DETECTION OF CARDIOVASCULAR CONDITION USING PPG & ECG

A Dissertation for

Course code and Course Title: ELO-401 & Project

Credits: 8

Submitted in partial fulfilment of Masters Degree

M.Sc in Electronics

by

Tukaram U. Rane

Shaileshkumar L. Nishad

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Roll Number:

21P036009

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Under the Supervision of / Mentor

Dr. Marlon Sequeira

School of Physical and Applied Sciences
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COMPLETION CERTIFICATE

This is to certify that the dissertation "DETECTION OF CARDIOVASCULAR CONDITION USING PPG & ECG" is a bonafide work carried out by Mr. Tukaram U. Rane, Mr. Shaileshkumar L. Nishad, Mr. Vaman G. Govekar under my supervision/mentorship in partial fulfilment of the requirements for the award of the degree of **M.Sc** in Electronics Discipline at the School Of Physical & Applied Sciences, Goa University.

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Date:
Place: Goa University

ACKNOWLEDGEMENT

We would like to express our sincerest thanks to everyone who has contributed to this project. First and foremost, we would like to thank all the students who have voluntarily participated in this study and have provided us their time to collect their data.

We express our deep gratitude towards all the teaching faculty Prof. Rajendra. S. Gad, Dr. Jivan. S. Parab, Dr. Marlon Sequeira, Dr. Narayan Vetrekar and Dr. Aniketh Gaonkar for their support and guidance throughout the completion of the project. Their knowledge and suggestions have been crucial in helping us plan, carry out, and execute the project.

We would like to express our gratitude to our families and close friends for their unfailing support and inspiration during this project.

DECLARATION BY STUDENT

We hereby declare that the data presented in this Dissertation entitled, "DETECTION OF CARDIOVASCULAR CONDITION USING PPG & ECG" is based on the results of investigations carried out by me in the Electronics Department at the School of Physical and Applied Sciences, Goa University under the Supervision/Mentorship of Dr. Marlon Sequeira and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will be not be responsible for the correctness of observations / experimental or other findings given the dissertation.

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ABBREVIATIONS

ω3	Omega 3
(D)BP	Diastolic Blood Pressure
(S)BP	Systolic Blood Pressure
PPG	Photoplethysmography
ANS	Autonomic nervous system
CAN	Cardiac Autonomic Neuropathy
CNN	Cellular Neural Network
CVD	Cardiovascular Disease
CHD	Coronary heart disease
LTV	Long term variation
STV	Short time variation
ECG	Electrocardiogram
SCD	Sudden cardiac death
RNN	Recurrent Neural Networks
HF(P)	High Frequency Power
MA	Motion Artefacts
HR	Heart Rate
HRV	Heart Rate Variability
LF(P)	Low Frequency Power
INA	instrumentation amplifier
SDM	Sigma Delta Modulator
WCT	Wilson Central Terminal

LF/HF	Low Frequency to High Frequency ratio
LOD	Lead Off detect
AHR	Average Heart Rate
IHR	Instantaneous Heart Rate
BPM	Beats per Minutes
AV	Atrio Ventricular
RMSSD	Square Root of the Mean Squared Differences of Successive
R-R	Normal to Normal
RSA	Respiratory Sinus Arrhythmia
SDANN	Standard Deviation of the Average Normal to Normal Interval
SDNN	Standard Deviation of the Normal to Normal Interval
GRU	Gated recurrent units
SNS	Sympathetic Nervous System
TP	Total Power
ADC	Analog-to-digital converter
ULF	Ultra Low Frequency
VLF	Very Low Frequency

ABSTRACT

Cardiovascular disease is a major global health concern and the leading cause of death worldwide. Effective cardiovascular disease prevention and treatment depend on early detection and monitoring of cardiovascular function. Electrocardiograms (ECGs) and photoplethysmography (PPGs) are two frequently used non-invasive methods for tracking cardiovascular function. Both of these techniques can provide substantial information regarding heart rate, rhythm, and other cardiovascular parameters. The analysis of biological signals using machine learning algorithms has shown significant promise recently, and it has the potential to increase the precision and effectiveness of cardiovascular monitoring.

In this project, we collected photoplethysmography (PPG) and electrocardiogram (ECG) signals from a group of subjects and applied machine learning techniques to classify them. Using standard medical sensors and apparatus, We recorded PPG signals from the fingertip and ECG signals from the chest. The project's objectives was to investigate the viability of using PPG signal, using ECG signal and using the combination of PPG and ECG signals for non-invasive cardiovascular monitoring and to assess how well different machine learning algorithms performed in this setting.

CHAPTER 1

INTRODUCTION

1.1 Electrocardiogram (ECG):

Since ECG was discovered in the late 1800s the ECG has become established as a mainstay tool to assess cardiac function in medical. Important functional properties of the myocardium are related to the timing, size, and duration of the ECG deflections (such as the QRS complex and the PR interval). The SA node is the origin of ECG which acts as the pacemaker of the heart [7].

The signal from an ECG is a recording of the heart's bioelectrical activities. Through effective treatment, early diagnosis of heart illnesses (abnormalities) can lengthen life and improve quality of life [3]. Due to the numerous contemporary medical applications where this issue can be expressed, the significance of ECG categorization is extremely high. There are numerous machine learning (ML) tools available right now that can be used to analyse and categorise ECG data. However, the usage of heuristic hand-crafted or manufactured features with shallow feature learning architectures is the fundamental drawback of these ML achievements [6].

1.1.1 Cardiovascular diseases:

Cardiovascular disease (CVD) is a general term that describes a disease of the heart or blood vessels. With more than 50% of all deaths in the world, the cardiovascular disease (CVD) is

the largest single cause of death of people. It is the leading cause of death and mortality in industrialized nations. Cardiovascular diseases are the diseases that affect the Cardio vascular system. Blood flow to the heart, brain or body can be reduced because of a: blood clot (thrombosis) build-up of fatty deposits inside an artery, leading to the artery hardening and narrowing (atherosclerosis).

1.1.2 Types of CVD

There are four main types of CVD:

- Coronary heart disease
- Stroke
- Peripheral arterial disease
- Aortic disease

Each type is discussed in more detail below.

I. Coronary heart disease

Coronary heart disease (CHD) occurs when your heart muscle's blood supply is blocked or interrupted by a build-up of fatty substances (atheroma) in the coronary arteries.

The coronary arteries are the major blood vessels that supply your heart with blood.

If your coronary arteries become narrow due to a build-up of atheroma, the blood supply to your heart muscle will be restricted. This can cause angina (chest pains).

If a coronary artery becomes completely blocked, it can cause a heart attack. This is a medical emergency.

II. Stroke

A stroke is a serious medical condition that occurs when the blood supply to the brain is disturbed.

Like all organs, your brain needs a constant supply of oxygen and nutrients to function properly. This is provided by the blood, so if your blood flow is restricted or stopped, brain cells will begin to die. This can lead to brain damage and possibly death.

Therefore, a stroke is a medical emergency and prompt treatment is essential. The sooner a person receives treatment, the less damage is likely to occur.

The main stroke symptoms can be remembered with the word FAST which stands for:

Face – The face may have drooped on one side, the person may not be able to smile or their mouth or eye may have drooped

Arms – The person with suspected stroke may not be able to lift their arm and keep it raised due to weakness or numbness

Speech – The person's speech may be slurred or garbled, or they may not be able to talk at all despite appearing to be awake

Time – It is time to dial 999 immediately if you see any of these signs or symptoms

III. Peripheral arterial disease

Peripheral arterial disease, also known as peripheral vascular disease, occurs when there is a blockage in the arteries to your limbs (usually your legs).

The most common symptom of peripheral arterial disease is pain in your legs when walking. This is usually in one or both of your thighs, hips or calves.

The pain can feel like cramp, a dull pain or a sensation of heaviness in the muscles of your legs. It usually comes and goes and gets worse during exercise that uses your legs, such as walking or climbing stairs.

IV. Aortic disease

The aorta is the largest blood vessel in the body. It carries blood from your heart to the rest of your body.

The most common type of aortic disease is aortic aneurysm, which is where the wall of the aorta becomes weakened and bulges outwards. You will usually experience pain in your chest, back or abdomen (tummy).

1.2 Heart Rate Variability (HRV)

Heart rate variability (HRV) is the variation of time of the period between consecutive heartbeats. Heart rate variability gives the state of the Autonomic nervous system (ANS) responsible for regulating the cardiac activity and also the overall cardiac health. HRV refers to the variations in the beat intervals or correspondingly in the instantaneous Heart rate.

The circulatory system and the autonomic neural regulation of the heart gives the normal variation in the Heart rate. HRV provides the information about the sympathetic-parasympathetic autonomic balance and the risk for sudden cardiac death (SCD) in the patients. Surveillance of post-infarction and diabetic patients can be one of the most

important applications of HRV analysis. HRV measurements are non-invasive, easy to perform, if used under standardized conditions. Heart rate variability, i.e., the amount of HR fluctuations around the mean HR, can be used as a mirror of the cardiorespiratory control system.

1.2.1 How does heart rate variability work?

Your heart beats at a specific rate at all times. That rate changes depending on what you're doing at the time. Slower heart rates happen when you're resting or relaxed, and faster rates happen when you're active, stressed or when you're in danger. There is variability in your heart rate based on the needs of your body and your respiratory patterns. Certain medications and medical devices — such as pacemakers — can also affect your heart rate variability. Your heart rate variability also tends to decrease normally as you get older.

Whether you're awake or asleep, calm or stressed, your heart has to be able to react to changes in your life and surroundings. But it doesn't know when to react on its own, so it relies on another body system for help.

1.2.2 Methods

- **Time domain analysis:**

In time domain analysis the HRV indices are distinguished into two types namely Beat to Beat or Short time variation (STV) indices represent fast changes in Heart rate. Long term variation indices (LTV) are slower fluctuations (fewer than 6 min-1). Both the mentioned indices can be calculated from the RR intervals occurring in the chosen time window (usually between 0.5 and 5 minutes)

- **Frequency domain analysis:**

The time domain methods are computationally simple, but lack the ability to discriminate between sympathetic and para-sympathetic contributions of HRV.

In the frequency domain, ratio of low frequency to the high frequency is high for the CHB and Ischemic/ dilated cardiomyopathy abnormalities are high, because the RR variation is very small. This RR variation will be more (as compared to the normal) in the case of LBBB, AF, SSS, PVC and VF. Hence, this ratio will be more. So, for the abnormal cases, this ratio either decreases or increases from the normal range.

1.2.3 Devices for Monitoring Heart Rate Variability

- **Pulse Oximeter:**

It is a device frequently used in exercise studies. Pulse oximetry works by passing a beam of red and infrared light through a pulsating capillary bed, usually an ear or finger. The oxygen saturation can be measured by taking the ratio of red light to infrared light transmitted. The oximeter detects the pulse and then subtracts the intensity of colour detected when the

pulse is absent. The remaining intensity of colour represents only the oxygenated red blood. The percentage amount of oxygen saturation in blood is displayed on the electronic screen along with the Heart Rate.

- **ECG Devices:**

ECG devices offer the most accurate way to measure ambulatory HRV, either by using only the fiducial point of the QRS complex or, better yet, by using the entire ECG complex processed by computer algorithms to account for arrhythmias.

1.3 Photoplethysmography (PPG):

Photoplethysmography (PPG) is a non-invasive optical technique used to detect changes in blood volume in peripheral blood vessels. PPG is an optically obtained plethysmogram that can be used to detect blood volume changes in the microvascular bed of tissue. A PPG is often obtained by using a pulse oximeter which illuminates the skin and measures changes

in light absorption. As the blood volume in the vessels changes with each cardiac cycle, the amount of light absorbed or reflected also changes, resulting in a pulsatile signal known as the photoplethysmogram.

CHAPTER 2

LITERATURE SURVEY

1) Atrial Fibrillation Detection and ECG Classification based on CNN-BiLSTM

Jiacheng Wang & Weiheng Li performed the implementation of an Automated ECG signal detection system which can help diagnosis arrhythmia in order to improve the accuracy of diagnosis. They implemented and compared an automatic system using two different frameworks of the combination of CNN & BiLSTM. The dataset used was taken from MIT-BIT Arrhythmia Physionet.

The classification was done normal sinus signal, Atrial fibrillation & other noisy signals. After the Implementation of the Model, the normal class was easily discriminated then the other two classes [1].

2) Feature Extraction and Analysis of ECG signal for Cardiac Abnormalities – A Review, International Journal of Engineering Research & Technology (IJERT)

Afseen Naaz & Mrs Shikha Singh discussed and investigated various techniques of extracting and selecting the vital features from the ECG signal in order to analyze the ECG signal automatically. Feature extraction, classification of feature and optimization of extracted feature are some of the common steps of automatically analyze the ECG data. Detecting the P,Q,R,S and T wave (QRS complex) in ECG signal comes under the feature extraction [2].

Amplitude(mV)	Duration(Seconds)
P Wave – 0.25mV	PR interval- 0.12s to 0.20s
R Wave – 1.60mV	QT interval- 0.35s to 0.44s
Q Wave – 25% of R wave	ST interval- 0.05s to 0.15s
T Wave – 0.1 to 0.5mV	QRS interval- 0.09s

Table 1. ECG waveform parameters

3) **Classification of ECG Arrhythmia using Recurrent Neural Networks, International Conference On Computational Intelligence and Data Science(ICCIDS)**

Shraddha Singh , Saroj Kumar Pandey , Urja Pawar , Rekh Ram Janghel

In this paper, Recurrent Neural Networks (RNN) have been applied for classifying the normal and abnormal beats in an ECG. They have tried to enable automatic separation of regular and irregular beats. The MIT-BIH Arrhythmia database is being used to classify the beat classification performance. They divided the data set as training and testing sub-data. The effectiveness, accuracy and capabilities of our methodology ECG arrhythmia detection is demonstrated and quantitative comparisons with different RNN models have also been carried out [3].

4) **Classification of Normal and Abnormal ECG Signals Based on their PQRST Intervals, International Conference on Mechanical, System and Control Engineering**

Noman Naseer, Hammad Nazeer

Developed a system that is capable of automatically differentiating between normal and abnormal heartbeats of patients using signals acquired from electrocardiography (ECG). The components of the ECG signals, that are PQRST intervals, were studied to acquire features for classification. Different time intervals of p-wave, QRS complex and t-wave were used as features. The results demonstrate the feasibility of development of a machine that is able to automatically detect all potential heart related diseases that can be identified from ECG signals manually[4].

5) **A comparison of photoplethysmography and ECG recording to analyse heart rate variability in healthy subjects, Journal of Medical Engineering & Technology, Vol. 33, No. 8, November 2009**

G. LU, F. YANG, J. A. TAYLOR and J. F. STEIN

They investigated the feasibility of using earlobe PPG to analyze HRV by applying the same analytic process to PPG and ECG recordings made simultaneously. There results confirm that PPG provides accurate inter pulse intervals from which HRV measures can be accurately derived in healthy subjects under ideal conditions, suggesting this technique may prove a practical alternative to ECG for HRV analysis [5].

6) **Deep Learning for ECG Classification , J. Phys.: Conf. Ser. 913 012004, 2017**

B Pyakillya, N Kazachenko and N Mikhailovsky

This work presented some ECG classification results about use of 1D convolutional neural network with FCN layers on preprocessed time-series data. The best resulted accuracy on validation data is about 86%. In future there can be some upgrade in accuracy by means of some other pre-processing [6].

7) **A Review of Heart Rate Variability and its Applications, ICBET, 2013**

Hoang ChuDuc , Kien NguyenPhan, Dung NguyenViet.

In this paper they have discussed the various applications of HRV and different linear, frequency domain, wavelet domain, nonlinear techniques used for the analysis of the HRV. Heart rate variability (HRV) is the physiological phenomenon of variation in the time interval between heartbeats. It is measured by the variation in the beatto-beat interval. Further research on a large sample size and on different stressful conditions will help to further elucidate the findings of this study and effectiveness of HRV analyses for differentiation between low and high condition [7].

8) **Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis, Biomedical Signal Processing and Control, 2015**

R. Castaldoa, P. Melillo b, U. Bracalec, M. Casertaa,c, M. Triassi c, L. Pecchiaa,

This study systematically reviewed existing literature investigating, in healthy subjects, the associations between acute mental stress and short term Heart Rate Variability (HRV) measures in time, frequency and non-linear domain. The goal of this study was to provide reliable information about the trends of HRV measures during mental stress [8].

9) **gHRV: Heart rate variability analysis made easy, Department of Computer Science, ESEI, University of Vigo, 2014**

L. Rodríguez-Linares , M.J. Lado , X.A. Vila , A.J. Méndez , P. Cuesta

In this paper, the gHRV software tool is presented. It is a simple, free and portable tool developed in python for analysing heart rate variability. It includes a graphical user interface and it can import files in multiple formats, analyse time intervals in the signal, test statistical significance and export the results. This paper also contains, as an example of use, a clinical analysis performed with the gHRV tool, namely to determine whether the heart rate variability indexes change across different stages of sleep [9].

10) **Non-contact heart rate and heart rate variability measurements: A review , Faculty of Electrical Engineering, University of Ljubljana, 2014**

J. Kranjec , S. Begus , G. Gersak , J. Drnovsek

The following paper investigates published work on non-contact human physiological parameter measurement, more precisely measurement of the human heart rate (HR) and consequently the heart rate variability (HRV), which is considered to be an important marker

of autonomic nervous system activity proven to be predictive of the likelihood of future health related events and also includes a short description of the two conventional methods,

electrocardiogram (ECG) and photoplethysmography (PPG), and later on focuses on the novel methods of non-contact measuring of HR with capacitively coupled ECG, Doppler radar, optical vibrocardiography, thermal imaging, RGB camera and HR from speech. Our study represents a comparative review of these methods while emphasising their advantages and disadvantages [10].

