ABSTRACT

Technological advancements in healthcare and medical field have saved millions of lives and improved many others .But in context of Nepal still peoples are deprived of proper health service. There are only few numbers of doctor available in remote areas. Also, in city area people are busy doing their job so people are not aware about their present health condition and unascertained about health problems like hypertension, arrhythmia, heart attack, high blood pressure, sugar etc. Medical check-up has skyrocket price due to which bourgeois and proletarian family couldn't get chance to know their present health condition. To control this types of health problem economically there requires something to instruct and warn about their present health condition and make them aware about risk in near future. Considering above problem, we are trying to make "Selcouth Health Care" a device which can measure 20 different body parameters such as (Blood pressure, Heart beat, Weight, Height, Fat, BMI, Muscular muscles , temperature, Intracellular water, bone mass , ECG etc.). Our device will store body parameters of each person weekly and relates its result with previous data and calculates there present health score. Using ECG output image, it will detect chance of arrhythmia and heart attack in near future. It will co-relates its previous health state with prevent health state and predicts there future health state. A single device will work as personal health assistance for many people. People will not only get their health check-up but also get suggestion and risk of different health problem which will aware about their health condition.

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2 LIST OF SYMBOLS

ECG: Electrocardiogram

BIA: Bioelectrical Impedance Analyzer

BMI: Body Mass Index

AC: Alternating Current

IR: Infra-Red

IIR: Infinite Impulse Response

MIT-BIH: Massachusetts Institute of Technology-Beth Israel Hospital

CNN: Convolutional Neural Network

PVC: Premature ventricular contractions

PAB: Premature Arrhythmia Beats

RBB: Right Bundle Branch Block

LBB: Left Bundle Branch Block

APC: Atrial Premature Complexes

VFW: Ventricular fibrillation

3 INTRODUCTION

3.1 Objectives

The main objectives of this proposal is highlighted below:

- To measure 20 different body parameters (Blood pressure, Heart beat, weight, Height, Fat, BMI, Muscular muscles , temperature, Intracellular water, bone mass , ECG etc.
- To provide better health service in remote areas of Nepal.
- To provide health assistance to each person to take care of their health.
- To predict risk of heart diseases(arrythmia) and related health problems.
- To provide suggestion in their nutrients.
- To calculate health score, suggest and warn about their health status.

3.2 Problem Statement

Technology has dramatically changed different fields of study. It has made our life standard easier and more convenient. In the field of medical science, different machine and technology has been invented, which made possible to detect and cure different human diseases. But in developing country like Nepal, there is still lack of medical health services. There are very few number of doctors in remote areas due to which doctors are not able to provide proper health care to all people. Also, in city area people are busy in doing their job so that they couldn't take care of their health status and are unware about their health condition. Many people are suffering from different health problems such as hypertension, arrhythmia, heart attack, high blood pressure, sugar etc. Medical checkup has skyrocket price due to which bourgeois and proletarian family are deprived of different health facility. To control this types of health problem economically there requires something to instruct and warn about present health condition and to make them aware about risk related to health in near future. So considering above problems we have proposed a new idea and solutions.

3.3 Theoretical background

- **Lidar :** It is a acronym for *light detection and ranging*. It is a device used for the precision and accurate measurement of the distances. It generates Laser pulse train, which sent to the surface/target to measure the time and it takes to return to its source.

  Lidars are mainly used to map the built environment (such as buildings, road networks and railways) as well as creating digital terrain (DTM) and elevation models (DEMs) of specific landscapes because of their ability to collect three dimensional measurements.

- **BIA :** BIA stands for the Bio Impedance Analyser.)It is a commonly used method for estimating body composition, in particular body fat and muscle mass with the analysis of the impedance of the body.BMI(Body Mass Index) is not sufficient to analyze a patient's health status and body composition thoroughly.So this technology uses a weak electric current to flow through the body and the voltage is measured in order to calculate impedance (resistance) of the body.This technology uses the impedance to calculate the body parameters like Muscle Rate,Body Water,Bone Mass,Metabolic Rate,Protein Rate,Visceral Fat Index,Muscle Mass,Fat Mass,Protein Mass. Estimates of body composition using BIA are facilitated using empirically validated equations, which consider variables including gender, race, height, weight, and age.

  The Prediction Marker or Impedance Ratio is the ratio between the impedance measurement at 200 kHz and 5 kHz. At 200 kHz the current is strong enough to penetrate the cell membrane and therefore total body water (TBW) can be measured. However, at 5 kHz the membrane cannot be penetrated and only Extracellular Water (ECW) can be measured. Intracellular water (ICW) is derived by TBW-ECW. The greater the variance between the two impedance values at 5 kHz and 200 kHz, the healthier the body cells. To allow easy monitoring of change, these figures are expressed as a ratio. A ratio closer to 1.00 indicates poor cellular health or extreme fluid overload. Figure 3 illustrates the normal ranges as experienced by Bodystat.

Figure 1: Lidar

- **Oxymeter :** Pulse oximetry is a noninvasive method for monitoring a person's oxygen saturation (SO_2). Though its reading of peripheral oxygen saturation SpO_2 is not always identical to the more desirable reading of arterial oxygen saturation (SaO_2) from arterial blood gas analysis, the two are correlated well enough that the safe, convenient, noninvasive, inexpensive pulse oximetry method is valuable for measuring oxygen saturation in clinical use.

  In its most common (transmissive) application mode, a sensor device is placed on a thin part of the patient's body, usually a fingertip or earlobe, or in the case of an infant, across a foot. The device passes two wavelengths of light through the body part to a photodetector. It measures the changing absorbance at each of the wavelengths, allowing it to determine the absorbances due to the pulsing arterial blood alone, excluding venous blood, skin, bone, muscle, fat, and (in most cases) nail polish.

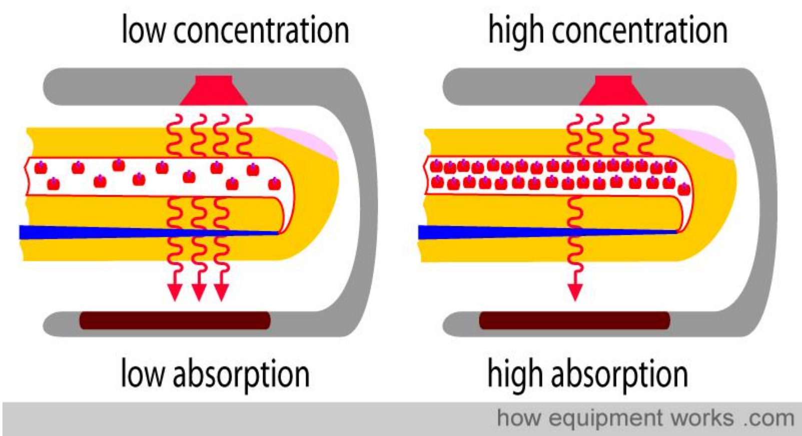

Figure 3: Working of oxymeter

- **ECG Sensor :** Electrocardiography is the process of producing an electrocardiogram (ECG or EKG), a recording – a graph of voltage versus time – of the electrical activity of the heart using electrodes placed on the skin. ECG sensor consists of a sensor module along with three electrodes. These electrodes detect the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle (heartbeat). These electrical signals are modulated by the module and sent as analog value to the processor for further processing. The ECG graph thus obtained can be interpreted to know the health condition of a person.

