A Modular Approach to Finer Classification of ECG Signals

Neethu S. Ravi[1], Prof. Paul Thomas[2]

PG Student [Signal Processing], Dept. of ECE, Mar Baselios College of Engineering and Technology, Kerala, India [1]

Professor [Dean (PG)], Dept. of ECE, Mar Baselios College of Engineering and Technology, Kerala, India [2]

ABSTRACT: ECG is electrocardiogram which determines the electrical activity of human heart. Cardiologists visually analyse lengthy ECG records to arrive at appropriate conclusion regarding diagnosis. But this a time consuming process and at the same time we cannot rule out the possibility of missing some minutiae details of ECG. Thus automated analysis of ECG signals plays an important role for detecting different cardiac arrhythmia. A modular approach for classification of ECG signals using a classifier module consisting of ANN and Fuzzy Logic is specified in this paper. The work includes two levels for classification. First level classification includes detection of common cardiac disorders into four classes which includes Normal Sinus Rhythm (NSR), Atrial Arrhythmias (AA), Ventricular Arrhythmias (VA) and Myocardial Infarction (MI). Second level classification includes categorization of classes in first level into more specific disorders. Atrial Arrhythmias are further classified into Atrial Fibrillation (AF) and Supraventricular Arrhythmia (SVA). Ventricular Arrhythmias are further classified into Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VT) and Maligant Ventricular Ectopy (MVE). ECG signals used for this work are taken from the standard MIT-BIH database, Physionet database and CU database. A novel method is used to findout the signal length mathematically. Temporal and spectral features are extracted from the ECG signals. These fundamental features are used in the classification section, where the classifier module classifies the signal into its corresponding classes. This work achieved a classification accuracy of about 96.7%.

KEYWORDS: ECG, Atrial Arrhythmias, Ventricular Arrhythmias, NSR, MI, PVC, VT, AF, SVA, LTAF, MVE, ANN, Fuzzy Logic.

I.INTRODUCTION

There are different types of cardiac disorders prevailing in our society. Some of them are fatal and an early diagnosis can save lives. ECG is a commonly used technique for monitoring electrical activities of human heart. It is a non stationary quasi periodic signal which shows a series of P, Q, R, S and T waves[1]. Cardiologists visually analyze lengthy ECG records to arrive at appropriate conclusions regarding diagnosis. But this a time consuming process and at the same time we cannot rule out the possibility of missing some minutiae details of ECG. Thus automated analysis of ECG signals plays an important role for detecting different cardiac arrhythmia [2]. Different methods for ECG signal analysis are reported so far. Those methods include Principal Component Analysis (PCA), Wavelet Transform (WT), Fourier Transform (FT), Independent Component Analysis (ICA), Artificial Neural Network and Support Vector Machine (SVM) [1],[2]. Rajendra Acharya et. al. proposed a method for ECG beats classification using PCA, Linear Discriminant Analysis (LDA) and ICA [1]. Rahime Ceylan and Yuksel Ozbay proposed another method for ECG arrhythmia classification using Fuzzy C-means Clustering (FCM), PCA, and WT technique[2]. Amit Gothiwarekar et. al. proposed Wavelet Decomposition to extract feature vectors from ECG signals [3]. Felipe Alinso Atienza et. al. proposed a method for classification using SVM classifier by using temporal, spectral and complexity features extracted from ECG signals [4]. The method proposed by Emran M Abu et. al. uses temporal features for classification of ECG signals [5]. The method proposed by Karthika V. S. includes extraction of temporal, spectral, statistical and complexity features from ECG signals. These features are fed to ANN for classification [6]. The method proposed by Sambhu D. and Umesh A. C includes classification of ECG signals using ANN and SVM by extracting temporal, spectral and statistical features [7]. The method proposed by Vessela Tzventanova Krasteva and Irena Ilieva Jekova includes spectral analysis of ECG signals [8]. Roger Dzwonczyk et. al. proposed a method to extract median frequency from ECG signals and it is considered as a fundamental feature for determining cardiac arrest duration [9]. Anton Amann et. al. proposed a method for classification of ECG signals by extracting features like Spectral Moment, VF

leakage and Spectral Band Amplitude [10]. JCTB Moraes et. al. proposed a method for classification of ECG signals by using Leakage Measure as a feature [11]. Yun Chi The et. al. proposed a method for classification of ECG signals using Fuzzy logic [12].