11) Norms of vagal nerve activity, indexed by Heart Rate Variability, in cancer patients, The International Journal of Cancer Epidemiology, Detection, and Prevention, 2013

M. De Couck , Y. Gidron

This research showed the role of the activity of the vagus nerve in cancer prognosis. However, it remained unknown whether cancer severity can impair vagal nerve activity. This study combined data (N = 657) of five different cancers (colorectal, pancreas, prostate, lung and ovarian) concerning patients' Heart Rate Variability (HRV), a vagal nerve activity index. These data were compared to HRV levels of a healthy sample in another study. In addition, They examined the moderating effects of age, gender and cancer stage on HRV. The mean HRV of the cancer patients sample was significantly lower (HRV = 22 ms) compared to the healthy sample (HRV = 50 ms). While age and gender did not significantly affect HRV, cancer patients with advanced stages had significantly lower HRV than those with early stages. A possible bi-directional relation between cancer and vagal nerve activity is discussed. These findings are of importance for prognostication since they provide researchers and clinicians with expected values of vagal nerve activity in cancer patients [11].

12) **A review on wearable Photoplethysmography sensors and their potential future applications in health care Int J Biosens Bioelectron, 2018**

Denisse Castaneda, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and Homer Nazeran

The aim of this article is to briefly consider some of the current developments and challenges of wearable PPG-based monitoring technologies and then to discuss some of the potential applications of this technology in clinical settings [12].

13) **An Advanced Bio-Inspired PhotoPlethysmoGraphy (PPG) and ECG Pattern Recognition System for Medical Assessment**.

Francesco Rundo , Sabrina Conoci , Alessandro Ortis and Sebastiano Battiato

In this paper the Authors propose a physiological ECG/PPG "combo" pipeline using an innovative bio-inspired nonlinear system based on a reaction-diffusion mathematical model, implemented by means of the Cellular Neural Network (CNN) methodology, to filter PPG signal by assigning a recognition score to the waveforms in the time series.

The proposed pipeline was tested and validated by using the SiPM based sensor hardware with LabView for sampling PPG signals [13].

14) **An algorithm for extracting the PPG Baseline Drift in real-time, Edith Cowan University Research Online, 2016**

Tuan Ngoc Nguyen

This thesis aims to explore Wavelet Transform, Cubic Spline Interpolation, Morphological Operators and Fourier-Based filtering techniques in order to develop an algorithm that can be used to condition the signal against the baseline drift in real-time, while being able to achieve good computational efficiency and the preservation of the signal form [14].

15) **Evaluation of the Possible Use of PPG Waveform Features Measured at Low Sampling Rate, Faculty of Systems Engineering, Wakayama University, Japan, 2019**

Daisuke Fujita AND Arata Suzuki

This paper investigates the possibility of using photoplethysmograms measured at a low sampling rate. The Authors statistically compared photoplethysmogram waveform features obtained from 63 male subjects free of circulatory diseases, at a sampling rate of 240 Hz, with waveform features obtained at low sampling rates (120, 60, 30, 20, and 10 Hz) through down-sampling, and evaluated possible commercial use.

In this study, features acquired from PPG measurement at 240 Hz and the fluctuation of features at low sampling rates of 120 Hz, 60 Hz, 30 Hz, 20 Hz, and 10 Hz. The nine feature types dealt considered in this study showed little fluctuation even down at a sampling rate of 60 Hz; these can therefore be considered commercially usable. However, at a sampling rate lower than 30 Hz, only some features can be considered commercially usable [15].

16) **Photoplethysmogram (PPG) Signal Analysis And Wavelet De-Noising, International Conference on Magnetics, Machines & Drives(iCMMD), 2014**

Greeshma Joseph , Almaria Joseph , Geevarghese Titus , Rintu Mariya Thomas , Dency Jose

The aim of this study was to know in deep about the different parameters of PPG signal. Peak and transition points of the pulse signal are determined as a part of pulse wave analysis. Wavelet transform is now commonly used in a wide variety of signal processing applications. In this work wavelet de-noising is used for removing AWGN from the PPG signal. Various mother wavelets are studied and the performance of them are evaluated based on the cross correlation with the original signal.

The work deals with the detailed study of PPG signal in which, the important parameters associated with the PPG signal, signal components, advantages and disadvantages of PPG etc. were studied [16].

17) **Photoplethysmography based atrial fibrillation detection: a review, npj Digital Medicine, 2020.**

Tania Pereira , Nate Tran , Kais Gadhoumi , Michele M. Pelter , Duc H. Do , Randall J. Lee , Rene Colorado , Karl Meisel and Xiao Hu

This review is a summary of a body of work on AF detection using PPG. A thorough account of the signal processing, machine learning, and deep learning approaches that was used in these studies is presented, followed by a discussion of their limitations and challenges towards clinical applications. A review of statistical and machine learning approaches applied to AF detection using PPG is presented by the Authors [17].

18) **Blood glucose prediction based on imaging photoplethysmography in combination with Machine learning, Biomedical Signal Processing and Control, 2023**

Zihan Nie , Meng Rong & Kaiyang Li

A review of statistical and machine learning approaches applied to AF detection using PPG is presented. Blood glucose has a strong absorption capacity in the near-infrared band, and other components in blood (water, hemoglobin, etc.) have different absorption characteristics in this band compared with blood glucose. In this method, glucose from blood was detected by receiving the near-infrared light reflected back after blood glucose absorption.

Four kinds of machine learning algorithms (PCR, PLS, SVR, RFR) were used to build models. The blood glucose prediction model is established by using random forest regression algorithm [18].

19) **Working principle of Arduino and using it as a tool for Study and Research, International Journal of Control, Automation, Communication and Systems (IJCACS), Vol.1, No.2, April 2016**

Leo Louis

This paper explores the working principle and applications of an Arduino board. This also explores on how it can be used as a tool for study and research works. Arduino board can provide a quick tool in development of VLSI test bench especially of sensors. Main advantages are fast processing and easy interface. Today, with increasing number of people

using open source software and hardware devices day after day, technology is forming a new dimension by making complicated things look easier and interesting. These open sources

provide free or virtually low costs, highly reliable and affordable technology. This paper provides a glimpse of type of Arduino boards, working principles, software implementation and their applications [19].

20) **Study of arduino microcontroller board, "Science and Education" Scientific Journal , Vol. 3 Issue 3 , March 2022**

Alisher Shakirovich Ismailov , Zafar Botirovich Jo'rayev

In this paper the Authors discussed Arduino microcontroller working principle and applications. In this paper, they also discuss how the Arduino microcontroller can be used as a tool for study and research works, the paper provides a glimpse of the type of Arduino boards, working principles, software implementation, and Arduino applications [20].

21) **A brief review: history to understand fundamentals of electrocardiography, Article in Journal of Community Hospital Internal Medicine Perspectives , April 2021**

Majd AlGhatrif , Joseph Lindsay

The last decade of the 19th century witnessed the rise of a new era in which physicians used technology along with classical history taking and physical examination for the diagnosis of heart disease. The introduction of chest x-rays and the electrocardiograph (electrocardiogram) provided objective information about the structure and function of the heart. In this article, the Authors reviewed the important steps in the evolution of electrocardiogram [21].

22) Heart Rate Variability Analysis as a Means of Real-time Hypercapnia Detection, National Library of Medicine , June 2022

Joseph Dituri

The study population included 15 males between the ages of 18 and 50 years old and excluded those with pulmonary concerns, as identified by a physician, because of HRV confounding factors. Each subject was normalized with respect to the known drivers for HRV and then tested breathing four different breathing mixtures. After being informed by the initial results of this clinical research study, a standalone device with an HRV sensing mechanism using a 3 lead ECG and proprietary software designed by the authors to manipulate the data collected and present it in a novel methodology was developed at the system level. The ultimate goal was to detect CO2 prior to the onset of hypercapnic symptoms.

23) Design, evaluation, and application of Heart Rate Variability Analysis Software

John T Ramshur

Purposes of this study were to design, evaluate, and apply an easy to use and open-source HRV analysis software package (HRVAS). HRVAS implements four major categories of HRV techniques: statistical and time-domain analysis, frequency-domain analysis, nonlinear analysis, and time-frequency analysis. Software evaluations were accomplished by

performing HRV analysis on simulated and public congestive heart failure (CHF) data. Results from the rat hyperaldosteronism model showed that 5 of 26 HRV measures were statistically significant ($p<0.05$).

24) The effect of age on the heart rate variability of healthy subjects

Leopoldo Garavaglia, Damián Gulich, Magdalena M. Defeo, Julieta Thomas Mailland, Isabel M. Irurzun

In this work the Authors study the characteristics of heart rate variability (HRV) as a function of age and gender. The mean value of the RR intervals shows a power-law behaviour independent of gender. Magnitudes such as the standard deviation or pNN50 show abrupt changes at around the age of 12 years, and above that age they show gender dependence, which mainly affects short-time (or high frequency) scales. The results obtained in this work are discussed in terms of the effects of basal metabolic rate, hormonal regulation, and neuronal activity on heart rate variability. This work finally discusses how these findings influence the interpretation of HRV measurements from records of different lengths.

25) Development of a Heart Rate Variability Measurement System using Embedded Electronics

Naresh Kumar Velmurugan

This project consists of two systems: transmitter and a receiver side system. The transmitter section composed of sensor, amplifier, processing unit, and display unit, and transmitter module. The sensors, which are pasted on the body, are used to sense the electrical activity of the heart. These electric signals are given to an amplification unit. This amplification unit

is designed with IC ADS1293 to amplify and filter the signals, and also reduce the noise. The output of the amplifier is given to the processing unit. Here, the microcontroller is programmed to process the input signal, and calculate the heart rate. The output of the microcontroller is transmitted to the display unit. The display unit shows the current value of

the heart rate. The continuous measurement of heart rate variability is done in the transmitter side system. In case of abnormalities, a GSM module is used to transmit the heart rate alert, which has been processed by the control unit, to the user's mobile phone and GSM receiver modem. In the receiver system, GSM receiver modem receives the data and processed with Visual Basic program to display, and, in the mobile phone, data is received and displayed as a text message. This kind of health monitoring system can offer flexibilities and cost saving options to both health care professionals and patients.

The above literature survey includes different methods of classification of EEG and PPG based on HRV configuration. Atrial Fibrillation Detection and ECG Classification based on CNN-LSTM, Feature Extraction and Analysis of ECG signal were done by different researchers. Different machine learning algorithms and techniques such as RNN ,CNN were implemented. Software tools like gHRV were used for research on Heart rate variability analysis so that the analysis was made easy.

Some research papers were also based on Non-contact heart rate and heart rate variability measurements. Some of the research papers were based on vagal nerve activity, in cancer patients. Different PPG baseline extracting algorithms were done. In some research paper they have shown about different types of system which can be designed to capture PPG and ECG using microcontroller.

Based on this literature survey we have developed two different systems for recording PPG and ECG data. Based on this acquired data set we have calculated the HRV, which can be used for Normal and Abnormal patient classification. The different Machine learning algorithms tried in the project for the classification are RNN-GRU, KNN, Decision tree and Random forest.

CHAPTER 3

BASIC BIOMEDICAL CONCEPTS

3.1 Photoplethysmography(PPG)

Photoplethysmography (PPG) is an uncomplicated and inexpensive optical measurement method that is often used for heart rate monitoring purposes. PPG is a non-invasive device that measures the volumetric fluctuations in blood circulation by using a light source and a photodetector at the skin's surface.

Important health-related information can be found in the second derivative wave of the PPG signal. The evaluation of several cardiovascular-related disorders, including atherosclerosis and arterial stiffness, can thus be aided by the examination of this waveform for researchers and doctors [12]. It carries rich information about the cardiac activity, cardiovascular condition, the interaction between parasympathetic and sympathetic nervous systems, and hemoglobin level. Many physiological parameters can be derived from PPG, including oxygen saturation, heart rate, blood pressure, and cardiac output [17].

Additionally, analysing the second derivative wave of the PPG signal can help with the early detection and diagnosis of a variety of cardiovascular diseases that could potentially manifest later in life.

PPG, is a technique that measures the volumetric fluctuations in blood circulation using an infrared light. This measurement offers important insights about the cardiovascular system [12]. The PPG technology has lately gained popularity as a substitute for traditional heart rate monitors, largely because of how easy it is to use, how comfortable it is for people to wear, and how affordable it is. PPG can be used to quickly monitor a number of physiological indicators, including heart rate, breathing rate, tissue perfusion, and various vascular and cardiac diseases [14].

The inability of PPG-based monitoring systems to accurately follow PPG signals during daily activities and modest physical activity is one of their main drawbacks. Due to the PPG signals' high susceptibility to Motion Artefacts (MA) brought on by hand movements, this constraint exists. Additionally, other variables like environmental noise could influence the PPG signal acquisition, which would therefore influence the accuracy of the HR prediction. The detailed analysis of this signal can also help with the timely identification and diagnose of various cardiovascular diseases [12].

The scientific community has been inspired to create more low-cost, highly accurate wearable PPG-based devices for monitoring daily routine activities by the PPG's capacity to measure blood variations in various parts of the body and its potential capacity to detect physiological parameters linked to the cardiovascular and respiratory systems [12].

3.1.1 PPG based Monitoring devices

A typical PPG device contains a light source and a photodetector. The light source emits light to a tissue and the photodetector measures the reflected light from the tissue. The reflected light is proportional to blood volume variations.

The primary light source for the majority of PPG sensors is an infrared light emitting diode (IR-LED) or a green LED. While green light is typically used to calculate the absorption of oxygen in oxyhemoglobin (oxygenated blood) and deoxyhemoglobin (blood without oxygen present), IR-LEDs are most frequently used to measure the flow of blood that is more deeply concentrated in certain parts of the body, such as the muscles. Although there are other LED sensors with different colors to measure hemoglobin, green LED is considered the most commonly used. This is simply because it penetrates more deeply into tissue and therefore can provide measurements that are more accurate.PPG sensors also use a photodetector to measure the intensity of reflected light from the tissue [12].

The levels of accuracy vary between different measuring sites. While using particular body parts, such as the finger, earlobe, and forehead, is most typical [12]. PPG sensors are designed in two different distinct forms: transmission mode (Figure 1a) and reflectance mode (Figure 1b). Each mode comes with advantages and disadvantages.

In reflectance mode, the photo detector is positioned next to the light source on the same side of the tissue to measure the reflected light. Since the reflected light is measured, this can be

used at any part of the body. In transmission mode the light source and detector are separated by the tissue. Both sensor types can provide non-invasive measurements [16]. As only a limited amount of light passes through the organ tissue the transmittance PPG is applicable only to a body parts such as the finger or the ear lobe [16].

PPG sensors can operate more effectively if they are placed at specific easily accessible anatomical positions such as the earlobe and fingertip where the desired PPG signals are collected with higher quality.

The choice of a measuring site depends on the applications. The tip of the finger and the earlobe are frequently employed in transmission mode. The wrists, forearm, ankle, and forehead serve as the measuring bodies for the reflectance mode sensors.

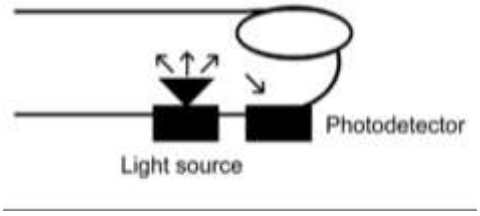


Figure 1 a. (Reflective mode)

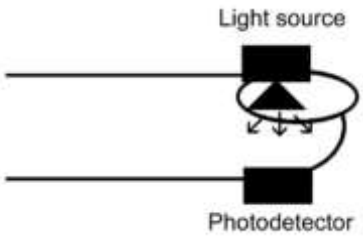


Figure 1 b. (Transmission mode)

3.1.2 Types of PPG based Devices

Wristband-type PPG-based Devices

In comparison to the various types of PPG-based HR monitoring devices in existence, the wristband-type PPG is considered the most popular and preferred device. The reason for its popularity is partly due to its remarkable properties such as being inexpensive, highly portable, and very convenient to wear by its users [12].

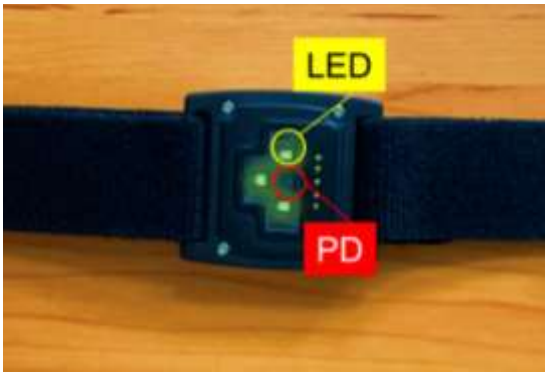


Figure 2. Wristband-type PPG-based Devices

Forehead-type PPG-based devices

A PPG device can also be used to monitor heart rate on the human forehead as a substitute location. Typically, the optical signal's reflection from a person's forehead is quite strong. This is due to the fact that the human skull is covered by relatively thin skin and that the area around the forehead has a higher density of blood vessels. The placement of the reflectance mode PPG sensors on someone’s forehead has shown an improved reaction to pulsatile signal variations in low perfusion environments [12].