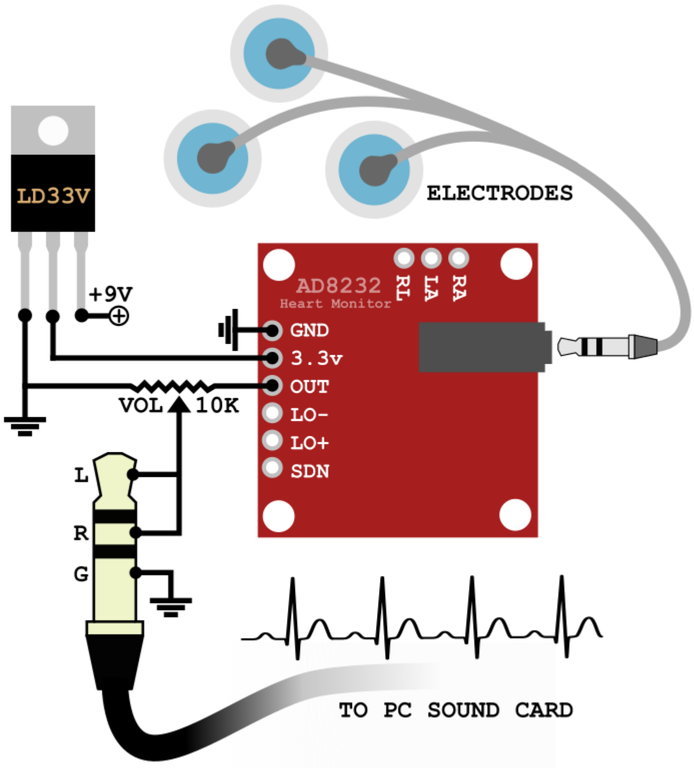

Figure 4: ECG

- **Temperature Gun :** An infrared thermometer is a thermometer which infers temperature from a portion of the thermal radiation sometimes called black-body radiation emitted by the object being measured. They are sometimes called laser thermometers as a laser is used to help aim the thermometer, or non-contact thermometers or temperature guns, to describe the device's ability to measure temperature from a distance. By knowing the amount of infrared energy emitted by the object and its emissivity, the object's temperature can often be determined within a certain range of its actual temperature. Infrared thermometers are a subset of devices known as "thermal radiation thermometers". The device essentially consists of a lens to focus the infrared thermal radiation on to a detector, which converts the radiant power to an electrical signal that can be displayed in units of temperature after being compensated for ambient temperature. This permits temperature measurement from a distance without contact with the object to be measured.

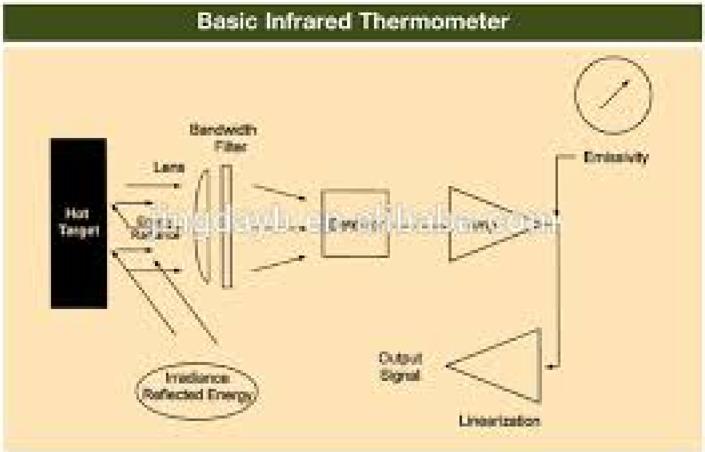

Figure 5: Basic Infrared Thermometer

- **Blood Pressure :** Blood pressure is the force that moves blood through our circulatory system. It is an important force because oxygen and nutrients would not be pushed around our circulatory system to nourish tissues and organs without blood pressure. The device used here to measure blood pressure is a digital one.Digital meters employ oscillometric measurements and electronic calculations rather than auscultation. With an oscillatory device, a cuff is inflated over the upper arm or wrist. The new models use “fuzzy logic” to decide how much the cuff should be inflated to reach a pressure about 20 mm Hg above systolic pressure for any individual. When the cuff is fully inflated to this pressure, no blood flow occurs through the artery. As the cuff is deflated below the systolic pressure, the reducing pressure exerted on the artery allows blood to flow through it and sets up a detectable vibration in the arterial wall. When the cuff pressure falls below the patient’s diastolic pressure, blood flows smoothly through the artery in the usual pulses, without any vibration being set up in the wall. Vibrations occur at any point where the cuff pressure is sufficiently high that the blood has to push the arterial wall open in order to flow through the artery. The vibrations are transferred from the arterial wall, through the air inside the cuff, into a transducer in the monitor that converts the measurements into electrical signals.

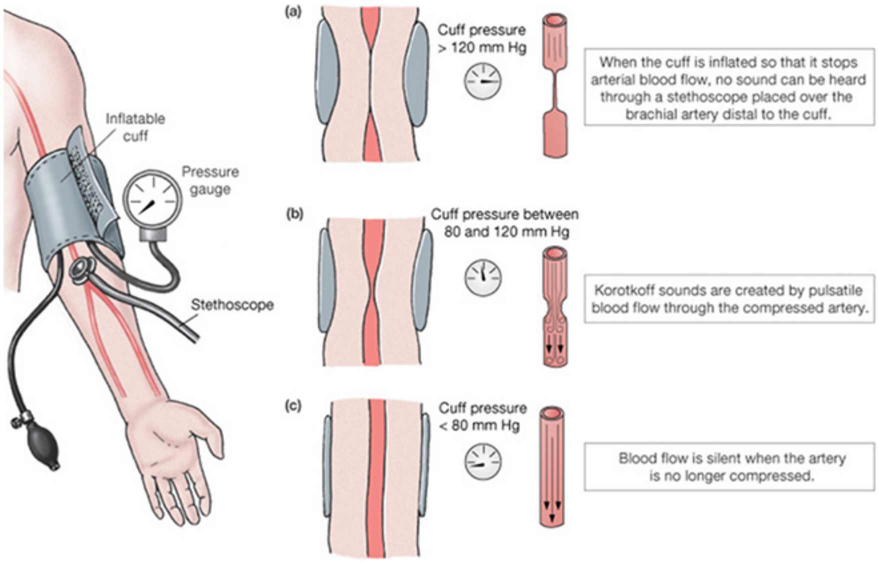

Figure 6: BP Working

4 DISCUSSION

4.1 Sensors Interfacing

To interface different devices with our microcontroller we have done reverse engineering and decoded its usefull data. All sensors data is recovered sucessfully and is used for prediction.

Microlife Blood pressure Monitor:

Blood pressure Monitor have 30 storage data capacity, it stores its data in EEPROM. EEPROM uses I^2C protocals so I^2C pins of Arduino Mega is connected with pins of EEPROM and finally stored data is fetched to raspberry pi via arduino.

Figure 7: Connection of EEPROM of BP with Arduino

SHENGDE Non-contact Infrared Thermometer:

Non-contact Infrared Thermometer have 30 storage data capacity, it stores its data in EEPROM. EEPROM uses I^2C protocals so I^2C pins of Arduino Mega is connected with pins of EEPROM and finally stored data is fetched to raspberry pi via arduino.

Figure 8: Connection of EEPROM of thermometer with Arduino

BerryMind Pulse Oximeter:

Pulse oximeter uses Bluetooth low energy(BLE) which transmits data via wireless so we captured bluetooth packet and used Wireshark to decode captured packet. Finally we decoded all information from each packet and data is send to raspberry pi for further processing.

