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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

02 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 : ____________________________

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Date : 02 June 2020

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Throughout this project, the author was very fortunate to receive the guidance and encouragement from his supervisor…

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 account and password, electronic card certificate, which is easy to be stolen and posing. Biometrics is far superior to traditional identification. First, it has higher security. It will not be lost. It is unique, cannot be impersonated, and has better anti-counterfeiting performance. Second, it's convenient. Biometrics do not need to carry the extra things. Third, it is confidential and cannot be copied. Fourth, biological characteristics are stable and will not change. These advantages make it more powerful than traditional identification.

Therefore, we are thinking to build a low-cost biometrics identification method to give a new choice to the identification technical area.

Background:

Biometric identification mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprint, face, iris, handwriting, sound, gait etc. This identification technique combining computer with high-tech methods such as optics, acoustics, biosensors and biometric principles. We introduce the ECG biometric identification because it is new, and keep the tester is alive when it is testing.

Goal:

We'll using Arduino UNO, AD8232 Heartbeat / ECG Collecting Shield as the hardware. Python 3 with Jupyter Notebook or Google Colaboratory as the software and platform. SVM with scikit-learn is the deep learning algorithm to implement the biometric personal identification system. The final goal is implementing the GUI applicaiton by Tkinter with 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 is 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 identification mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprints, face, iris, handwriting, voice, gait, hand geometry etc. This identification technique combining computer with high-tech methods such as optics, acoustics, biosensors and biometric principles.

Traditional identification uses account and password, electronic card certificate, which is easy to be stolen and posing. Biometrics is far superior to traditional identification. First, it has higher security. It will not be lost. It is unique, cannot be impersonated, and has better anti-counterfeiting performance. Second, it's convenient. Biometrics do not need to carry the extra things. Third, it is confidential and cannot be copied. Fourth, biological characteristics are stable and will not change. These advantages make it more powerful than traditional identification.

For these reasons, biometric recognitions are being increasingly deployed in more and more government agencies and civilian applications. This technology is widely used in fields such as transfer, withdrawal, payment settlement, remote insurance business and so on.

This technology also permeates into daily life. You will be in contact with it even the first moment you get up. When you wake up and pick up your phone to check the information, you don't need to enter the password verbatim, just press your fingerprint or swipe your face. You can immediately unlock the phone.

Biometric identification mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprint, face, iris, handwriting, sound, gait etc. This identification technique combining computer with high-tech methods such as optics, acoustics, biosensors and biometric principles.

Like fingerprints and irises, everyone's heartbeat is unique. An electrocardiogram (hereinafter referred to as ECG) is a test that records the potentials produced by the atria and ventricles during contraction and relaxation.

With so many biometric technologies, why do we need ECG recognition? The reason for that is different biometric identification technologies have obvious differences in many aspects such as security, accuracy, stability, convenience, recognition speed, cost, etc. Thus, they have different advantages and disadvantages in different application fields. Fingerprint recognition is the most widely used in biometrics currently.

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 electrocardiographic signals not only meets the stability, uniqueness and convenience required for fingerprint identification, but also has unique anti-counterfeiting properties. ECG will be affected by factors such as the physical fitness state and mental state of the human body, but these factors will only cause the scaling and deformation of the ECG waveform and will not change its structure, so each person's ECG is still unique.

CHAPTER 2. LITERATURE SURVEY AND RELATED WORK

Biometric identification mainly uses the inherent physiological and behavioural characteristics of the human body to identify individuals. It includes fingerprint, face, iris, handwriting, sound, gait etc. This identification technique combining computer with high-tech methods such as optics, acoustics, biosensors and biometric principles.

Traditional identification uses account and password, electronic card certificate, which is easy to be stolen and posing. Biometrics is far superior to traditional identification. First, it has higher security. It will not be lost. It is unique, cannot be impersonated, and has better anti-counterfeiting performance. Second, it's convenient. Biometrics do not need to carry the extra things. Third, it is confidential and cannot be copied. Fourth, biological characteristics are stable and will not change. These advantages make it more powerful than traditional identification.

2.1 Fingerprint recognition

Biometric technology is used in transfer and withdrawal, payment 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 lines that protrude on the epidermis of each person's fingerprint, the starting point, ending point, joining point, and bifurcation point of the line are all different.

They are unique and unchanged for life. Fingerprint recognition technology generally uses the overall characteristics of the fingerprint to classify, and then uses local characteristics such as location and orientation to identify the user. In recent years, fingerprint recognition has been widely used, such as mobile phone unlocking, electronic payment, security, etc. It's fast to scan, read and use fingerprints. Also, the device 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 lead to recognition errors. In addition, fingerprints left behind are easily stolen and copied. It may cause some security problem.

2.2 Face recognition

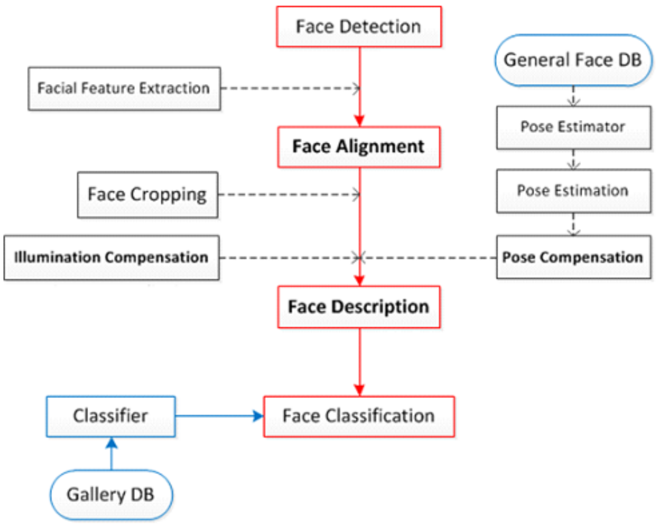


Figure 2: The flowing diagram of face detection and face recognition (Capture by [2])

Face recognition refers to how to recognize and understand a face. It is based on the facial feature information of a person, using a video camera or a camera to collect an image or video stream containing the face. Face recognition is one the most popular computer research technology now.

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

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

Face recognition requires the system to store a large number of different face and identity information in advance, in order to compare the face with the database at runtime.

However, it is difficult for the system to perform face recognition when the light is dim, or the face is obscured, and the side faces. This can lead to failure of face recognition. It has its limitations. In addition, the appearance of the face changes with age.

Face recognition is a widely used biometric approach. Face recognition technology has developed rapidly in recent years and it is more direct, user friendly and convenient compared to other methods. But face recognition systems are vulnerable to spoof attacks made by non-real faces. It is an easy way to spoof face recognition systems by facial pictures such as portrait photographs. A secure system needs Liveness detection in order to guard against such spoofing. In this work, face liveness detection approaches are categorized based on the various type's techniques used for liveness detection. This categorization helps understanding different spoof attacks scenarios and their relation to the developed solutions. A review of the latest works regarding face liveness detection works is presented. The main aim is to provide a simple path for the future development of novel and more secured face liveness detection approach.

Here, liveness detection approaches are categorized based on the type of liveness indicator used to assist the liveness detection of faces. Three main types of indicators were mainly used: motion, texture and life sign.

The most common problems that have been observed in case of many liveness detection techniques are the effects of illumination change, effects of amplified noise on images which damages the texture information. For blinking and movement of eyes-based liveness detection methods, eyes glasses which causes reflection must be considered for future development of liveness detection solutions. Furthermore, the datasets, which play an important role in the performance of liveness detection solutions, must be informative and diverse that mimics the expected application scenarios. Non-interactive video sequences must include interactive sequences where the users perform certain tasks. Future attack datasets must consider attacks like 3D sculpture faces and improved texture information. Our main aim is to give a clear pathway for future development of more secured, user friendly and efficient approaches for face liveness detection.

