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The Electrocardiogram (ECG) Based Biometric Identification

by

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Final Project Report submitted in partial fulfillment
of the requirements of the Degree of
Bachelor of Science in Computer Science

Project Supervisor

Prof. Liming ZHANG

05 June 2020

DECLARATION

I sincerely declare that:

1. I and my teammates are the sole authors of this report,
2. All the information contained in this report is certain and correct to the best of my knowledge,
3. I declare that the thesis here submitted is original except for the source materials explicitly acknowledged and that this thesis or parts of this thesis have not been previously submitted for the same degree or for a different degree, and
4. I also acknowledge that I am aware of the Rules on Handling Student Academic Dishonesty and the Regulations of the Student Discipline of the University of Macau.

Signature : ___________________________

Name : Oscar, KUAN KA MENG

Student No. : DB526258

Date : 05 June 2020

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ABSTRACT

This document serves the final year project of the electrocardiogram (ECG) biometric identification with deep learning living personal identification as the report.

Motivation:

Traditional identification uses accounts and passwords and electronic card certificates, which can be easily stolen and disguised. Biometric technology is far superior to traditional identification technology. First, it has higher security. It will not be lost. It is unique, cannot be imitated, and has better anti-counterfeiting performance. Second, it is convenient. Biometric technology does not need to carry extra things. Third, it is confidential and cannot be copied. Fourth, the biological characteristics are stable and will not change. These advantages make it more powerful than traditional recognition functions.

Therefore, we are considering establishing a low-cost biometrics recognition method to provide new options for the field of recognition technology.

Background:

Biometric technology mainly uses the inherent physiological and behavioral characteristics of the human body to identify individuals. It includes fingerprints, face, iris, handwriting, sound, gait, etc. This recognition technology combines computers with high-tech methods (such as optical, acoustic, biosensor and biometric principles). We introduced ECG biometrics technology because it is a new technology that allows testers to remain active during the testing process.

Goal:

We will use Arduino UNO, AD8232 heartbeat/ECG collection hood as hardware. Python 3 using Jupyter Notebook or Google Colaboratory as software and platform. SVM with scikit-learn is a deep learning algorithm used to implement a biometric personal identification system. The ultimate goal is to use Tkinter to implement GUI applications using Python 3.

Major function:

User personal identification with hardware in low-cost and with reasonable accuracy.

Major result:

We collected 3 personal user ECG signal dataset. The result and accuracy are quite reasonable and acceptable.

Major work distribution:

In this project, we are in a group of two, we separate and distribute the work to all members, for:

Oscar, Kuan Ka Meng (DB526258):

- Deep learning training model coding and training
- ECG signal collecting implementation
- Graphical user interface (GUI) implementation.

Elaine, Guo Yan Jia (DB301736):

- Papers and Literatures Viewing
- Deep learning training model coding and training
- Tuning and test the training set

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CHAPTER 1. INTRODUCTION

Biometric technology mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprints, face, iris, handwriting, sound, gait, etc. This recognition technology combines computers with high-tech methods (such as optical, acoustic, biosensor and biometric principles).

Like fingerprints and irises, everyone's heartbeat is unique. An electrocardiogram (ECG) is a test that records the electrical potential generated by the centre and ventricles during contraction and relaxation.

With so many biometric technologies, why do we need ECG recognition? The reason is that different biometric technologies have obvious differences in security, accuracy, stability, convenience, recognition speed, cost and many other aspects. Therefore, they have different advantages and disadvantages in different fields of application. Fingerprint recognition is the most widely used technology in biometrics.

In addition, ECG recognition **can be guaranteed** the tester have heartbeat, which means **the tester alive**.

Currently, fingerprint recognition is dominant in biometrics.

The identification technology based on ECG not only meets the stability, uniqueness and convenience required for fingerprint identification, but also has a unique anti-counterfeiting function. ECG will be affected by factors such as physical health and mental state, but these factors will only cause the scaling and deformation of the ECG waveform without changing its structure, so everyone's ECG is still unique.

CHAPTER 2. LITERATURE SURVEY AND RELATED WORK

Biometric technology mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprints, face, iris, handwriting, sound, gait, etc. This recognition technology combines computers with high-tech methods (such as optical, acoustic, biosensor and biometric principles).

Traditional identification uses accounts and passwords and electronic card certificates, which can be easily stolen and disguised. Biometric technology is far superior to traditional identification technology. First, it has higher security. It will not be lost. It is unique, cannot be imitated, and has better anti-counterfeiting performance. Second, it is convenient. Biometric technology does not need to carry extra things. Third, it is confidential and cannot be copied. Fourth, the biological characteristics are stable and will not change. These advantages make it more powerful than traditional recognition functions.

2.1 Fingerprint recognition

Biometrics technology is used in transfer, withdrawal, payment and settlement, remote insurance business and other fields.

Figure 1: Fingerprints are lines formed by the uneven skin on the fingertips of human fingers. (Capture by [1])

The line on the skin that protrudes everyone's fingerprint is different from the line's start point, end point, junction and branch point.

They are unique and will remain unchanged for life. Fingerprint recognition technology generally uses the overall characteristics of fingerprints for classification, and then uses local features such as location and orientation to identify users. In recent years, fingerprint recognition has been widely used, such as mobile phone unlocking, electronic payment and security. It can quickly scan, read and use fingerprints. Moreover, the equipment used for fingerprint collection is inexpensive. This provides an economic basis for the popularity of fingerprint recognition. However, the fingerprints of relatives are similar. If the accuracy of the algorithm is not high, it may cause recognition errors. In addition, the fingerprints left are easily stolen and copied. This may cause some security problems.

2.2 Face recognition

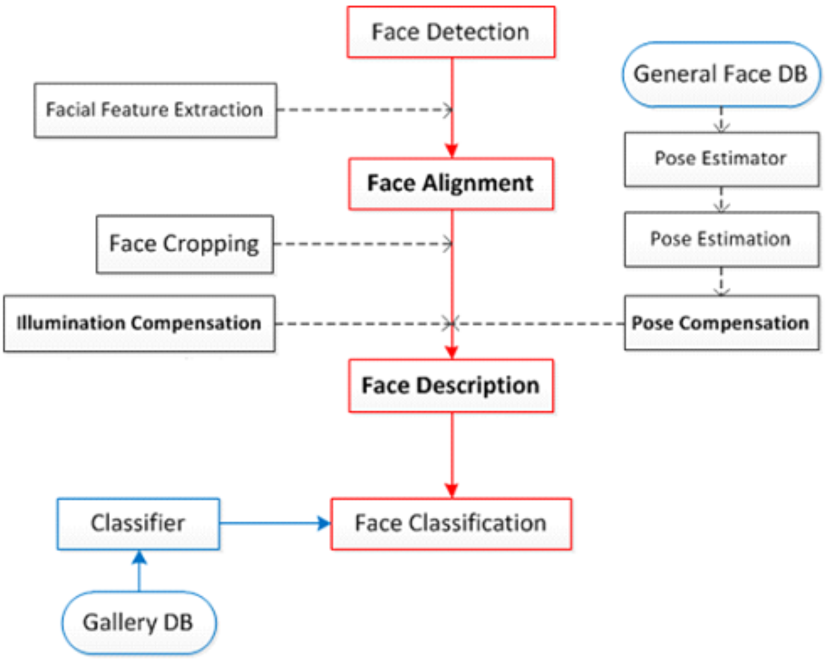


Figure 2: The flowing diagram of face detection and face recognition (Capture by [2])

Face recognition refers to how to recognize and understand faces. It uses a video camera or a camera to collect images or video streams containing human faces based on facial feature information. Face recognition is one of the most popular computer research technologies today.

Face recognition problems are mainly divided into face verification and face recognition.

Face verification is a one-to-one comparison. It determines whether the two pictures are the same person. Usually used to unlock the phone's face. Face recognition is a one-to-many comparison. Determine whether the person the system is currently viewing is one of the databases. This technology is mainly used for criminal suspect tracking, residential access control, etc.

Face recognition requires the system to store a large number of different face and identity information in advance, so that the face can be compared with the database at runtime.

However, when the light is dim or the face is covered and the sides are not clear, it is difficult for the system to perform facial recognition. This may cause facial recognition to fail. It has its limitations. In addition, the appearance of the face changes with age.

Face recognition is a widely used biometric method. In recent years, facial recognition technology has developed rapidly. Compared with other methods, it is more direct, user-friendly and convenient. However, face recognition systems are vulnerable to fraudulent attacks by fake faces. This is a convenient way to deceive the facial recognition system through facial pictures (such as portrait photos). A secure system requires dynamic detection to prevent such fraud. In this work, facial motion detection methods are classified according to various techniques used for motion detection. This classification helps to understand the different spoofing attack scenarios and their relationship with the developed solutions. Introducing the latest works of facial motion detection. The main purpose is to provide a simple method to develop new and safer facial movement detection methods in the future.

Here, the expression detection method is classified according to the type of expression indicator used to assist facial expression detection. Three main types of indicators are used: exercise, texture and vital signs.

In the case of many activity detection technologies, the most common problem is the effect of lighting changes, the effect of amplified noise on the image, which can damage texture information. For blinking and motion based on eye motion detection methods, glasses that because reflection must be considered in the development of future motion detection solutions. In addition, the data set that plays an important role in the performance of the activity detection solution must have rich information and diverse characteristics in order to mimic the expected application scenario. Non-interactive video sequences must include interactive sequences where users perform certain tasks. Future attack datasets must consider attacks, such as 3D sculpture faces and improved texture information. Our main purpose is to provide clear methods for developing safer, user-friendly and effective facial motion detection methods in the future.

“An Identity Authentication Method Combining Liveness Detection and Face Recognition” [14] also proposes a liveness detection approach based on infrared radiation (IR) images acquired using a Kinect camera.

IR images from human faces are used as positive samples, and IR images from photos or videos are used as negative samples. The above sample is input into a convolutional neural network (CNN) for training to distinguish live faces from spoofing attacks.

After performing activity detection, the improved FaceNet will continue to recognize the face and provide the corresponding ID or unknown output for accurate identity verification.

The rest of the article is organized as follows. Section 2 briefly reviews related work and the latest activity detection methods. The third part proposes a framework that combines activity detection and facial recognition, and then introduces an activity detection method based on infrared image features and an improved FaceNet model IFaceNet.

