DEVELOPMENT OF ANDROID BASED HEALTH MONITORING SYSTEM

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DEVELOPMENT OF ANDROID BASED HEALTH MONITORING SYSTEM

by

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BN	Batch Normalization
CNN	Convolutional Neural Network
CPOD	Crew Physiologic Observation
DESA	Department of Economic and Social Affairs, Population Division
DSP	Digital Signal Processing
ECG	Electrocardiogram
FN	False Negative
FP	False Positive
IoT	Internet of Things
IR	Infrared Ray
LFW	Labeled Faces in Wild
LS-SVM	Least Square Support Vector Machine
MA	Motion Artifacts
m-CNN	Multi-task Convolutional Neural Network
OpenCV	Open Source Computer Vision Library
O-net	Output Network
PCB	Printed Circuit Board
PPG	Photoplethysmographic
P-net	Proposal Network
R-net	Refine Network
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
YFW	Youtube Faces in Wild

PEMBANGUNAN SISTEM PENGAWASAN KESIHATAN BERASASKAN ANDROID

ABSTRAK

Jumlah populasi berumur antara 25 hingga 29 yang tinggi menunjukkan kepentingan perkhidmatan kesihatan untuk mengekalkan kesihatan mereka. Walau bagaimanapun, terdapat banyak alat pengukur kesihatan hanya dapat mengukur satu parameter kesihatan sahaja. Selain itu, kebanyakan alat pengukur hanya dapat menyimpan rekod dengan bilangan yang terhad. Tambahan pula, alat pengukur ini tidak meramal keadaan kesihatan pengguna selepas data kesihatan diperolehi. Oleh itu, tujuan projek ini adalah untuk membangunkan sistem pengawasan kesihatan yang diperbaiki. Sistem ini mempunyai pelbagai penderia. Sistem ini menggunakan modul klik denyut jantung untuk menangkap kadar denyutan jantung dan tahap tepu oksigen, dan penderia TMP007 untuk mendapatkan suhu badan. Penderia-penderia ini disepadukan ke mikropengawal Arduino bagi perolehan data. Data-data tersebut akan dihantar kepada Raspberry Pi 3 melalui komunikasi siri. Data yang diperolehi oleh Raspberry Pi 3 akan digunakan untuk meramal keadaan kesihatan melalui model pengelasan Sokongan Vektor Mesin (SVM). Setelah itu, semua data informatik kesihatan dan keadaan kesihatan akan disimpan dalam pangkalan data Microsoft Azure Cloud. Semua nilai parameter kesihatan dan keadaan kesihatan disimpan bersama dalam jadual yang mempunyai enam lajur di bawah pangkalan data Cloud dengan menggunakan arahan permintaan MySQL. Aplikasi telefon bimbit boleh mengambil semua data dari pangkalan data Cloud dengan menggunakan arahan pertanyaan MySQL, mengikuti nama pengguna. Bagi menambahkan keselamatan data kesihatan yang disimpan, projek ini telah membangunkan aplikasi berasaskan Android yang mempunyai sistem log pengenalan wajah untuk pengguna melihat data kesihatan mereka. Model klasifikasi SVM mencapai ketepatan keseluruhan 93.33% daripada 60 data ujian sementara model klasifikasi FaceNet untuk pengenalan muka mencapai ketepatan keseluruhan 99.0%. Kedua-dua model pengelasan diterima untuk digunakan bagi projek ini.

DEVELOPMENT OF ANDROID BASED HEALTH MONITORING SYSTEM

ABSTRACT

The large number of population within the age between 25 to 29 implied the importance of health care services to maintain their wellbeing. However, a lot of health measuring devices are only able to measure one health parameter. Besides, most of the measuring devices stored only a limited number of records. Furthermore, these measuring devices do not predict user's health condition after health data is obtained. Therefore, this project aims to develop an improved health monitoring system. The system consists of multiple sensors. The system utilized heart rate click module to capture heart rate and oxygen saturation level, and TMP007 sensor to obtain body temperature. These sensors are integrated into Arduino microcontroller for data acquisition. The data will then be sent to Raspberry Pi 3 via serial communication. The data read by Raspberry Pi 3 will be used for health condition prediction through Support Vector Machine (SVM) classification model. After that, all the health informatic data and health condition will be stored in Microsoft Azure Cloud database. All the health parameter values and health condition are stored together in a table of six columns under Cloud database using MySQL query command. The mobile apps can be retrieved all data from Cloud database using MySQL query command as well correspond to user name. To add security to the stored health data, this project has developed an Android based app having face recognition login system for the users to view their health data. The SVM classification model achieved an overall accuracy of 93.33% from 60 testing data meanwhile FaceNet classification model for face recognition achieved an overall accuracy of 99.0%. Both classification models are accepted to be used for this project.

CHAPTER ONE

INTRODUCTION

1.1 Background

The world's population is growing since year 1950. Figure 1.1 shows the trend for population of the world. According to , the world's population had arrived at a number of nearly 7.6 billion as of mid-2017. Asia occupied with the most number of people in the world, which is approximately 4.5 billion people (i.e. 60% from the world population). Department of Economic and Social Affairs, Population Division (DESA) had made statistical analysis that the world's population may reached up to between 9.4 and 10.2 billion in 2050 (United Nations, 2017).