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

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

After liveness detection, an improved FaceNet will continue to recognize a face and provide the corresponding ID or UNKNOWN output for accurate identity authentication.

The rest of the paper is organized as follows. Section 2 briefly reviews the related works and recent liveness detection methods. Section 3 presents a framework that combines liveness detection and face recognition, and then the proposed liveness detection method based on IR image features and an improved FaceNet model, called IFaceNet, are described.

2.3 Iris recognition

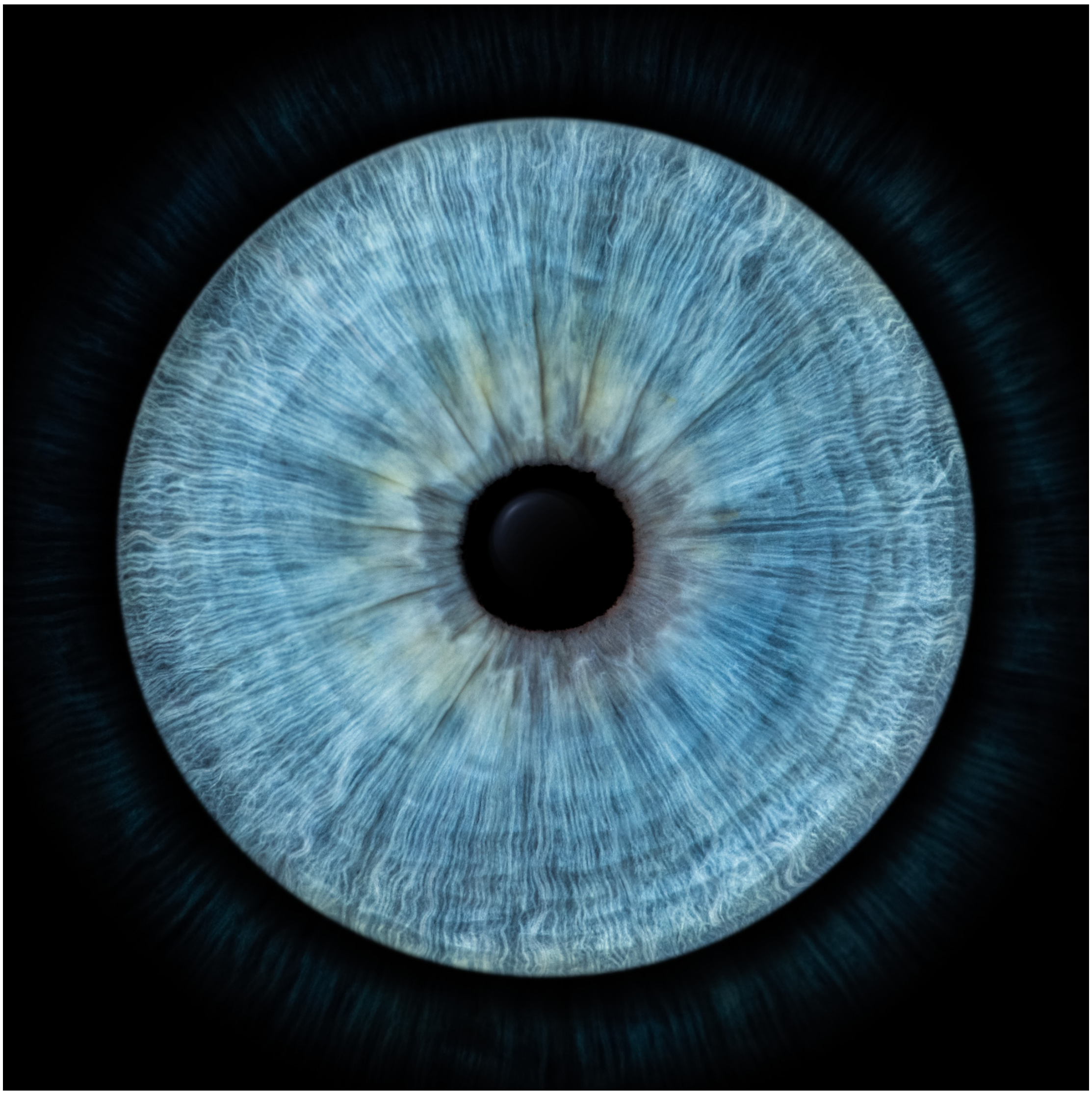


Figure 3: Iris (Capture by [3])

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, it analyzes a person's voice to verify their identity. Voiceprint refers to the spectrum of sound waves that carry speech 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 can't judge a person's identity by one word at present, through a large amount of training speech data, the system can learn to intelligently learn your voiceprint. It can determine your identity when you say several words.

This identification technology can be divided into two types of content-related and content-independent technologies. "Content-related" refers to the system's assumption that users only say that the system prompts the content or a small range of permitted content, and "content-agnostic" does not limit what users say content.

Compared to other forms of authentication, speech recognition has several key advantages. Today's mobile phones are basically equipped with a microphone, and identity authentication can be performed on the mobile phone. The microphone can be integrated into other devices, such as cars and home appliances. It is cost-effective. It is convenient and familiar for most users.

Some disadvantages are as follow, it is not as accurate as other biometrics (such as facial recognition). The background noise will affect the quality of the sample and then the matching performance. So, it is not ideal 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.

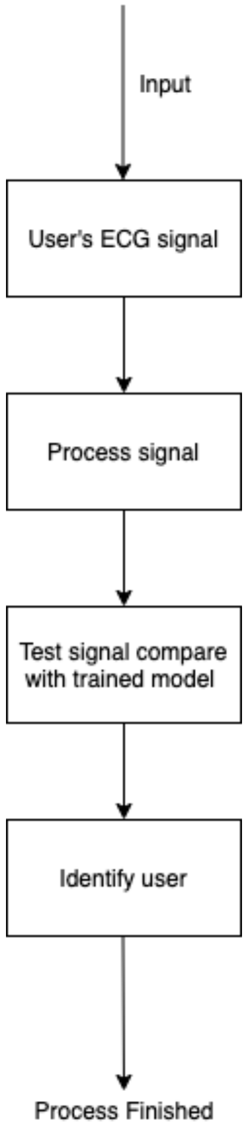


Figure 5: Abstract system workflow diagram

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

3.2 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.

