Study of Enhanced Subsystems based ECG Signal Classification & Processing Using Deep Neural Networks & Amor, Undecimated Wavelet Transforms

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***Abstract* – The electrocardiogram (ECG) shows the plot of the bio-potential produced by the movement of the heart and is utilized by doctors to foresee and treat different cardio vascular illnesses. Arrangement of electrocardiogram (ECG) signals assumes a significant function in conclusions of heart illnesses An exact ECG grouping is a difficult issue. Early and precise discovery of arrhythmia, Congestive Cardiovascular breakdown types is significant in distinguishing heart infections and picking suitable treatment for a patient. Various classifiers are accessible for ECG order. Among all classifiers, Convolution Neural Organizations (CNNs) like ALEXNET have become exceptionally famous and most broadly utilized for ECG grouping In this project, we examined the issues engaged with ECG order and presents a definite study of pre-handling strategies, ECG information bases, highlight extraction methods, CNN based classifiers, and execution measures to address the referenced issues.**

Keywords – ECG, Alexnet, Deep Neural Network, CNN, Wavelet Transforms, MATLAB, Confusion Matrix, Training

I. INTRODUCTION

An electrocardiogram (ECG) is a clinical test which identifies cardiovascular irregularity by estimating the electrical action produced by the heart. A heart produces little electrical driving forces which spread through the heart muscle. These motivations can be recognized by an ECG machine. An ECG machine records the electrical movement of the heart and showcases this information as a follow on a paper. This information is then deciphered by a clinical expert. ECG assists with finding the reason for manifestations or chest torment and furthermore assists with identifying anomalous heart musicality or cardiovascular (heart) irregularities.

ECGs from ordinary sound hearts have a trademark shape. Any abnormality in the heart mood or harm to the heart muscle can change the electrical movement of the heart, so state of the ECG gets changed. A specialist may suggest an ECG for patients who may in danger of coronary illness due to family background of coronary illness, smoking, overweight, diabetes, elevated cholesterol or hypertension. The heart issues that can be identified utilizing ECG incorporate unusual heart rhythms, cardiovascular failure, and a developed heart.

ECG is the account of the electrical property of the pulses and has gotten one of the main apparatus in the conclusion of heart sicknesses. Because of high death pace of heart sicknesses, early identification and exact separation of ECG signal is fundamental for the therapy of patients.

II. OBJECTIVE

Arrangement of ECG signals utilizing AI methods can give significant contribution to specialists to affirm the finding. Characterization and recognition of arrhythmia types can help in recognizing the variation from the norm present in ECG sign of a patient. In the wake of distinguishing the anomaly, the heart sicknesses can be identified and the better therapy of the patient should be possible. Precise ECG arrangement into arrhythmia types gives adequate data to identify the heart infections and helps specialist in discovering best treatment for patients. There are numerous ECG Grouping Methods like yet every one of them managed just a single ECG Signal at an at once, at a time and will arrange it.

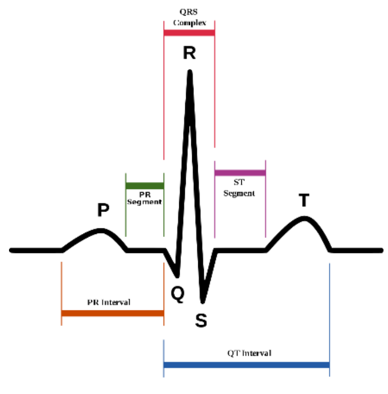


Fig1:Different types of signal peaks in a ideal ECG Signal

In this Paper, we are discussing a Wavelet Based Neural Organization approach, that can take different and numerous ECG Signals as input at a time, Analyze them and will characterize them dependent on the sort of Heart Issue it found from that ECG Signal.

