMSSD is one of the statistical parameter that measures the variability within a data set. SE is the another statistical parameter that measures the uncertainty of a random variable. TPR is a statistic that measures the random fluctuations occurred in the given data set. The algorithm that is used for this paper is based on the increased variability and complexity in the RR intervals series due to the atrial fibrillation[1]. In this proposed algorithm we consider the RR intervals, then each series of RR intervals was divided into 128 overlapping beat segment. Every set of beat segment start with 1RR interval, after the beginning of the previous set of beat segment. Then these three statistical methods used for the analysis, whether each 128 beat segment contains the characteristics of AF on not. Among the three tests RMSSD and SE are parametric test, and TPR is a non-parametric test. Here the two parametric tests were affected by distribution assumptions. So, from each 128 beat segment the shortest 8 beats and the longest 8 beats were removed. Each set of 128 beat segments was flagged as AF if all the three statistical methods determined it to be AF

Root Mean Squares of Successive Differences (RMSSD):

RMSSD is one of the statistical parameter that is used to measure the variability within a data set. It is one of the few time domain tools that is used to measure heart rate variability (HRV). As the RMSSD is a parametric test it is sensitive to the outlier. So its shortest 8 and longest 8 RR intervals is actually the sum of the squares of each difference between the consecutive RR intervals. So the expression of RMSSD that is used in our algorithm is [13],

$$\text{RMSSD}=\sqrt{\frac{1}{112-1}} * \sum_{1}^{112-1} \text{rr}_{i+1} - \text{r}_i \qquad (1)$$

For compensating with the changes occured in the premature ventricular contractions and heart rate overtime also the RMSSD was divided by the mean RR value of each segment. In this algorithm RMSSD/(mean RR) > 0.1 was selected as the threshold for AF detection.

Shannon Entropy (SE):

SE is a statistical parameter that is used for the measurement of the uncertainty of random variable.SE is also a parametric test that is sensitive to outlier. So as we do in the case of RMSSD, we have to remove the shortest 8 and longest 8 RR intervals. SE is a parameter that measures the complexity of a data set and the ability to predict future data point from past data point. The higher the value of SE represents higher uncertainty of the random variable. The lower value of SE represents lower uncertainty of the random variable. In this algorithm, it is shows that SE will be higher than the Normal Sinus Rhythm (NSR). After removing the 8 longest and 8 shortest outliers a histogram was constructed with 16 equally spaced bins using the remaining data points in each 128 beat segment. For this using 16 bins was found to provide sufficient resolution. And too many bins will results the significant distortion. The value of SE will approaches to zero if the number of bins are approaches to infinity. Then compute the count of RR interval. The probability for each bin is computed as [13],

$$\text{Probability, } p(i) = \frac{N_i}{l - N_{Outliers}} \quad (2)$$

Where, N_i = the number of beats in a particular bin

l = the segment length,

$N_{Outliers}$ = the number of outliers.

Then SE is

$$\text{Shannon entropy SE} = \sum_{i=1}^{16} p(i)\frac{\log(p(i))}{\log(\frac{1}{16})} \quad (3)$$

In this SE>0.7 as the threshold for AF detection

Turning Point Ratio (TPR):

TPR is a non-parametric statistic that is used to measure the degree of randomness in a particular time series. Turning points are the points which are greater than or less than both the succeeding and proceeding terms. TPR compares the amount of turning points in each set of data and to the maximum number of possible turning points. Each beat in RR irregularity (RRI) segment compared to its 2 nearest neighbors is designated a turning point if it is greater than or lesser than both. That statistical test that use in this algorithm is if the sequence is stationary then the RR intervals are random which corresponds to AF. And if the sequence is non-stationary then the RR intervals are non-random corresponds to normal sinus rhythm. For random data points of arbitrary length (l) the expected number of turning point is,

Generally during decision making process taking opinions from people is a common criterion.

$$\mu_{TP} = \frac{(2l-4)}{3} \quad (4)$$

Standard deviation is

$$\sigma_{TP} = \sqrt{\frac{(16l-29)}{90}} \quad (5)$$

If any data does not exhibit random behavior will have a TPR significantly greater than or less than the expected value of 0.66. In proposed algorithm, the interval which corresponds to a TPR of $\mu \pm 3.2\sigma$ was marked as AF. For the selected beat segment length of 128, $0.54<TPR<0.77$ will be marked as AF.

