



# **Cuffless Blood Pressure Estimation**

## **MINIPROJECT REPORT**

submitted by

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of

Bachelor of Technology  
in  
Electronics and Communication Engineering



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## CERTIFICATE

This is to certify that, the report titled “ **Cuffless Blood Pressure Estimation**” is a bonafide account of the **ECD 334: MINI PROJECT** presented by **Mr. Aravind T S, (Reg.No: LMDL19EC133), Mr. Rizwan Mohammed, (Reg.No: MDL19EC097 ), Mr Sajio C S , (Reg.No: MDL19EC105 ), Mr. Syam Joseph, (Reg.No:MDL19EC120)**, Sixth Semester B. Tech in Electronics and Communication, in partial fulfillment of the requirements for the award of the Bachelor’s degree, **B. Tech in Electronics and Communication Engineering** from APJ Abdul Kalam Technological University during the academic year 2021-2022.

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# ABSTRACT

Measurement of arterial blood pressure (BP) by the brachial cuff sphygmomanometer has been a cornerstone of modern medicine, and notwithstanding its limitations of intermittent BP monitoring, the cuff sphygmomanometer has not been surpassed by any other noninvasive methodology. However, advances in sensor technology for arterial pulse detection have paved the way for the potential development of devices for cuffless measurement of BP, with the prospect of continuous monitoring. Here we get the ECG and PPG using respective sensors. Do the necessary scaling and send through the bluetooth module in Arduino and feed the input to a ML model to a website in mobile application. The ML model to predict BP is deployed on the Website. Also the mobile application has an added feature of breathing exercise which helps you to reduce stress. We can also read more about ECG, PPG and BP on the application. As a future development and scope we can add sleep monitoring, deep sleep patterns and its effect on BP can be measured.

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# List of Abbreviations

<b>BP</b>	Blood pressure
<b>ECG</b>	Electrocardiogram
<b>PPG</b>	Photoplethysmography
<b>API</b>	Application programming interface
<b>AMMI</b>	Association for the Advancement of Medical Instrumentation
<b>ISO</b>	International Organization for Standardization

## Chapter 1

### INTRODUCTION

Blood Pressure (BP) is one of the most important physiological indicators that provides useful information in the field of health-care monitoring. Blood pressure may be measured by both invasive and non-invasive methods. Cuffless blood pressure (BP) measurement is an all-inclusive term for a method that aims to measure BP without using a cuff. However, BP is conventionally measured using inconvenient cuff-based instruments, which prevents continuous BP monitoring. Recent cuffless technology has made it possible to estimate BP with reasonable accuracy.

An electrocardiogram (ECG) is a simple test that can be used to check your heart's rhythm and electrical activity. Sensors attached to the skin are used to detect the electrical signals produced by your heart each time it beats.

Photoplethysmography (PPG) is an uncomplicated and inexpensive optical measurement method that is often used for heart rate monitoring purposes. PPG is a non-invasive technology that uses a light source and a photodetector at the surface of skin to measure the volumetric variations of blood circulation.

Electrocardiogram (ECG) is one of the best indicators for the assessment of physical health and heart function, while photoplethysmography (PPG) uses light sensor to detect the change of blood volume in the vessel, and is thus less susceptible to power supply noise and electromagnetic interference.

The project demonstrates cuffless measurement of BP, with the prospect of continuous monitoring. Here we get the ECG and PPG using the respective sensors in Arduino and send the same through a Bluetooth module to the mobile application. Inputs from the android app, hit the API (which contains the pickled format of our ML model, API will accept the data measured from a user and pass it to the machine learning model which will predict the output), and the response from the API display back in the Android app. The application displays the predicted BP. Real time ECG and PPG is also available in the app. Cuff less blood pressure monitoring allows us to continuously monitor an individual's blood pressure. This feature will be immensely useful particularly in the sports industries for the evaluation of their athletes. The supporting mobile application will be helpful for all its users as it provides tips for a healthy lifestyle and also has a breathing exercise feature for relaxation.

## Chapter 2

### LITERATURE SURVEY

Many models have been proposed to predict Blood Pressure Although the literature covers a wide variety of such models, this review will focus on major themes which emerge repeatedly throughout the literature reviewed.

#### **Real-Time Cuffless Continuous Blood Pressure Estimation Using Deep Learning Model**

[1]Blood pressure monitoring is one avenue to monitor people's health conditions. Early detection of abnormal blood pressure can help patients to get early treatment and reduce mortality associated with cardiovascular diseases. Therefore, it is very valuable to have a mechanism to perform real-time monitoring for blood pressure changes in patients. In this paper, we propose deep learning regression models using an electrocardiogram (ECG) and photoplethysmogram (PPG) for the real-time estimation of systolic blood pressure (SBP) and diastolic blood pressure (DBP) values. We use a bidirectional layer of long short-term memory (LSTM) as the first layer and add a residual connection inside each of the following layers of the LSTMs. We also perform experiments to compare the performance between the traditional machine learning methods, another existing deep learning model, and the proposed deep learning models using the dataset of Physionet's multiparameter intelligent monitoring in intensive care II (MIMIC II) as the source of ECG and PPG signals as well as the arterial blood pressure (ABP) signal. The results show that the proposed model outperforms the existing methods and is able to achieve accurate estimation which is promising in order to be applied in clinical practice effectively

