FINAL REPORT

SEM1-2021-2022

Topic: IOT based ECG System

Study Project: EEE F266

HAARIKA MANDA

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Contents

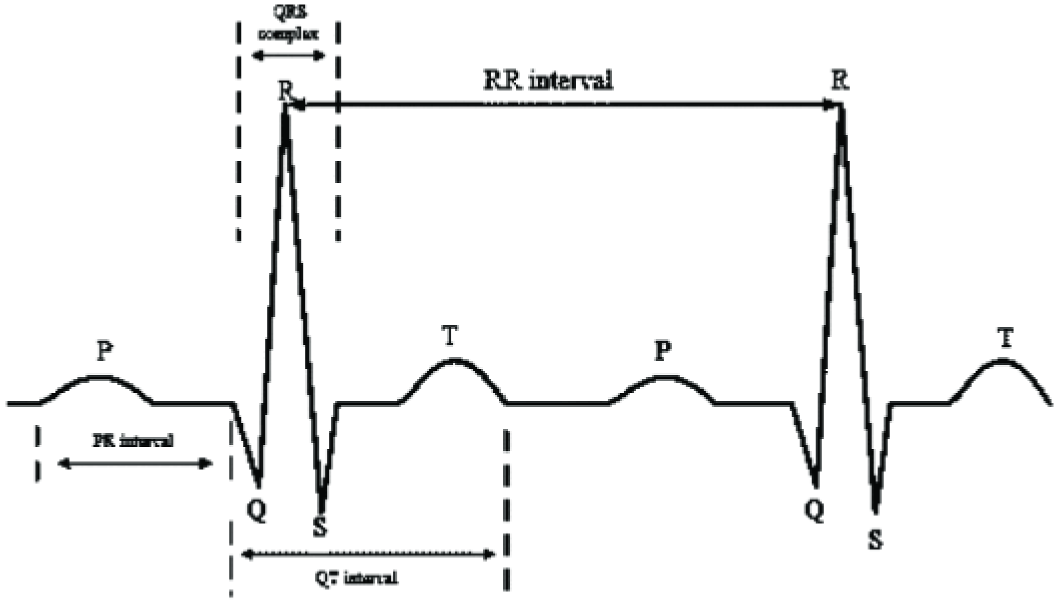
ABSTRACT:

This project will be delving into how an iot based ecg machine can be made practically as well as showing a basic hardware prototype that can be used. The electrodes must be selected for the hardware and proper pre-processing must be done to remove the noise. Then feature extraction is done as well as machine learning techniques for classification based on the features. The IOT cloud must use specific servers to maximise the performance as well. This combination of elements will be used to make the IOT based Electrocardiogram machine.

What is an ECG signal ?

An ECG signal or Electrocardiogram signal is the signal which measures the electrical currents and activity of the heart with the help of a varying number of electrodes which are placed in the skin. The data acquired from the electrodes is presented in the form of a Voltage versus time graph.

The ECG signal consists of 3 main components or 5 types of waves, the P wave, the QRS complex (consists of 3 waves) and T wave. These components occur during various instances of the cardiac cycle. [1]



P wave: An electrical signal travels to the right and left atria and causes them to contract to pump blood into the right and left ventricles. It is thus shown as a bump in the signal.

QRS complex:

Then a signal travels to the ventricles which causes them to pump blood to the lungs for oxygen as well as to the rest of the body, These signals occur rapidly and are thus grouped together as the QRS complex. It consists of a Q wave which is a negative deflection then a positively deflected R wave and ending with a negatively deflected S wave.

T wave: Here the T wave signal characterises the repolarization of the heart muscles where they rest and allow the atria to fill with blood and get ready for the next cardiac cycle.

There are also many intervals present in the ECG signal. These intervals have a general range which are considered normal to the human body. The ECG signal can measure these intervals and any deviation from the norm can help in diagnosing any cardiac problems.[2]

RR interval:
It is used to measure the period of the ECG signal or the length of one cardiac cycle. It is the time interval between one R peak and the next R peak, as mentioned before excessive deviation in the RR interval can indicate there might be a heart disease like an arrhythmia.

PR interval: It measures the time for the start of the P wave and the start of the QRS complex. It indicates the time for the signal to travel from the sinus node to the ventricle.

QT interval: It measures the time between the beginning of the QRS complex and the end of the T interval. This interval gives information about the ventricle depolarization and repolarization of the heart and if its length exceeds normal values it can be a sign of cardiac death.

How do electrodes work?

Electrodes are conductive pads attached to the skin which enable people to record minute electrical currents which flow through the body. The human body has many ions present like potassium, sodium and calcium ions which flow inside and outside cellular membranes. This makes the cells of our body depolarize and repolarize. This process of depolarization and repolarization can generate electrical current. These electrodes measure the electrical potential between them to accurately measure the electrical currents present. The ECG machine thus takes the information of electrical potential and amplifies and filters it to present it in the format of an ECG lead. Adding more electrodes increases the ECG leads and paints a more accurate picture of the health of the heart organ.

Types of Electrodes:

There are generally two types of electrodes used on the skin for ECG machines, wet electrodes and dry electrodes.

For many years wet electrodes made of Silver/Silver Chloride were used. A gel had to be used which acted as a conductor between the skin and the electrode. However wet electrodes often lead to degradation of the signal. Also, some disadvantages included being unable to conduct long term monitoring as well as need for skin preparation before application. Therefore dry electrodes are preferred nowadays.[3]

Among dry electrodes, there are active and passive electrodes.

Active electrodes have a pre-amplification module which amplifies the signal before it is passed to the machine for processing.

Passive electrodes however lack the pre-amplification module and relays the signal directly from the conductor to the ECG machine.

However active electrodes are heavier, have more price and restrict movement much greater than passive electrodes. When there is more movement of the body active electrodes can better capture and amplify the signal through the noise as compared to the others.

12 electrodes vs 3 electrodes:

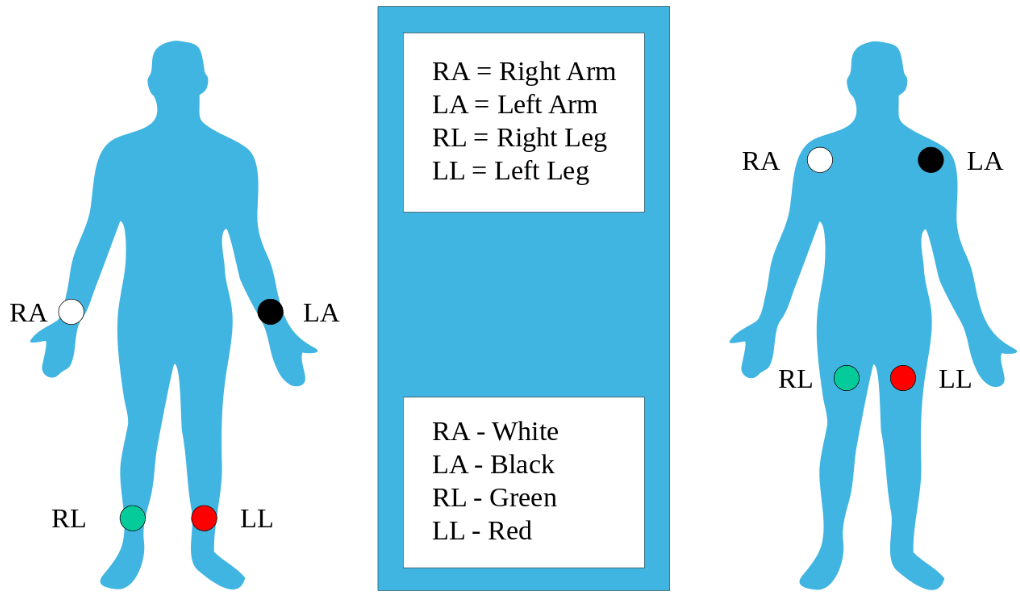
Originally 3-lead ECG devices were used throughout history. 2 electrodes are placed near the arms and the 3rd electrode is placed on the left side of the chest as the heart is present on the left side of a person. These ECG devices used 3 electrodes to measure the average potential across all the electrodes. The potential is obtained by comparing the potential obtained from 2 electrodes. There is one exploring electrode and another which is being used as a reference electrode. The 3 lead ECG machine thus gives us 6 different views of the heart. However 3 lead ECG machines may still pick up some minor interference.

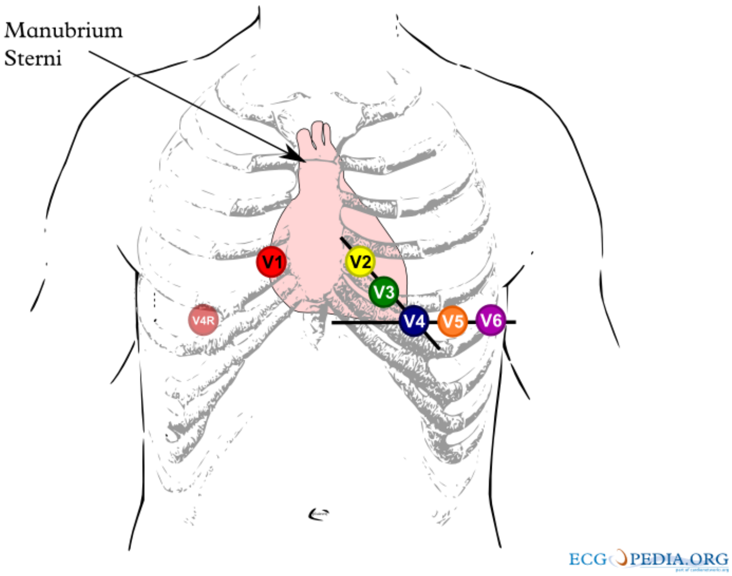
A 4 lead ECG device is not used normally but when we add a 4th electrode it is added to the right leg. This 4th electrode solves the problem of the interference generated from the other 3 electrodes and acts like a ‘ground’ for the machine to measure and accordingly remove interference so that the signal is clearer.

Hospitals use the 12-lead ECG electrodes which is done by adding 6 more electrodes to the chest in addition to 4 extremity electrodes present on the limbs of the body. In this case the other 4 electrodes are placed on the ends of the limbs of the body. This helps add 6 more leads to the heart bringing the total to 12-leads. 6 electrodes are added to the left and front of the chest in very specific placement. Of the 6 because each electrode measures signals from a different muscle in the heart. By adding these electrodes the doctor can narrow down which specific area of the heart the patient has a problem rather than indicating a general cardiac problem which the 3-lead ECG is limited too.