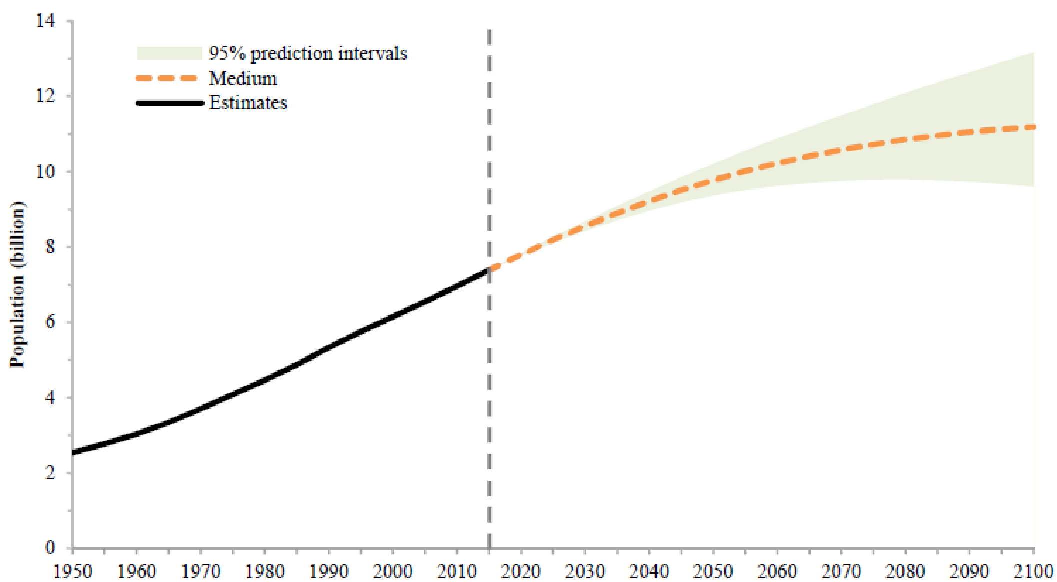


Figure 1.1: Population of the world (United Nations, 2017)

In Figure 1.2, the chart shows the percentage of population in broad age groups for the world and by the region in 2017. By referring to the world statistic in the chart, majority of the population are in age group of 25 to 59, which is 46%. The total of 26% are in age group of 0 – 14, 16% are in age group 15 – 24 and the rest of 13% are in age group of 60 and above (United Nations, 2017).

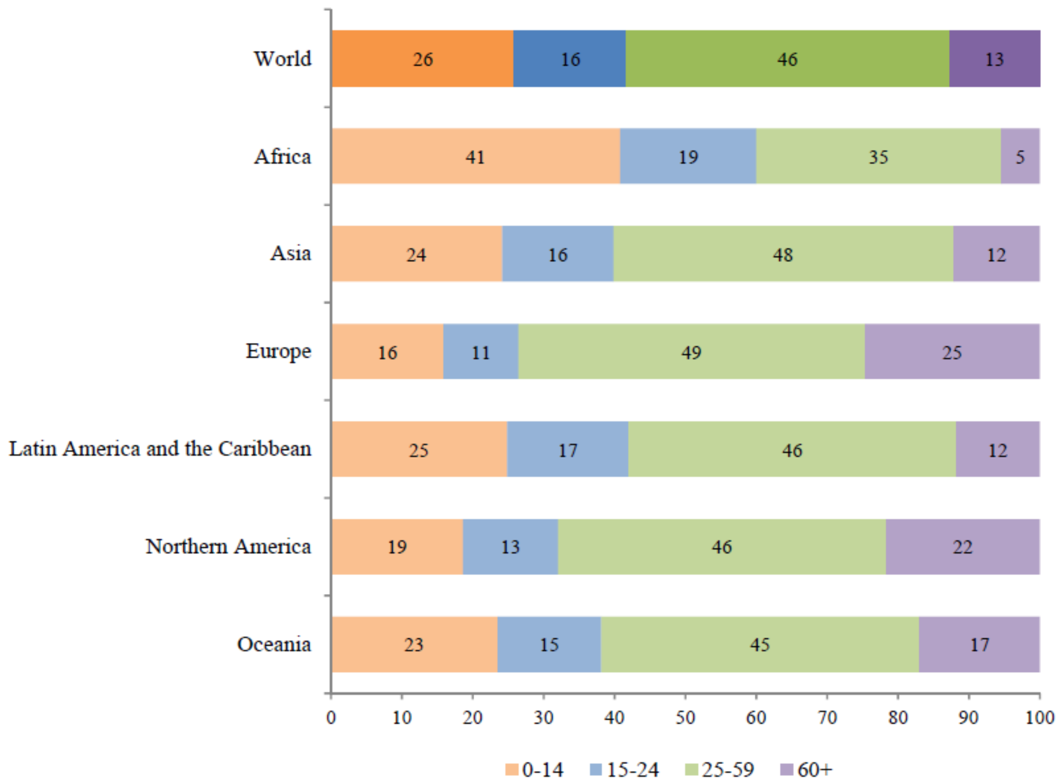


Figure 1.2: Percentage of population in broad age groups for the world and by region, 2017 (United Nations, 2017)

The large number of population who age group in between 25 to 59 implied that the development of health care services is needed to maintain their good health before it is too late. However, in some rural areas, the medical coverage is limited due to the lack of qualified medical experts. Thus, the development of telemedicine become a significant important in providing a fast and high-quality medical consultancy without doctor required to be at the geographical location with the patient (Görs, Albert, Schwedhelm, Herrmann, & Schilling, 2016).

Telemedicine is defined as a technology that involving medical information to be exchanged from one site to another via electronic communications to improve the quality status of patients' clinical health (Burke & Hall, 2015). Telemedicine plays many important roles in helping different kinds of people. Telemedicine can help people who has diabetes diseases. According to the study by Romero-Aroca, Sagarra-Alamo, Pareja-Rios, and López (2015), the insufficient number of experts and the different studies on effectiveness of screening lead to problems of diabetes screening. Besides that, a necessary training is required to professionals for different cases of diabetes so that they able to recommend patient for taking treatment as quickly as possible. The existence of telemedicine had helped a lot in diabetes screening by making correct diagnosis through images and some information.

Magdalena and Bujnowska-Fedak (2015) had stated a few benefits of telemedicine towards aging people. One of the benefit is that telemedicine helps to reduce number of hospitalizations and its duration by providing health care services through tele-devices at home. Besides that, telemedicine helps to make decisions on aging's health condition on behalf of doctors. Telemedicine also provided advise to people who had aware of his or her health condition so that they can take action to move forward into healthy lifestyle.

Wearable device is one of the application from telemedicine. According to Kajornkasirat, Chanapai, and Hnusuwan (2018), wearable device is a type of device that connected to internet and works with computer system to approach data. The available wearable devices in the market can be used to measure heartbeat rate, blood pressure (Yvette E. Gelogo & Haeng-Kon Kim, 2015), oxygen saturation, body temperature (Kos & Kramberger, 2017) and so on.