E.MI detection method

In myocardial infarction inversion of T-wave, changes occurring on ST elevation, hypercute T-waves or pathological Q-wave are the pathological characteristics seen in the ECG signals.. During infraction one of the above case is involved. The detection block comprises of filtering using moving average filter, feature analysis using discrete wavelet transform and a neural network classifier such as PNN classifier is used to designate the ECG signal abnormality. In the filtering part moving average filter is utilized to remove the frequency content present in the signal and it eliminate the baseline wandering signal, power line interference present in the signal. Wavelet decomposition of the ECG signals segments the components at different sub bands for feature extraction. The PNN classifier is used to classify the normal and myocardial infracted.

Moving Average Filter:

A moving average, is a type of FIR filter used for the analysis of a set of data points there by creating a set of series of averages of that different subsets of its full data set. It is also called also called rolling average filter, rolling mean filter or running average filter. A series of the numbers and its fixed size subset is given, the first element of the MAF is obtained by taking their averages of their initial fixed subset of its number series. Then these subsets is obtained by "shifting forward", that is which can eliminating the first number in the series and also including the next number that following the original subset in the series. This will obtain a new subset of numbers, which is averaged. This process is repeated throughout the data series. The obtained plot line are connected to all the (fixed) averages is the moving average. Let’s say there are N data points in an ECG signal and we create subsets of size M then our first element of Moving Average Type Filter will be the average of 1st subset containing M data points. The next subset will start from 2nd element to (M+1)th element that means it also have a size of M and again this subset will be averaged and this average will become 2nd element of filtered signal. Likewise the entire data series is extrapolated using this algorithm. At the end of the data series when only M- x data points are left (where x is an integer less than M) then x number of data points having zero value will be included by default to complete the subset of M data points. Due to this, there will be some error in the filtered data series but it will be negligible since x<<<<< n.

Feature Extraction:

The ECG signals can be decomposed into a time-frequency representation, for this using Discrete Wavelet Transform (DWT). In recent years, DWT technique mainly used for signal processing tasks. The main dvantage of a DWT is that it will provide a good time resolution. Good resolution at high frequency and good frequency resolution at low frequency. DWT has great frequencyand time localization ability, so it can reveals the local characteristics of the given input signal.

Discrete Wavelet Transform is also defined as the decomposition by wavelet filter banks. Because the DWT can uses two filters, one is low pass filter (LPF) and another one is a high pass filter (HPF) and this will decomposes signal in different scales. The output coefficients of a LPF is called as approximations and the output coefficients of a HPF is called as details. The approximations of the signal defines its identity and details only imparts nuance.

In this work the noise is filtered using moving average filter. We decompose the ECG signal into 4 levels by using DWT and obtain the approximation (A4) and detail (D4) signals at level 4 as shown below

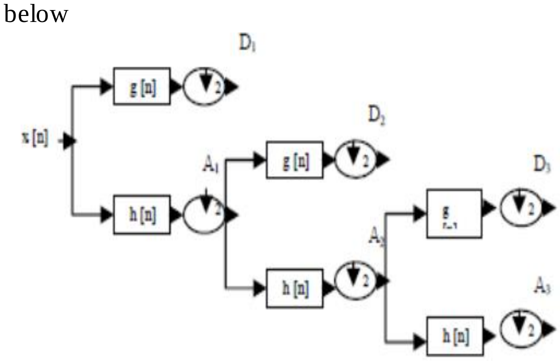

Fig.5. Decomposition of DWT

Each stage of DWT consists of 2 digital filters and two downsamplers by 2 for obtaining the digitized signal. The first filter will be the discrete mother wavelet, which is a high-pass filter, and the second one is a low-pass filter. The outputs of its first high pass filters and its low-pass filters provide the detailed, D1 and the approximation, A1. The first approximation coefficient,A1 is again decomposed and this process will continued. The decomposition of these ECG signal in different frequency bands can be obtained by the successive highpass and lowpass filtering of the time domain signal. Wavelet coefficients obtained from all ECG leads with J level wavelet decomposition are arranged in J + 1 subband matrices.