It is important to note that the 12-lead ECG machine only views the front portion of the heart as well as the right ventricle, if the posterior portion of the heart needs to be viewed a 15 lead EKG machine needs to be used by attaching electrodes on the back of the body.

For the purpose of more portable ECG machines that often involve the use of IOT technology, 3-lead systems or even 1-lead ECG systems are generally sufficient to give the vital information important for health. This is because 12-lead electrode systems are often uncomfortable to be attached to the patient for long periods of time.





[4]

Effect of adding electrodes to the ECG machine:

There are a few ways the 12-lead ECG machine which has more electrodes is different from the 3-lead ecg machines. The 3-lead ecg is used for general cardiac health like heart rate as well any change in the cardiac rhythm. It is mostly used for looking how the general ecg generated wave looks like, which is the P wave, T wave and the QRS complex. Therefore a complex view of the heart is not present.

By adding more electrodes we are able to monitor specific regions of the heart, and the more we add we can have a greater number of views and information.

The 12-lead ECG is able to monitor the heart in much greater detail beyond the general 3 electrode ECG signal and enable to see a vast greater amount of information regarding the individual parts of the heart. This allows doctors to use it to diagnose patients with specific rhythmic and ischemic abnormalities. The 12-lead ECG has less filters than the 3 lead ecg so that it can see specific values that the 3-lead ECG may miss.

However one trade-off of adding a more number of electrodes is that they are not ideal for long term patient monitoring as they can hinder the patient's movements.

ECG Signal Classification:

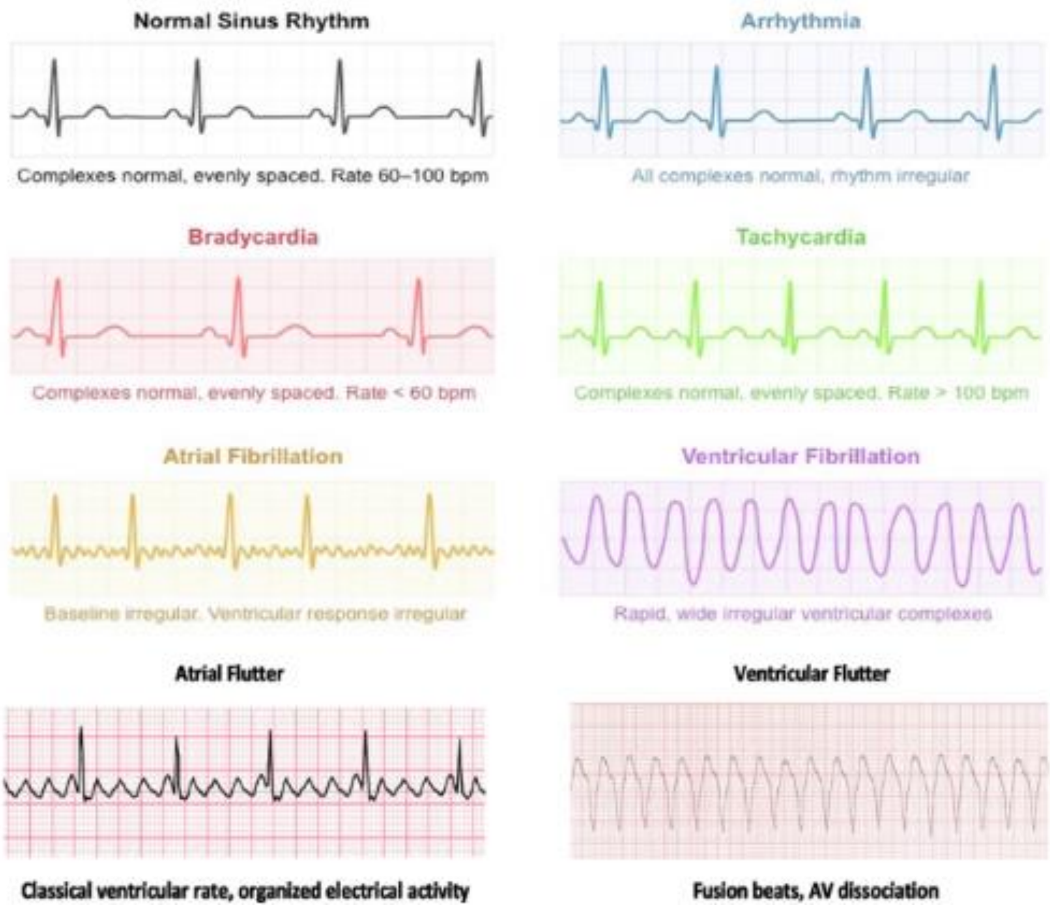
Once the relevant data from the ECG signal is obtained there are a series of steps that must be done in order to classify the signal appropriately so that it will be helpful for patient diagnosis.

The first step that should be done is the pre-processing step because the signal in its raw format is not suitable for classification or the implementation of various algorithms for differentiating the signals.

The pre-processing methods aim is for noise reduction. This is usually done through median filters which can be adjusted according to the case for maximum efficacy. Also a thinning process must be done to remove data which is not needed through the convolution process. The data removed from the signal is that which is useless in reading a cardiac cycle.

Next a process of baseline adjustment and detection is done so that the baseline of the ecg signal will be modified and connected to each block of the signal. This is done to ensure that the baseline drift is close to zero or negligible.

After all these processes are done the true features of the ECG signal can be observed. The signal can be observed in order to detect various abnormalities. However with the advent of various technologies these abnormalities can be classified and detected automatically. Most of the methods can be either supervised or unsupervised learning methods and the most common ones use machine learning techniques for classification. Some examples of these techniques include wavelet based packet techniques, machine learning model, spectral correlation and support vector machines, empirical mode decomposition and using neural networks. [5]



Types of Cardiac Signals:

As can be seen from the figure above [6], these various techniques can differentiate between these ECG signals and can arrive at a classification for the given wave.

The average heart rate shown in the signal should be between 60-100bpm for a normal heart. Each part of the ECG signal also has specific parameters which if deviated from may indicate a cardiac abnormality.

A normal cardiac signal with correct amplitude and ECG components as well as rhythm is called as a normal sinus rhythm (NSR). A deviation from NSR is medically called a cardiac arrhythmia. A sinus rhythm which is too fast (>100 bpm) is called as sinus tachycardia, and one which is too slow (<60 bpm) is called a sinus bradycardia. A sinus rhythm is said to be present if there is a one to one ratio of P wave to QRS complex.

There are cases when the sinus rhythm is not present as well.

Atrial Fibrillation:

In this case the heart beats at 600 bpm which is much higher than the baseline. There is also the absence of the P wave as well as irregular QRS complexes.

Atrial Flutter:

Here the heart rate is around the limit of 300 bpm. It is often shows a sawtooth waveform accompanied by the QRS complex.

Ventricular flutter:

Here there is no QRS complex nor P wave but rather it takes the form of a sine wave. It ranges between 250-300 bpm.

ECG Signal Features:

Amplitude:

Parameter	Normal value
P wave	Amplitude: 0.25±0.05 mV Interval : 110 ± 20ms
QRS complex	Amplitude: 1.60 ± 0.5 mV Interval: 100 ms ± 20 ms
R wave	Amplitude: 1.60 ± 0.5 mV
Q wave	Amplitude: 0.25 times the R Wave
T wave	Amplitude: -0.5 mV Interval: 160ms

Many projects often use the set parameters of amplitude to develop algorithms in order to determine whether a signal is abnormal or not.

Another important feature is the R-R interval which is the time taken between each consecutive heartbeat.

The ECG signal will be different depending on factors such as BPM as well as whether the QRS complex is evenly spaced.

Frequency:

Modern ECG machines often record from 0.05 Hz to 100 Hz as a common industry wide standard. However there are different frequencies present in each part of the ECG signal. The P wave consists of frequencies between 5-30Hz and the T wave goes from 0 to 10Hz. Similarly a normal QRS complex will be between 8-50Hz in frequencies. Wherever there are notches present in the QRS complex however that indicates the presence of higher frequencies usually above 70Hz. These are usually caused by cardiac abnormalities. [7]

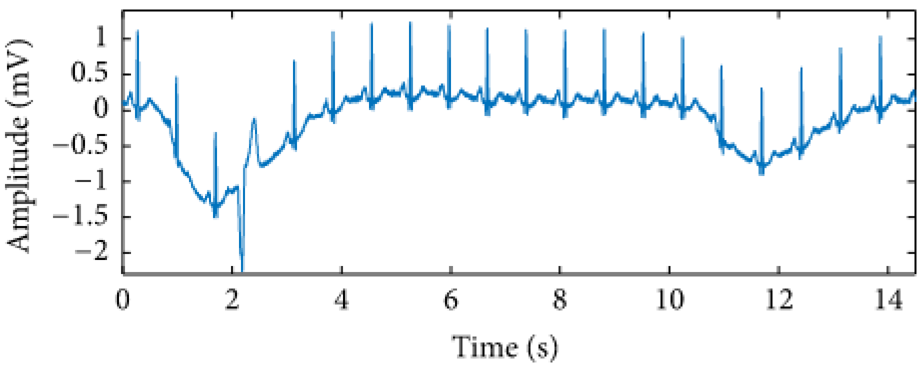
Pre-processing for an ECG signal:

Once the raw data has been extracted with the help of electrodes, pre-processing techniques can be used to improve the signal quality and reduce the noise.

Causes for Noise:

Baseline Wandering:

It is a low frequency artifact which is added to the ecg signal, and can lead to wrong classification of the signal and a wrong diagnosis. Baseline wandering often happens due to exercise and movement as well as perspiration. This causes a changing impedance between the electrode and the patient's skin. It has a massive effect on the ST segment of the signal which is relevant for analysis while exercising. Therefore portable ECG signals will be particularly affected by this noise, which is typically below lower than 1 Hz however it can go to high frequencies during vigorous exercise.