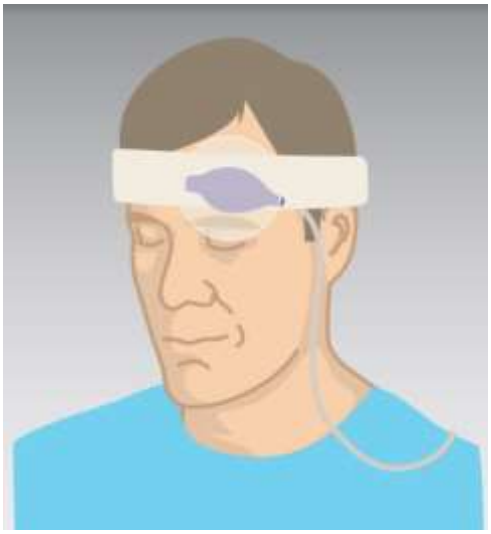


Figure 3. Forehead-type PPG-based devices

Ear-type PPG-based devices

The earlobe is one of the most frequently used measurement sites for PPG-based devices. This is because earlobes maintain significant blood supply despite not being made of cartilage, according to science. Additionally, compared to other extremities, earlobes are much less susceptible to the effects of motion artefacts. In the past, PPG signals have been obtained using magnetic ear clips and headphones [12].

After a PPG sensor is placed in the ear, the sensor earbuds could be positioned against the tragus to be able to sense the light reflected from the subcutaneous blood vessels. Alternatively, a PPG sensor can be placed in the ear canal.

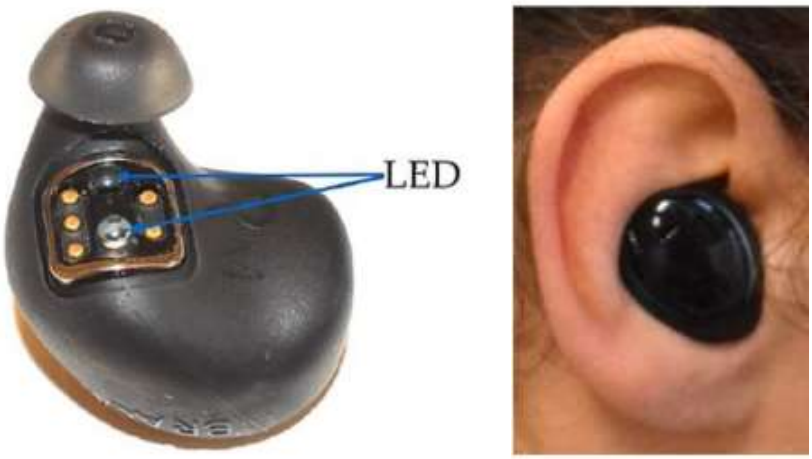


Figure 4. Ear-type PPG-based devices

3.1.3 PPG sensors

Although photoplethysmography sensors come in a variety of designs, they all assess changes in blood volume and produce comparable results. Atypical PPG sensor emits light at the tissue site with one or more LEDs and the photodiode measures the intensity of the non-absorbed light reflected from the tissue.

Longer wavelength light can reach deeper into the tissue. For instance, compared to green light, infrared light effectively penetrates the skin more. Infrared light is more prone to motion artefacts, though. As a result, for some applications, green LED with a shorter wavelength may be preferable [12].

Motion artefacts are usually caused by the movement of the PPG sensor over the tissue, skin deformation, blood flow dynamics, and ambient temperature. Additionally, accelerometers could be added to wearable technology to capture motion direction and lessen movement artefacts [12].

Figure 5. PPG sensors

3.1.4 Factors affecting PPG sensor recordings

Several factors can affect PPG recordings. These factors are Sensor Geometry, Emitted light intensity, sensor skin interface, photodiode sensitivity, arterial blood flow etc.

Alterations of interior tissues, such as muscular movement and tissue dilatation, can result from tissue modifications produced by deliberate or involuntary motions. These movements will alter the receiving light, producing a new signal.

Another factor that can modify the signal is the displacement of the sensor. Physical activities and body movements may result in the displacement of the sensor relative to its original location.

The motion artefacts brought on by the patient's movement are among the numerous noise sources that interfere with the PPG signal, and they are extremely difficult to eliminate. The

signal may be corrupted and the pulsatile component may no longer be visible from it because of the patient whose PPG is being measures continuous motion [16].

3.1.5 PPG signal

Generally, a single-pulse PPG waveform characteristically consists of three peaks and valleys. These are called the systolic peak, dicrotic notch, and diastolic peak (Figure. 6). There are many cases of PPG waveform features using these values [15].

PPG waveforms have typical morphological components corresponding to landmark events in the cardiac cycle. During the contraction of the left ventricle, blood is ejected out of the heart and propagates along the arterial tree, this corresponds to the initial positive slope of a PPG pulse. The systolic peak marks the maximum of the waveform. A decrease in amplitude following the systolic peak is marked by a local minimum, or the dicrotic notch, which corresponds to the closing of aortic valves separating the systolic and diastolic phases.

The third peak , the dicrotic notch, it relates to a forward wave component that has been reflected at numerous locations, including vessel bifurcations [17].

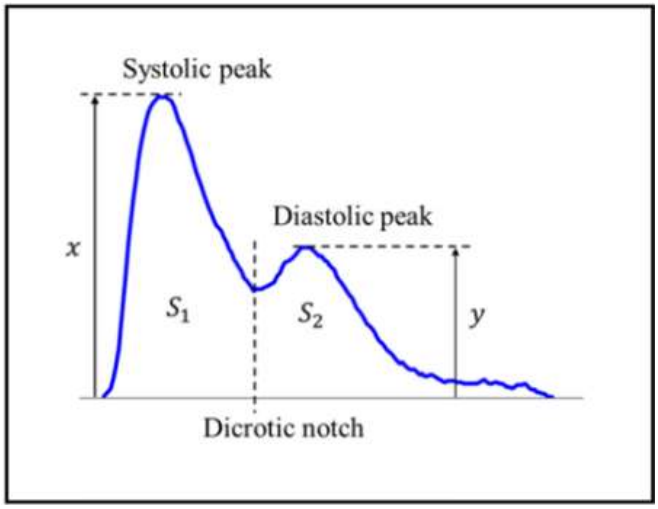


Figure 6. PPG Signal

AC and DC Components

The PPG signal comprises pulsatile (AC) and superimposed (DC) components (Figure 7.)

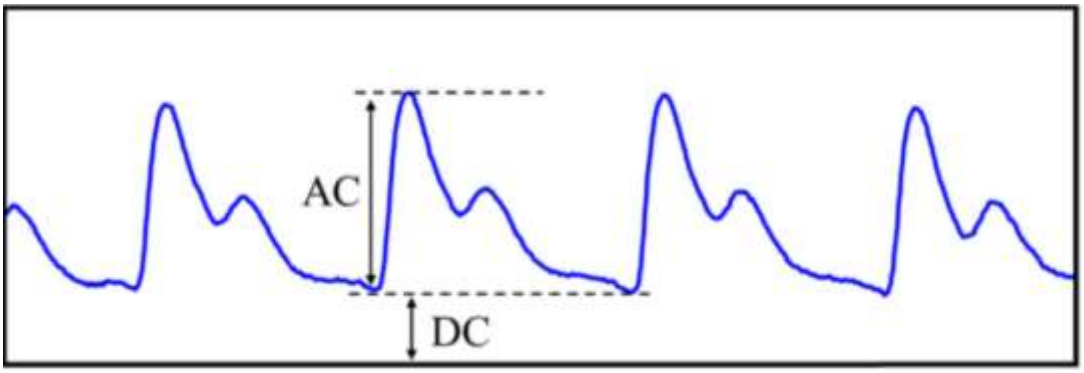


Figure 7. AC & DC Components

AC Component

The AC component is provided by the cardiac synchronous variations in blood volume that arise from heartbeats. The DC component is shaped by respiration, sympathetic nervous system activity, and thermoregulation.

The AC component of the PPG signal, which makes up the pulsatile portion, is created as light travels through arterial blood. Blood in veins, bones, and tissues absorb light, which results in the DC component, or non-pulsatile portion [16].

Systolic Amplitude, Stiffness Index, Crest Time, Pulse Width, Pulse Area, and Peak to Peak Interval are some of the properties of a PPG signal. Systolic amplitude, which also depends on stroke volume, provides an indicator of the pulsatile fluctuations in blood volume. The time interval between the systolic and diastolic maxima is connected to the stiffness index, which is dependent on a person's height and age. Crest time plays a key role in the diagnosis of cardiovascular disorders. It is the amount of time between the PPG waveform's base and peak [16].

The AC Component containing the higher frequencies of the signal is composed by individual fluctuations known as Pulse Waves (PW), whom vary in shape and size depending on the state of the individual's cardiovascular health. The "Diastolic valley" and the "Systolic peak" are the two major points that define the PW, which represents a single cardiac cycle and shows the systolic and diastolic activity of the heart. The "Diastolic Valley" corresponds to the heart's resting phase, during which blood flows back into the heart as it gets ready for the next pump. The "Systolic Peak" corresponds to the time when the heart's pumping action is at its most rapid [14].

The "Dichrotic peak" is a phenomenon that occurs in healthy patients and is associated with blood reflecting off the ends of the distal arteries and returning to the heart. By calculating

the systolic peaks that take place during a specific period of time, the average heart rate (AHR) can be determined [14].

On the other hand, the instantaneous heart rate (IHR) is considered as a more precise measurement of the HR since it uses the distance between a peak that is currently occurring and its previous neighbor to calculate the potential number of beats that can occur in a minute (BPM). The heart rate variability (HRV) pattern is created when the IHR is measured over extended periods of time. An abnormal IHR may correlate to arrhythmia caused by the influences of drugs, or fatal neurological disorders such as autonomic neuropathy found in diabetic patients [14].

DC Component

The DC component normally existing at 0.1-0.5Hz on the frequency spectrum, is superimposed onto the AC component which causes additional fluctuations to the signal PW known as the “Baseline drift” [14]

The sympathetic nervous system's reactions to many stimuli, including temperature and occasionally breathing, are tied to the DC component. Studies have been conducted on it because of its connection to respiratory activity in an effort to determine an individual's respiratory rate from the PPG signal [14].

3.2 Electrocardiogram (ECG)

The last decade of the 19th century witnessed the rise of a new era in which physicians used technology along with classical history taking and physical examination for the diagnosis of heart disease. Chest x-rays, introduced in 1895, and the electrocardiograph (electrocardiogram), introduced in 1902, gave us objective knowledge of the composition and operation of the heart. To capture the potential difference between the extremities arising from the heart's electrical activation, the original electrocardiograph used a string galvanometer. . The original electrocardiograph employed a string galvanometer to record the potential deference between the extremities resulting from the heart's electrical activation. The 12-lead electrocardiogram that we know today was developed by a remarkable series of discoveries and inventions made in the first half of the 20th century by a number of creative people [21].

ECG plays an important role as a non-invasive, cost-effective tool to evaluate arrhythmias and ischemic heart disease. Electrocardiogram is the electrical activity of the heart. The electrodes/leads are placed on specific locations of the body of the person to record ECG either on graph paper or on monitors.

The four chambers of the human heart are the right atrium, left atrium, right ventricular, and left ventricular. The two Atria are the upper chambers, and the two Ventricles are the lower chambers. The Sino Atria (SA) node in the right atrium, where the heartbeat normally starts, is responsible for transmitting electrical signals across the heart.

The Atrio Ventricular (AV) node receives this signal as it travels from the atria. The lower chamber's Ventricles, which contain a network of fibres that channel electricity and convey impulses to all of its regions, are connected to the AV node.

The basic structure of heart is depicted in Figure 8:

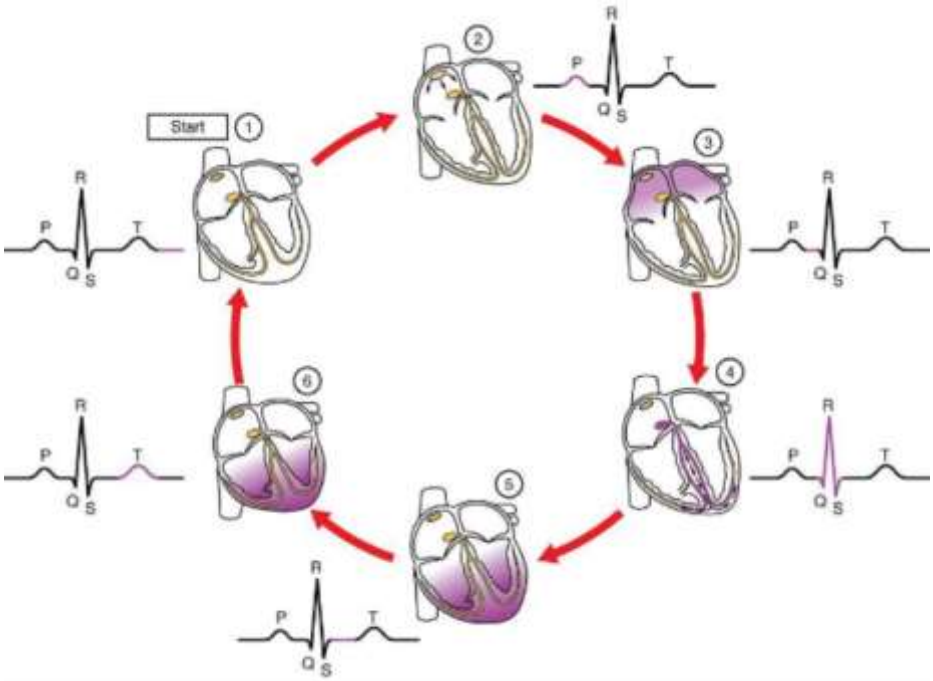


Figure 8. Common cardiac cycle with the associated waves of an ECG signal

3.2.1 Devices used to capture ECG

AliveCor

AliveCor is a wireless device that is approved by the Food and Drug Administration (FDA) and ConformitéEuropéenne (CE), it used a Smartphone case with two electrodes that transmit ECG signal data [22]. As shown in figure 9.

Once a patient presses their fingers against the case, a single-lead ECG recording is saved to the smartphone app and web server, where it may be accessed by medical professionals.

According to a 2018 prospective cross-sectional study, traditional external loop recorders only picked up arrhythmias in 20.4% of participants, whereas the AliveCor Kardia Mobile device picked up symptoms in 33.7% of the 33 participants who had heart palpitations but no clear diagnosis.

According to a different study from Columbia University Medical Centre, patients who utilized the AliveCor device had a detection rate of atrial fibrillation and atrial flutter of 61%, compared to only 30% for patients who got regular periodic in-office cardiac monitoring treatment.

Figure 9. AliveCor

ZioPatch

The ZioPatch is a 14-day ambulatory adhesive device that is worn over the left pectoral region (Figure 10). It is a water-resistant patch that records a 3-lead ECG strip and subsequently sends it to ZioPatch for analysis [22].

Figure 10. ZioPatch

3.2.2 ECG Electrodes

Electrodes are devices that convert ionic potentials into electronic potentials. The anatomical location of the bioelectric event to be detected determines the type of electrode used for the measurements. It will be preferable to transform ionic conduction into electronic conduction in order to process the signal in electronic circuits [22].

Types of Electrodes:-

Disposable adhesive electrodes:

The most popular kind of ECG electrodes are disposable adhesive electrodes, which are typically constructed from a thin adhesive substance with a conductive gel on the surface. Since they are disposable and simple to apply and remove, they are hygienic.

Figure 11. Disposable adhesive electrodes

Suction electrodes:

These have a suction cup shape that clings to the skin using a hoover and are frequently utilized in critical care situations. In comparison to adhesive electrodes, they offer a more reliable attachment and can be utilized for long-term monitoring.

Figure 12. Suction electrodes

Metal snap electrodes:

These are small discs of metal with snap connectors that attach to the skin. They are less comfortable than adhesive electrodes and are primarily used for short-term monitoring.

Figure 13. Metal snap electrodes

Wet-gel electrodes:

Before attaching these electrodes, a gel for these electrodes is applied to the skin. They have a good signal quality and are often utilized for long-term monitoring.

Figure 14. Wet-Gel eletrodes

Dry electrodes:

These electrodes are attached to the skin with a strap or band and don't need any gel or adhesive. They are less comfortable than other kinds of electrodes and are frequently employed in research settings.

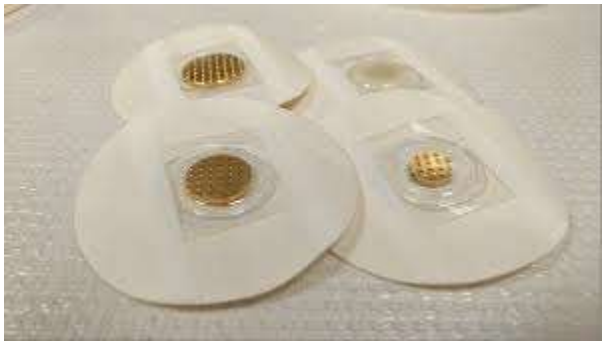


Figure 15. Dry electrodes

3.2.3 PQRST WAVE

The analysis of the ECG is widely used for diagnosing many cardiac diseases. Since most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its significant points, the development of accurate, quick, and reliable methods for automatic and real-time ECG delineation is one of the basic research fields in the biomedical engineering domain.

As a matter of fact, QRS detection is necessary to determine the heart rate and as a reference for beat alignment.

The most noticeable wave in an ECG signal is the QRS complex (Figure 16), which shows how long the heart has been depolarized. QRS detection is easier than with other waves due to its high amplitude and steep slope. Thus it is generally used as a reference within the cardiac cycle.

Most methods for defining P and T waves start from a predetermined QRS complex and use a search window on the left and right of the complex to find the onset, peak, and removal of P and T wave features, respectively. The detection of QRS peak is the starting point for any ECG signal analysis process.

