Advanced subsystems based ECG signal classification & processing using Deep Learning and Wavelets: An evolution of digital health records

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

In

Electronics and Communication Engineering

by

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VIT, Vellore.

May, 2022

DECLARATION

I hereby declare that the thesis entitled "*Advanced subsystems based ECG signal classification & processing using Deep Learning and Wavelets: An evolution of digital health records*" submitted by Kasaragadda Tarun Sai, Telaprolu Dinesh Ram Sai and Ogirala Uday Venkat Rahul for the award of the degree of *Bachelor of Technology in Electronics and Communication Engineering* to VIT is a record of bonafide work carried out by us under the supervision of Prof. Jasmine Pemeena Priyadarsini M.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Vellore

Date: 04-05-2022

Kasaragadda Tarun Sai

Telaprolu Dinesh Ram Sai

Ogirala Uday Venkat Rahul

Signature of the Candidate

CERTIFICATE

This is to certify that the thesis entitled "*Advanced subsystems based ECG signal classification & processing using Deep Learning and Wavelets: An evolution of digital health records*" submitted by Kasaragadda Tarun Sai (18BEC0052), Telaprolu Dinesh Ram Sai (18BEC0042) and Ogirala Uday Venkat Rahul (18BEC0034), SENSE, VIT, for the award of the degree of *Bachelor of Technology in Electronics and Communication Engineering*, is a record of bonafide work carried out by him / her under my supervision during the period, 01.01.2022 to 31.05.2022, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets all the required and necessary standards for submission.

Place: Vellore

Date: 04-05-2022

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Kasaragadda Tarun Sai

Telaprolu Dinesh Ram Sai

Ogirala Uday Venkat Rahul

EXECUTIVE SUMMARY

This project aims to tackle the problem of timely disease detection and classification within a stipulated time inorder to save the patients during the golden hour period of diagnosis process. Inorder to do so, we took the most prevalent , common disorder i.e heart disorder and developed a system to detect and classify disorders from the multiple ECG signals at a time by deploying the wavelet transforms for preprocessing and BPM calculation and the Alexnet Deep CNN for the classification purpose.

We considered the three types of ECG Signals: Arrhythmia, Chronic Heart Failure, Normal Sinus Rhythm for this purpose. We employed three algorithms using AMOR wavelet, SYMLET wavelet and ALEXNET Deep CNN.

We developed a prototype IoT server model which upload the diagnosis to the cloud and provides the medical history of a patient to the doctor and suppose if the patient may fall ill in the future, then the doctor would have access to concrete medical history of patient to diagnose the illness. In real-world practice, based on this cloud data we could also issue RFID cards to the patients, which provides them access to their medical history similar to the health ID cards under AYUSHMAN BHARAT health scheme.

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List of Abbreviations

CNN	Convolutional Neural Network
ECG	Electrocardiogram
DNN	Deep Neural Network
DLM	Deep Learning Model
QRS	Q Peak, R Peak, S Peak combined
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
GPU	Graphical Processing Unit
RGB	Red Green Blue
ARR	Arrhythmia
CHF	Congestive Heart Failure
NSR	Normal Sinus Rhythm
CPU	Central Processing Unit
SQL	Structured Query Language

1. INTRODUCTION

1.1 Objective

The main objective of this project is to classify heart disorders by employing wavelet transforms and deep learning techniques. We developed a system to classify various heart disorders namely: Arrhythmia, Normal Sinus Rhythm and Congestive Heart Failure with the help of datasets from MIT-BIH Arrhythmia consisting of the ECG Signals of various heart disorders in .mat format. We also implemented a system to check and calculate the BPM of an ECG Signal based on R-Peaks detection. In practice, these two systems can be implemented contemporary to each other which leads to the BPM calculation during the detection process.

1.2 Motivation

Heart disease refers to any condition affecting the cardiovascular system. There are several different types of heart disease, and they affect the heart and blood vessels in different ways, in turn affects the pumping mechanism of heart which can be detected through the abnormality in the ECG Signals. Assessing Abnormalities in the ECG Signal can actually helps to detect various cardiovascular diseases such as heart disease, heart attack, an enlarged heart, or abnormal heart rhythms that may cause heart failure and cardiovascular arrest.

According to WHO, Cardiovascular diseases (CVDs) are the leading cause of death globally. An estimated 17.9 million people died from CVDs in 2019, representing 32% of all global deaths. Of these deaths, 85% were due to heart attack and stroke. Over three quarters of CVD deaths take place in low- and middle-income countries. Out of the 17 million premature deaths (under the age of 70) due to noncommunicable diseases in 2019, 38% were caused by CVDs. Most cardiovascular diseases can be prevented by addressing behavioural risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol. It is important to detect cardiovascular disease as early as possible so that management with counselling and medicines can begin.

Detection of these diseases at early stages of infection can, in many cases, drastically increase the chances of survival and can prevent a large number of deaths. Due to the changes in lifestyle, food habits and increasing global pollution, 21st century is witnessing a drastic increase in the heart disorders. Aided by the increasing population, the number of heart disorders increases and hospitals are flocking by these heart disorder cases. Hence, in order to save the multiple patients by quickly assessing their disorders during their golden hours at a time, we planned to develop a system that classifies the multiple ECG's based on their heart disorder and also tells their BPM

1.3 Background

One of the best techniques currently used in medical image analysis are CNNs which have a remarkable efficiency in classifying the images. Adding the deployment of wavelet transforms for the pre-processing of the ECG's signals would help to achieve the true potential of the CNN's by elevating their accuracy.

Mohamed Hammad, Abdullah M. Iliyasu, Abdulhamit Subasi, Edmond S. L. Ho, Ahmed A. Abd El-Latif proposed the DNN strategy using the feature extraction protocol for the detection of heart disorders in their published journal "*A Multitier Deep Learning Model for Arrhythmia Detection*". They divided their proposed DLM into three units: Local Learning Unit, Global Leaning Unit, Classification Unit. They employed a fivefold cross-validation method is employed in this study, and the performance of the system was evaluated in each fold. This requires the training and testing process to be done for 5 times, which for sure increases the accuracy of the model, but increases the complexity of the system and required much more dedicated hardware for the processing power. The proposed DLM is capable of detecting more than one type of ECG Signal.

Wenliang Zhu , Xiaohe Chen, Yan Wang, and Lirong Wang proposed in their published journal, "*Arrhythmia Recognition and Classification Using ECG Morphology and Segment Feature Analysis*" the strategy that includes(in the order of the process) Heartbeat Segmentation Detector, R peaks detection and Feature Extraction algorithms. The feature extraction methodology is based mostly on physiological meaning, which allows also medical doctors to better understand it. Since, the process of R peaks detection which means the Q and S peaks elimination takes first, and only the ECG with R peaks is considered for evaluation, the results may actually differ from the true results, since Q and S peaks may not contain necessary information for BPM detection, but they surely do contain information about the cardiovascular disorder of that ECG. Also, the proposed method is capable of detecting only one type of cardiovascular disorder.

Xuexiang Xu, Hongxing Liu proposed in their published journal, "*ECG Heartbeat Classification Using Convolutional Neural Networks*", proposed a system of applying CNN algorithms through the steps of pre-processing and classification using coupled-convolution layer structure. It includes the application of the two convolution mechanisms one by one followed by sub-sampling and again the application of two convolution mechanisms. Since, the CNN would undergo multiple convolution mechanisms, it would go through the good training and definitely it's accuracy would be high. But it increases the complexity of the system and requires the more processing power and dedicated hardware in order to implement the system in large-scale.

Hanjie Chen, Koushik Maharatna proposed a novel automated ECG feature extraction algorithm in their published journal, "*An Automatic R and T peak Detection Method Based on the Combination of Hierarchical Clustering and Discrete Wavelet Transform*" using the hierarchical clustering mechanism. They discussed the sequences of R-Peak Identification, R-Peaks Estimation with the later being done with a time window of 200ms. Since, the model of identification R-peaks depends on a fixed time window, it needs manual maneuvering of the time-window for the different ECG signals and there's given a probability of human error in manual operations and thereby result may probable to minor errors.

2. PROJECT DESCRIPTION AND GOALS

One of the best techniques currently used in medical image analysis are CNNs which have a remarkable efficiency in classifying the images. Various Algorithms namely, Continuous Wavelet algorithm, Alexnet Deep CNN Algorithm, Feature Extraction Algorithm(Discrete Wavelet). The main objective of this project is to develop a model which can classify lung cardiovascular disorders from ECG signals provided in the .mat format

The model is trained using a set of images from publicly available datasets found on MIT-BIH Arrhythmia Database. Pre-processing techniques like Data Truncation and Segment Division are employed to effeciantly make the all the signals with same number of signals, in order to make sure that the training model will be trained with all three types of disorder signal equally. The model, after extensive training will be able to classify new ECG signals accurately.

After the simulation, the results will be uploaded to IoT server through which the patients can access them. The main objective of this IoT server is to facilitate the availability of concrete medical history of the patients which can be used for further diagnosis in the future.

Developing various models for various diseases and comparing the accuracy between the models as well as with other currently published papers will give an insight of how viable the model is. Achieving high accuracies on small datasets is a very big challenge. Various parameters have to be tweaked, reconfigured and the training process repeated each time to see how it affects the model.

3. TECHNICAL SPECIFICATIONS

MATLAB – Matlab is a proprietary multi-paradigm programming language and numeric computing environment which allows for matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages.

MORLET WAVELET – Morlet wavelet is a continuous wavelet composed of a complex exponential carrier multiplied by a Gaussian window envelope. It have equal variance in both time and frequency domain.

SYMLET 4 WAVELET – Symlets are examples of least asymmetric wavelets. Their shape is equal and similar to an QRS complex. They are modified versions of the classic Daubechies db wavelets. Due to their resemblance with ECG, these are used for segment analysis and feature extraction techniques in operations involving ECG signals.

ALEXNET – Alexnet is a leading architecture and a Deep Learning based CNN, which is suitable for any object-detection task. The Alexnet has eight layers with learnable parameters. The model consists of five layers with a combination of max pooling followed by 3 fully connected layers.

PHP - PHP is a general-purpose scripting language geared toward web development. It's the first server-side languages that could be embedded into HTML, making it easier to add functionality to web pages without needing to call external files for data.

MYSQL - MySQL is an open-source relational database management system. It stores that information in separate "tables" and connects it with "keys", which is why it's relational.

APACHE HTTP – It is a free and open-source cross-platform web server software. As a Web server, Apache is responsible for accepting directory (HTTP) requests from Internet users and sending them their desired information in the form of files and Web pages

4. DESIGN APPROACH AND DETAILS

4.1 Design Approach

The preprocessing and data augmentation methods and the various algorithms used are discussed in detail below. The workflow for the project is presented in a flowchart form in Fig 1.