2.3 Iris recognition

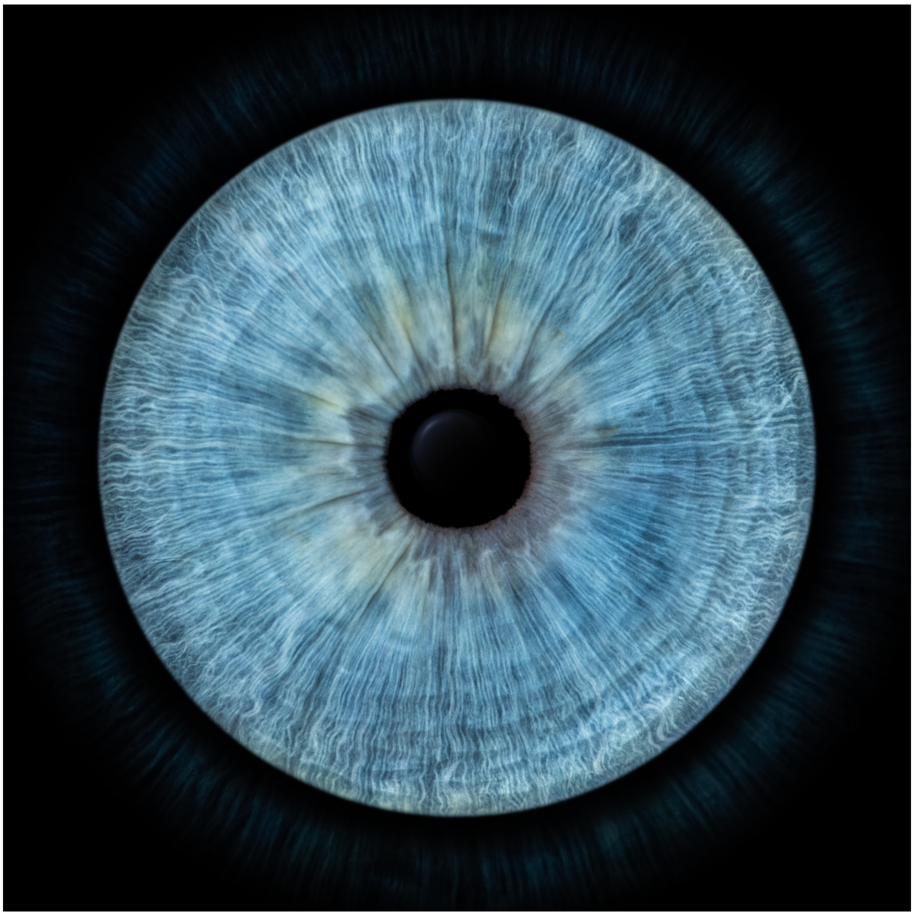


Figure 3: Iris (Capture by [3])

Iris recognition technology is based on the identification of the iris in the eye. The iris is a coloured circle that surrounds the pupil. It contains many interlaced spots, filaments, crowns, stripes, crypts and other detailed features. The iris determines the colour of our eyes, and the iris on each of us is unique. Even identical twins have different irises. So, it can used for identification.

Compared with fingerprint recognition and face recognition in biometrics, iris recognition starts late. However, iris recognition is more accurate, and the rate of misrecognition can be as low as one part per million. It is currently the most accurate biometric identification technology.

However, the equipment cost of iris recognition is high and cannot be widely promoted.

In addition to fingerprint recognition, iris recognition, and face recognition in the field of biometrics, ECG recognition has now become a new research direction.

2.4 Voiceprint recognition

Figure 4: Voiceprint recognition (Capture by [4])

Voiceprint recognition (also called speaker recognition or voice authentication) analyzes a person’s voice to verify their identity. Voiceprint refers to the sound wave spectrum that carries voice information in human speech. Like fingerprints, voiceprints have unique biological characteristics. It is not only specific but also relatively stable. Everyone has a unique voiceprint. Although the computer cannot judge a person's identity with one word at present, the system can still learn your voiceprint intelligently through a large amount of training voice data. When you say a few words, it can determine your identity.

Recognition technology can be divided into two types: content-related and content-independent. "Related to content" means that the system assumes that the user only speaks a small part of the content that the system prompts or allows, while "irrelevant to content" does not restrict the user to speak content.

Compared with other forms of authentication, speech recognition has several key advantages. Today's mobile phones are basically equipped with microphones and can perform identity verification on the mobile phone. The microphone can be integrated into other devices, such as cars and household appliances. Cost effective. For most users, it is both convenient and familiar.

Some disadvantages are as follows, it is not as accurate as other biometrics (such as facial recognition). Background noise will affect the quality of the sample, which in turn affects the matching performance. Therefore, it is not an ideal choice in noisy or public places.

2.5 Technical issues use to implement electrocardiogram (ECG) recognition

We use:

- Hardware:

  Arduino UNO (with USB cable)

  AD8232 Heart Beat / ECG Collecting Shield (with sensors / electrode)

- Software Platform:

  Python 3 with Jupyter Notebook or Google Colaboratory

- Algorithm:

  SVM with scikit-learn

- Graphical User Interface (GUI) appliation:

  Tkinter with Python 3

CHAPTER 3. OVERALL SYSTEM DESIGN

3.1 Abstract system workflow

In this project, we needed to use the ECG Collecting Kit (Arduino UNO + AD8232 ECG Collecting Shield) to get the user's ECG signal. After, we process the signals and training the model. In this chapter, we are going to tell you what we needed to do in the overall views.

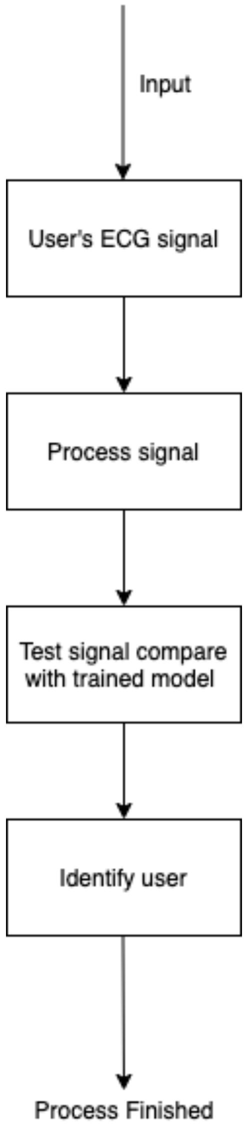


Figure 5: Abstract system workflow diagram

The abstract system workflow of our project as shown as Figure 5. First, we need to set up the ECG collection kit and paste the sensor on the user's body, the kit will detect and collect the user's ECG signal. The system then processes the signal by converting and trimming the signal to the appropriate format. The converted signal will be tested and compared with the trained deep learning model. Finally, we can identify users by comparing accuracy.

3.1.1 Overall system workflow

After showing the abstract workflow of our system, we introduce the overall workflow. First, our system is an identification system, we need the user to connect with the ECG Collecting Kit to make sure the tester alive. Therefore, we will break down the overall workflow into two parts: 1) How the user can run through the identification process with our system. 2) What we need to do behind when a new user appears.

3.1.2 User Routine of using the system

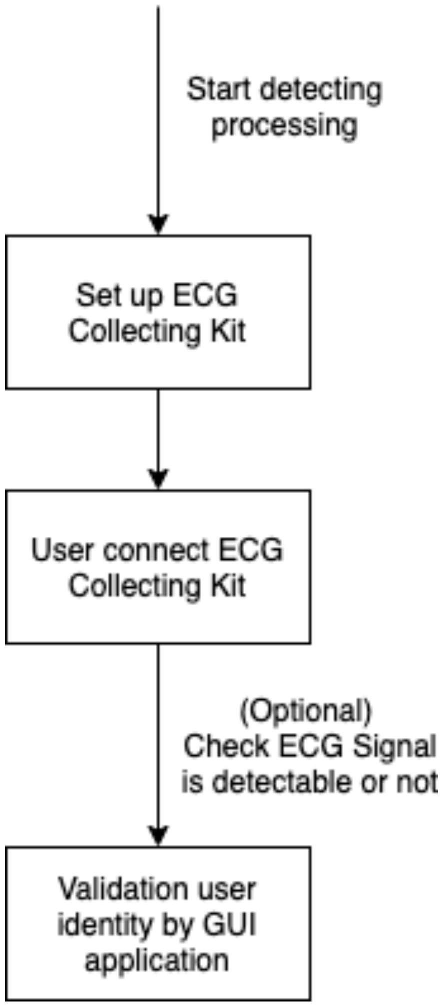
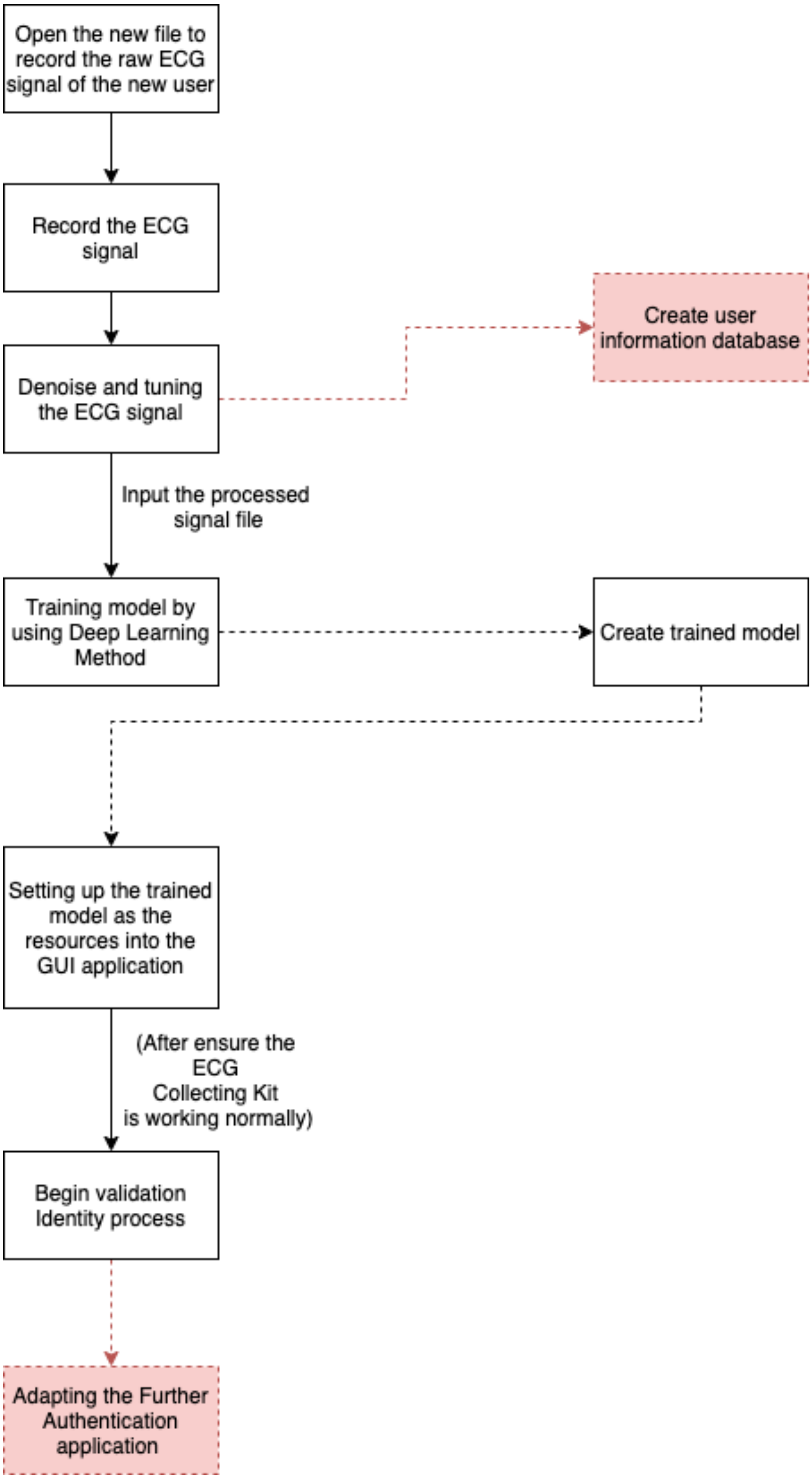


Figure 6: The routine of the user

In Figure 6, When the user wants to use our ECG biometric system, it will show the user a simple routine. After completing the setup and collecting the ECG collection kit, you can start the verification and identification process. Or, before the verification process begins, we can check whether the ECG signal is detectable and whether the shape of the ECG signal is normal.