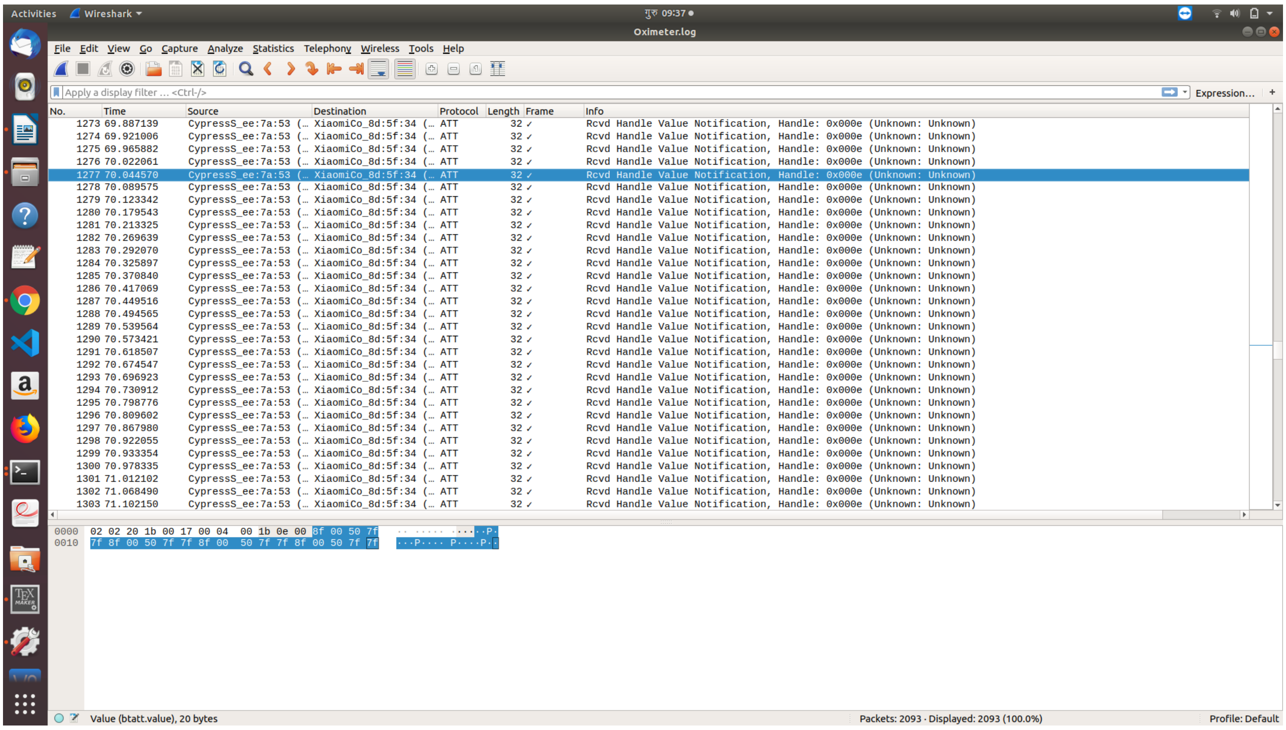

Figure 9: Wireshark output of oximeter

Heslay BIA:

Pulse oximeter uses Bluetooth low energy(BLE) which transmits data via wireless so we captured bluetooth packet and used Wireshark to decode captured packet. Finally we decoded all information from each packet and data is send to raspberry pi for further processing.

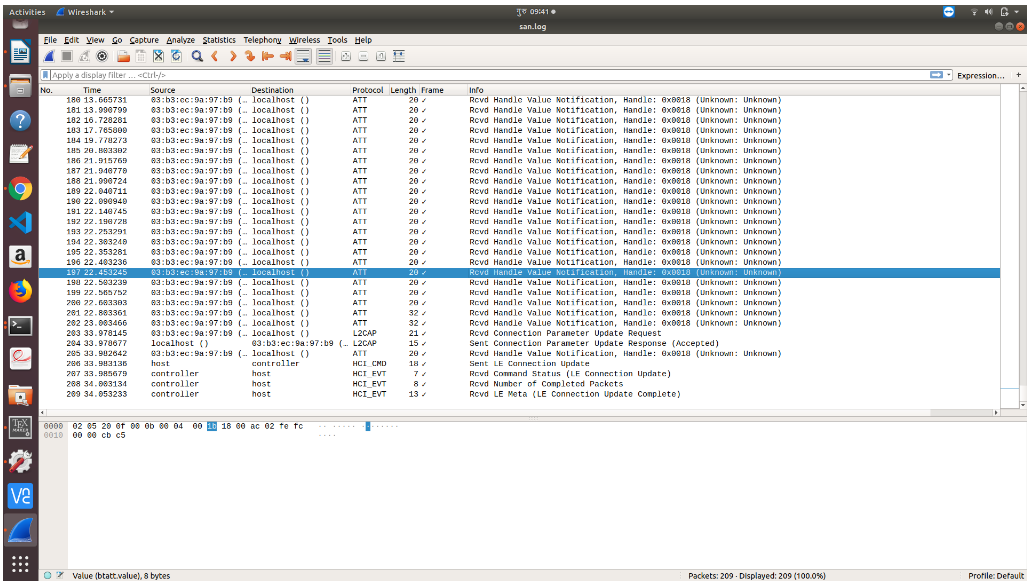

Figure 10: Wireshark output of BIA

AD8232 ECG Sensor

The ECG module was interfaced via on-board 10-bit **ADC** of **Arduino Mega** in which the real-time data of patient's heart is monitored at about 1KHz and the data was sent to Raspberry Pi for further processing.

The circuit setup is given in figure11.

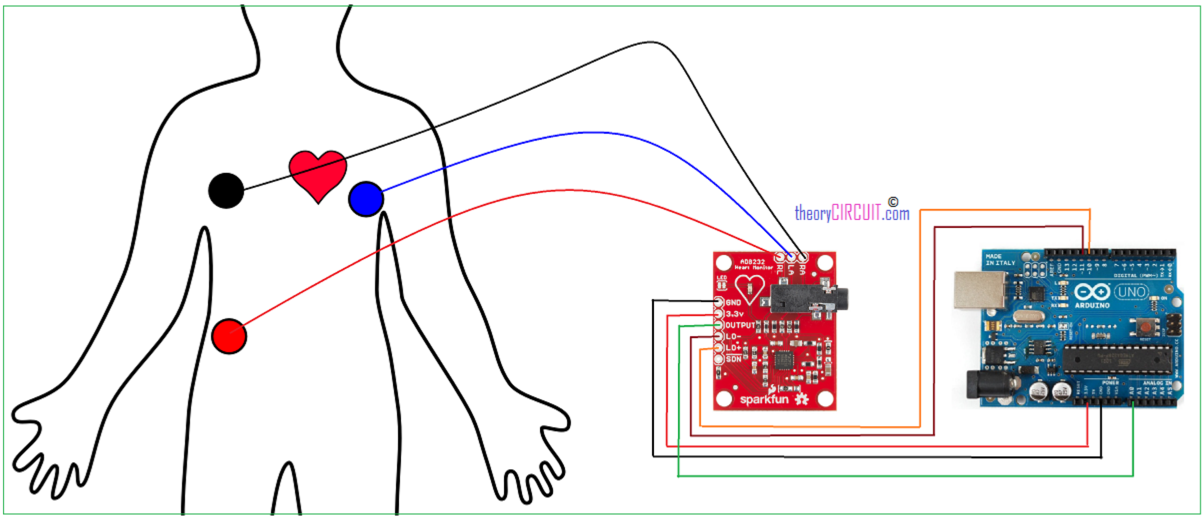

Figure 11: Circuit Diagram

The waveform of the ECG Signal after plotting these discrete samples is seen as shown in figure 4.2