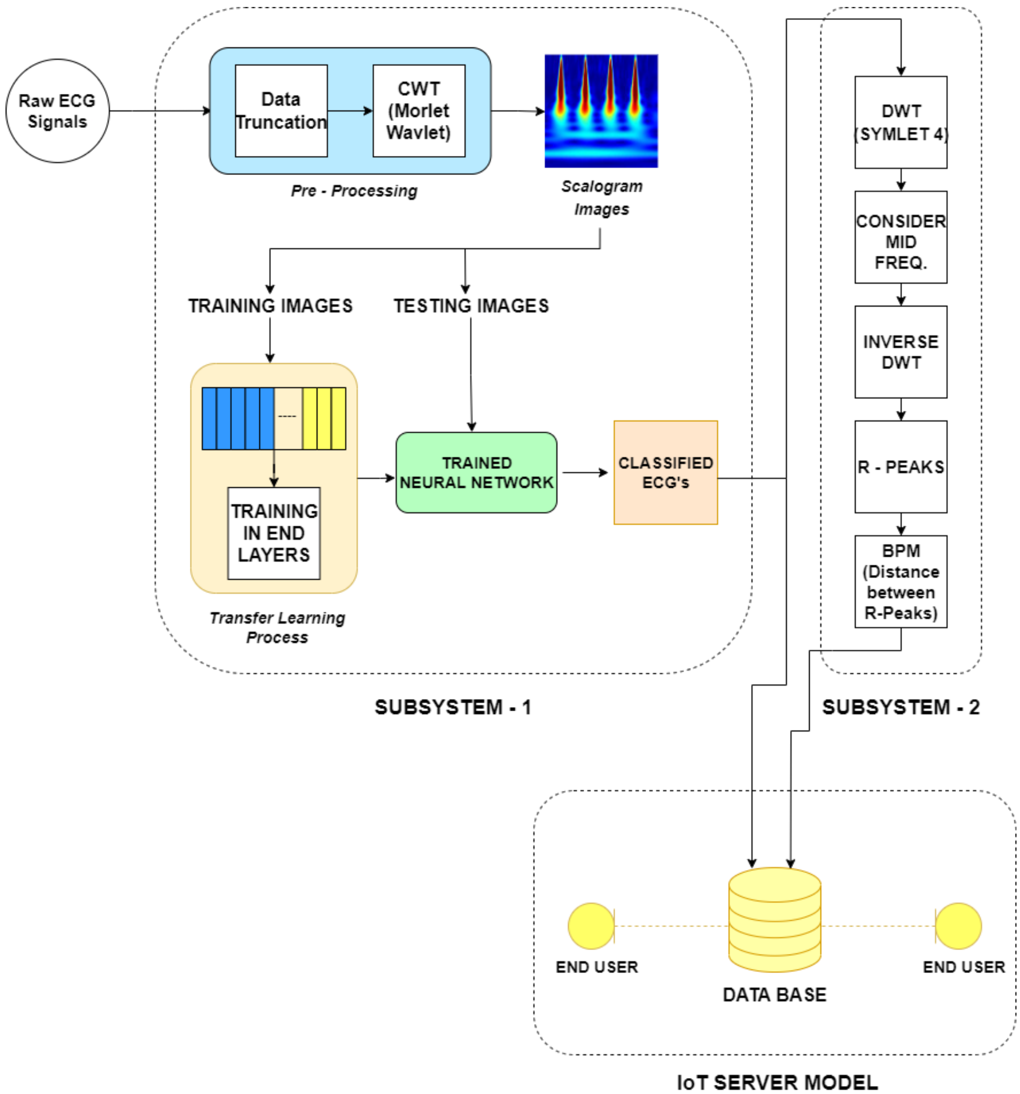

Fig 1: Project Flowchart

Each ECG signal consists of 65536 samples. However, we don't need such an enormous amount of samples for the operation. Hence, we truncate each ECG signal upto 5000 samples and cut those 5000 samples into 10 data pieces, each piece consisting of 500 samples. Hence, in this way we augment and convert the data to be suitable for the necessary operation .

Data Augmentation is a common support method used to significantly increase the training data volume by introducing slight variations of an signal in each. The variations used in this work are signal truncation, sample division. This technique is essential to get high levels of accuracy as the CNN model is able to train efficiently with the effective and necessary data by ignoring or removing the large but similar ECG data.

Three different model algorithms were used in this work. They are explained in detail in the following subsections:

4.1.1 ECG Extraction Algorithm:

This algorithm deals with all the pre-processing of the ECG data to producing scalogram images. Flow model extraction algorithm can be described in Fig 2.

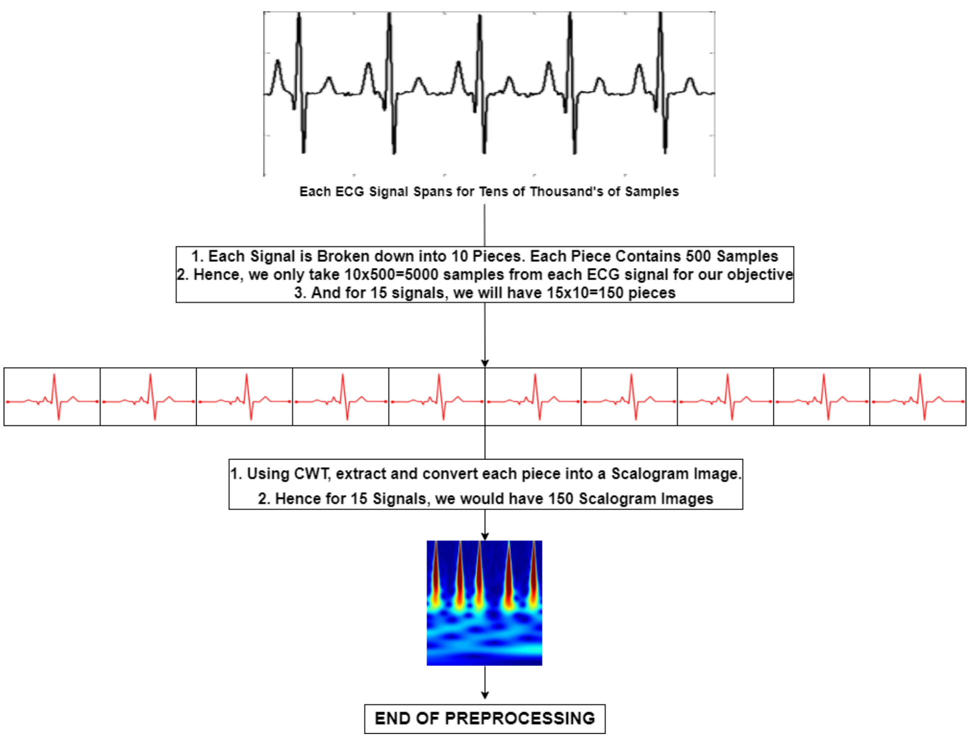

Fig 2: Pre-processing workflow

First, the proposed algorithm, loads the ECG data which is originally in matrix format from .mat file and converts into an identifiable ECG signal. As said earlier, it removes all the unnecessary samples of the ECG data and considers only 5000 samples, further truncates them into 10 piece, 500 samples per piece. Hence, an ECG signal is divided into 10 pieces.

Further, each piece will undergo the CWT by Morlet wavelet. Morlet wavelet is an continuos wavelet, it haves equal variance in both time and frequency domain. This trait proves to be useful when we change the ECG data from time domain to frequency domain because there wouldn't be any data loss. So when CWT is applied, each piece would be converted and extracted into a scalogram. This scalogram is then written into the memory as an image of RGB color index with 227 x 227 dimensions. The reason is, alexnet only accepts RGB color indexed images for the training and testing purposes.

4.1.2 Training Algorithm:

The training algorithm has more flexibility than the other algorithms. It is the most essential implementation part of the system. ALEXNET is a Convolution Neural Network model, which uses Deep Learning for the achieving it's objectives. As deployed

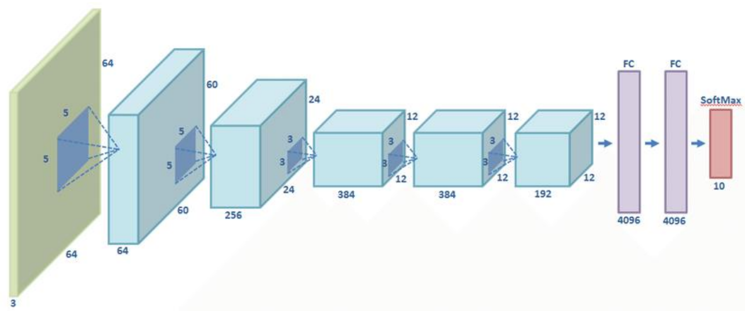

Fig 3: Internal Layers Architecture of Alexnet

worldwide, it deep neural layers are already trained with millions of sample and only the last three layers are available for the **Transfer Learning.** Architecture of Alexnet is described in Fig 3.

Finetuning a pretrained CNN to perform classification on a new collection of images is called "TRANSFER LEARNING". Transfer learning is quick and easier rather than training a CNN from scratch, which requires millions of inputs, lots of training time, and high-speed, efficient hardware The Last three layers are: 2 Fully Connected Layers, 1 Softmax Layer.

Alexnet has eight layers with learnable parameters. The model consists of five layers with a combination of Max Pooling Layers followed by 2 Fully Connected Layers. It also have a dropout layer, that prevented the model from overfitting. Further, the model is trained on the Imagenet dataset. The Imagenet dataset has almost 14 million images across a thousand classes. Hierarchy at the end is : 1st FC Layer, 2nd FC Layer, Dropout Layer.

The Input to the Alexnet is RGB Image. The activation function of a node defines the output of that node given an input or set of inputs. Activation function used in the Dropout layer is SoftMax. Hence, Dropout layer is called "SoftMax Layer".

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

We use the images produced by the analytic morlet wavelet to train these last three layers and hence thereby tuning the CNN to identify and respond to the inputs which are associated with our objective(ECG classification).

4.1.3 Feature Extraction Algorithm:

This algorithm uses symlet4 wavelet to extract the R-peaks from the ECG signal, thereby the distance between the R-peaks could effectively be used in an efficient BPM calculation. Symlet wavelets resemble the QRS complex as shown in Fig 4.

