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# CLASSIFICATION OF ARRHYTHMIC ECG DATA USING ARTIFICIAL NEURAL NETWORK

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**Abstract -** *MIT-BIH arrhythmia indicates abnormal electrical activity of heart that can be a great threat to human. So it needs to be identified for clinical diagnosis and treatment. Analysis of ECG signal plays an important role in diagnosing cardiac diseases. At the first QRS components have been extracted from the noisy ECG signal by rejecting the background noise using MATLAB. Neural network model with back propagation algorithm is used to classify arrhythmia cases into normal and abnormal classes based on previous extracted features. Networks models are trained and tested for MIT-BIH arrhythmia.*

***Key Words***: MIT-BIH Arrhythmia, Feature Extraction, Peak detection, Regression, MSE *.*

## 1. INTRODUCTION

Electrical signals arising in the SA node (located in the right atrium) stimulate the atria to contract and travel to the atrioventricular node(AV node), which is located in the interatrialseptum. After a delay, the stimulus diverges and is conducted through the left and right bundle of His to the respective Purkinjefibers for each side of the heart, as well as to theendocardium at the apex of the heart, then finally to the ventricular epicardium.

SA node: P wave

Under normal conditions, electrical activity is spontaneously generated by the SA node, the cardiac pacemaker. As the electrical activity is spreading throughout the atria, it travels via specialized pathways, known as internodal tracts, from the SA node to the AV node.

AV node and bundles: PR interval

The AV node functions as a critical delay in the conduction system. Without this delay, the atria and ventricles would contract at the same time, and blood wouldn't flow effectively from the atria to the ventricles. The delay in the AV node forms much of the PR segment on the ECG and part of atrial repolarization can be represented by the PR segment.

Purkine fibers/ventricular myocardium: QRS complex

The two bundle branches taper out to produce numerous Purkinje fibers, which stimulate individual groups of myocardial cells to contract. The spread of electrical activity through the ventricular myocardium produces the QRS complex on the ECG. Atrial repolarization occurs and is masked during the QRS complex by ventricular depolarization on the ECG.

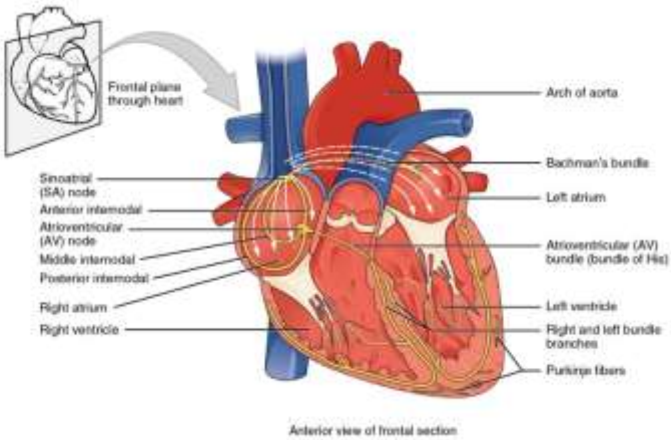


**Fig 1 -**Conduction of electrical activity in heart

### 1.1 ECG representation

One of the ways to diagnose heart diseases is to use Electrocardiogram (ECG) signals. ECG signals are formed of P wave, QRS complex, and T wave. They are designated by capital letters P, Q. R, S, and T. In the normal beat phase of a heart, the main parameters, inspected include the shape, the duration, and the relationship with each other of P wave, QRS complex, and T wave components and R-R interval. The changes in these parameters indicate an illness of the heart that may occur by any reason. All of the irregular beat phases are generally called arrhythmia and some arrhythmias are very dangerous for patient. Some automatic ECG interpreting systems is available. Moreover, the computer-based interpreter systems are currently being developed to diagnose arrhythmia in time, and various methods are applied to these systems with one of them being Artificial Neural Networks (ANN).

