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DIAGNOSIS OF TACHYCARDIA ARRHYTHMIA USING MEMD AND CONVOLUTIONAL NEURAL NETWORKS

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Abstract - *Heartbeats are crucial to the medical sciences' study of heart ailments because they reveal significant details about heart problems and irregular heart rhythms. Electrocardiogram (ECG) represents the electrical activity of the heart showing the regular contraction and relaxation of heart muscle. The heart condition is used to diagnose by an important tool called Electrocardiography. The ECG spectrogram is used for diagnosing the heart diseases. The different types of noises present in ECG signal are Base-Line Wander, Power-Line Interface, Muscle Artefacts, Electrode contact noise. One of these is arrhythmia, in which the heart's regular rhythm is altered by damage to its muscles and an electrolyte imbalance. A hybrid technique is utilized to identify and categorize arrhythmia by combining Multivariate Empirical Mode Decomposition (MEMD) and Artificial Neural Network (ANN). Multilayer feed forward neural networks are utilized for classification, and these networks are trained utilising back propagation algorithms. Two key properties, the RR interval and Heart Rate, are retrieved from the ECG signal for the identification of Arrhythmia when MEMD is employed to denoise multichannel signals. Tachycardia and bradycardia are two subtypes of arrhythmia based on these characteristics. The Extraction of features and classification is to be done using Convolution neural network (CNN) classifier and the results obtained using CNN.*

Index terms: **Baseline Wander, Powerline Interface, Muscle Artifacts, Arrhythmia, Tachycardia, Electrocardiogram, Multivariate Empirical Mode Decomposition (MEMD), Artificial Neural Network (ANN), Convolution Neural Network (CNN)**

1. INTRODUCTION

1.1 Electrocardiography (ECG)

An electrocardiogram (ECG or EKG), a recording of the electrical activity of the heart, is made using the electrocardiography technique. When the cardiac muscle depolarizes and repolarizes throughout each cardiac cycle, these electrodes detect the minute electrical changes that result from these processes (heartbeat). The typical ECG pattern is altered by a number of cardiac conditions, including irregular heartbeat (like atrial fibrillation and ventricular tachycardia), inadequate coronary artery blood flow (like myocardial ischemia and myocardial infarction), and electrolyte issues (such as hypokalemia and hyperkalemia).Traditionally, The term "ECG" has been used to refer to a 12-lead lying-down ECG, as detailed below. Other tools, like a Holter monitor, can record the electrical activity of the heart, despite the fact that some smart watches models may also record an ECG. ECG signals may be captured using various equipment and in different settings. Ten electrodes are placed on the patient's chest and extremities as part of a standard 12-lead ECG. The magnitude of the heart's total electrical potential is then calculated and recorded over time utilising twelve different angles (or "leads") (usually ten seconds). The overall amount and direction of the heart's electrical depolarization at each point in the cardiac cycle may therefore be quantified. The three main components of an ECG are the P wave, which denotes depolarization of the atria, the QRS complex, which denotes depolarization of the ventricles, and the T wave, which denotes repolarization of the ventricles. The heart is the most vital and crucial organ in the human body. The heart controls a number of biological processes. The heart's main job is to pump blood to various body parts, which is the most important thing our body needs to do. Since the heart emits electrical signals at very low voltages (on the order of 60mV), which are required to evaluate and confirm the operations of a healthy heart, electrocardiogram (ECG) signals are used to record the electrical activity of the human heart.The ECG signal having the important peaks as shown in the figure1.

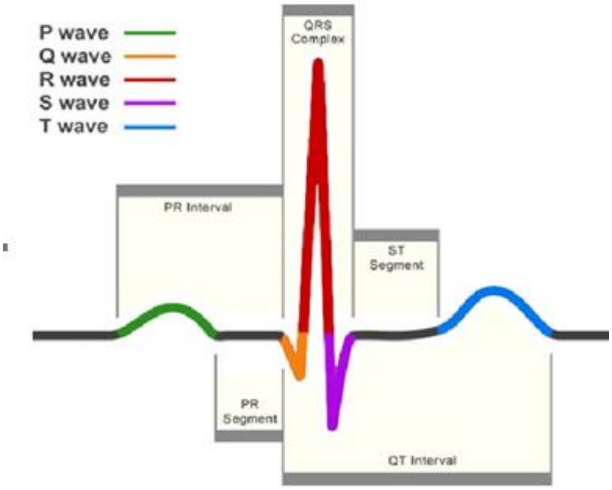


Figure 1: An ECG signal showing the most important peaks

Table 1: Normal ECG signal wave amplitude and durations

Features	Amplitude(mV)	Duration(sec)
P wave	0.25	0.06-0.08
Q wave	25% of R wave	0.09-0.1
R wave	1.60	0.08-0.12
T wave	0.1-0.5	0.12-0.16
U wave	0.05	0.1