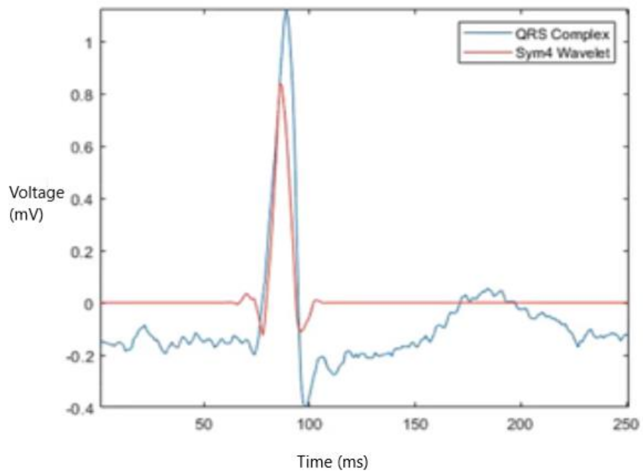

Fig 4: Similarity between QRS Complex and Symlet4 Wavelet

Here, we actually want to preserve f2 for BPM calculationwhile other frequencies must be suppressed. Hence, we need a BANDPASS Filter. This action can be achieved with the help of symlet 4 wavelet Transform, which is more efficient and robust than other methods because **f1<f2<f3** which is described in Fig 5.

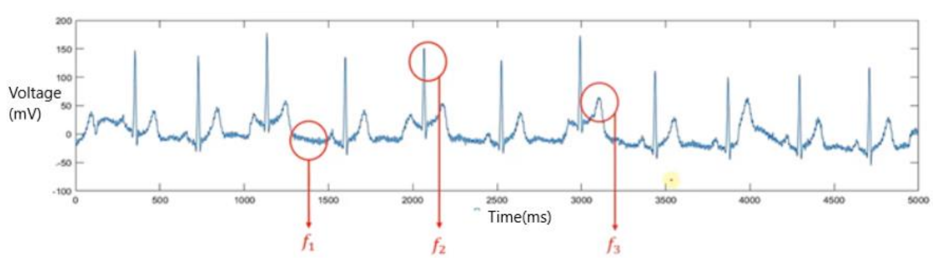

Fig 5: Types of frequencies associated with different regions in an ECG signal

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. a4 is approximation coefficient and it has all low frequency components. Similarly, d1 and d2 carry high frequency components. Hence, we only use d3 and d4 inorder to achieve band pass filtration. These frequency components are described in a detailed manner in Fig 6.

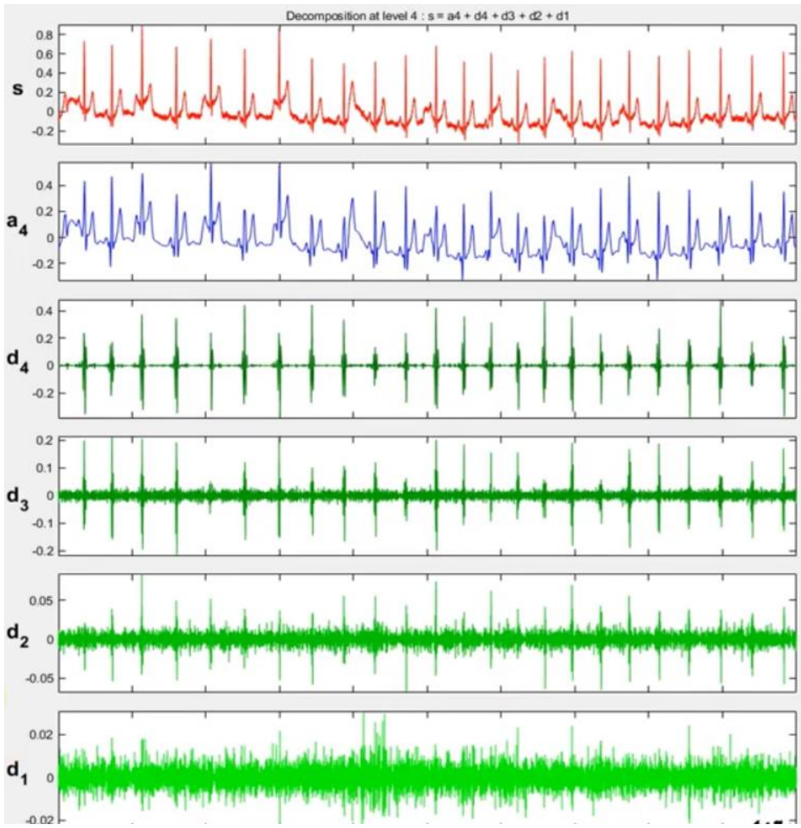

Fig 6: Detail Coefficients and Approximate Coefficients

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.

4.2 Constraints, Alternatives and Tradeoffs

One of main constraints in this project are the number of ECG signals available for training and testing. To get a very high accuracy model, we need to train the model with as much data as possible. Artificially increasing the data helps us in the short run but fails to help reach high standards in the long run. Big companies train their models with humongous amounts of data. Some of the models have been trained with more than ten thousand images. These models can be used as they have been rigorously trained and tested.

We had to rely on the data from MIT-BIH database since we couldn’t get any data from the hospitals in order to test the system on different inputs. According to The Medical Council of India's Code of Ethics Regulations, patients medical data shall be withheld confidentially, unless if there is an warrant for disclose of such information by the judiciary or whether under the circumstances where the patients gives his/her consent for sharing of their medical data. Hence, even if we tried to get any ECG data from the hospitals, we couldn’t get it.

Another big constraint is the processor power required to achieve the training process. Deep learning model need high processing powers to able to learn features at an incredible pace. Some of the best models known have been trained using high end industrial grade graphical processing units which cost around 6000$. Some of the papers referenced have accessed labs with high end equipment and carried their research and experiments there. We have used a standard Dell laptop with Intel Core i3 7^{th} Gen processor of 2.4GHz due to which our average simulation time(provided the same learning parameters) is around 25 mins and due to this, the accuracy ranges from 92-98(in %). When simulated in an high-end machine(which we had access only once), the accuracy went upto 99%.

Initially, we planned to execute the IoT server model using either Azure or AWS. But their subscription plans outruns our budget for the project and we couldn’t able to afford them. So, we had to rely on Apache local server inorder to design, demonstrate and execute the model. Yet, stll we were able to achieve the desired results using Apache server. But using AWS/Azure will give us a top-over edge over apache because then we would be able to control the real-time parameters such as cloud design, scalability, robustness, complexity etc. using which we would be able to simulate and achieve real-world insights. Along with that, we used Thingspeak to upload the BPM data, as it have an robust feature of representing BPM over regular intervals in terms of graphical representation

5. SCHEDULE, TASKS AND MILESTONES

The following schedule was followed

February – Project Selection, 1st review (Literature Survey, Basic Setup)

March – 2nd review (Implementation of the Detection model)

April – Draft of Paper and Poster

May – Final touches and completion of project. Submission of report and poster

The various tasks associated with this project are –

1) Gathering information on different model architectures with the help of journals
2) Gathering the datasets which contain the ECG Signals of different cardiovascular disorders
3) Developing Deep Learning based CNN model from scratch and training it
4) Testing the developed model, tweaking the parameters and attempting to increase the accuracy
5) Plotting of Graphs and Simulation Results
6) A Statistical Conclusion of which model is better used for the objective will be drawn.

6. PROJECT DEMONSTRATION

6.1 ECG Extraction Algorithm

The dataset consists of 162 signals, out of which 96 signals belongs to arrhythmia, 30 belongs to normal sinus rhythm, 36 belongs to congestive heart failure. Each signal, spans for 65536 samples, out of which we only consider 5000 samples. To do this, we truncate the signal into pieces, each piece consisting of 500 samples. The sample distribution of ECG signals can be seen in Fig 7.

For the equality in training purpose and for the equal probability detection of cardiovascular disorder by the AlexNet, we took equal number of signals for each specific type of cardiovascular disorder i.e 30. Each signal will be truncated and sample shortened into 10 scalogram images. For overall 30x3=90 signals, we would have 90x10=900 images. Out of this 900 images, 750 are used for training purpose and 150 for testing purpose.

The logic that follows is for each type of cardiovascular disease, out of 30 signals, 25 will be used for training, 5 will be used for testing. Hence for total 3 types of cardiovascular disorders, we would have 3x25x10=750 images for training and 3x5x10=150 for testing

	1	2	3	4	5	6	7	8	9	10
1	-0.0979	-0.1569	-0.1378	-0.1372	-0.1477	-0.1685	-0.1759	-0.1702	-0.1811	-0.1465
2	0.1194	0.1876	0.1696	0.1786	0.2118	0.1966	0.0729	0.1659	0.0832	0.1992
3	-0.0246	-0.0363	-0.0360	-0.0302	-0.0458	-0.0931	-0.0914	-0.1290	-0.1125	-0.1273
4	-0.5083	-0.8080	-0.7217	-0.7897	-0.7677	-0.7744	-0.7725	-0.7943	-0.7949	-0.7781
5	-0.3120	-0.4953	-0.4426	-0.4652	-0.4284	-0.4444	-0.4176	-0.4533	-0.4292	-0.4419
6	-0.0314	-0.0470	-0.0457	-0.0389	-0.0104	-0.0113	0.0195	-0.0050	0.0032	-0.0380
7	-0.3927	-0.6256	-0.5561	-0.6010	-0.5661	-0.5737	-0.5839	-0.6057	-0.5891	-0.5811
8	-0.2268	-0.3273	-0.3408	0.0664	1.0295	2.0360	2.1763	0.7462	-1.1559	-1.3592
9	-0.6265	-0.9974	-0.8866	-0.9506	-0.9440	-0.9892	-0.9472	-0.9233	-0.9468	-0.9633
10	-0.5650	-0.9012	-0.7969	-0.8421	-0.8435	-0.9343	-1.0356	-1.0892	-1.0578	-1.0614
11	-0.6755	-1.0702	-0.9613	-1.0138	-0.9547	-1.0139	-1.0267	-1.0357	-1.0008	-0.9930
12	-0.2350	-0.3701	-0.3344	-0.3340	-0.3217	-0.3167	-0.3090	-0.3084	-0.2883	-0.2910
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14	-0.5290	-0.8401	-0.7502	-0.7950	-0.7377	-0.7638	-0.7460	-0.7587	-0.6964	-0.7138
15	-0.5456	-0.8670	-0.7754	-0.8547	-0.8274	-0.8653	-0.9263	-0.9912	-1.0200	-1.0025
16	-0.6777	-1.0777	-0.9586	-0.9960	-0.9574	-0.9898	-0.9700	-0.9568	-0.9532	-0.9600
17	0.2466	0.3619	0.3684	0.1809	-0.3609	-0.2711	-0.2060	-0.1929	-0.2447	-0.2392
18	-0.1760	-0.2806	-0.2493	-0.2635	-0.2149	-0.2034	-0.1679	-0.1686	-0.1666	-0.1719
19	5.3544e-04	-9.7952e-04	0.0013	-3.4085e-05	0.0313	0.0177	0.0445	0.0476	0.0727	0.0878
20	-0.1803	-0.2740	-0.2580	-0.1818	-0.3781	-0.3041	-0.3108	-0.2770	-0.0756	-0.3588
21	-0.2906	-0.4646	-0.4108	-0.4636	-0.4540	-0.4531	-0.4665	-0.4772	-0.4720	-0.4560