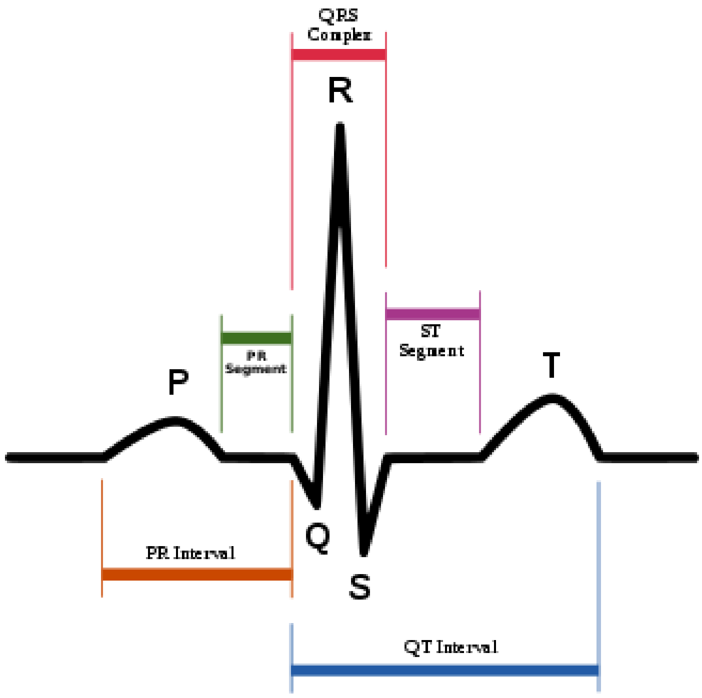

Figure 12: ECG Signal Waveform

4.2 Prediction Heart arrhythmia

Electrocardiogram (ECG) is used as a measure to monitor the functionality of the cardiovascular system. 2D Convolutional neural network of 11-layer is used for the prediction of arrhythmia. Our proposed architecture model

	Type	Kernel size	Stride	# Kernel	Input size
Layer1	Conv2D	3 x 3	1	64	128 x 128 x 1
Layer2	Conv2D	3 x 3	1	64	128 x 128 x 64
Layer3	Pool	2 x 2	2		128 x 128 x 64
Layer4	Conv2D	3 x 3	1	128	64 x 64 x 64
Layer5	Conv2D	3 x 3	1	128	64 x 64 x 128
Layer6	Pool	2 x 2	2		64 x 64 x 128
Layer7	Conv2D	3 x 3	1	256	32 x 32 x 128
Layer8	Conv2D	3 x 3	1	256	32 x 32 x 256
Layer9	Pool	2 x 2	2		32 x 32 x 256
Layer10	Full			2048	16 x 16 x 256
Layer11	Out			8	2048

In our system, 1D signal obtained from ecg sensor is converted into 2D signal which is input to our CNN model. Every ECG beat was transformed into a two dimensional grayscale image as an input data for the CNN classifier.when the ECG signal is converted to the two-dimensional image, proposed CNN model can automatically ignore the noise data while extracting the relevant feature map throughout the convolutional and pooling layer. Thus, proposed CNN model can be applied to the ECG signals from the various ECG devices with different sampling rates and amplitudes. CNN model classfy 8 different types of arrhythmia including normal condition.

Our classification method consists the following steps: data acquisition, ECG data preprocessing, and CNN classifier. ECG signal data treated in is obtained from the MIT-BIH database which is generally used as an arrhythmia database in ECG arrhythmia classification research. With these ECG recordings, we transformed every single ECG beat into 128 x 128 grayscale image since our CNN model requires two-dimensional image as an input.

Methods

1. **ECG data pre-processing**
   Two-dimensional CNN requires image as an input data. Therefore, we trans-formed

ECG signals into ECG images by plotting each ECG beat as an individual 128 x 128 grayscale image. In the MIT-BIH arrhythmia database, every ECG beat is sliced based on Q-wave peak time. More specifically, the type of arrhythmia is labeled at the Q-wave peak time of each ECG beat. Thus, we defined a single ECG beat image by centering the Q-wave peak signal while excluding the first and the last 20 ECG signals from the previous and afterward Q-wave peak signals. Based on the time information, a single ECG beat range can be defined in following:

$$T(Q_{peak}(n-1)+20) \leq T(n) \leq T(Q_{peak}(n+1)-20)$$

As a result, we obtained 100,000 images from the MIT-BIH arrhythmia database where each image is one of eight ECG beat types. Fig 2 describes the eight ECG beat types with 128 x 128 grayscale images obtained from the ECG data pre-processing scheme.

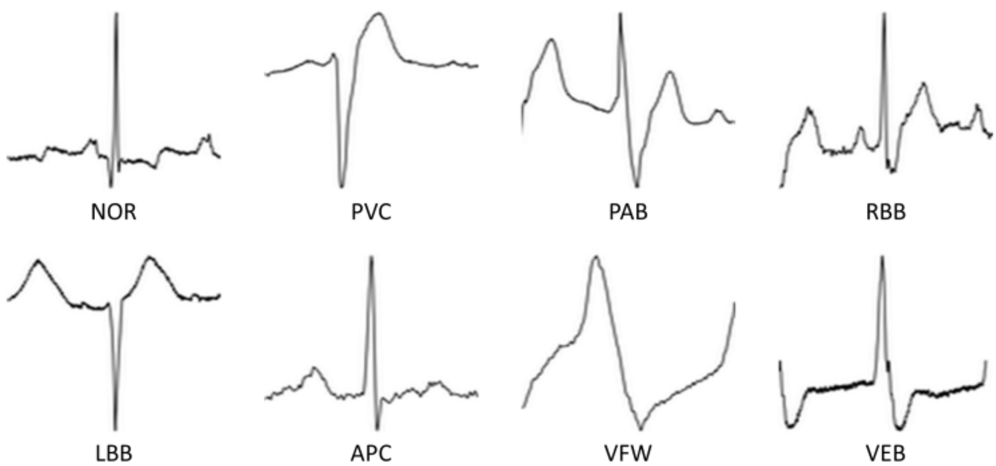

Figure 13: Normal beat and seven ECG arrhythmia beats

Type	Records	#Beats
NOR	100,101,103,105,108,112,113,114,115,117,121,122,123 202,205,219,230,234	75052
PVC	106,116,119,200,201,203,208,210,213,215,221,228,233	7130
PAB	102,104,107,217	7028
RBB	118,124,212,231	7259
LBB	109,111,207,213	8075
APC	209,220,222,223,232	2546
VFW	207	472
VEB	207	106
Total		**106501**