Different methods reported in the literature survey include only a small set of diverse characteristic features of ECG signals. But this work uses a modular approach for classification of ECG signals using a classifier module consisting of ANN and Fuzzy Logic and the extracted temporal and spectral [3] features from ECG signals which rule out the hidden information from ECG signals and its diverse characteristics. Signals taken from CU database, MIT-BIH database and Physionet database are used for this automated analysis. Fundamental features extracted from the ECG signals are used for classifying the signal into multiple cardiac disorders. The work uses one set of normal ECG signals and 7 sets of diseased ECG signals. In this modular approach, classifier module I in first level classification categories the signal into four classes. Second level classification categories the first level classes like Atrial Arrhythmias and Ventricular Arrhythmias into 2 and 3 subgroups by using classifier modules II and III respectively. Extracted features are given as input to ANN for training and to the trained ANN architecture fundamental feature extracted from the test signals are given as input. Output obtained from ANN is fed to fuzzy inference system to obtain fuzzified output and classification of ECG signal is done based on this fuzzy output.

II.MATERIALS

Data collection plays an important role in this work. Signals collected from CU database, MIT-BIH database and Physionet database are used in this work. The collected ECG signals include 124 signals belonging to MI with a sampling frequency of 1000Hz, 12 signals belonging to NSR with a sampling frequency of 128Hz, 47 signals belonging to Premature Ventricular Contraction (PVC) with a sampling frequency of 360Hz, 12 signals belonging to Maligant Ventricular Ectopy (MVE) with a sampling frequency of 250Hz , 17 signals belonging to Ventricular Tachycardia (VT) with a sampling frequency of 250Hz, 50 signals belonging to Supraventricular Arrhythmias (SVA) with a sampling frequency of 128Hz, 60 signals belonging to Long Term Atrial Fibrillation (LTAF) with a sampling frequency of 128Hz and 12 signals belonging to Atrial Fibrillation (AF) with a sampling frequency of 250Hz. Database also consists of other details regarding the signals. The work uses designing tools like MATLAB, Neural Network toolbox (nnstart), Fuzzy Inference System (FIS) toolbox and Guide (GUI) toolbox. Programming tool used to implement this work is MATLAB and nnstart is used for classification and FIS is used to improve the classification. The final work is made user friendly with GUI.

III.ECG SIGNAL LENGTH SELECTION

Selection of signal length plays a very important role for determining the quality of features during ECG signal analysis. From various literature surveys it is seen that for ECG signal analysis the commonly used signal length is 3seconds and there is no information regarding the choice of signal length is available. So this work used a novel method to find out the signal length mathematically. The long train Normal ECG signal is broken down into fifty small segments of a common duration starting with 1 second. All features are extracted and the process is repeated for different time periods of the signal. The extracted features are analyzed for best consistency. Duration of the signal is increased in steps of 1 seconds and feature extractions repeated. It is seen that a signal segment of 10seconds duration is a good fit for the different features and across different diseases.

IV. FEATURE EXTRACTION METHODS

This work includes the extraction of temporal and spectral features from the ECG signals during the analysis. Temporal features include Mean Absolute Value (MAV) and Threshold Crossing Count (TCC). Spectral features include Wavelet Mean (WM), Wavelet Standard deviation (WSD), Skewness (SKW), and Kurtosis (KURT), Peak frequency (PF), Mean frequency (MF),Spectral moment (SM), Spectral band amplitude (SBA) and VF-leakage (VFL).
1. Threshold Crossing Count (TCC)
TCC [4] is the number of times the signal crosses a pre-defined threshold value. Threshold is set as 80% of the maximum amplitude of the ECG signal.

2. Mean Absolute Value (MAV)
MAV [4],[5] is the mean of absolute value of ECG samples calculated using the formula,

$$MAV = \frac{1}{L} \sum_{i=1}^{L} x_i \qquad\qquad (1)$$

where, x is the absolute amplitude values of the signal, Lis the signal length.

3. Wavelet Mean (WM)

4-level (Daub4) wavelet decomposition is applied on to the ECG signal and mean 4th level approximation coefficient is calculated by using the formula [6],[7],

$$WM = \frac{1}{L}\sum_{i=1}^{L}(x_i) \tag{2}$$

where, L is the length of 4th level approximation coefficients, x is the approximation coefficients.