## Cuffless Blood Pressure Estimation Using Single Channel Photoplethysmography: A Two-Step Method

[2] Traditional cuff-based blood pressure (BP) monitoring procedure causes inconvenience and discomfort to the users. To overcome these limitations, cuffless BP estimation based on pulse transit time (PTT) and single-channel photoplethysmography (PPG) has been proposed. However, existing studies based on PTT and PPG for BP estimation did not achieve AAMI/ISO standard criteria for BP measurement (mean difference within  $\pm 5$  mmHg and SD of difference within  $\pm 8$  mmHg) under each BP category (Hypotensive, Normotensive and Hypertensive). This study aims to validate an innovative two-step method for PPG-based cuffless BP estimation. A combined database was derived from two online databases (Queensland and MIMIC II) to cover a wide range of corresponding BPs. In total, there were 18010 raw PPG signal segments (5 seconds for each) with corresponding BPs, separated into two halves for training and testing of algorithms (independent datasets). Each PPG signal segment was pre-processed to extract 16 signal features. Later, three significant features have been selected using multicollinearity test. The traditional generic (trained with uncategorized BP) algorithm and two-step algorithm (specifically optimized for each BP category) were developed using machine learning. Generally, the two-step algorithm achieved the AAMI/ISO standard in estimating systolic BP (mean  $\pm$ SD:  $0.07 \pm 7.1$  mmHg,  $p_i$ ; 0.001) and diastolic BP ( $-0.08 \pm 6.0$  mmHg,  $p_i$ ; 0.001). Categorically, the two-step method also achieved standard accuracy in all BP categories except Hypotensive systolic BP whereas generic algorithm did not conform to standard accuracy in any BP category except Hypotensive diastolic BP and Normotensive categories. Compared to the traditional generic algorithm, the two-step algorithm specifically designed for three different BP category patients and achieved standard accuracy for cuffless BP estimation.

## **Investigation on the effect of Womersley number, ECG and PPG features for cuffless blood pressure estimation using machine learning**

[3]Regulation and inhibition of high blood pressure, known as hypertension are intricate, and it demands a continuous, accurate blood pressure measurement system. All the existing continuous non-invasive techniques own challenges such as exact placement of the sensor, reconstruction of arterial pressure from finger cuff, frequent and subject based calibration. This paper presents an algorithm based on new time-domain features for continuous blood pressure monitoring which is crucial in intensive care units and can be used to predict cardiovascular ailments. Here, we propose the method to estimate BP that extracts informative features like Womersley number ( $\alpha$ ), QRS, QTc interval, SDI from ECG and PPG signals and regression techniques which are employed to estimate blood pressure continuously. Performance metrics like MAE, RMSE,  $r$ , bias 95

## **Non-invasive cuff-less blood pressure estimation using a hybrid deep learning model**

[4]Conventional blood pressure (BP) measurement methods have different drawbacks such as being invasive, cuff-based or requiring manual operations. There is significant interest in the development of non-invasive, cuff-less and continual BP measurement based on physiological measurement. However, in these methods, extracting features from signals is challenging in the presence of noise or signal distortion. When using machine learning, errors in feature extraction result in errors in BP estimation, therefore, this study explores the use of raw signals as a direct input to a deep learning model. To enable comparison with the traditional machine learning models which use features from the photoplethysmogram and electrocardiogram, a hybrid deep learning model that utilizes both raw signals and physical characteristics (age, height, weight and gender) is developed. This hybrid model performs best in terms of both diastolic BP (DBP) and systolic BP (SBP) with the mean absolute error being  $3.23 \pm 4.75$  mmHg and  $4.43 \pm 6.09$  mmHg respectively. DBP and SBP meet the Grade A and Grade B performance requirements of the British Hypertension Society respectively.

## Chapter 3

# SYSTEM ARCHITECTURE

### 3.1 ARDUINO

The Arduino UNO R3 is the perfect board to get familiar with electronics and coding as shown in Figure 3.1. This versatile microcontroller is equipped with the well-known ATmega328P and the ATmega 16U2 Processor. This board will give you a great first experience within the world of Arduino.

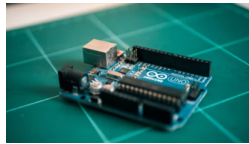


Figure 3.1: Arduino

#### 3.1.1 Features of ATmega328P Processor

##### 1. Memory

- AVR CPU at up to 16 MHz
- 32KB Flash
- 2KB SRAM
- 1KB EEPROM
- security
- Power On Reset (POR)
- Brown Out Detection (BOD)



## 2. peripherals

- 2x 8-bit Timer/Counter with a dedicated period register and compare channels
- 1x 16-bit Timer/Counter with a dedicated period register input capture and compare channels
- 1x USART with fractional baud rate generator and start-of-frame detection
- 1x controller/peripheral Serial Peripheral Interface (SPI)
- 1x Dual mode controller/peripheral I2C
- x Analog Comparator (AC) with a scalable reference input
- Watchdog Timer with separate on-chip oscillator
- Six PWM channels
- Interrupt and wake-up on pin change

### 3.1.2 Functional Overview of arduino board

#### 1. Board Topology

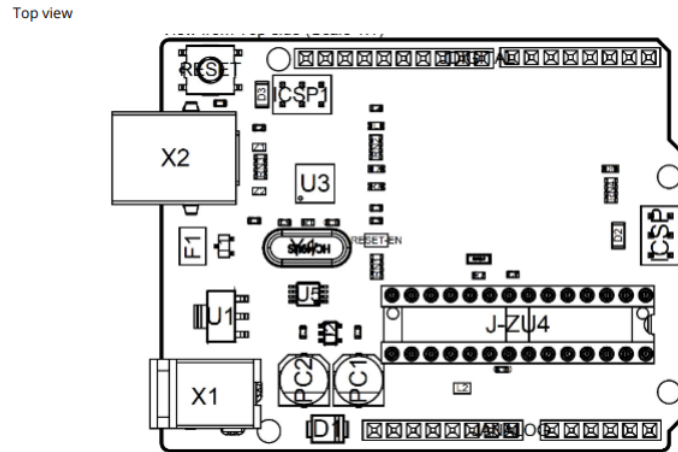


Figure 3.2: Board Topology of arduino

## 2. Processor

The Main Processor is a ATmega328P running at up to 20 MHz. Most of its pins are connected to the external headers, however some are reserved for internal communication with the USB Bridge coprocessor.