1.2 ECG Spectrogram

A spectrogram is a graphic representation of a signal's frequency spectrum as it evolves over time. Spectrograms are sometimes referred to as sonographs, voiceprints, or voicegrams when they are applied to an audio input. Waterfall displays are what you might refer to when the data is displayed in a 3D plot. Sonar, radar, voice processing, seismology, linguistics, music, and other disciplines frequently use spectrograms.

An ECG signal can also be transferred into a spectrogram. The ECG spectrogram can be then applied with all of the required processes. An ECG spectrogram can be converted into any other domain for a better operations over the process. The ECG spectrogram contains information of the signal that the original signal does. The information in a spectrogram can never deviates from the original ECG signal captured from the patient.

The converting of a signal into its spectrogram will result greatly in the vibration analysis. The way the spectrograms work is, they makes easier for the implementation of any processes.

1.3 Tachycardia

A heart rate that is higher than the typical resting rate is referred to as tachycardia. Adults are generally considered to have tachycardia if their resting heart rate exceeds 100 beats per minute. Heart rates that are higher than the resting rate might be healthy (like during activity) or unhealthy (such as with electrical problems within the heart). Age determines the highest limit of a typical human resting heart rate. Different age groups have reasonably well-standardized cutoff levels for tachycardia; normally, deadlines are 1-2 days: tachycardia >166 bpm after 3–6 days of tachycardia >159 bpm.

1.4 Bradycardia

A slow rate of heart is known as Bradycardia. For adults is from 60 to 100 times per minute while they are at rest. Your heart beats less frequently than 60 times each minute if you have bradycardia. If the heart doesn't pump enough oxygen-rich blood to the body and the pulse rate is exceedingly sluggish, bradycardia can be a major issue. You might experience this and feel weak, exhausted, and out of breath. Bradycardia can occasionally occur without any symptoms or problems. It's not necessarily dangerous to have a slow heartbeat. For instance, a resting heart rate of 40 to 60 beats per minute is typical for some people, especially healthy young adults and trained athletes. If bradycardia is severe, a pacemaker implant may be required to assist the heart.

Table 2: Parameters of Arrhythmia

Parameters	Heart rate(in bpm)
Normal heart rate	60-90 bpm
Abnormal heart rate	Less than 60 bpm or greater than 90 bpm
Tachycardia	Greater than 90 bpm
Bradycardia	Less than 60 bpm

1.5 Multi-Variate Empirical Mode Decomposition (MEMD)

For the adaptive processing of multichannel data, the multivariate empirical mode decomposition (MEMD) has lately made significant advances. Despite MEMD's excellent efficiency in time-frequency analysis of nonlinear and non-stationary signals, its wider applicability has been constrained by high computing load and over-decomposition.

For breaking down non-linear and non-stationary signals into a sequence of Intrinsic Mode Functions, Huang et al. devised the multivariate empirical mode decomposition (MEMD) in 1998. (IMFs). IMF records the signal's repetitive activity at a specific time frame. The empirical mode decomposition breaks down a time signal into a collection of basis signals similarly to the Fourier or wavelet transforms, however unlike those transformations, the basis functions are obtained directly from the data. As a result, the results maintain the signal under consideration's complete non-stationarity. The instantaneous frequency and amplitude of the signal can be calculated when the Hilbert transform is used on the IMFs. This method is known as the Hilbert-Huang transform (HHT).

Multiscale non-linear, non-stationary signals are broken down into a number of adaptive, entirely data-driven AMFM zero mean signals, known as Intrinsic Mode Functions (IMF). This process is known as mutlivariate empirical mode decomposition (MEMD). The fundamental premise of EMD is that any signal is made up of several IMFs, each of which represents an embedded distinctive oscillation on a distinct time scale.