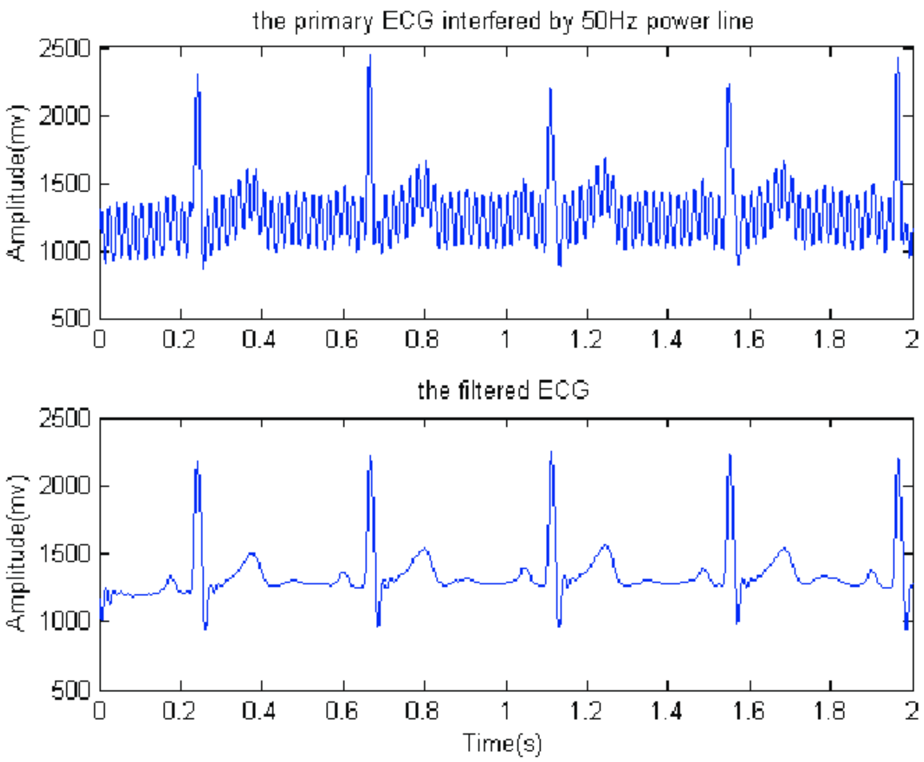


The most common method used for removing baseline wandering is a high pass butterworth filter. The cutoff frequency can be varied from 0.5 to higher value as well.

Wavelet transform can also be used to decompose the signal using low pass and high pass filters and subsequently remove the baseline wander at a frequency of approximately 0.5Hz.

Powerline Interference:

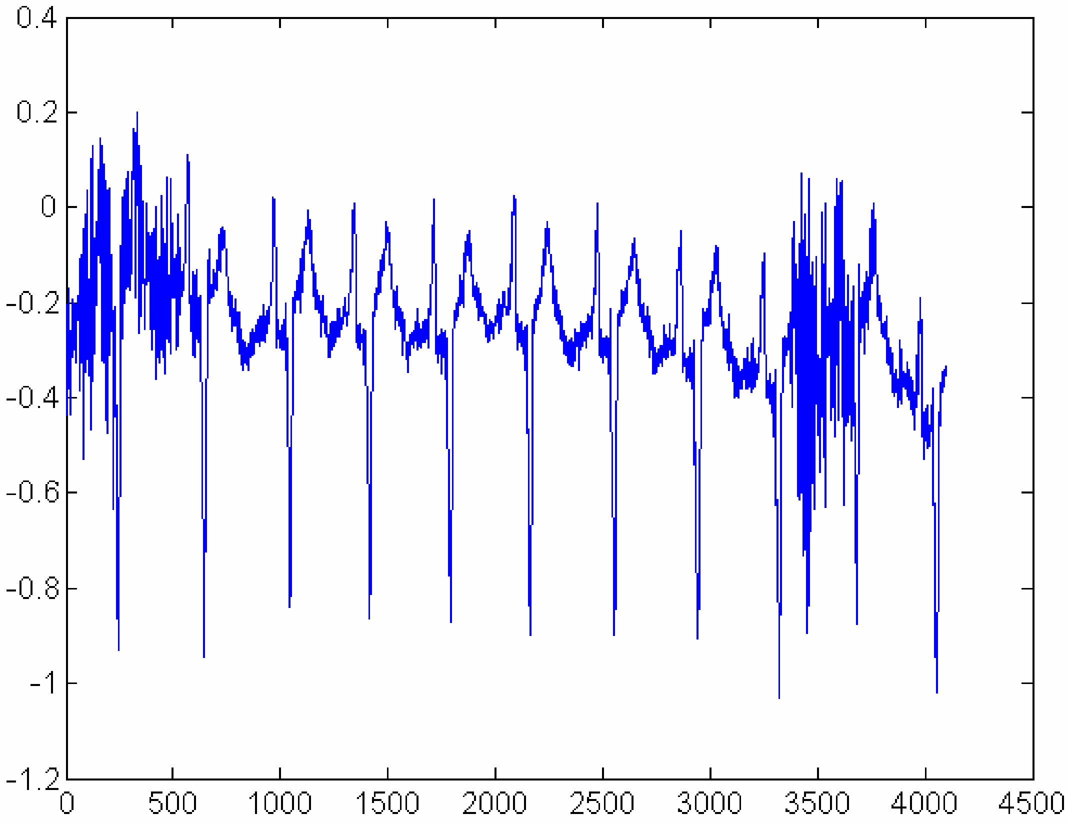
It has a frequency from approximately 50Hz to 60Hz where there is sinusoidal interference accompanied by harmonics. It can drown out minute and small features that may be critical for diagnosis. It is caused due to electromagnetic fields due to power lines. It interferes with low frequency waves like P wave and T wave. It can be removed using adaptive filters as well as the most common method which is a notch filter. [10]



[11]

Muscle Noise:

It occurs due to contraction of the skeletal muscle and the patient moves. The spectrum of muscle noise overlaps with the PQRST complex which poses a big problem in noise reduction. Unlink other noises this is a high frequency noise. It is a difficult problem as it can appear at random in the signal and cannot be predicated and it is not deterministic in nature. Thus it can be mitigated by using a moving average filter which can smoothen the signal by taking the samples over different time periods.



[12]

Electrode Motion Artifacts:

It happens due to stretching of the skin which changes the impedance between the skin and the electrode. Therefore it is slightly similar to baseline wander but unlike baseline wander it alters the PQRST complex and has a range from 1Hz to 10Hz. Their presence leads to the false detection of heartbeats.

Adaptive filters are often used to remove electrode motion artifacts. Usually either the Least Mean Square algorithm or the recursive least square algorithm is used in this adaptive filter.

Heart rate in ECG signal:

Calculation of the heart rate of the ecg signal can be done with the help of some signal processing algorithms on the original ecg signal.

Heart rate is an important parameter as it can reflect any underlying symptoms present in the patient and can expand the diagnosis of the conditions.

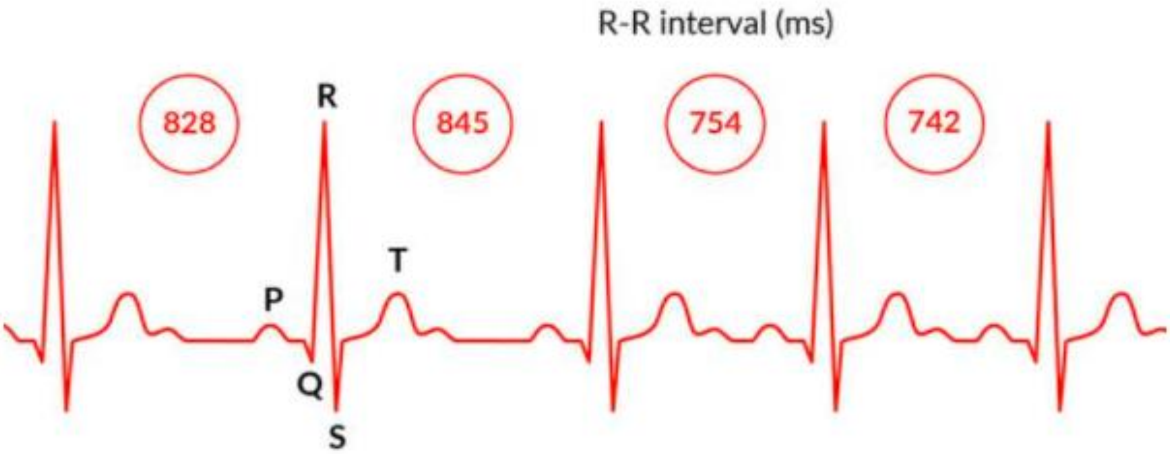
The signal needs to undergo pre-processing as detailed in the previous section regarding removal of noise like the baseline wandering and the powerline interference.

In order to gauge the health of the overall heart of the body we need to use the Heart Rate Variability (HRV) which is the change or fluctuation in the time intervals between consecutive heartbeats.

Heart rate variability depends on the autonomous nervous system and it's two branches, the sympathetic part which is responsible for stressful situations requiring action and the parasympathetic part which requires the body to rest and recover. HRV generally decreases during exercise and increases during the period when the body is doing relaxing activities.

The ECG based methods for calculating HRV generally measure the time between 2 successive R peaks by detecting the R peak in the QRS complex.

The algorithmic implementation of finding HFV involves feature extraction, detecting the R peak and R-R interval calculation.(R-R interval is also called as interbeat interval by the medical community)[11]



[12]

Filtering must be done to remove some false R peaks as well for more accurate data.
The RR interval has a range of between 0 and 0.6 and anything deviating is considered to be abnormal. Common R peak detection algorithms use filtering. The Pan Hopkins algorithm is the most famous peak detection algorithm normally used. [13]

First derivative methods and wavelet transform methods are also widely used in the field.

There are many pros and cons of various R detection methods which depend on the time taken for execution as well as the complexity of the algorithm and resources required for it. The appropriate algorithm can be chosen based on the need.

For Iot based system which might require fast analysis, we need a short time and low complexity. One method that might prove suitable is using Hilbert transform and first differential of the data to locate R peak.

The R peak detected is then used to segment the signal into smaller periods and compute the RR interval.

Once the RR interval is calculated the Heart rate can be calculated according to the following formula

$$HR=60/(RR/Fs)$$

Where RR is the time between two consecutive peaks and Fs is the sampling frequency.

The normal heart rate is between 60 and 100bpm so an unusually high or low heart rate can help aid in diagnosis of cardiac abnormalities.

The RR interval can also be used to calculate the HRV which is the root mean square of the RR which can paint a clearer picture of the heart health.

Coronary artery disease:

It involves the build-up of plaque over many years in the arteries which supply oxygen rich blood to the heart. It can slow blood flow and cause chest pain and shortness of breath. It is also called ischemic heart disease.