The diagnostic information of an ECG signal are distributed in different wavelet subbands based upon their bandwidth or frequency content. It shows that the lower frequency subbands contain most of the diagnostically significant information of the ECG signal. If all 12-standard ECG leads are decomposed with same mother wavelet and decomposition levels, it results in similar subbands with equal number of coefficients. Then extract the specific features entropy and covariance from the transformed signals.

Probabilistic Neural Networks Classifier:

A probabilistic neural network (PNN) classifier is a neural network based on feed forward probability. A probabilistic neural network is good for classification problems. Figure 6 shows the entire architecture of the PNN classifier that recognizes two distinct output classes, but also it can be extended to many number K of classes[10]. The input layer contains N number of nodes: one is for each of the N input features forming the feature vector. When the input is feeded into the classifier, the first layer will be calculate the distance between input vectors and training input vectors, and it will produce a vector which shows the closeness between the input data points and the training vector points These are called the fan-out nodes because each input feature node branches to all nodes in the hidden (pattern) layer so that each hidden node in the structure receives the complete input feature vector for the entire data. The hidden nodes are connected to one node called group nodes: one group is assigned for each of the K classes as shown in the figure.

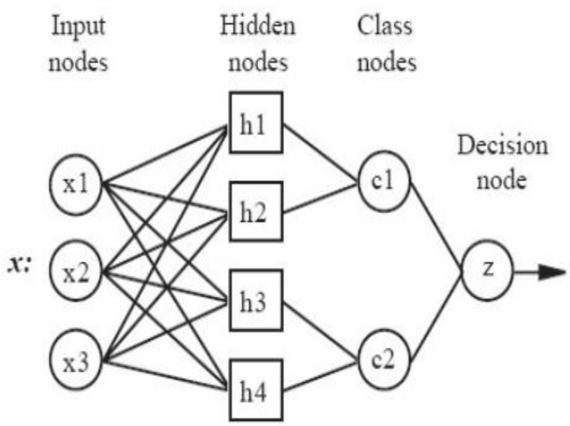

Fig.6. Architecture of Probabilistic Neural Network

Each node in a single group of hidden layer is correspond to number of observations that are taken for training. These nodes represents a Gaussian function which centered on corresponding feature vector in the kth class. There are k number of groups available in the hidden layer. Output layer will pick the maximum of the probabilities on the second layer, and it will also provide a one for that class and a zero for the other classes[11].

F. Performance Criteria

In this paper, three performance criteria used such as sensitivity, specificity, accuracy to verify the results of proposed algorithm. To test those performance criteria, the Intracardiac Atrial Fibrillation database is used from where we take the ECG signal. Beside the main ECG signal the database also contains annotation files. Those annotation files contain the information of each beat, whether the beat is normal or abnormal signal. Then that information is compared with simulation results of proposed work. The result of any segment is counted as the result of the first beat of that segment. After the comparison, we separated the beats into four categories. They are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP beats are those beats that annotated as 1 in both the database and in the result. TN beats are those beats that annotated as 0 in the database and also in the result. FP beats are those beats that is annotated as 0 in the database but annotated as 1 in the result. FN beats are those beats that is annotated as 1 in the database but annotated as 0 in the result. The number of TP, TN, FP, and FN are used to calculate the three performance criteria of the algorithm, like:

$$\text{Sensitivity} = \frac{\text{Number of true positive assessment}}{\text{Number of all positive assessment}} = \frac{(TP)}{(TP+FN)} \tag{6}$$

$$\text{Specificity} = \frac{\text{Number of true negative assessment}}{\text{Number of all negative assessment}} = \frac{(TN)}{(TN+FP)} \tag{7}$$

$$\text{Accuracy} = \frac{\text{Number of corrected assessment}}{\text{Number of all assessment}} = \frac{(TN+TP)}{(TN+TP+FN+FP)} \tag{8}$$

III.SIMULATION RESULTS

At first we have to take an input ECG signal for analysis in MATLAB environment. As mentioned before, we import ECG signals from the intracardiac Atrial Fibrillation database. To reach our main objective we have to detect the R-peaks of the signal. The signals that are stored in the intracardiac Atrial Fibrillation database usually have some baseline noise that shifts the baseline of the ECG signals. So, to define the threshold level for the R peak for this remove the noise. Then detecting the R wave peaks. After finding the R peaks we have to calculate the difference between each successive R peaks. Then we plot the RR interval against each beat, After getting the signal of RR intervals we calculate RMSSD, SE and TPR for every single beat. On the next section removing the noise from the imported ECG using moving average filter. Then the given features from ECG signal is extracted using DWT. After that classifying the signal use probabilistic neural network classifier. PNN classifier output will get the maximum of the probabilities on its second layer, and the output provides one for that MI and zero for the Normal condition.