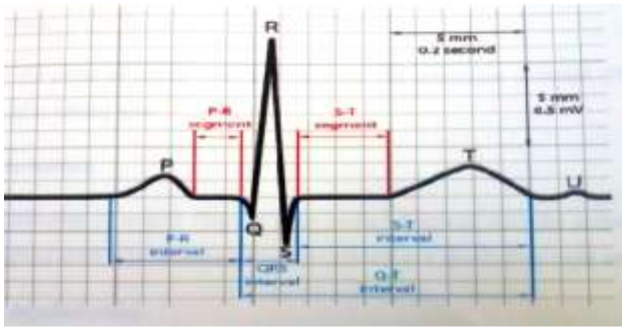


**Fig 2-**ECG signal and intervals

## 2. METHODOLOGY

Now we discuss how the ECG signal processing can be done and how it can be extracted to give input and create a data set using various ECG signals and to classify them as Normal and Abnormal.

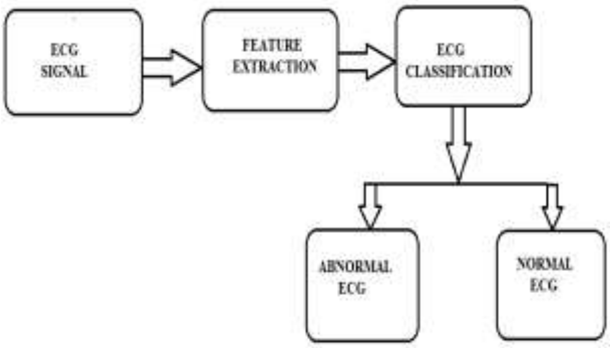


**Fig 3-**Overall methodology for Arrhythmia prediction

### 2.1 Feature extraction from ECG Signal

The ECG signal can be taken by physionet.org website. With the help of MIT-BIH arrhythmia database we can get normal as well as abnormal patient database. We have extracted normal and abnormal database of various patients through text file.Run the specified code to obtain the ECG signal and then calculated R-R interval.

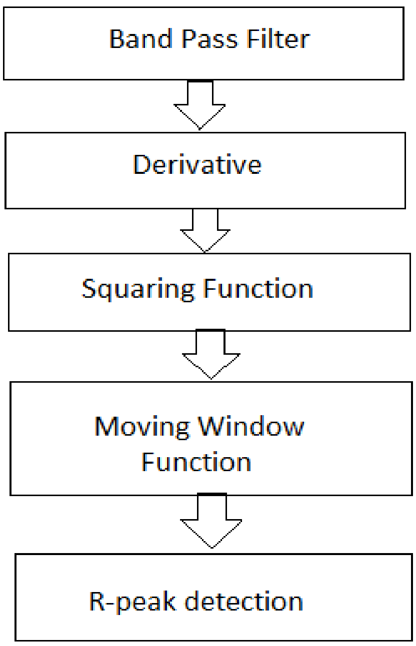


**Fig 4-**Block diagram representation to detect R-peak

The ECG signal goes through a BPF to attenuate the P and T wave of ECG signal, so that to remove lower frequency components. The signal is then differentiated to amplify the QRS edges. The differentiated signal has positive and negative points, it is then squared to get a signal which has only positive peaks. To make the signal smoother moving window function is used, finally R-peaks are detected, corresponding R-R intervals and amplitudes are calculated.