3.2.1 User Routine of using the system

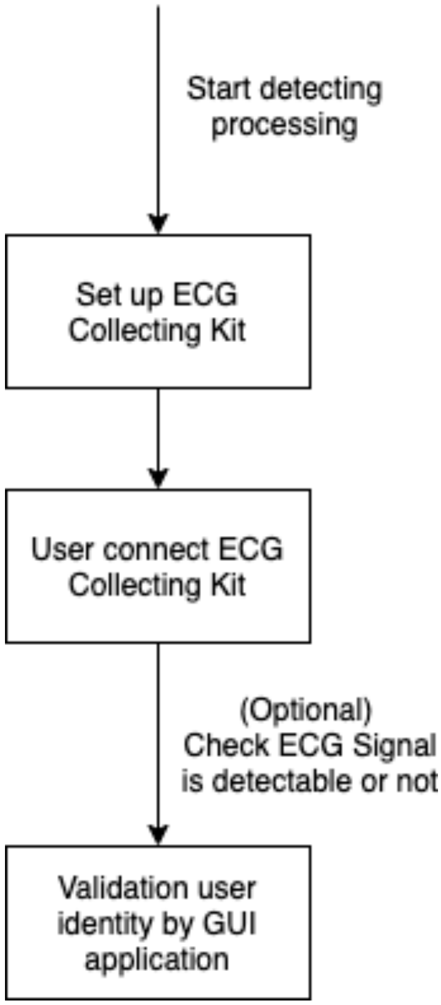
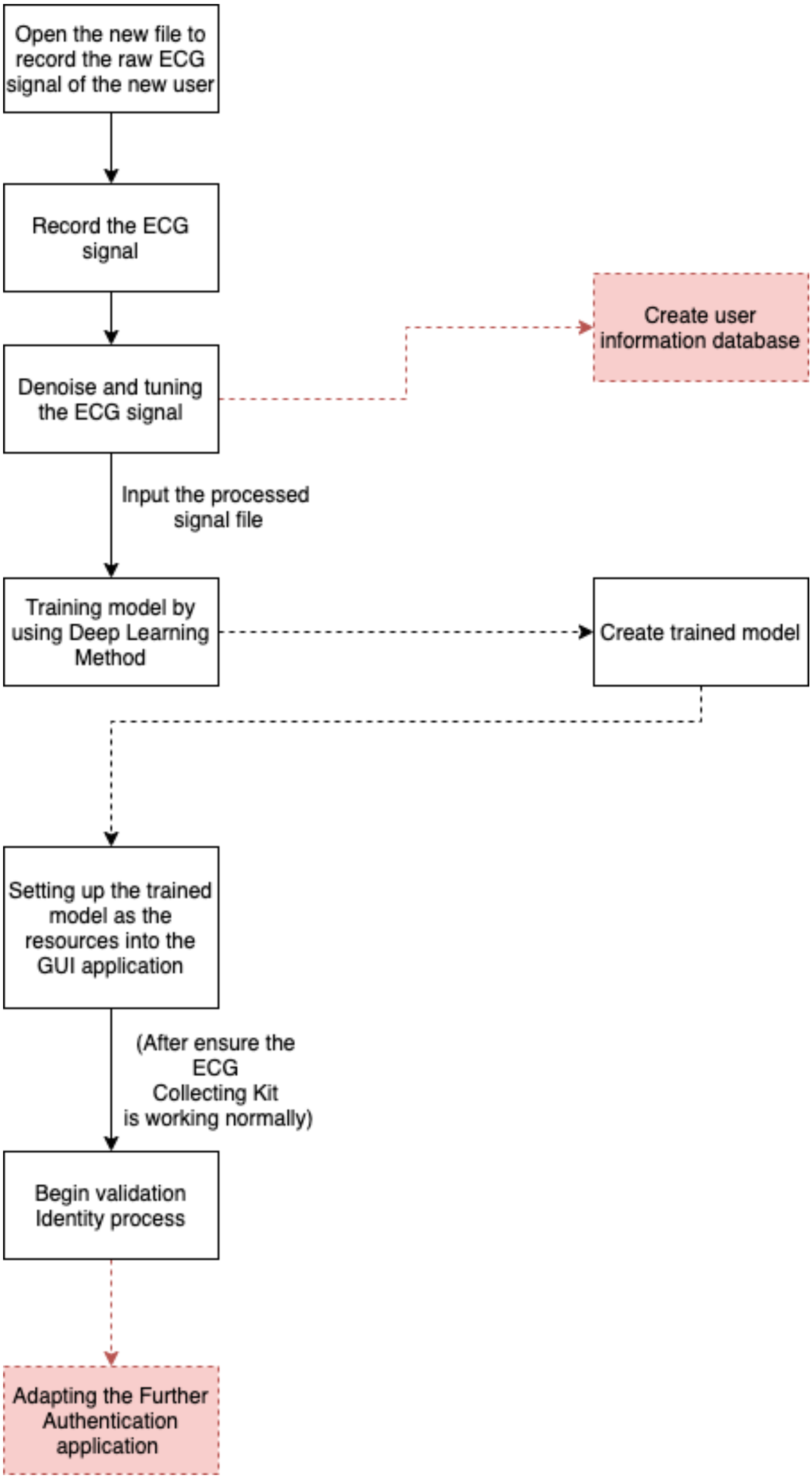


Figure 6: The routine of the user

In Figure 6, it shows the easy routine of the user when they want to use our ECG biometric identification system. After finishing the set up and collect the ECG Collecting Kit, then it can the validation identification process can be started. In optional, before the validation process begin, we can check the ECG signal is detectable or not, and the shape of ECG signal is normal or not.

3.2.2 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, the things we needed to do when a new user arrive, first our developer or system administrator needed to open a new file to record the raw ECG signal of the new user. Then, we can record the ECG signal by ECG Collecting Kit. By the practice of the collecting experience, there are always some noise will be collected during the recording step. Therefore, we needed a step to denoise and tune the raw ECG signal. As in the figure shown, for the future implementation, creating the user information database is necessary.

After the signal is finely tuned, we put all the signal of all users into the deep learning training program to create the trained model after the deep learning process. During the learning process, we'll monitoring the F1-score / accuracy indicator to make sure the training is relatively accurate.

Finally, after the validation identity process, it will show the selected user is clear the identity test. Also, our system can be further implement an API to connect with the other system or software.

To be aware that, because of the time and resources are limited and the COVID-19 virus outbreak, some ideas we didn't have time to implement, for future implementation and work, we marked as dotted line in Figure 7, such as building the user information database, and develop the API after the identification process, and have the more powerful hardware resources to make the training time less and the accuracy higher.

3.3 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.