In recent days, smart phones had been integrated with wearable devices. This is because smart phones able to help patients to instant view the records, reminds patients to make appointment with medical doctors, help patients to search nearby clinical center and so on (Mahmud, Wang, Esfar-E-Alam, & Fang, 2017). Smart phone based telemedicine system involved in many applications such as ECG state monitoring, oximetry and respiratory sensing (Mahmud et al., 2017), and seasonal health monitoring (McNamara & Ngai, 2018).

Thus, Internet of Things (IoT) played a very important role to help the communication among smart phones, Cloud server and wearable devices. A lot of wireless sensor technologies, such as Wi-Fi, Zigbee, Bluetooth, WiMAX are built in with the wearable devices so that health informatics data can be forwarded to the cloud data center (He, Ye, Chan, Guizani, & Xu, 2018). Besides, 5G network system also built into some of the wearable devices as it has greater bandwidth, higher rate of air interface technology and greater capacity (Ma, Wang, Yang, Miao, & Li, 2017).

1.2 Problem Statements

Wearable devices had been widely used by most of the teenagers and aging people to replace some traditional medical services and keeping them health aware (Sundaravadivel, Kougianos, Mohanty, & Ganapathiraju, 2018). However, currently, there are still a lot of health measuring devices that are measuring only one health parameter from each person. This bring inconvenience to most of the users because users may need a lot of devices to get different health parameters (Andreu-Perez, Leff, Ip, & Yang, 2015) and it will become costly if many devices are required (Soh, Vandenbosch, Mercuri, & Schreurs, 2015).

There are a lot of health data that had already collected all around the world. However, a problem that will be encountered is that data by themselves are useless and unable to use for health monitoring. The health data have to be analyzed, interpreted and acted on so that useful information can be obtained for correct decision making in health monitoring (Obermeyer & Emanuel, 2016).

Another problem that encountered by many users is that they are unable to view back their health record history which were obtained previously. This is because most of the heath measuring devices have low memory spacing, which only can store a few records. Therefore, users face difficulty to send their health data to healthcare providers to seek for advice (Yvette E. Gelogo & Haeng-Kon Kim, 2015).

There are many devices including mobile phone or mobile app able to view most of the users' personal data. However, all these devices are still using traditional authentication techniques, like login ID and password combination technique. this technique is not secured as it is very easy to be hacked by any person or by any tools. Besides that, users cannot login into a system if he or she forget the password (Pawle & Pawar, 2013).

1.3 Objectives

The main goal of this project is to create an Android apps which able to monitor a person's body health. To achieve the goal, there are several objectives need to be accomplished:

1. To develop a data acquisition system which consists of three sensors, which are temperature sensor, pulse oximeter sensor and heart rate sensor.
2. To develop Support Vector Machine (SVM) based machine learning algorithm which is suitable to monitor health condition.
3. To develop Android based app having face recognition login system and integrate the data system with the Cloud.

1.4 Project Scope

The scope of this project is to develop an Android based app for monitoring a person's health condition. This project is only limited to only three major parts, which are development of Android mobile apps, data integration between Cloud and Android, and health data training. Android based was used for creating app instead of iOS because Android is an open source operating system. Therefore, a lot of APIs that can be used for app development can be found from the internet.

The data collection is only limited to be done by three measuring instruments, which are body temperature sensor, heart rate sensor and pulse oximeter sensor. Thus, health data that will be collected in this project are body temperature, heart beat rate and blood pressure. The reason why heart beat rate was focused because majority of death was due to heart's health issue. Benjamin et al. (2017) stated that 12.2% of adults who 20 years old and above are having heart attack.

The machine learning that will be used in this project for health informatics will be Support Vector Machine. It is because SVM give a better accuracy result compared to other algorithm (Hijazi, Page, Kantarci, & Soyata, 2016). For face recognition, convolutional neural network (CNN) algorithm will be used. The face recognition system will be applied into mobile apps as login system purpose.

1.5 Thesis Organization

This thesis consists of four chapters, namely Introduction, Literature Review, Methodology, Results and Discussion, and Conclusion. Chapter One introduces about wearable devices and its importance in most of the medical check-up. This chapter stated the problem statements that will be focused on throughout the projects. There are a few objectives stated in this chapter as well to be achieved at the end of the project. The project scope in this chapter emphasized on the type of wearable sensor and type of machine learning to be used throughout the project.

Chapter Two describe the literature review of the project. The literature review helped to support on the theory and method that had been used for this project. Chapter Three described the methodology of the project. The content of this chapter included the theoretical step for the method used in this project. This chapter included the flow chart to make the whole project flow looked clear and easy. Chapter Four presented the results and discussion of the project where the outcome of the project will be shown and discussed. Chapter Five conclude everything that had been done throughout the project. Several future improvements that could be done also stated in this chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, the findings of theoretical and knowledge of each part of Android based health monitoring system will be discussed. This chapter will be divided into six main sections. First, various biomedical wearable systems with different type of sensors will be discussed in Section 2.2. This section is mainly focus on system that implemented with pulse oximeter sensor, pulse rate sensor and temperature sensor. Then, Section 2.3 will present health data informatics, including type of sensors to be used and the health condition corresponding to health parameter. Next, Different type of algorithms used to train health data informatics will be discussed in Section 2.4. After that, in Section 2.5, face detection algorithm will be reviewed while in Section 2.6, face recognition algorithm will be presented. Finally, Section 2.7 will summarize this literature review.

2.2 Biomedical Wearable System Review

The increasing of population in recent years had raised the awareness of many researchers to involve in developing health care technologies. A lot of wearable sensors for health monitoring, such as pulse oximeter sensor, pulse rate sensor, blood pressure sensor, temperature sensor and electrocardiogram (ECG) electrodes have been developed (Andreu-Perez et al., 2015). Different sensor consists of different function as well as its placement on human body. Andreu-Perez et al. (2015) and Soh et al. (2015) have reviewed some of the available technologies at that time. Some of their findings are summarized in Table 2.1.