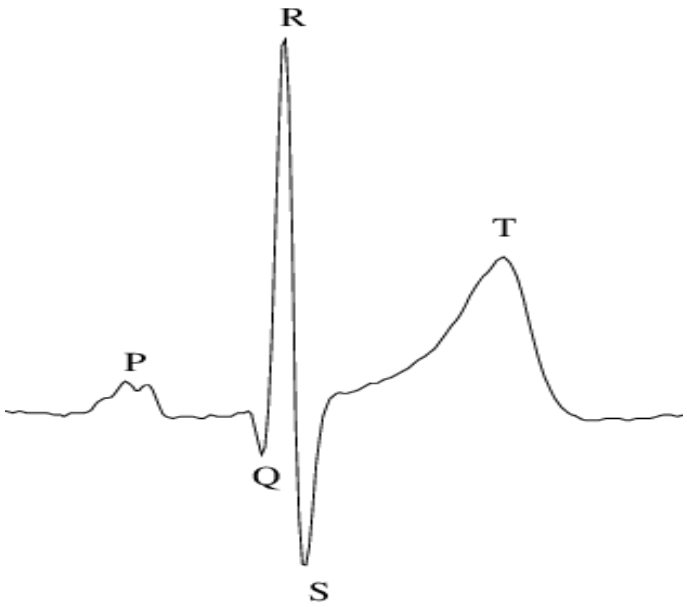


Figure 16. PQRST wave

3.3 Heart Rate Variability

Heart rate variability, or HRV, measures how much the time between heartbeats varies, thereby reflecting the regularity of heartbeats. Lower the HRV greater the regularity, and vice versa. The intervals between succeeding heartbeats are used to calculate the regularity of heartbeats in milliseconds (ms), they are known as R-R intervals.

The 'normal-to-normal' (NN) inter-beat intervals, or NN intervals, are utilized to determine all HRV characteristics. These intervals are brought about by regular cardiac contractions timed by sinus node depolarization.

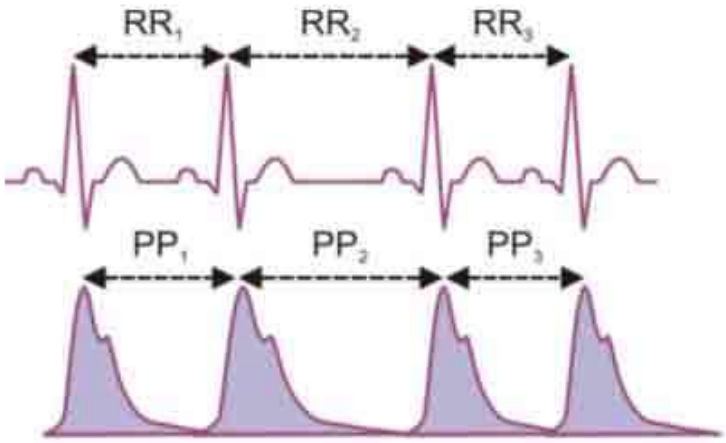


Figure 17. HRV

3.3.1 Analysis of HRV is done with the R-R intervals by:-

1. Time domain
2. Frequency domain
3. Non – linear methods.

Time domain methods

Here, the intervals between subsequent normal QRS complexes—also known as normal-to-normal (N-N) intervals—or the instantaneous heart rate are both monitored.

- SDNN

SDNN stands for standard deviation of the NN intervals, which is the square root of their variance. A variance reflects all cyclic components of the variability in recorded series of NN intervals since it is theoretically comparable to the overall power of spectral analysis. The length of the recording determines the real values of SDNN; the longer the recording, the higher the SDNN values. Therefore, it is inappropriate in practise to compare SDNN values obtained from NN recordings of various lengths. SDNN is measured in milliseconds.

- SDANN

The SDANN, which is calculated for each 5-minute segment of a 24-hour ECG recording, is the mean of the standard deviations of all the normal NN intervals and the mean of all the normal NN intervals. The Index is thought to be primarily a measurement of the autonomic influence on heart rate variability.

- RMSSD

RMSSD is the square root of the mean squared differences of successive NN intervals. In short-term NN recordings, this measure calculates high-frequency changes in heart rate that are thought to be caused by the parasympathetic nervous system. RMSSD is measured in milliseconds

FREQUENCY DOMAIN METHODS

This approach is typically chosen for recordings which last no more than five minutes.

The common frequency bands in humans are:

- **Total Power (TP)**

Total Power is a short-term estimate of the total power of power spectral density in the range of frequencies between 0 and .4 Hz. This measure reflects overall autonomic activity where sympathetic activity is a primary contributor. Total Power is calculated in milliseconds squared (ms2).

- **High Frequency (HF)**

High Frequency is a power spectrum band with a frequency range of 0.15 to 0.4 Hz. This measurement captures vagal (parasympathetic) activity. Because it matches the NN changes brought on by breathing, or respiratory sinus arrhythmia (RSA), HF is frequently referred to as a "respiratory" band. During inhaling, the heart rate rises, and it falls during exhale. High Frequency band is calculated in milliseconds squared (ms2).

- **Low Frequency (LF)**

Low Frequency is a power spectrum band with a frequency range of 0.04 to 0.15 Hz. Both sympathetic and parasympathetic activity is captured by this measurement. Generally speaking, it is a powerful sign of sympathetic activity. When respiration rate is less than 7 breaths per minute or when taking a deep breath, LF represents the parasympathetic impact. Therefore, the LF values might be extremely high when the individual is relaxed and

breathing slowly and evenly, indicating higher parasympathetic activity rather than increased sympathetic regulation. . Low Frequency band is calculated in milliseconds squared (ms2)

- **Very Low Frequency (VLF)**

Very Low Frequency is a power spectrum band with a frequency range of 0.0033 to 0.04 Hz. This measure, which generally shows overall activity of several slow mechanisms of sympathetic function, is well-known. Very Low Frequency band is calculated in milliseconds squared (ms2).

- **Ultra low frequency (ULF)**

The ULF band, which ranges from 0 to 0.0033 Hz. ULF is mostly expressed in 24-hour recordings and depicts fluctuations between day and night.

- **LF/HF RATIO**

Although the ratio of low to high frequency spectral power (LF/HF) has been proposed as a measure of the sympathetic to parasympathetic asymmetry, it is controversial since it lacks a clear understanding of how the LF component is produced. VLF, LF, and HF component values are often expressed as absolute power levels. Additionally, LF and HF measurements can also be made in normalised units, which show the relative values of each power component in relation to the overall power minus the VLF component.

The representation of LF and HF in normalised units emphasises how both the sympathetic and parasympathetic nervous systems act in a controlled and balanced manner. Total power is

expressed as a percentage in the Power Spectral Density (PSD), a measure of autonomic regulation.

NON – LINEAR METHODS

The term "non-linear methods" refers to the application of mathematical techniques to investigate the complex and non-linear interactions between the various elements of the HRV signal. Non-linear approaches enable the detection of deeper and more complex interactions that may exist between these components, as opposed to linear methods, which presume that the relationships between the various frequency components of the HRV signal are linear.

Non-linear techniques are being employed more frequently in HRV analysis because they can give a deeper and more comprehensive comprehension of the complex structure of the cardiovascular system. The development of more individualised and efficient treatments for these problems may result from the use of these techniques, which have the potential to spot minute variations in the HRV signal that may be a marker of underlying cardiovascular disorders. HRV is a physiological phenomenon which occurs mainly due to the cardiac activities which varies during respiratory cycle. The resting heart rate varies among participants, with some people having a rate of 100 beats per minute and others having a rate of 60.

3.3.2 Uses of HRV

- One noninvasive technique for assessing autonomic function in the cardiovascular and noncardiac systems.
- To evaluate the prognosis and effectiveness of the treatment.
- To assess the efficiency of a programme for stress relief.
- To identify any potential disease or functional issue at its earliest stages of development.

- It is utilised for exercise training in sports physiology.
- It discusses the influence of diabetic autonomic neuropathy's early warning signals.
- It is employed as an arrhythmia and Myocardial Infarction risk predictor.
- It is helpful in confirming sympathovagal imbalance and identifying an individual's tendency to develop hypertension.

3.3.3 Factors affecting HRV

Non Alterable factors of HRV	Alterable factors of HRV
Age	Smoking
Gender	Blood pressure
Genetic determinants	Excess Body weights
	Exercise & lifestyle
	Diet supplementation

Table 2. Factors affecting HRV

CHAPTER 4

INSTRUMENTATION

4.1 Arduino Board

4.1.1 Introduction:-

Arduino is an open source microcontroller which can be easily programmed, erased and reprogrammed at any instant of time. The Arduino platform, which was first introduced in 2005, it was created to give professionals, students, and amateurs a simple and affordable way to build gadgets that use sensors and actuators to interact with their surroundings. It is a simple microcontroller board-based open source computing platform for creating and programming electronic devices. It can act as a minicomputer, receiving inputs and directing outputs for a variety of electronic devices, much like other microcontrollers can [19].

With the aid of numerous Arduino shields, it can also send and receive data over the internet. Arduino uses a hardware known as the Arduino development board and software for developing the code known as the Arduino IDE (Integrated Development Environment). These microcontrollers can be programmed easily using the C or C++ language in the Arduino IDE [19].

4.1.2 Why is there a need to use Arduino in specific?

- Active User Community: A group of people using a similar product can hold posted message conversations and share their experiences or solve the problems of the other users in the communities with their own experiences [20].

- Growth of Arduino: Arduino was developed with intent to provide an economical and trouble-free way for students and professionals to build devices that interact with their situation using sensors and actuators. This makes it perfect for newcomers to get started quickly [20].
- Inexpensive Hardware: Since Arduino is an open source platform the software is not purchased and only the cost of buying the board or its parts is incurred, thus making it very cheap. The hardware designs are also available online for free from its official website [20].
- Arduino Board as a Programmer: To make Arduino board function easy and also making it available everywhere these boards come with a USB cable for power requirements as well as functioning as a programmer [20].
- Multi-platform Environment: The Arduino IDE is capable of running on a number of platforms including Microsoft, Linux and Mac OS X making the user community even larger [20].

4.1.3 Arduino Uno

Uno is a microcontroller board based on 8-bit ATmega328P microcontroller. Along with ATmega328P, it consists other components such as crystal oscillator, serial communication, voltage regulator, etc. to support the microcontroller.

The Arduino Uno has 14 I/O digital ports, a USB interface, and 6 analogue input pins for connecting to external electronic circuits. Six pins of the 14 I/O ports can be utilised for PWM output. The designers can use it to interact with and sense actual external electronic equipment [23].

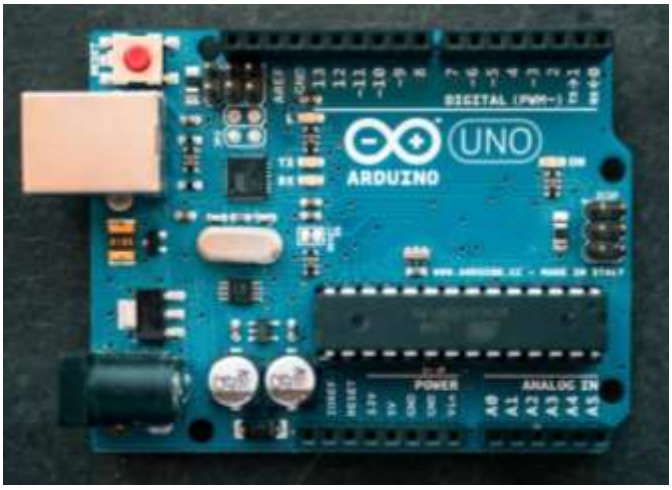


Figure 18. Arduino Uno Board

The Arduino Uno has been extremely popular with electronics enthusiasts, from beginning hobbyists to experienced programmers, ever since it was initially introduced. Because it is an open-source platform, anyone can change and improve the boards' capabilities. The boards and software are widely available. IDE (Integrated Development Environment) is the name of the free to use, basic-skills-required software that is utilised for Arduino devices. It can be written in the programming languages C and C++ [23].

Arduino Uno Pinout

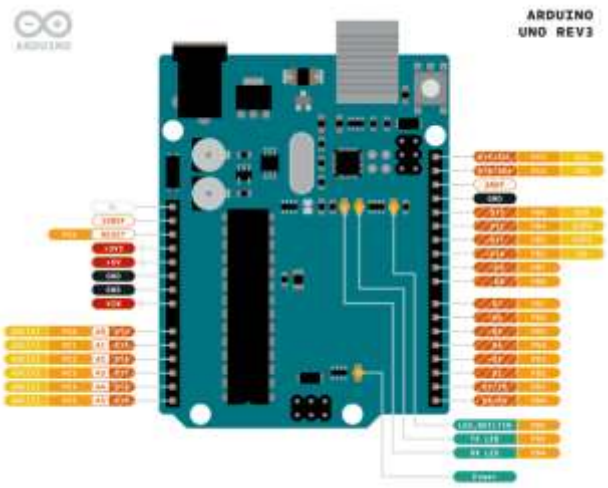


Figure 19. Arduino Uno Pinout

Arduino Uno Specifications

The specifications of Arduino Uno is as given in the table below.

Microcontroller	ATmega38P – 8 bit AVR family microcontroller
Operating Voltage	5V
Recommended Input Voltage	7-12V
Input Voltage Limits	6-20V
Analog Input Pins	6 (A0-A5)
Digital I/O Pins	14
DC Current on I/O Pins	40mA
DC Current on 3.3V Pin	50mA
Flash Memory	32KB
SRAM	2kB
EEPROM	1kB
Frequency (Clock Speed)	16MHz

Table 3. Arduino Uno Specifications Table

4.2 AFE4490

Texas Instruments AFE4490 Integrated Analog Front End is a fully-integrated AFE that is ideally suited for pulse-oximeter applications (Figure 20). This TI device consists of a low-noise receiver channel with a 22-bit analog-to-digital converter (ADC), an LED transmit section, and diagnostics for sensor and LED fault detection. AFE4490 is a very configurable timing controller. One of the prominent features of the chip is its low power requirement.

The user has total control over the device timing characteristics because to this flexibility. A low-jitter oscillator that draws its power from an external crystal is also incorporated to help with clocking requirements and give the AFE4490 a reliable clock. Using an SPI interface, the gadget communicates with a host processor or external microcontroller.

Figure 20. AFE4490Board

4.2.1 Features

- Fully-Integrated Analog Front-End for Pulse Oximeter Applications
  - Flexible Pulse Sequencing and Timing Control
- Transmit
  - Integrated LED Driver (H-Bridge or Push/Pull)
  - 110dB Dynamic Range Across Full Range (Enables Low Noise at Low LED Current)
  - LED Current: Programmable Ranges of 50mA, 75mA, 100mA, 150mA, and 200mA, Each with 8-Bit Current Resolution
  - Low Power: 100µA + Average LED Current
  - LED On-Time Programmability from (50µs + Settle Time) to 4ms
  - Independent LED2 and LED1 Current Reference

- Receive Channel with High Dynamic Range
  - Input-Referred Noise
  - 50pARMS (at 5µA PD Current)
  - 13.5 Noise-Free Bits (at 5µA PD Current)
  - Analog Ambient Cancellation Scheme with Selectable 1µA to 10µA Ambient Current
  - Low Power: < 2.3mA at 3.0V Supply
- Integrated Fault Diagnostics
  - Photodiode and LED Open and Short Detection
  - Cable On/Off Detection

Steps to alter register values on AFE4490:

1. Start Arduino IDE and write the code to acquire the ppg signal of any patient.

2. Then open AFE44X0SPO2EVM GUI software.

3. Goto Rx Stage tab and change the Common_CF and Common_RF

4. Then go to Low Level Configuration and check the value for the specific register.

5. Note the value of this register and save it somewhere.

6. Next open "This PC" go to Documents → Arduino → Libraries → ProtoCentral_AFE4490_PPG_and_SpO2_boards_library → src

7. Open protocentral_afe44xx.cpp file and change the register value which you have earlier copied and saved.

8. In a similar way repeat the above steps for other registers till you get proper output or results.

9. Now Save the protocentral_afe44xx.cpp file and open the Arduino IDE where you have written the code.

10. Compile and Upload the code to the Arduino Microcontroller.

4.2.2 AFE4490 Graphical User Interface(GUI)

AFE44x0SP02EVM GUI

The GUI allows the user to easily configure the various functions of the AFE, such as receiver gain, bandwidth settings, LED current settings, and timing and clocking control settings. The GUI supports both AFE4400 and AFE4490 devices.

The main tabs consist of:

1) **The Device Configuration Tab**

The Device Configuration tab allows configuration of the various registers of the AFE44x0 device. This subtab contains five subtabs:

Global Settings, Tx Stage, Rx Stage, Timing Controls, and Low Level Configuration.