3.1.3 Our overall workflow when a new user appears



(Note: Dotted line for future implementation)

Figure 7: The workflow when a new user arrive

In Figure 7, What do we need to do when a new user arrives? First of all, our developer or system administrator needs to open a new file to record the original ECG signal of the new user. Then, we can record the ECG signal through the ECG collection kit. Through the practice of collecting experience, some noise is always collected during the recording step. Therefore, we need to take measures to reduce noise and tune the original ECG signal. As shown in the figure, for future implementation, a user information database must be created.

After fine-tuning the signals, we put all the signals of all users into the deep learning training program to create a trained model after the deep learning process. During the learning process, we will monitor the F1 score/accuracy indicators to ensure that the training is relatively accurate.

Finally, after the authentication process, it will show whether the selected user has cleared the identity test. Similarly, our system can further implement APIs to connect with other systems or software.

Please note that due to limited time and resources and the COVID-19 virus outbreak, we have no time to implement some recommendations. For future implementation and work, we mark it as a dotted line in Figure 7, such as a user information database, and develop APIs after the recognition process and have more powerful hardware resources, thereby reducing training time and improving accuracy.

3.2 Detail system workflow

After the overall views of our system, we are going to explain what we need to do in each section, which is corresponding to the overall workflow.

3.2.1 ECG Signal collecting workflow

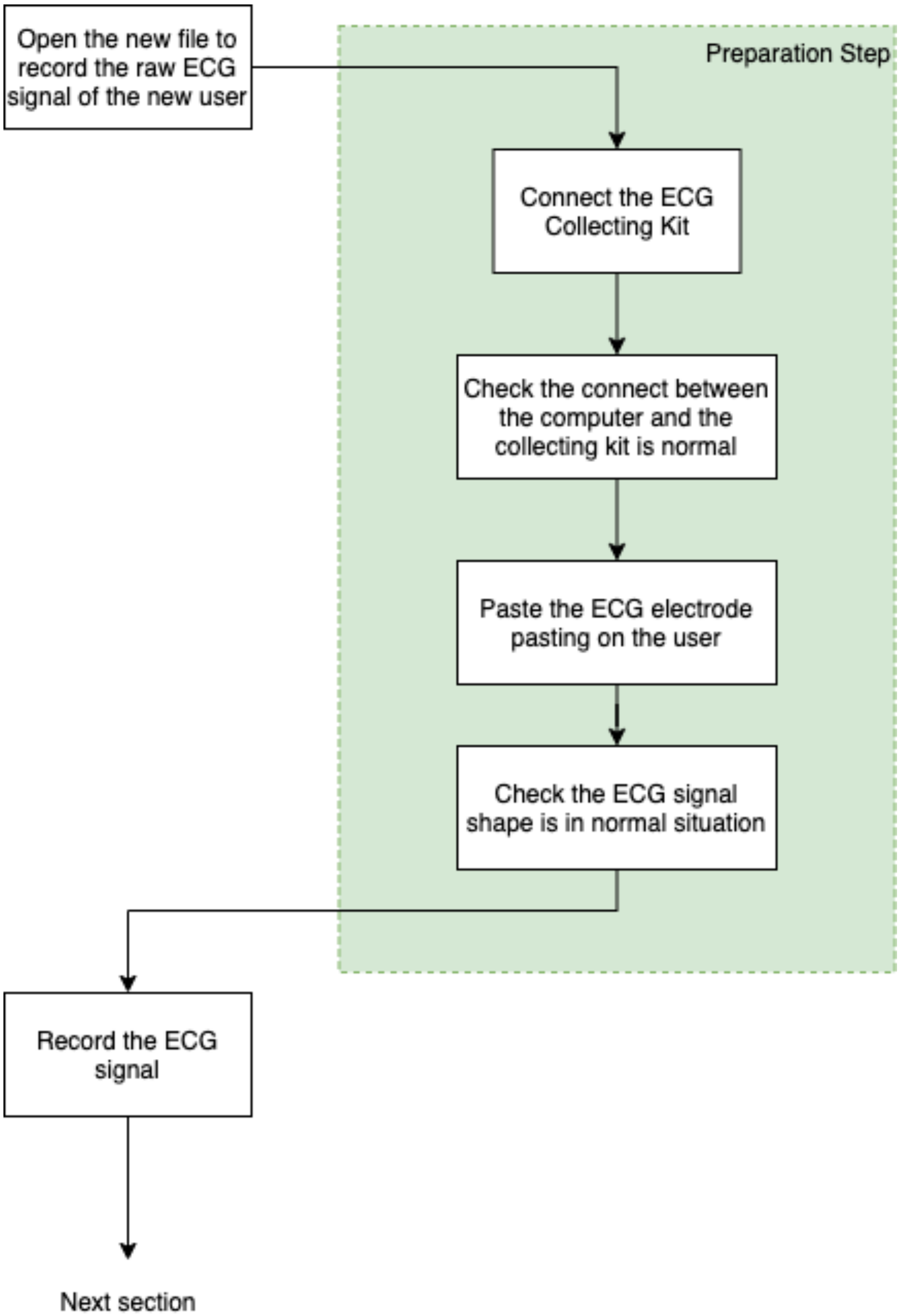


Figure 8: The workflow of record the ECG signal

From the Figure 8, we can see that this is the preparation step of the record the ECG signal. It is done by the system developer or administrator manually.

For the preparation steps to check whether the shape of the ECG signal is normal, we can take advantage of this by using the Arduino IDE monitor to see if the shape is normal. We will discuss more about the realization of all functions and work. So let's look at the next part.

3.2.2 Connection with ECG Collecting Kit workflow

This is an important part of our system. If the connection model does not work properly, everything else is useless. Therefore, we say how to connect the ECG acquisition kit is very important. As mentioned earlier, for the ECG collection kit, it consists of the Arduino UNO and the AD8232 ECG collection board. The following is a workflow showing how to connect to the ECG collection kit.

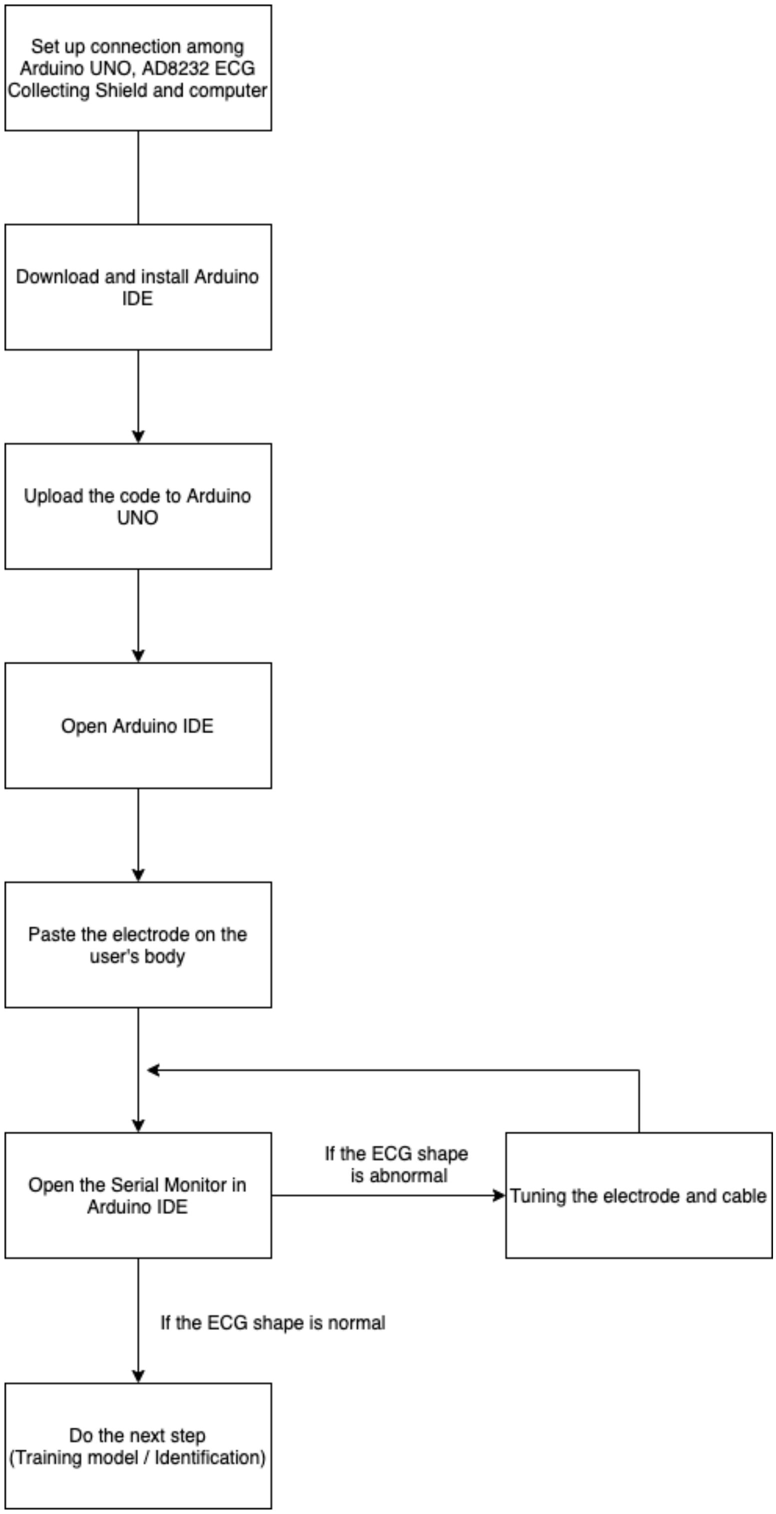


Figure 9: The workflow of connection with ECG Collecting Kit

In Figure 9, We can see that we need to download the Arduino IDE. After the connection between the ECG collection kit and the computer is working and uploading the code to the Arduino UNO, we can paste the electrode on the user's body. In order to implement the ECG collection function, this code will be discussed in the next chapter. The next step is to train the model process.