2 Convolutional Neural Network (CNN)

In deep learning, a Convolutional Neural Network (CNN) is a class of artificial neural network, most commonly applied to analyze 1D signals like all of the Bio-medical signals such as, ECG, EMG, EEG and voice and speech signals and 2D as well as 3D signals such as, visual imagery. Convolutional neural networks are distinguished from other neural networks by their superior performance with bio-medical signals, image, speech, or audio signal inputs. The three basic types of layers in a CNN are convolutional, pooling, and fully connected (FC). The convolutional layer, along with convolutional layers or pooling layers, is the first layer of a convolutional network, while the fully-connected layer is the last layer. The CNN becomes more complicated with each layer, detecting more chunks of the signals as well as the picture. The CNN begins to detect greater features or forms of the item as it advances through the layers, eventually identifying the desired object.

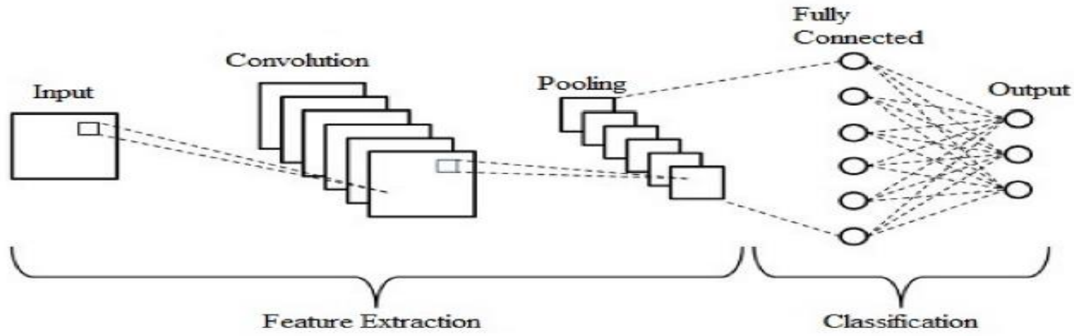


Figure2: CNN Architecture

2.1 Convolutional layer

The convolutional layer, which makes up the majority of the computation in a CNN, is its core component. Input data, a filter, and a feature map are among the things it requires. Assume that a signal with a 1D matrix of values will be used as the input. In order to detect if the feature is present, we also have a kernel or filter that traverses the signal's receptive fields. This procedure is known as convolution. The quantity of filters affects the output's depth.

As an illustration, three separate filters might produce three different feature maps, providing a depth of three. The kernel's traversal of the input matrix is measured by its stride. A longer stride yields a lower output notwithstanding the rarity of stride values of two or higher. Usually, zero-padding is used when the filters don't fit the input signal. By setting any elements that aren't a part of the input matrix to zero, this produces an output that is bigger or more evenly proportioned. Three types of padding are available: These terms include valid padding and no padding. The last convolution is discarded in this case if the dimensions do not match. The input layer and the output layer are made to be the same size using the same padding. Full padding increases the output size by adding zeros to the boundary input.

2.3 Pooling Layer

Down sampling, sometimes referred to as pooling layers, reduces the dimensionality of the input by lowering the number of parameters. The pooling operation sweeps a filter across the whole input, much like the convolutional layer, with the exception that this filter has no weights. As a substitute, the kernel fills the output array by applying an aggregation function to the values in the receptive field. Pooling may be broken down into two categories: When the filter passes over the input, max pooling chooses the input pixel with the greatest value to transmit to the output array. As a side note, this method is applied more frequently than traditional pooling. Average pooling is used to get the average value within the receptive field. This value is provided to the output array when the filter traverses the input. Many pieces of information are lost due to the pooling layer, but the CNN gains a number of advantages as a result. They improve effectiveness, decrease complexity, and lower the risk of over-fitting.

2.4 Fully-Connected Layer

The full-connected layer is what its name suggests it to be. As was previously stated, partly linked layers do not directly link the input image's pixel values to the output layer. In contrast, every node in the output layer of the fully-connected layer is directly linked to every node in the layer above it. The characteristics that were collected from the levels above and their corresponding filters are used in this layer to carry out the classification process. FC layers frequently produce a probability between 0 and 1 using a softmax activation function to classify inputs properly. ReLu functions are commonly employed in convolutional and pooling layers.