On the first case, take input from the intracardiac database file #1 16. After that check whether it is affected by MI and AF. The final output shows that the given signal is affected by myocardial infarction and atrial fibrillation. The value of RMSSD,SE and TPR cross the threshold level so the signal is affected by AF. Also classifier output shows signal is affected by MI.

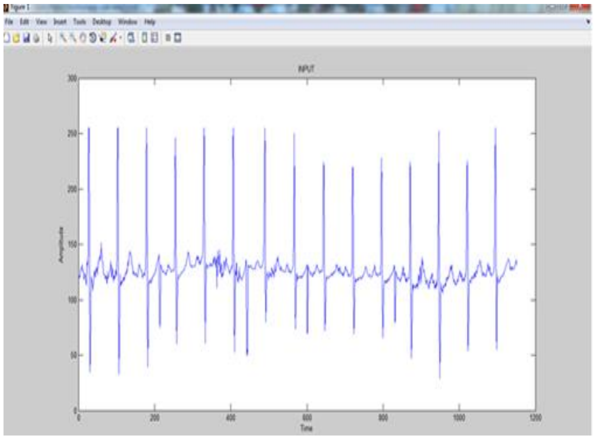

Fig.7. Time domain representation of original ECG signal(File#116)

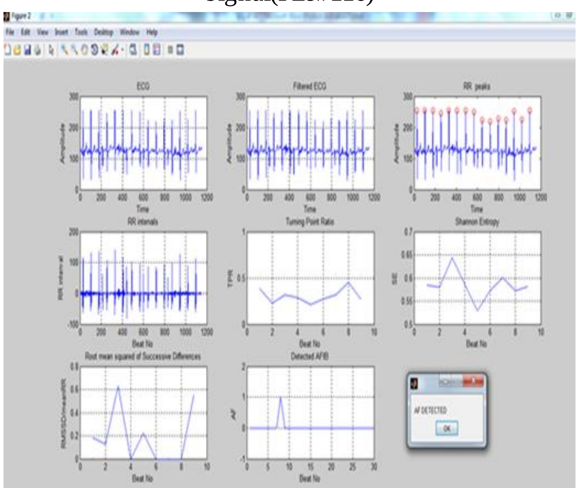

Fig.8. AF detection result(File#116)

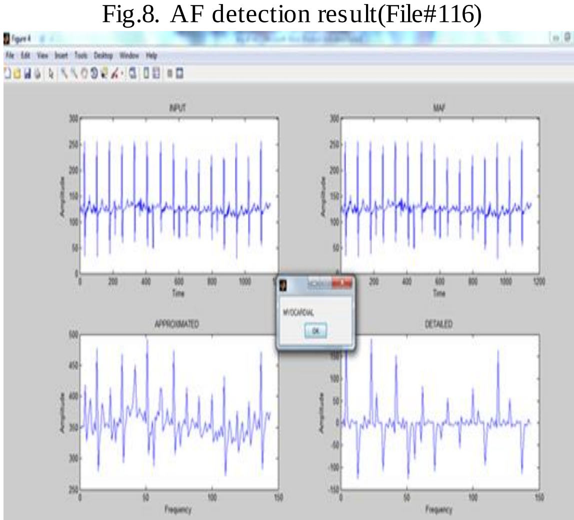

Fig.9. MI detection result(File#116)

On the second case we have to import signal file#104 from the given database and the conditions for diseases. The final for this case shows that the given ECG signal is affected by atrial fibrillation but there no chance to cause myocardial infarction.