III. PRACTICAL CASE SCENARIO

For the reasonable methodology of this model, think about the accompanying Situation:

- Consider a Down to earth situation, where in an emergency clinic, there are numerous Coronary illness Patients.
- In that situation, it is very tedious to inspect every single patient's ECG record and figuring out what illness he have.
- This additionally cause delay in the drug, which may cost Patient's life.
- Additionally, there is additionally an opportunity for Human measurable blunder in deciding the illness.

Consequently, we built up a model which takes a huge contribution of ECG Signals and further characterizes them as per the sickness and will tell the pulse by QRS Pinnacles Location.

Since, the model needs to decide the heart issue from the ECG Signal itself, we offer preparing to the model utilizing Profound Learning and Convolution Neural Organizations.

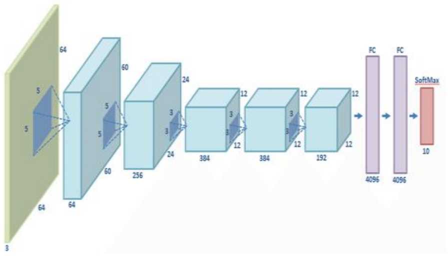


Fig 2: Depiction of various layers in the Alexner Deep CNN. Last three layers are Fully Connected Layer, Soft Max Layer & Classification Layer

We are utilizing Wavelet Changes and Profound Neural Organizations in this model. Thus, for away from of the Target and Working of the Model, we partitioned it into 2 Subsystems. Thus, we are not utilizing single code yet utilizing numerous codes for various subsystems. In functional cases, these subsystems can be assembled into one single Framework by consolidating the Gadgets in Equipment Case and Utilizing Circles in Programming Case

IV METHODOLOGIES USED

We used the techniques like:

1. ***CONTINUOS WAVELET TRANSFORM(AMORLET TRANSFORM)***
2. TRANSFER LEARNING USING A DEEP CONVOLUTION NEURAL NETWORK – ALEXNET
3. DISCRETE WAVELET TRANSFORM(UNDECIMATED TRANSFORM)

A wavelet is a wave-like swaying with a plentifulness that starts at zero, increments, and afterward diminishes back to zero. It can regularly be envisioned as a "brief wavering" like one recorded by a seismograph or heart screen.

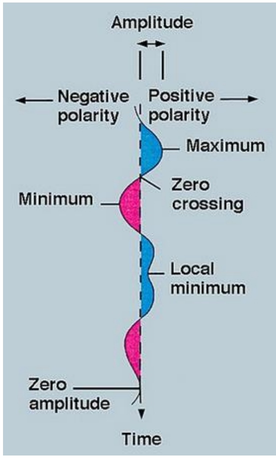


Fig3: Figure depicting a wavelet

V EQUATIONS

A. CONTINUOS WAVELET TRANSFORM(AMORLET TRANSFORM):

The **continuous wavelet transform (CWT)** is a formal (i.e., non-numerical) tool that provides an overcomplete representation of a signal by letting the translation and scale parameter of the wavelets vary continuously. The continuous wavelet transform of a function x(t) at a scale (a>0) and translational value is expressed by the following integral

$$X_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt$$

where it is a continuous function in both the time domain and the frequency domain called the mother wavelet and the overline represents operation of complex conjugate. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets which are simply the translated and scaled versions of the mother wavelet.

The Morlet wavelet (or Love Wavelet) is a wavelet made out of an unpredictable remarkable (transporter) duplicated by a Gaussian window (envelope). This wavelet is firmly identified with human recognition, both hearing and vision.