3 Physionet Database

The physionet database contains datasets of different types of heart conditions. That maybe, arrhythmias of any kind like, tachycardia or bradycardia etc. The arrhythmia condition dataset has been taken from the physionet database. The different conditions are normal or arrhythmia and arrhythmia are also of two kinds like, tachycardia as well as, bradycardia etc. Physionet often provides the samples of patients of different conditions that might be, healthy or unhealthy. Not only heart related condition signals but all types of signals that include Electro-Myography (EMG), Electro-Encephalography (EEG) and many more such as, X-Ray samples, CT scan samples and even MRI scan samples to everyone for free.

4. ResNet 101 Layers

Let's now describe this block with a recurring name. A ResNet in below figure3 is made up of multiple blocks, one for each layer. This is due to the fact that ResNets typically increase the number of operations within a block to go deeper, while the total number of layers—four—remains constant. With the exception of the final operation in a block, which lacks the ReLU, an operation in this context refers to a convolution, batch normalisation, and ReLU activation to an input.

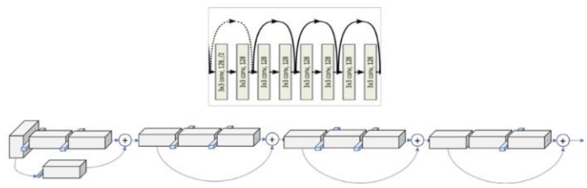


Figure3: ResNet 101 Network

As a result, the PyTorch implementation makes a distinction between blocks with 2 operations, known as Basic Blocks, and blocks with 3 operations, known as Bottleneck Blocks. Although we are already using the term layer for a group of blocks, each of these processes is typically referred to as a layer.

We can confirm that the kernel size is [3x3, 64] and the output size is [56x56] by looking at the table from the paper again. We can observe that, as we previously indicated, the volume's size remains constant within a block. This is due to the use of a padding of 1 and a stride of 1. Let's see how this applies to the 2 [3x3, 64] that is shown in the table as a whole block.

5 Proposed Method

The raw ECG signal is taken from the dataset that contains multiple samples of ECGs of different people having different types of health conditions that maybe, arrhythmia that maybe, tachycardia or bradycardia and maybe perfect rhythms of heartbeats as in the figure4. The taken raw ECG signal maybe affected from noise that maybe any of the commonly occurring noises, such as, baseline wander, power line interface and muscle artifacts.

The ECG sample must be noise free or it should be minimized to a desired level for a better results, for that, we have applied multivariate empirical mode decomposition (MEMD). Multi-Variate Empirical Mode Decomposition (MEMD) will represents the signal in Intrinsic Mode Functions (IMFs). We can remove the noise from the signal by decomposing the signal in its IMFs.

The noise free ECG signal will then be converted into spectrograms of containing same data with easy representation. The spectrogram is a de-noised sample means, the sample will be ready for extracting the P or Q or R or S or T waves. The denoising of the signal makes the peaks to be visible directly for detecting. The spectrogram will then be transferred to the next stage where, the classification of the different kinds of arrhythmias are done using the convolutional neural networks architecture.

The noise removed ECG spectrogram will then, be, transferred to, the Convolutional Neural Networks (CNN) for classification of different kinds of health conditions. The dataset will be divided into training and testing for process. The CNN will be fed with the training samples which contains majority of the samples of the dataset.

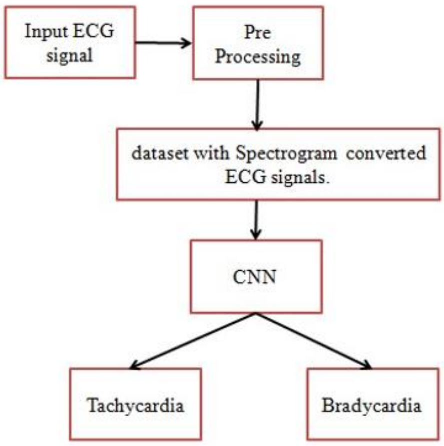


Figure4: Proposed Architecture

The trained CNN network will then, be, tested using the test data that was separated during the previous phase of the process. The CNN is classifying the data at better rate than any other existing methods such as, ANN. Comparison of various parameters of CNN with the existing ANN. It is evident that, our proposed CNN has performed better than existing ANN in various parameters.