## 3. Power Tree of arduino

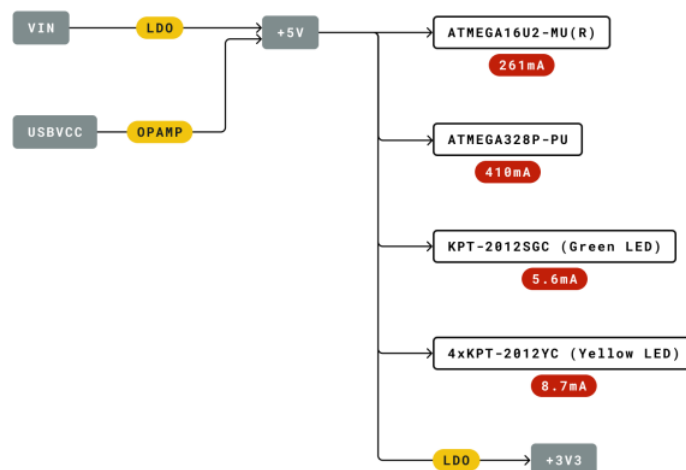


Figure 3.3: power tree of arduino

#### 4. Connector Pinouts

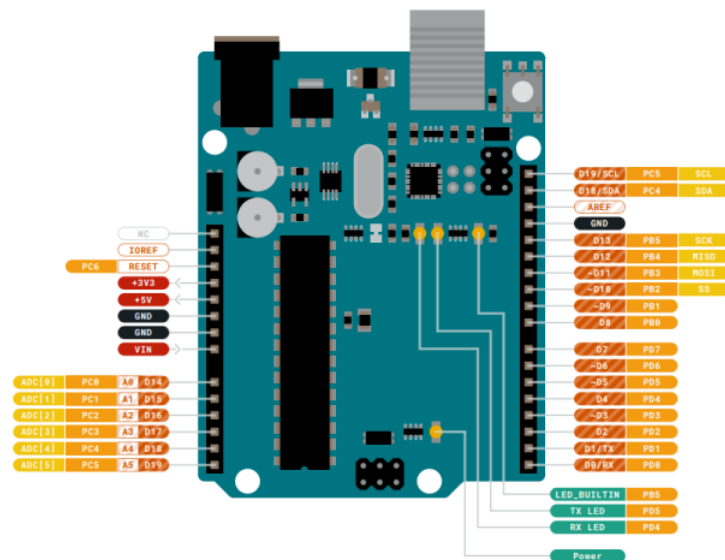


Figure 3.4: pinout diagram of arduino

### 3.2 Bluetooth

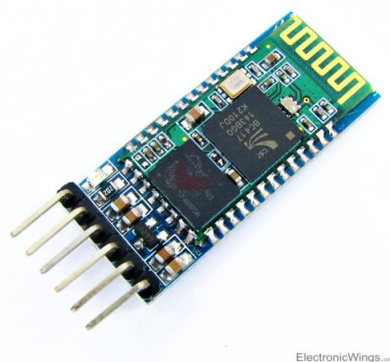


Figure 3.5: Bluetooth module

Bluetooth is a wireless technology standard used for exchanging data between fixed and mobile devices over short distances using short-wavelength UHF radio waves in the industrial, scientific and medical radio bands, from 2.402 GHz to 2.480 GHz, and building personal area networks (PANs). It was originally conceived as a wireless alternative to RS-232 data cables. Bluetooth is managed by the Bluetooth Special Interest Group (SIG), which has more than 35,000 member companies in the areas of telecommunication, computing, networking, and consumer electronics. The IEEE standardized

### **Communication and connection**

A master BR/EDR Bluetooth device can communicate with a maximum of seven devices in a piconet (an ad-hoc computer network using Bluetooth technology), though not all devices reach this maximum. The devices can switch roles, by agreement, and even the slave can become the master (for example, a headset initiating a connection to a phone necessarily begins as master—as an initiator of the connection—but may subsequently operate as the slave). The Bluetooth Core Specification provides for the connection of two or more piconets to form a scatternet, in which certain devices simultaneously play the master role in one piconet and the slave role in another. . At any given time, data can be transferred between the master and one other device (except for the little-used broadcast mode). The master chooses which slave device to address; typically, it switches rapidly from one device to another in a round-robin fashion. Since it is the master that chooses which slave to address, whereas a slave is (in theory) supposed to listen in each receive slot, being a master is a lighter burden than being a slave. Being a master of seven slaves is possible; being a slave of more than one master is

possible. The specification is vague as to required behavior in scatternets. The specifications were formalized by the Bluetooth Special Interest Group (SIG) and formally announced on 20 May 1998.[60] Today it has a membership of over 30,000 companies worldwide.[61] It was established by Ericsson, IBM, Intel, Nokia and Toshiba, and later joined by many other companies. All versions of the Bluetooth standards support downward compatibility.[62] That lets the latest standard cover all older versions.