- Global Settings Subtab

The Global Settings subtab for the AFE4490 device has the following features:

1. View the Device ID and Firmware Revision

2. Device Reset button that resets the device.

3. Enables the user to set or reset:

(a) SPI Read; (b) XTAL Disable; (c) En Bypass ADC

(d) Powerdown AFE (e) Powerdown TX (f) Powerdown RX

(g) Enable Slow Diag Clock

4. Click on Diagnostic Enable and view the Alarm status flags triggered through Diagnostic Enable

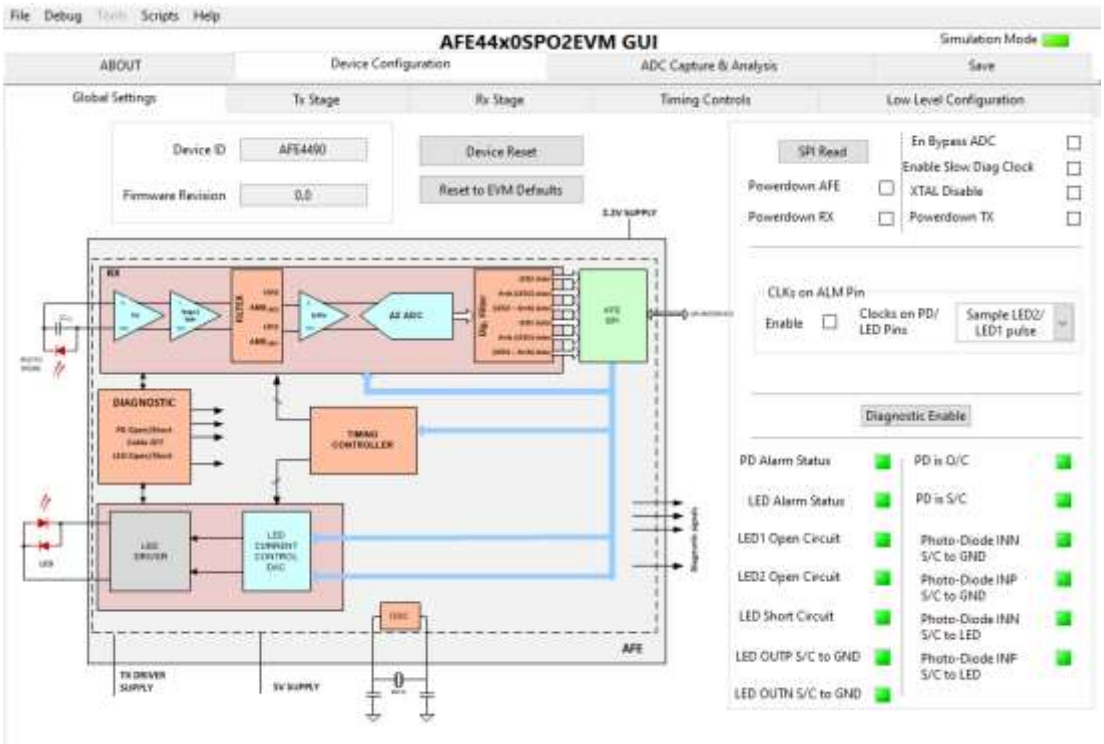


Figure 21(a). Device Configuration Tab

- Tx Stage Subtab

The Tx Stage subtab under the Device Configuration tab consists of the settings to:

1. Set LED1 and LED2 currents.

2. Program LED current control DAC through a pull-down menu.

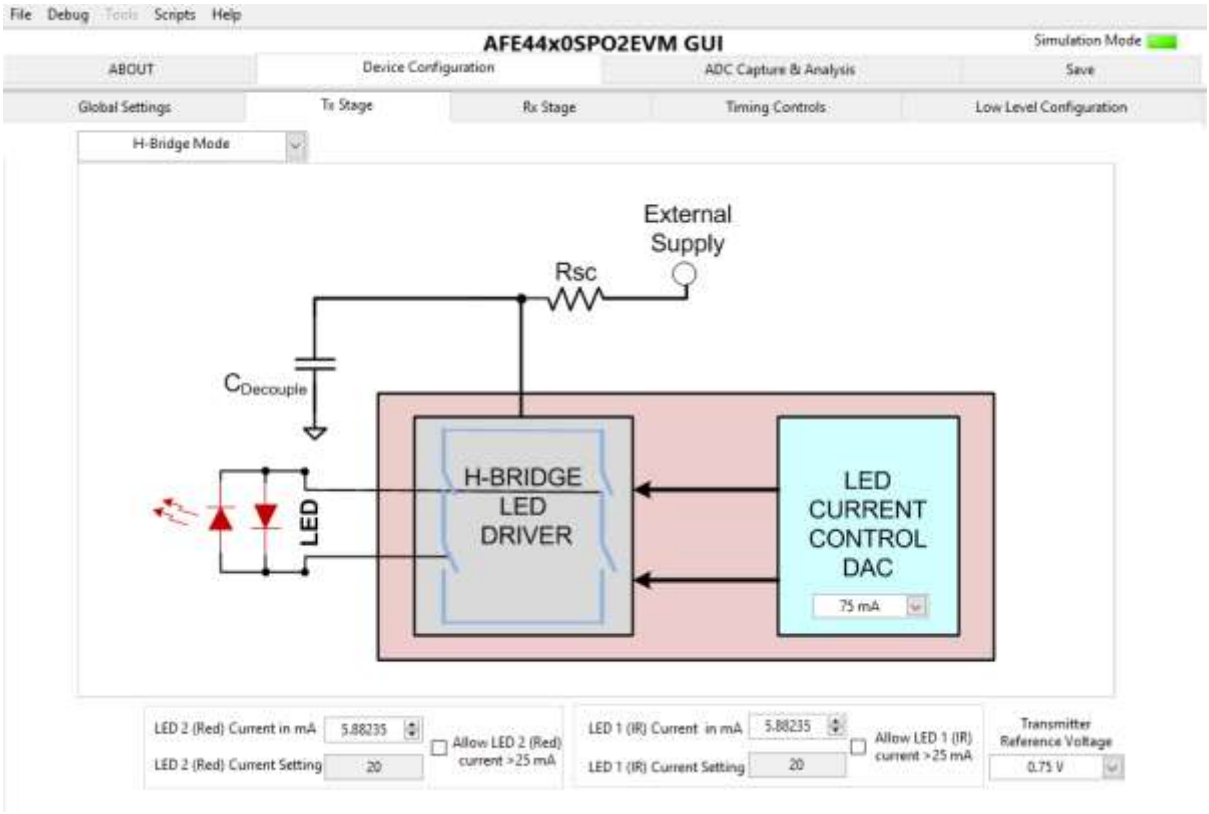


Figure 21 (b). Tx Stage

- Rx Stage Subtab

The Rx Stage subtab under the Device Configuration tab consists of the settings to:

1. Enable separate gain mode (available for AFE4490 device only).

2. Set feedback resistance and capacitance for the trans-impedance amplifier with separate gain mode disabled.

3. Set feedback resistance and capacitance for the trans-impedance amplifier with separate gain mode enabled (available for AFE4490 device only).

4. Enable second-stage and set gain for the second-stage amplifier.

5. Set ambient DAC current.

6. Select filter corner frequency (available for AFE4490 device only).

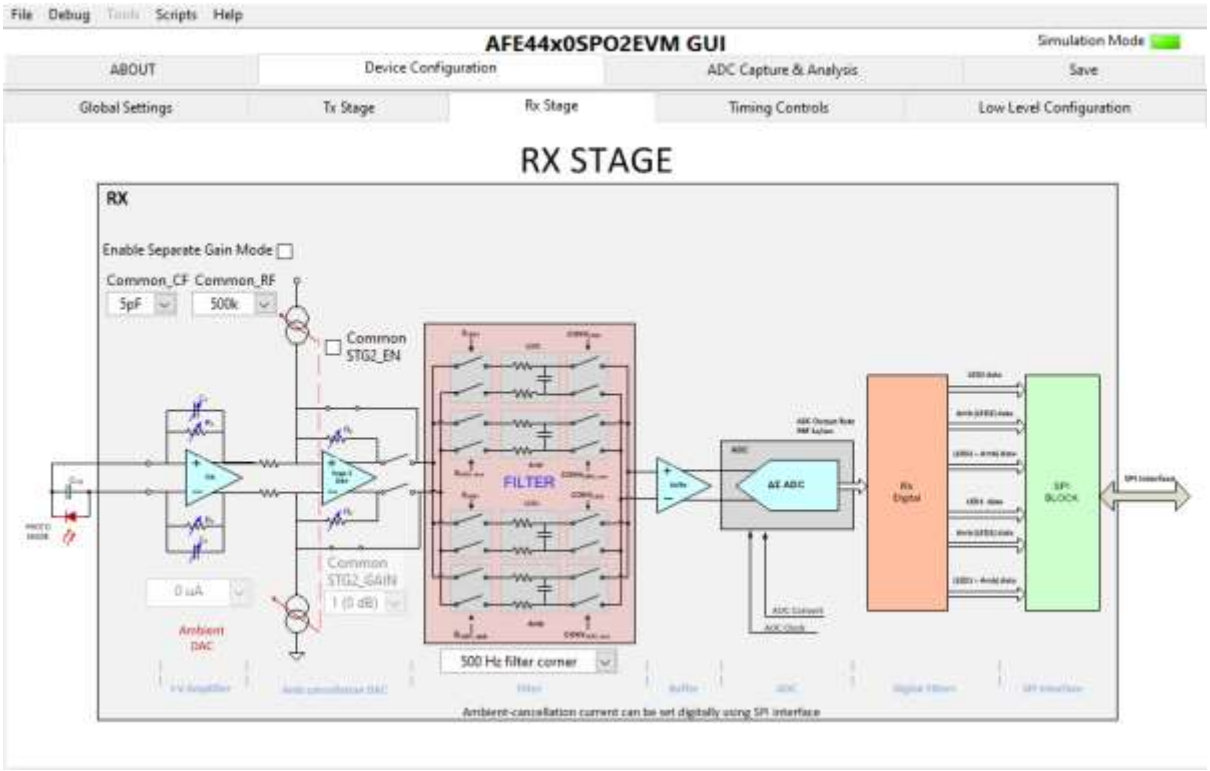


Figure 21 (c). Rx Stage

- Timing Controls Subtab

The Timing Controls subtab under the Device Configuration tab consists of the following settings:

1. Enter the Pulse Repetition Frequency (PRF) and Duty Cycle % and click the SET button to automatically set the following:

(a) LED1 (IR) and LED2 (Red) ON and OFF time,

(b) Rx sample start and end time for 4 channels (LED1, LED1 Ambient, LED2, LED2 Ambient)

(c) Rx convert start and end time for 4 channels (LED1, LED1 Ambient, LED2, LED2 Ambient)

2. Save the timing settings based on PRF and duty cycle to a configuration file

3. Load the timing settings based on PRF and duty cycle from a configuration file

4. Timer Counter RESET button

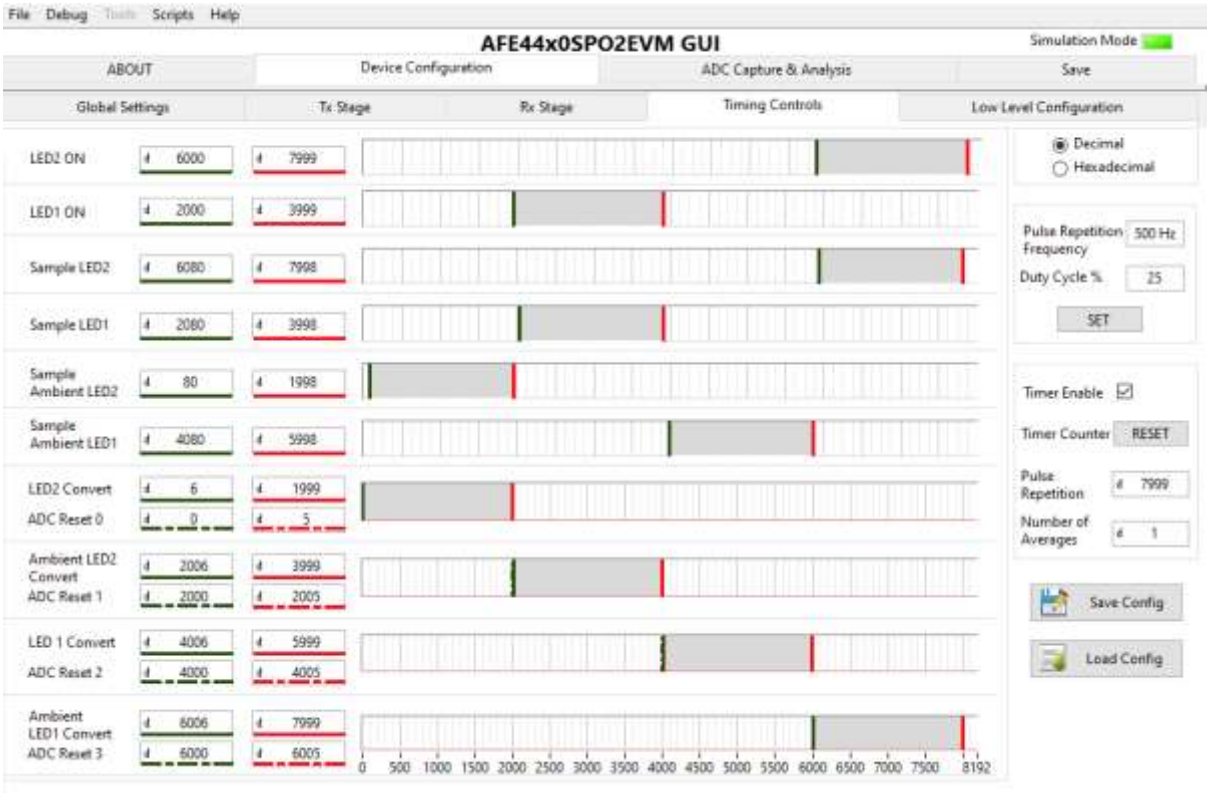


Figure 21 (d). Timing Controls

- Low Level Configuration Subtab

The Low Level Configuration subtab under the Device Configuration tab is used to directly configure the various registers of the AFE44x0 devices. Refer to the AFE44x0 data sheet (SBAS601, SBAS602) for the register details of the chip.

The Register Map portion of the sub-tab shows the EVM default values of the registers after the GUI is loaded under the EVM Default column. From the Register Map section, when any register is selected, the bit-level details about the register are explained in the Register Description section. The ability to read and write the register and modify the individual bits of the register are provided in the Register Data section. The values of all the registers are read by clicking the Read All button.

Click on Transfer Read to Write to copy the contents of the Read Data to Write Data. Then click on Write Register to write to the data to the register of the AFE44x0.

By clicking on the Save Config button, the register configuration is saved to a configuration file. The register configuration is loaded from a configuration file by clicking the Load Config button.

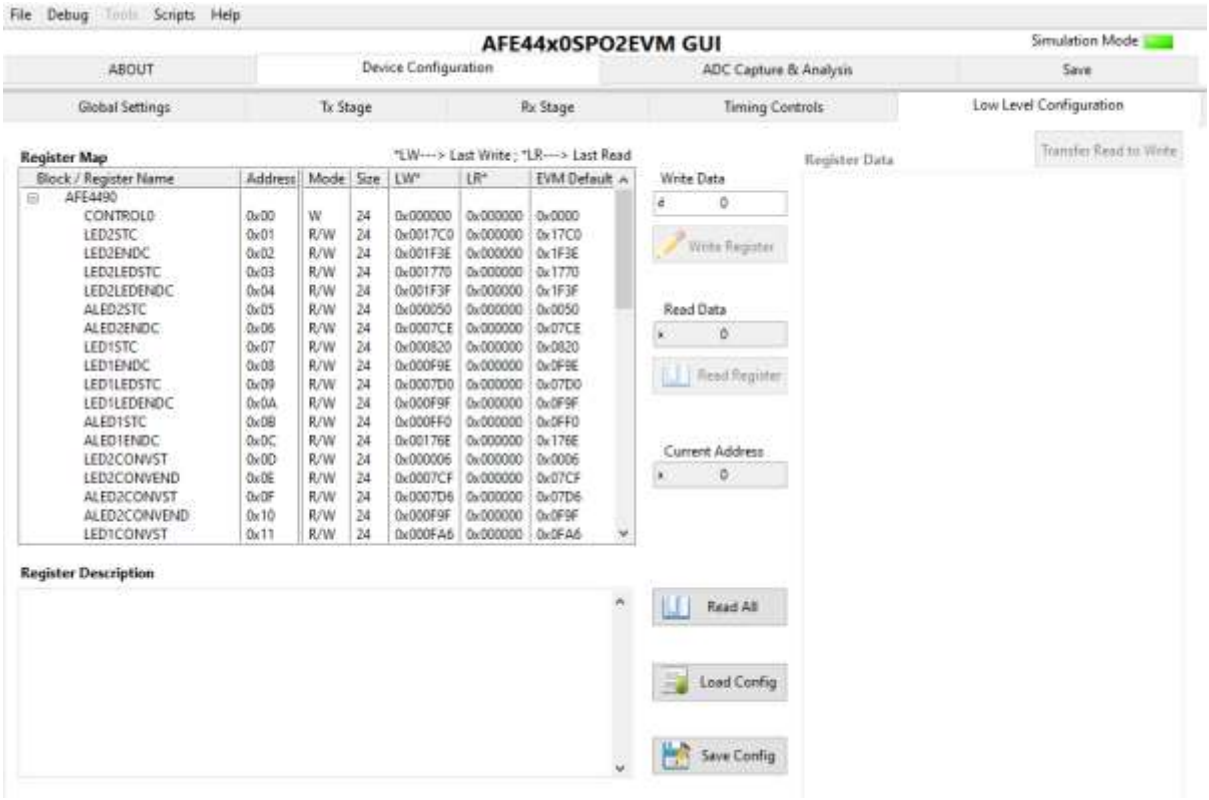


Figure 21 (e). Low Level Configuration

2) ADC Capture and Analysis

The ADC Capture and Analysis tab consists of various analysis routines and displays. This tab is used to:

• Set the capture mode to finite or continuous

• Set the number of samples (block size) in Finite Capture mode

• Set the filter type to None or Notch

• Set the Notch Freq to 50 or 60 Hz when the filter type is set to Notch

• Auto save after capture selector

• Acquire the data by clicking the Capture button

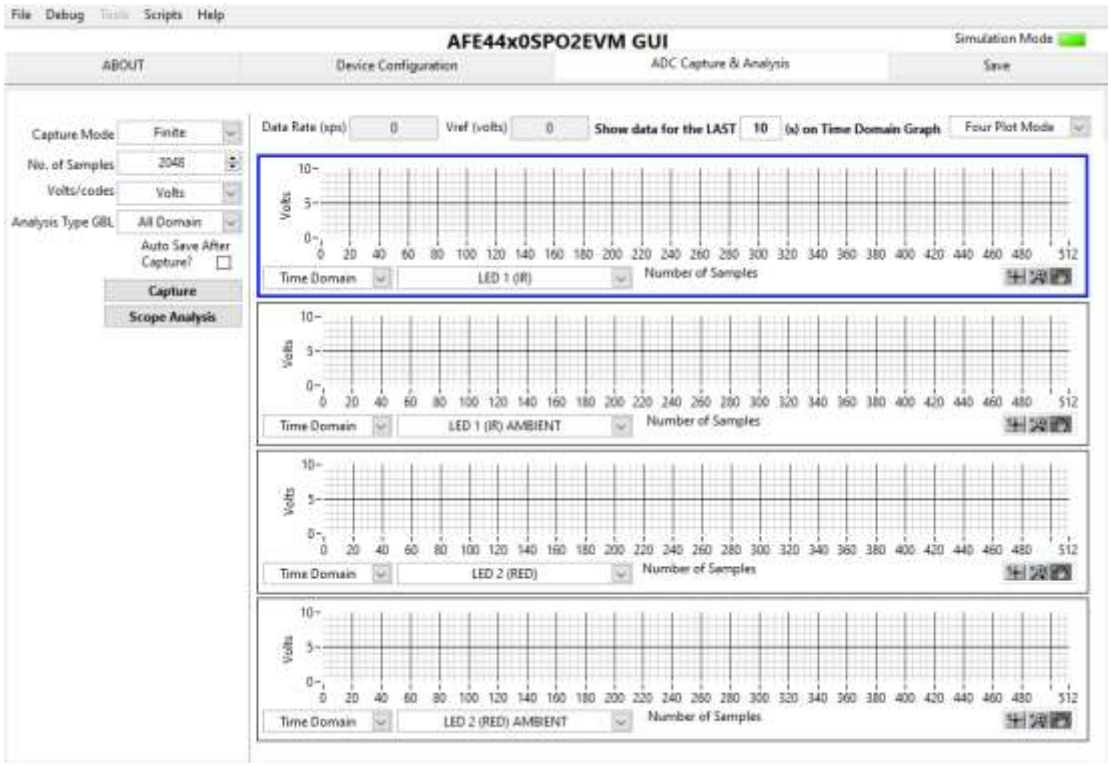


Figure 21(f). ADC Capture and Analysis

3) The Save Tab

The Save tab shown in Figure 33 provides provisions to save the analysis or data to a file. By default, the data are saved to the following location:

• On a Windows XP machine – C:\Program Files\Texas Instruments\AFE44x0SPO2EVM GUI\Log

• On a Windows 7 or Windows 8 machine – C:\Program Files(x86)\Texas Instruments\AFE44x0SPO2EVM GUI\Log Use the Directory to Save Files option to select the folder where data are to be saved.