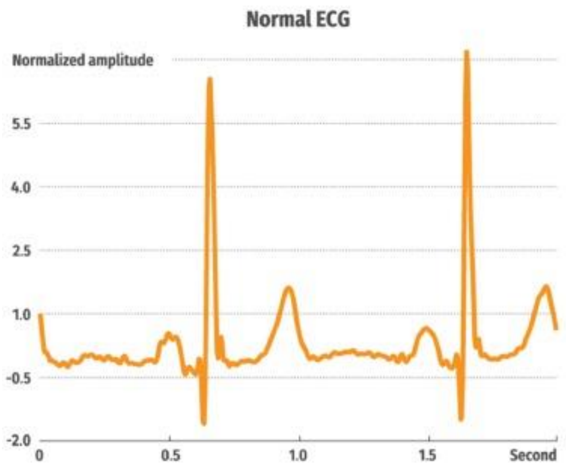
This ischemia disorder primarily affects the ST segment and the T wave in the signal. This is called ST-T changes in the ECG signal.
The changes occurring include

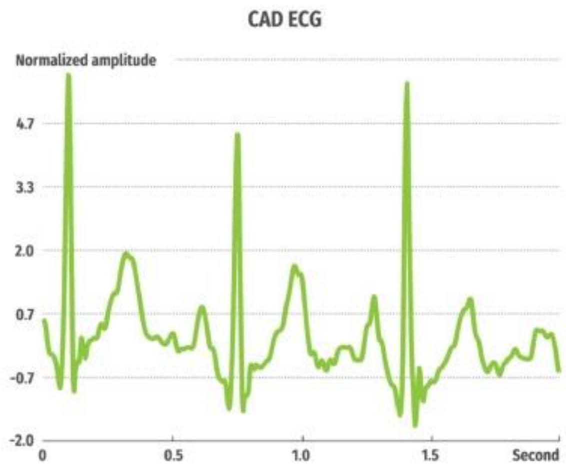
- ST segment elevation
- ST segment depression
- T wave inversion

The T wave may also be flattened or it may increase beyond the norm in amplitude.

The changes in the ST segment may be only one or multiple of the changes in the segment as listed above.

The changes in the ECG signal during the beginning manifestation of ischemia may differ between the changes in the ST segment in the later stages of ischemia.





Feature Extraction:

This is the most important step in the electrocardiogram machine. While some features are relevant for some types of heart diseases others are irrelevant to that particular heart disease classification as well as analysis.

Therefore various algorithms can be used for estimation of the parameters required like the QRS complex.

There are three main types of feature extraction techniques used commonly that are time based methods, frequency based methods like fast fourier transform and a combination of the two involving both time and frequency based extraction like Wavelet transform.

Some other algorithms used include filter techniques, autocorrelation function feature extraction method and principal component analysis feature extraction.

Sometimes more than one technique can be used in combination to get better results and to improve classification of the abnormalities of the heart.

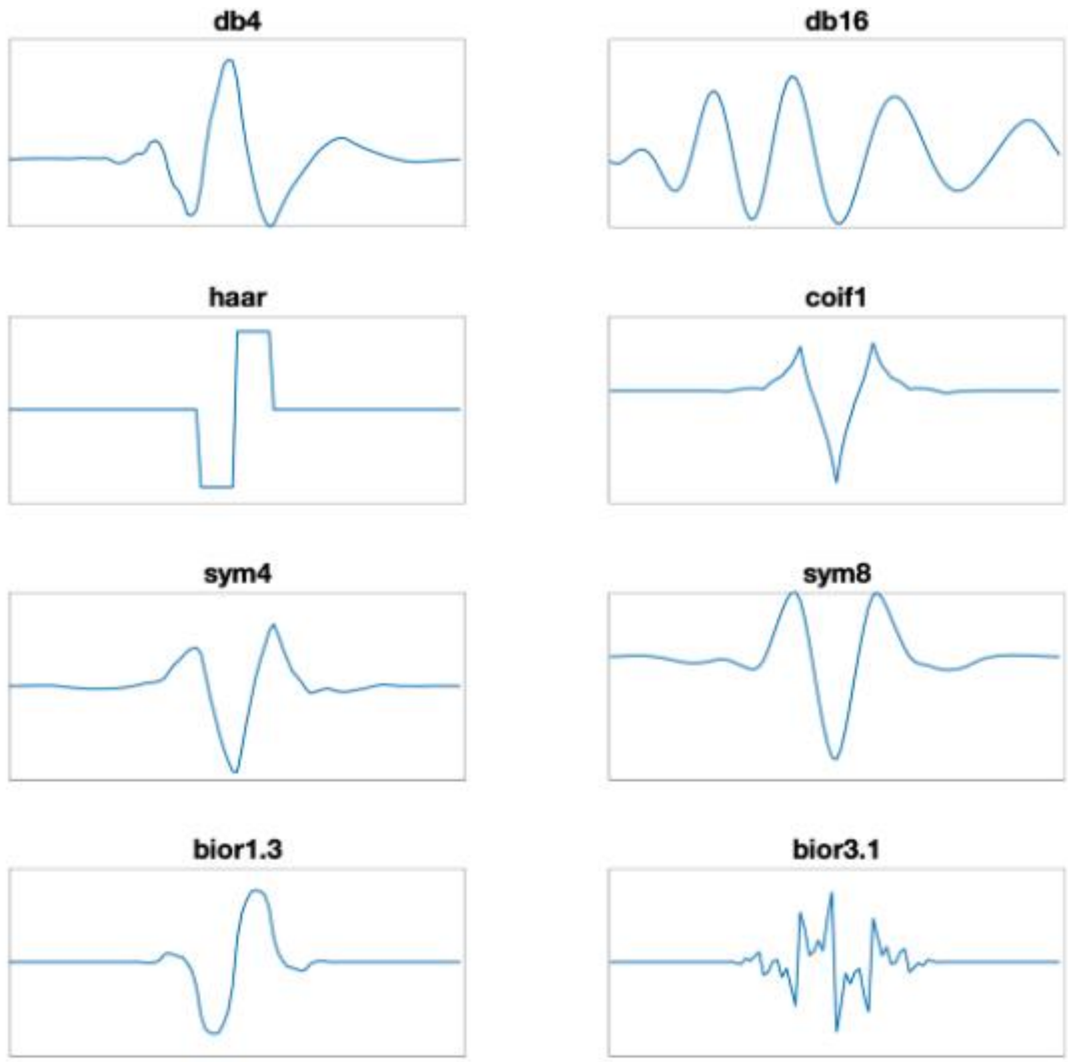
We will be focusing on different wavelet transform techniques that can be used for feature extraction.

Wavelet Transform:

Wavelet transform has grown popular for ecg processing and extraction over the years for its ability to convert the signal in the form of both time as well as frequency decomposition and to separate its various components in a clean manner.

Even though the Fourier transform is a basic algorithm for finding frequencies of a signal, the wavelet transform is much more suitable and robust for its ability to be applied to many signal shapes.

There are many types of wavelet functions that are available that can be chosen according to the signal being analysed, however fourier analysis is restricted only to the sinusoidal signal.



[15]
Different function families that can be used for wavelet transform.
Usually the wavelet function of approximate shape of QRS complex is used as above in “db4”.

Wavelet transform is unique in its ability to split the data up into various sets which can each be individually analysed.

It can break up a signal which contains large amounts of information into different frequency components with an appropriate resolution.
It allows one to look at the minutiae of complex signals like the ecg signal.

In order for Wavelet transform to be applied it must satisfy some basic admissibility conditions which are required so that the signal is capable of being reconstructed perfectly without major differences.

One type of Wavelet transform method is discrete Wavelet Method which is preferred due to reduced computational time needed.

Discrete Wavelet Method:

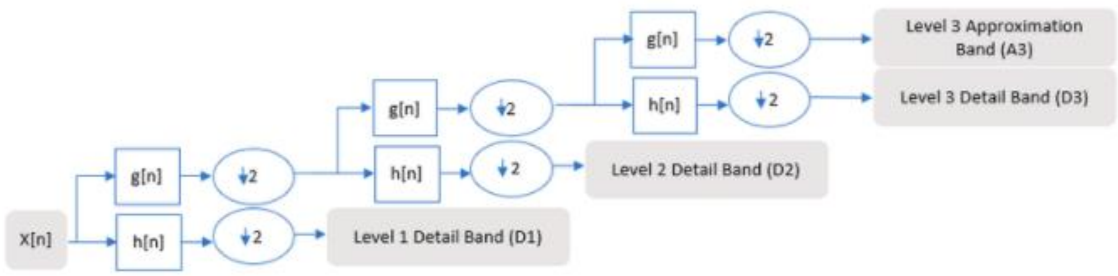
Discrete Wavelet Transform is a very common method in particular used for feature extraction. The signal is passed through a series of low pass and high pass filters which implement the scaling and the wavelet function respectively. The scaling function produces approximation coefficients whereas the wavelet function produces detailed coefficients. The approximation coefficients are decomposed at every level whereas the detail coefficients remain the same.

The input signal undergoes convolution with the scaling and wavelet filter to make approximation and detailed signals as seen below.

$$y_{\mathrm{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

$$y_{\mathrm{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

After each level of computation through filters half the frequencies are discarded and the resolution is thereby doubled.
The level decomposition can be visualized below where g is the low pass filter and h is the high pass filter



[16]

The above method can be used with different frequency bands and changing the number of levels to obtain different coefficients.

In ECG signals the DWT method can be used to extract either only R wave or only Q and S wave. This is done by keeping some of the detailed coefficients and removing others in order to obtain the QRS parameter one needs.

The basic DWT equation can be written as

$$DWT_{j,k}(t) = \sum_{j,k} f(t)2^{-j/2}\psi(2^{-j}t - k)$$

Where j and k are the dilation and the translation coefficients. [17]

Pan Tompkins Method:

It is an extremely popular ECG feature extraction technique that is used to detect the QRS complex.

Different filters are applied to remove the noise and amplify the relevant frequency content of the QRS complex for extraction.
It has 3 parts for the process. Application of a bandpass filter, a derivative filter and finally the last part which is squaring and then integration. [18]

Bandpass Filter:

The bandpass filter is often applied by cascading a low pass filter and high pass filter together to reduce the time and space complexity of the algorithm thereby making it more efficient.

It is suggested that the bandpass filter has a bandwidth of between 5-15Hz. This is the ideal frequency to maximize the energy of the QRS complex and reduce the overall effects of the muscle noise. It also is ideal in reducing various noises discussed in previous sections like baseline wandering and powerline interference.

Depending on the sampling rate the bandwidth taken may vary but it is advised to keep it near the ideal values.