The CNN will be trained using the training samples over many iterations for a better performance. The training samples contains all kinds of health conditions. The different kinds of health conditions are fed to the CNN with labels. The data provided to the CNN training phase will be labelled such that, it will learn the patterns of the different kinds of the health conditions.

6 Simulation Results

The raw ECG signal which are corrupted by different kinds of noises are taken from the dataset of ECG signals from the Physionet Database and represented in the below waveform. The raw ECG signal will always be corrupted because of the many reasons, so, it has be de-noised for that reasons. To make sure it doesn't affect our process.

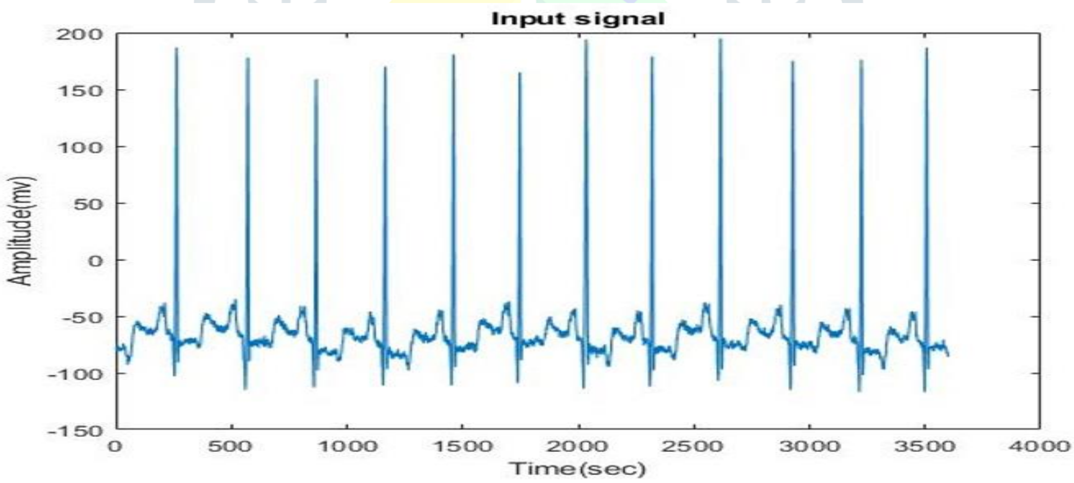


Figure 5: Raw ECG Signal

The application of EMD to a raw ECG signal will decompose the signal into its IMFs. The IMFs are used to do any operation to the ECG signal.

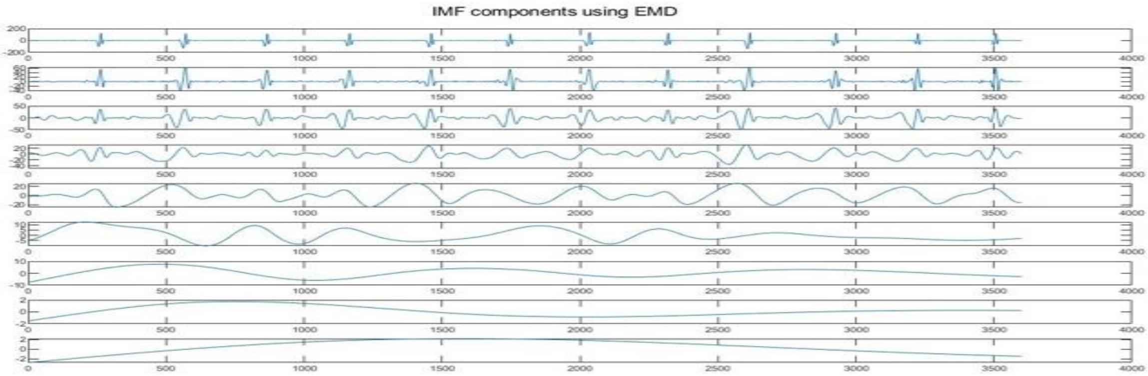


Figure 6: Decomposition into IMFs after application of EMD

The application of MEMD to a raw ECG signal will decompose the signal into its IMFs. Unlike EMD, an MEMD will be applied to many parameters of the raw ECG signal. The IMFs are used to remove noise from the raw ECG signal.