- The Bluetooth Core Specification Working Group (CSWG) produces mainly 4 kinds of specifications
- The Bluetooth Core Specification, release cycle is typically a few years in between
- Core Specification Addendum (CSA), release cycle can be as tight as a few times per year
- Core Specification Supplements (CSS), can be released very quickly
- Errata (Available with a user account: Errata login)

### 3.2.1 Bluetooth 5

The Bluetooth SIG released Bluetooth 5 on 6 December 2016. Its new features are mainly focused on new Internet of Things technology. Sony was the first to announce Bluetooth 5.0 support with its Xperia XZ Premium in Feb 2017 during the Mobile World Congress 2017. The Samsung Galaxy S8 launched with Bluetooth 5 support in April 2017. In September 2017, the iPhone 8, 8 Plus and iPhone X launched with Bluetooth 5 support as well. Apple also integrated Bluetooth 5 in its new HomePod offering released on 9 February 2018. Marketing drops the point number; so that it is just

”Bluetooth 5” (unlike Bluetooth 4.0).[citation needed] The change is for the sake of ”Simplifying our marketing, communicating user benefits more effectively and making it easier to signal significant technology updates to the market.” Bluetooth 5 provides, for BLE, options that can double the speed (2 Mbit/s burst) at the expense of range, or up to fourfold the range at the expense of data rate. The increase in transmissions could be important for Internet of Things devices, where many nodes connect throughout a whole house. Bluetooth 5 adds functionality for connectionless services such as location-relevant navigation[98] of low-energy Bluetooth connections. The major areas of improvement are:

The Bluetooth Core Specification, release cycle is typically a few years in between

Slot Availability Mask (SAM)

Mbit/s PHY for LE

LE Long Range High Duty Cycle Non-Connectable Advertising

LE Advertising Extensions

LE Channel Selection Algorithm

### **3.2.2 Bluetooth 5.2**

On 31 December 2019, the Bluetooth SIG published the Bluetooth Core Specification Version 5.2. The new specification adds new features:

LE Audio: Announced in January 2020 at CES by the Bluetooth SIG,

LE Audio will run on the Bluetooth Low Energy radio lowering battery

consumption, and allow the protocol to carry sound and add features such as one set of headphones connecting to multiple audio sources or multiple headphones connecting to one source. It uses a new LC3 codec. BLE Audio will also add support for hearing aids.

- Enhanced Attribute Protocol (EATT), an improved version of the Attribute Protocol (ATT)
- LE Power Control
- LE Isochronous Channels

### 3.3 AD8232 Sensor



Figure 3.6: AD8232 Sensor

The AD8232 is an integrated signal conditioning block for ECG and other biopotential measurement applications. It is designed to extract, amplify, and filter small biopotential signals in the presence of noisy conditions, such as those created by motion or remote electrode placement. This design allows for an ultralow power analog-to-digital converter (ADC) or an embedded microcontroller to acquire the output signal easily. The AD8232 can implement a two-pole high-pass filter for eliminating motion artifacts and the electrode

half-cell potential. This filter is tightly coupled with the instrumentation architecture of the amplifier to allow both large gain and high-pass filtering in a single stage, thereby saving space and cost. An uncommitted operational amplifier enables the AD8232 to create a three-pole low-pass filter to remove additional noise. The user can select the frequency cutoff of all filters to suit different types of applications. To improve common-mode rejection of the line frequencies in the system and other undesired interferences, the AD8232 includes an amplifier for driven lead applications, such as right leg drive (RLD). The AD8232 includes a fast restore function that reduces the duration of otherwise long settling tails of the high-pass filters. After an abrupt signal change that rails the amplifier (such as a leads off condition), the AD8232 automatically adjusts to a higher filter cutoff. This feature allows the AD8232 to recover quickly, and therefore, to take valid measurements soon after connecting the electrodes to the subject.

### 3.3.1 Features

- Fully integrated single-lead ECG front end
- Low supply current: 170  $\mu\text{A}$  (typical)
- Common-mode rejection ratio: 80 dB (dc to 60 Hz)
- Two or three electrode configurations
- High signal gain ( $G = 100$ ) with dc blocking capabilities
- 2-pole adjustable high-pass filter
- Accepts up to  $\pm 300$  mV of half cell potential
- Fast restore feature improves filter settling



- Uncommitted op amp
- 3-pole adjustable low-pass filter with adjustable gain
- Leads off detection: ac or dc options
- Integrated right leg drive (RLD) amplifier
- Single-supply operation: 2.0 V to 3.5 V
- Integrated reference buffer generates virtual ground
- Rail-to-rail output
- Internal RFI filter
- 8 kV HBM ESD rating
- Shutdown pin
- 20-lead, 4 mm × 4 mm LFCSP and LFCSP-SS package
- Qualified for automotive applications

### 3.3.2 Applications

- Fitness and activity heart rate monitors
- Portable ECG
- Remote health monitors
- Gaming peripherals
- Biopotential signal acquisition