Table 2.1: A summary of wearable sensors, their measurement parameters and placement

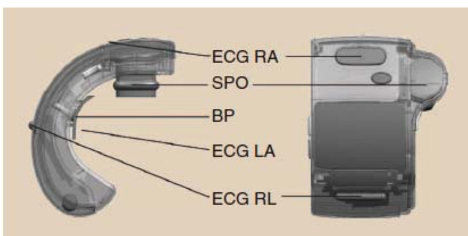
Wearable Sensors	Measurements	Sensor Placement
Pulse oximeter sensor	Blood oxygen saturation	• Hand/fingers
Pulse rate sensor	Heart rate	• Hand/fingers • Chest
Blood pressure sensor	Blood pressure	• Hand/fingers
Temperature sensor	Body temperature	• Forehead • Hand/fingers • Chest
Electrocardiogram (ECG) electrodes	Cardiac activity	• Chest

The evolution of wireless technology helped the integration of wearable sensor with wireless devices such as Wi-Fi module, Bluetooth module, ZigBee module and GSM module (Soh et al., 2015). These had created many advanced telemedicine systems. According to Andreu-Perez et al. (2015), the evolution of telemedicine application is divided into three generations. The first generation was the application that consisted of single sensing modality with wireless connectivity that able to predict health status. These application was widely found from any wearable sensors in the market.

The continuous monitoring with multiple sensors integrated together with wireless technology created second generation of telemedicine applications (Andreu-Perez et al., 2015). Ubiquitous healthcare systems are one of the second generation applications. Ubiquitous healthcare (u-Healthcare) is referred as technology that people can receive medical treatment regardless of location and time (Yvette E. Gelogo & Haeng-Kon Kim, 2015; Rodgers, Pai, & Conroy, 2015). Heart rate sensor, pulse oximeter sensor, temperature sensor, pulse rate sensor and ECG sensor are the most common devices used in u-Healthcare system.

In the past few years, all these sensors are attached onto printed circuit board (PCBs) which is very inconvenience to most of the users (Andreu-Perez et al., 2015). However, the development of flexible sensors help to solve the problem. Flexible sensor is not constraint to any planar geometric and able can be stretched. These properties provide convenient to users to attach the sensor onto their body surface or placed inside their clothes (Rodgers et al., 2015).

Some of the sensors can be integerated together into a wrist-worn device. The sensors were blood pressure sensor, temperature sensor, ECG sensor, heart rate sensor and pulse oximeter sensor. Figure 2.1 shows the wrist-worn device which is AMON project financed by European Union Fifth Framework Information Society Technologies (IST) program. Blood pressure sensor, ECG sensor, pulse oximeter sensor and temperature sensor were integrated in the device. The device was meant for patients who were having high-risk cardiac (Soh et al., 2015).



ECG RA: ECG right arm
SPO: SpO_2 sensor
BP: Blood pressure
ECG LA: ECG left arm
ECG RL: ECG right leg

Figure 2.1: Wrist-worn device under AMON project (Soh et al., 2015)

A crew physiologic observation (CPOD) device was developed through LifeGuard project. This device is a multiparameter wearable physiologial monitoring system including respiratory rate, body temperature, heart rate, blood oxygen saturation, blood pressure and body movement. The device also integrated with Bluetooth to allow health data recorded in base station. Figure 2.2 showed the CPOD device developed from LifeGuard project (Soh et al., 2015).

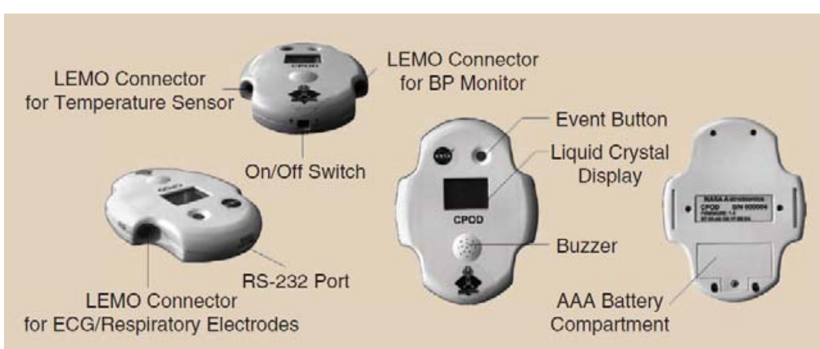


Figure 2.2: CPOD device (Soh et al., 2015)

Cell phone based- wearable platform also developed in Heart-ToGo program. It was to use monitor ECG via wireless ECG sensor. An artifical neural network-based machine learning was integrated together with the device to identify any abnormal patterns of the ECG pulse. Besides, it was also implemented with Bluetooth device to allow the transmission data between mobile phone and ECG sensor for data analyzing in mobile phone (Soh et al., 2015).

Health data also had been obtained via finger-placed pulse oximeter (Soh et al., 2015). This health data collected was blood oxygen saturation and heart rate. The measurements require microwave (Popovic, Momenroodaki, & Scheeler, 2014) or infrared ray (Keränen et al., 2010) which is exposed through the finger’s skin.

European Commission and 33 partners from ten different countries were working together to develop MyHeart project. In this project, sensor modules were attached on a piece of clothing as shown in Figure 2.3. The sensors that involved were ECG and activity sensor. This innovative project provide a confortable werable system to every users. However, there is no wireless module on it and therefore the size of overall system was small. An algorithm was also implemented into the system to classify different daily activities (Soh et al., 2015).

Figure 2.3: MyHeart instrumented shirt with ECG and activity sensor (Soh et al., 2015)

The latest third generation of telemedicine application integrates the artificial intelligent technologies with second generation devices. The technologies involved are stream processing, data mining, genetic and multiomics data (Andreu-Perez et al., 2015). An example for this type of telemedicine as proposed by H. Yin and Jha (2017) was health decision support system (HDSS). This system was developed to analyze the ECG signals using machine learning to identify a person's health condition.

2.3 Biomedical Informatics

Biomedical informatics are important in deciding a person's health condition. Different parameter for biomedical informatics will be measured using different kind of sensors or tools. Therefore, this section will be divided into three sub-sections to discuss on three type biomedical informatics, which are body temperature, heart rate and oxygen saturation level.

2.3.1 Body Temperature

Kakria, Tripathi, and Kitipawang (2015) mentioned that body temperature is one of the health parameters to be measured for early detection and diagnosis purposes. In general, body temperature was measured via temperature sensor and the sensor was widely found on most of the wearable systems. There are a lot of different kind of sensors that can be used to measure body temperature.