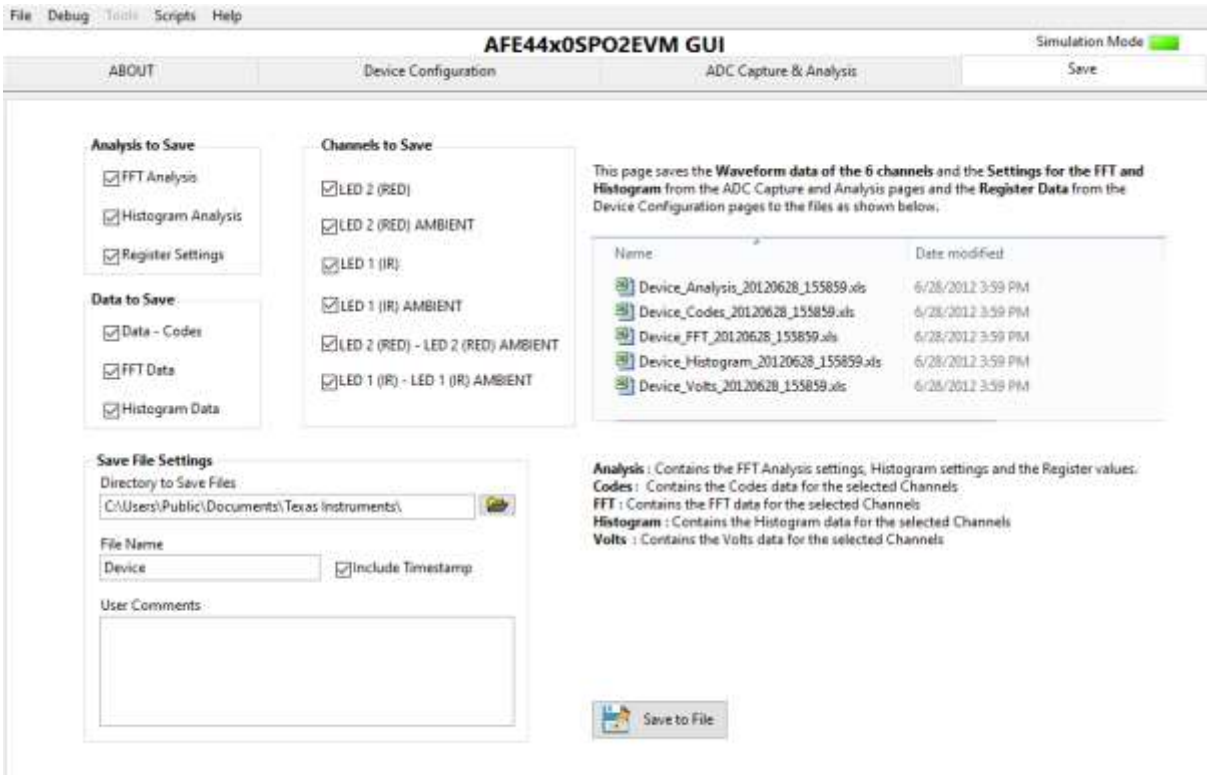


Figure 21 (g). Save tab

4.3 Nellcor Probe:

The Nellcor probe is a medical device that is used to measure a patient's oxygen saturation levels in the blood (Figure 22). It is named after its manufacturer, Nellcor Puritan Bennett, which is a division of the medical technology company Medtronic. The Nellcor probe is a

small, non-invasive sensor that is placed on a patient's fingertip, toe, or earlobe. The probe measures the amount of oxygen that is linked to haemoglobin in the blood using a technique known as pulse oximetry. The oxygen saturation level, or SpO2, which is reported as a percentage, is the measurement.

The Nellcor probe is frequently used in hospitals, emergency rooms, and other healthcare facilities to monitor patients getting oxygen therapy or at risk of hypoxemia, a condition marked by low blood oxygen levels. To make sure the patient is getting enough oxygen, the probe is also utilised during operations and other treatments that call for anaesthesia.

The Nellcor probe, in general, is a commonly used and trustworthy medical equipment that aids healthcare professionals in real-time monitoring and management of a patient's oxygen levels, which can be crucial for guaranteeing their safety and recovery.

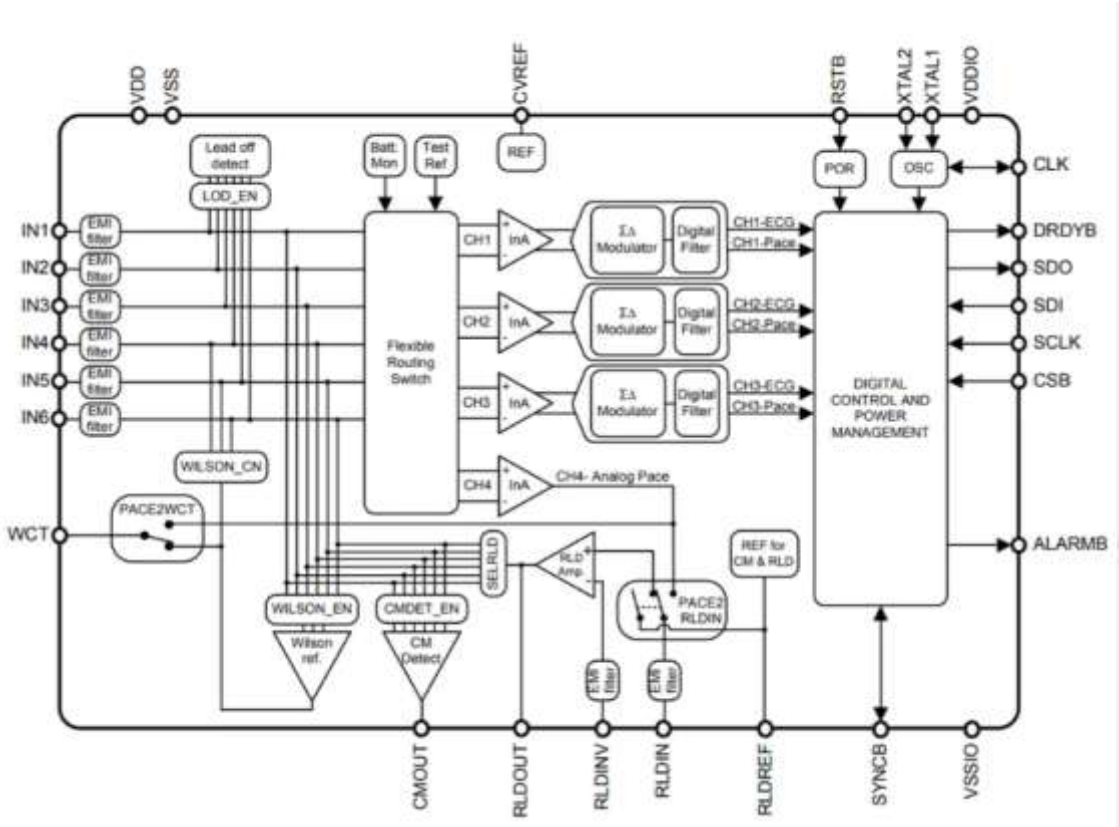
Figure 22. Nellcor Probe

4.4 ADS1293:

Texas Instruments ADS1293 Analog Front End (AFE) incorporates all features commonly required in portable, low-power medical, sports and fitness electrocardiogram (ECG) applications (Figure 23 (a)). The ADS1293 features three high-resolution channels capable of operating up to 25.6ksps. Each channel can be independently programmed for a specific sample rate and bandwidth allowing users to optimize the configuration for performance and power.

Scalable medical instrumentation systems can be produced because of the ADS1293 technology. An EMI filter is built into every input pin, which may then be routed to any channel using a flexible routing switch. Additionally, independent lead-off detection, right leg drive, and Wilson/Goldberger reference terminal generation are made possible by flexible routing without the need for external lead reconnection. For applications that do not use digital pace detection, a fourth channel enables external analogue pace detection. A self-diagnostics alarm mechanism is included into the ADS1293 to alert users when the system is operating outside of its normal parameters. Error flags get reports of these events. There is a signal on a specific ALARMB pin that indicates the overall status of the error flags.

Figure 23 (a) ADS1293



(b) ADS1293 Block Diagram

- Select Lead Configuration
  - Use the “Lead Configuration” combo box to select a 3-Lead or 5-Lead wire configuration.

- Configure Channel
  - The flexible routing switch can connect the inputs of the three analog front end channels as well as the inputs of the analog pace channel to any of the 6 input pins. This allows system flexibility and even on-the-fly reconfiguration of the ECG monitoring system.

- Configure InA
    - The instrumentation amplifier (INA) provides a high input impedance to interface with signal sources that may have relatively high output impedance, such as ECG electrodes. The maximum differential input voltage of the INA is +/- 400 mV, and the INA has a gain of 3.5x. The input common mode voltage range of the INA is 0.95V to (VDD-0.95V). The INA can also be configured in low-power mode or low-noise mode.

- Configure Modulator
    - The Sigma Delta Modulator (SDM) takes the output signal of the InA and converts this signal into a high resolution bit stream that is further processed by the digital filters. The SDM can operate at a clock frequency of 102.4 kHz or 204.8 kHz.

- Program Digital Filter
    - The digital filter behind the modulator reconstructs the signal from the modulator output bit stream. The filter consists of 3 programmable SINC Filters. The first filter stage can be programmed using the R1 RATE CHx bit for channel x. The second filter stage can be programmed using the R2 RATE bits. The third filter stage can be programmed using the R3_RATE_CH bits.

- Select CLOCK options
    - The ADS1293 is designed to operate from a 409.6 kHz clock. This clock can either be provided externally on the bidirectional CLK pin, or it can be provided externally with a 4.096MHZ XTAL oscillator.

- Enable Analog Pace channel
    - The ADS1293 features an additional analog PACE channel to process pulses from a pace maker.

- Configure Wilson Reference
    - The ADS1293 features a Wilson reference block consisting of three buffer amplifiers and resistors that can generate the voltages for the Wilson Central Terminal (WCT) or Goldberger terminals. There are typically 3 electrodes to be measured for an ECG application: right arm (RA), left arm (LA), and the left leg (LL). The WCT is defined as the average of these three limb electrodes: WCT (RA+LA+LL)/3.

- Configure Common Mode
    - The Common Mode Detector averages the voltage of up to six input pins, and its output can be used in a right leg drive feedback circuit.

- Configure RLD
    - The right leg driver (RLD) is a programmable op-amp that is intended to control the common-mode (CM) level of the patient connected to the inputs of the ADS1293. The CM level of the patient's body is measured and is externally fed to

the negative input of the RLD op-amp to create a negative feedback loop by driving the body with an inverted common-mode signal. The negative feedback loop restricts the common-mode movement to a narrow range, and its loop gain and stability are set using external resistors and capacitors

- Select Internal Reference
  - Select to enable or disable the internal reference (VDD-VSS)/2.2

- Configure Lead Off Detect
  - The lead off detect (LOD) block of the ADS1293 can be used to monitor the connectivity of the 6 input pins to electrodes. The LOD block injects a programmable DC or AC excitation current into selected input pins and detects the voltages that appear on the input pins in response to that current. If a lead is not making a proper contact, the electrode impedance will be high and as a result the voltage in response to a small test current will be relatively large.

- Configure Battery Monitoring
  - In this mode, the POSX of channel x will sample the voltage supplied on the VDD pin. At the same time, the NEGX of channel x will sample the reference voltage, VREF, generated on or provided by to the CVREF pin. As a result, the output signal of the sigma delta modulator is a measure for (VBAT-VREF)

- Configure Test signals
  - If enabled, a positive DC test signal is provided to the input of the instrumentation amplifier for internal testing of the channel

- Configure Digital Control
    - Click on the Digital Control block to set the DRYDB and standby mode

- Set Alarms
    - The ADS1293 has multiple warning flags to diagnose possible fault conditions in the ECG monitoring application

- View EVM Configuration
    - Click on the "View Board Settings" button to see how to configure the evaluation board for this application.

- View Performance
    - Click on this step to view the estimated device and measured system performances.

Features

- Three High-Resolution Digital ECG Channels With Simultaneous Pace Output
- EMI-Hardened Inputs
- 0.3mW/channel low power
- Input-Referred Noise: 7µVpp (40Hz Bandwidth)
- 175pA Input Bias Current
- Up to 25.6ksps data rate
- Differential Input Voltage Range: ±400mV
- Analog Supply Voltage: 2.7V to 5.5V

- 1.65V to 3.6V Digital I/O Supply Voltage
- Right-Leg Drive Amplifier
- AC and DC Lead-Off Detection
- Wilson and Goldberger Terminals
- ALARMB Pin for Interrupt Driven Diagnostics
- Battery Voltage Monitoring
- Built-In Oscillator and Reference
- Flexible Power-Down and Standby Modes

4.5 AFE4490 - Arduino Uno Interface

- The AFE4490 is a pulse oximeter sensor that measures blood oxygen saturation and heart rate using photoplethysmography (PPG) technology. The Arduino Uno is a microcontroller board that can be used to interface with sensors and other electronic components.

- We must connect the AFE4490 sensor's pins to the corresponding pins on the Arduino Uno in order to attach it to the board. Power, ground, data output, and control signals, including clock signals, are commonly connected to the AFE4490's pins.

- After attaching the AFE4490 to the Arduino Uno, you can read data from the sensor and process it as necessary using Arduino code. The sensor's settings, such as the sampling rate and LED current, can also be managed by the Arduino.

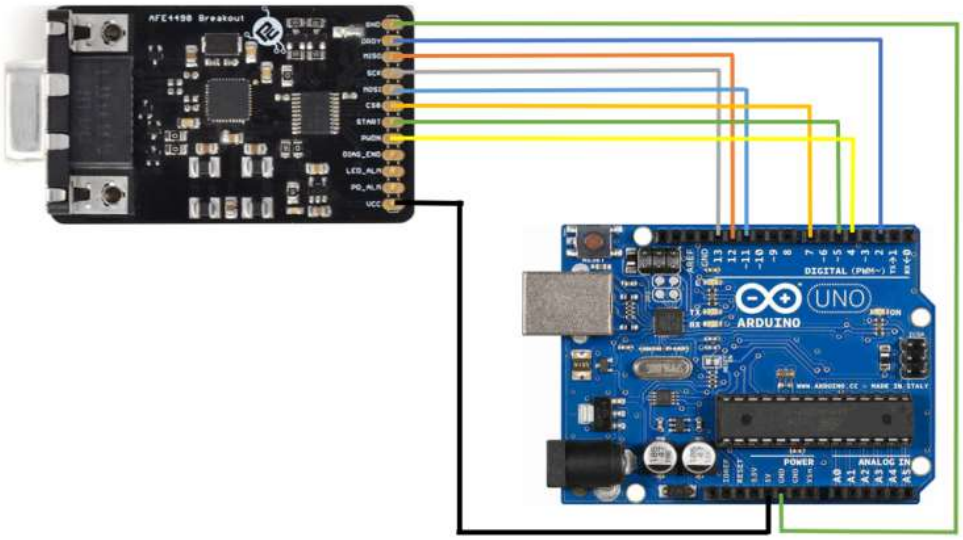


Figure 24.(AFE4490 - Arduino Uno Interface)

AFE4490 pin label	Arduino Connection	Pin Function
GND	Gnd	Ground
DRDY	D2	Data Ready(interrupt)
MISO	D12	Slave out
SCK	D13	SPI clock
MOSI	D11	Slave in
CS0	D7	Slave select
START	D5	Conversion start Pin
PWDN	D4	Power Down/ Reset
DIAG_END	NC	Diagnostic output
LED_ALM	NC	Cable fault indicator
PD_ALM	NC	PD sensor fault indicator
VCC	+5v	Supply voltage

Table 4. AFE4490 & Arduino Uno Interface

CHAPTER 5

Methodology

The major task of the project was database generation of Photoplethysmography and Electrocardiography signals.