### 3.3.3 Functional Block Diagram of AD8232 Sensor

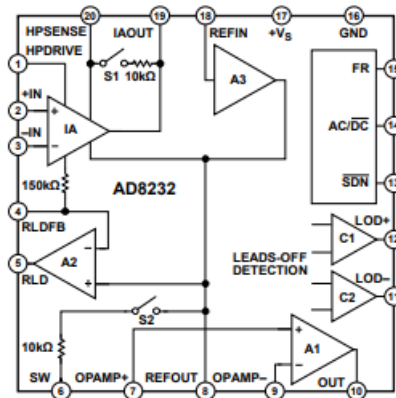


Figure 3.7: Block Diagram of AD8232 Sensor

### 3.3.4 Pin Configuration of AD8232 Sensor

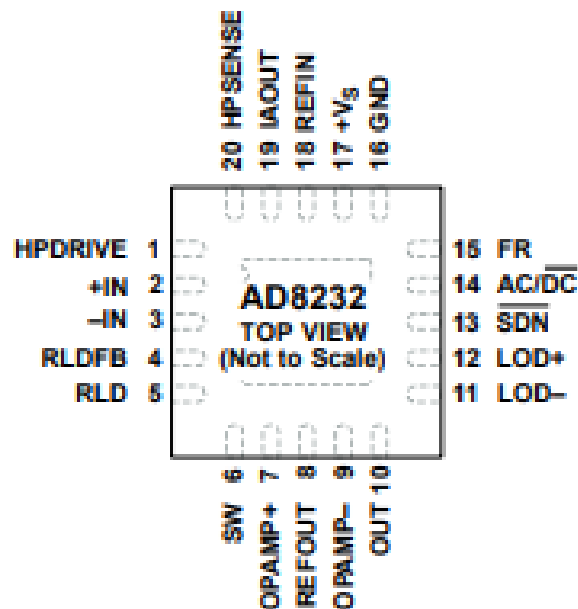


Figure 3.8: pin configuration of AD8232 Sensor

## 3.4 Pulse Sensor-Sen11574

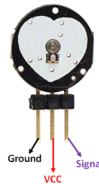


Figure 3.9: Pulse Sensor-Sen11574

The Pulse Sensor is a plug-and-play heart-rate sensor for Arduino. It can be used by students, artists, athletes, makers, and game mobile developers who want to easily incorporate live heart-rate data into their projects. It essentially combines a simple optical heart rate sensor with amplification and noise cancellation circuitry making it fast and easy to get reliable pulse readings. Also, it sips power with just 4mA current draw at 5V so it's great for mobile applications. Simply clip the Pulse Sensor to your earlobe or finger tip and plug it into your 3 or 5 Volt Arduino and you're ready to read heart rate! The 24" cable on the Pulse Sensor is terminated with standard male headers so there's no soldering required. Of course Arduino example code is available as well as a Processing sketch for visualizing heart rate data.

### 3.4.1 Features and Specifications

- Biometric Pulse Rate or Heart Rate detecting sensor
- Plug and Play type sensor
- Operating Voltage: +5V or +3.3V
- Current Consumption: 4mA

- Inbuilt Amplification and Noise cancellation circuit.
- Diameter: 0.625"
- Thickness: 0.125" Thick

### 3.4.2 Working

The working of the Pulse/Heart beat sensor is very simple. The sensor has two sides, on one side the LED is placed along with an ambient light sensor and on the other side we have some circuitry. This circuitry is responsible for the amplification and noise cancellation work. The LED on the front side of the sensor is placed over a vein in our human body. This can either be your Finger tip or you ear tips, but it should be placed directly on top of a vein.

Now the LED emits light which will fall on the vein directly. The veins will have blood flow inside them only when the heart is pumping, so if we monitor the flow of blood we can monitor the heart beats as well. If the flow of blood is detected then the ambient light sensor will pick up more light since they will be reflected by the blood, this minor change in received light is analysed over time to determine our heart beats.

## Chapter 4

### SYSTEM DESIGN

The blood pressure estimation system proposed is implemented using a mobile application that is connected to a website in which the ML model is deployed. The system helps user to get the estimated blood pressure. Figure 4.1 shows the block-diagram of the system.

This system consists of an Arduino UNO R3 that is used to collect ECG and PPG values and send it through Bluetooth module to mobile application, which in turn can be entered in the website to get the BP values.

Arduino is powered with a powerbank for portability. Also if BP is high user can use the feature of Breathing Exercise to relax, Application also suggests health tips for good health and well being. The overall system is embedded in a cardboard box casing for easy portability and usage.

## 4.1 Block Diagram

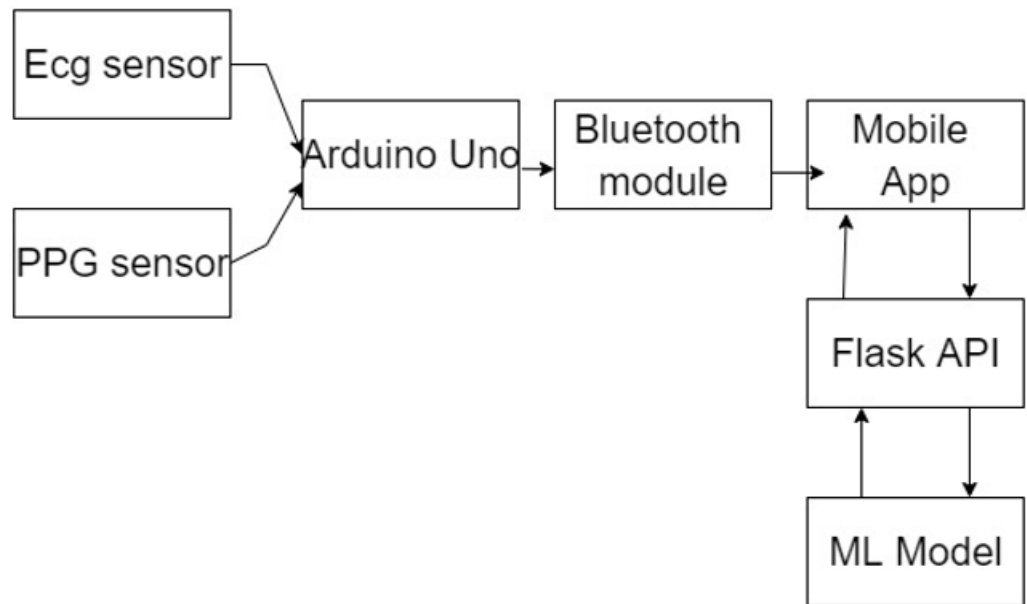


Figure 4.1: Block diagram

The analog ECG sensor AD 8232, the pulse sensor collects the sensor data and send it to arduino then through bluetooth send to mobile application. The resulted values can be entered manually to get the predicted BP values in a website.