Infrared ray (IR) is also utilized to measure body temperature has been mentioned previously in Section 2.2. The advantage of IR temperature sensing was it can measure the temperature without the need for the object direct contact the sensor. The concept of IR sensing is based on Boltzmann's law where the intensity of IR radiation emitted by surface depends on its temperature (Keränen et al., 2010). Figure 2.4 showed the traditional optomechanical design for IR sensing. Equation (2.1) was used to determine the target temperature.

$$P_{rad} = K'\left(\varepsilon_t T_t^4 - \varepsilon_s T_a^{\,4}\right) \tag{2.1}$$

where P_{rad} is the total heat power received from the target, ε_t the emissivity of the target, T_t the target absolute temperature, ε_s the emissivity of the sensor, T_a the ambient absolute temperature measured at the sensor element, and *K'* is the empirical factor containing Stefan–Boltzmann constant.

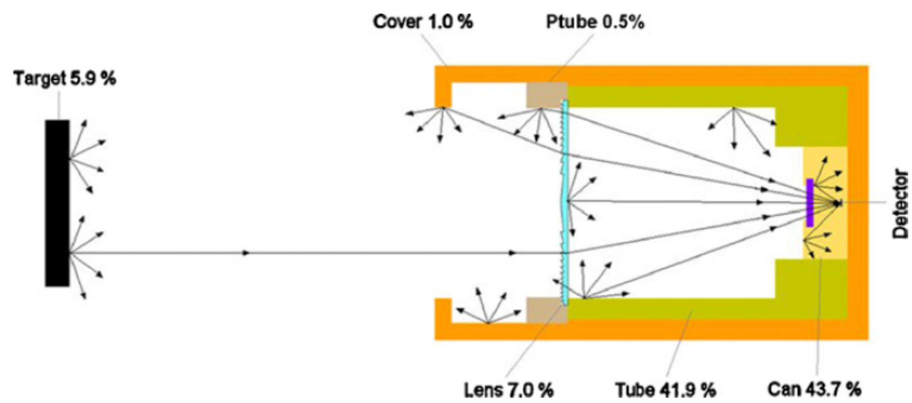


Figure 2.4: Traditional optomechanical design for IR sensing (Keränen et al., 2010)

As mentioned in Section 2.2, body temperature can be measured with the aid of microwave. At this point, the knowledge on human skin structure will be very useful for measuring body temperature. In Figure 2.5, it is showed that the measurement of body temperature was taken through three layers of human skin tissues. Each radiometer of different frequencies corresponding to the penetration depth will measure the total power received from each layer. The received signal by radiometer will undergoes several processes, such as noise filtering and digitalization to estimate the temperature increase and its location. However, electromagnetic interference was the main drawback to the system which will result in errors in the temperature estimation (Popovic et al., 2014).

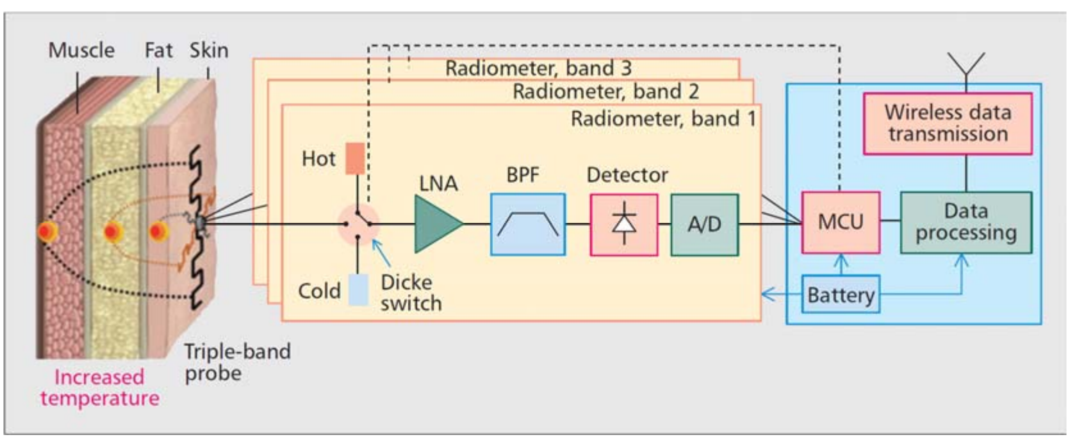


Figure 2.5: Block diagram of a 3-frequency internal body temperature measurement system (Popovic et al., 2014)

According to Popovic et al. (2014), dielectric properties of tissues was the main concerned in designing the radiometer in measuring body temperature. A study was made by Popovic et al. (2014) telling that dielectric properties tissues various according to the frequency of microwave in range between 10 Hz to 100 GHz. Table 2.2 showed the dielectric constant for each layer of skin corresponding to 1 GHz of microwave.

Table 2.2: Dielectric constant for skin layers corresponding to 1 GHz of microwave (Popovic et al., 2014)

Skin Layers	Dielectric Constant (S/m)
Epidermis	0.9
Fat	0.05
Muscle	0.98

A thermopile temperature sensor used by Kos and Kramberger (2017) in wearable device to acquire biometric data during sports. The temperature of human skin was measured through the passive infrared energy reading obtained by the sensor. Figure 2.6 showed the body skin temperature and module temperature obtained during sport practice for 20 minutes. However, the temperature of body skin does not get a perfect reading because of no calibration is made on the sensor.