3.3.1 ECG Signal collecting workflow

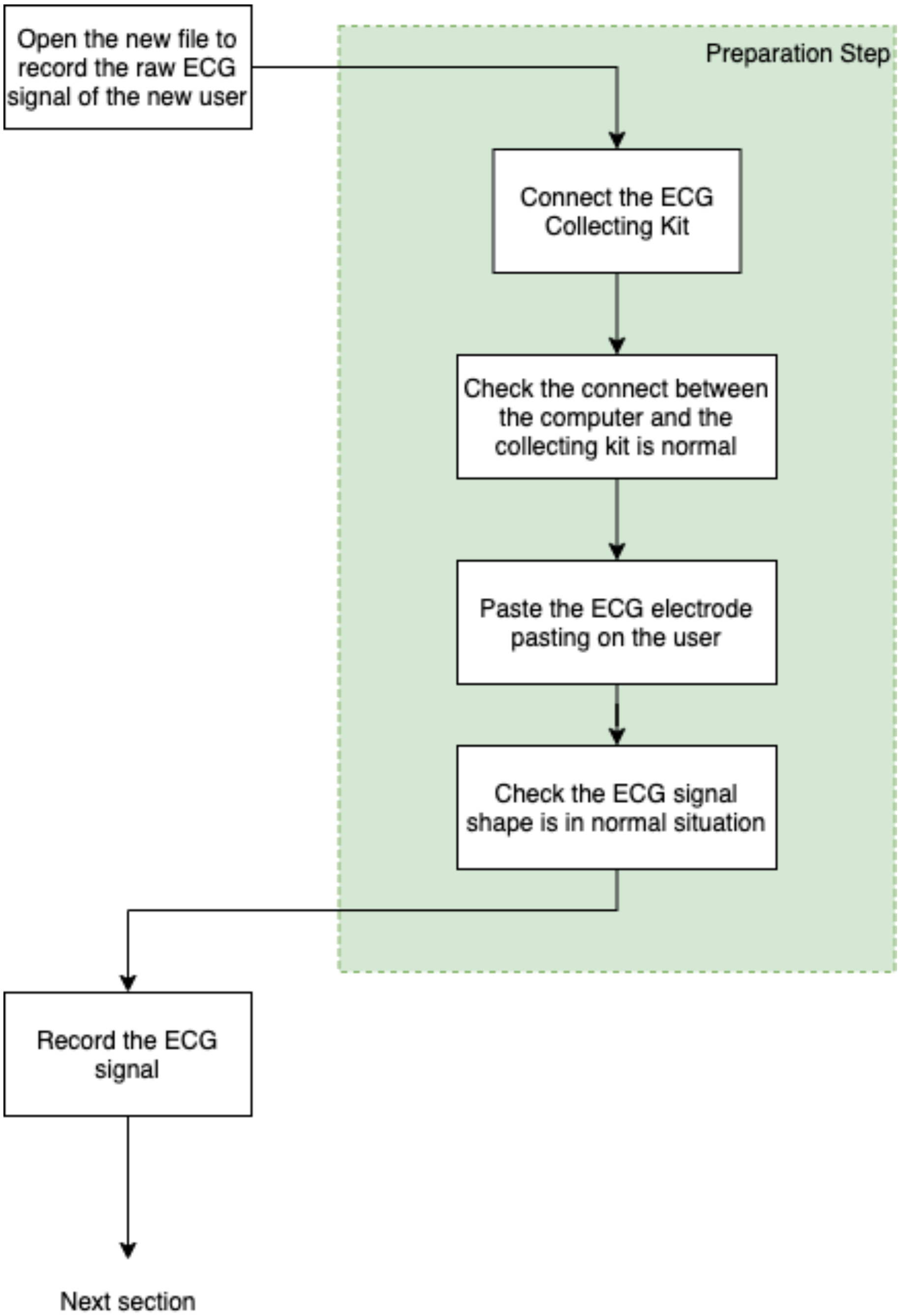


Figure 8: The workflow of record the ECG signal

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 preparing step of check the ECG signal shape is in normal situation, we can use the advantage by using Arduino IDE monitor to see the shape is normal or not. We will have more discussion of the implementation part of all function and work. Therefore, let us to see the next part.

3.3.2 Connection with ECG Collecting Kit workflow

This is an important part of our system. If the connect model cannot work normally, everything else are useless. Therefore, we say how to connect the ECG Collecting Kit is very essential. For the ECG Collecting Kit, as we mentioned before, it components with Arduino UNO, and AD8232 ECG Collecting Shield. The following is the workflow to show how to connect the ECG Collecting Kit.

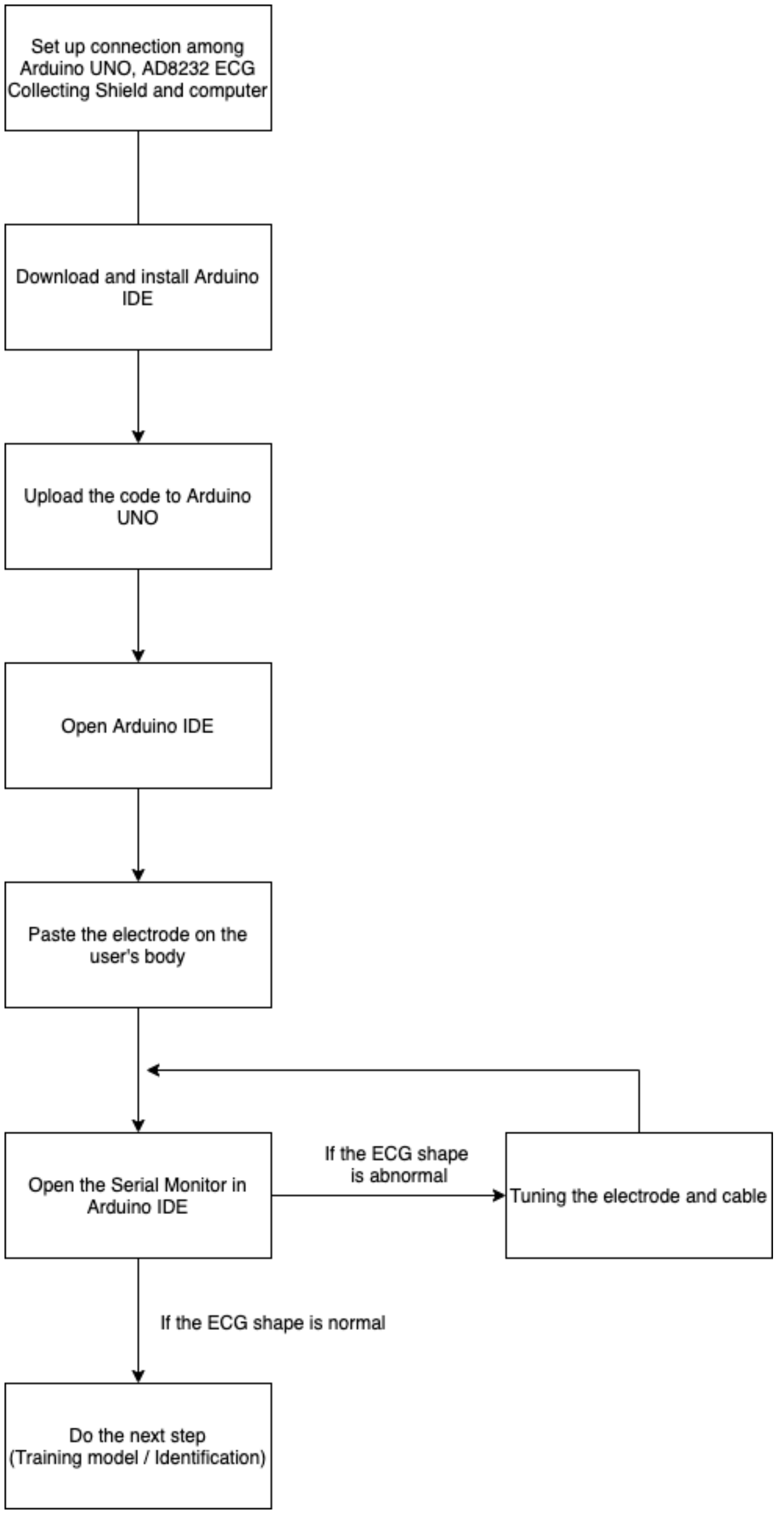


Figure 9: The workflow of connection with ECG Collecting Kit

In Figure 9, we can see we needed to download the Arduino IDE. After the connection between ECG Collecting Kit and computer is working, and also uploaded the code to Arduino UNO, we can paste the electrode on the user's body. In order to implement the ECG collecting function, the codes will discuss in the following chapter. The next step is the training model process.