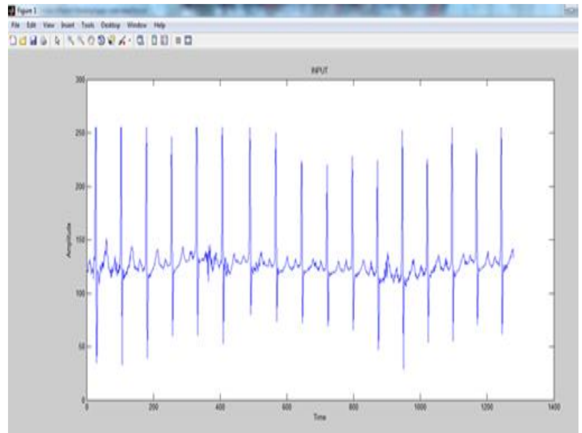

Fig. 10. Time domain representation of original ECG signal(file#104)

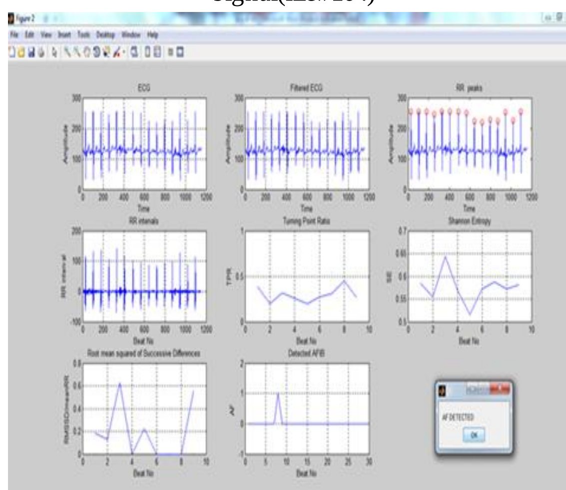

Fig.11. AF detection result(File#104)

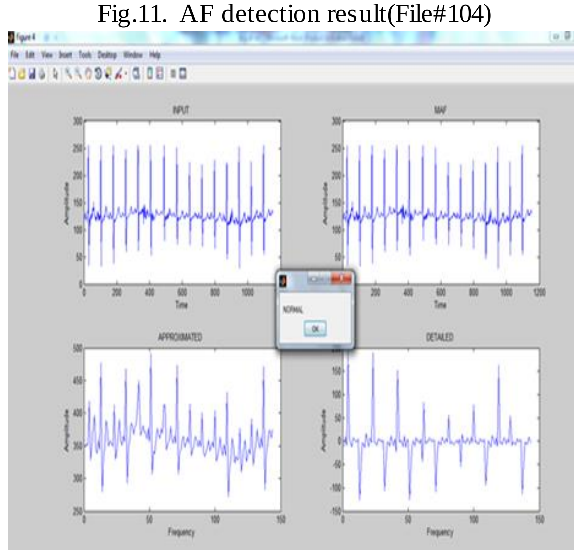

Fig.12.MI detection result(File#104)

On the third case we take signal from the database and check the conditions for MI and AF. The final output show that the given ECG signal is affected by myocardial infarction but not the affected by AF

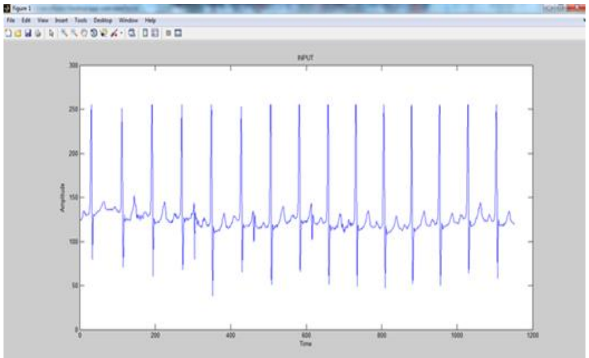

Fig. 13. Time domain representation of original ECG signal(File#113)

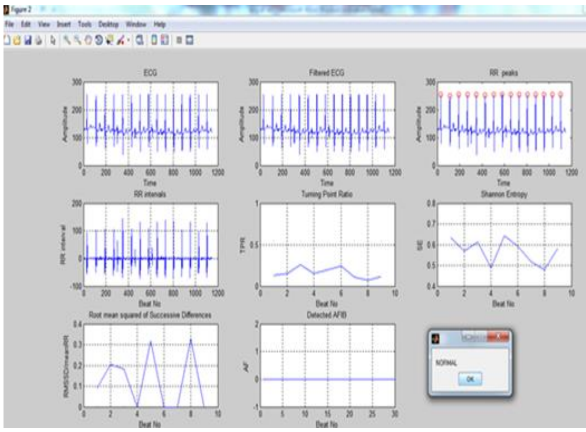

Fig.14. AF detection result(File#113)