The low pass filter function is given below. It has a cutoff frequency of 11Hz. There is a delay of around 6 samples when this filter is applied to the signal. It has a gain of around 36 as well.

$$H(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2}.$$

The high pass filter function is given below with a cutoff frequency of around 5Hz. It has a longer delay of 16 samples and a gain of 32.

$$H(z) = \frac{(-1 + 32z^{-16} + z^{-32})}{(1 + z^{-1})}.$$

Derivative Filter:

The objective of this filter is to provide the slope of the QRS complex.

$$H(z) = (1/8T)\,(-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}).$$

Signal Squaring:

This amplifies the R peak in particular which is an already dominant peak so as to reduce the chances of smaller peaks like in the T wave to be recognised.

It is a nonlinear amplifier so it enhances the higher frequencies present in the signal.

Moving Window Integration:

Finally a common moving window integration is used to give information regarding the waveform after having obtained the Slope information. The window size in moving window integration should be chosen with caution according to the sampling frequency. A window which is too long can cause the different components of the signal to merge like the QRS complex and the T wave but a window which is too small can cause excess peaks which were originally not present to appear.

Fiducial marks are used to determine the temporary location of the QRS waveform. It is found by seeing the moment the signal changes direction. It is determined from the rising edge of the waveform.

Thresholds:

Thresholds are also used in order to reduce the chances of errors in detection of noise instead of the signal. The threshold is updated each time a new peak is detected in order to have the best possible output. It is determined from already detected QRS complexes and the overall noise levels.

RR interval averages:

The algorithm also accounts for the chances of missing the QRS complexes due to thresholds which are set too high. It involves maintaining two RR interval averages. It uses these averages to decide where to backtrack to find out what has been missed.

The Pan Hopkins algorithm is very much useful in heartbeat detection and uses the same formula for calculation of heart rate as discussed earlier.

The advantage of Pan Tompkins algorithm is it can be used in real time detection due to the simultaneous updating of it’s various parameters like threshold and it’s RR time averages.

Processing and Analysis of ECG Signal:

Once the feature extraction has been done many different types of processing are used in order to classify the ECG signal into various types.

A popular method of ECG classification nowadays involves the use of Neural Networks and Decision trees for classification of ailments. There is also a growing popularity of deep learning for the automatic classification of ECG signals as well as the use of convolutional neural networks.

There are also examples of other machine learning algorithms being used with the iot based ecg system as well.

ECG Classification using Convolutional Neural Networks:

Convolutional Neural Networks or CNNs are used to classify the ECG signal into the types of arrhythmias. That is it classifies them into Normal, Premature ventricular contractions (PVCs) and right bundle branch block (RBBB).

This requires the use of the QRS complexes which have already been taken from the Pan Tompkins algorithm which has already been discussed in detail above.

From this data of the QRS complexes we should be able to obtain the spectrogram of the ecg signal. This is done through the short time fourier transform as seen below.

$$X_n(e^{j\Omega}) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]\ e^{-j\Omega m}$$

We are using Short Time Fourier transform (STFT) instead of normal fast Fourier transform (FFT) because STFT has smaller time frames leading to the frequency spectrum moving smoother over time, therefore it is more accurate.

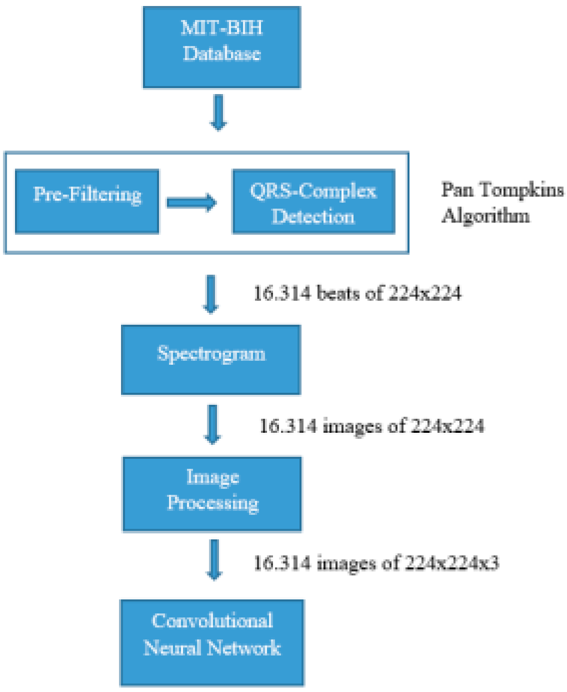
By squaring the magnitude of STFT coefficient we can thus get the spectrogram of the signal.

In order to use CNNs we need to convert the signal into an image using image processing techniques. Once converted into an image CNNs can be used by adding appropriate layers such as convolutional layer, normalization layer, pooling layer as well as a fully connected layer.

Feature extraction is done usually by the first 3 layers and the fully connected layer is used for image classification. After every convolutional layer batch normalisation must take place as it is used to standardize the given input after each layer. Pooling Layer is also in important process as it reduces the dimensions of the input features which is in the form of a matrix, this decreases the number of parameters the server has to store and decreases computational complexity. This in turn can speed up the classification process especially in cases like the real time ECG signal which involves large amounts of data. Fully connected layer is used for final classification after reducing the size of data needed to be used and extracting the features.

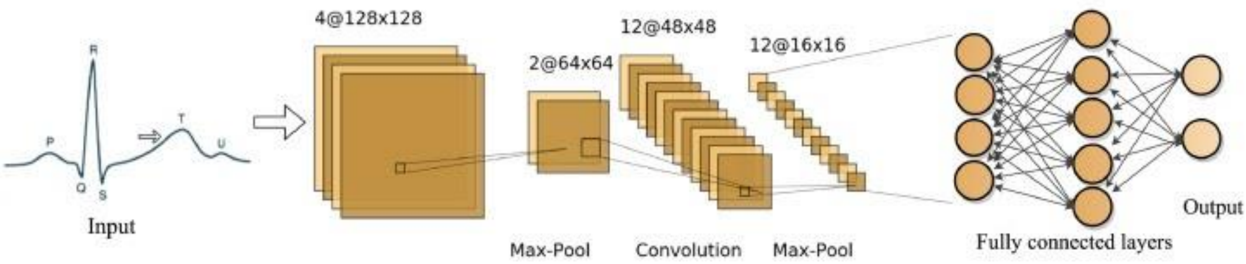
There should finally be 3 outputs for the CNNs that is they are the outputs for classifying the beats into 3 types of classes of Arrhythmias.

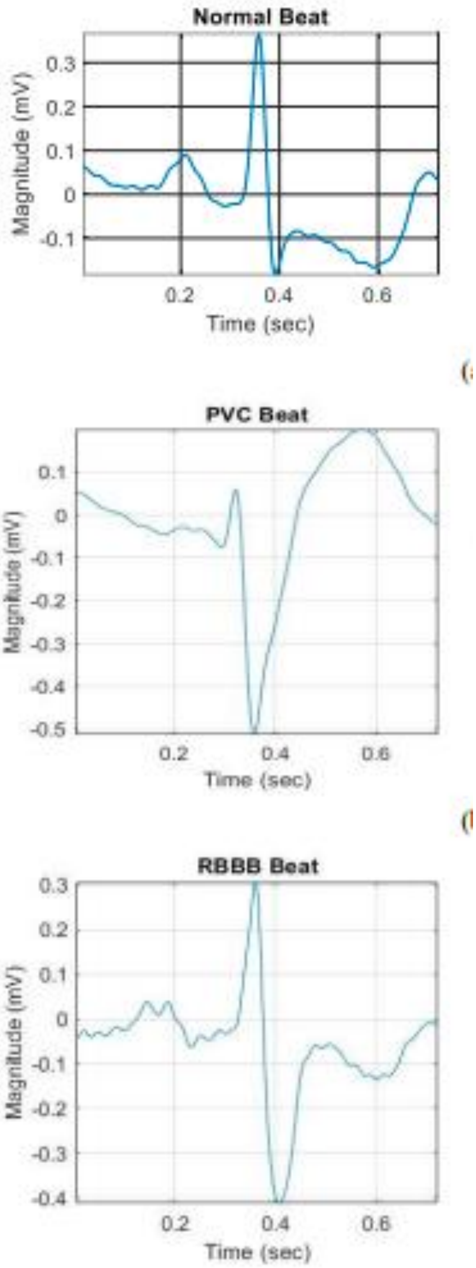
Below is a flow chart showing the overall methods of using the CNNs for Classification. The layers of CNNs can have activation functions such as ReLU activation functions and the output should make use of a softmax function which is used often for multiclass classification of input data. We often use ReLU activation function in these cases because it simplifies the process of backpropagation. Updating the CNN weights requires the derivative of the activation function, because the derivative of the ReLU function is one it ensures we don't have to keep track of additional parameters for weight updation thereby decreasing the storage space required.



[19]

The CNN Network will look similar to the picture below with more layers added on an as needed basis.





[19] The generalized shape of the 3 beat classifications

The final classification can be evaluated by using the parameters of Sensitivity, Specificity and Accuracy which are a good gauge of whether a model is successful in it’s classification methods. In case of bad results the model can be tweaked by adding or removing layers from the CNN or by changing various activation functions.

$$Sensitivity = \frac{TP}{TP + FN} * 100(\%)$$

$$Specificity = \frac{TN}{TN + FP} * 100(\%)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} * 100(\%)$$

The method of using Convolutional Neural Networks is not the only method of classification as other methods involving trees and other methods of supervised deep learning.

