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Improved method to detect common cardiac disorders from ECG signals using ANN and Fuzzy Logic

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ABSTRACT: In Electrocardiogram (ECG) is a common technique to monitor electrical activities of human heart. Physicians visually examine lengthy ECG records to arrive at appropriate diagnosis. This is a time consuming process. At the same time we cannot rule out the possibility of missing some minutiae details of ECG. Thus automated analysis of ECG signals are important for the detection of different arrhythmias. This work is a technique for automated feature extraction and classification of ECG signals, to detect common cardiac disorders into four high level categories which includes Normal Sinus Rhythm (NSR), Atrial Arrhythmias, Ventricular Arrhythmias and Myocardial Infarction (MI). The high level categorization is further classified into more specific disorders like Atrial Arrhythmias is further classified into Atrial Fibrillation (AF), Supraventricular Arrhythmia (SVA) and Ventricular Arrhythmias are further classified into Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VT) and Maligant Ventricular Ectopy (MVE). ECG signals for this work are taken from the standard MIT-BIH database and Physionet database. Both temporal and spectral features are used in this work. Length of the ECG signal is selected for optimal performance. Artificial neural network (ANN) and Fuzzy logic are used for classification. Use of Fuzzy logic in conjunction with ANN is seen to provide improved classification accuracy.

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 among various sects of people. Many of them are fatal and an early diagnosis can save lives [1]. ECG is the standard technique commonly used for monitoring the electrical activities of the human heart. It is a non stationary quasi periodic signal which shows a series of P, Q, R, S and T waves. Cardiologists visually analyze ECG reports to arrive at appropriate conclusions. This is a time consuming process and the possibility of missing some minutiae details cannot be ruled out [2]. This calls for automated analysis of ECG signals.

Various methods for the ECG signal analysis are reported. Those methods use Fourier Transform, Principal Component Analysis (PCA), Wavelet Transform, Independent Component Analysis (ICA), Support Vector Machine (SVM) and Artificial Neural Network [1],[2]. Each of the methods use only a small subset of the diverse characteristic features of ECG signals. This paper includes all the features which show the diverse characteristics of ECG signals. This study is based on extracting spectral [3] and temporal features which represent the hidden information of the ECG signal. The signals from MIT-BIH database and Physionet database are taken for this feature extraction study. Features are extracted from normal ECG signals and the seven sets of diseased ECG signals. These features are used for classifying the signal into multiple cardiac disorders. Firstly ANN is trained by giving the extracted features as input. Once training is completed neural network architecture is formed and by using the created network testing of signals can be done. Output obtained from ANN is fed to fuzzy inference system to obtain improved classification accuracy.

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II.MATERIALS

Data collection plays an important role in this work. Signals are obtained from MIT-BIH database and Physionet database. These ECG signals include 18 signals belonging to NSR with a sampling frequency of 128Hz, 127 signals belonging to MI with a sampling frequency of 1000Hz, 102 signals belonging to Ventricular Arrhythmias of which 47 signals belonging to Premature Ventricular Contraction (PVC) with a sampling frequency of 360Hz, 22 signals belonging to Maligant Ventricular Ectopy (MVE) with a sampling frequency of 250Hz and 33 signals belonging to Ventricular Tachycardia (VT) with a sampling frequency of 250Hz, and 183 signals belonging to Atrial Arrhythmias of which 78 signals belonging to Supraventricular Arrhythmias (SVA) with a sampling frequency of 128Hz, 84 signals belonging to Long Term Atrial Fibrillation (LTAF) with a sampling frequency of 128Hz and 21 signals belonging to Atrial Fibrillation (AF) with a sampling frequency of 250Hz. Other details regarding the signals are available in the databases. Designing tools used in this work are MATLAB, Neural Network toolbox (NN), Fuzzy Inference System (FIS) toolbox and Guide (GUI) toolbox. MATLAB is the programming tool used to implement this work and NN is used for classification and FIS is used to improve the classification. The final work is made user friendly with GUI.