4. Wavelet Standard Deviation (WSD)

4-level (Daub4) wavelet decomposition is applied on to the ECG signal and standard deviation 4th level approximation coefficient is calculated by using the formula [6],[7],

$$WSD = \left(\frac{1}{L}\sum_{i=1}^{L}(x_i - m)^2\right)^{1/2} \tag{3}$$

where, L is the length of 4th level approximation coefficients , x_i is the wavelet coefficient and m wavelet coefficients mean.

5. Skewness (SKW)

Skewness is the measure of asymmetry of the signal and is calculated by applying 4-level (Daub4) wavelet decomposition on to the ECG signal [6],[7]. Skewness of the 4th level approximation coefficient is calculated using the formula,

$$SKW = \frac{1}{L}\frac{\sum_{i=1}^{L}(x_i - m)^3}{(SD)^3} \tag{4}$$

where, L is the length of 4th level approximation coefficient SD is the standard deviation, x is the approximation coefficient, m is the mean of the approximation coefficients.

6. Kurtosis (KURT)

Kurtosis is used to check whether the samples are flat or peaked with respect to normal distribution [6],[7]. KURT is calculated by applying 4-level (Daub4) wavelet decomposition on to the ECG signal by using the formula,

$$KURT = \frac{1}{L}\frac{\sum_{i=1}^{L}(x_i - m)^4}{(SD)^4} \tag{5}$$

where, L is the length of 4th level approximation coefficient, SD is the standard deviation, x is the approximation coefficient, m is the mean of approximation coefficient.

7. Peak Frequency (PF)

Frequency corresponding to the maximum amplitude in the spectral domain is the Peak Frequency [8]. 2-level wavelet decomposition is applied on to the ECG signal and an N-point FFT is done on to the 2nd level approximation coefficients .PF is computed from the obtained spectrum.

$$PF = \max(x_i), \quad 1 \le i \le L \tag{6}$$

where, x_i is the spectral amplitude at the FFT point i.

8. Mean Frequency (MF)

Central frequency of power spectrum is known as Mean Frequency [9]. ECG signal is subjected to an N - point FFT is to obtain FFT sample values and frequency in spectral domain. Power is calculated by taking square of FFT samples values. MF is calculated by using the formula,

$$MF = \frac{\sum_{i=1}^{L}(f_{pi} * p_i)}{\sum_{i=1}^{L} p_i} \tag{7}$$

where p_i is the spectral power at the frequency f_{pi}.

9. Spectral Moment (SM)

FFT is applied on to the ECG signal to calculate SM [10] of the using the formula,

$$SM = \frac{\sum_{j=1}^{L}(x_j * f_j)}{\sum_{j=}^{L}(x_j)} \tag{8}$$

where, x is the FFT sample values, f is the frequency corresponding to each sample value and L is the length of the signal.

10. Spectral Band Amplitude (SBA)

ECG signal is applied with FFT to obtain FFT sample values and frequency in spectral domain. SBA [10] is obtained by taking the ratio of the sum of FFT sample value between 0.7f and 1.4f and the sum of FFT sample values between 0.5Hz and minimum of 20f and 100Hz where f is the peak frequency.

11. VF Leakage (VFL)

ECG signal is applied with FFT to obtain FFT sample values and VFL is calculated using the formula [10],[11]

$$VFL = \frac{\sum_{i=T/2}^{L} |(x_i + x_{i-\frac{T}{2}})|}{\sum_{i=T/2}^{L} (|x_i| + |x_{i-\frac{T}{2}}|)} \qquad (9)$$

where, T/2 is the half time period of the signal, L is the length of ECG signal and x is the amplitude of the signal and T=f/fs where, fs is the sampling frequency and f is the amplitude corresponding to the highest amplitude in spectral domain.

By using above methods temporal and spectral features from ECG signals are extracted and corresponding feature vectors are obtained. Features from 72 signals are used as training set. For classification of Atrial arrhythmias and Ventricular arrhythmias two neural network architectures are trained using 36 samples respectively.