3.3.3 Training model workflow

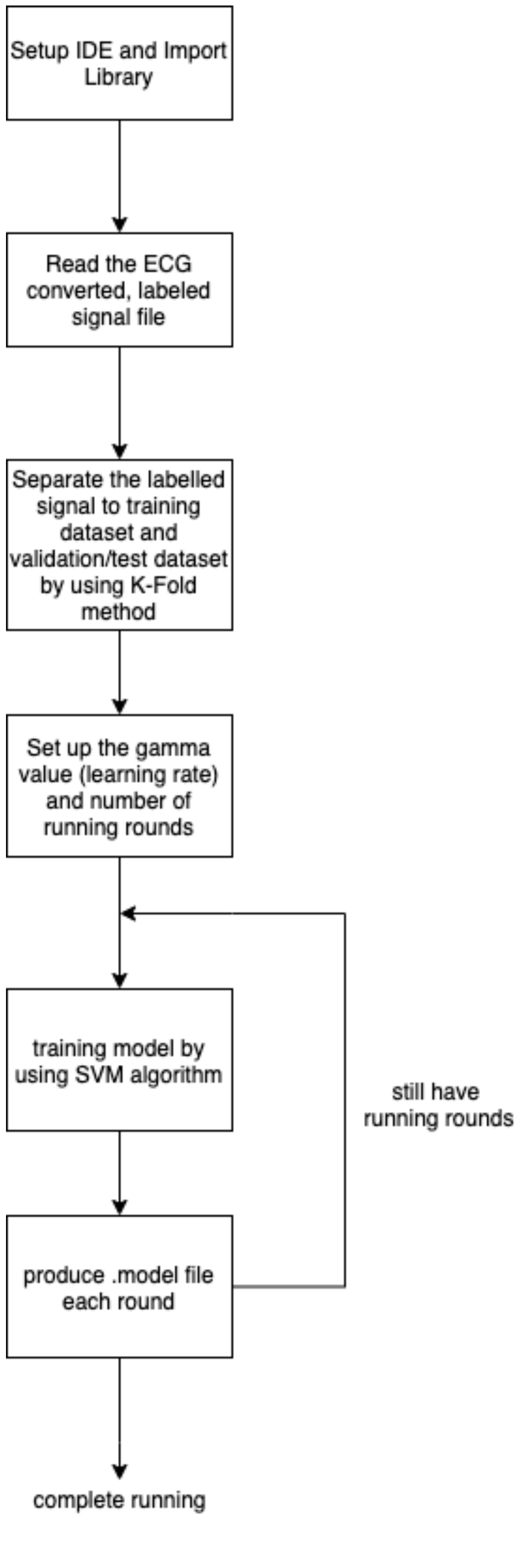


Figure 10: The workflow of training model

In Figure 10, we can see the workflow of training model, first we set up the IDE and important the library. We used the Jupyter Notebook and Google Colaboratory as the IDE and using Python 3 as the main programming language. Then, the ECG converted signal process is implemented by developer and system administrator. We will discuss the detailed implementation in the following chapters.

As the following steps, it is implemented by Python 3 code. We used the K-Fold method to separate the labelled signal records into training dataset and validation/testing dataset. Then, we set the gamma, also called learning rate and number of training rounds. Next, we run the training model by using SVM algorithm. We will also discuss the detailed information in the following chapters.

In the final part of the training model section, each training round will produce a .model file. This .model file we will use it as the key of biometric identification part.

3.3.4 Identification process workflow

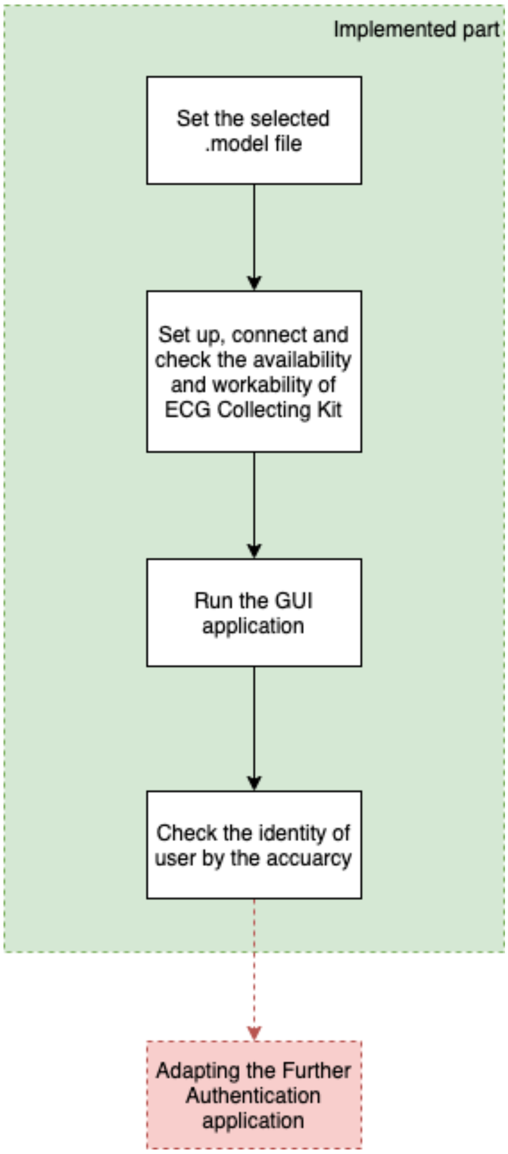


Figure 11: The workflow of identification process

In Figure 11, we can notice about the implemented part. As the previous section mentioned, we needed to set up the selected .model file into the system setting. Then, the connecting ECG Collecting Kit is required and the step is same as before.

The key part of this section is running the GUI application, it is implemented by Python 3 with Tkinter library. We will check the accuracy of the ECG signal segment to determine the identity of user. The detailed part will discuss in the following chapters.

3.3.5 Interface workflow

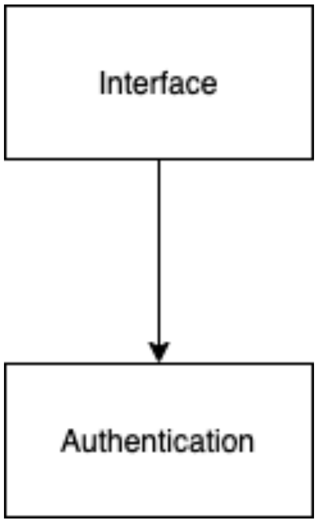


Figure 12: The interface of our identification system

The last thing is the interface of our identification system. Our interface is pretty simple, as shown in Figure 12. The interface contains only one authentication part. It likes the login page, but using the ECG biometric identification method. It is also the key part of our whole system.

To the end of CHAPTER 3. The next chapter will discuss our implementation part. From CHAPTER 4, the content with my groupmate will be different because we are working in different part with each other. We will only write the part which belongs to our job.