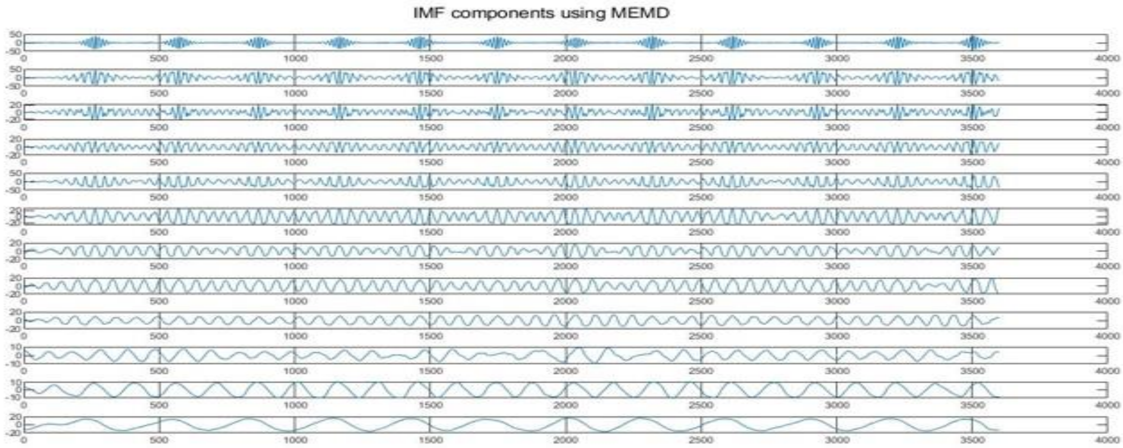


Figure 7: Decomposition into IMFs after application of MEMD

The R peaks are detected after the application of MEMD to the raw ECG signal which was decomposed into its IMFs.

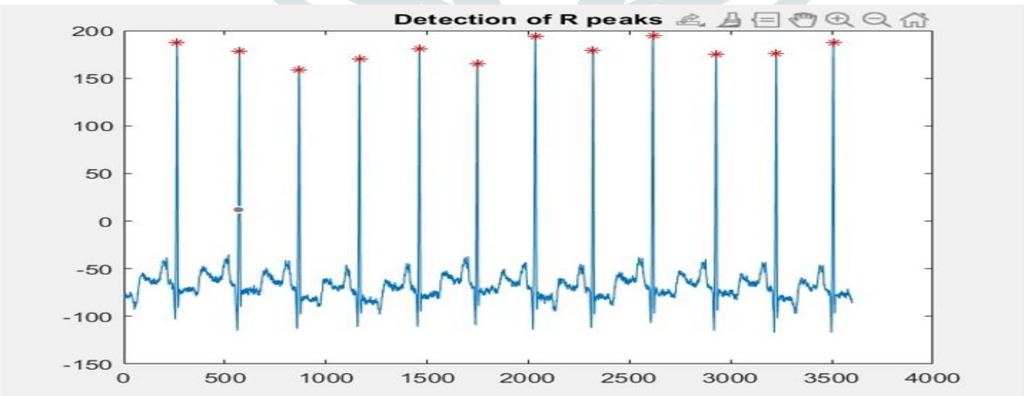


Figure 8: Detected R peaks

The filtered ECG signal was plotted in the below waveform. After the application of MEMD to the raw ECG signal the noise will be filtered out and the signal will be filtered in many parameters.