V. CLASSIFICATION METHOD

Classifier module consisting of ANN and Fuzzy is used for the classification of multiple cardiac disorders. ANN is used to model biological neurons using mathematical operations [6],[7]. Neurons are the main processing elements of ANN which functions similar to that of biological neurons. ANN is trained using supervised learning rule. By proper and correct selection of features during training can reduce the error occurring at the ANN output and makes ANN better than other classifiers. ANN consists of three layers - input layer, hidden layer and output layer. Input layer is the layer through which inputs are given to ANN. Number of input neurons in the input layer is equal to the number of features that we are giving as input to ANN. Hidden layer is the layer which all computations are carried out and has no contact with the outside world. Output layer is used to obtain the output and the number of output neurons in output layer is equal to the number of classes in classification. Selection of neural network is done by trial and error method. ECG signal classification is done using pattern recognition network and linear vector quantisation. A total of 110 signals are taken for this selection purpose. 50 signals are used for training the network. Out of 110 signals 105 signals are correctly detected by pattern recognition network. Only 80 signals out of 110 signals are correctly detected by linear vector quantisation network. Based on these obtained results an inference is made that, pattern recognition neural network gives better classification accuracy than linear vector quantisation network. This work uses pattern recognition network for classifying multiple cardiac disorders.

For First Level classification, classifier module-I consisting of ANN-I and FIS-I is used. 72 samples are used as the training set for training ANN-I. 11 features from each sample are given as input (number of input neurons=11) to the input layer of ANN-I. 11 features given as input to ANN are TCC, MAV, WM, WSD, SKEW, KURT, PF, MF, SM, SBA and VFL. The number of hidden neurons in hidden layer is taken as 20. The output layer of ANN-1 consists of 4 output neurons since first level classification classifies the ECG signal into 4 classes. Once the neural network is trained, a neural architecture is obtained and using this architecture the classification of test signal is achieved. Feature vector from the test signal is given as input to the obtained architecture for ANN-I and corresponding ANN output is obtained. Obtained ANN output is given to Fuzzy Inference System [12]. Fuzzy logic is based on degrees of truth and its value ranges from 0 to 1. In fuzzy systems, with the help of membership function the range of input from ANN and output from fuzzy can be specified. It also consists of rule set which are used to specify the relation between inputs. Different membership functions used in fuzzy are sigmoid, trapezoidal, triangular etc. This work uses trapezoidal membership function because the range of values can be clearly specified at input and output side. Trapezoidal membership function is given by equation 10. ANN-I output with 4 values is given as input to FIS-I. Low and high range of vales are set at the input and output side of membership function is based on ANN output. FIS-I with 4 inputs, 4 outputs and 4 rules is made. Based on the input, output and rule set given to the fuzzy system a '.fis file' is created. In MATLAB 'evalfis' function is used to evaluate the output from ANN and the .fis file. Using this fuzzy output classification of ECG signals is done. Based on the obtained fuzzy output from FIS-I first level classification of multiple cardiac disorder is achieved. The classifier module-I classifies the signal into four classes which include Normal Sinus Rhythm (NSR), Atrial Arrhythmias (AA), Ventricular Arrhythmias (VA) and Myocardial Infarction (MI). If the test signal belongs to NSR or MI then the classification stop in this first level. If it belongs to Atrial

Arrhythmias or Ventricular Arrhythmias then it goes to second level of classification. ANN architecture for First level, Trapezoidal Membership Function and FIS for Level-I are shown in Figure1, 2 and 3respectively. Rule set for Level-I is shown in Table I.
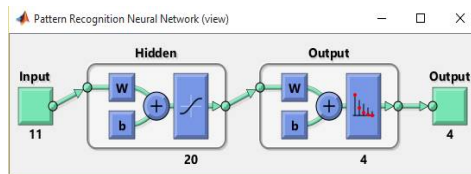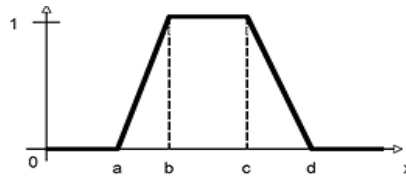

Fig. 1. Level I ANN Architecture
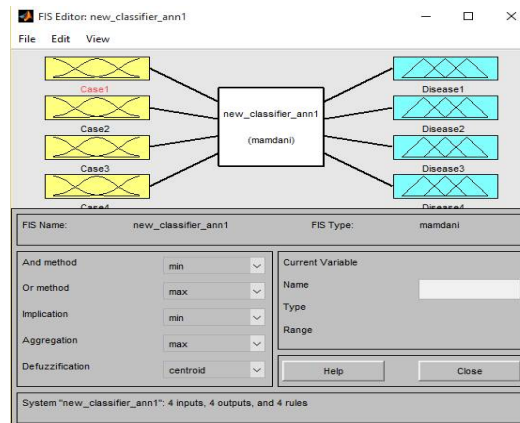

Fig. 2. Trapezoidal Membership Function

Fig. 3. FIS for Level-I Classifier

$$f(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \qquad (10)$$

where, x is the input, a,b,c and d are the parameter specifying the range.