The wavelet is characterized as a steady deducted from a plane wave and afterward confined by a Gaussian window

$$\Psi_\sigma(t) = c_\sigma \pi^{-\frac{1}{4}} e^{-\frac{1}{2}t^2} \left(e^{i\sigma t} - \kappa_\sigma\right)$$

$$\text{where } \kappa_\sigma = e^{-\frac{1}{2}\sigma^2}$$

and

$$c_\sigma = \left(1 + e^{-\sigma^2} - 2e^{-\frac{3}{4}\sigma^2}\right)^{-\frac{1}{2}}$$

The main property of Amor Wavelet is,

It has equal variance in time and frequency domain. These are also one-sided spectra, and are complexed valued in the time domain

B. ALEXNET DEEP CNN:

AlexNet is the name of a convolutional neural organization (CNN). AlexNet contended in the ImageNet Huge Scope Visual Acknowledgment Challenge on September 30, 2012. The organization accomplished a main 5 blunder of 15.3%, more than 10.8 rate focuses lower than that of the second place. The first paper's essential outcome was that the profundity of the model was fundamental for its superior, which was computationally costly, however made plausible because of the use of illustrations preparing units (GPUs) during preparing. AlexNet is viewed as one of the most persuasive papers distributed in PC vision, having prodded a lot more papers distributed utilizing CNNs and GPUs to quicken profound learning. Starting at 2020, the AlexNet paper has been refered to more than 70,000 times as indicated by Google Researcher.

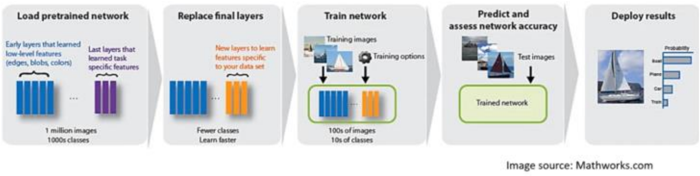


Fig4: Figure showing the layers distribution inside the Alexnet Deep CNN

Finetuning a pretrained CNN to perform classification on a new collection of images is called "TRANSFER LEARNING".

C. *DISCRETE WAVELET TRANSFORM(UNDECIMATED TRANSFORM):*

In numerical analysis and functional analysis, a **discrete wavelet transform** (**DWT**) is any wavelet transform for which the wavelets are discretely sampled Likewise with other wavelet changes, a key preferred position it has over Fourier changes is fleeting goal: it catches both recurrence and area data (area as expected). In the group of DWT, We are utilizing **SIMLET4 WAVELET** Change. Since Symlet4 Wavelet takes after the QRS Complex, which settles on it a decent decision for QRS Identification **Symlets** are almost even wavelets proposed by Daubechies as changes to the db family. The following are the properties of Undecimated Wavelet Transform:

Order	:	N (2, 3, ……, 45)
Orthogonal	:	Yes
Biorthogonal	:	Yes
Compact support	:	Yes
DWT	:	Possible
CWT	:	Possible
Support width	:	2N-1
Filters length	:	2N
Regularity	:	-
Symmetry	:	Near from
No. of vanishing moments for φ	:	N

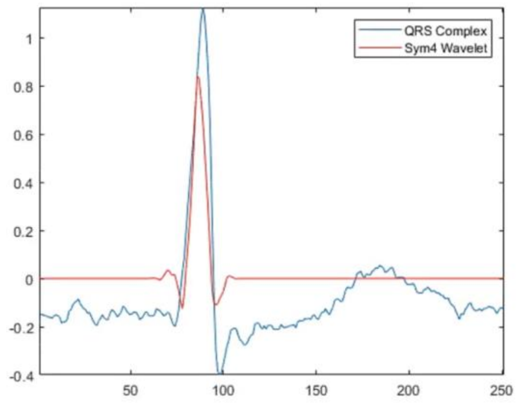


Fig5: Comparison between an ECG Signal and Sym4 wavelet

Dissimilar to the discrete wavelet change (DWT), which down examples the estimate coefficients and detail coefficient at every deterioration level, the undecimated wavelet change (UWT) doesn't fuse the down inspecting tasks. In this way, the guess coefficients and detail coefficients at each level are a similar length as the first sign.