### NORMAL ECG SIGNALS

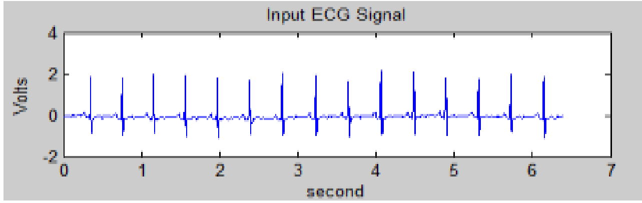


**Fig 5.1-**Input ECG Signal

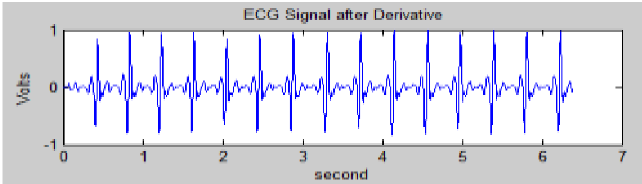


**Fig 5.2-**ECG Signal after Derivative

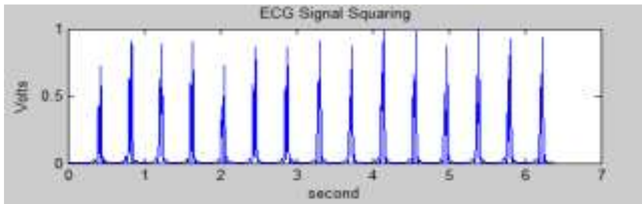


**Fig 5.3-**ECG signal Squaring

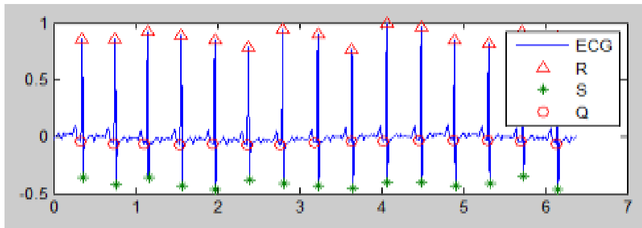


**Fig 5.4-**QRS peaks detection

### ABNORMAL ECG SIGNALS

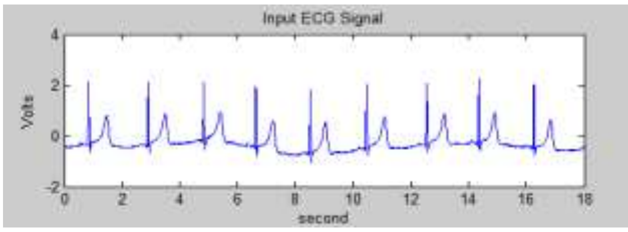


**Fig 6.1-**Input ECG Signal

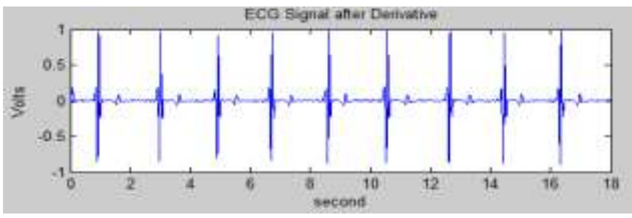


**Fig 6.2-**ECG Signal after Derivative

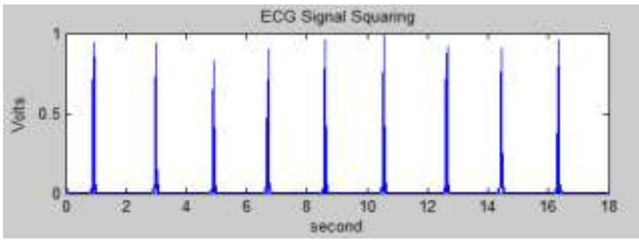


**Fig 6.3-**ECG signal Squaring

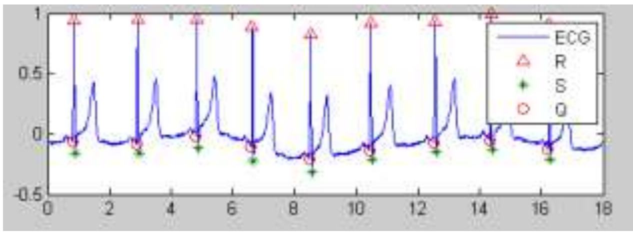


**Fig 6.4-**QRS peaks detection

Heart rate is the speed of the heartbeat measured by the number of contractions of the heart per minute (bpm). The normal resting adult human heart rate is probably a range between 50 and 90 bpm . During sleep a slow heartbeat with rates around 40–50 bpm is common and is considered normal .The heart rate for different age groups is as shown in below chart.

**Table 1-**Heart rate range of different age groups

| Age | 18-25 | 26-35 | 36-45 | 46-55 | 56-65 | 65+ |
|---|---|---|---|---|---|---|
| Athlete | 49-55 | 49-54 | 50-56 | 50-57 | 51-56 | 50-55 |
| Excellent | 56-61 | 55-61 | 57-62 | 58-63 | 57-61 | 56-61 |
| Good | 62-65 | 62-65 | 63-66 | 64-67 | 62-67 | 62-65 |
| Above Average | 66-69 | 66-70 | 67-70 | 68-71 | 68-71 | 66-69 |
| Average | 70-73 | 71-74 | 71-75 | 72-76 | 72-75 | 70-73 |
| Below Average | 74-81 | 75-81 | 76-82 | 77-83 | 76-81 | 74-79 |
| Poor | 82+ | 82+ | 83+ | 84+ | 82+ | 80+ |

## 3. ARTIFICIAL NEURAL NETWORK CLASSIFIER

The Artificial Neural Networks (ANN) is the mathematical modeling tool for human cognition or neural biology. ANN is characterized by pattern of connections between the neurons i.e. architecture and determining the weights on the connections i.e. training, or learning algorithm.