TABLE I.   RULE SET FOR FIRST LEVEL

Rule Set			
2	1	1	1
1	2	1	1
1	1	2	1
1	1	1	2

Second level classification mainly classifies Atrial Arrhythmias and Ventricular Arrhythmias into smaller 2 and 3 subgroups respectively. For Atrial Arrhythmias, Classifier module-II consisting of ANN-II and FIS-II is used. ANN-II is trained by giving 11 features from each 36samples are given as input (number of input neurons=11). 11 features given as input to ANN are TCC, MAV, WM, WSD, SKEW, KURT, PF, MF, SM, SBA and VFL. Number of hidden neurons in hidden layer is taken as 20. Number of output neurons in the output layer is taken as 2 since Atrial Arrhythmias is classified into 2 classes. Once the network is trained, a neural architecture is obtained and using this architecture the classification of test signal is achieved. Feature vector from the test signal is given as input to the obtained architecture for ANN-II and corresponding ANN output is obtained. Obtained ANN output is given to FIS. '.fis file' with 2 inputs, 2 output and 2 rules is created using fuzzy toolbox and the obtained .fis file and ANN-II output is evaluated to obtain the corresponding FIS-II output. Based on the obtained FIS-II output classification of Atrial Arrhythmias into Atrial Fibrillation (AF) and Supraventricular Arrhythmia (SVA) is achieved. ANN architecture and FIS for Atrial Arrhythmias are shown in Figure 4 and 5 respectively. Rule set for Atrial Arrhythmias is shown in Table II.

TABLE II.   RULE SET FOR ATRIAL ARRHYTHMIAS

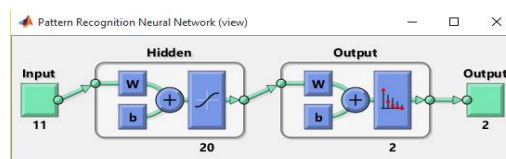| Rule Set	
2	1
1	2

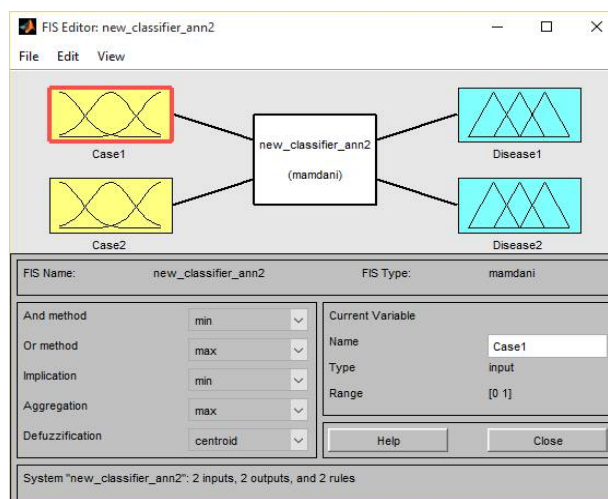Fig. 4. ANN Architecture for Atrial Arrhythmias

Fig. 5. FIS for Atrial Arrhythmias

For Ventricular Arrhythmias, Classifier module-III consisting of ANN-III and FIS-III is used. ANN-III is trained by giving 7 features from each 36 samples are given as input (number of input neurons=7). 7 features given as input to ANN are TCC, MAV, PF, MF, SM, SBA and VFL. Number of hidden neurons in hidden layer is taken as 20. Number of output neurons in the output layer is taken as 3 since Ventricular Arrhythmias is classified into 3 classes. Once the network is trained, a neural architecture is obtained and using this architecture the classification of test signal is achieved. Feature vector from the test signal is given as input to the obtained architecture for ANN-III and corresponding ANN output is obtained. Obtained ANN output is given to FIS. '.fis file' with 3 inputs, 3 output and 3 rules is created using fuzzy toolbox and the obtained .fis file and ANN-III output is evaluated to obtain the

corresponding FIS-III output. Based on the obtained FIS-III output classification of Ventricular Arrhythmias into Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VT) and Maligant Ventricular Ectopy (MVE) is achieved. ANN architecture and FIS for Ventricular Arrhythmias are shown in Figure 6 and 7 respectively. Rule set for Atrial Arrhythmias is shown in Table III.