VI PROPOSED MODEL EXPLAINATION

We classified the System into 2 Sub-Systems

A. SUBSYSTEM – 1:

We took three types of ECG Signals as INPUT to this model. They are:

1. **Arrhythmias(ARR)** - An arrhythmia describes an irregular heartbeat. With this condition, a person's heart may beat too quickly, too slowly, too early, or with an irregular rhythm.

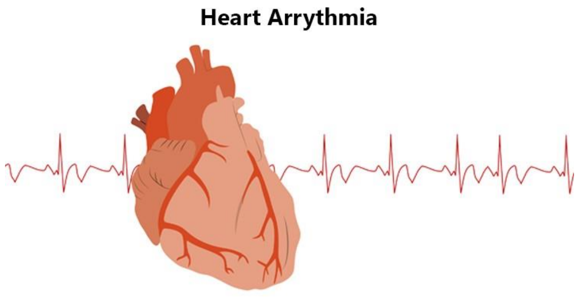


Fig 6: Figure depicting the ECG of a Arrhythmiac Heart

2. **Congestive Heart Failure(CHF)** - is a chronic progressive condition that affects the pumping power of your heart muscles. While often referred to simply as "heart failure," CHF specifically refers to the stage in which fluid builds up around the heart and causes it to pump inefficiently.

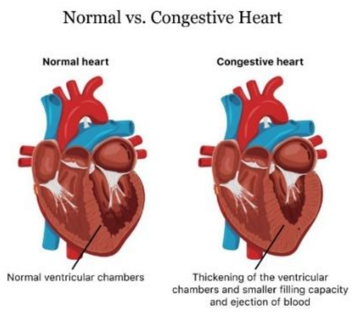


Fig 7: A comparision between a Normal heart and heart suffering from Conjestive Heart Failure(CHF)

3. **Normal Sinus Rhythm(NSM) -** is the rhythm that originates from the sinus node and describes the characteristic rhythm of the healthy human heart. The rate in NSR is generally regular but will vary depending on autonomic inputs into the sinus node.

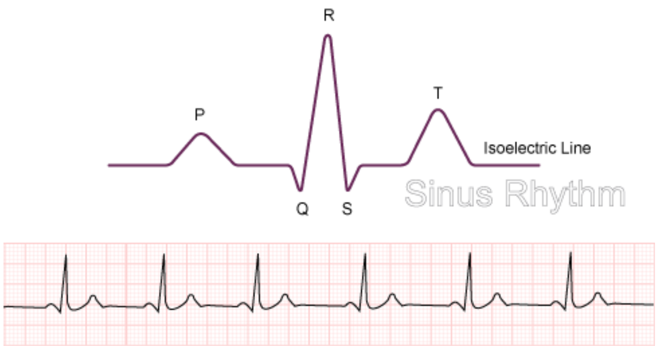


Fig 8:Figure decpiting sinus rhythm

Using the dataset with above ECG Signals, we will:

a) Convert 1D ECG Signals to Scalogram Images using CWT

b) Perform Transfer Learning via pretrained AlexNet deep CNN

We took a bunch of ARR, CHF and NSR Signals from **MIT-BIH/Physionet.org** and grouped it into one single '.mat' file

In this subsystem, our goal is to train a **Continuous Neural Network (CNN)** to distinguish between ARR, CHF and NSR

The ECG Signal Set is obtained from 162 ECG recordings from these PhysioNet databases:

- MIT-BIH Arrhythmia Database(96 ARR Signals)
- MIT-BIH NSR Database – 30 Recordings
- BIDMC CHF Database – 36 Recordings

We preprocessed the Database for CNN Learning. Each recording is 65,536 samples therefore, it can be broken into small signals of length 500 samples to increase the size of database to make it appropriate to train a CNN. Hence:

- We considered 30 recordings of each type to have equal Distribution
- Each recording is broken into 10 pieces, each piece is of length of 500 Samples
- Hence there will be 300 recordings of each ECG type with each recording sample size 500(Means each recording is one piece, comprises of 500 Samples) and for 3 datatypes, we will have 900 recordings
- Out of 900, we will use 750 recordings for Training and 150 recordings for Testing.