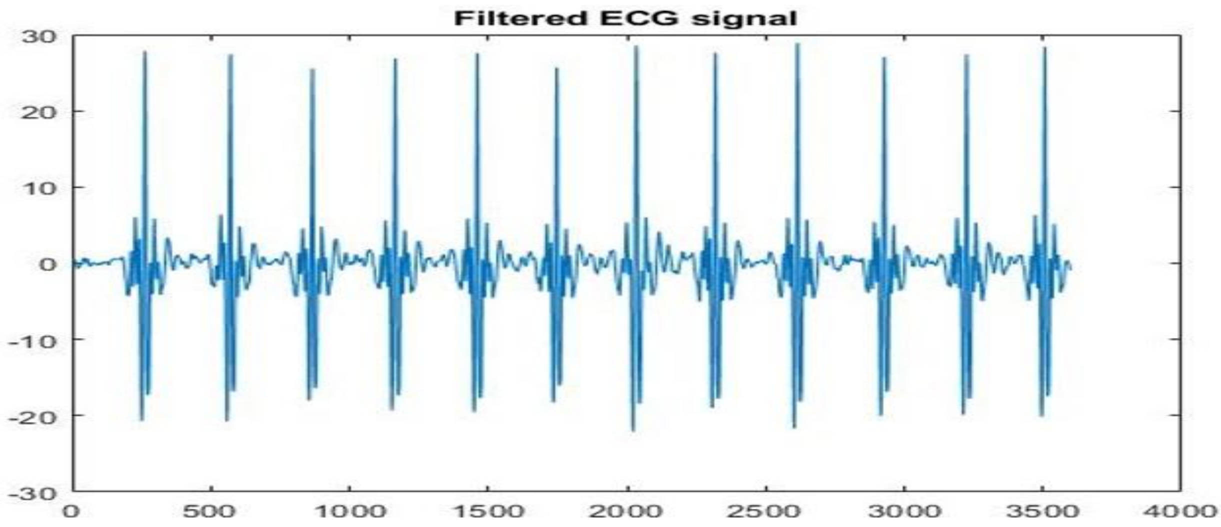


Figure 9: Filtered ECG signal

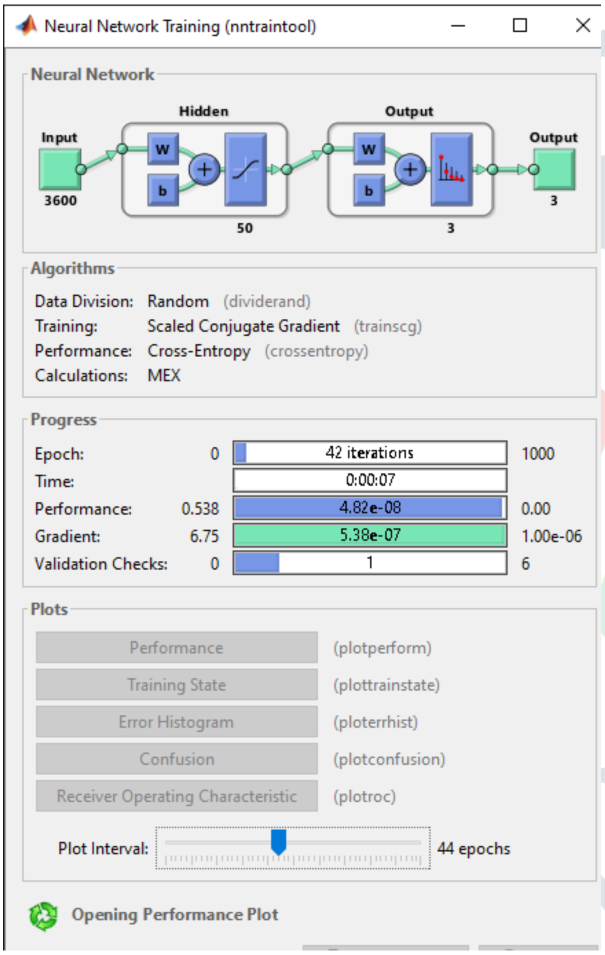
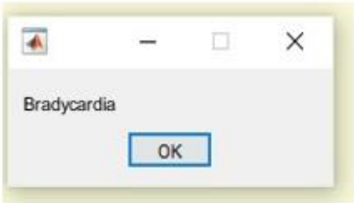


Figure 10: Network details

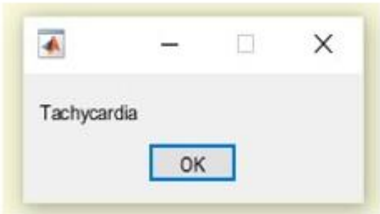
Figure 11: Confusion matrix

Confusion Matrix: Confusion Matrix is used to calculate the Performance of the Classifier . In the Confusion Matrix it is represented in the matrix form. It Compares the True Label Correctly Predicted to the Actually Predicted Values. Confusion Matrix is of a NXN Matrix here N represents the number of Classes considered for Classification it show in figure11.