The detailed methodology is described in this chapter and same can be seen in the

Figure 24:

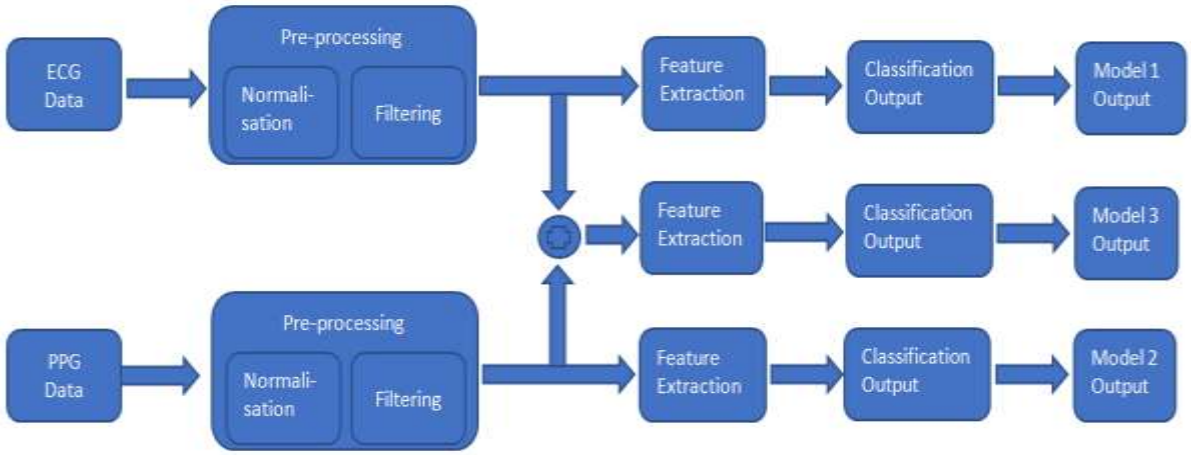


Figure 25. System Block Diagram

5.1 Data Acquisition

- **PhotoPlethysmoGraphy (PPG)**

To Acquire the PPG data of the subjects we used the AFE4490 pulse oximeter sensor. The Arduino Uno microcontroller board, which was used to control the sensor and collect data, was attached to the AFE4490 sensor. To ensure precise data collection, we followed to the setup instructions in the sensor's datasheet.

The sensor was then placed on the fingertip of the subject, the LED was turned ON and the light was emitted on the subject's finger. The light was then detected by the photodiode, which generated an electrical signal that was proportional to the amount of light absorbed by the tissue.

Setup:

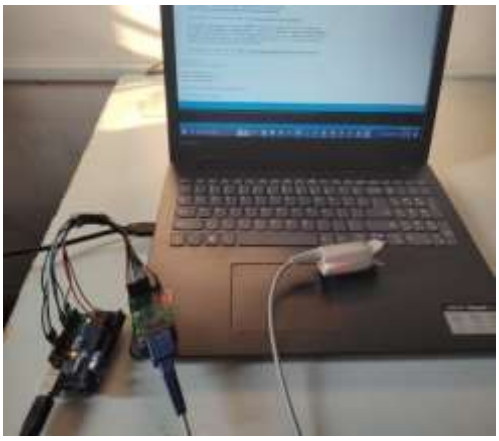


Figure 26 (a). Experimental setup

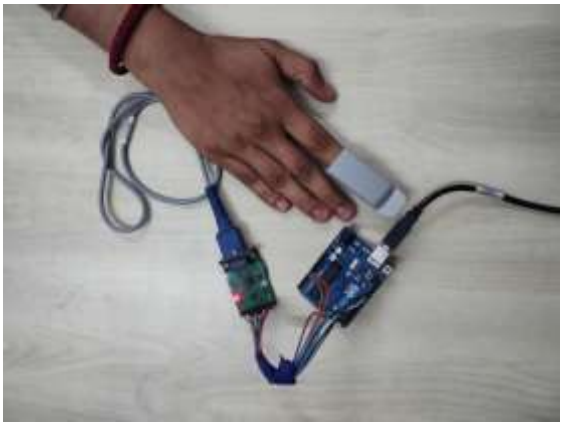


Figure 26 (b). Data Acquisition setup

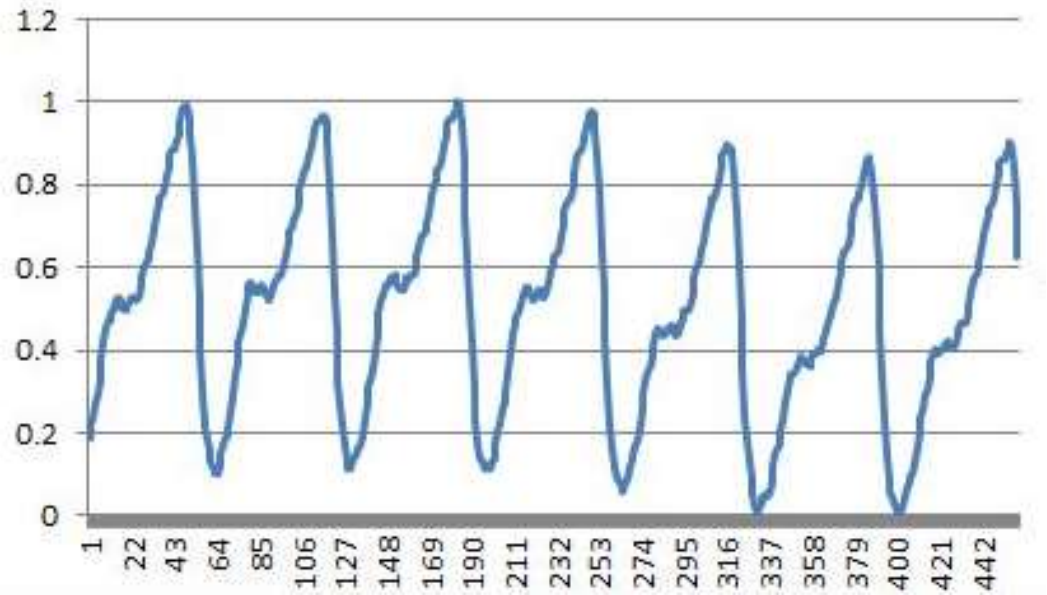


Figure 27. PPG data taken in our Lab

- **Electrocardiography (ECG)**

To acquire the ECG data we used the ADS1293 board, a multi-channel analog-to-digital converter (ADC) designed specifically for biopotential measurements. Electrodes were connected to the ADS 1293 board, we used 3 lead configuration for the electrodes to collect the signal. Right leg was taken as the Reference.

The real time ECG signal was simulated on the ADS1293 software and later was saved for further processing.

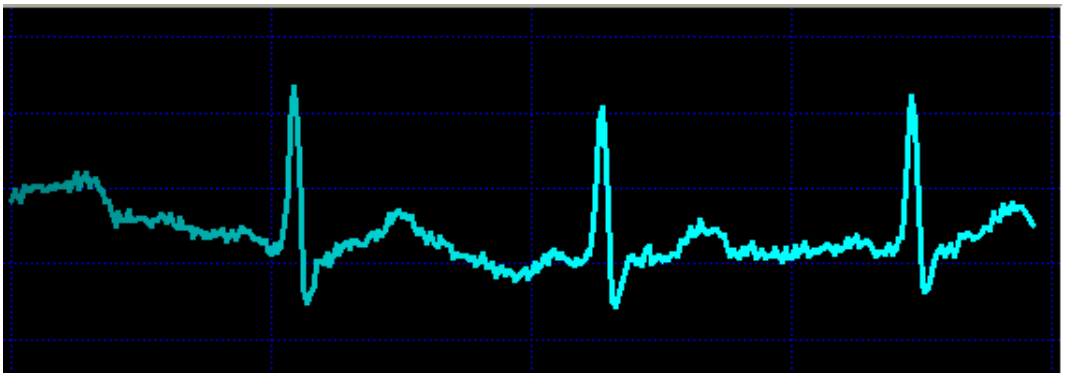


Figure 28. ECG data taken in our Lab

To interface disposable ECG electrodes to the ADS1293, the following steps were taken:

- Prepare the Skin:

  To get rid of any oils or other things that can affect the signal quality, thoroughly clean and dry the area where the electrodes will be mounted.

- Attach the Electrodes:

  We placed the electrodes on the prepared skin in the recommended positions, later the electrodes were connected to the shielded cable that is then connected to the ADS1293 board

To connect the ADS1293 board to the PC, we first installed the required software drivers on the PC, then we configured the ADS1293 board. The recorded data can be saved and analyzed later.

Setup:

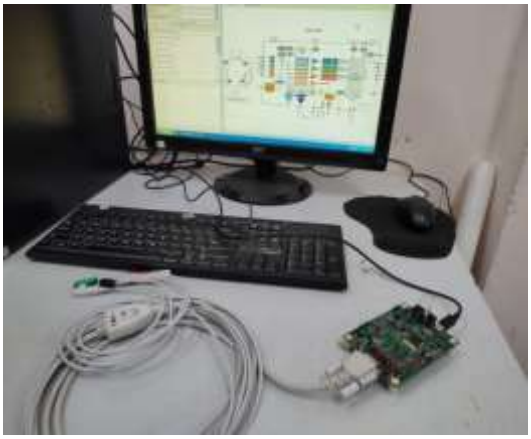


Figure 29(a). Experimental setup

Figure 29(b). Data Acquisition setup

5.2 Pre-processing & Feature Extraction

PPG Signal Pre-processing

- Normalization and Filtering:

We first normalized the data, then the band-pass filter was implemented to filter the signal.

The Low cut off and High cut off frequencies were set to 0.5Hz and 5Hz respectively.

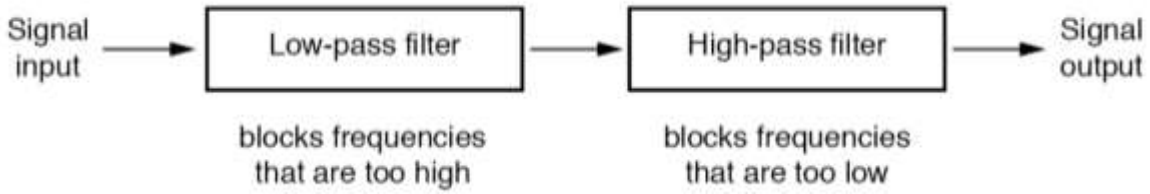


Figure 30. System level block diagram of a band-pass filter

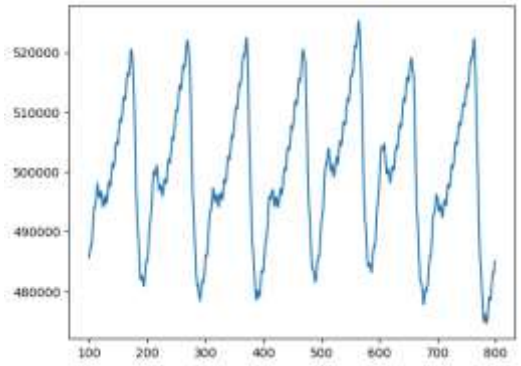


Figure 31 (a).Original Signal

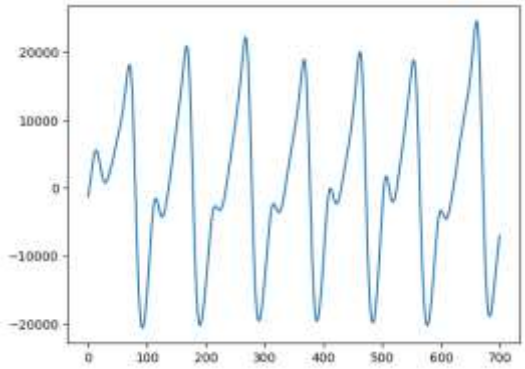


Figure 31 (b). Filtered Signal

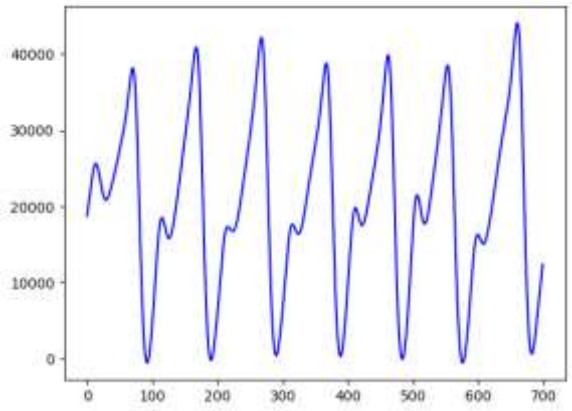


Figure 31 (c). Baseline Corrected Signal

- Peak Detection:

Peak detection was done using the Scipy library which included the ‘find peaks’ function to detect the peaks in the PPG signal.

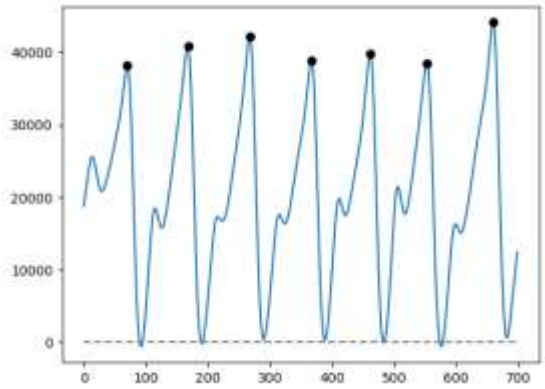


Figure 32 (a). PPG Peaks Detected

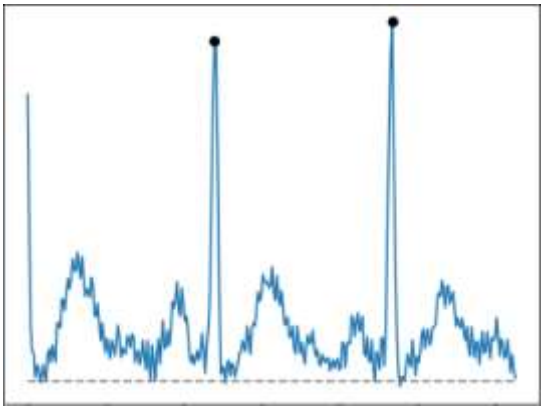


Figure 32 (b). ECG Peaks Detected

- Plotting:

For plotting of the data we used matplotlib to generate the Plots. Matplotlib is a data visualization library in Python, Including line plots, scatter plots, bar charts, histograms, and more, it enables users to construct a wide variety of graphs and charts.

5.3 Feature Extraction & Classification of Data:

In this study, we managed to develop different classification model using a recurrent neural network (RNN) with Gated recurrent units (GRU), K-Nearest Neighbors , Decision Tree, Random Forest classifier. The collected preprocessed data was classified using these models.

Recurrent Neural Network

What is a Neural Network?

A neural network is a collection of interconnected layers that mimics the organization and operation of the human brain. It trains a neural network using complex algorithms and learns from huge quantities of data.

Different problems can be helped by a variety of neural networks.

- Feed-Forward Neural Network: Used to solve generic classification and regression issues.
- Convolutional Neural Network: Used in picture categorization and object detection.
- Deep Belief Network: Used in the medical field to find cancer.
- RNN: Used for natural language processing, time series forecasting, voice recognition, and speech recognition.

RNN functions on the principle that it can predict a layer's output by capturing and re-inputting that layer's output.

The following details how a feed-forward neural network becomes a recurrent neural network:

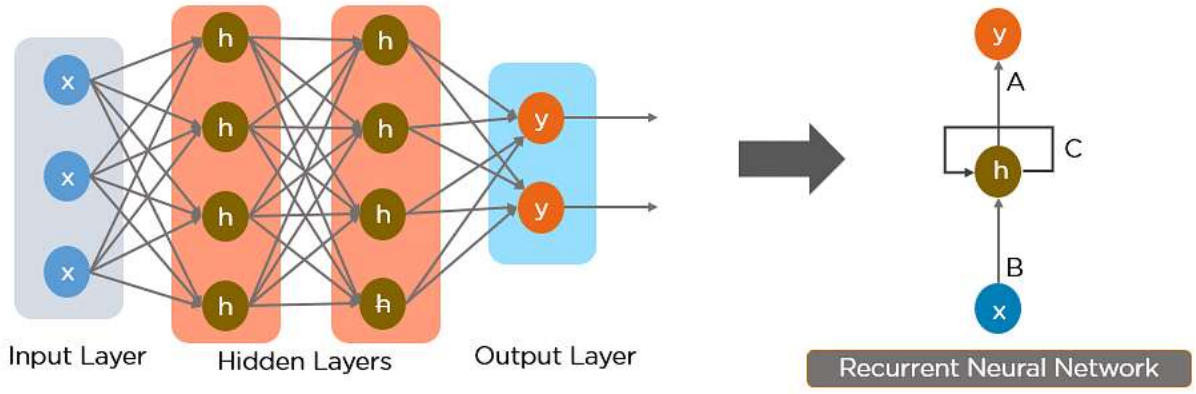


Figure 33. Simple Recurrent Neural Network

To create a single layer of recurrent neural networks, the nodes from several layers of the neural network are compressed.