TABLE III.   RULE SET FOR VENTRICULAR ARRHYTHMIAS

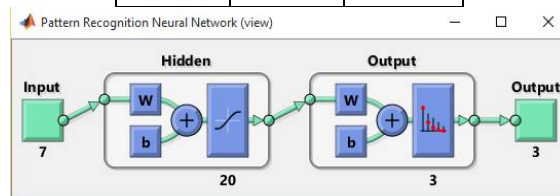| Rule Set		
2	1	1
1	2	1
1	1	2

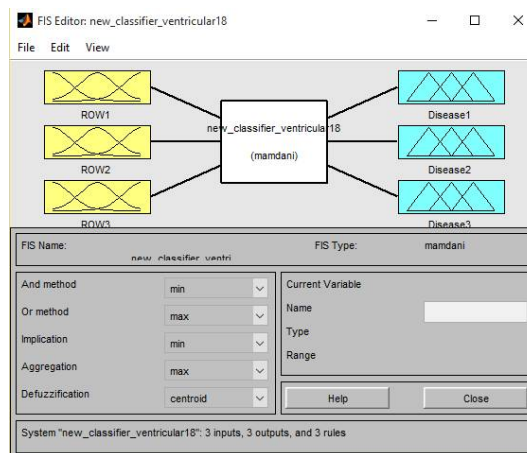Fig. 6. ANN Architecture for Ventricular Arrhythmias

Fig. 7. FIS for Ventricular Arrhythmias

V. RESULTS AND DISCUSSIONS

Temporal and Spectral features are extracted from 10 second long ECG signal. ECG signals include NSR, AF, MI, PVC, VT and SVA. Tables IV and V show temporal and spectral features respectively. These obtained fundamental features gives better result than those obtained in previous works which includes classification of signal into normal and abnormal diseases. These features are given to the classifier module consisting of ANN and Fuzzy Logic. Test signals are given to classifier module for classification. These fundamental feature vectors from test signal are given as input to ANN which classifies the signal into the group it belongs to. Classification section includes two levels. Level I classification includes detection of common cardiac disorders into four classes which includes NSR, Atrial Arrhythmias, Ventricular Arrhythmias and MI. Level II classification includes categorization of first level classes into more specific disorders. Atrial Arrhythmias are further classified into AF and SVA. Ventricular Arrhythmias are further classified into PVC, VT and MVE. Accuracy, sensitivity and specificity are the parameters used for performance evaluation [8].

TABLE IV.   TEMPORAL FEATURES

Cardiac Disorders	Temporal Features	
	MAV(mV)	TCD(ms)
NSR	0.384	5
AF	0.5894	6
MI	1.3754	1
PVC	0.8872	2
SVA	0.3332	2
VT	0.2649	3
LTAF	0.6199	7
MVE	0.4445	2

TABLE V.   SPECTRAL FEATURES

Cardiac Disorders	Spectral Features								
	WM (mV)	WSD (mV)	SKEW (mV)	KURT (mV)	PF (Hz)	MF (Hz)	VFL (mV)	SM (mV)	SBA (mV)
NSR	-42.5308	0.589	1.085	3.095	15.25	19.7	0.7703	0.1094	0.1463
AF	-203.7498	72.352	0.3083	2.82	26	38.8	0.9657	0.148	0.9685
MI	-299.65	1.4793	2.1738	4.675	108.67	158.65	0.9825	0.5078	1.0061
PVC	3.903	123.45	1.5774	6.8995	37.6	79.98	1	0.0182	0.3398
SVA	34.7345	74.16	0.3133	2.901	14.17	20.12	0.8818	0.1082	0.2729
VT	1.7137	1.2766	1.4587	5.35	25.64	40.25	0.8989	0.5711	0.1135
LTAF	-12.68	4.5265	0.7928	1.69	13.34	16.67	0.8744	0.02	0.0658
MVE	3.8464	92.42	0.2475	4.46	26.47	24.92	0.9998	0.48	0.1268

TABLE VI.   CLASSIFICATION ACCURACY FOR CLASSIFIER MODULES

Parameters	Classifier Module-I	Classifier Module-II	Classifier Module-III
Accuracy (%)	96.7	100	95