3.2.3 Training model workflow

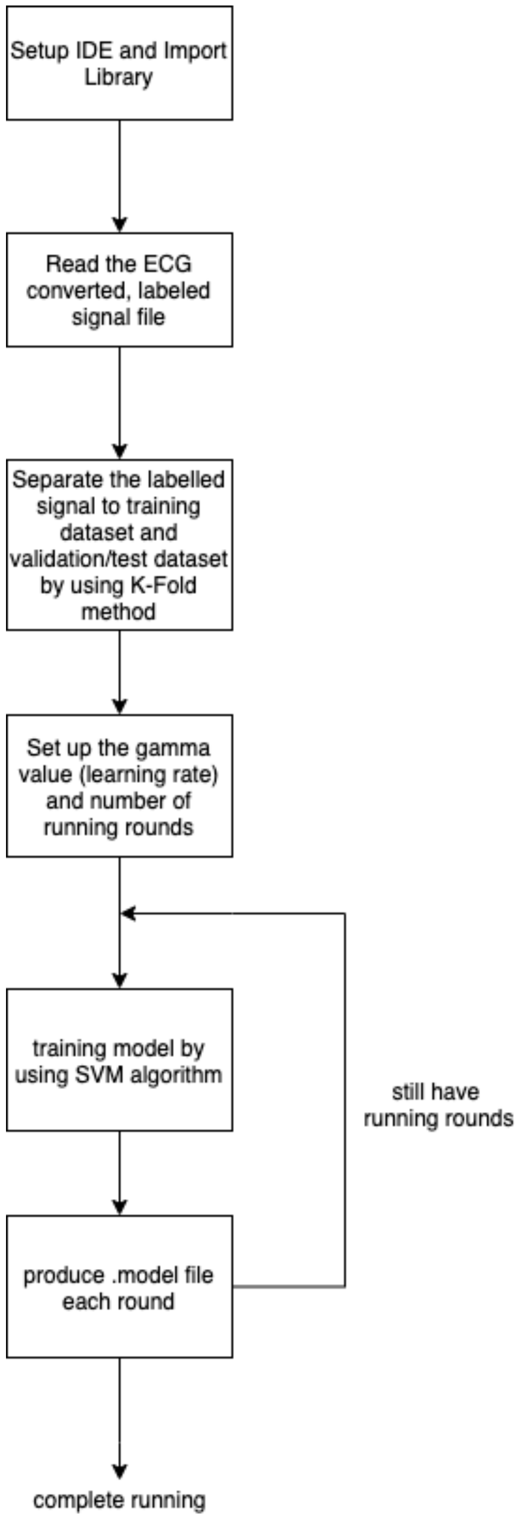


Figure 10: The workflow of training model

In Figure 10, We can see the workflow of training the model, first we must set up the IDE and important libraries. We use Jupyter Notebook and Google Colaboratory as IDE, and Python 3 as the main programming language. Then, developers and system administrators will perform ECG conversion signal processing. We will discuss the detailed implementation in the following chapters.

Please follow the steps below, it is implemented by Python 3 code. We use the k-fold method to divide the labelled signal records into training data sets and verification/test data sets. Then, we set the gamma, also known as the learning rate and the number of training rounds. Next, we use the SVM algorithm to run the training model. We will also discuss detailed information in the following chapters.

In the last part of the training model section, a .model file will be generated for each training round. The .model file will be used as the key for the biometric part.

3.2.4 Identification process workflow

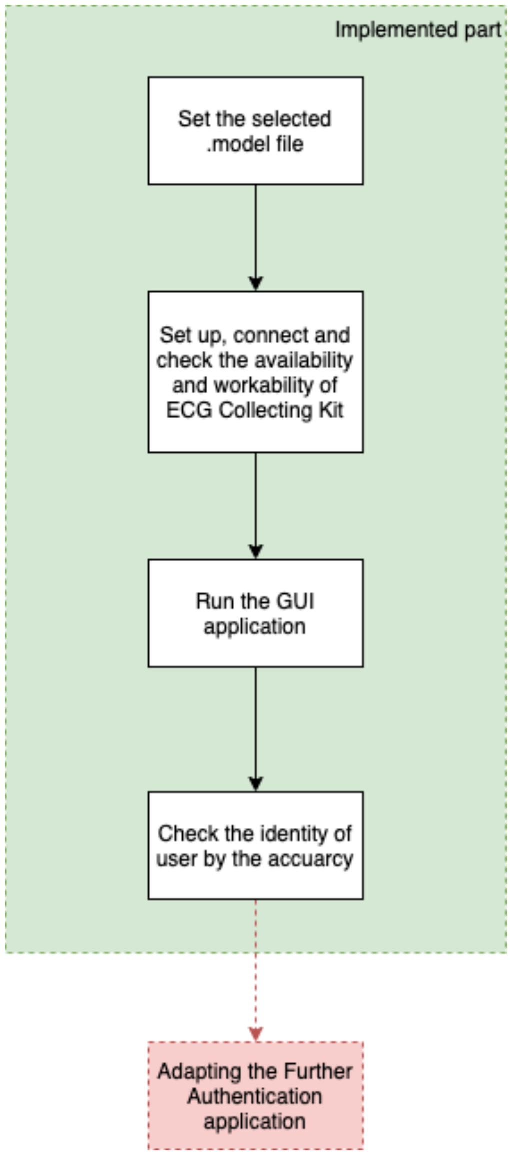


Figure 11: The workflow of identification process

In Figure 11, We can notice the implementation part. As mentioned in the previous section, we need to set the selected .model file as the system setting. Then, you need to connect the ECG collection kit, and the steps are the same as before.

The key part of this section is to run the GUI application, which is implemented by Python 3 and the Tkinter library together. We will check the accuracy of the ECG signal segment to determine the identity of the user. The detailed part will be discussed in the following chapters.

3.2.5 Interface workflow

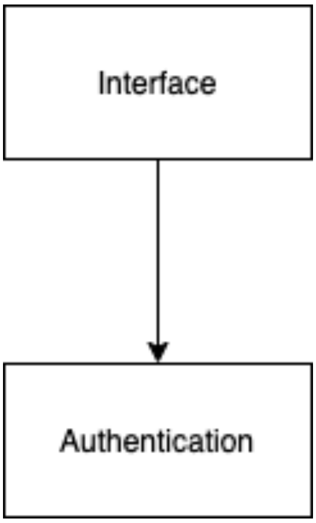


Figure 12: The interface of our identification system

The last thing is the interface of our identification system. Our interface is very simple, as shown in Figure 12. This interface contains only one authentication part. It likes the login page, but uses ECG biometrics. This is also a key part of our entire system.

At the end of CHAPTER 3, the next chapter will discuss our implementation. Starting from CHAPTER 4, the content of my teammates will be different because we work differently. We only write the part that belongs to our work.

CHAPTER 4. IMPLEMENTATION OF THE ECG CLASSIFICATION SYSTEM

From this chapter, we will write our own part of the project in the group. Here are my parts:

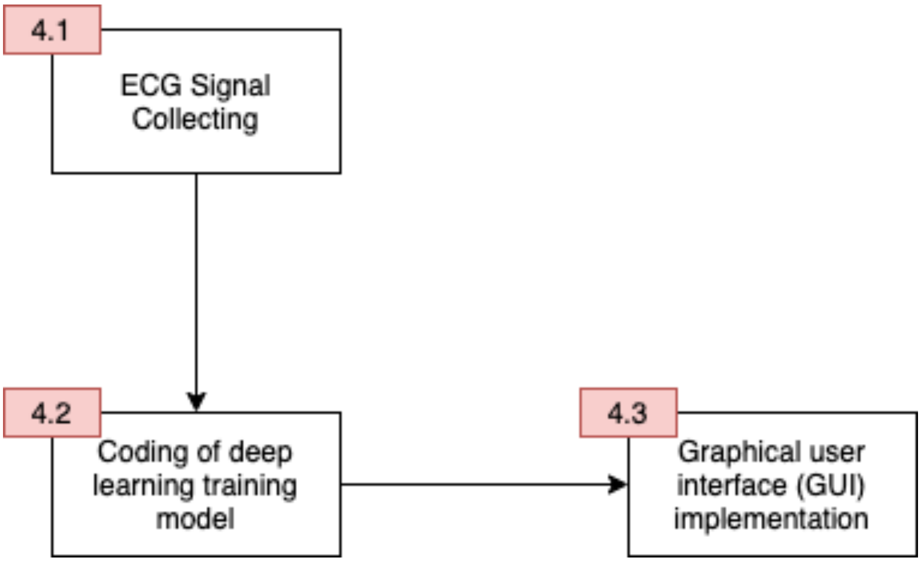


Figure 13: My work in our project

In CHAPTER 3, we have a briefly introduction about each part of our work, In this chapter we will have a implementation description and method.

In this project, we selected Arduino UNO and AD8232 ECG Collecting Shield as hardware, Arduino IDE as platform, and C++ as programming language to collect ECG signals.

In the training model section, we chose Jupyter Notebook and Google Colaboratory as platforms, and Python 3 as the main programming language.

Since our GUI recognition program also uses Python 3 (with Tkinter) as the programming language, it has good compatibility with the operating system. Our GUI recognition program can run on Windows, Linux and Mac OS.

This is some information about my work. Let's start in detail:

4.1 Implementation of ECG Signal Collecting

Based on Figure 13, we firstly needed to collect the ECG signal. We needed two hardware:

1) Arduino UNO

Figure 14: Arduino UNO R3 (Capture by [9])

2) AD8232 ECG Collecting Shield

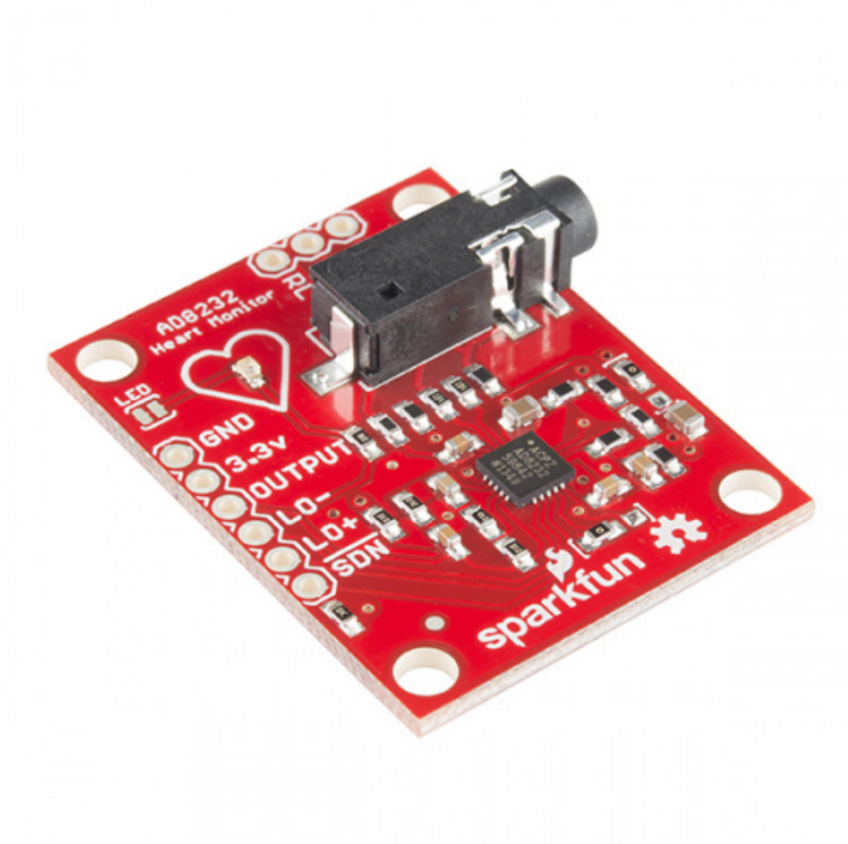


Figure 15: AD8232 ECG Collecting Shield (Capture by [10])