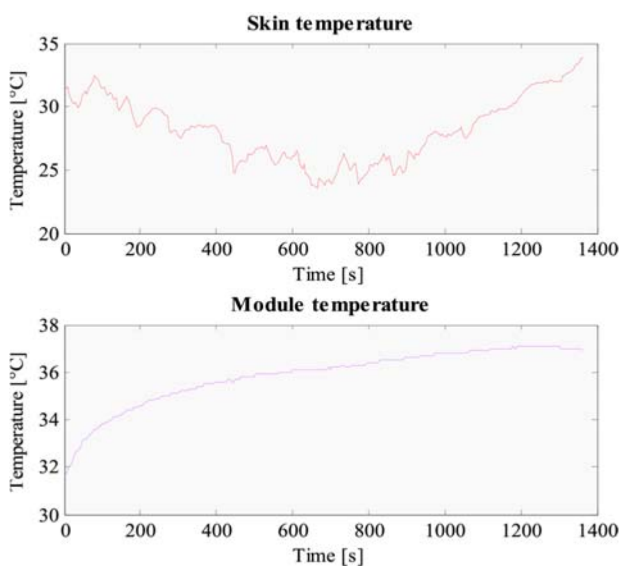


Figure 2.6: Temperature reading for skin and module during sport activities for 20 minutes (Kos & Kramberger, 2017)

Another method to measure body temperature suggested by Pardeshi, Sagar, Murmurwar, and Hage (2017) was using LM35 temperature sensor. LM35 temperature is the simplest and basic sensor to measure surface temperature of skin. LM35 had an advantage of its output voltage linearly proportional to the Centigrade temperature and it does not require any conversion from Kelvin to Centigrade.

A normal body temperature value will be different for people with different age. Table 2.3 below showed the normal temperature range for each people corresponding to different age. The person will be considered as fever if his or her body temperature above the temperature range specified in Table 2.3 (Kakria et al., 2015).

Table 2.3: Normal body temperature range for people with different age (Kakria et al., 2015)

Age	Normal Body Temperature
18 – 35	< 37.2 ºC
36 – 64	< 37.5 ºC
Above 64	< 36.9 ºC

There are three types of sensors proposed by different researchers. Different sensors have its own usage to measure the body temperature. A summary on type of sensors used for measuring body temperature by different researchers were summarized in Table 2.4.

Table 2.4: Summary of sensors used in measuring body temperature.

	Infrared sensing	Microwave sensing	Thermopile sensor	LM35 sensor
Keränen et al. (2010)	✓			
Popovic et al. (2014)		✓		
Kos and Kramberger (2017)			✓	
Pardeshi et al. (2017)				✓

2.3.2 Heart Rate

Heart rate is one of the important key for body health because heart rate issue always is the root cause for people death which had been mentioned in Section 1.4. In general, heart rate is measured by heart rate sensor. Heart rate sensor can also be found in most of the wearable sensor which had been discussed in Section 2.2.

Devi and Roy (2017) proposed a solution by using electrocardiogram (ECG) signal obtained from electrocardiography module to calculate the heart rate. Figure 2.7 showed one of the basic ECG waveform illustrated in a graph of volts against time. The heart rate is then obtained through several calculations which involving point R as shown in Figure 2.7. A total of 10 ECG waveform samples was collected and the time at point R on each ECG waveform were recorded. The time difference, t_{diff} between each consecutive pair of R-peak and finally obtained its average time, μ_{time} (Devi & Roy, 2017) as shown in Equation (2.2).

$$\mu_{\text{time}} = \frac{\sum_{i=1}^{10} t_{\text{diff}}}{10} \tag{2.2}$$

With the average time obtained, the heart rate, BPM measured in beat per minutes is obtained by from Equation (2.3) (Devi & Roy, 2017):

$$\text{BPM} = \frac{60}{\mu_{\text{time}}} \tag{2.3}$$

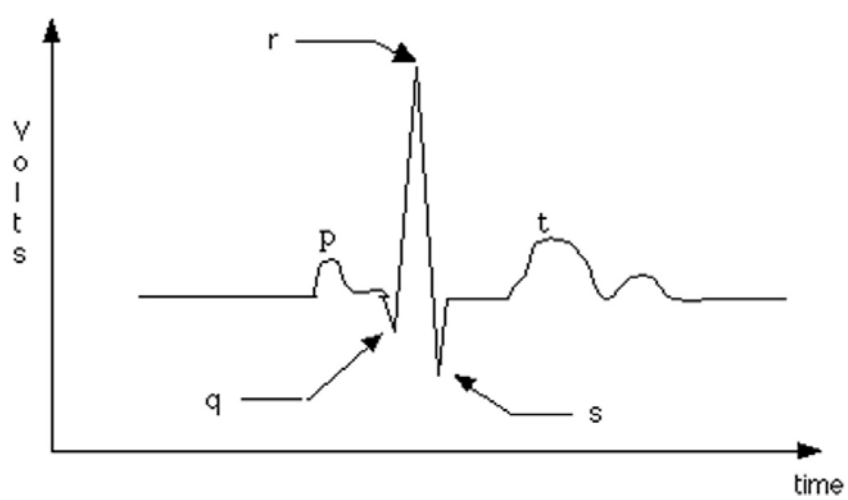


Figure 2.7: ECG waveform (Devi & Roy, 2017)

Another method that commonly used to obtain heart rate was photoplethysmographic (PPG) signal. Figure 2.8 showed the PPG signal acquisition using TI AFE4400 sensor. The PPG signal is obtained after measuring the changes in LED light absorption which caused by human pulses. Duong, Tran, and Bhowmik (2015) had demonstrated a system using VHDL based controller integrated with the sensors to obtain heart rate. After PPG signal data is obtained, it will be passed through three stages of digital signal processing (DSP), which is pre-processing, processing and post-processing as shown in Figure 2.9.

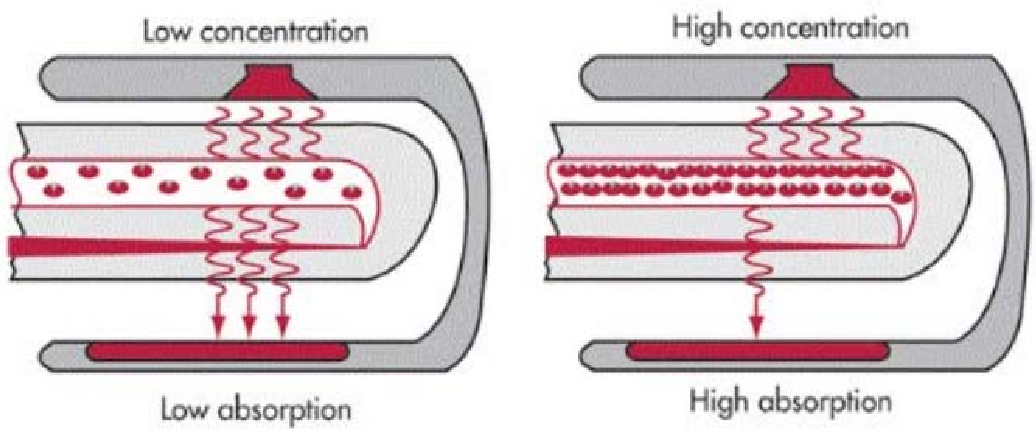


Figure 2.8: PPG signal acquisition (Duong et al., 2015)