## 4.2 Circuit Diagram

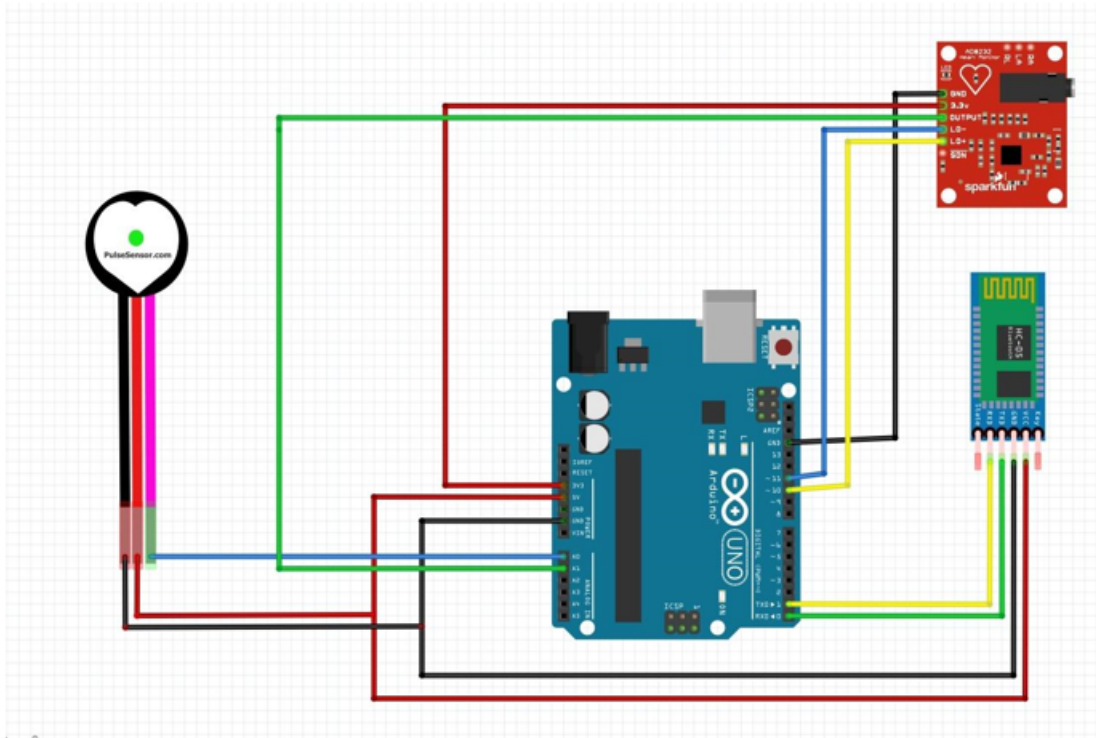


Figure 4.2: Circuit Diagram of hardware setup

Connection diagram shows the physical connections between Arduino UNO R3, ECG sensor AD8232, Pulse sensor and HC-05 Bluetooth module. Arduino is powered with a powerbank for portability.

## Chapter 5

### RESULT

The proposed system achieved all the objectives of the project that were stated. If an Electrocardiogram ECG and Photoplethysmography PPG values are given to the ML model, we get the predicted Blood Pressure value.

A mobile application in which receives the ECG and PPG values, which also provides the user with a feature of Breathing exercise for relaxation. The Mobile application can also be used to get Health tips, read about Electrocardiogram (ECG) and Photoplethysmography (PPG).

### Circuit setup

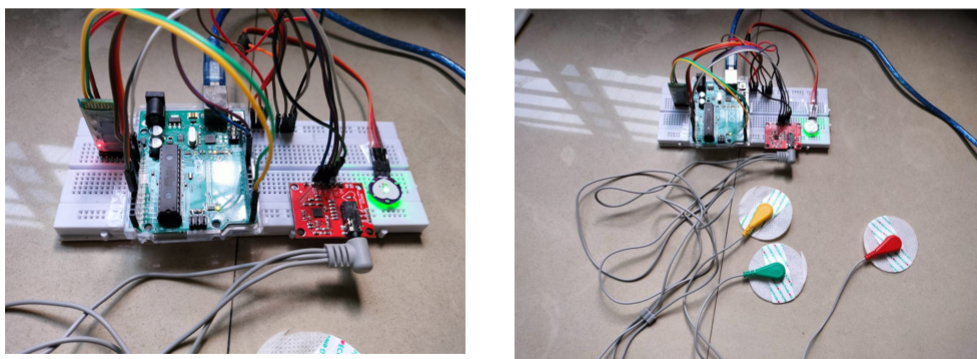


Figure 5.1: Cuff less blood pressure monitor system



## 5.1 ECG Output

The Figure 5.2 shown below shows the ECG output when tested in two condition the first one in relaxed state, and the second one in a tensed or heart rate increased state. This results were obtained in the testing phase of sensors.

### ECG output values

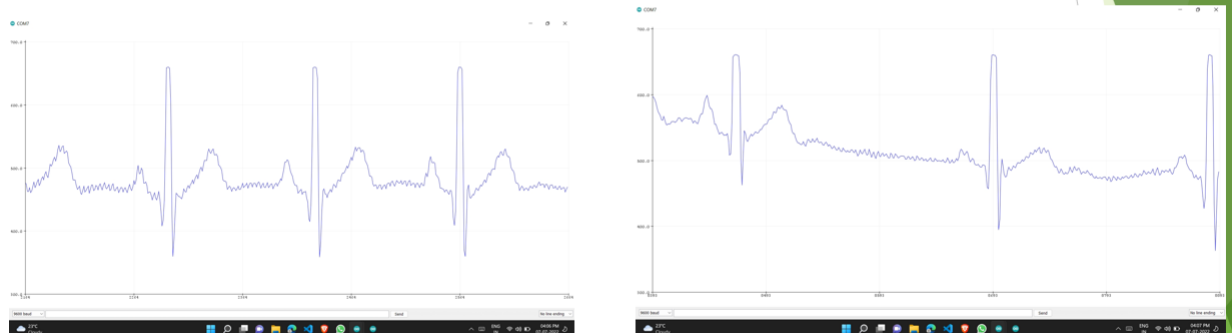


Figure 5.2: ECG Output

## 5.2 Pulse Sensor

The Figure 5.3 shown below shows the PPG output when tested in two condition the first one in relaxed state, and the second one just as the finger is removed from the sensor. The heightened pulse peak shows the exact time in which hand is removed and placed again. After a particular transient time the signal acquires its steady state. This results were obtained in the testing phase of sensors.