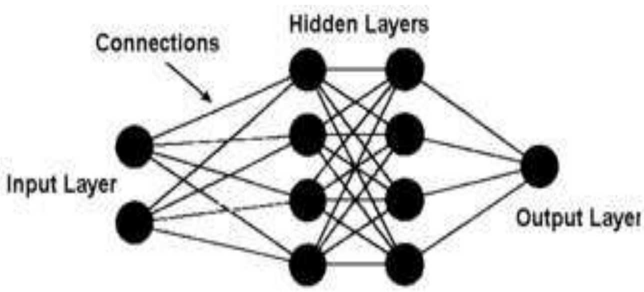


**Fig 7-**Neural Network architecture with two hidden layers

### 3.1 Traning and Testing

- Create input and output matrix and copy input and output of ECG data into it .Columns represents number of samples.
- Create test matrix that contains ECG test data that is used by network to predict outputs.
- nn-tool is a complete toolbox with gui to define & train our network.
- We should define the input and desired outputs of the network.

Suppose that we are going to approximate

- We should define the neural network structure.
- For the given network the most well known training algorithm is feed-forward back-propagation.

Feed Forward back propagation algorithm has been Chosen based on the below mentioned reasons:

- It has 2 hidden layers including input layer and output layer.
- As result of this fact that the numbers of existed neurons in hidden layer is an effective parameter for improvement of learning results, neuron numbers was chosen in order to achieve the optimum number based on output results.
- For training, utilization of BP algorithm and traingd function..
- For teaching of neural network, mean squared error (MSE) is used.

In feed forward back propagation, the network is Initialized by setting all its weights to small random numbers. Next the input pattern is applied and output is calculated this is called forward pass. We calculate the error and which is then used to update the weights in such a way that error is minimized, this is called reverse pass.

Neural network training function uses a cost function and it is usually defined as the MSE between ideal and real outputs of the network. We set the properties of layer such as,
**Training function :** TRAINGD which updates weights and bias values according to gradient descent.

**Adaptive learning function:** LEARNGD which is gradient descent weight and bias learning function.

**Performance function:** MSE is network performance function it measures networks performance according to mean of squared error.

**Transfer function:** TANSIG i,e a neuron with sigmoidal activation function.
Here we have choosen 30 neurons, as the number of neurons increases network is said to be more efficient. By setting the properties the neural network is created as shown below.

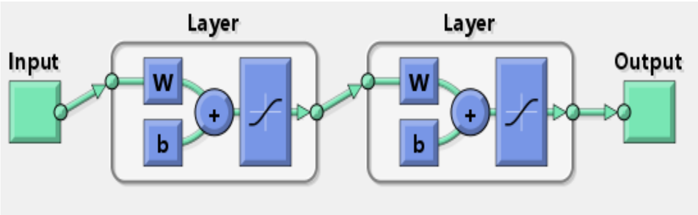


**Fig8-**Model of Neural Network using NNtool Box Matlab

Once the above network is obtained the next step is to train the network. When maximum epoch is reached neural network is trained .We check the performance ,training state and regression graphs as shown below.