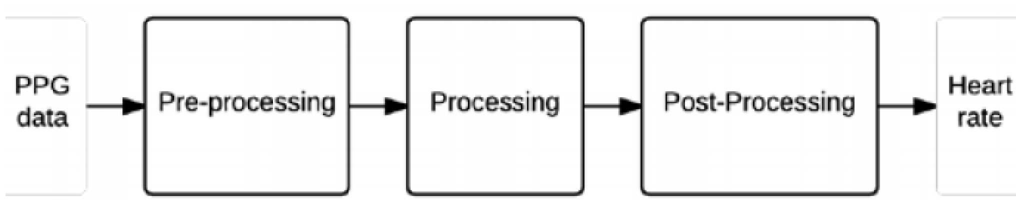
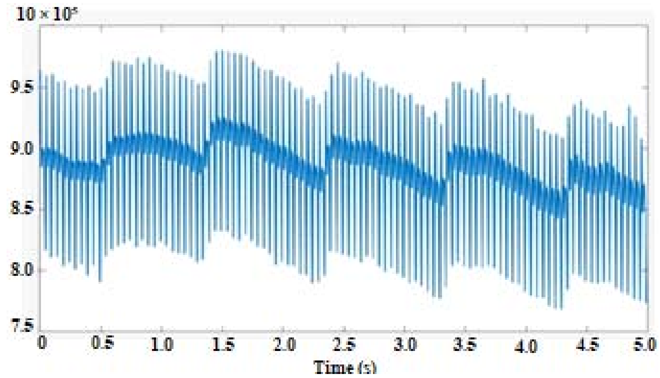


Figure 2.9: Three stages of digital signal processing (Duong et al., 2015)

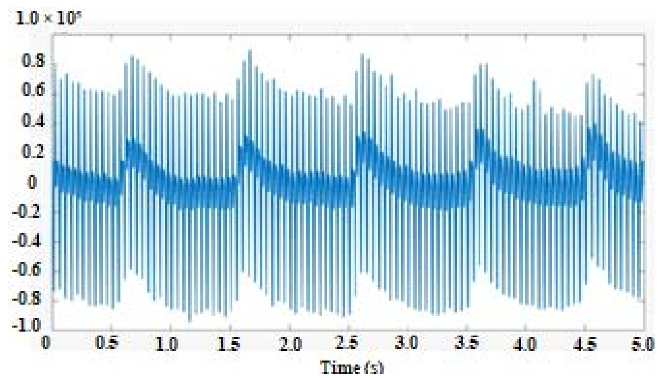
In pre-processing stage, the PPG data showed in Figure 2.10(a) was fetched to pre-filter which subtract the mean value of a number of previous input data from current input data. The process created zero-mean signal shown in Figure 2.10(b) which will be needed in filtering process. Equation (2.4) used to obtain the zero-mean signal output.

$$y[n] = x[n] - \frac{1}{N}\sum_{i=0}^{N-1} x[n-i] \tag{2.4}$$

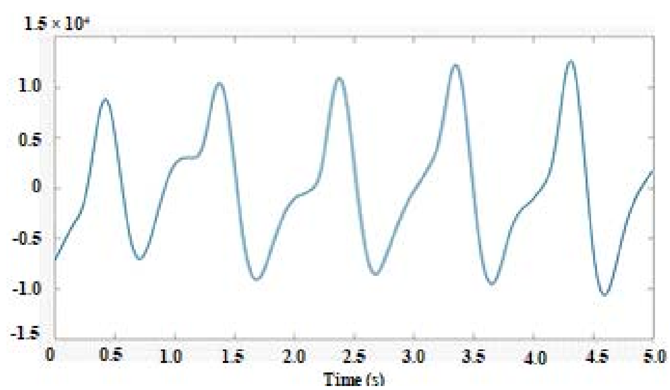
where $x[n]$ is input sampled signal, $y[n]$ is output sampled signal and $N = 2^m$, m is positive integer. The output signal will then be fed into bandpass filter in processing stage. The resulting output of filtered PPG data was shown in Figure 2.10(c) below. With the filtered output data obtained, the heart rate value was obtained through the same step as using ECG signal.



(a) Raw input of PPG data



(b) Pre-filter output of PPG data



(c) Filtered output of PPG data

Figure 2.10: Processing result of PPG data (Duong et al., 2015)

Asymmetric Least Squares Spectrum Subtraction and Bayesian Decision Theory were another method to process PPG signal proposed by Sun and Zhang (2015). This method has three stages. In first stage, motion artifacts (MA) in which PPG is sensitive to it was reduced by spectrum subtraction based on asymmetric least squares. The resulting output was then brought to second stage where Bayesian Decision Theory was used to track spectral peak. In final stage which known as post-processing stage, was to correct the wrong estimates made in second stage due to the presence of strong motion artifacts. After that, heart rate was calculated. Figure 2.11 showed the flowchart for method of processing the PPG data proposed by Sun and Zhang.

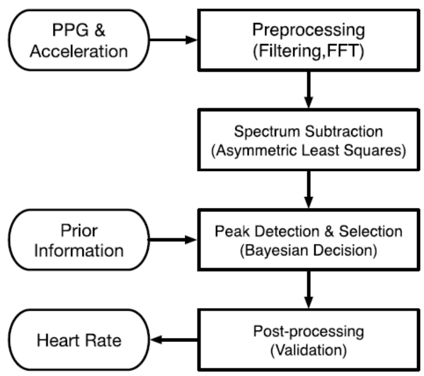


Figure 2.11: Asymmetric Least Squares Spectrum Subtraction and Bayesian Decision Theory method in processing PPG data (Sun & Zhang, 2015)

Similar to body temperature, the normal heart rate will also different for people with different age. Table 2.5 below showed the normal heart rate for each people corresponding to different age. The person will be considered to have abnormal heart rate if his or her heart rate value is not in between the range specified in Table 2.5.