### Pulse sensor output values

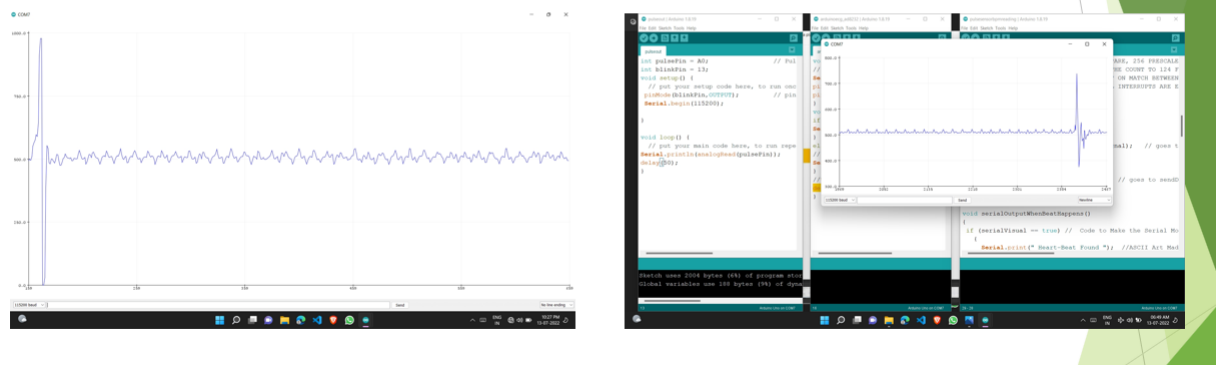


Figure 5.3: pulse sensor output

## 5.3 App Interface

The Figure 5.4 shows the Application interface. First the introduction page, then information about ECG, then home page of the application, then information about PPG, then values received, then health tips, then breathing exercise at last the developers info is also displayed.

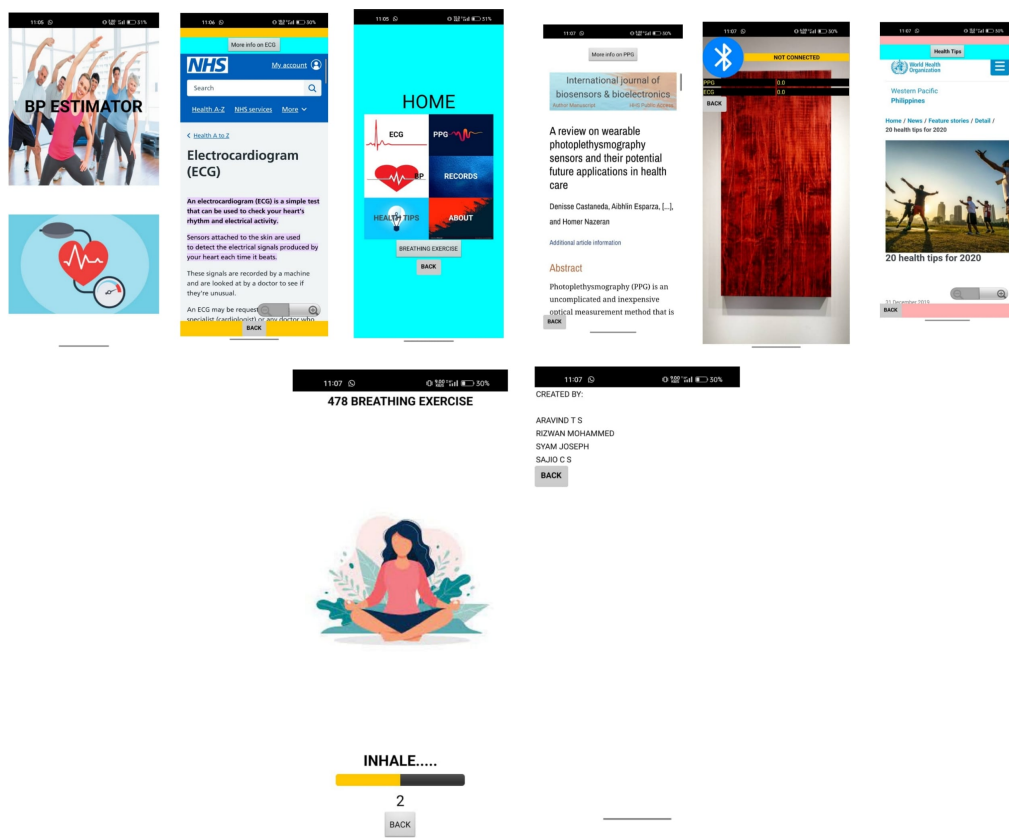


Figure 5.4: App Interface

## Chapter 6

### CONCLUSION

Accurate continuous blood pressure is important to understand the changes in BP and heart rate, the BP distribution pattern and other statistics are calculated. Currently the only continuous monitoring system is Ambulatory BP monitoring which yields many readings over a continuous period. In most cases, readings are taken every 20 to 30 minutes during the day and every hour at night. Your heart rate can be measured at the same time. These multiple readings are averaged over the 24-hour period. but with our method we can estimate blood pressure non-invasively every 1 second compared to 20-30 minutes and the average over the 24-hour period will be more precise and accurate. In this paper, the design, implementation, accurate and cost effective "cuffless blood pressure estimation" have been presented. This system uses the AD8232 ECG sensor to measure ECG and pulse sensor to measure PPG which in turn predicts the BP. This system is unique and requires no set-up. It is capable of predicting the accurate BP. This project helped us to be good with teamwork and made us deal with practical issues while doing a project. It makes us prepare to be work on the industry level.