III.METHODS

A. Choice of Signal Length

Choice of ECG signal size is an important factor which decides the quality of the features that are extracted from the signal. In the literature, no detail is available on choosing the length of an ECG signal for analysis. It is observed that the quality of the extracted features, in many cases, depend on the length of the ECG signal. A novel method to choose the length of the ECG signal for analysis is proposed. A long train of normal ECG signal of a single person is the base for this work. The signal is broken down into fifty small segments of 3 seconds duration each. All features are extracted. This is repeated for different time periods of the signal. The extracted features are analyzed for best consistency. The consistency of a feature is evaluated in terms of its variance in the experimented signal segments. It is seen that a signal segment of 10seconds duration is a good fit for the different features and across different diseases.

B. Feature Extraction Methods

Quality of extracted features is very important in the automated analysis of cardiac disorders. Spectral features included in this work are Mean frequency (MF), Peak frequency (PF), VF-leakage (VFL), Spectral moment (SM), and Spectral band amplitude (SBA), Wavelet Mean (WM), Wavelet Standard deviation (WSD), Skewness (SKW), and Kurtosis (KURT). Temporal features included in this work are Mean absolute value (MAV), and Threshold Crossing Count (TCC).

1. Mean Frequency (MF)

Mean Frequency [4] is the central frequency of the power spectrum. An N - point FFT is applied on the signal and we get the amplitude and frequency in spectral domain. To obtain the power take the square of the FFT samples and MF is calculated by using the formula,

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

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

2. Peak Frequency (PF)

Peak frequency [5] is the frequency corresponding to the maximum amplitude in the spectral domain. For a healthy ECG signal this matches with the QRS complex. The ECG signal is first subjected to a two level Daub 4 wavelet decomposition. An N-point FFT is done on the approximation coefficients and PF is computed from the obtained spectrum.

$$PF = \max(a_i), \quad 1 \leq i \leq L \qquad (2)$$

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

3. VF Leakage (VFL)

ECG signal is first bandpass with 0.5 Hz and 20Hz as upper and lower cut off frequencies. FFT is then applied on this and spectral leakage is computed using the formula [6],[7]

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$$\mathrm{VFL} = \frac{\sum_{i=T/2}^{L} |(x_i + x_{i-\frac{T}{2}})|}{\sum_{i=T/2}^{L} (|x_i| + |x_{i-\frac{T}{2}}|)} \tag{3}$$

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.

4. Spectral Moment (SM)

Spectral Moment [7] is computed from FFT of the using the formula,

$$\mathrm{SM} = \frac{\sum_{j=1}^{L} (a_j * f_j)}{\sum_{j=}^{L} (a_j)} \tag{4}$$

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

5. Spectral Band Amplitude (SBA)

FFT is applied on the signal of length L to obtain the amplitude and frequency in spectral domain. Spectral Band Amplitude [7] is calculated by taking the ratio of the sum of sample amplitude between 0.7p and 1.4p and the sum of sample amplitudes between 0.5Hz and minimum of 20p and 100Hz where p is the peak frequency.

6. Wavelet Mean (WM)

The ECG signal is subjected to a four level (Daub4) wavelet decomposition and mean [8],[9] of the approximation coefficient is calculated by using the formula,

$$\mathrm{WM} = \frac{1}{L} \sum_{i=1}^{L} (x_i) \tag{5}$$

where, L is the length of the approximation coefficients, x is the approximation coefficients.

7. Wavelet Standard Deviation (WSD)

ECG signal is subjected to a four level (Daub4) wavelet decomposition and standard deviation [8],[9] of the approximation coefficient is calculated by using the formula,

$$WSD = \left(\frac{1}{L} \sum_{i=1}^{L} (x_i - m)^2\right)^{1/2} \tag{6}$$

where, L is the length of the signal, x_i is the wavelet coefficient and m is the mean of the wavelet coefficients.