CHAPTER 4. IMPLEMENTATION OF THE ECG CLASSIFICATION SYSTEM

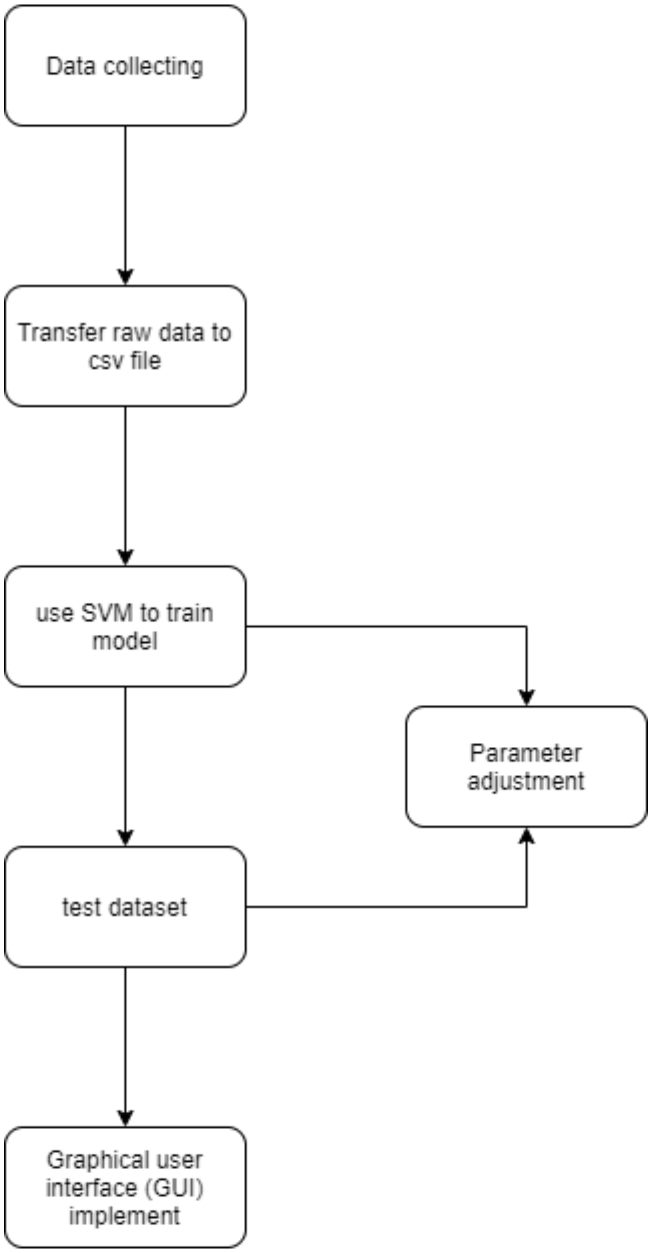


Figure 13 flowchart of the project

4.1 Tool

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

The training model section, we select Jupyter Notebook and Google Colaboratory as the platform, Python 3 as the main programming language.

Because of our GUI identification program also using Python 3 (with Tkinter) as the programming language, the OS compatibility is good. Our GUI identification program can be run in Windows, Linux and also Mac OS.

This is some information about my work. Let us begin in detailed:

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

The Arduino Uno is an open-source microcontroller board. It based on the Microship ATmega328P microcontroller. It has several digital and analog input/output pin which can connect it to other board.

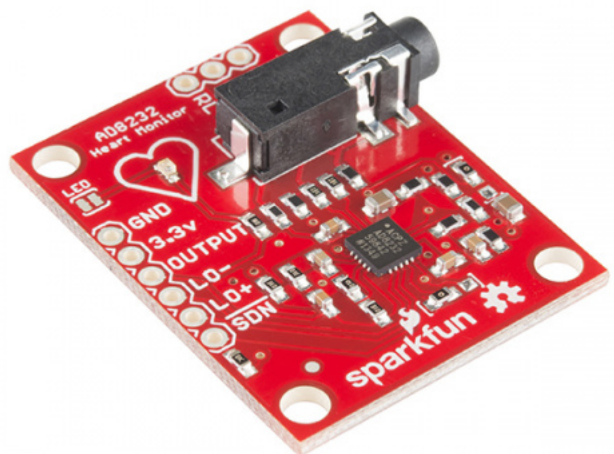


Figure 15: AD8232 ECG Collecting Shield (Capture by [10])

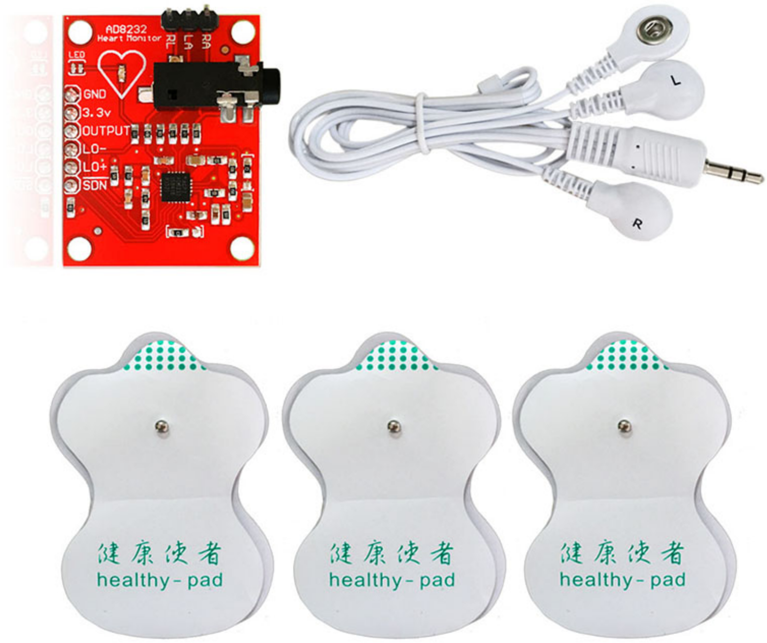


Figure 16 AD8232 with Biomedical Sensor Pad (Capture by [11])

The AD8232 is an integrated signal conditioning module suitable for ECG and other biopotential measurement applications.

Although the official website said that 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. However, in our attempts, we found that it is best to use it in a stationary state. Otherwise, the ECG shape may be incorrect.

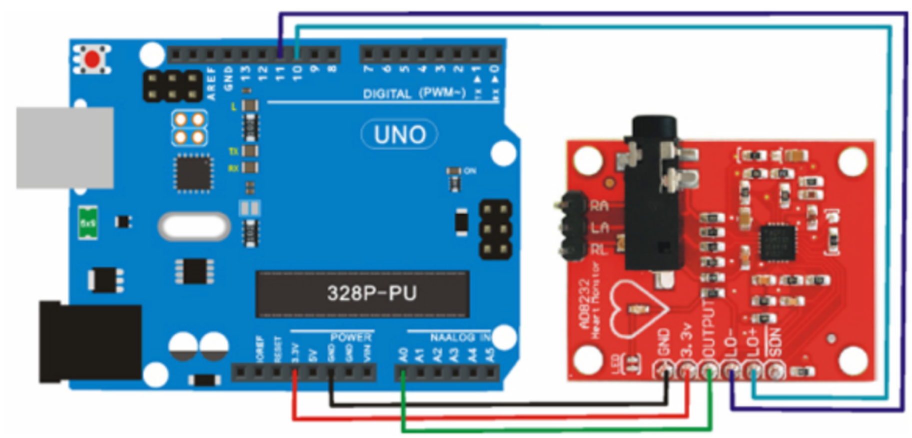


Figure 17 The wiring of Arduino UNO and AD8232 ECG detecting module (Capture by [12])

4.2 Signal collecting and pre-processing

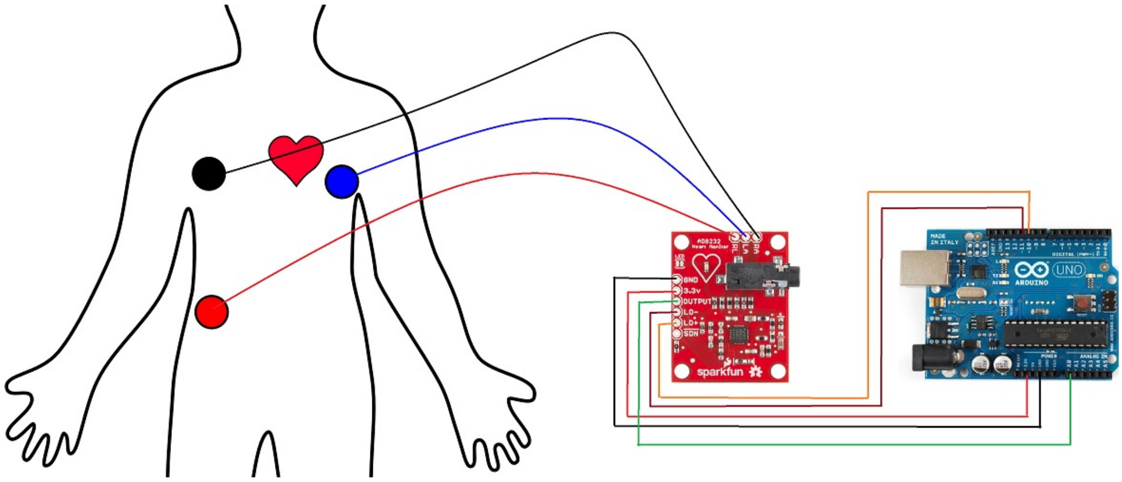


Figure 18 Typical sensors placement (Capture by [13])

Place biomedical sensor pad on different parts of the human body and connect them to the positive and negative electrodes of the electrocardiograph current meter through the lead line. This circuit connection method for recording the electrocardiogram is called the electrocardiogram lead.