We use **ALEXNET**, a DEEP CNN for training purpose which is an efficient CNN and takes input only as Images. Hence we will use CWT to transform 1D ECG Signals into Scalogram Images. CWT is a family of wavelets. We use **amor** wavelet from CWTs

- We take CWT of each 1D signal and all the coefficients are arranged to form a CWT Scalogram
- Each Scalogram is represented in colormap of **JET** type of **128** colours
- These Scalograms are converted into images and will be saved in corresponding folders
- Hence, each image is of size 227x227 pixels(To be used for AlexNet) in RGB color format.

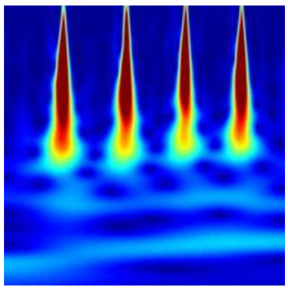


Fig 9: Scalogram image of an ECG Signa with 500 samples. Every signal will be divided into 10 types of these images each with 500 samples

For CWT, we use following Parameters:

- 'Analytic Morlet' (amor) Wavelet. It has equal variance in time and frequency domain. These are also one-sided spectra, and are complexed valued in the time domain.
- We use 12 wavelet bandpass filters per octave(Interval between two notes one of which has twice the pitch of other)

Finetuning a pretrained CNN to perform classification on a new collection of images is called "**TRANSFER LEARNING**".

We are not going to build a CNN from scratch. Because, Transfer Learning is quick and easy rather than training a CNN from scratch which requires millions of input Images, lots of training time and high speed efficient hardware. We will be inputting the Images to Last three layers of these Alexnet for Training Process.

We will be using 250/300 images from each folder(arr,chf,nsf) to for training and 50/300 images from each folder for testing purpose

B. *SUBSYSTEM – 2:*

In this system, we will be estimating the heart rate by QRS/R peak detection

What is QRS Complex?

The QRS Complex is the combination of three deflections(Q,R and S) seen on a typical ECG. P,T – First and Third Positive Deflections. Q,S – First and Second Negative Deflections. R – Second Positive Deflection & Largest Positive Deflection

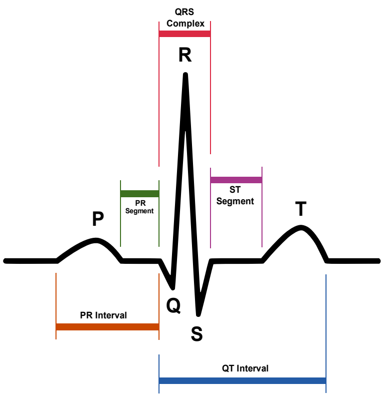


Fig 10: Figure showing the relation between frequencies of PT region, QRS peak and the normal base of ECG Signal

QRS Complex corresponds to the depolarization of the right and left ventricles of the human heart and contraction of the large ventricular muscles. Amplitude to normal QRS is 5 to 30mm and the duration is 0.06 to 0.12 sec. Width, amplitude and shape of QRS complex in diagnosing Cardiac Arrhythmias, Conduction Abnormalities, Ventricular Hypertrophy, Myocardial Infarction, Electrolyte derangements, and other disease states. Sometimes it has only QR or RS or QS or Q etc. complexes

In this system, we are going to use, **SYMLET4 WAVELET** for ECG Signal Analysis.Because Symlet4 Wavelet resembles the QRS Complex, which makes it a good choice for QRS Detection. Symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family

Proposed DWT based QRS detection System:

f1=frequency of the base line,

f2=frequency of QRS Peak,

f3=frequency of P and T regions

In general, f1>f2>f3

Here, we actually want to preserve f2 while other frequencies must be suppressed. Hence, we need a BANDPASS Filter.