8. Skewness (SKW)

Skewness gives the measure of asymmetry of the signal and is calculated by doing four level (Daub4) wavelet decomposition of the signal [8],[9]. Skewness of the approximation coefficient is calculated using the formula,

$$\mathrm{SKW} = \frac{1}{L} \frac{\sum_{i=1}^{L} (x_i - m)^3}{(SD)^3} \tag{7}$$

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

9. Kurtosis (KURT)

Kurtosis determines whether the samples are flat or peaked with respect to normal distribution[8],[9]. It is calculated by applying four level (Daub4) wavelet decomposition of the signal. Kurtosis of the approximation coefficient is calculated using the formula,

$$\mathrm{KURT} = \frac{1}{L} \frac{\sum_{i=1}^{L} (x_i - m)^4}{(SD)^4} \tag{8}$$

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

10. Mean Absolute Value (MAV)

Mean of the absolute value [10],[11] of the ECG sample amplitudes of length L are calculated.

$$\mathrm{MAV} = \frac{1}{L} \sum_{i=1}^{L} x_i \tag{9}$$

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

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11. Threshold Crossing Count (TCC)
Threshold Crossing Count [10] is the number of times the signal crosses a threshold which is 80% of the maximum amplitude.

Features from the signals are calculated using the above methods and feature vector for different features are obtained. Thus features from 72 signals are used as training data for training ANN. Inorder to classify the signals for atrial and ventricular arrhythmias two neural network architecture is trained using 36 samples respectively.

C. Classification Methods
ANN together with fuzzy is used for classification of multiple cardiac disorders. Type of classifier used is ANN to model neural biology using mathematical operations [8],[9]. It consists of neurons which are the processing elements with performance similar to biological neurons. ANN consists of three layers input, hidden and output. Supervised learning rule is used to train ANN. Error occurring at the ANN classifier output can be reduced by proper feature selection during training. This makes the ANN better than any other classifier. The extracted 11 features are fed to the input layer through input neurons (number of input neurons=11), the hidden layer consists of 20 hidden neurons and the output layer consists of 4 neurons. 72 samples are used for training and 15% for validation and 20% for testing. Training of neural network is done using these parameters and the neural network architecture is obtained. Using the obtained architecture testing is done.

1. Neural Network Selection
Classification of cardiac disorders using pattern recognition network and linear vector quantisation is done. Training is done using 50 signals out of 110 signals. Pattern recognition network classifier correctly classifies 105 signals out of 110 signals whereas the linear vector quantisation network correctly classifies only 80 signals out of 110 signals. An inference is made based on correctly classified signals and finally concluded that pattern recognition neural network gives better classification accuracy than linear vector quantisation network. So this paper uses pattern recognition network for classifying of multiple cardiac disorders. Obtained architecture for classifying into 4 cases, atrial arrhythmias and ventricular arrhythmias are shown in figures given below.

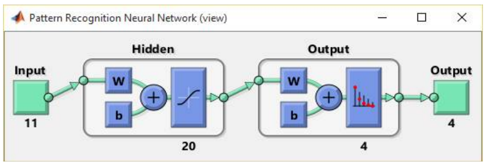

Fig. 1. Level I ANN Architecture

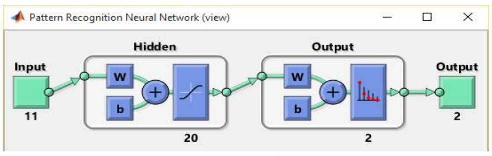

Fig. 2. ANN Architecture for Atrial Arrhythmias

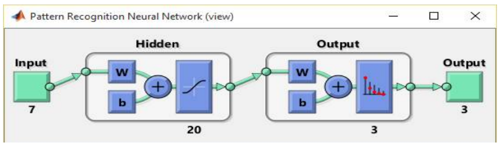

Fig. 3. ANN Architecture for Ventricular Arrhythmias

2. Fuzzy Logic
Output from three ANN is fed to the corresponding FIS for improving the classification accuracy [12]. Fuzzy logic approaches used for computations based on degrees of truth. Fuzzy logic values ranges between 0 and 1. The logic for using fuzzy with ANN is that, in fuzzy the range of input from ANN and output from fuzzy can be specified with the help of membership function whereas ANN classifies the signals based on its output. Also fuzzy can interpret the

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relation between inputs by generating rule sets. A fuzzy inference system with 4 inputs, 4 outputs and 4 rules is made by using fuzzy logic toolbox. There are different types of membership functions used in fuzzy, they are sigmoid, trapezoidal, triangular etc. This work uses trapezoidal membership function at the input and output side. Trapezoidal membership function is used because the range of parameters at input and output side can be defined very clearly. The equation is given by,