TABLE VII.   SENSITIVITY FOR CLASSIFIER MODULE-I

Cardiac Disorder	Classifier Module-I
Atrial Arrhythmias	98.36%
VentricularArrhythmias	95%
Myocardial Infraction	100%

TABLE VIII.   SPECIFICITY FOR CLASSIFIER MODULE-I

Cardiac Disorder	Classifier Module-I
NSR	58.3%

TABLE IX.   SENSITIVITY FOR CLASSIFIER MODULE-II

Cardiac Disorders	Classifier Module-II
AF	100%
SVA	100%

TABLE X.   SENSITIVITY FOR CLASSIFIER MODULE-III

Cardiac Disorders	Classifier Module-III
PVC	100%
VT	100%
MVE	97%

Classifier Module-I, II and III gives a classification accuracy of 96.7%, 100% and 95% respectively. Sensitivity for Classifier Module-I 98.36%, 95% and 100% Atrial Arrhythmias, Ventricular Arrhythmias and Myocardial Infraction respectively. Specificity for Normal signal is 58.3%. For second level classification, Classifier Module-II gives 100% sensitivity for both AF and SVA whereas Classifier Module-III gives a sensitivity of 97% for MVE and 100% for both VT and PVC. Thus the overall classification accuracy achieved by this modular approach is about 96.7%. When compared with literature surveys better classification accuracy is obtained for this modular approach. The work is made more user-friendly with the help of Graphical User Interface (GUI). GUI model consists of input parameters (input signal and the corresponding sampling frequency), the graphical display showing the selected input signal, start button which holds the feature extraction and classification section, Cardiac Arrhythmia display showing the classified output and clear button to clear both the displays. GUI Model created for the work is shown in Figure 8.
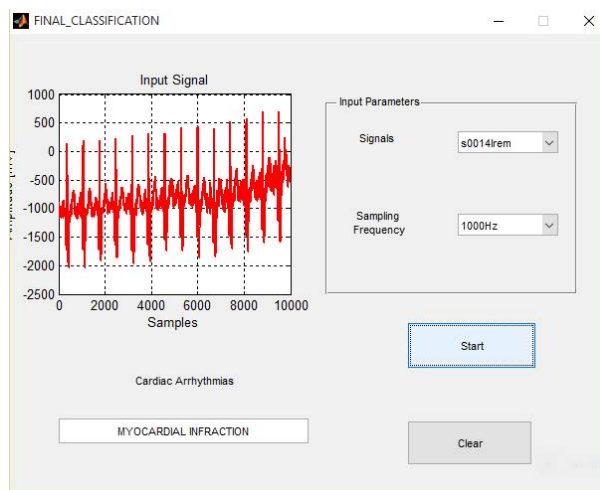

Fig. 8. GUI Model

VI.CONCLUSION

A modular approach for classification of ECG signals using a classifier module consisting of ANN and Fuzzy Logic is specified in this paper. By mathematical computations we arrived at a standard signal length of 10seconds. Fundamental features like temporal and spectral features are extracted from the ECG signals by applying FFT, wavelets and several mathematical computations on the ECG signals. These features are used to classify multiple cardiac disorders. The main challenge to overcome in this paper is the overlapping of features. Quality of the features extracted in this paper is better than those obtained in previous works which includes feature extraction for classification of normal and abnormal signals. ANN and Fuzzy logic is used for classification of ECG signals. This work uses pattern recognition neural network since it gives better classification accuracy than any other neural network.

ANN output is given to FIS where the .fis file and ANN output is evaluated using 'evalfis' function and based on this obtained fuzzy output classification of ECG signal is achieved. Classification section includes two levels. First level classification classifies the ECG signal into four classes like Normal Sinus Rhythm, Atrial Arrhythmias, Ventricular Arrhythmias and Myocardial Infarction by using Classifier Module-I. Second level classification classifies the first level classes into more specific disorders. Atrial Arrhythmias is further classified into two subgroups, which includes Atrial Fibrillation (AF) and Supraventricular Arrhythmia (SVA) by using Classifier Module-II. Ventricular Arrhythmias is further classified into three subgroups, which includes Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VT) and Maligant Ventricular Ectopy (MVE) by using Classifier Module-III. When compared with literature surveys better classification accuracy is obtained for this modular approach for the classification of Normal and seven cardiac disorders. Overall classification accuracy achieved by using this modular approach is about 96.7%.

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