Message box indicates normal.



Message box indicates Bradyacardia.



Message box indicates Tachycardia.

Figure 12: Message alerts indicating trachycadia, bradycardia, normal ecg signals

The normal rhythm spectrogram representing the normality of the particular person who has been classified as normal it shown in figure13.

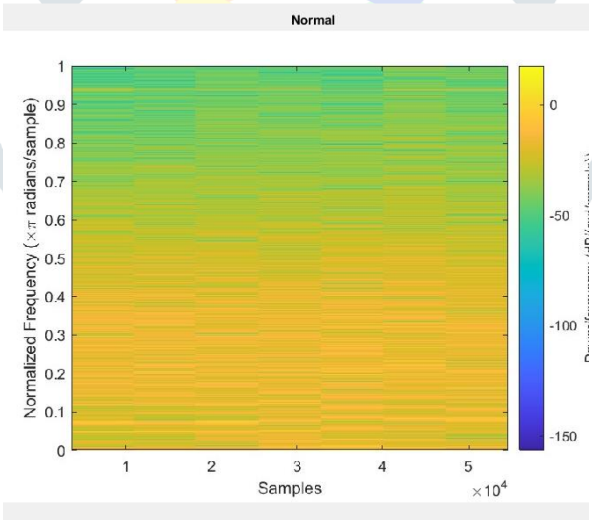


Figure 13: Normal rhythm spectrogram

The tachycardia rhythm spectrogram representing the level of the particular person who has been classified as tachycardia it shown in figure 14.

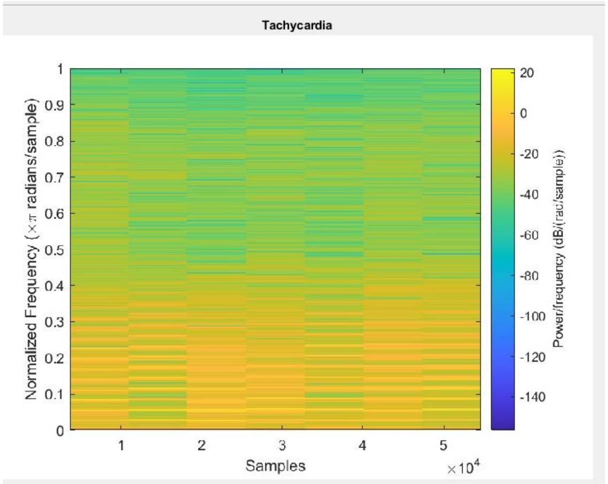


Figure 14: Tachycardia rhythm spectrogram

7 Parametric Evaluation:

a. **Accuracy:** It is the number of correctly classified cases divided by total number of instances

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

b. **Sensitivity:** It is the probability of True Positives in the Class.

Sensitivity = $\frac{TP}{TP+FN}$

c. **Specificity:** It is the probability of True Negatives in the Class.

Specificity = $\frac{TN}{TN+FP}$

d. **Precision:** It is defined as how accurately correctly predicted to the total positive predictions.

Precision = $\frac{TP}{TP+FP}$

PARAMETERS	ANN	CNN
ACCURACY	89.583333	93.750000
SENSITIVITY	89.189189	94.927536
SPECIFICITY	97.058824	96.323529
PRECISION	97.058824	98.127341

Table 3 Comparison of CNN with existing ANN

It is evident that, our proposed CNN has performed better than existing ANN in various parameters.

8 Conclusion

Finally, we can conclude that, the application of MEMD removed the noise from many parameters which made the PQRST waves to be easily detected by the Convolutional Neural Network (CNN). The CNN needs true peaks as clear as possible, for a better training over the different kinds of health conditions associated with the Human Heart. The CNN has a better accuracy and sensitivity than the existing methods such as, Artificial Neural Networks (ANN).

9 Discussion

The Convolutional Neural Network (CNN) worked better than any other existing methods or techniques. The CNN achieved a greater accuracy than the artificial neural networks. The conversion of an ECG signal into spectrograms made our signal easy for processing. The Multi-Variate Empirical Mode Decomposition (MEMD) is very great at reducing the noise in the spectrograms of ECG signals. MEMD worked better than any other existing methods or techniques.

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