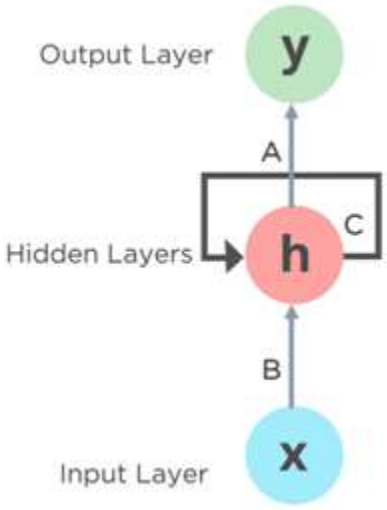


Figure 34. Fully Connected RNN

"X" stands for the input layer, "h" for the hidden layer, and "y" for the output layer in this instance. The network parameters A, B, and C are used to enhance the model's output. The input at any time t is a mixture of the input at times x(t) and x(t-1). The output is periodically fetched back to the network to be improved.

How does RNN work?

The data in recurrent neural networks loops around a loop before reaching the intermediate hidden layer.

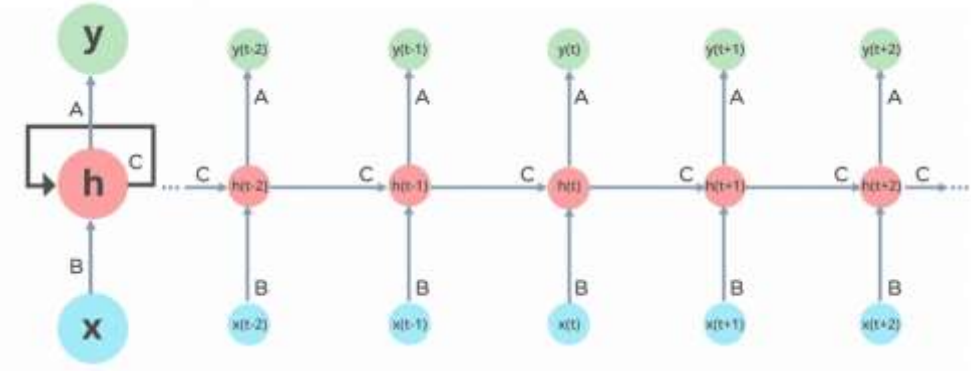


Figure 35. Working of RNN

The neural network's input is received by layer 'x', which processes it before sending it to middle layers. The middle layer ‘h’ can consist of multiple hidden layers, each with its own activation functions and weights and biases.

As the hidden layer has the same parameters, the recurrent neural network will standardize the various activation functions, weights, and biases. Then, it will create one hidden layer and loop over it as many times as necessary rather than multiple hidden layers.

RNN-GRU

RNNs with gated recurrent units (GRUs) were developed to solve some of the drawbacks of conventional RNNs. GRUs can better capture long-term dependencies in sequences than regular RNNs since they have a more complex architecture. GRUs can selectively understand or forget information from earlier time steps because they have "gates" that regulate the flow of information through the network.

The "update gate," which determines how much of the prior memory to keep and how much of the incoming input to add, is the fundamental component of a GRU. Additionally, there is a "reset gate," which chooses how much of the prior memory to erase. The output of the GRU is a weighted combination of the fresh input and the old memory from the update gate.

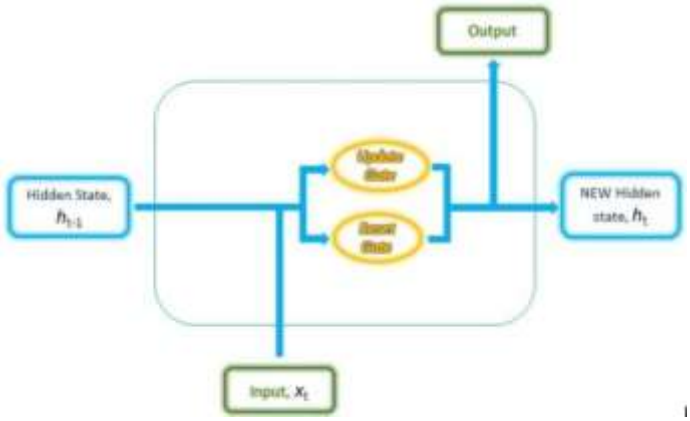


Figure 36. Overall structure of within a GRU cell

K-Nearest Neighbors

The k-nearest neighbors algorithm (k-NN) was created by Evelyn Fix and Joseph Hodges in 1951 and was later improved by Thomas Cover. It is a non-parametric supervised learning technique. It is used for classification and regression.

According to the KNN classification method, an item is categorized by a majority of its neighbours, with the object being given to the class that is most popular among its k nearest neighbours (k is a positive integer, often small). The object is simply put into the class of its one nearest neighbour if k = 1. The k-nearest neighbour algorithm's objective is to locate a query point's closest neighbours so that we can classify that point.

On a straight line the Euclidean Distance is the distance which is calculated between 2 points. Assuming the points to be (x1,y1) and (x2,y2) in a two-dimensional plane, the Euclidean distance is calculated as:

$$d = [(x1 – y1)2+ (x2 – y2)2]1/2$$

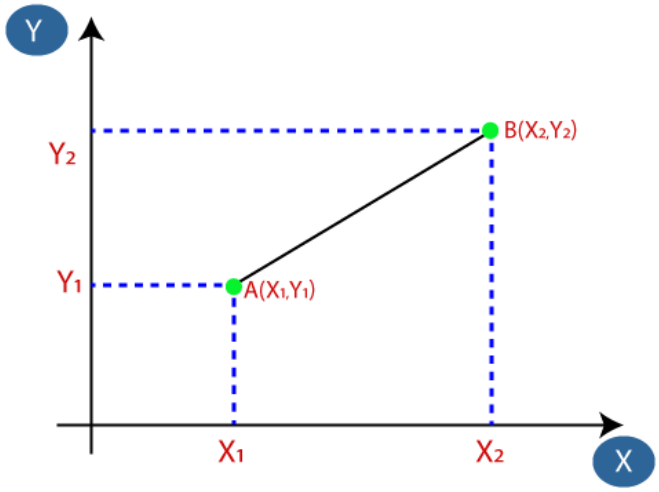


Figure 37. Euclidean Distance

where,

- (x11, y11) are the coordinates of one point.
- (x22, y22) are the coordinates of the other point.
- d is the distance between (x11, y11) and (x22, y22).

Decision Tree

A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks.

Decision trees are used to assist people in making decisions when based on a complex set of criteria or when analysing several options and their possible risks and advantages in a variety of disciplines, including business, finance, medicine, and computer science.

The decision tree consists of three types of nodes:

- Decision Nodes:

These nodes stand in for a choice that must be made. The decision-maker must select one of two or more possibilities at each decision node.

- Chance Nodes:

These nodes stand for an unpredictable event or result. The decision-maker must calculate the likelihood of each potential result at each chance node.

- Terminal Nodes:

The conclusion of the decision-making process is represented by these nodes. Each terminal node stands for a conclusion or output.

Random Forest classifier

A popular supervised learning approach for categorization issues is Random Forest. It is an ensemble method since it mixes the outcomes of various decision trees to boost prediction accuracy. To generate a Random Forest classifier, the algorithm first creates a collection of decision trees using a random portion of the training data and a random subset of the features. Each tree is trained individually to categorize the data.

The algorithm uses a majority vote of the expected class labels from all the trees to categorize a new data point after running it through each decision tree in the forest. By doing this, the Random Forest model is able to forecast outcomes more accurately than a single decision tree.

Chapter 6

Result and Conclusion

The Starting Phase of our project was more focused on the setting up of Hardware system that would collect the PPG and ECG signals from our subjects using the AFE4490 board and ADS1293 board respectively. Once the required hardware was ready we started the collection of data, however during this process we encountered some challenges that affected our process of collecting the data.

One of the main issues was the muscle movement, which can cause artefacts in the signal. Secondly the Electrical continuity or the ability of Electrodes to make good contact with the skin can cause interference in the signal.

As some of the Subjects were not able to be rest properly before collecting the data, there might be possibility that there might be noise generated in their collected data.

After we collected the PPG and ECG data from the same person, we calculated their HRV (Heart Rate Variability) for the classification purpose as It is an important indicator of overall cardiovascular health. We used PP intervals, which count the intervals between PPG signal peaks, to calculate HRV using PPG. Whereas for ECG we calculated the ECG's RR intervals from the QRS complex, which measure the intervals between R peaks.

In addition to this, we also downloaded an online dataset, which was tested for different Machine learning models like, K-nearest neighbour, Decision tree, Random Forest and RNN-GRU. After the execution of the online dataset on the K-nearest neighbour classifier we were

able to get a training accuracy of 95.7% and testing accuracy of 92.6%. Similarly on execution of the Decision tree classifier we got a training accuracy of 100% and testing accuracy of 91.6%. Also when tested for the Random Forest Classifier we obtained a training accuracy of 100% and testing accuracy of 97.1%. On execution of this data on RNN-GRU model we were able to get testing accuracy of 97.8%

The online database downloaded was the PTB Diagnostic ECG Database. The ECG signals were of Normal case and affected case.

- Number of samples: 14552
- Number of Categories: 2
- Sampling Frequency: 125Hz
- Data Source: Physionet's PTB Dianostic Database

Data Files

This dataset consists of a series of CSV files. Each of these CSV files contain a matrix, with each row representing an example in that portion of the dataset. The final element of each row denotes the class to which that example belongs.

Future Advancement

In our project we have acquired the ECG and PPG data samples of different subjects, which can be further used for classification. Starting from first we worked on the development of the hardware which will be used to capture the ECG and PPG data of the subjects, using these hardware setups we were able to capture the data from the subjects. Till now we have started the pre-processing of the data, different Machine learning algorithms tried for data pre-processing and classification are RNN-GRU, KNN, Decision tree and Random forest. The pre-processed data can be further used to differentiate between normal and abnormal on the bases of different factors such as HRV, QRS complex time etc. which evaluates the automatic nervous system regulation and can be used as a monitoring tool in conditions such as cardiovascular diseases, neuropathies and sleep staging . We can extract HRV from both ECG and PPG. On the basis of the values which we will be getting from calculating HRV, the classification can be done. We can also find heart rate, respiratory rate, pulse wave velocity from PPG. The combination of both the ECG and PPG could give us a more accurate and powerful machine leaning model which can be used for a lot of medical assistance.

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APPENDIX

1) Pre-processing of PPG signal

```
%%bash
git clone https://github.com/obss/biobss.git
cd biobss
pip install .

!pip install -U matplotlib
import shutil
from biobss import FIXTURES_ROOT
shutil.move("/content/biobss/sample_data",FIXTURES_ROOT.parent)

import biobss
import os
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import io

#PPG data sample
from google.colab import files
uploaded = files.upload()
fs = 100

df2 = pd.read_csv(io.BytesIO(uploaded['"name".csv']))
df2 = df2.reset_index(drop=True)
#segmentation
segment=df2.iloc[100:800,0]
plt.plot(segment)
```

```
#Filter PPG signal by defining the filter parameters
f_sig= biobss.preprocess.filter_signal(segment,sampling_rate=fs,filter_type='bandpass',N=2,f_lower=0.5,f_upper=5)
plt.plot(f_sig)

# Baseline
! pip install BaselineRemoval
from BaselineRemoval import BaselineRemoval
# baseline correction
polynomial_degree=2 #only needed for Modpoly and IModPoly algorithm
#baseObj=BaselineRemoval(segment)
baseObj=BaselineRemoval(f_sig)
Modpoly_output_O=baseObj.ModPoly(polynomial_degree)
plt.plot(Modpoly_output_O,color="blue")

# peak detection for filtered wave
from scipy.signal import find_peaks
x= Modpoly_output_O
plt.plot(x)
peaks_p, _ = find_peaks(x, height=30000)
#peaks_n, _ = find_peaks(-x, height=0)

#plt.plot(Modpoly_output,color="orange")
plt.plot(peaks_p, x[peaks_p], "o",color="black",label="Peaks")
#plt.plot(peaks_n, x[peaks_n], "o",color="red",label="Valleys")
plt.plot(np.zeros_like(x), "--", color="grey")
plt.show()
```

2) Pre-processing of ECG signal

```
%%bash
git clone https://github.com/obss/biobss.git
cd biobss
pip install .

!pip install -U matplotlib
import shutil
from biobss import FIXTURES_ROOT
shutil.move("/content/biobss/sample_data",FIXTURES_ROOT.parent)

import biobss
import os
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import neurokit2

from google.colab import files
uploaded = files.upload()
fs = 100
import io
df2 = pd.read_csv(io.BytesIO(uploaded[”’name”.csv']))
df2 = df2.reset_index(drop=True)
plt.plot(df2)
```

Filter ECG signal by defining the filter parameters

```
f_sig= biobss.preprocess.filter_signal(sig=df2, sampling_rate=fs, filter_type='bandpass',N=2,
f_lower=1,f_upper=5)
plt.plot(f_sig)
```

```
# Baseline without filter
! pip install BaselineRemoval
from BaselineRemoval import BaselineRemoval
df=df2.iloc[:,0]
# baseline correction
polynomial_degree=2 #only needed for Modpoly and IModPoly algorithm
baseObj=BaselineRemoval(df)
Modpoly_output=baseObj.ModPoly(polynomial_degree)
plt.plot(Modpoly_output,color="blue")

# Baseline with filter
! pip install BaselineRemoval
from BaselineRemoval import BaselineRemoval
df=f_sig
# baseline correction
polynomial_degree=2 #only needed for Modpoly and IModPoly algorithm
baseObj=BaselineRemoval(df)
Modpoly_output=baseObj.ModPoly(polynomial_degree)
plt.plot(Modpoly_output,color="orange")

# peak detection
from scipy.signal import find_peaks
x= Modpoly_output_O
plt.plot(x)
peaks_p, _ = find_peaks(x, height=0.0005)
#peaks_n, _ = find_peaks(-x, height=-10000)

#plt.plot(Modpoly_output,color="orange")
plt.plot(peaks_p, x[peaks_p], "o",color="black",label="Peaks")
```

```
#plt.plot(peaks_n, x[peaks_n], "o",color="red",label="Valleys")
plt.plot(np.zeros_like(x), "--", color="grey")
plt.show()
```

3) Classification Using RNN-GRU

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import tensorflow as tf

dfs = [pd.read_csv('C:/Users/Admin/Desktop/classification files/normal,abnormal/ptbdb_' + x
+ '.csv') for x in ['normal', 'abnormal']]

for df in dfs:
    df.columns = list(range(len(df.columns)))

data = pd.concat(dfs, axis=0).sample(frac=1.0, random_state=1).reset_index(drop=True)

data = data.rename({187: 'Label'}, axis=1)

y = data['Label'].copy()
X = data.drop('Label', axis=1).copy()
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)

inputs = tf.keras.Input(shape=(X_train.shape[1],))

expand = tf.expand_dims(inputs, axis=2)
gru = tf.keras.layers.GRU(256, return_sequences=True)(expand)
flatten = tf.keras.layers.Flatten()(gru)
```

```
outputs = tf.keras.layers.Dense(1, activation='sigmoid')(flatten)
model = tf.keras.Model(inputs=inputs, outputs=outputs)
print(model.summary())

model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=[
        'accuracy',
        tf.keras.metrics.AUC(name='auc')
    ]
)

history = model.fit(
    X_train,
    y_train,
    validation_split=0.2,
    batch_size=32,
    epochs=100,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        )
    ]
)
results = model.evaluate(X_test, y_test, verbose=0)
print("Test Accuracy: {:.2f}%".format(results[1] * 100))
print("     Test AUC: {:.4f}".format(results[2]))
```

4) Classification Using Decision tree, KNN, Random forest

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

dfs = [pd.read_csv('C:/Users/Admin/Desktop/classificationfiles/normal,abnormal/ptbdb_' + x
+ '.csv') for x in ['normal', 'abnormal']]

for df in dfs:
    df.columns = list(range(len(df.columns)))

data = pd.concat(dfs, axis=0).sample(frac=1.0, random_state=1).reset_index(drop=True)
data = data.rename({187: 'Label'}, axis=1)

y = data['Label'].copy()
X = data.drop('Label', axis=1).copy()
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)

dec_tree_model = DecisionTreeClassifier(random_state=0)
dec_tree_model.fit(X_train, y_train)
predicted = dec_tree_model.predict([X_test.iloc[0,:]])
 print('predict value using the DecisionTreeClassifier model: ', end='')
 print(predicted)
 print('The true value: ',end='')
 print(y_test.iloc[0])
```

```
print(f'The accuracy of the DecisionTreeClassifier model on train data =
        {dec_tree_model.score(X_train,y_train)*100:.5}%')

print(f'The accuracy of the DecisionTreeClassifier model on test data =
        {dec_tree_model.score(X_test,y_test)*100:.3}%')
```

#KNN

```
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)

predicted = knn_model.predict([X_test.iloc[0,:]])
print('predict value using the knn model: ', end='')
print(predicted)
print('The true value: ',end='')
print(y_test.iloc[0])

print(f'The accuracy of the knn model on train data =
        {knn_model.score(X_train,y_train)*100:.3}%')

print(f'The accuracy of the knn model on test data =
        {knn_model.score(X_test,y_test)*100:.3}%')
```

#Random Forest

```
from sklearn.ensemble import RandomForestClassifier

rand_model = RandomForestClassifier()
rand_model.fit(X_train, y_train)

rand_model = RandomForestClassifier()
```

```
rand_model.fit(X_train, y_train)


predicted = rand_model.predict([X_test.iloc[0,:]])
print('predict value using the knn model: ', end='')
print(predicted)
print('The true value: ',end='')
print(y_test.iloc[0])


print(f'The accuracy of the knn model on train data =
      {rand_model.score(X_train,y_train)*100:.5}%')


print(f'The accuracy of the knn model on test data =
      {rand_model.score(X_test,y_test)*100:.3}%')
```