Hardware Implementation of ECG system:

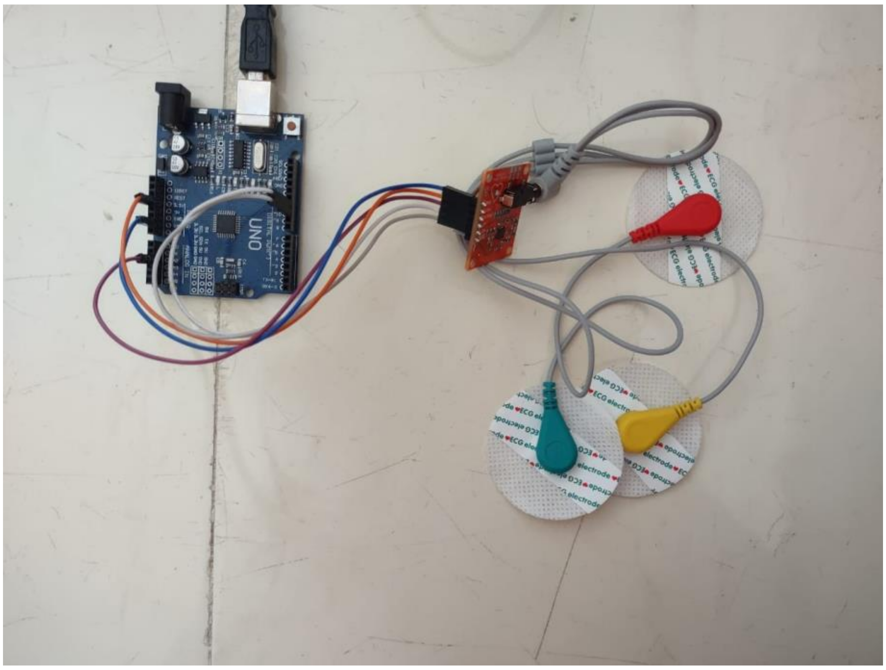


Figure: Hardware implementation of the ECG done

In this project we have implemented a prototype model for the iot based ECG system. The system which is light weight can be made more portable with modifications in the future.

The system consists of 3 electrodes where the electrode pad can be removed after each use and a new electrode can be inserted to ensure sanitation and no spreading of germs. They can be used up to 2 times before they need to be replaced. We are not using a pre amplification unit so that the device is wearable.

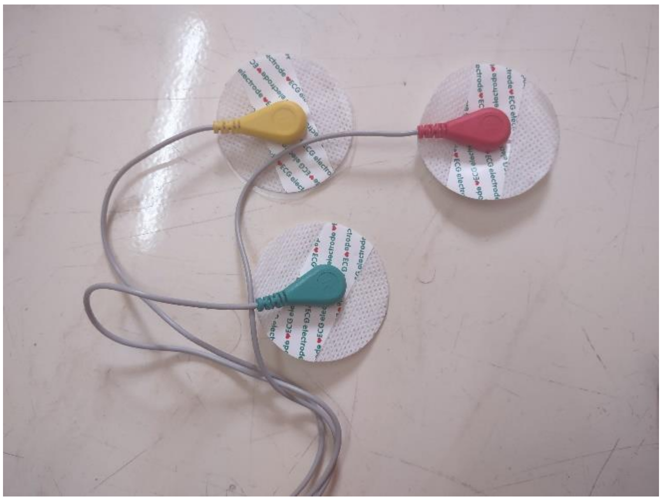


Fig: 3 detachable electrode pads and wires used for taking readings.

These 3 electrodes are connected to the sensor AS8232 which is an ECG sensor. AD8232 is essentially a commercial ECG sensor used to calculate the electrical activity of the human heart. The AD8232 is well known for its ability to reduce the noise taken from the signal automatically with no pre-processing. This is because the AD8232 is acting like an operational amplifier.

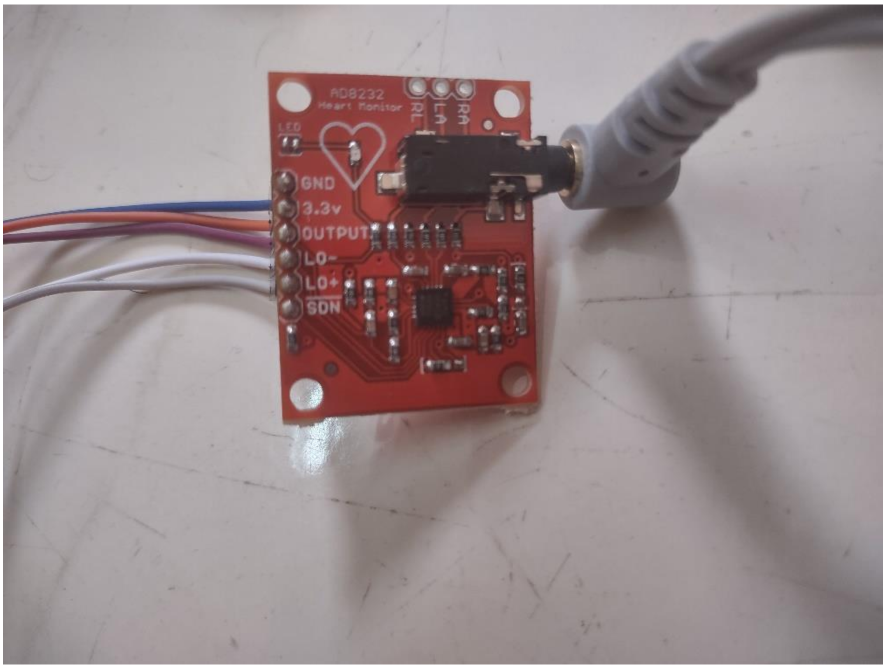


Fig: AD8232 chip which connects electrodes to Arduino UNO

In addition to the AD8232 chip we use an Arduino UNO commercial chip which acts like an interface and microcontroller for the purposes of our project. The Arduino is used due to it’s easy to use pin diagram with both input and output analog as well as digital ports and for it’s ease of use for programming methods by programming using the language of C/C++.

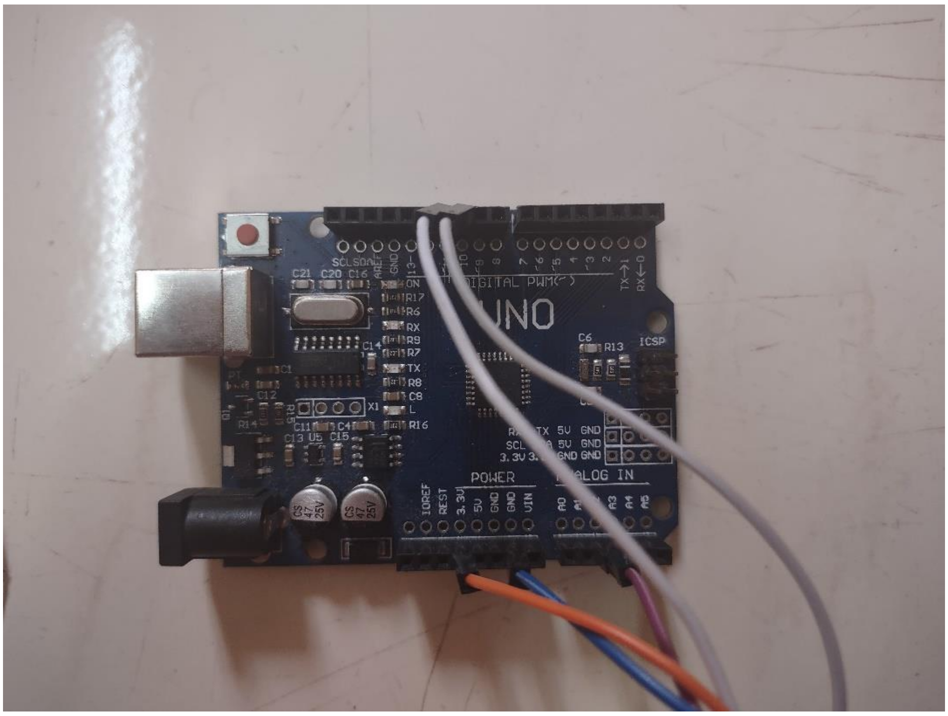
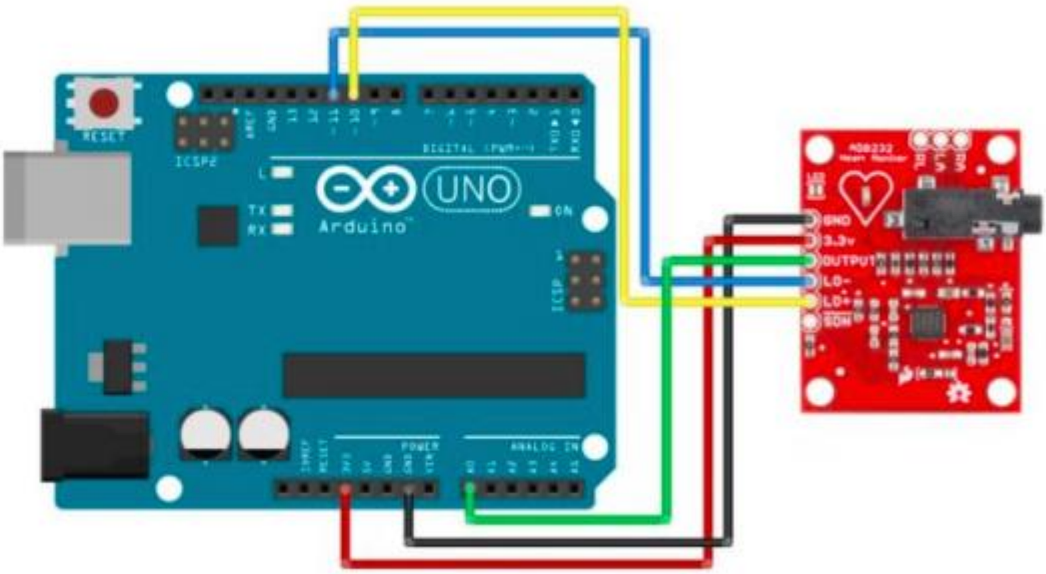


Fig: Arduino UNO used to connect sensors

For the purpose of our prototype we are providing power to the system by using a USB cord to connect it to the computer. In the future we will add a more portable power source.

Fig: USB chord to connect system to computer

The AD8232 chip is connected to the Arduino such that ecg output is sent to the analog pins of the chip. We use a circuit diagram similar to the one as seen below for taking in serial information.



[20]

We are taking in analog input from ANALOG INPUT Pin A2 in this circuit. We can use the Arduino IDE to write a program to take in the input in the form of either a serial plotter which gives the ECG signal graphically or in the form of raw data which can be used for processing and signal classification.