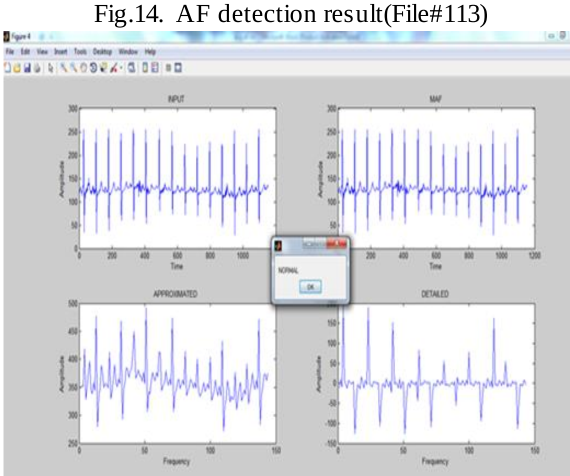

Fig.15.MI detection result(File#113)

To evaluate the performance of proposed algorithm, we calculate several performance criteria, such as, sensitivity, specificity and accuracy. To calculate those factors, at first, we have to calculate TP, TN, FP and FN. TP beats are those in thr algorithm and database. Then we can easily calculate the sensitivity, specificity and accuracy of the algorithm. Sensitivity is the ability of the algorithm to detect the AF and MI beats. Specificity is defined as the ability of the algorithm to detect Normal beat. Accuracy is the overall detection ability of algorithm. In most of the cases proposed algorithm has a very high sensitivity, specificity and accuracy.

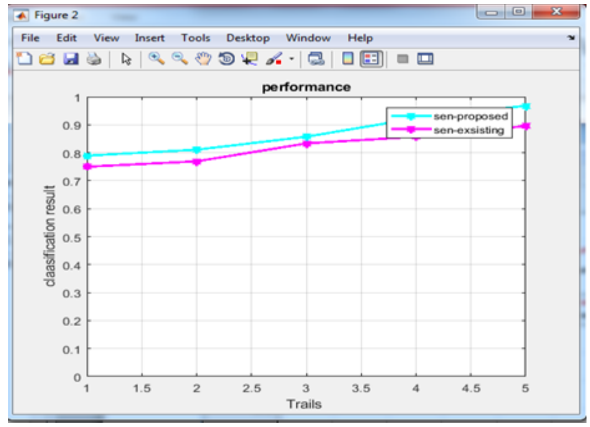

Fig.16. Sensitivity

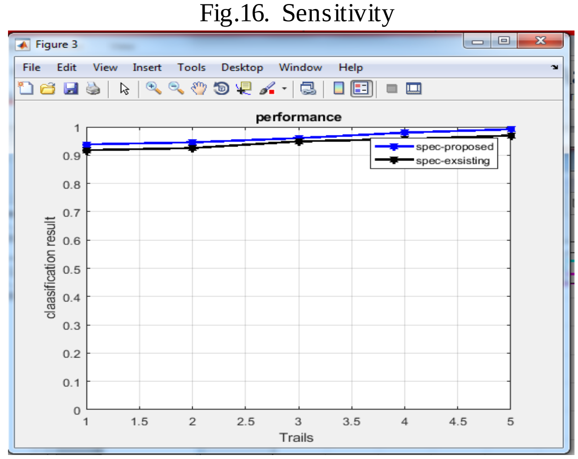

Fig. 17.:Specificity

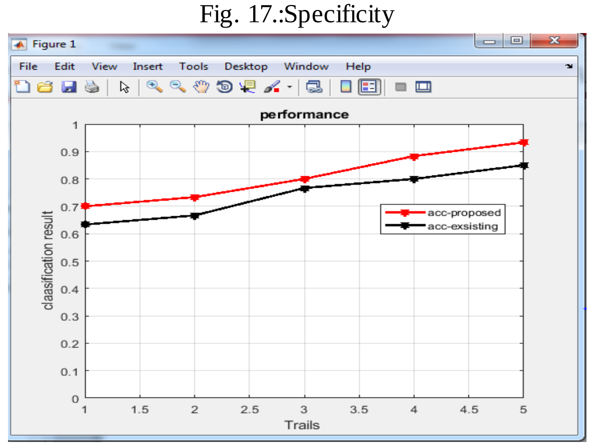

Fig. 18.Accuracy

IV.CONCLUSION

A novel approach is proposed for detection of MI and AF. The algorithm that is used in this paper is used to detect the MI and AF with high degree of accuracy.