Figure 14: ECG dataset from MIT-BIH

2. **ECG arrhythmia classifier**

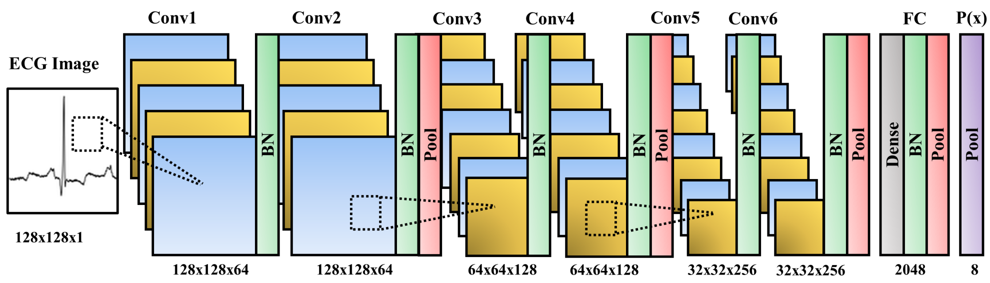

Figure 15: Normal beat and seven ECG arrhythmia beats

3. **Data Augmentation**

   We have $75,000$ normal data where other classes have only data range from 200 to 8000 so to balance number of classes, we augmented seven ECG arrhythmia beats (PVC, PAB, RBB, LBB,APC, VFW, VEB) with nine different cropping methods: left top, center top, right top, center left, center, center right, left bottom, center bottom, and right bottom. Each cropping method results in two of three sizes of an ECG image, that is 96 x 96. Then, these augmented images are resized to the original size which is 128 x 128. Fig 3 shows nine example cropped images with the original image with PVC. These augmented images are produced inside the model and it is saved in disk memory.

Training

Proposed classifier models are deployed in Python language with TensorFlow which is an open source software library for deep learning launched by Google. Since CNN requires a lot of free parameters to train and it takes hour to train our model so, we have

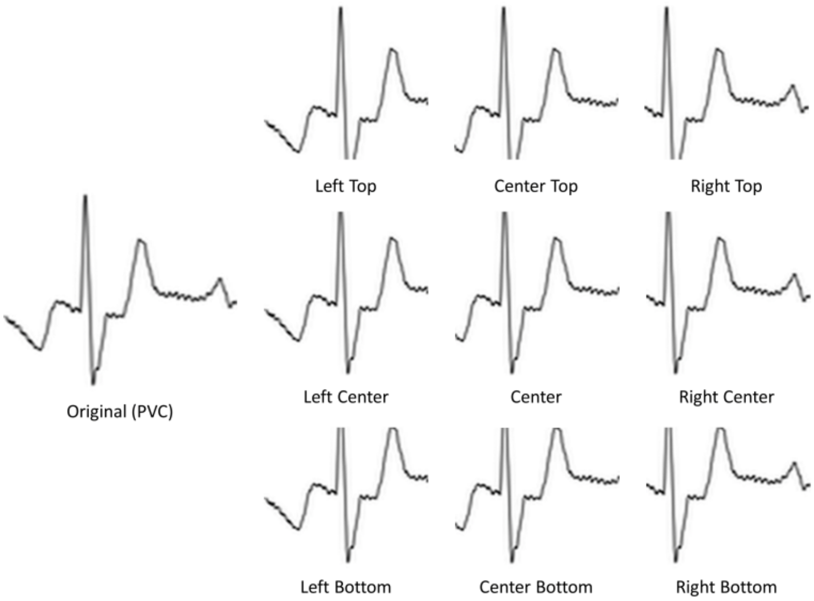

Figure 16: Original PVC image and nine cropped images

trained our model in **Google colab** GPUs. With these NVIDIA GPUs, TensorFlow is accelerated by using CUDA and CUDNN. Versions of each software are TensorFlow r1.0, CUDA 8.0, and CUDNN 5.5. Our model is train for 100 epcohs with 80,000 training data set.Exponential decay learing rate with initial learing rate 0.001 is used All parameters are initilaized with Xavier initialization.

Experiments and Results

Experiment is done in MIT-BIH data set and accuracy is found to be 98.32% in training set, 92.425% in test set. Following is clasess accuracy measured with our proposed CNN model

4.3 Problem encountered and solutions

Problems Encountered

ECG is a biomedical signal which gives electrical activity of heart. This ECG signal is corrupted by various noises like **power line interference**, **baseline wandering**, **channel noise**, **contact noise**, **muscle artifacts** etc.

- *Powerline Interference:* Frequency range of ECG signal is nearly same as the frequency of power line interference. ECG signal has frequency range from $0.5Hz$ to

Class	Total	Loss	Accuracy(%)
0	37509	0.34	0.9871498
1	103	0.1424	0.9528302
2	7130	0.05325	0.9813323
3	8072	0.0554	0.9824
4	7056	0.67468	0.8693495
5	2544	0.86515	0.7948113
6	472	0.09157	0.9661017
7	7024	0.0153	0.99615604

Figure 17: Classes Accuracy

$80Hz$ and power line interference introduces 50 to $60Hz$ frequency component in that signal which is the major cause of corruption of ECG.

A visualization of powerline interference in our ECG signal is as shown in figure 18.

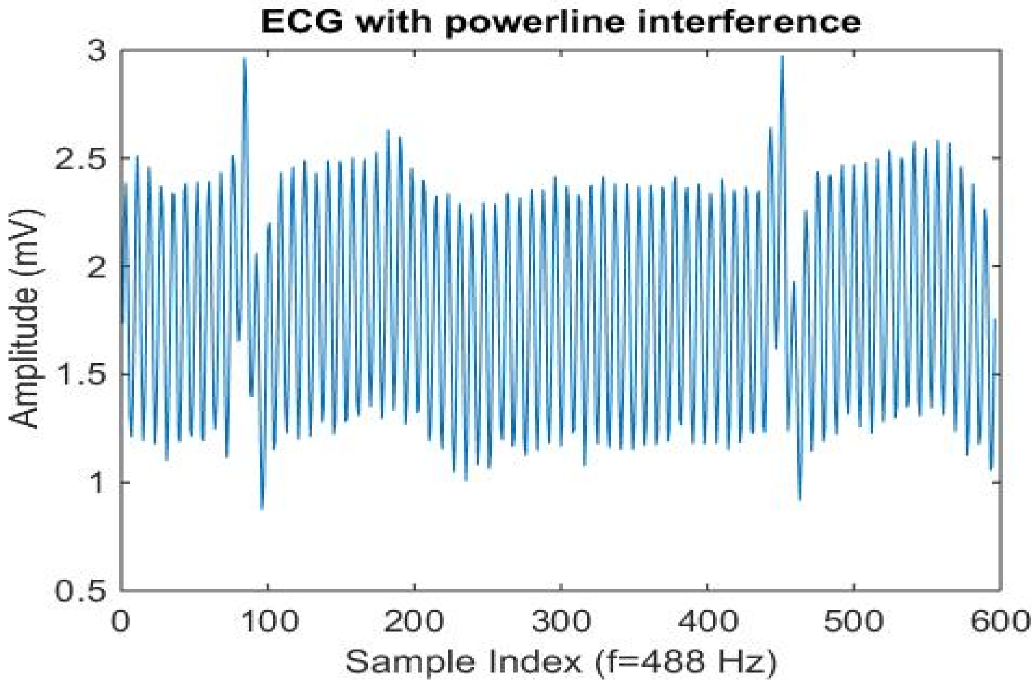

Figure 18: Powerline Interference in ECG Signal

- *Baseline Wander:* Another problem is Baseline Wander which is a low-frequency component present in the ECG system. This causes the base line to shift from the original position(i.e. horizontal axis). This is due to offset voltages in the electrodes, respiration, and body movement. Baseline wander has frequency greater than $1Hz$.

  An example of baseline wander is shown in figure 19.

Solutions

In order to get rid of these above mentioned problems, we tried out a number of methods which can be briefly categorized into two topics.