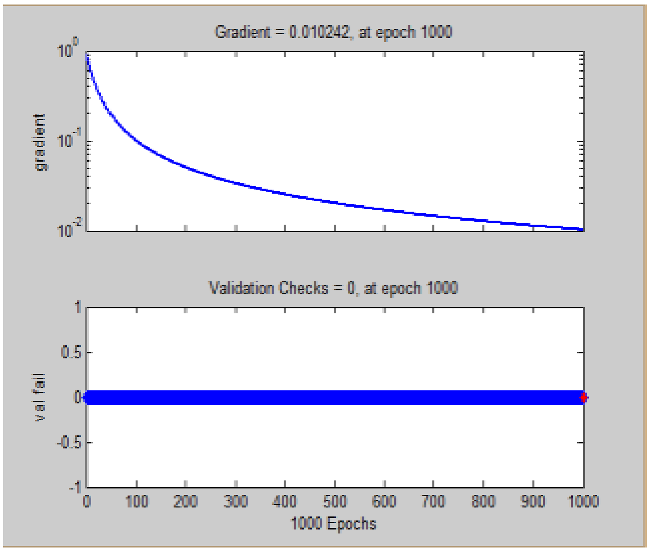


**Chart 1-**Training state

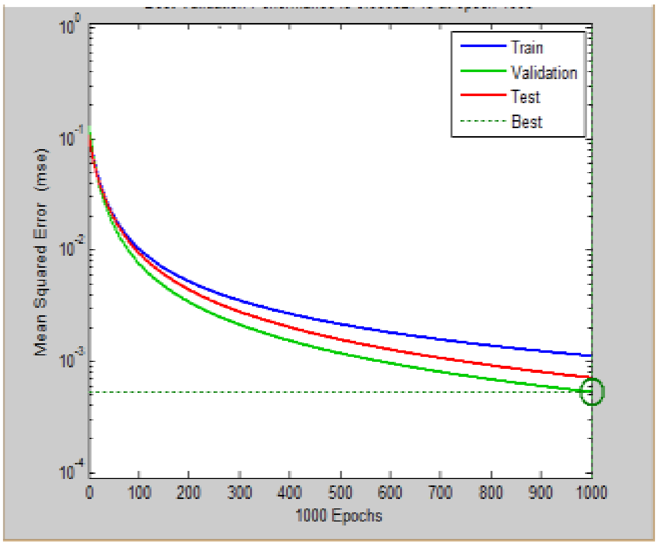


**Chart 2-**Performance

Data is divided into three sets namely train set, validation and test set as shown in below graph. The error on training set which is training error. validation set error reaches a minimum when network is fully trained and when the network is overtraining(becoming too accurate) the validation set error starts rising. without validation set ,we would just compute the error on the test set and get an estimate on accuracy.

Test set is that ,just by using whole data for training won't give a good estimate on the accuracy for optimizing the model ,a test set will give an estimate on the accuracy of model subjected to outside data. The output of neural network is obtained in order to classify ECG signal as normal or abnormal by simulation, to get actual output values nearer to the desired output values.

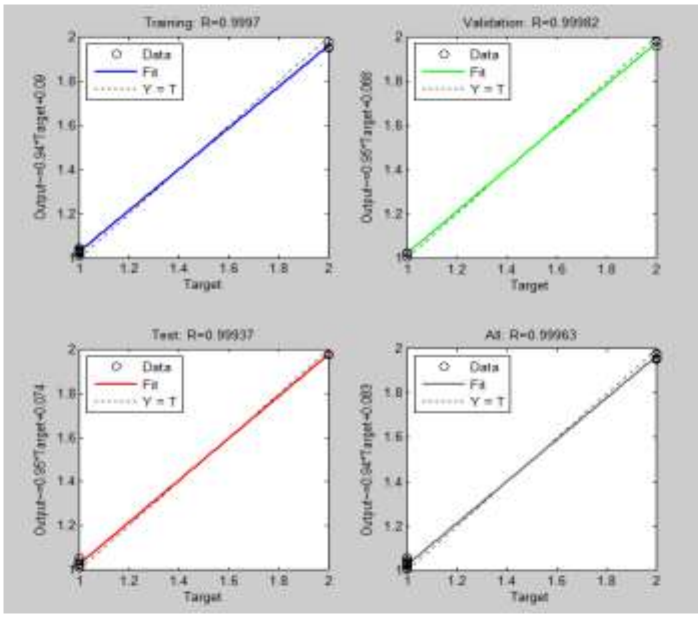


**Chart 3-**Regression plot

## 4. CONCLUSION AND FUTURESCOPE

This project proposes an effective automated ANN based system for Cardiac Arrhythmia classification from ECG signal data. Neural network has been tested and compared with the desired databases. Thus, based on the results, the ANN's approach is shown to be capable of dealing with the ambiguous nature of the ECG signal. Then based on R-R interval and amplitude of ECG signal we can detect whether the signal is normal or abnormal. Future work of our project can be done in real time, by extracting the real time data of various patients.

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