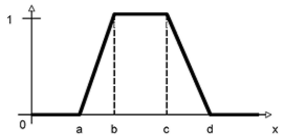

Fig. 4. Trapezoidal Membership Function

$$f(h;p,q,r,s) = \begin{cases} 0, & h \le p \\ \frac{h-p}{q-p}, & p \le h \le q \\ 1 & q \le h \le r \\ \frac{s-h}{s-r}, & r \le h \le s \\ 0, & s \le h \end{cases} \tag{10}$$

where, h is the input, p, q, r and s 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

TABLE II. Rule Set for Atrial and Ventricular Arrhythmias

Rule Set				
AtrialArrhythmias		Ventricular Arrhythmias		
2	1	2	1	1
1	2	1	2	1
0	0	1	1	2

By using fuzzy inputs, fuzzy outputs and the fuzzy rules a fis file is created with the extension .fis. Based on the obtained output from fuzzy inference system classification of cardiac disorders is done. Table I and Tables II given above shows the rule sets for classifying into 4 cases, atrial and ventricular arrhythmias respectively.

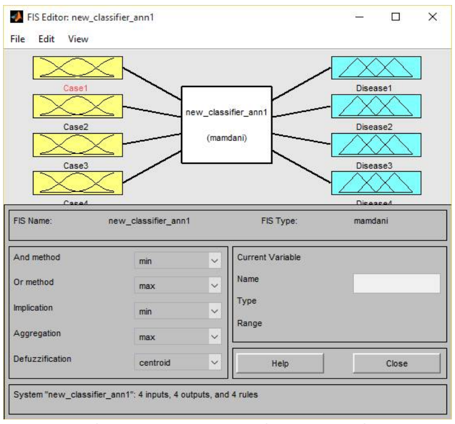

Fig. 5. Fuzzy Inference System for classifying into 4 cases

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Once the fuzzy inference system is generated the output is evaluated using 'evalfis' function in MATLAB. This function evaluates the output from artificial neural network and the fis file. Fuzzy logic designer is shown in the Figure 5, 6 and 7.

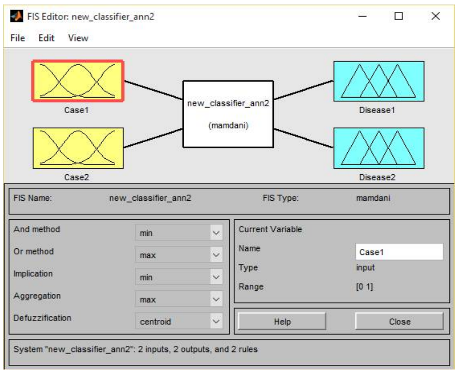

Fig. 6. Fuzzy Inference System for classifying Atrial Arrhythmias

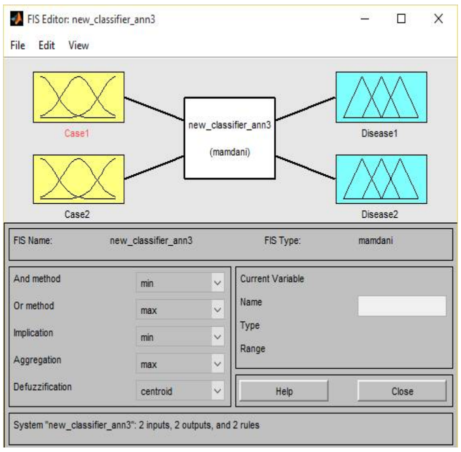

Fig. 7. Fuzzy Inference System for classifying Ventricular Arrhythmias

IV.RESULTS AND DISCUSSIONS

From the ECG signal of selected signal length we extract the spectral and temporal features. The ECG signals include NSR, AF, MI, PVC, VT and SVA. Extracted temporal and spectral features are listed in following Tables: III and IV 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 fed to the classifier section which includes ANN and fuzzy logic. Classifier is tested with the signals taken from the databases. Features obtained from the ECG signals are given as the input feature vector to the ANN. Based on the extracted features from the test signal the classifier decides the class to which the signal belongs to. The paper uses two methods, method 1 includes classification using ANN and method 2 includes ANN together with fuzzy logic for classification of test signals into their corresponding classes. The performance evaluation of classifier is done using three parameters sensitivity, specificity and accuracy shown. Sensitivity is the percentage value for correct detection of diseased condition. Specificity is the percentage value for correct detection of non diseased condition [8].