I. **Hardware Approach** We tried out tweaking of different things in our hardware section including circuit board, power supply, ECG Electrodes, using rectifiers circuit, etc. Some techniques that did right for us are enlisted below:

   - *Grounding*

     The major cause for ECG signal distortion is the presence of AC harmonics

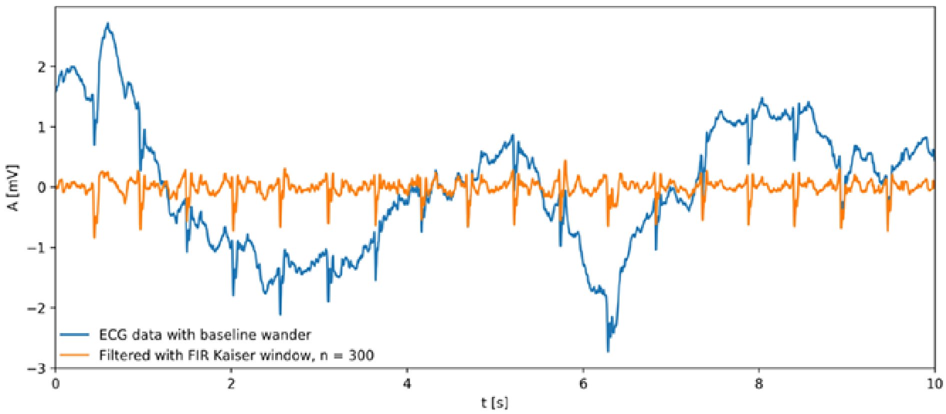

Figure 19: Presence of Baseline Wander in ECG Signal

that gets mixed up with our original signal. Some part of this noise was reduced by gounding our device's GND with the earth's ground.

- *AC Noise Filter Circuit*

  We implemented a simple LC filter circuit for the removal of AC harmonics that may be present in the DC output from the SMPS of our system. The picture of our filter circuit is shown below in figure 20

- *AC Isolation*

  Even the proximity of our circuit board wires with the AC signal carrying wires caused signal distortion, therefore we decided to isolate the whole AC segment from our system during ECG monitoring mode using relay, while the device will be backed up with $12V$ reliable DC supply.

II. **Software Approach**

Even after the implementation of above techniques in hardware, there were some traces of AC hums in our output signal which we decided to remove it through software filter i.e. **IIR Notch Filter** along with **ButttterWorth Filter** for smoothing written in **Scipy** library of **Python** language. The major steps we took for the software filtration of the data are given below:

- At first, the ecg data were imported as discrete time-amplitude pairs in csv format. In order to normalize the amplitude of the signal, we divided the sample values with $ampGain = 100$

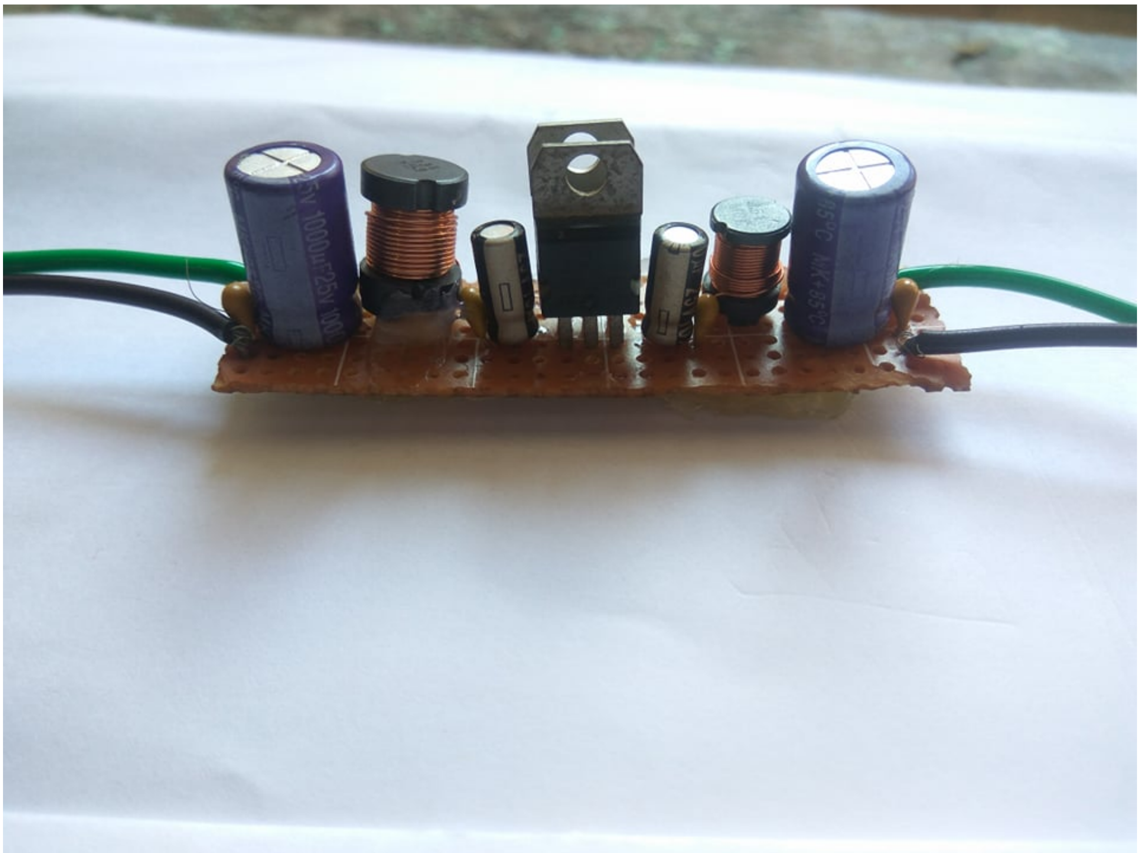

Figure 20: AC Noise Filter Circuit

- We analyzed the frequency components present in the signal by applying Fast Fourier Transform and plotted the resulting graph which is as shown in the figure 22.
- From the graph, we can clearly point out the unwanted AC harmonics are at $200Hz$ and $375Hz$
- A suitable filter i.e (IIR Notch+ Butterworth) was designed by using the **signal.butter** function from the Scipy library for order 4 with sampling frequency of $781Hz$ which in turn gave two parameters, a(denominator) and b(numerator). We then used these parameters in **signal.lfilter** function in order to obtain the filtered out values.
- The above step was performed in two stages i.e for both frequencies. The resulting graph in frequency domain after software filtration is shown in figure 23

Results

After performing the above methods, we were finally able to achieve a smooth ECG signal with detectable P ,QRS complex and T peak points.
We can compare between the waveforms of ECG before filtration in figure 21 and that after filtration in figure 24.