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3	-0.3386	-0.3279	-0.3084	-0.2824	-0.2694	-0.2488	-0.2476	-0.1917	-0.1861	-0.1300	-0.1224	
4	-0.9515	-0.9534	-0.9434	-0.9715	-0.9886	-0.9949	-0.9967	-1.0154	-1.0427	-1.0407	-1.0482	
5	0.3054	0.3921	0.4347	0.5235	0.5929	0.6630	0.7438	0.8094	0.8225	0.7872	0.6843	
6	-0.2131	-0.1588	-0.2090	-0.3971	-0.6270	-0.7177	-0.5160	-0.1810	-0.2463	-0.6153	-0.6165	
7	-0.8333	-0.8107	-0.8093	-0.8186	-0.8040	-0.7549	-0.7160	-0.7092	-0.6829	-0.6501	-0.6488	
8	-1.1463	-1.1698	-1.1847	-1.1993	-1.1832	-1.1826	-1.2135	-1.2021	-1.1792	-1.1871	-1.2212	
9	-0.9004	-0.9250	-0.9287	-0.8874	-0.8971	-0.9260	-0.9293	-0.9203	-0.9148	-0.9121	-0.9225	
10	1.3032	1.3797	1.3755	1.2649	1.3180	1.4423	1.4546	1.4794	1.5491	1.6356	1.6329	
11	-0.7293	-0.6852	-0.6239	-0.5869	-0.5731	-0.5614	-0.5425	-0.5537	-0.6435	-0.7337	-0.8080	
12	-0.3765	-0.3832	-0.3782	-0.3865	-0.3888	-0.3896	-0.3776	-0.3728	-0.3807	-0.3782	-0.3881	
13	-0.9653	-0.9634	-0.9415	-0.9398	-0.9560	-0.9586	-0.9476	-0.9353	-0.9512	-0.9630	-0.9433	
14	-1.0072	-0.9693	-0.9758	-0.9621	-0.9624	-0.8607	-0.8440	-0.7981	-0.7997	-0.7780	-0.8094	
15	-0.7760	-0.7876	-0.8004	-0.8195	-0.8069	-0.7715	-0.7995	-0.8303	-0.8051	-0.7789	-0.7885	
16	-0.6683	-0.6640	-0.6333	-0.6576	-0.6391	-0.4646	-0.2920	-0.3058	-0.4503	-0.0434	0.7019	
17	0.6148	0.5826	0.5656	0.5094	0.4738	0.3932	0.3027	0.2255	0.1979	0.1047	0.0485	
18	-0.2004	-0.2134	-0.1803	-0.2063	-0.2320	-0.2319	-0.2404	-0.2503	-0.2611	-0.2666	-0.2849	
19	-0.2438	-0.2659	-0.2450	-0.2278	-0.1745	-0.1928	-0.1779	-0.1819	-0.1933	-0.2226	-0.2347	
20	0.0500	0.1389	0.2398	0.3547	0.4789	0.5809	0.7344	0.8383	0.9888	1.0509	1.1345	
21	-0.3788	-0.3918	-0.3945	-0.3690	-0.3600	-0.3793	-0.3878	-0.3671	-0.3500	-0.3642	-0.3735	

Fig 7: Raw ECG Data in matrix format, spans upto 65536 samples

6.2 Training Algorithm:

As mentioned earlier, the scalogram images from the pre-processing unit will be redirected to the Alexnet CNN for training and testing purpose. The training flow of the alexnet CNN through Deep Learning is described in Fig 8.

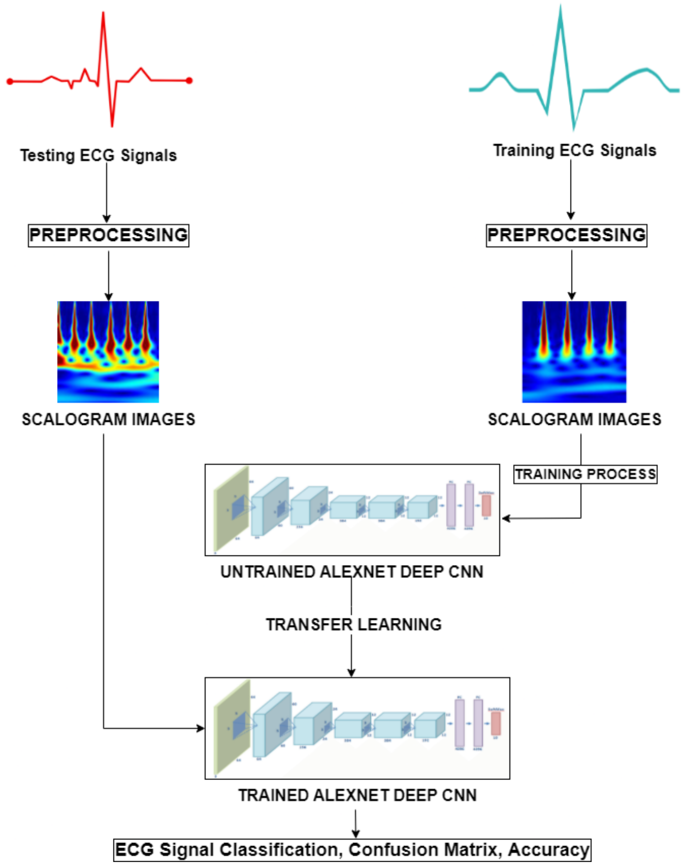


Fig 8: Training Flow of Alexnet through Transfer Learning

First, alexnet gets trained in it's local layers(Last 3, 2 are Fully Connected Layers and one is a Softmax Layer) through the process called Transfer Learning. Transfer learning (TL) is a research problem that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. The entire block of transfer learning is depicted by Fig 9.

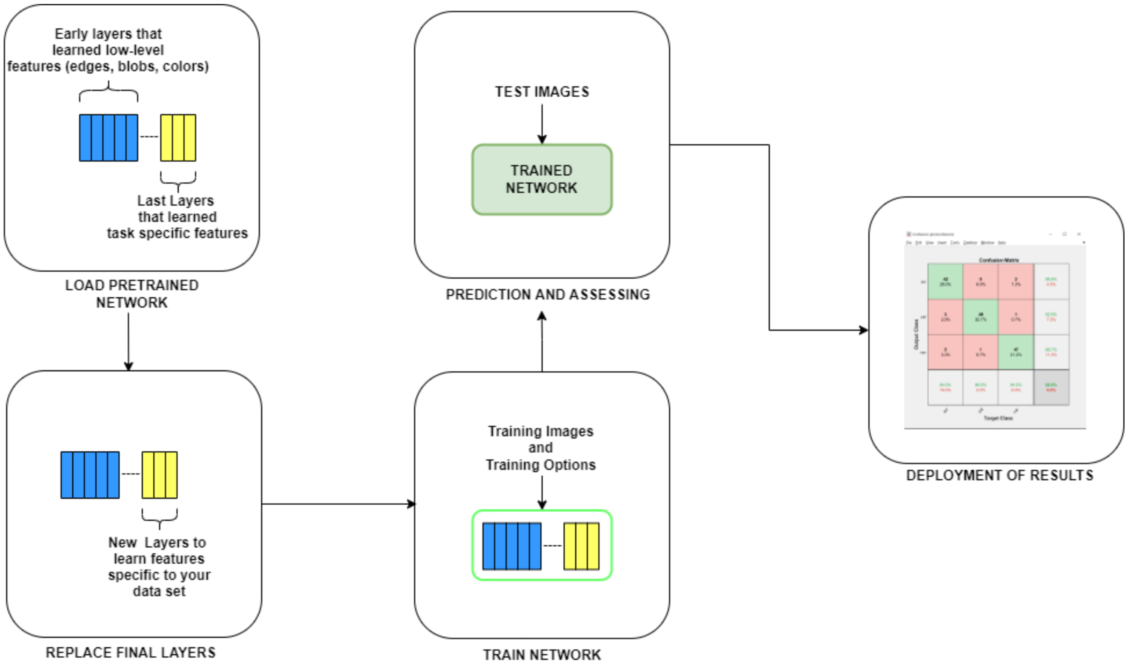


Fig 9: Transfer Learning

6.3 Feature Extraction Algorithm:

When the ECG signal is passed to the subsystem-2, there applies the SYMLET4 wavelet transform, which yields 4 detail coefficients, 1 approximation coefficient out of which we only consider d3 and d4 because they carry the frequency ranges associated with R-peaks and then apply invert symlet4 wavelet transform, to get the ECG signal but with only R-peaks.

After that, with the help of the distance between the R-peaks, we can actually calculate the BPM of that ECG signal, which proves to be more accurate and robust than the most available techniques. The feature extraction flow of the algorithm is mentioned in Fig 10.

One might actually wonder, why this is a separate system but not includes in the subsystem-1 to give BPM as soon as the confusion matrix produces. The reason is the complexity of the system but also the efficiency that comes along.

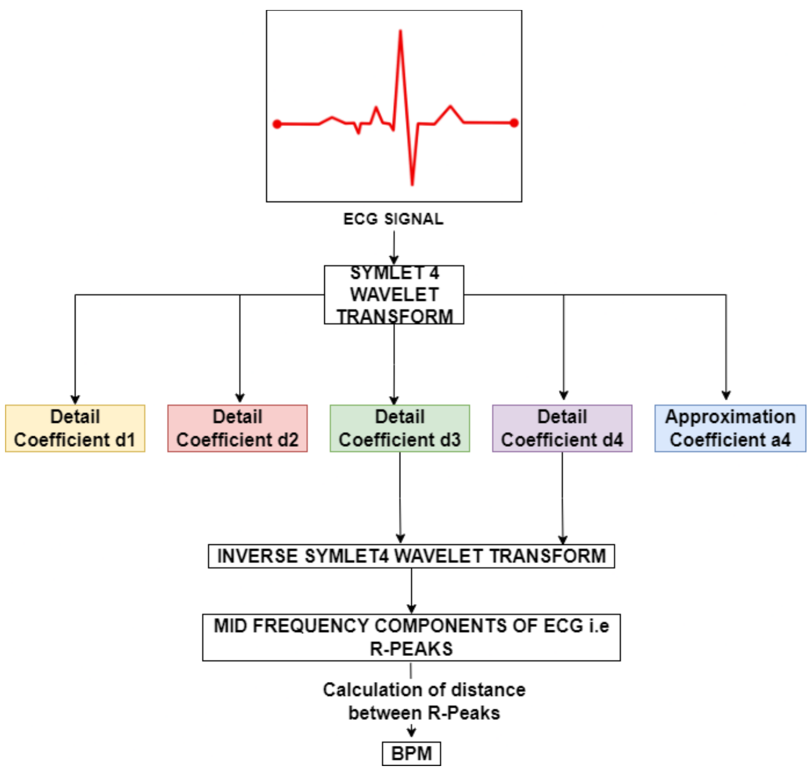


Fig 10: Flowchart of R-peaks detection

Also, suppose if we implement the subsystem-2 inside the subsystem-1 using the loops based on the test ECG Signals, then still we can actually run it, but it requires a lot of processing power and dedicated hardware components.