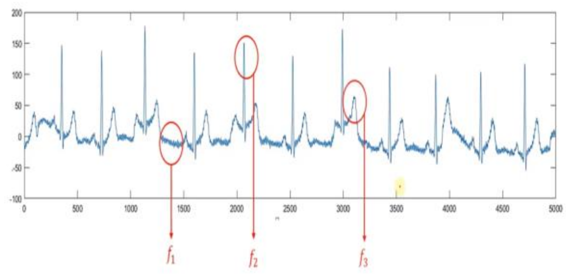


Fig 11: Figure showing the fi,f2,f3 frequency components in a practical ECG Signal.

This action can be achieved with the help of Wavelet Transform. Which is more efficient and robust than other methods. Because, sometimes QRS peak can be wider and in normal selective methods, these QRS peaks can also be vanished along with f3 frequencies. The wavelet transform separates signal components into different frequency bands. The bandpass filtering can be achieved by eliminating some frequency bands. In the wavelet transform, the band pass filtering can be achieved by eliminating wavelet coefficients of some lower scales(high frequency) and high scales(low frequency) of ECG Signal. When we perform a symlet4 wavelet transform on the signal, it will produce four detail coefficients(d1,d2,d3,d4) and one approximation coefficient at 4 levels.

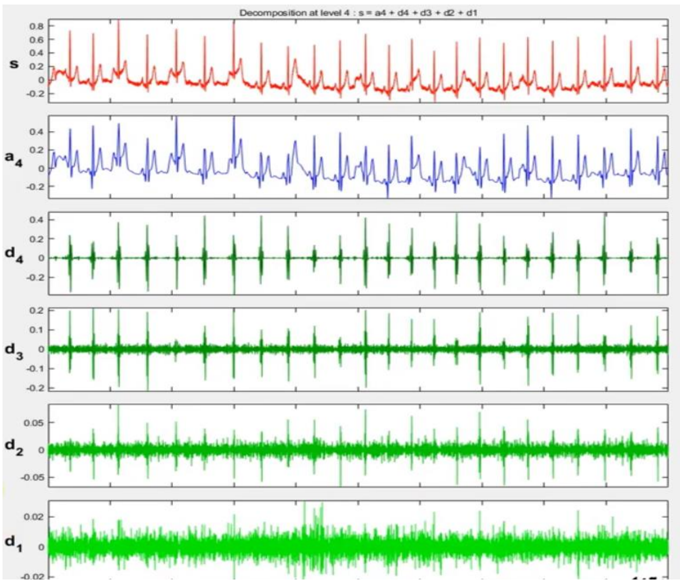


Fig 12:A Closure look at the Detail Coefficients and Approximation Coefficient of Undecimated Wavelet Transform(from the family of Symlet wavelet transform)

For this we will be using Undecimated WT using simlet4 **a4** is approximation coefficient and it has all low frequency components

Similarily, **d1** and **d2** carry high frequency components. Hence, we only use d3 and d4 inorder to achieve Band pass filtration.

After considering, **d3** and **d4** we use inverse wavelet transform, to get the signal back. In this reconstructed signal most of the times R peaks are preserved and these can be used for Heart Rate Detection.

We are using **UNDECIMATED WAVELET TRANSFORM** in the family of **SYMLET4** Wavelet Transforms which are actually Discrete Wavelet Transforms because,

Unlike the discrete wavelet transform (DWT), which down samples the approximation coefficients and detail coefficients at each decomposition level, the undecimated wavelet transform (UWT) does not incorporate the down sampling operations. Thus, the approximation coefficients and detail coefficients at each level are the same length as the original signal.

VII OUTPUT/RESULT PROCESS

A. *SUBSYSTEM – 1 :*

In the system we actually, performed these actions.