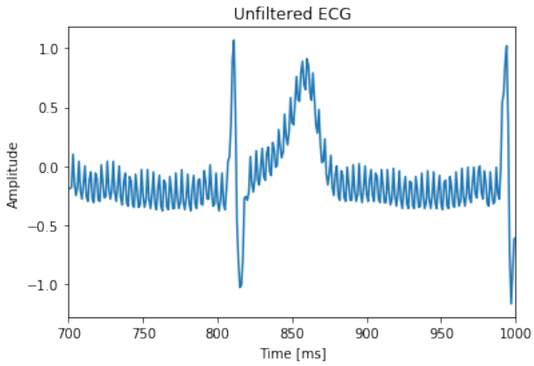

Figure 21: ECG Signal before software filter

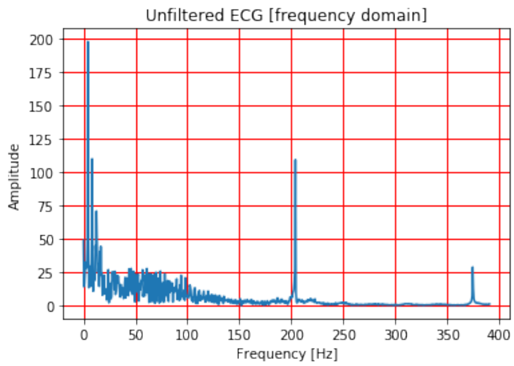

Figure 22: Frequency Spectrum before filtering

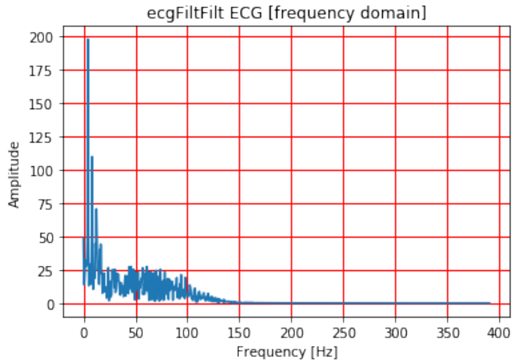

Figure 23: Frequency Spectrum after filtering

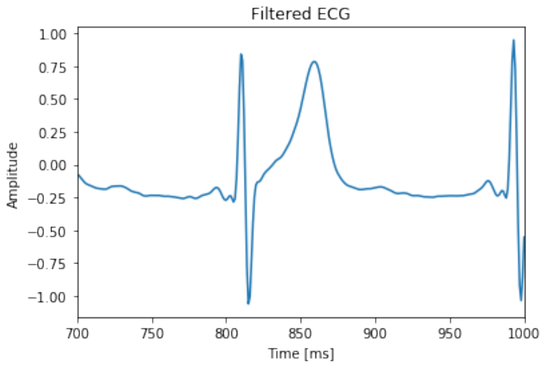

Figure 24: ECG Signal after software filter

PCB circuit design

To integrate all of the above sensors we designed a printed circuit board (PCB). This circuit board integrates all the invasive sensors with the embedded microcontroller system (Arduino Mega 2560). We used Ki-CAD for designing our PCB. The designing of the PCD included various stages. First we designed a simple circuit which would integrate all the devices with the Arduino Mega 2560 and a communication channel for Raspberry pi. But the power section started to create problems and thus now the power section was also integrated with the main circuit board which included additional RLC filter circuit for different level of noise distortions the π-model as well as T-model of RLC filter circuit. Additional bypass capacitors were also added in different parts of the circuits for more efficient noise filtering. Moreover the most problem faced was in the ECG sensor, so a simple RC filter was also added there which resulted the ECG signal to be filtered to some extent.

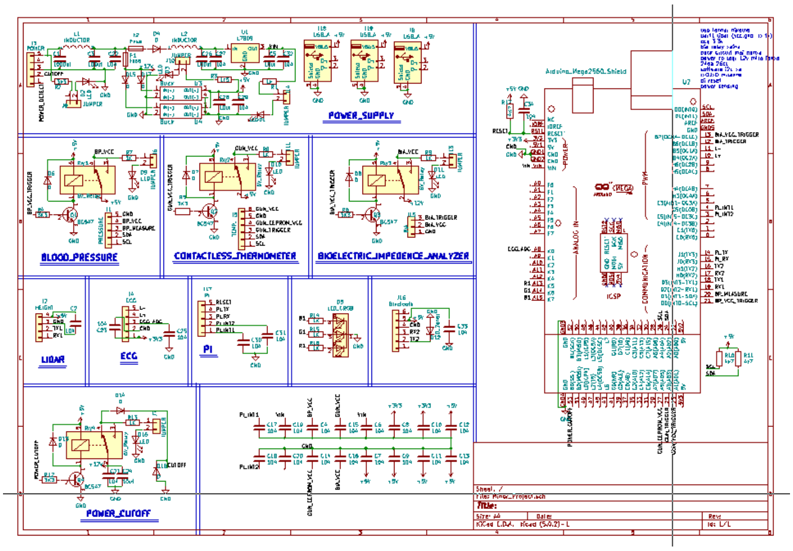

Figure 25: Schematic of Circut board

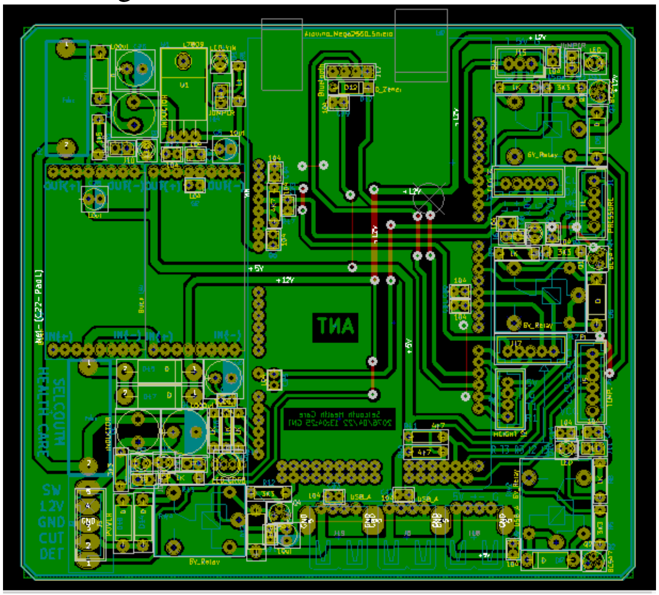

Figure 26: Circut board

5 OUTPUT

5.1 Proposed Device

Mechanical Body

Our proposed model is showed in figure 27

Figure 27: Selcouth Health care

Login Screen

Login screen to enter password and ID for our device.