Hence, for the smooth running and efficiency case, we decided to set it up as subsystem-2 based on it's complexity and efficiency of the detection algorithm. But in practice, with the efficient and necessary processing power, we could actually run it along with the subsystem-1, so in reality, when the doctor is detecting and classifying the cardiovascular disorder in the golden hours of the patient, the subsystem-2 will run on par with the subsystem-1 as a single system and continuously indicates the BPM such that the doctor may take a prior notice if the heart beat of the patient is dropping.

6.4 IoT SERVER:

The purpose of this server is to facilitate a platform to upload the patients' diagnosed ECG data and to store it in a cloud, such that when the patient may fall ill in the nearby future, the consulting doctor would have a concrete medical history of the patient to detect, diagnose and treat the patient illness within a stipulated time period. The working flow of this database is shown in Fig 11.

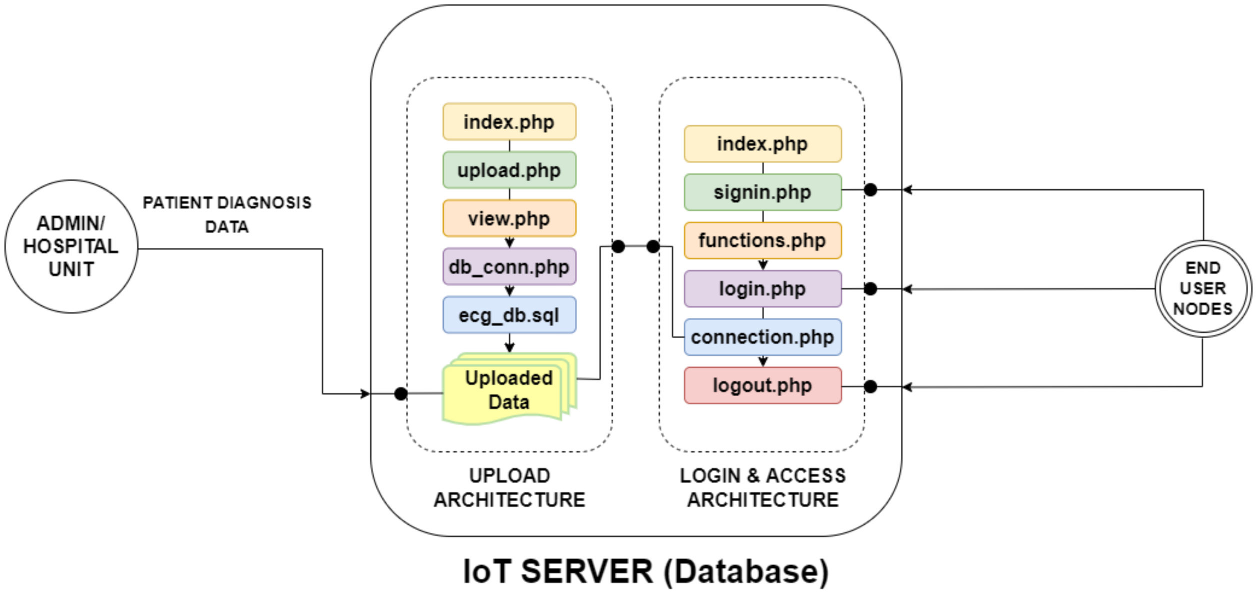


Fig 11: Architecture of IoT Server(Database)

Through this database, even the end -users like patients also can login and can access their medical history through which they would have a basic understanding of their health. Here, as depicted, the hospital unit will upload the patients' ECG data to the server, in which the data is uploaded to the upload architecture which embeds the number of working and processing units that helps in it's functionality. When the end user access the database, they uses several functionalities such as signin, login, logout. When the enduser logins, they can access the ECG data stored in the upload architecture through the other workings units of the login & access architecture.

For uploading the BPM from subsystem-2 to the cloud, we will be using the Thingspeak because of it's robust feature to plot the BPM into a graph such that we always knows if there are any major irregularities in the BPM and can consult doctor because the primary symptom of Arrhythmia is the irregular heartbeat.

7. RESULT AND DISCUSSION

7.1 ECG Extraction:

After the pre-processing, folders dedicated to each cardiovascular disorder are created, in which there are scalogram image versions of the truncated ECGs. This can be seen in Fig 12.

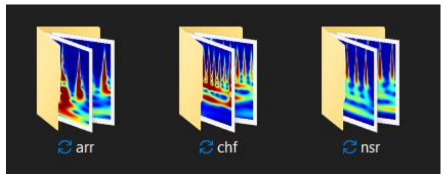


Fig 12: Created folders for each individual disorder

The scalogram is the absolute value of the continuous wavelet transform (CWT) of a signal, plotted as a function of time and frequency. The scalogram can be more useful than the spectrogram for analyzing real-world signals with features occurring at different scales — for example, signals with slowly varying events punctuated by abrupt transients. The difference between the scalogram images of ARR, CHF and NSR(in the order of their appearance) is clearly described in Fig 13. One can actually clearly spot the difference between them, which indicates the specific type of disorder that the scalogram represents.

ARR –

CHF –

NSR –

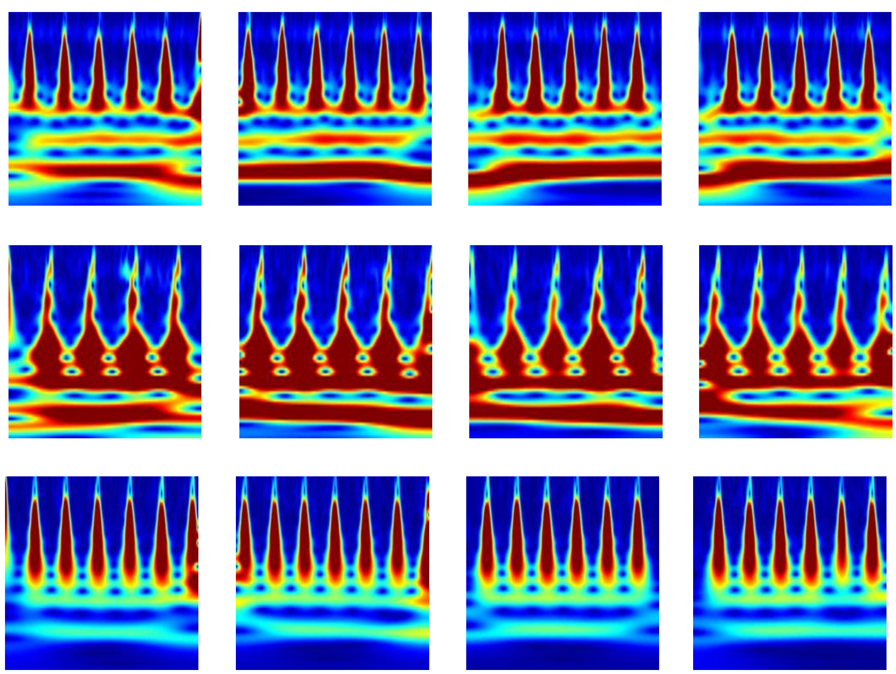


Fig 13: Types of Scalogram Images associated with each disorder

In ARR, even though a peak is present, it’s not uniform indicating that the ECG is irregular in shape. In CHF, there is no peak present which indicated there in no proper and clear heartbeat hence the congestive heart failure. In NSR, the peaks are sharp and uniform indicating thet the ECG signals belongs to a healthy personwith uniform heart beat.

7.2 Training Algorithm:

Both the testing and training datasets undergoes preprocessing and produces scalogram Images. These images are feeded to the alexnet for Training and Testing Purposes First, the last three layers that is fully connected layers and softmax layer will learn from the testing images about the ECG signals corresponding to the individual heart disorder. For this purpose, we will specify the training options like number of epochs, iterations, learning rate based on which training process will start. Once the training is completed, network is ready to test and classify the test images as per the heart disorder.

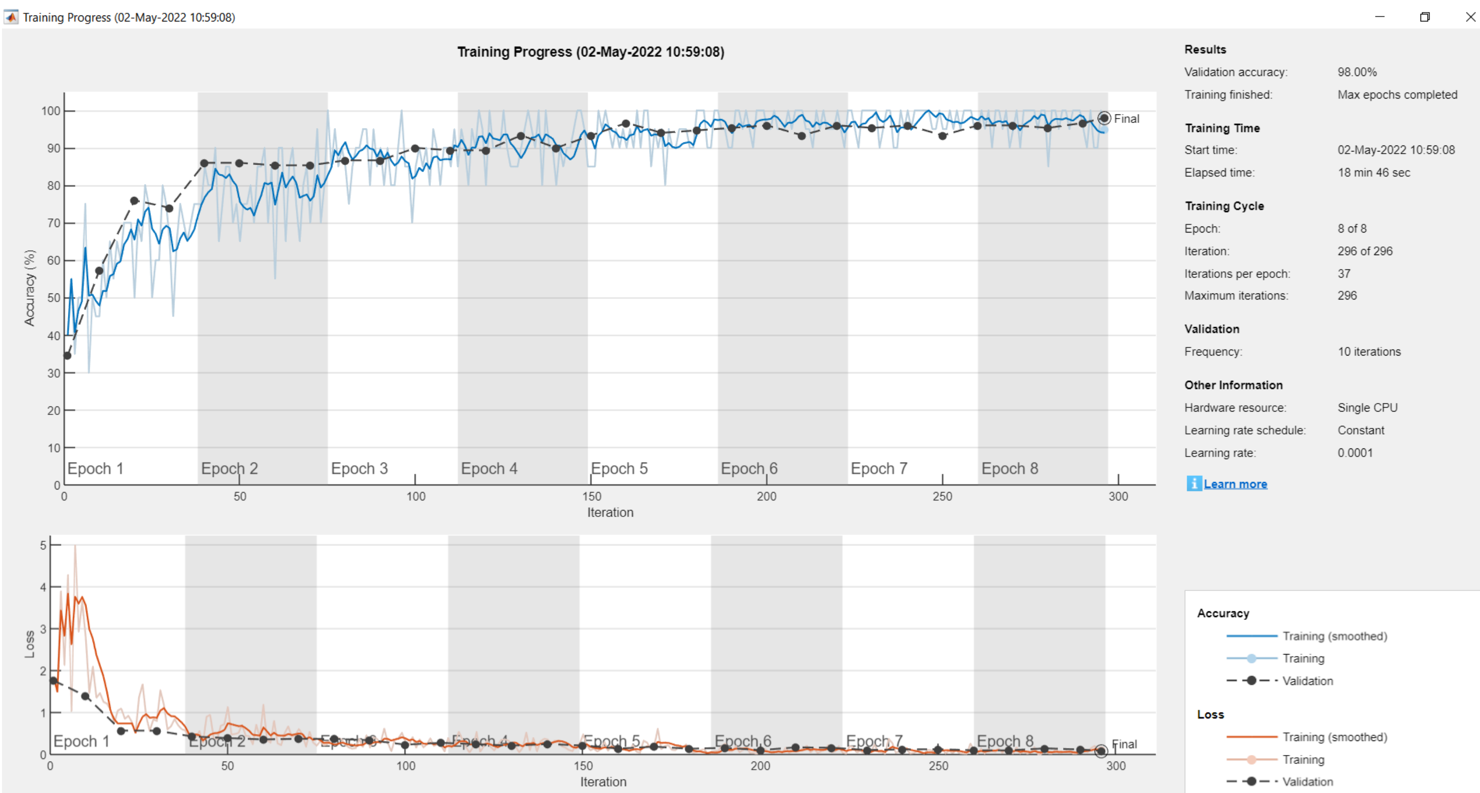


Fig 14: Training Progress of Alexnet

It takes test images as input and classifies them. Then it produces the confusion chart which shows how the images are classifies and also specifies if any of the images are presumed to be misclassified at the beginning and finally shows the total accuracy of the model. Training process is depicted in Fig 14.