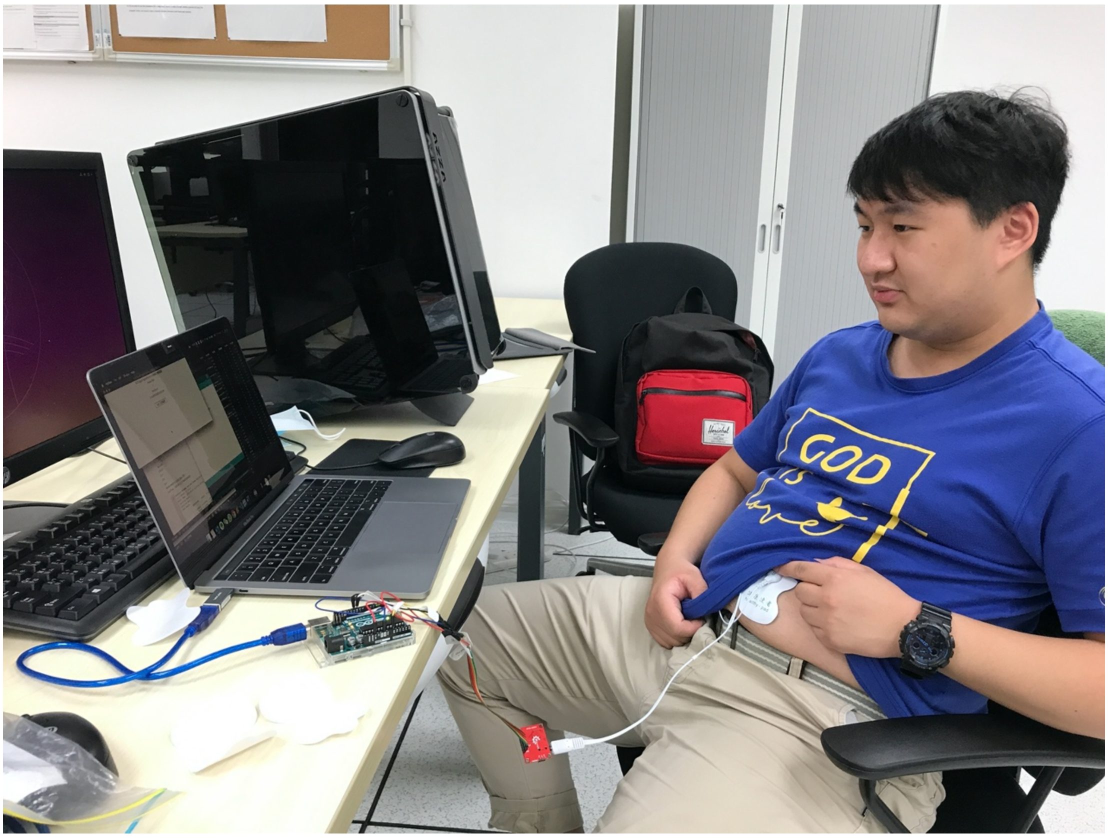


Figure 19 place sensor pad and collect signal data on classmate's body

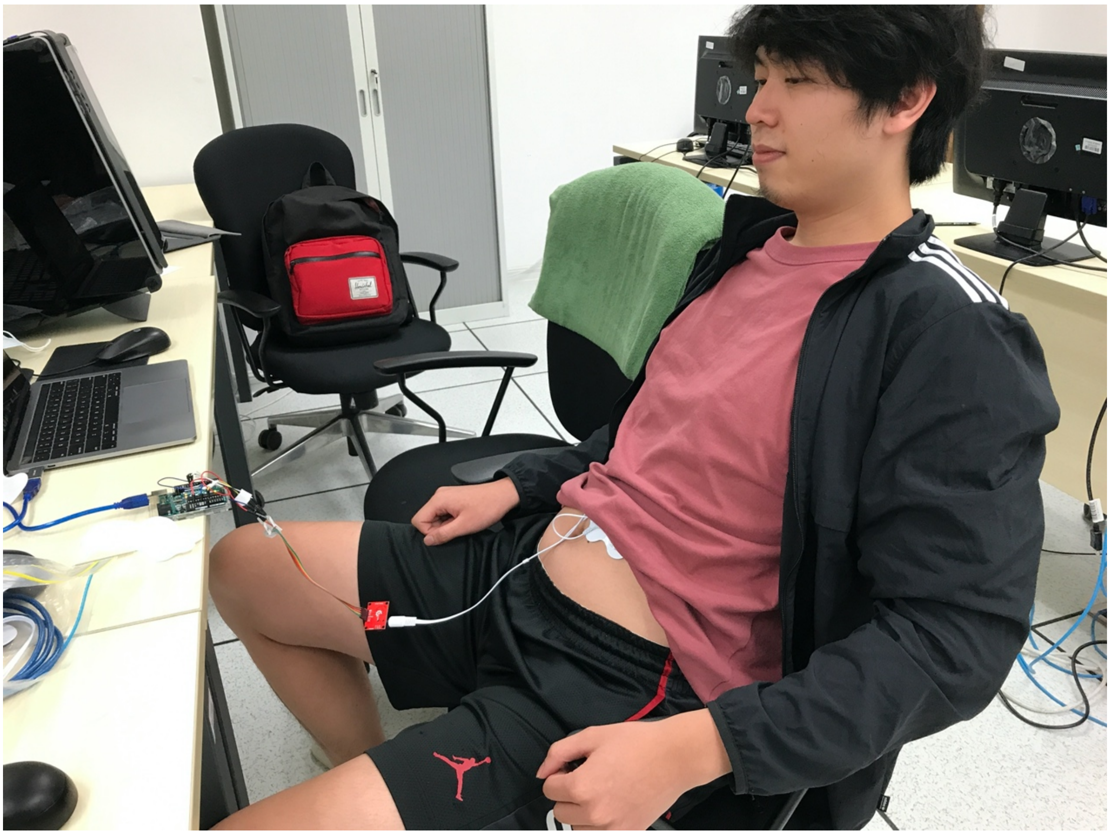


Figure 20 place sensor pad and collect signal data on classmate's body

After placed biomedical sensor pad on body, we can start to collect the ECG signal. The position of the sensor pad should be placed correctly, sometimes we had to change and replaced it in order to get less signal noise.