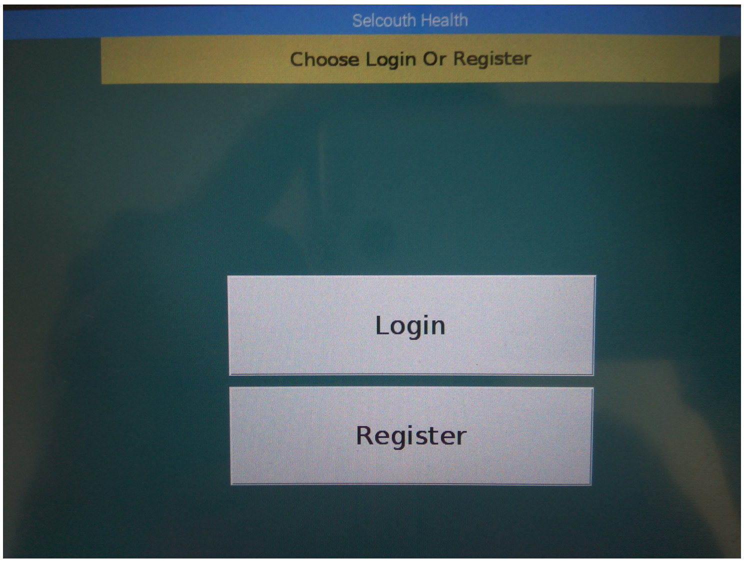

Figure 28: Login screen

Home page

After login our model enters into our home page

Figure 29: Home page

Analysing body paramter

Figure 30: Analysing weight and body parameters

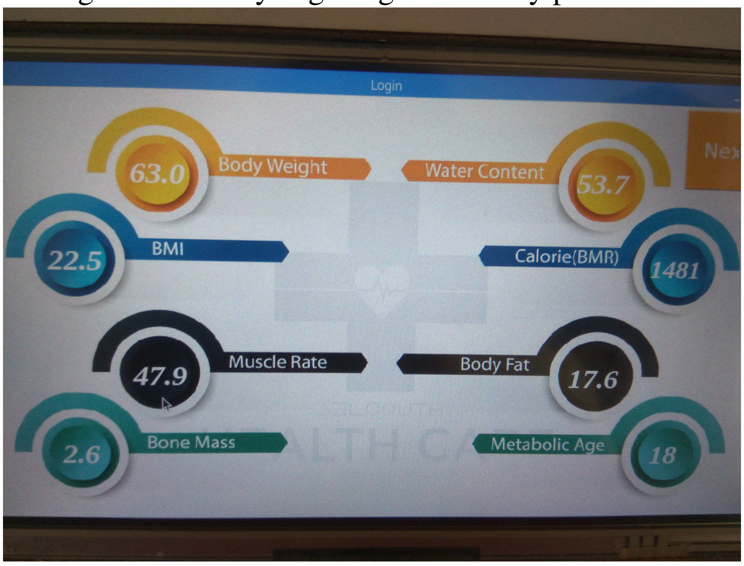

Figure 31: Output body parameters

Output Measured form different sensor

Output results form sensors is mentioned in following table.

Sensor	Body Parameters	Value
Height	Lidar	167 cm
Weight	BIA	65 Kg
Temperature	Temperature Gun	37 °C
Blood Pressure	Pressure Meter	163/95 mmHg
Pulse	Oximeter	60 bpm
Oxygen Saturation	Oximeter	98%
Muscle Rate	BIA	45%
Body Water	BIA	56.5%
Bone Mass	BIA	2.9 kg
Metabolic Rate	BIA	1445 Kcal
Protein Rate	BIA	8%
Visceral Fat Index	BIA	15%
Muscle Mass	BIA	30.5 kg
Subcutaneous Fat	BIA	5%
Fat Mass	BIA	5 kg
Protein Mass	BIA	8 kg

Figure 32: Measured data

5.2 Recommendation System

We have utilized the data obtained from the sensors which gives health condition of person. Analyzing the data we also implemented a recommendation system which recommends to improve the health condition of the patients. Recommedation system implemented here includes recommendation system for obesity and body fat control.

1. *Exercise Recommendation System*

   The Exercise Recommendation system is targeted to individuals with overweight and obesity problems.It recommends time to perform different exercises to reduce the body fat.

   It utilizes two parameters of individuals :body weight,body fat percentage and age. First the body weight and the body fat measurement are obtained from the BIA. Then these values are compared with the average values for the age group of the individual.Now the excess fat present in the body is calculated.

$$excess\_fat = (body\_fat - desired\_fat) * body\_weight$$

The amount of fat multiplied with the calorific value of a pound of fat gives the total caloric value of the excess fat present in the body of individual.

$$caloroie = excess\_fat * 0.454 * 3500kcal$$

So this gives the amount of energy an individual need to expend in order to achieve the desired percentage of body fat.

Energy expenditure while performing different exercise is function of body weight and the MET value of the exercise.

The metabolic equivalent of task (MET) is the objective measure of the ratio of the rate at which a person expends energy, relative to the mass of that person, while performing some specific physical activity compared to a reference, set by convention at 3.5 ml of oxygen per kilogram per minute, which is roughly equivalent to the energy expended when sitting quietly. The value of MET is dependent on the nature of exercise.

In our recommendation system we have enlisted 20+ exercises which individual can try according to their choice which are enlisted as

1. jogging_in_place
2. jogging_general
3. running_up_stairs
4. running_on_track
5. basketball_general
6. basketball_practice
7. football_general
8. volleyball
9. backpacking
10. hiking_cross_country
11. walking_exercise

12. walking_work
13. swimming_lake
14. bicycling_general
15. bicycling_leisure_5.5
16. bicycling_leisure_9.4
17. bicycle_general_stationary
18. calisthenics_moderate
19. home_exercises
20. yoga_hatha
21. yoga_power
22. yoga_surya_namaskar
23. fishing
24. hunting
25. sit_quitely
26. sleeping
27. reading

Now our system recommends time of different exercises which is function of calorie expenditure, MET and the body weight of the individual.

$$time = calorie/(alpha * weight * met)minperday$$

So the time for different exercise to loose the required amount of fat is recommended to the individual.

Printed Circuit board

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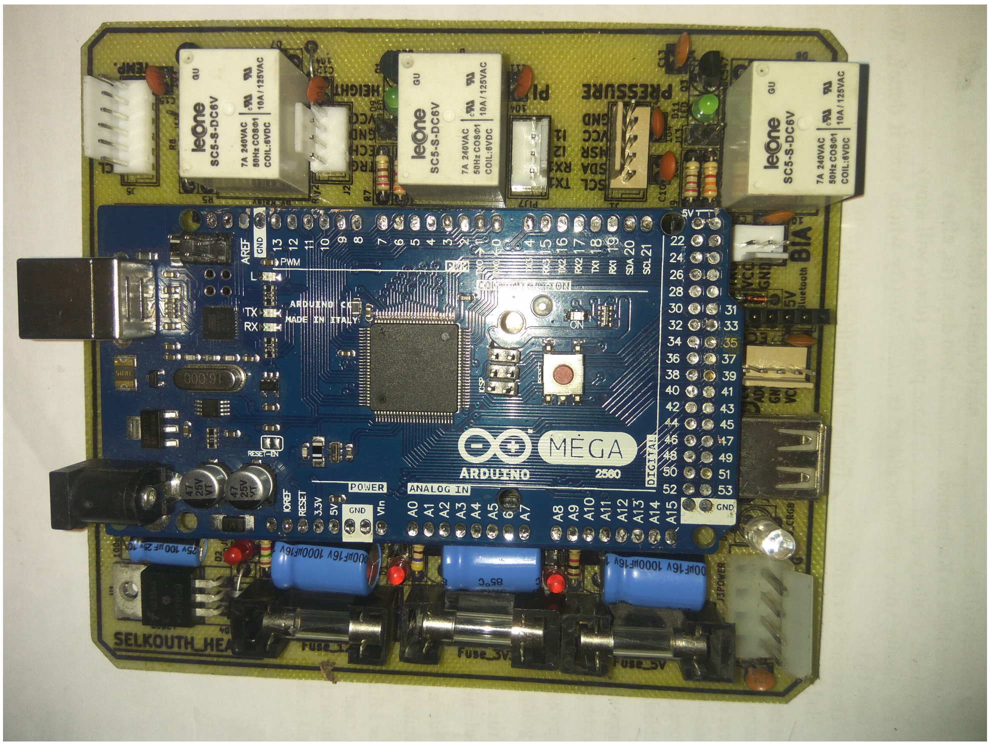

Figure 33: PCB

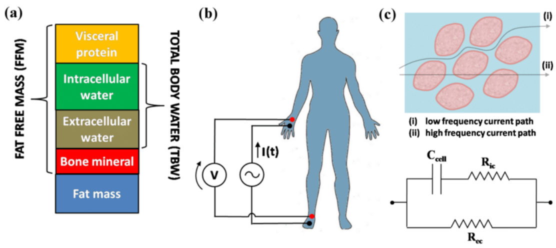

Figure 2: BIA