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. Here, the confusion matrix tells us if any of the Test ECG Signals are wrongly classifies and rates accuracy of the model based on it's knowledge from training using the training ECG Signals. Confusion matrix is depicted in Fig 15.

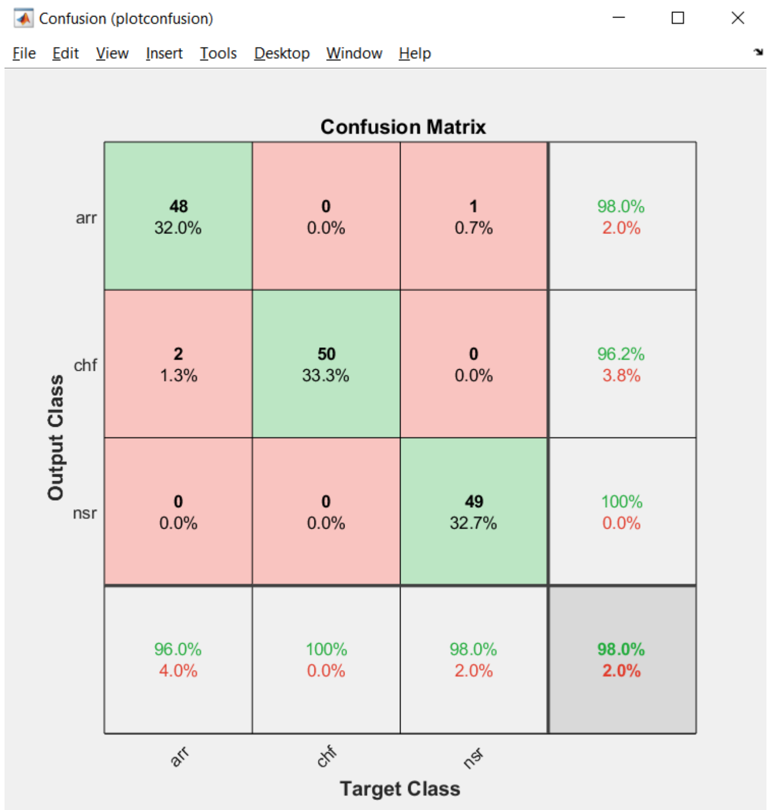


Fig 15: Confusion Matrix

The results shows that out of 50 pieces in Arr, only 42 actually belongs to Arrhythmia and 3 belongs to CHF, 5 belongs to NSR

Out of 50 pieces in CHF, only 49 pieces are CHF, 1 piece is NSR.

Out of 50 pieces in NSR, only 47 pieces are NSR, 2 pieces are ARR, 1 piece is CHF.

The accuracy of the model is evaluated as 98% and is subjected to oscillated change from 92% - 98% depending on the processing power, number of CPU cores and GPU performance. The table is stated below:

Table 1: Accuracy comparison of our model with the existing works on ECG classification and R peaks detection

RESEARCH PAPER	TITLE	AUTHORS	TECHNIQUES	ACCURACY
R1	A Multitier Deep Learning Model for Arrhythmia Detection	Mohamed Hammad,Abdullah M. Iliyasu, Abdulhamit Subasi, Edmond S. L. Ho, Ahmed A. Abd El-Latif	Deep Neural Network (DNN), Feature extraction protocol, Genetic algorithm (GA)	98%
R2	Arrhythmia Recognition and Classification UsingECG Morphology and Segment Feature Analysis	Wenliang Zhu , Xiaohe Chen, Yan Wang, Lirong Wang	Deep Learning, Feature Extraction Protocol	97.8%
R3	"ECG Heartbeat Classification Using Convolutional Neural Networks"	Xuexiang Xu, Hongxing Liu	CNN algorithms based ECG heartbeat classification method.	98%
R4	An Automatic R and T peak Detection Method Based on the Combination of Hierarchical Clustering and Discrete Wavelet Transform	Hanjie Chen, Koushik Maharatna	Hierarchical Clustering, Discrete Wavelet Transform (DWT)	97.8%
Our Model			**Alexnet CNN, Wavelet Transforms, Feature Extraction**	**98% ***

* Subjected to change and can go upto 99% depending on the processing power, number of CPU cores, GPU performance. 98% when run on intel i3 core 7th Gen processor.

7.3 Feature Extraction:

Subsystem-2 yields the BPM of the classified and disease diagnosed ECG Signal using the Symlet4 wavelet transform. The result is depicted in Fig 16.

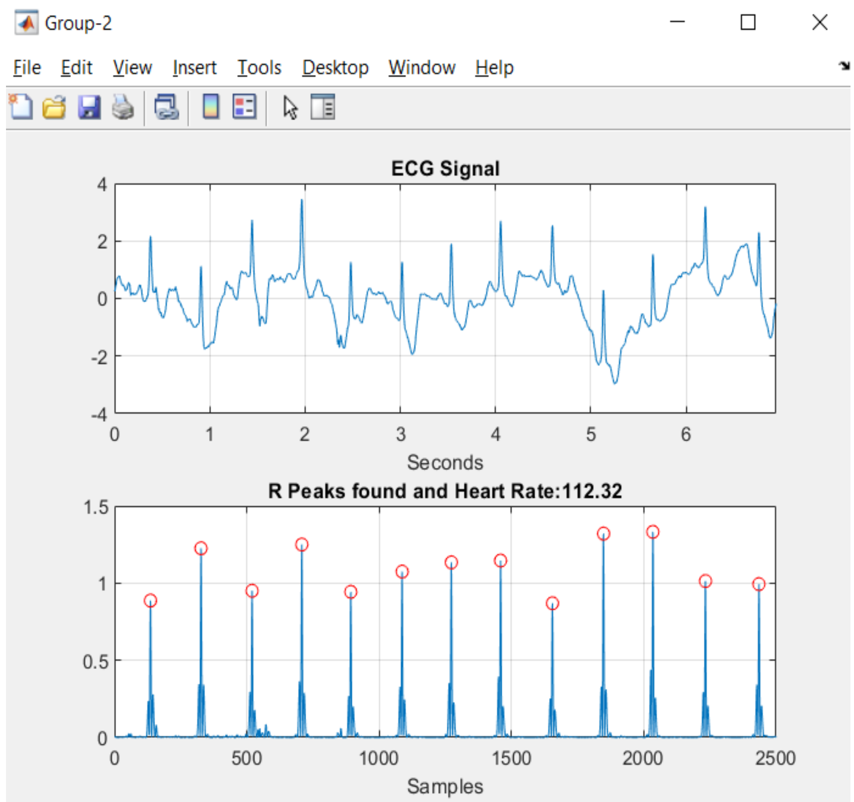


Fig 16: Plot of ECG and it's extracted R-peaks

Sometimes, if the R peak is not of appropriate amplitude than it used to be, then the other BPM detection system will eventually discard it. But with the detection of the R-peaks, even though the amplitude of R peak is not of appropriate amplitude, it still carries that frequency component based on which the R peak can be detected.

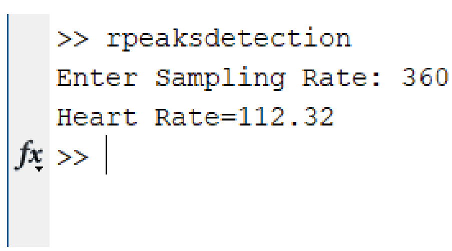


Fig 17: Heart Rate

7.4 IoT Server:

7.4.1 UPLOAD:

First, in order to start the Apache server, we use XAMPP. After starting server, we need to upload the ECG simulating results using the uploading page. Uploading page is '**localhost/ecgs1/upload-images**'

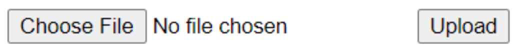


Fig 18: Upload Page

Choose the ECG classification simulation results and upload.

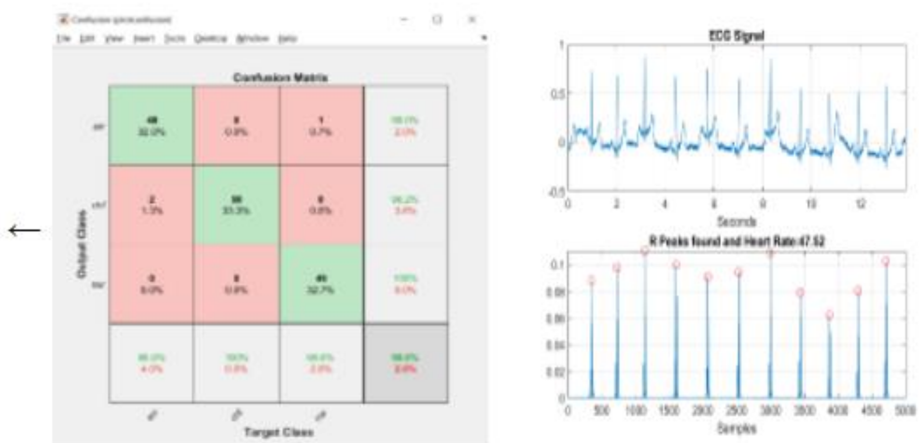
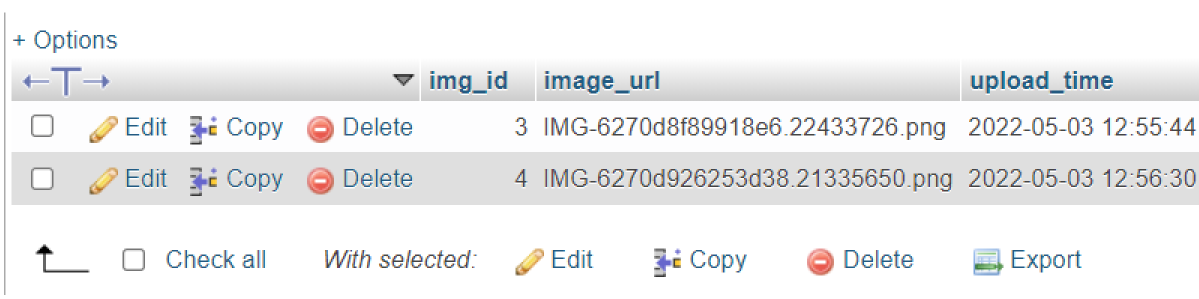


Fig 19: Uploaded Images

The arrow symbol takes us back to the uploading page. After uploading, the details of the uploaded images are stored in the server, as depicted below.