Comparing with other algorithms that are commonly used for the MI and AF detection, it is seen that, this algorithm has higher degree in both sensitivity and specificity. The intracardiac Atrial Fibrillation database is used to import ECG data for the analysis purposes. RR interval of the ECG signal is calculated for AF detection. We are used the algorithm that mainly follows statistical method for detection of AF. Here parametric statistic such as RMSSD and SE, and non-parametric statistic, TPR are used for the analysis. The result of RMSSD, SE and TPR of each beat was checked whether it crosses the given threshold level or not. If all the three parameters cross the threshold level then the beat flagged as AF. And in the case of MI moving average filter is used to remove noise from the signal. Wavelet decomposition of an ECG signals can be grossly segments the important components at different sub bands and extract the entropy and covariance value. PNN classifier detected the MI signals. It shows excellent result when compared with the annotations of the database, and then the sensitivity, specificity and accuracy is determined.

ACKNOWLEDGEMENT

I would like to express profound to my guide Ms.Chinchu.S for his encouragement and for providing all facilities for my work. I would like to extend my gratitude to our Head of the Department Ms. Sangeeta T. R and for providing the necessary guidance and serious advice for my work.

REFERENCES

[1] Fatema Tuj Johura, Sheikh Md. Rabiul Islam, Md. Maniruzzaman, Mahdi Hasan "ECG Signal for Atrial Fibrillation Detection" February 16-18, 2017

[2] C. Brüser, J. Diesel, M.D.H. Zink, S. Winter, P. Schauerte and S. Leonhardt, "Automatic Detection of Atrial Fibrillation in Cardiac Vibration Signals," IEEE J. Biomed. Health Informatics, vol. 17, no. 1, pp. 162-171, 2013

[3] L. N. Sharma, R. K. Tripathy and S. Dandapat, "Multiscale energy and eigenspace approach to Detection and Localization of Myocardial Infarction" IEEE transactions on biomedical engineering, vol.xx, no.xx, 2015

[4] N. Larburu, T Lopetegi and I Romero, "Comparative Study of Algorithms for Atrial Fibrillation Detection," Computing in Cardiology 2011, Hangzhon: IEEE, vol. l. pp. 265-268.

[5] Saleha Khatun and Bashir I. Morshed,"Detection of Myocardial Infarction and Arrhythmia from Single-Lead ECG Data using Bagging Trees Classifier", IEEE 2017

[6] Xujia Zhang, "Neural Network-Based classification of single phase distribution transformer fault data", 2006.

[7] G. Moody and R. Mark, "A New Method for Detecting Atrial Fibrillation Using RR Intervals," Computers in Cardiology, Aachen: IEEE Computer Society Press, vol. 10, pp. 227–230, 1983.

[8] De Chazal, P. and et al, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," Biomedical Engineering, IEEE Transactions on, vol. 51, no. 7, pp. 1196–1206, 2004.

[9] S. Cerutti, L.T. Mainardi, A. Porta, A.M. Bianchi, "Analysis of the dynamics of RR interval series for the detection of atrial fibrillation episodes," Computers in Cardiology, vol.24, pp. 77-80, 1997.

[10] Reddy, M.R.S. and et al, "Neural network versus electrocardiographer and conventional computer criteria in diagnosing anterior infarct from the ECG," in Computers in Cardiology 1992, Proceedings of, oct 1992, pp. 667 –670.

[11] Bo Heden and et al, "Acute myocardial infarction detected in the 12-lead ECG by artificial neural networks," in Circulation, 1997, pp. 1798–1802.

[12] S. Hargittai "Is it Possible to Detect Atrial Fibrillation by Simply using RR Intervals?," Computers in Cardiology, vol. 41, pp. 897-900, 2014.