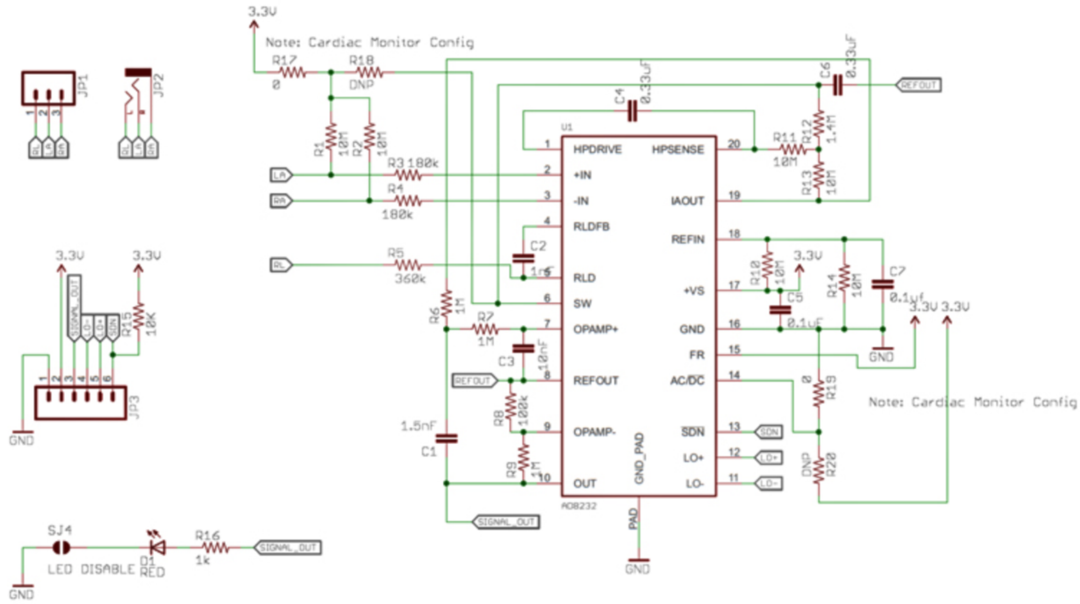


Figure 16: The schematics of AD8232 ECG detecting module (Capture by [11])

Here is the technical specification (see Table 1) and the pins usage of AD8232 module (see Table 2):

Table 1: Technical specification of AD8232 module

Input Voltage (recommended)	DC 3.3V
Output	Analog output
Plots	RA, LA, RL (3 pins, by using 2.54 pins or headphone holder)

Table 2: Usage of pins of AD8232 module

GND	Ground
3.3V	DC Voltage in
OUTPUT	The output of operating amplifier, it outputs the fully adjusted ECG signals.
SDN	Cut the input control. SDN drives to low level of voltage, change the module into low-power consumption mode.

The following is the wiring diagram that describe the connection of Arduino UNO and AD8232 ECG detecting module.

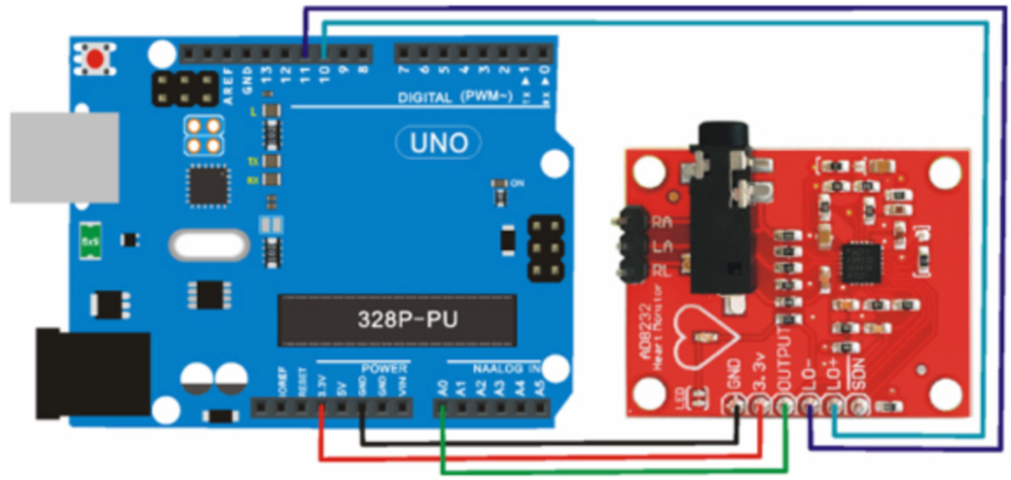


Figure 17: The wiring of Arduino UNO and AD8232 ECG detecting module (Capture by [12])

1. Arduino IDE and coding
   The Arduino software IDE is a java-based written cross-platform software application. Arduino has its own language called "sketch", which likes C/C++.

Figure 18: The user interface of Arduino IDE

The following is the Arduino *sketch* code that we used:

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

}

void loop() {

if((digitalRead(10) == 1)||(digitalRead(11) == 1)){
Serial.println('!');
}
else{
// send the value of analog input 0:
Serial.println(analogRead(A0));
}
//Wait for a bit to keep serial data from saturating
delay(1);
}
```

Figure 19: the Arduino code (Capture by [13])

After the coding, we verify the above code and upload to the Arduino UNO board.

2. Overserving the output ECG signals

The following shows the real setup image of the ECG equipment (see Figure 20, Figure 21) and the output ECG signals (see Figure 22) we get:

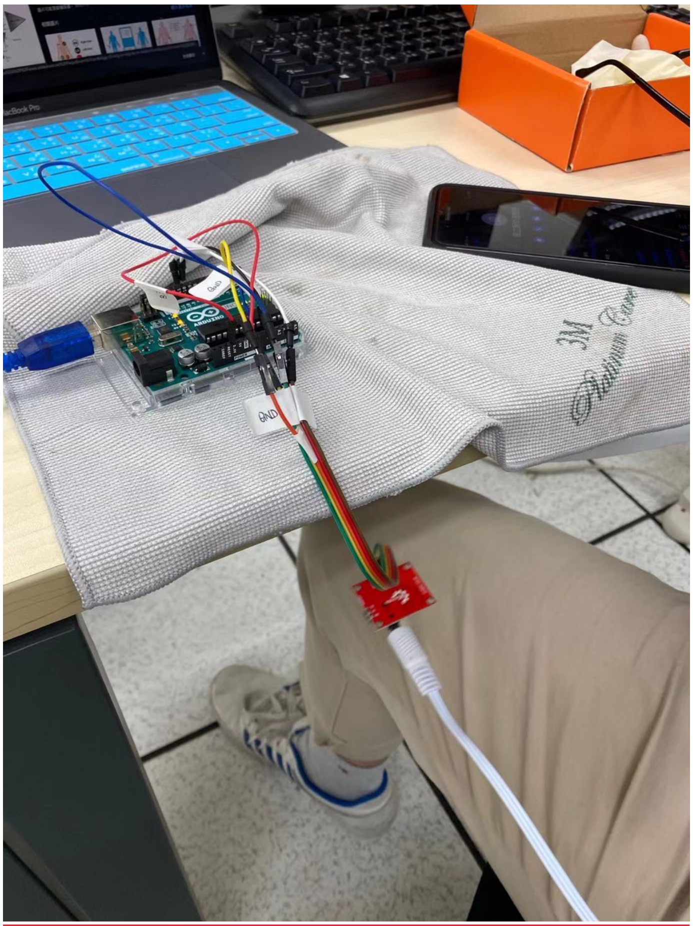


Figure 20: The real setup of the ECG equipment

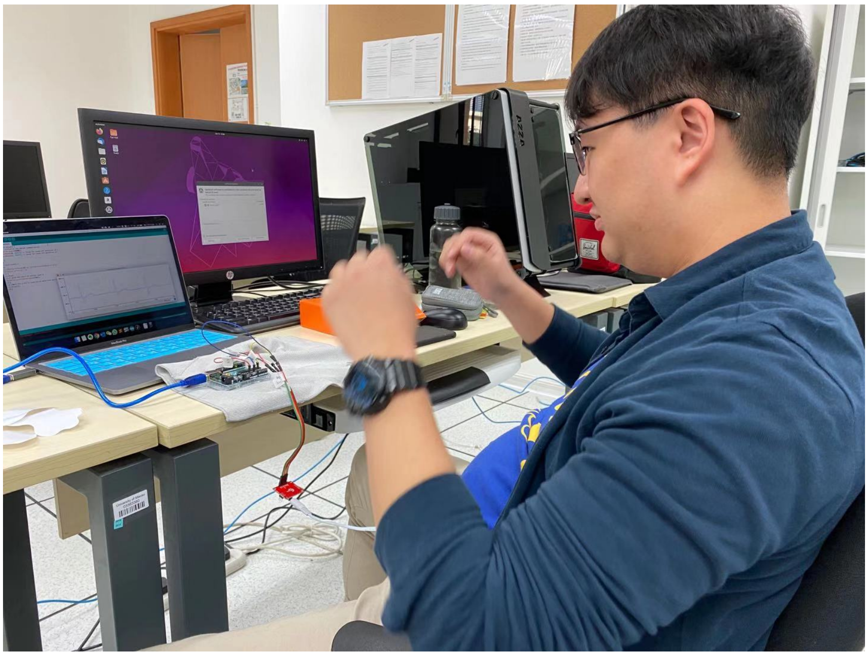


Figure 21: The testing experiment of ECG equipment to collect the ECG signal

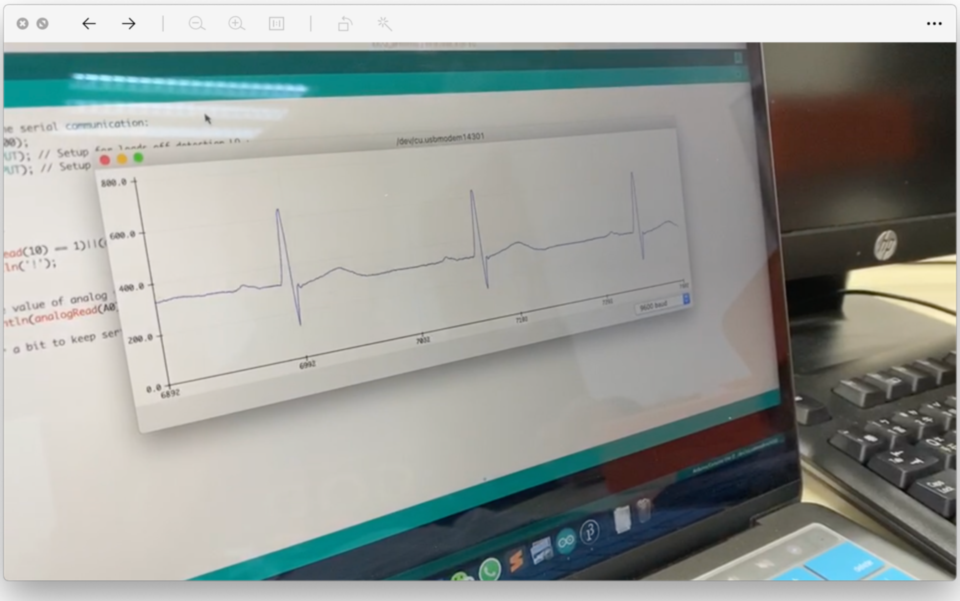


Figure 22: The ECG signal in Arduino IDE

4.2 Coding of deep learning training model

In the developing step we used the ECG database, ECG-ID Database in Physionet [14] to develop the Python 3 coding. For the dataset, we need to convert the .dat files to .csv files to make the dataset can be work in training process.

Here is the code I modified by *Abhishek Patil*'s code to the convert process:

```
"""
Code to convert all .dat files (ECG signals) in a folder to CSV format
@author: Abhishek Patil
@modified by: Oscar, Kuan Ka Meng
"""

import wfdb #WaveForm-Database package. A library of tools for reading, writing,
and processing WFDB signals and annotations.
import pandas as pd
import numpy as np
import glob2 as glob
import os

def create_dataset(person_id):
    db_folder = "ECGID_DB/"
    dataset_folder = "ECGID_DB_DATASET/"

    if (person_id < 10):
        person_path = "0" + str(person_id)
    else:
        person_path = str(person_id)

    person_folder = "Person_" + person_path + "/"


    dat_files=glob.glob(db_folder  +  person_folder  +  '*.dat')  #Get  list  of
all .dat files in the current folder
    df=pd.DataFrame(data=dat_files)
    df.to_csv("files_list_"+person_path+".csv",index=False,header=None)  #Write
the list to a CSV file
    files=pd.read_csv("files_list_"+person_path+".csv",header=None)
    print(dat_files)

    for i in range(0,len(files)):
        recordname=str(dat_files[i])
        temp=recordname.split('.')
        temp2=temp[0].split('/')
        recordname = temp2[2]

        print(recordname)

        record = wfdb.rdsamp(db_folder + person_folder + recordname) # rdsamp()
returns the signal as a numpy array
        record=np.asarray(record[0])
        path=dataset_folder + str(person_id) + "/" + recordname + ".csv"
        print(path)

        dataset_path = dataset_folder + str(person_id) + "/"

        if not os.path.exists(dataset_path):
            os.mkdir(dataset_path)

        np.savetxt(path,record,delimiter=",") #Writing the CSV for each record
        print("Files done: %s/%s"% (i+1,len(files)))

    print("\n [ " + person_folder + "] All files done!\n")

def main():
    for x in range(1,91):
        create_dataset(person_id=x)

if __name__ == "__main__":
    main()
```

Figure 23: The full code of dat2csv.ipynb

In Figure 23, The full code of *dat2csv.ipynb*. It gives the function of conversion is shown. We use libraries [15] from Python: wfdb, pandas, numpy, glob2 and os.

Either using ECG-ID database or collecting dataset by ourselves, we needed to label all the records. Then, I modify another program to label the dataset.

```
import os
import csv
dataset_path = '/content/drive/My Drive/FYP_ECG_ID/coding/ECGID_DB_DATASET/'
person_id = '3'
rec_id = '3'
temp_data = []
train_X = []
train_Y = []

with open(dataset_path + person_id + '/rec_' + rec_id + '.csv', newline='') as
csvfile:
    spamreader = csv.reader(csvfile, delimiter=' ', quotechar='|')
    for row in spamreader:
        temp_data.append(', '.join(row))

    for i in range(len(temp_data)):
        temp = temp_data[i].split(',')
        train_X.append(temp[0])
output_path = '/content/drive/My Drive/FYP_ECG_ID/coding/LABELED_DATASET/'
with open(output_path + 'person_id_' + person_id + '_' + rec_id + '.csv', 'w+',
newline='') as csvfile:
    spamwriter = csv.writer(csvfile, delimiter=' ',
                            quotechar='|', quoting=csv.QUOTE_MINIMAL)

    for i in range(len(temp_data)):
        temp = train_X[i]
        spamwriter.writerow([temp, person_id])
```

Figure 24: The full code of label_dataset.ipynb

For the main training program (*ECG_Prediction_SVM.ipynb*), we also use some essential libraries of Python. Here is the code snipper

```
import numpy as np
import os
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.model_selection import KFold
import joblib
from sklearn.metrics import accuracy_score
from sklearn.metrics import matthews_corrcoef
from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
import datetime
```

Figure 25: code snipper: libraries of main training program

From Figure 25, we use numpy, matplotlib, sklearn, joblib and datetime. It can all find in PyPI [15].

Then, we see the driven program of the main training program.

```
if __name__ == '__main__':
    path = '/content/drive/My Drive/FYP_ECG_ID/coding/LABELED_DATASET/'
    outfile = 'seq_encoded.txt'
    outdir = 'KFold'
    a = []
    # encode the original dataset
    window_Mat = seq_encoding(path,outfile)

    # split the feature matrix into N fold
    train_all, test_all = splitDataSetbyKFold(window_Mat, 10, outdir)

    print("Generate dataset end and cross validation start")

    clf = svm.SVC(C=1, kernel='rbf', gamma=0.2, probability=True)
    curdir = '/content/drive/My Drive/FYP_ECG_ID/coding'
    clfname = 'SVM'

    crossValidation(clf, clfname, curdir, train_all, test_all)
```

Figure 26: code snipper: driven program

In Figure 26, there are some parameter we need to notice. First is the number of training rounds. In the setting, we set 10 rounds as usual. (We also set 100 in experimental training). Second, we focus on the *gamma* value, also known as *learning rate*. The following shown the learning rate we tested:

Table 3: Tested learning rate

Gamma value	***Accuracy***
0.0001	***0.336***
0.001	***0.40***
0.01	***0.58***
0.1	***0.61***
0.5	***0.624***
0.6	***0.55***
0.7	***0.54***
0.8	***0.55***

From the practice, we notice that the range from 0.1 to 0.5 is the relatively good range of the accuracy. No matter we take the value form the range of 0.1 to 0.5, the accuracy just change a bit. In the final setting, we choose 0.2 as the *gamma* value.

```
Generate dataset end and cross validation start
----- Round  0  -----
Start Time:  2020-05-21 16:32:51.437781
 training begin...
 training end.
 test begin.
              precision    recall  f1-score   support

           1   0.524452  0.525714  0.525083      3325
           2   0.790276  0.676919  0.729219      3674
           3   0.632395  0.713195  0.670369      4062

    accuracy                       0.644788     11061
   macro avg   0.649041  0.638610  0.641557     11061
weighted avg   0.652388  0.644788  0.646242     11061

 test end.
1748.0
0.0
0.0
0.0
Wrote results to output.data...EOF...
End Time:  2020-05-21 17:09:09.290636
---------------

----- Round  1  -----
Start Time:  2020-05-21 17:09:09.293146
 training begin...
 training end.
 test begin.
              precision    recall  f1-score   support

           1   0.526155  0.514816  0.520424      3341
           2   0.801849  0.694422  0.744279      3747
           3   0.618870  0.708281  0.660563      3973

    accuracy                       0.645150     11061
```

Figure 27: sample output of the training model program

In Figure 27, we can see the sample output of the training model. We mainly focus on the accuracy part.

4.3 Graphical User Interface (GUI) Implementation

For the GUI application, we used the Tkinter in PyPI [15] as the main library of implementation.

Here is the full code of the GUI implementation

```
from tkinter import ttk
import tkinter as tk
import math
import numpy as np
from sklearn import svm
```

```
import joblib
import serial

def ECG_identify():
    model_dir = "/Users/oscarkuan/coding/fyp_ecgid/ML_Model/"
    filename = "train_SVM1.model"
    detect_length = 14

    X_test = np.arange(detect_length).reshape(detect_length,1)
    Y_test = np.arange(detect_length).reshape(detect_length)

    for i in range(0,detect_length):
        Y_test[i] = person_id

    arduino = serial.Serial('/dev/cu.usbmodem1412201', 9600, timeout=.1)

    i = 0
    while (i<detect_length):
        data = arduino.readline()[:-2] #the last bit gets rid of the new-line
chars
        if (data and data.decode("utf-8") != '!'):
            testdata = data.decode("utf-8")
            print(testdata)
            X_test[i, 0] = testdata
            i = i + 1

    loaded_model = joblib.load(model_dir + filename)
    result = loaded_model.score(X_test, Y_test)
    print(result)

    acc.set(result)

window = tk.Tk()
window.title('ECG Signal Authenticator 心電圖訊號驗證器')
window.geometry('800x350')
window.configure(background='white')

acc = tk.StringVar()
person_id = 1

header_label = tk.Label(window, text='ECG Signal Authenticator 心電圖訊號驗證器')
header_label.pack()

ecgid_frame = tk.Frame(window)
ecgid_frame.pack(side=tk.TOP)

person_label = tk.Label(ecgid_frame, text='Person ID#: ')
person_label.pack()
personid_label = tk.Label(ecgid_frame, text='1')
personid_label.pack()


ecgid_label = tk.Label(ecgid_frame, text='Accuracy: ')
ecgid_label.pack(side=tk.TOP)
acc_label = tk.Label(ecgid_frame, textvariable=acc)
acc_label.pack()

blank_label = tk.Label(ecgid_frame, text='')
blank_label.pack(side=tk.TOP)

calculate_btn = ttk.Button(window, text='Auth 立即驗證', command=ECG_identify)
calculate_btn.pack(side=tk.TOP)