+ Options

←T→	img_id	image_url	upload_time
Edit Copy Delete	3	IMG-6270d8f89918e6.22433726.png	2022-05-03 12:55:44
Edit Copy Delete	4	IMG-6270d926253d38.21335650.png	2022-05-03 12:56:30

Check all *With selected:* Edit Copy Delete Export

Fig 20: Uploaded Image stored in server along with it's details

Also, the 'uploads' folder in the server folder in the local disk(since we use the same laptop as server), stores the uploaded image. Notice, the image names are same on the server and in the uploads folder, which suggests that as soon as we uploaded results, it stores the results in the server's 'uploads' folder.

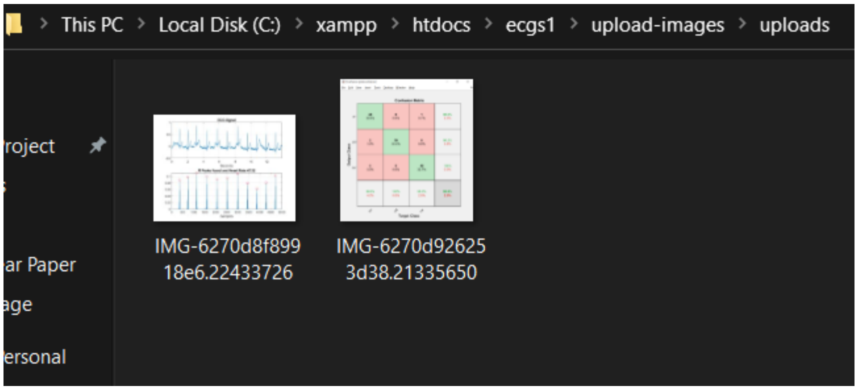


Fig 21: Uploaded Images stored in the server folder

7.4.2 LOGIN & ACCESS:

In order to prevent unauthorized access, the server only allows registered users to access it's contents. The login address is **'localhost/ecgs1/login'**. Hence one needs to register using signup option.

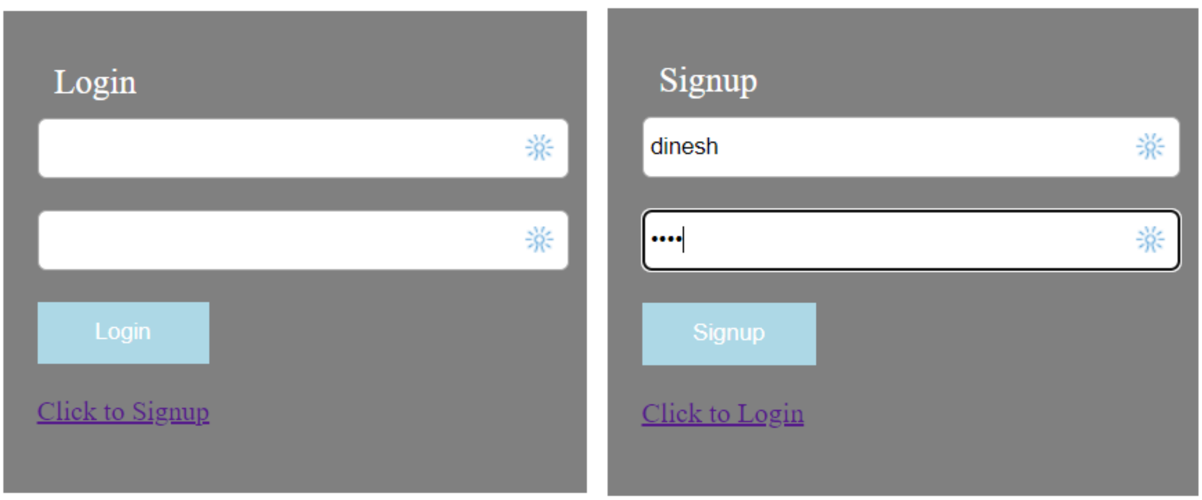


Fig 22: Login and Signup Windows

The above figure shows the Login and Signup windows. After a successful signup, the login details of the registered user are stored in the server.

←T→	id	user_id	user_name	password	date
Edit Copy Delete	2	55821	dinesh	abcd	2022-05-03 13:11:14

Check all With selected: Edit Copy Delete Export

Fig 23: Login details stored in the server

Using these registered login credentials, one can login and access their ECG medical data as follows. After viewing, the ‘Logout’ button can be used to navigate back to login page.

Logout

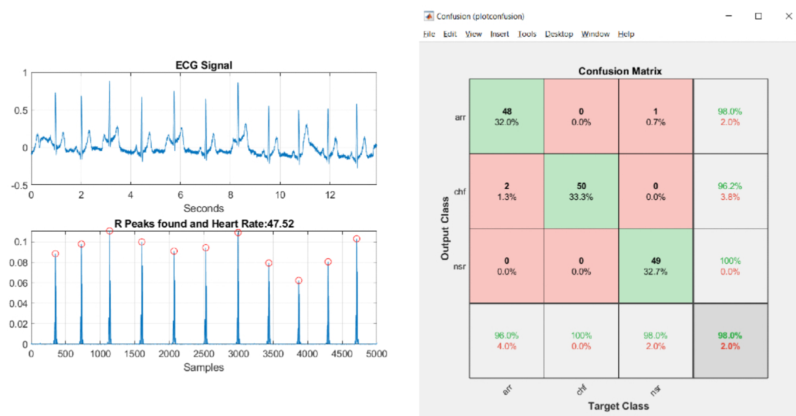


Fig 24: Accessing uploaded images through login

For BPM, as we said earlier, we used Thingspeak because of it’s ability to plot the graphs from the data received from matlab. Hence, in the graph we can see the trends of the heartbeat as it changed over time.

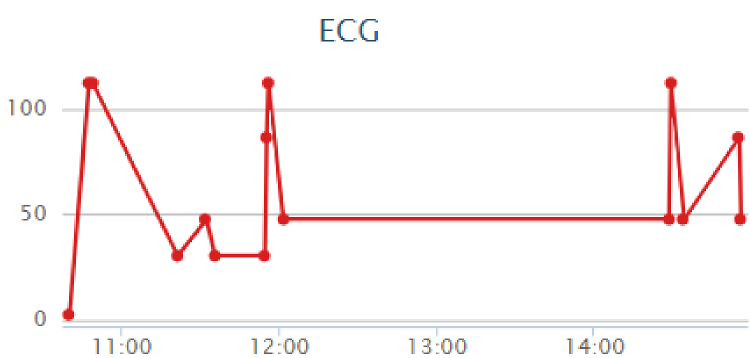


Fig 25: Changes in Heart rate updated in Thingspeak over time

Also, not the previous BPM, but the present BPM can be updated and depicted through numeric and gauge display.

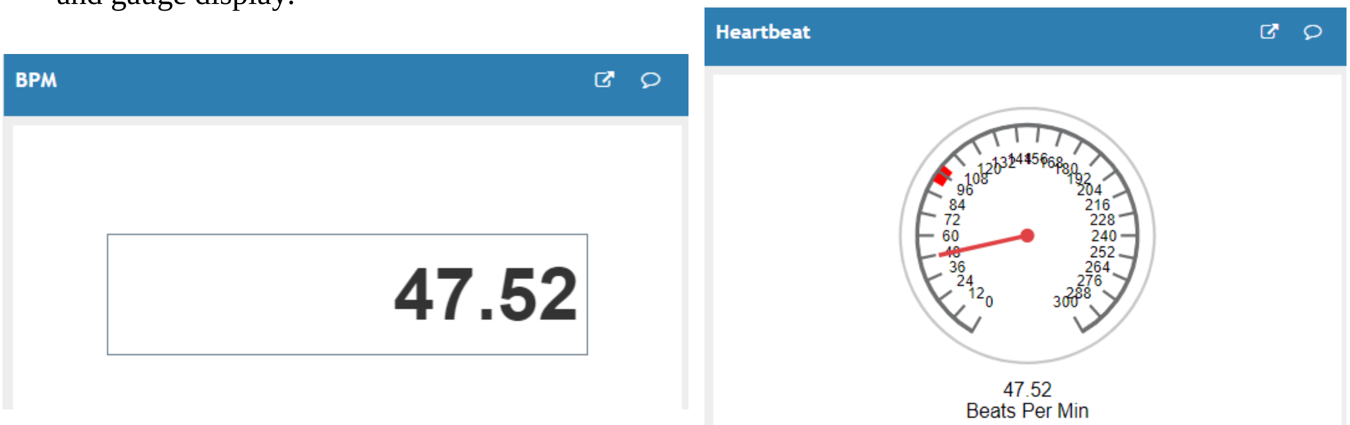


Fig 26: At present heart rate, indicated by numeric and gauge display

8. SUMMARY

Deep learning is a new and upcoming field which is an extension of Machine Learning where CNNs are trained to extract and learn features from a dataset of images. The primary objective of this work is to detect and classify various Cardiovascular Disorders such as Arrhythmia, Congestive Heart Failure and Normal Sinus Rhythm from standard ECG signals samples packed in a .mat file. We implemented three the system in three stages: ECG Extraction, Training Model, Feature Extraction. We also validated our models on the datasets and compared their performance with other existing models. Our models were able to reach the same levels of accuracy as the best performing models if simulated on machines with higher processing power, CPU speed and GPU. The advantage of our approach is the smaller number of trainable parameters which is computationally less expensive than existing pre-trained models. Our model uses Alexnet which prevents the overfitting phenomenon in the softmax layer.

We have proposed three different algorithms to assist in each individual step of system execution. Out of them, Alexnet deep CNN is train on various ECG signal datasets which are publicly available. The trained model was used to predict the labels of some test images which have not been seen by the model. The results of the proposed models indicated that it is light-weighted and performed better than other related works.

We also designed a prototype web system involving a local server, to which all the ECG data can be uploaded which can be accessed through the registered user login system and the main objective is to facilitate the concrete medical history of the patient incase of the further diagnosis in the future.

In future, changing the optimizers, learning rate and introduction of more data augmentation, deploying cloud platforms such as Azure or AWS could potentially lead to further improvements in classification accuracy of the proposed CNN models and the scalability, robustness of the web platforms to which all the ECG data would be uploaded to.