- Define and Call the Continuous Wavelet Transform to load the ECG Signal database and Classify them and hence save them as images
- Using the images produced as input to ALEXNET CNN for training purpose and will calculate the accuracy

OUTPUT CHARTS:

The folders as shown above should be created each with 300 images(recordings).
The below is the training process.

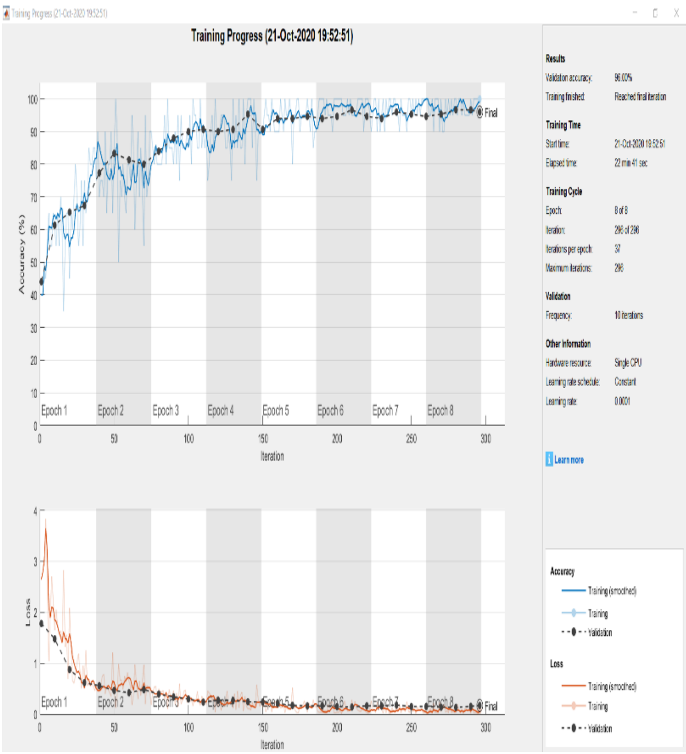


Fig 13: Training Process

The below is the **CONFUSION MATRIX.**

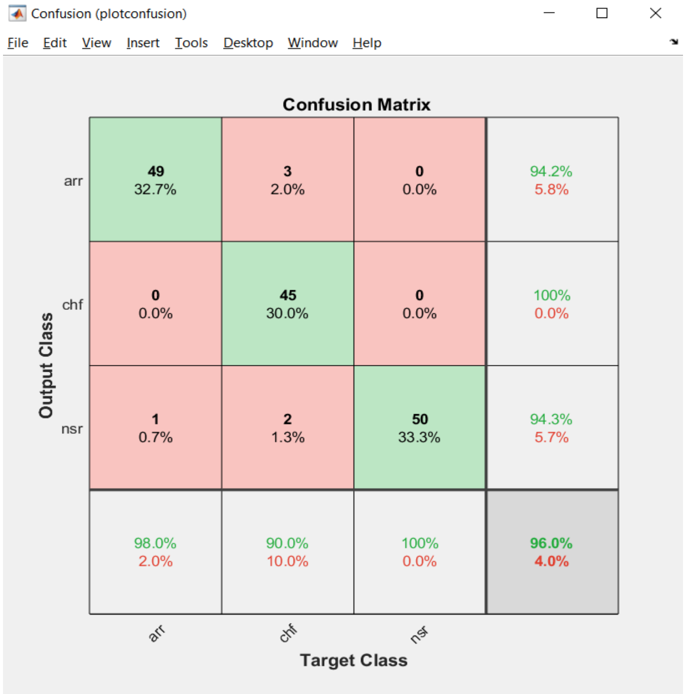


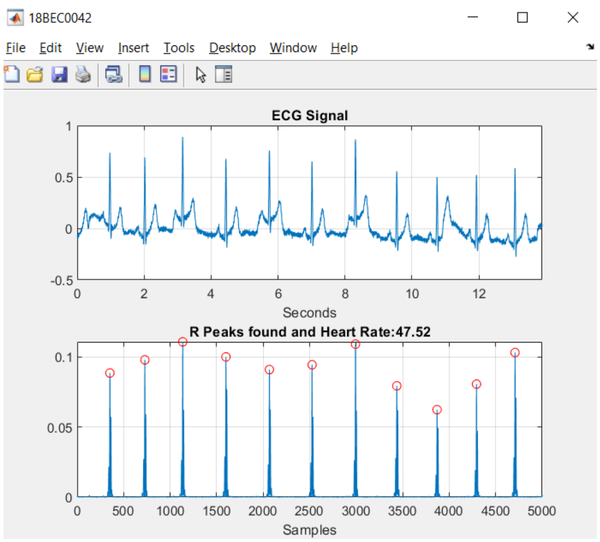
Fig 14: Confusion matrix

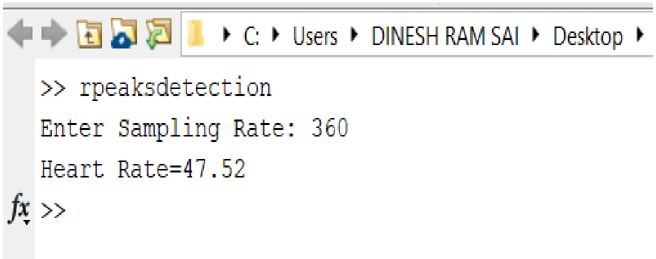
The confusion matrix validates how many ECG Signals are classified correctly out of 50 Recordings from each type. And from the training Process, the Accuracy is **96.00%**

B. *SUBSYSTEM – 2 :*

We could directly give the ECG data from the SUBSYSTEM-1 to this system, which benefits our model but will decrease the output interval time, leading to a decrease in performance and accuracy. So, we modelled this to examine the single ECG Signal. But in practical we could modify this code to execute for multiple input signals using 'LOOPS' and high performing GPU Hardware. All the operations in SUBSYSTEM – 2 are performed by considering the sampling rate of 360. Because, these signals were taken from MIT-BIH Database, in which all the ECG signals have a standard sampling rate of 360. Hence, with 360 sampling rate, there is a high probability to get the result with maximum accuracy.

OUTPUT RESULTS:





The main advantage of this system in par with present ECG signal systems is, **in some cases, the PT peaks and R peaks are of approximate, same height. In that case, the normal Bandpass filters will cutoff and block the R Peaks along with PT Peaks. But in this model, we used UNDECIMATED WAVELET TRANSFORM, hence even when PT Peaks are of approximate same length as R peak, then still R peak can be filtered out.**

VIII FUTURE SCOPE THE MODEL

The scenario which is told in the Introduction Section is the best example of how this model could be useful. Other than this this model could be useful by integrating with **ANDROID Application API's** and hence can be modified into an APP so that the people could examine their ECG without actually going to hospital at cheap cost.

This model can integrate with '**IoT**' so that if there is any abnormality detected in the Person's Heart beat, then quickly the information can be send to the Doctor or to the Hospital Staff automatically without human intervention.

The model can be integrated with **'CLOUD'** to store the ECG Signals timely, so that we can even Deploy **Machine Learning** Algorithms to check out the pattern of the ECG Signal from a long time which can be used to forecast the upcoming Heart Diseases

IX FUTURE PROGRESS

This model can be progressed in future regarding this Point Of View, since the model is divided into 4 parts(3 in Subsystem-1 and 1 in Subsystem-2), it might be time consuming to deploy all these. It would be best if we grouped all this into a singularity.

X CONCLUSION

We successfully, classified the ECG Signals using **AMOR** wavelet and ALEXNET DEEP NEURAL NETWORK with an accuracy of 90% and also Processed it by Finding the R-Peaks hence the Beats Per min. using **UNDECIMATED** wavelet

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