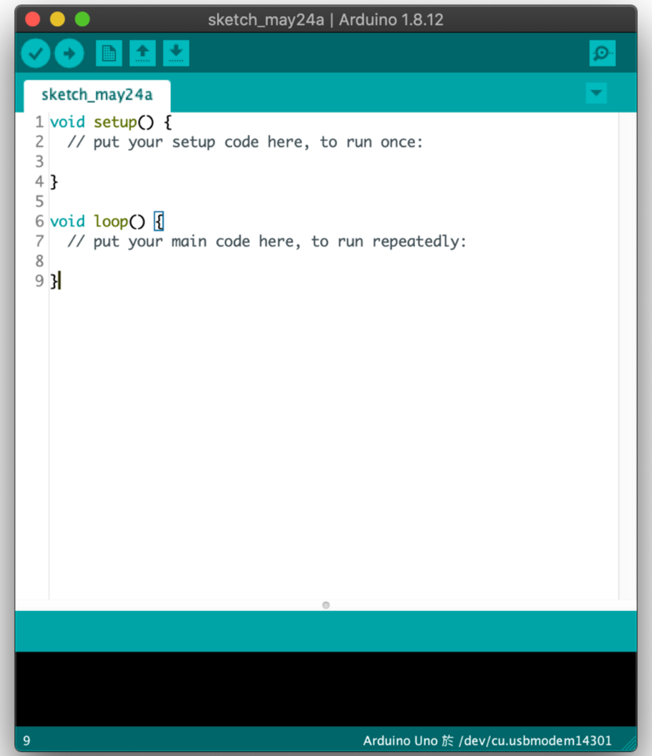


Figure 21 the GUI of Arduino

Run the program, signal began to collect and record. We can got the ECG signal plot, showing as follow.

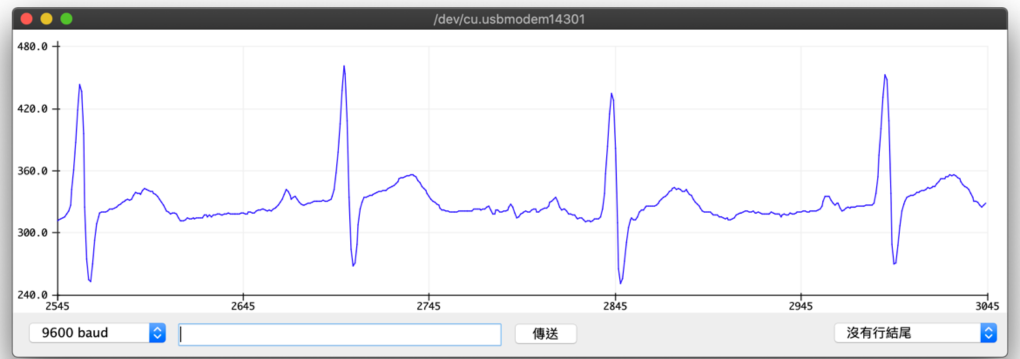


Figure 22 ECG signal collected by Arduino

Figure 23 numeric data

Also, we can see the numeric data in the collecting system.

```
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)
```

Figure 24 code of transform data to csv file

We converted data to csv format and targeted them with label.

```
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 library that we used

Python has many powerful libraries and tools. We choose support vector machine (hereinafter referred to as SVM) to train our model.

```
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)
```

```
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
```

Figure 26 code snipper: driven program

SVM is a supervised learning method. After we train the model, we can see that different weight of gamma will have influence on the result. We set the gamma to various value and find that it works better when gamma is between 0.1~0.5.

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***

Figure 27 value of gamma and their accuracy

At the end, we set the gamma value on 0.2 which has the best performance on accuracy. The sample is showing as follow.

```
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 28 sample of program run

CHAPTER 5. ETHICS AND PROFESSIONAL CONDUCT

Here we emphasize, for ethics and professional conduct, all our related works, research, and code have been marked by reference.

In our project, we have used Arduino UNO R3 (buy from TaoBao), AD8232 ECG collecting shield (buy from TaoBao), Arduino IDE 1.8.12 (free, open-source), Jupyter Notebook (free), Google Colaboratory (free), Library from PyPI: jupyter, wfdb, pandas, numpy, glob2, tensorflow, matplotlib, math3, scikit-learn, joblib, pyserial, tkinter (all free, support with Python 3).

For our project, we firstly trained with ECG-ID database in Physionet (free). Then, collected 3 personal ECG signal data from me and our classmates. For future implementation, we will collect more personal ECG signal dataset to train the model with no discrimination.

Further the main goals of our project give a new biometric identification implementation, to help everyone have a new choice of identification method. We hope that this idea can pay a positive contribute to society and if we have chance to do some future implementation, we will try our best to achieve the best quality. Hope one day this idea and more complete implementation or product in the real society.

CHAPTER 6. Conclusion

For the reason of virus outbreak, we cannot use the powerful GPU computer to train the model. We needed to decide keep the original deep learning method, or change to the another algorithm (such as *traditional recognition* method).

After consideration, we decided to use a simple SVM algorithm to implement this project. Although SVM is a simple algorithm, it still takes many time to train the model.

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.

We didn't get the ideal accuracy since we couldn't use the powerful deep learning model. Also, the training data is not large enough. If we want to train huge data, it takes several days to finish one round. The third reason is our limited funding. Our collecting device is simple and low cost. It may get noise signal.

I'm glad that we got through the difficulties and finished the project. I truly appreciate for the helps of Prof. Liming Zhang and my teammate Oscar.

CHAPTER 7. 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 also by deep 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.

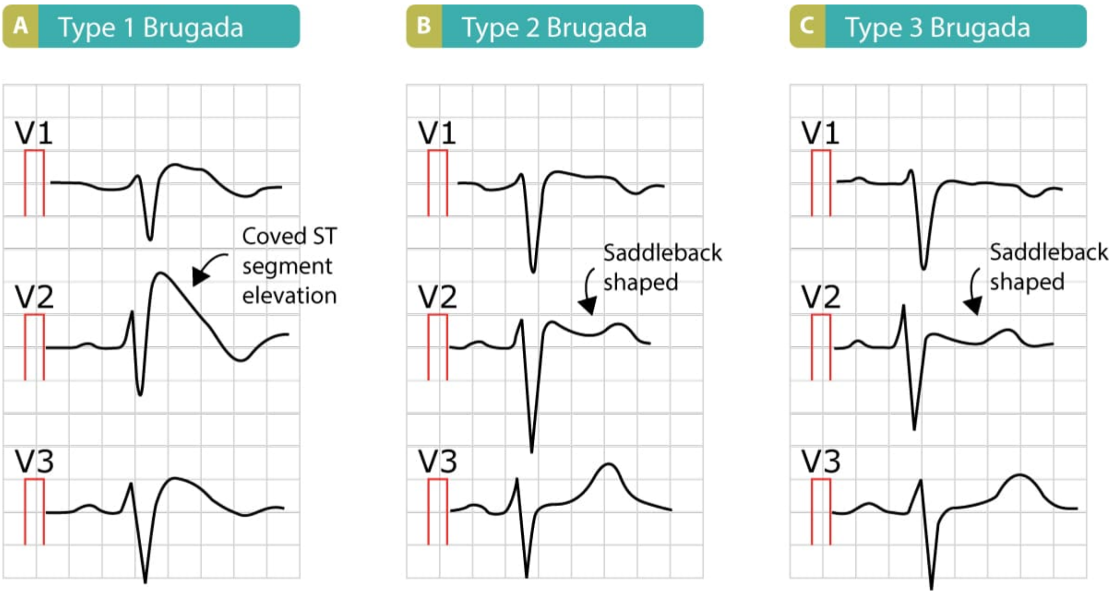


Figure 29: Information of ECG diagnosis of Brugada Syndrome (Capture by [14])

CHAPTER 8. REFERENCES

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CHAPTER 9. 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