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TABLE III. TEMPORAL FEATURES

Cardiac Disorders	Temporal Features	
Signals	***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 IV. SPECTRAL FEATURES

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

The sensitivity, specificity and accuracy measures are calculated for both methods. Sensitivity, specificity and accuracy for second method is better when compared with first method (ANN). Classification accuracy obtained for ANN is 94.02% and for Fuzzy with ANN is 96.7%. Thus Fuzzy with ANN gives an improved accuracy than using ANN alone at the classification section as fuzzy uses membership function with specified range and rule set. In second level classification, second method (fuzzy logic with ANN) gives a sensitivity and accuracy better than that of first method (ANN alone) for both Atrial Arrhythmias and Ventricular Arrhythmias. For Atrial Arrhythmias, classification accuracy obtained for ANN is 88% and for Fuzzy with ANN is 100%. For Ventricular Arrhythmias, classification accuracy obtained for ANN is 93.42% and for Fuzzy with ANN is 95%.

TABLE V. CLASSIFICATION ACCURACY FOR LEVEL I SPECTRAL FEATURES

Methods	**ANN**	**Fuzzy Logic**
Accuracy (%)	94.02	96.7

TABLE VI. CLASSIFICATION ACCURACY FOR LEVEL II FOR ATRIAL ARRHYTHMIAS SPECTRAL FEATURES

Methods	**ANN**	**Fuzzy Logic**
Accuracy (%)	88	100

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TABLE VII. CLASSIFICATION ACCURACY FOR LEVEL II FOR VENTRICULAR ARRHYTHMIAS SPECTRAL FEATURES

Methods	**ANN**	**Fuzzy Logic**
Accuracy (%)	93.42	95

The GUI model for the work is shown in Fig given below.

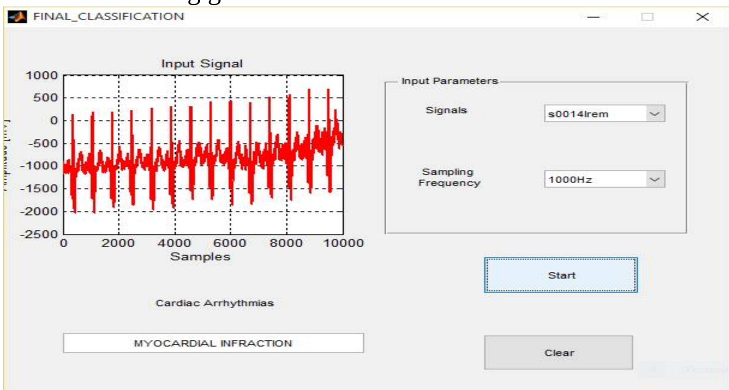

Fig. 8. GUI Model

VI.CONCLUSION

The paper describes a suitable method for extracting fundamental features from different ECG signals and classification of cardiac disorders. By mathematical computations we arrived at a standard signal length of 10seconds. FFT, wavelets and several mathematical computations, are used for extracting spectral and temporal features respectively from the ECG signal. The target is to classify multiple cardiac disorders using these features. 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. These extracted good features are used for classification of multiple cardiac disorders by using ANN and fuzzy logic. By several computations we arrived at pattern recognition neural network since it gives better classification accuracy than any other neural network. Output from ANN is fed to FIS. Based on the output from FIS the test signal is classified into their corresponding high level classes. The four high level classes are NSR, Atrial Arrhythmias, Ventricular Arrhythmias and MI. The high level categorization is further classified into more specific disorders like Atrial Arrhythmias is further classified into AF, SVA, and Ventricular Arrhythmias are further classified into PVC, VT and MVE. Fuzzy logic gives an improved classification accuracy of about 96.7%, 100% and 95% for Level I classifier, Level II Atrial Arrhythmia classifier and Level II Ventricular Arrhythmia classifier respectively, when combined with ANN. The overall classification accuracy achieved for this work is 96.7%.

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