window.mainloop()
```

Figure 28: The full code of dat2csv.ipynb

The coding is quite straight forward, we will not discuss it in detail.

In practice, we will change the serial USB port of Arduino UNO and the identity id with related to the corresponding trained model dataset.

Finally, we will show the screenshot of the GUI application.

Figure 29: Screenshot of the GUI application

This is the complete workflow of my own part. The next chapter will be talk more about the system quality and run through the result.

CHAPTER 5. SYSTEM QUALITY AND RESULT

5.1 ECG Signal Collecting

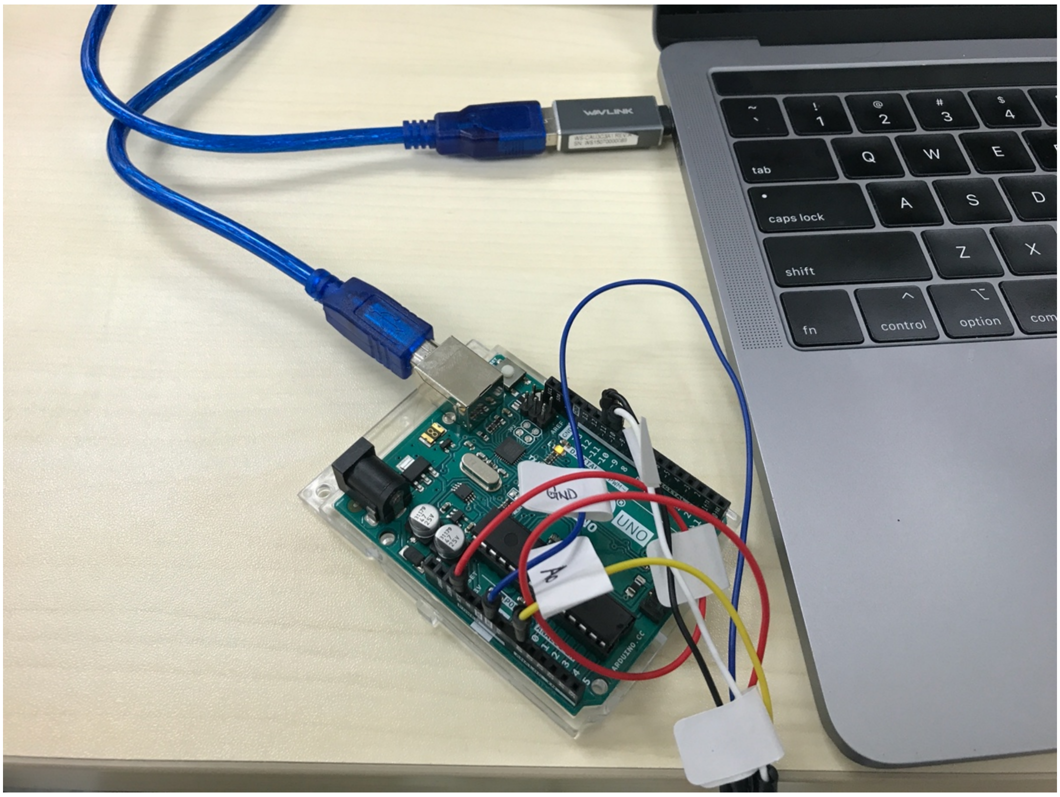


Figure 30: Arduino UNO with AD8232 ECG collecting shield connected to MacBook Pro

Then, we pasted the electrodes on our body then we testing to collect the signal. The following is the typical electrodes / sensors placement on our body.

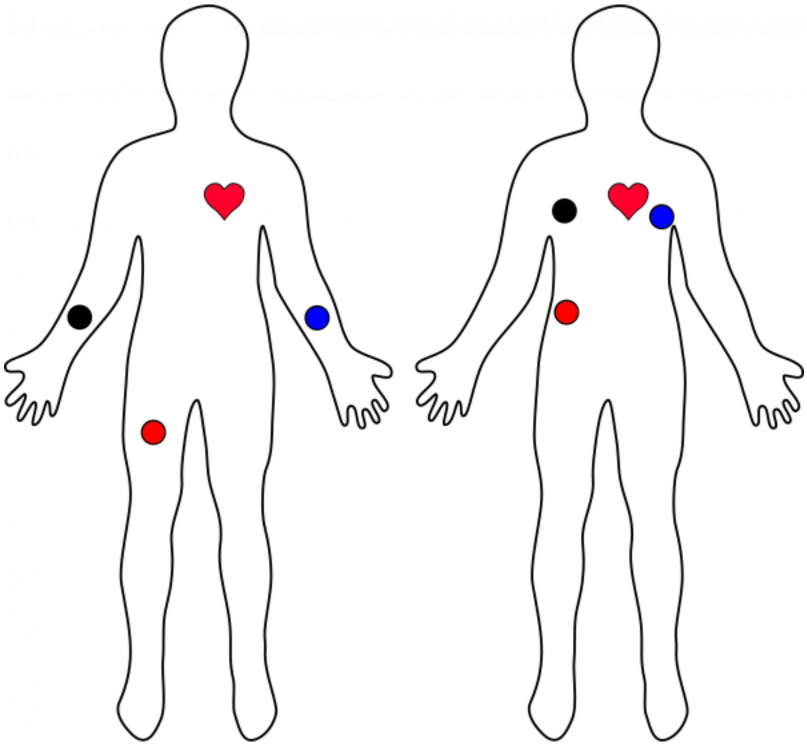


Figure 31: Typical sensors placement (Capture by [10])

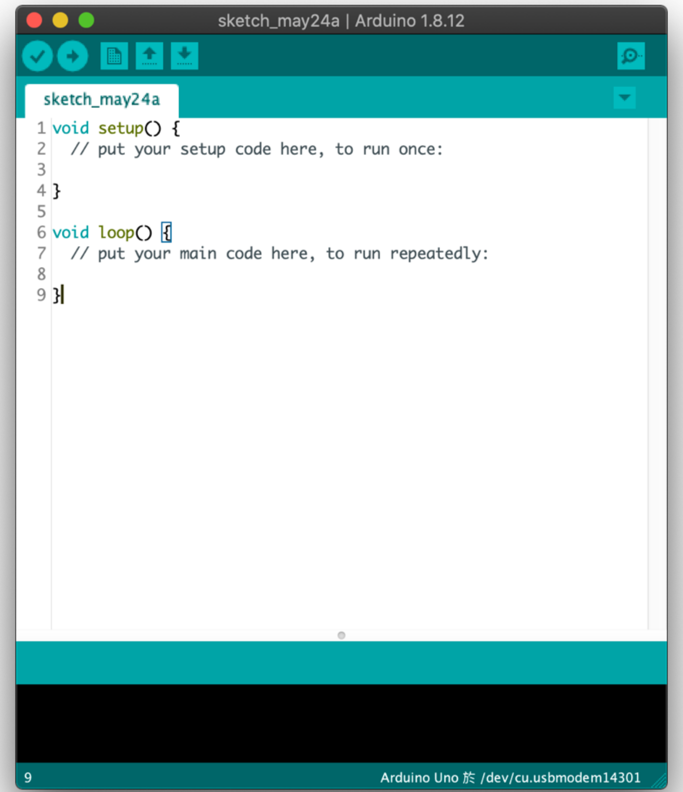


Figure 32: Arduino IDE GUI

Then, open the serial plotter in Arduino IDE, we can get the ECG signal plot:

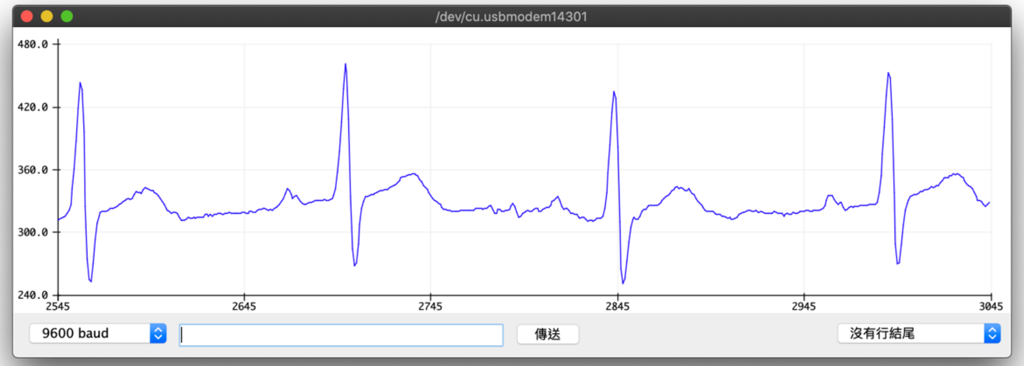


Figure 33: Arduino IDE: serial plotter

And we can see the signal in numeric form in the serial monitor.

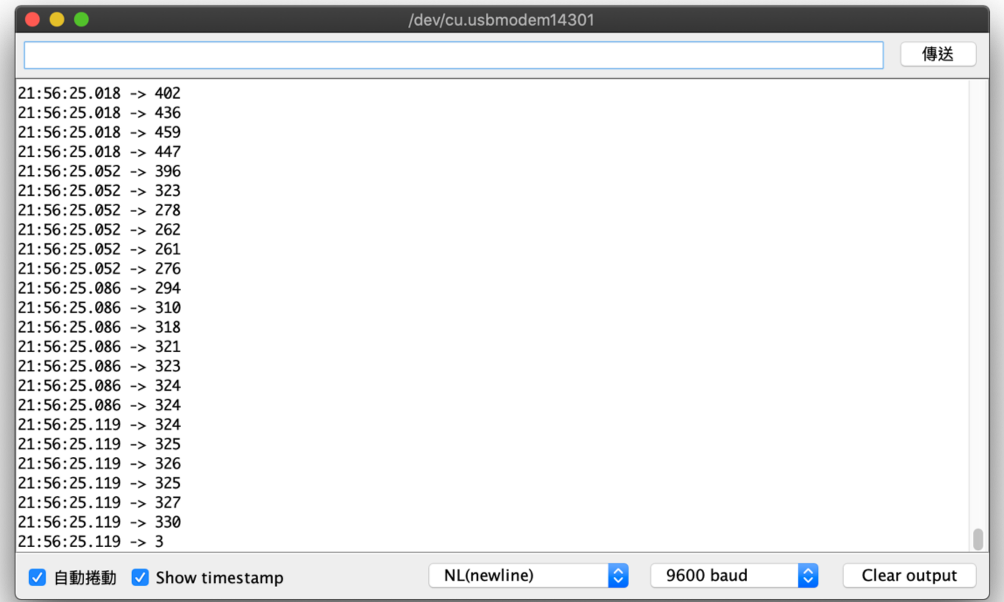


Figure 34: Arduino IDE: serial monitor

We can get the numeric data without the timestamp to collecting the ECG signal in our system. This is the part of signal collecting. The next section will introduce the another key part – User identification with GUI application by collected ECG signal.

5.2 User Identification

In this section, we used the collected instantly ECG signal to do the user identification. First, I and my classmate Steven is pasted of the sensors. Here is the photos to show the process during the user identification part:

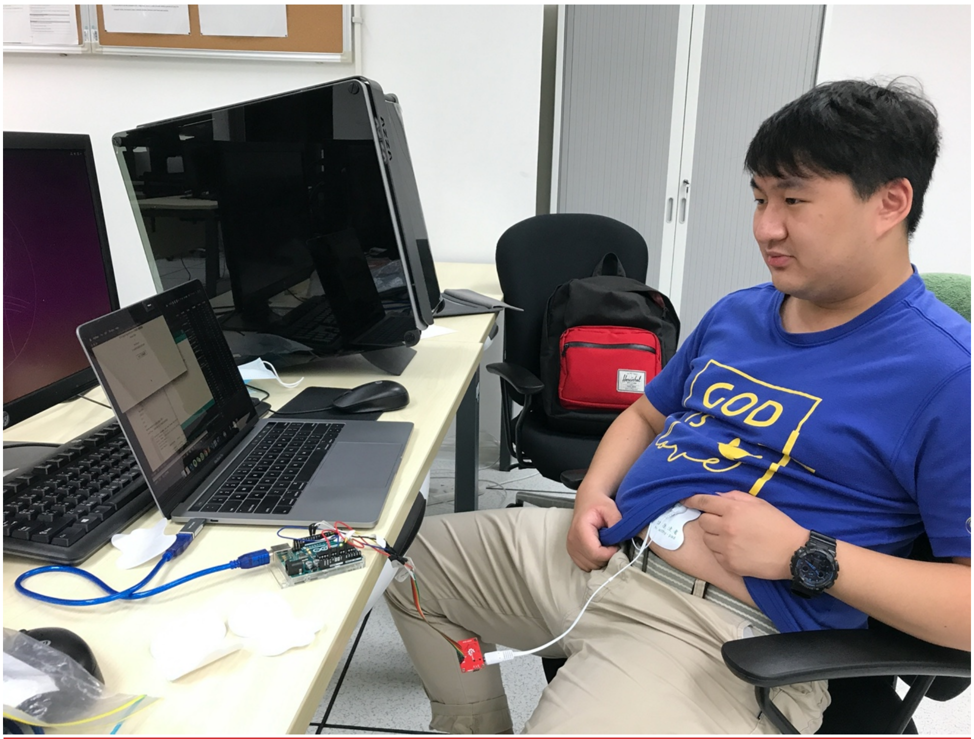


Figure 35: The testing identification process of me

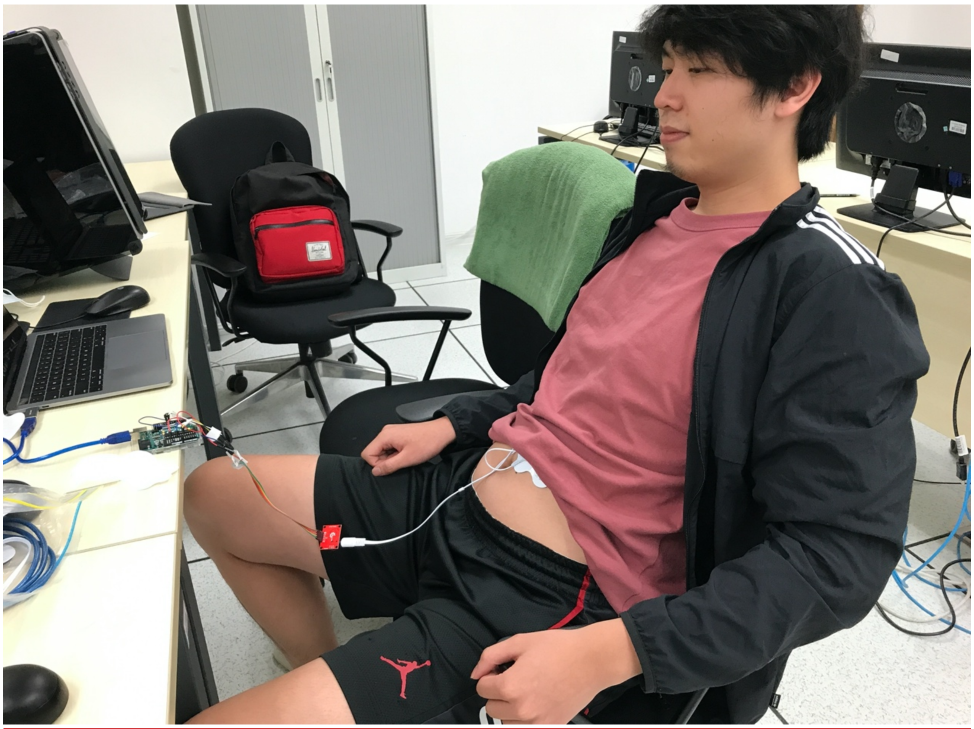


Figure 36: The testing identification process of my classmate, Steven

Previously, I train up the model with me and Steven, the user id is 1 and 2 respectively.

Here is the example,

Figure 37: The testing identification GUI - 1

Figure 38: The testing identification GUI - 2

Figure 39: The testing identification GUI – 3

Figure 40: The testing identification GUI – 4

In the Figure 37 – Figure 40, they are the GUI application of the user identification system. For GUI, it is a simple user interface.

For the result of identification, it is relatively sensible and correct to distinguish the user identity. However, sometimes the accuracy is not too clear. It may train the model again and modify the threshold.

5.3 Experiment result and discussion

In the experiment, we totally collected 3 person's ECG signal data. Here is the table to summarise the information, including user ID (label), corresponding number of data and accuracy (f1-score) of the datasets.

Table 4: Collected datasets information in the experiment

User ID (label)	Username	Number of data	Accuracy (f1-score)
1	Oscar	33682	0.52
2	Steven	37372	0.74
3	Yumi	39556	0.66

We trained about 10 rounds and get the model best accuracy round. The total accuracy is 0.65. (which is the average and reasonable accuracy)

CHAPTER 6. ETHICS AND PROFESSIONAL CONDUCT

Here, we emphasize that from the perspective of ethics and professional ethics, all our related work, research and regulations have been marked as references.

In our project, we used Arduino UNO R3 (purchased from Taobao), AD8232 ECG collection kit (purchased from Taobao), Arduino IDE 1.8.12 (free, open source), Jupyter Notebook (free), Google Colaboratory free). , Libraries from PyPI: jupyter, wfdb, pandas, numpy, glob2, tensorflow, matplotlib, math3, scikit-learn, joblib, pyserial, tkinter (all free, support Python 3).

For our project, we first use the ECG-ID database in Physionet for training (free of charge). Then, I collected three personal ECG signal data from my classmates and me. For future implementation, we will collect more personal ECG signal data sets to train the model without discrimination.

In addition, the main goal of our project also provides a new biometric method to help everyone have a new identification method. We hope this idea can make a positive contribution to society. If we have the opportunity to achieve certain goals in the future, we will do our best to achieve the best quality. I hope that one day this idea will be more fully implemented or generated in the real world.

CHAPTER 7. CONCLUSION AND FEELING

7.1 Feeling

Before to make the conclusion of the project, I wanted to share my feeling during finishing this project.

At the first beginning of this project, we didn't know what topic we should choose. We contact with some professors and get some opinion. After we discuss, we chose this ECG biometric identification project as our topic of final year project.

There is another team doing the related topic of ECG signal. They are also supervised by Prof. Liming Zhang. Actually, we can say we are the big team to cover and support each other. In the big team, I take a role as the coordinator of our team and a representative to contact with Prof. Zhang, our assistant Tonia, and lab technical assistant William. It is an extra work for me, but it is also worth to me. I can take more time to know more about my teammates and know how to discuss the academic and technical issue with my supervisor and assistants.