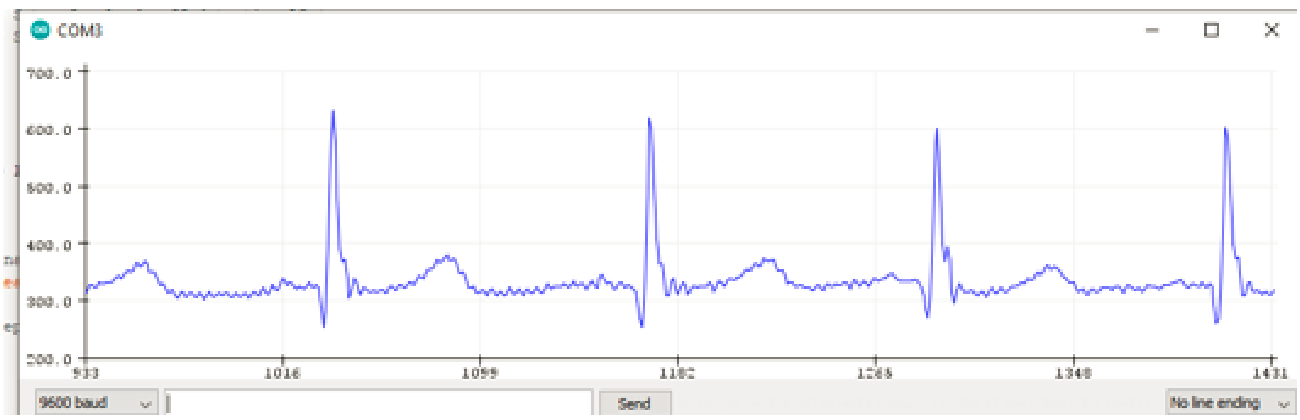


Fig: ECG signal taken in through the serial plotter of a 20 year old Female.

The following is the program used to taken such input from the analog pin of the Arduino:

```
void setup() {
// initialize the serial communication:
Serial.begin(9600);
pinMode(10, INPUT); // Setup for leads off detection LO +
pinMode(11, INPUT); // Setup for leads off detection LO -

}

void loop() {

if((digitalRead(10) == 1)||(digitalRead(11) == 1)){
Serial.println('!');
}
else{
// send the value of analog input 0:
Serial.println(analogRead(A2));
}
//Wait for a bit to keep serial data from saturating
delay(1);
}
```

We are using the baud rate of 9600 bit per second and this rate can be increased or decreased depending on the type of classification methods being used to ensure smooth processing of the data.

The data can be sent to a cloud server with the help of arduino cloud platforms like Ubidots which acts like an IOT platform for the prototype purposes of the project. For a device used for commercial use it is recommended to use a more stable cloud based platform like Amazon Web Services but Ubidots will satisfy the requirements of the prototype project.

Using Ubidots by entering the WIFI name, password and the token set up for cloud services the Serial data can easily be sent to the cloud based server. Thus the data can be visualized by anyone anywhere in the world and the processing will not have to occur at the location of taking of ECG readings. The processing and analysis of the signal can be done elsewhere and sent to a doctor for diagnosis for a smooth procedure.

In Ubidots we can get the API credentials in order to send the data with a token number.

One drawback of Ubidots is the graph won’t be smooth because the Ubidots database always tries to upload the data as fast as possible in less time which can degrade the signal and lead to a sharper graph.

The following code can be used to send the serial data to Ubidots cloud platform:

```
#include <ESP8266WiFi.h>
#include <PubSubClient.h>

#define WIFISSID "BITS-WIFI"                          // Put your WifiSSID here
#define PASSWORD "bits@123"                           // Put your wifi password here
#define TOKEN "BBFF-vsc3KUNWC8aD8tay2UU9cs0UE3MRgQ"         // Put your
Ubidots' TOKEN
#define MQTT_CLIENT_NAME "myecgsensor"                 // MQTT client
Name,

/****************************************
 * Define Constants
 ****************************************/
#define VARIABLE_LABEL "myecg" // Assing the variable label
#define DEVICE_LABEL "esp8266" // Assig the device label

#define SENSOR A2 // Set the A0 as SENSOR

char mqttBroker[]  = "industrial.api.ubidots.com";
char payload[100];
char topic[150];
// Space to store values to send
char str_sensor[10];

/****************************************
 * Auxiliar Functions
 ****************************************/
WiFiClient ubidots;
PubSubClient client(ubidots);

void callback(char* topic, byte* payload, unsigned int length) {
  char p[length + 1];
  memcpy(p, payload, length);
  p[length] = NULL;
  Serial.write(payload, length);
  Serial.println(topic);
}

void reconnect() {
  // Loop until we're reconnected
  while (!client.connected()) {
    Serial.println("Attempting MQTT connection...");

    // Attemp to connect
    if (client.connect(MQTT_CLIENT_NAME, TOKEN, "")) {
      Serial.println("Connected");
    } else {
```

```
      Serial.print("Failed, rc=");
      Serial.print(client.state());
      Serial.println(" try again in 2 seconds");
      // Wait 2 seconds before retrying
      delay(2000);
    }
  }
}

 * Main Functions

void setup() {
  Serial.begin(115200);
  WiFi.begin(WIFISSID, PASSWORD);
  // Assign the pin as INPUT
  pinMode(SENSOR, INPUT);

  Serial.println();
  Serial.print("Waiting for WiFi...");

  while (WiFi.status() != WL_CONNECTED) {
    Serial.print(".");
    delay(500);
  }

  Serial.println("");
  Serial.println("WiFi Connected");
  Serial.println("IP address: ");
  Serial.println(WiFi.localIP());
  client.setServer(mqttBroker, 1883);
  client.setCallback(callback);
}

void loop() {
  if (!client.connected()) {
    reconnect();
  }

  sprintf(topic, "%s%s", "/v1.6/devices/", DEVICE_LABEL);
  sprintf(payload, "%s", ""); // Cleans the payload
  sprintf(payload, "{\"%s\":", VARIABLE_LABEL); // Adds the variable label

  float myecg = analogRead(SENSOR);

  /* 4 is mininum width, 2 is precision; float value is copied onto str_sensor*/
  dtostrf(myecg, 4, 2, str_sensor);

  sprintf(payload, "%s {\"value\": %s}}", payload, str_sensor); // Adds the value
  Serial.println("Publishing data to Ubidots Cloud");
  client.publish(topic, payload);
```

```
  client.loop();
  delay(10);
}
```

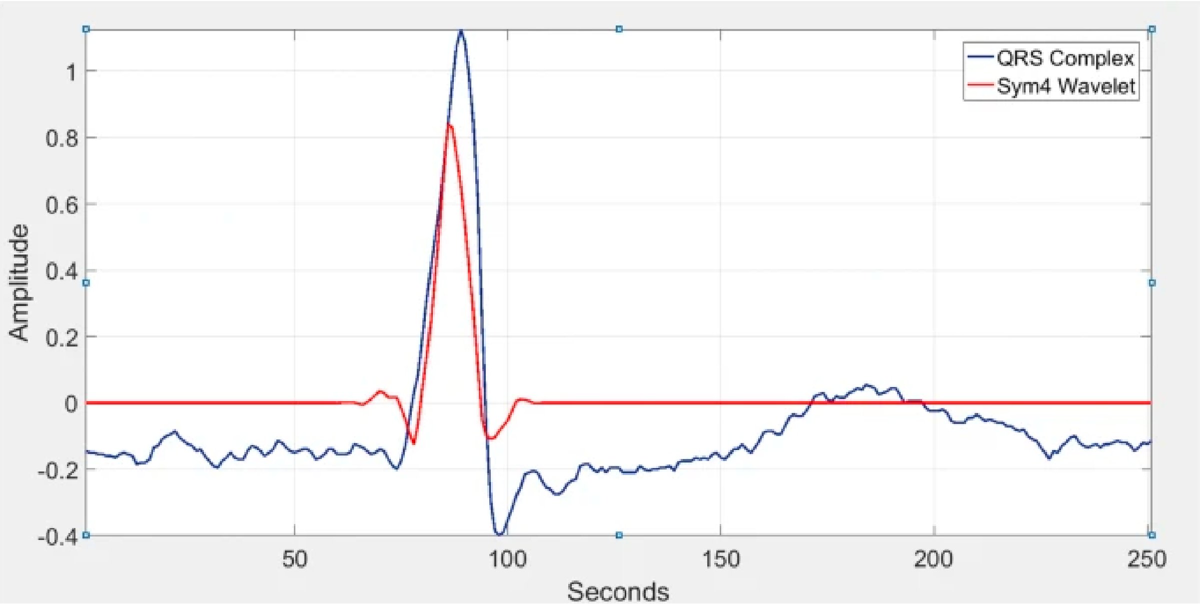
The data can also be stored locally for future reference with the help of programs which can store the serial data in the form of a text file. This can be used to take in data for matlab processing locally.

Examples for Basic Matlab processing:

Once loaded into the machine matlab can also be used to perform various feature extraction methods below.

These can include using the sym4 wavelet in order to compare with the QRS complex. This is a basic and relatively simple form of R peak detection.

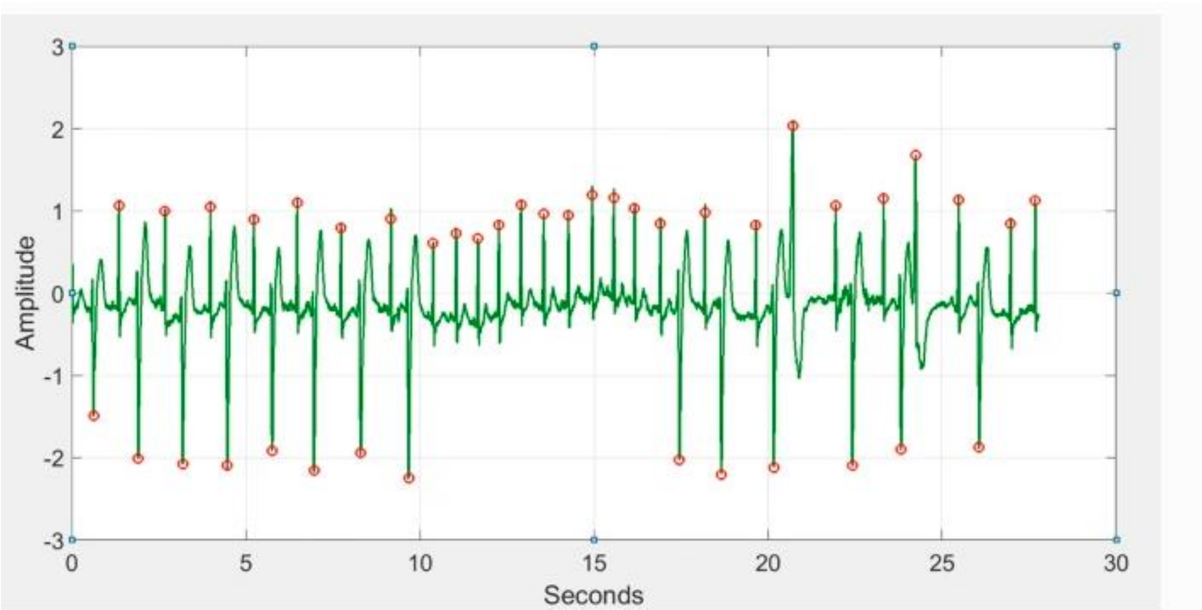
```
qrsEx = ecgsig(4560:4810);
[mpdict,~,~,longs] = wmpdictionary(numel(qrsEx),'lstcpt',{{'sym4',3}});
figure
plot(qrsEx)
hold on
plot(2*circshift(mpdict(:,11),[-2 0]),'r')
```