9. REFERENCES

[1] M. Hammad, A. M. Iliyasu, A. Subasi, E. S. L. Ho and A. A. A. El-Latif, "A Multitier Deep Learning Model for Arrhythmia Detection," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-9, 2021, Art no. 2502809, doi: 10.1109/TIM.2020.3033072.

[2] w. zhu, X. Chen, Y. Wang and L. Wang, "Arrhythmia Recognition and Classification Using ECG Morphology and Segment Feature Analysis," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 16, no. 1, pp. 131-138, 1 Jan.-Feb. 2019, doi: 10.1109/TCBB.2018.2846611.

[3] X. Xu and H. Liu, "ECG Heartbeat Classification Using Convolutional Neural Networks," in IEEE Access, vol. 8, pp. 8614-8619, 2020, doi: 10.1109/ACCESS.2020.2964749.

[4] H. Chen and K. Maharatna, "An Automatic R and T Peak Detection Method Based on the Combination of Hierarchical Clustering and Discrete Wavelet Transform," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 10, pp. 2825-2832, Oct. 2020, doi: 10.1109/JBHI.2020.2973982.

[5] S. Modak, L. Y. Taha and E. Abdel-Raheem, "A Novel Method of QRS Detection Using Time and Amplitude Thresholds With Statistical False Peak Elimination," in IEEE Access, vol. 9, pp. 46079-46092, 2021, doi: 10.1109/ACCESS.2021.3067179.

[6] J. Huang, B. Chen, B. Yao and W. He, "ECG Arrhythmia Classification Using STFT-Based Spectrogram and Convolutional Neural Network," in IEEE Access, vol. 7, pp. 92871-92880, 2019, doi: 10.1109/ACCESS.2019.2928017.

[7] E. Essa and X. Xie, "An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification," in IEEE Access, vol. 9, pp. 103452-103464, 2021, doi: 10.1109/ACCESS.2021.3098986.

[8] Y. Li, Z. Zhang, F. Zhou, Y. Xing, J. Li and C. Liu, "Multi-Label Classification of Arrhythmia for Long-Term Electrocardiogram Signals With Feature Learning," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-11, 2021, Art no. 2512611, doi: 10.1109/TIM.2021.3077667.

[9] W. Cai and D. Hu, "QRS Complex Detection Using Novel Deep Learning Neural Networks," in IEEE Access, vol. 8, pp. 97082-97089, 2020, doi: 10.1109/ACCESS.2020.2997473.

[10] J. Morales et al., "Model-Based Evaluation of Methods for Respiratory Sinus Arrhythmia Estimation," in IEEE Transactions on Biomedical Engineering, vol. 68, no. 6, pp. 1882-1893, June 2021, doi: 10.1109/TBME.2020.3028204.

[11] Strodthoff, Nils, Patrick Wagner, Tobias Schaeffter and Wojciech Samek. “Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL.” IEEE Journal of Biomedical and Health Informatics 25 (2021): 1519-1528.

[12] W. Sun, N. Zeng and Y. He, "Morphological Arrhythmia Automated Diagnosis Method Using Gray-Level Co-Occurrence Matrix Enhanced Convolutional Neural Network," in IEEE Access, vol. 7, pp. 67123-67129, 2019, doi: 10.1109/ACCESS.2019.2918361.

[13] S. Shimauchi, K. Eguchi, R. Aoki, M. Fukui and N. Harada, "R-R Interval Estimation for Wearable Electrocardiogram Based on Single Complex Wavelet Filtering and Morphology-Based Peak Selection," in IEEE Access, vol. 9, pp. 60802-60827, 2021, doi: 10.1109/ACCESS.2021.3070604.

[14] J. -N. Lee and K. -C. Kwak, "Personal Identification Using a Robust Eigen ECG Network Based on Time-Frequency Representations of ECG Signals," in IEEE Access, vol. 7, pp. 48392-48404, 2019, doi: 10.1109/ACCESS.2019.2904095.

[15] W. Li, "Wavelets for Electrocardiogram: Overview and Taxonomy," in IEEE Access, vol. 7, pp. 25627-25649, 2019, doi: 10.1109/ACCESS.2018.2877793.

[16] U. Satija, B. Ramkumar and M. S. Manikandan, "A New Automated Signal Quality-Aware ECG Beat Classification Method for Unsupervised ECG Diagnosis Environments," in IEEE Sensors Journal, vol. 19, no. 1, pp. 277-286, 1 Jan.1, 2019, doi: 10.1109/JSEN.2018.2877055.

[17] R. K. Tripathy, A. Bhattacharyya and R. B. Pachori, "Localization of Myocardial Infarction From Multi-Lead ECG Signals Using Multiscale Analysis and Convolutional Neural Network," in IEEE Sensors Journal, vol. 19, no. 23, pp. 11437-11448, 1 Dec.1, 2019, doi: 10.1109/JSEN.2019.2935552.

[18] D. Lai, X. Fan, Y. Zhang and W. Chen, "Intelligent and Efficient Detection of Life-Threatening Ventricular Arrhythmias in Short Segments of Surface ECG Signals," in IEEE Sensors Journal, vol. 21, no. 13, pp. 14110-14120, 1 July1, 2021, doi: 10.1109/JSEN.2020.3031597.

[19] Z. Wu, T. Lan, C. Yang and Z. Nie, "A Novel Method to Detect Multiple Arrhythmias Based on Time-Frequency Analysis and Convolutional Neural Networks," in IEEE Access, vol. 7, pp. 170820-170830, 2019, doi: 10.1109/ACCESS.2019.2956050.

[20] K. Karboub, M. Tabaa, F. Monteiro, S. Dellagi, F. Moutaouakkil and A. Dandache, "Automated Diagnosis System for Outpatients and Inpatients With Cardiovascular Diseases," in IEEE Sensors Journal, vol. 21, no. 2, pp. 1935-1946, 15 Jan.15, 2021, doi: 10.1109/JSEN.2020.3019668.L. Qiao, Y. Zhu and H. Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms," in IEEE Access, vol. 8, pp. 104292-104302, 2020, doi: 10.1109/ACCESS.2020.2993937.

[21] T. Mahmud, S. A. Fattah and M. Saquib, "DeepArrNet: An Efficient Deep CNN Architecture for Automatic Arrhythmia Detection and Classification From Denoised ECG Beats," in IEEE Access, vol. 8, pp. 104788-104800, 2020, doi: 10.1109/ACCESS.2020.2998788.

[22] A. Momeni Pour, H. Seyedarabi, S. H. Abbasi Jahromi and A. Javadzadeh, "Automatic Detection and Monitoring of Diabetic Retinopathy Using Efficient Convolutional Neural

Networks and Contrast Limited Adaptive Histogram Equalization," in IEEE Access, vol. 8, pp. 136668-136673, 2020, doi: 10.1109/ACCESS.2020.3005044.

[23] C. -H. Hua et al., "Convolutional Network With Twofold Feature Augmentation for Diabetic Retinopathy Recognition From Multi-Modal Images," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 7, pp. 2686-2697, July 2021, doi: 10.1109/JBHI.2020.3041848.

[24] L. Qiao, Y. Zhu and H. Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms," in IEEE Access, vol. 8, pp. 104292-104302, 2020, doi: 10.1109/ACCESS.2020.2993937.

[25] Zhou, Yi & Wang, Boyang & Huang, Lei & Cui, Shanshan & Shao, Ling. (2020). A Benchmark for Studying Diabetic Retinopathy: Segmentation, Grading, and Transferability. IEEE Transactions on Medical Imaging. PP. 1-1. 10.1109/TMI.2020.3037771.

[26] S. Qummar et al., "A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection," in IEEE Access, vol. 7, pp. 150530-150539, 2019, doi: 10.1109/ACCESS.2019.2947484.

[27] Y. Sun, "The Neural Network of One-Dimensional Convolution-An Example of the Diagnosis of Diabetic Retinopathy," in IEEE Access, vol. 7, pp. 69657-69666, 2019, doi: 10.1109/ACCESS.2019.2916922.

[28] M. T. Islam, H. R. H. Al-Absi, E. A. Ruagh and T. Alam, "DiaNet: A Deep Learning Based Architecture to Diagnose Diabetes Using Retinal Images Only," in IEEE Access, vol. 9, pp. 15686-15695, 2021, doi: 10.1109/ACCESS.2021.3052477.

[29] M. W. Condry and X. I. Quan, "Digital Health Innovation, Informatics Opportunity, and Challenges," in IEEE Engineering Management Review, vol. 49, no. 2, pp. 81-88, 1 Secondquarter,june 2021, doi: 10.1109/EMR.2021.3054330.

[30] K. Seol, Y. -G. Kim, E. Lee, Y. -D. Seo and D. -K. Baik, "Privacy-Preserving Attribute-Based Access Control Model for XML-Based Electronic Health Record System," in IEEE Access, vol. 6, pp. 9114-9128, 2018, doi: 10.1109/ACCESS.2018.2800288.

[31] M. W. Condry, "Using Requirements for Health Data Organization and Management," in IEEE Engineering Management Review, vol. 49, no. 3, pp. 109-118, 1 thirdquarter,Sept. 2021, doi: 10.1109/EMR.2021.3100418.

[32] R. Wang, J. Fan and Y. Li, "Deep Multi-Scale Fusion Neural Network for Multi-Class Arrhythmia Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 9, pp. 2461-2472, Sept. 2020, doi: 10.1109/JBHI.2020.2981526.

[33] H. Dang, Y. Yue, D. Xiong, X. Zhou, X. Xu and X. Tao, "A Deep Biometric Recognition and Diagnosis Network With Residual Learning for Arrhythmia Screening Using Electrocardiogram Recordings," in IEEE Access, vol. 8, pp. 153436-153454, 2020, doi: 10.1109/ACCESS.2020.3016938.

[34] H. Chen, G. Wang, G. Zhang, P. Zhang and H. Yang, "CLECG: A Novel Contrastive Learning Framework for Electrocardiogram Arrhythmia Classification," in IEEE Signal Processing Letters, vol. 28, pp. 1993-1997, 2021, doi: 10.1109/LSP.2021.3114119.

[35] B. Hou, J. Yang, P. Wang and R. Yan, "LSTM-Based Auto-Encoder Model for ECG Arrhythmias Classification," in IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 4, pp. 1232-1240, April 2020, doi: 10.1109/TIM.2019.2910342.

[36] Li JQ, Li R, Chen ZZ, Deng GQ, Wang H, Mavromoustakis CX, Song H, Ming Z. Design of a Continuous Blood Pressure Measurement System Based on Pulse Wave and ECG Signals. IEEE J Transl Eng Health Med. 2018 Jan 18;6:1900114. doi: 10.1109/JTEHM.2017.2788885. PMID: 29541556; PMCID: PMC5844675.