The unfortunate thing is the COVID-19 outbreak came this year. The impact is around all over the world. Of course, our plan to implement the idea of our final year project is also be affected. I will say we really try our best to finish training the model without a powerful GPU computer. The reason for that is we cannot enter the lab in campus during early period of outbreak. We try several methods to run the Python deep learning code, including running with our own MacBook Pro. Finally, we get a relatively good solution. It is running with Google Colaboratory with GPU, and it is free in charge. It helps us to finish the training step and the whole project.

Completing the project means that most potential graduate students need to face and step into the real world and have a new career. For me and us, this is an unknown world and situation. In the society facing COVID-19, this situation is a bit scary. The trend of social economic finance is not clear. But in any case, I will have the greatest hope to face the new career that is coming.

Lastly, I am very glad to finish the project together with my teammate – Elaine, and the group members of the related topic – Steven and Yumi. They are all my good partners and we learnt together how to solve the difficulties by doing the project. During this period, I know more about them and I think our friendship increases.

After sharing my feeling, I wanted to conclude about the project and discuss about the future implementation of our project.

7.2 Conclusion and Summary

In the beginning, I want to say thank you to my teammate – Elaine, the group members of the related topic – Steven and Yumi. Again, I want to say they are my very good partners. Also, I also want to thank our supervisor Prof. Liming Zhang, she takes care us very much and gives a lot of advices for us. Finally, I want to say thank you to our assistant Tonia, and lab technical assistant William. They give us a lot of technical advices and supports which smoothing our progression of the project.

By finishing this project, I use some knowledge of Arduino which I learnt before. In addition, I can combine what we learnt in the final year project. I think this is a good reason to prove I can have an opportunity to show what I learnt.

The new thing for me to learn in this project is deep learning and implement to solve the real-world problem. We step-by-step to implement the Python code of training model. Then, change the parameter and test it again and again. Finally, we get a relatively reasonable and good result for the model.

The final part is how to integrate the ECG Collecting Kit with model. Finally, I think a method is implement a GUI application to check the accuracy of the user identity with their user ID. It is simple, but really works.

In this project, I not only learn the academic knowledge, but also the soft skills, like problem-solving skills, collaborating skills, leading skills and communication skills. Again, thank you for all and hope them all good for the future life.

7.3 Future work

In this step for our project, it is not a stable version and the user dataset is not too much. Because of the COVID-19 outbreak and the time and resources are limited, we still have so many things to tune and implement to make our project more perfect.

Here, we will list some of the future work:

1. Build the user database

   For the real usage of the identification, the user information database is required. In addition, the management of the personal ECG signal should be securely storage. This is also a point why we needed to build the user database

2. Adapting the authentication application (API)

   After the identification process finished, the application should be sent out the result. With the authentication application, we need to build an API (Application Programming Interface). The API can help us to adapt to different application.

3. Tuning and trained model

   As we are using the SVM algorithm, we can use another training algorithm to train the model to get a higher accuracy. We also can tune the learning rate and other parameter to get the same goal.

CHAPTER 8. OTHER TOPIC

The ECG area have some other topic, which one of them is implemented by my related teammates. Therefore, I want to talk briefly about this topic.

They are implemented the ECG diagnosis by machine learning method.

There are several ECG databases to implement the diagnosis. The one that they use is PTB Diagnostic ECG Database [15] in Physionet.

Here is the sample information of ECG diagnosis of Brugada Syndrome.

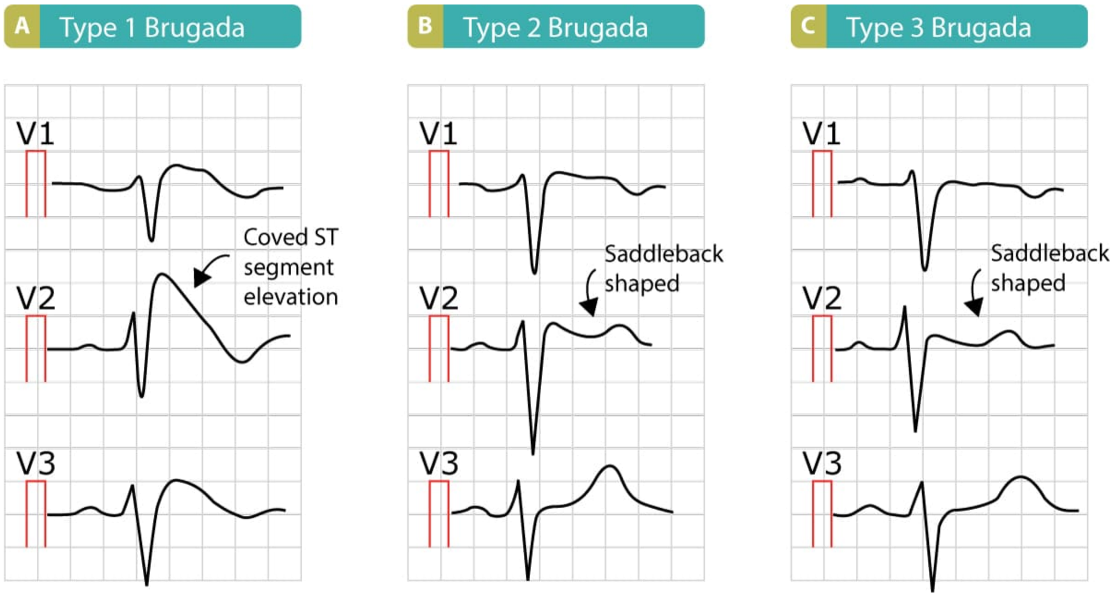


Figure 41: Information of ECG diagnosis of Brugada Syndrome (Capture by [17])

CHAPTER 9. REFERENCES

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CHAPTER 10. APPENDIX

For implement our project, we need:

1 Computer (with Windows/Linux/Mac OS)

2 Arduino UNO R3 (with USB cable)

3 AD8232 Heart Beat / ECG Collecting Shield (with sensors / electrodes)

4 Arduino IDE 1.8.12 (free, open-source)

5 Jupyter Notebook (free) or Google Colaboratory (free)

6 Library from PyPI (all free, support with Python 3).:

- 6.1 jupyter,
- 6.2 wfdb,
- 6.3 pandas,
- 6.4 numpy,
- 6.5 glob2,
- 6.6 tensorflow,
- 6.7 matplotlib,
- 6.8 math3,
- 6.9 scikit-learn,
- 6.10 joblib,
- 6.11 pyserial,
- 6.12 tkinter

END OF REPORT