[21]

Once Wavelet transform is done we can also use the matlab function findpeaks for automatic peak detection for a basic understanding of the signal's shape.

```
y = abs(y).^2;
[qrspeaks,locs] = findpeaks(y,tm,'MinPeakHeight',0.35,...
    'MinPeakDistance',0.150);
figure
plot(tm,y)
hold on
plot(locs,qrspeaks,'ro')
```



[22]

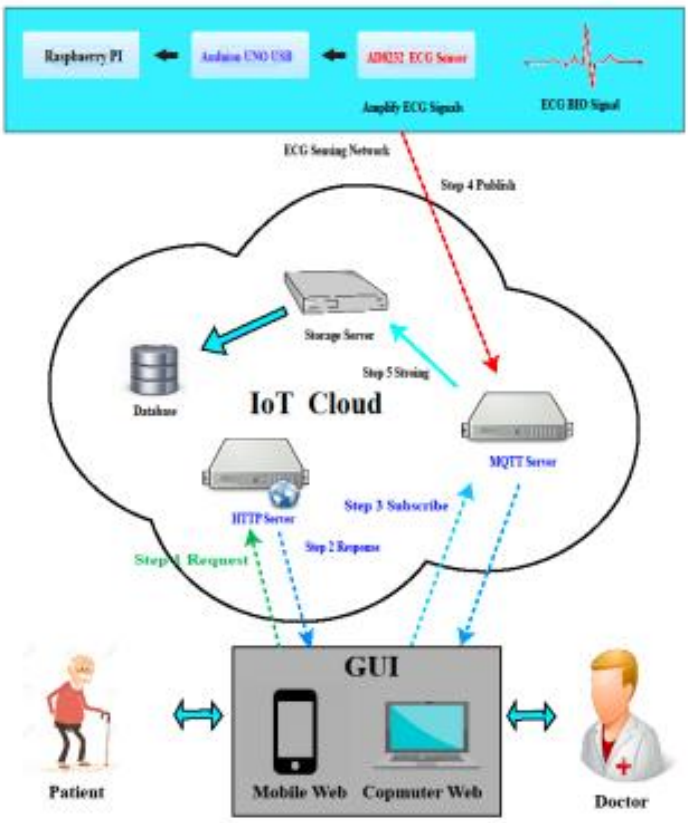
IOT in Real World ECG classification:

In an ideal scenario with the necessary hardware components the IOT based ecg systems can have powerful applications that can greatly improve the quality of life of a patient suffering from heart disease as well as the doctor for his cardiac diagnosis.

In the hardware used for the prototype, we have connected the ECG circuit to a laptop in order to send it to the cloud. However for the ECG system to be truly portable we should not require the use of the laptop for Wi-Fi capabilities. We can instead use a Raspberry Pi in addition to the Arduino Uno.

A Raspberry Pi is essentially a low cost microcontroller similar to the Arduino Uno but unlike the Arduino it comes with built in Wi-Fi capabilities which can be put to use. So we need not use a separate Wi-Fi module for data sending and the systems can be truly portable without the hindrance of a laptop.

Below is a picture depicting the 3 parts of the system graphically:



[23]

The first component should be the ECG system consisting of the Raspberry Pi, Arduino Uno and the AD8232 sensors along with the electrode pads.

The second component is the IOT cloud which can be used to store patient data as well as modify and process it. It can also be used for sending warnings to the patient or the doctor in case something wrong is detected. The architecture of the IOT cloud is detailed below

IOT cloud architecture:

The storage server, HTTP server and the MQTT server will be used by the iot clou.

<u>HTTP server</u>:

Used for user side responses and queries. Any action requested by the patient or the doctor will be done through the HTTP server. In essence it is used to show the graphical interface to the user in the form of an HTML file. Depending on the needs of the client there can be a login page which allows the user to access the relevant data including the prediction done by the program with the help of a server converting an HTML file to a user readable interface. This is all done by taking advantage of the HTTP protocol.

<u>MQTT server:</u>

Because the HTTP server is only important for the GUI we need another server for maintaining a long lasting transmission. Unlike other server types there is less latency so it is perfectly suitable for applications like ECG which require real time monitoring and even a delay of a few minutes can mean the difference between life and death.

<u>Storage server:</u>

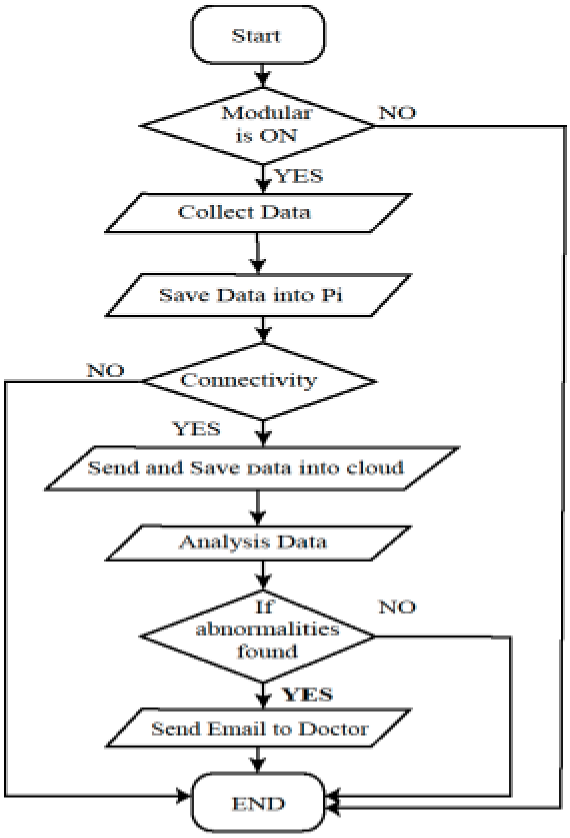
For a long time traditionally relational databases such as MySQL were used for storage of their information because of their ease of use and how it is relatively simple to set up. However these types of servers are still having a maximum threshold for read and write speed of the data. Nowadays non-relational databases which offer more flexibility are used to hold the data while also having much greater speed for input and output which is vital.

The procedure for these servers to work in tandem is the user sends a request to access the webpage which may be in the form of clicking a link and the HTTP server sends the webpage to the user’s computer. The user may also login to access data. Then the ECG systems in the form of raspberry pi will send the data to another server for processing the classification and the classification results and the final signal data will be sent to the MQTT server. The MQTT server establishes a link to the webpage and gives the information with low latency. All this while, the ECG data will also be sent to a preferably non-relational storage database to store the patient data for future reference.

GUI:

The 3rd component will be the Graphical User interface which should have ideal security to only be accessed by the patient as well as the doctor. The doctor can see patient's results as well as the classification done by the supervised machine learning modules to see the probabilities of the patient suffering from different types of cardiac ailments.

The overall working can also be shown through a flowchart



[23]

Here the analysis of data would mean using the Convolutional Neural Networks or Deep Learning in this case for classification of the signal.

There are many types of transfer protocols that can be used for ECG signal transmission. These include Wi-Fi, Bluetooth as well as Zig Bee based ECG transmission network.

In fact Bluetooth and ZigBee transmission modes have a power consumption of low compared to the medium consumption of Wi-Fi. Instead we still use Wi-Fi as it has a greater maximum coverage distance of around 200m compared to ZigBee and Wi-Fi which have a coverage of around 20-30 m. The table below taken from another IOT based paper shows the comparison between the 3 types.

Standards	***Wi-Fi* based ECG sensing network**	**Bluetooth based ECG sensing network**	**ZigBee-based ECG sensing network**
Protocol	IEEE 802.11	IEEE 802.15.1	IEEE 802.15.4
Coverage	20-200 m	20-30 m	2-20 m
Data rates	11-54 Mbps	3-24 Mbps	10-250 kbps
Power consumption	Medium	Low	Low
Terminal dependency	Data collection is independent of smart terminals	Smart terminals are needed for receiving and forwarding sensed data.	Smart terminals are needed for receiving and forwarding sensed data.

[23]

Challenges of ECG Classification and Future Work:

1. Especially with IOT based ECG systems which are meant to be portable and attached to the patient for long periods of time, one challenge is that the durability of the hardware. The patient has to be able to move around without accidentally damaging the hardware and sensors. Damage to the sensors may cause wrong readings and false positive classifications of heart diseases. This will cause undue stress on both the doctor as well as the patient. In order to combat this in the future these systems may come with more padding and more compact frames to reduce the chances of damage to the sensors or to the system.

2. Another challenge is signal quality which will be impacted by the real life activities of the wearer like physical exercise and running which can cause motion artefacts and deterioration. Thus the process of noise removal must not be skipped and special emphasis must be put on this step because of the added chances of high noise in this type of system

3. Another challenge is the power supplied to the device. The system must be able to run with low power and must be highly energy efficient in order to allow for long term monitoring. As Bluetooth requires less energy and power consumption in the future Bluetooth may be used for sending the signal instead of WIFI which consumes more power.

4. The storage of the ECG data is also cause for concern. Since the IOT type of systems requires the use of real time monitoring this leads to the production of large amounts of data in short periods of time. With such a large amount of data it becomes imperative to select only relevant data in specific time intervals which can be useful in diagnosis. Thus the feature extraction algorithm must be very precise in which parts of the signal to extract when dealing with large amounts of data in order to arrive at the most probably classification.

Conclusion:

Therefore we have delved into how a portable ECG machine can be made which also has IOT capabilities. The data in the ECG machine can be accessed from virtually anywhere in the world as long as it is connected to the Wi-Fi and has internet access. We also saw how the ECG data can be classified through various methods such as signal processing methods as well as with the help of various machine learning techniques. It was also important to remove noise with the help of digital filters at the right frequencies.

An IOT based cloud architecture was also highlighted to give a framework about how this system could function in the real world. This was done by detailing the transmission protocols used as well as what typed of servers are useful for the specific need of heart signal.

In the future, work can be done to further improve such systems to make both the lives of patient’s as well as the work of doctors easier and stress free.

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