**Development and deployment:** This project can be developed into a wearable watch which predicts BP, monitors sleep patterns and deep sleep quality. **Automated estimation:** This project can be automated to continuously send the ECG and PPG values automatically to the website for BP prediction. This project can be enhanced for tracking heart rate variability, ECG vari-

ations and even detect heart diseases from the abnormal ECG. This way of continuous BP monitoring can be used throughout the day to measure and find abnormality in BP throughout the measurement period for easy detection of diseases and to provide a detailed report to doctors.

# References

- [1] Y.-H. Li, L. N. Harfiya, K. Purwandari, and Y.-D. Lin, "Real-Time Cuffless Continuous Blood Pressure Estimation Using Deep Learning Model," *Sensors*, vol. 20, no. 19, p. 5606, Sep. 2020, doi: 10.3390/s20195606.
- [2] S. G. Khalid, H. Liu, T. Zia, J. Zhang, F. Chen and D. Zheng, "Cuffless Blood Pressure Estimation Using Single Channel Photoplethysmography: A Two-Step Method," in *IEEE Access*, vol. 8, pp. 58146-58154, 2020, doi: 10.1109/ACCESS.2020.2981903.
- [3] Geerthy Thambiraj, Uma Gandhi, Umapathy Mangalanathan, V. Jeya Maria Jose, M. Anand, "Investigation on the effect of Womersley number, ECG and PPG features for cuff less blood pressure estimation using machine learning", Volume 60, 2020,101942,ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2020.101942>.
- [4] Yang, S., Zhang, Y., Cho, SY. et al. "Non-invasive cuff-less blood pressure estimation using a hybrid deep learning model. " *Opt Quant Electron* 53, 93 (2021). <https://doi.org/10.1007/s11082-020-02667-0>

## Appendix A

### ARDUINO CODE

```
#include<SoftwareSerial.h>
int RX_pin=4;
int TX_pin=2;
SoftwareSerial BTserial(RX_pin,TX_pin);
String Arduino_data;
int pulsePin = A0;
int ecgout = A1;
void setup() {
    // put your setup code here, to run once:
    Serial.begin(9600);
    BTserial.begin(38400);
    pinMode(10, INPUT); // Setup for leads off detection L0 +
    pinMode(11, INPUT); // Setup for leads off detection L0 -
}
void loop() {

    if(((digitalRead(10) == 1)||(digitalRead(11) == 1))){
        char buffer4[7];
        dtostrf(analogRead(pulsePin)*0.002,5,3,buffer4);
        char buffer5[20];
        sprintf(buffer5,"0.000 %s",buffer4);
    }
    else{
        char buffer1[7];
        char buffer2[7];
        dtostrf(analogRead(ecgout)*0.001,5,3,buffer1);
        dtostrf(analogRead(pulsePin)*0.002,5,3,buffer2);
        char buffer3[20];
        sprintf(buffer3,"%s %s",buffer1,buffer2);
```

```

}
delay(1000);
}

```

#### PYTHON CODE:

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
import seaborn as sns
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout
from tensorflow.keras.callbacks import EarlyStopping
df=pd.read_pickle('syam')
d1=pd.DataFrame()
df.set_axis(['ECG','PPG','Blood Pressure'],inplace=True,axis=1)
df.iloc[0]
y=df['Blood Pressure']
X=df.drop('Blood Pressure',axis=1)
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.33,

random_state=42)
scaler=MinMaxScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)
model1=Sequential()
model1.add(Dense(30,activation='relu'))
model1.add(Dropout(0.5))
model1.add(Dense(15,activation='relu'))
model1.add(Dropout(0.5))
model1.add(Dense(1,activation='relu'))
model1.compile(optimizer='adam',loss='mse')
erl=EarlyStopping(monitor='val_loss',patience=20,mode='min',verbose=1)
model1.fit(x=X_train,y=y_train,batch_size=100,epochs=100,validation_data=
(X_test,y_test))
losses=pd.DataFrame(model1.history.history)
losses.plot()
model1.predict(scaler.transform(z))

```



```
import joblib as joblib
import tensorflow as tf
h5_model = "./mymodel.h5"
tf.keras.models.save_model(model1, h5_model)
```

HTML CODE:

```
<!HOME PAGE>
<html>
  <body bgcolor=#d4a3ae>

    <center>

      <h1> Blood Pressure Estimation</h1><br>

      <form method="POST", action="{{url_for('home')}}">
        <b> ECG :  <input type="text", name='a', placeholder="enter 1"> <br><
          PPG :  <input type="text", name='b', placeholder="enter 2"> <br><br>
          <br><br></b>
          <input type="submit" , value='predict!' >
        </form>

    </center>

  </body>
</html>
<!AFTER PAGE>
<html>
<body bgcolor=#a3cfb4>
  <center>
    <h1> PREDICTION :  </h1>
    <h1>data</h1>
    <br><br>
    <a href='/'>go back to home page</a>
  </center>
</body>
</html>
```