Table 2.5: Normal heart rate value for people with different age (Kakria et al., 2015)

Age	Normal Heart Rate
18 – 35	72 – 75 BPM
36 – 64	76 – 79 BPM
Above 64	70 – 73 BPM

Two types of signals were proposed by researchers that can be used to measure heart rate of a person. Different measuring devices are required to obtain each signal. A summary on type of signals used to determine heart rate by different researchers were summarized in Table 2.6.

Table 2.6: Summary of type of signal used in measuring heart rate

	ECG signal	PPG signal
Duong et al. (2015)		✓
Sun and Zhang (2015)		✓
Devi and Roy (2017)	✓	

2.3.3 Oxygen Saturation Level

Oxygen saturation level (SpO_2) in the blood is commonly measured by pulse oximeter sensor. The measurement of oxygen saturation level involved two different wavelengths of light, which is red light and infrared light. The wavelength of red light and infrared light are 660 nm and 940 nm respectively. The absorption of red light and infrared light by oxygenated haemoglobin and deoxygenated haemoglobin due to the pulsatile arterial blood determined the oxygen saturation level (Devi & Roy, 2017).

By mathematical calculation, the value of SpO_2 can be calculated from the ratio of two reflected intensities of lights (Jiang et al., 2016). The formula was shown in Equation (2.5).

$$\mathrm{SpO_2} = 10.002R^3 - 52.887R^2 + 26.817R + 98.293 \tag{2.5}$$

provided that

$$R = \frac{\mathrm{AC_{red}}/\mathrm{DC_{red}}}{\mathrm{AC_{IR}}/\mathrm{DC_{IR}}} \tag{2.6}$$

where AC_{red} and DC_{red} are AC and DC components of red light while AC_{IR} and DC_{IR} are AC and DC components of infrared.

A normal oxygen saturation level will be in between range of 94% and 100%. This value will be same for every people regardless of their age. However, it will be abnormal if oxygen saturation level below 94% (Kakria et al., 2015).

2.4 Machine Learning for Health Informatics

In this section, two type of machine learning algorithms for health condition prediction will be reviewed. They are Support Vector Machine (SVM) and Artificial Neural Network (ANN). The first part will be discussed SVM algorithm and its pseudo code. The second part will be presented ANN algorithm and its pseudo code.

2.4.1 Support Vector Machine (SVM)

Support vector machine (SVM) is a type of classifier machine learning algorithm that construct hyperplanes to separate data into several classes and keep them as far as possible. SVM can be used to classify two types of data which is linear and non-linear depending on type of kernel declared in the algorithm (Hijazi et al., 2016). SVM has an ability to model complex non-linear decision boundaries with extremely high accuracy. However, SVM required a longer time to train a set of data. The most basic pseudo code for perceptron learning using SVM (Vijayarani, Dhayanand, & Phil, 2015) is shown in Table 2.7.

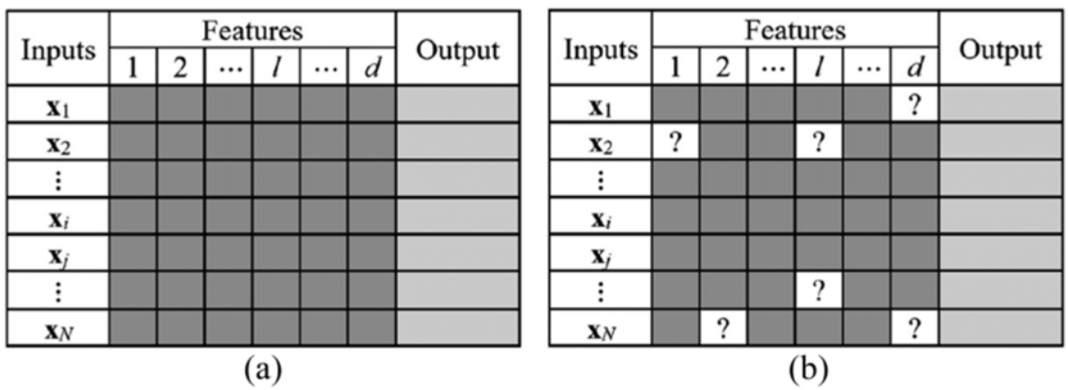
Table 2.7: Pseudo code for SVM (Vijayarani et al., 2015)

(1)	$w_0 = 0$; $b_0 = 0$; $k = 0$;
	// w_k is the weight vector, b_k is the bias term, k is the number of mistakes
(2)	$R = \max_{1 \le i \le l} \lVert x_i \rVert$
(3)	while at least one mistake is made in the for loop do
(4)	for $i = 1, \ldots, l$ do
(5)	if $y_i < w_k, x_i > b_k$ then
	// x_i is the training data value, y_i is the label of training data
(6)	$w_{k+1} = w_k + \eta y_i x_i$ // η is the learning
(7)	$b_{k+1} = b_k + \eta y_i \Re^2$

Table 2.7 (continue): Pseudo code for SVM

```
            k = k + 1
        end if
    end for
end while
Return w_k, b_k , where k  is the number of mistakes
```

In many real-time dataset, it is very difficult to obtain a complete filled data. Figure 2.12 showed the sample of complete dataset table and incomplete dataset table. The problem can be solved by Least Square-Support Vector Machine (LS-SVM) which had been proposed by Wang, Deng, and Choi (2018). LS-SVM had been used in some medical applications for predictions such as heart disease, muscle fatigue prediction in electromyogram (sEMG) signals and breast cancer (J. Zhang et al., 2017).



(a) Complete dataset sample (b) Incomplete dataset sample

Figure 2.12: Type of dataset sample (Wang et al., 2018)

According to J. Zhang et al. (2017), LS-SVM is a supervised machine learning that is based on statistical learning theory. For dataset containing two separable classes, which is +1 and –1, linear LS-SVM is widely used. If there are a set of training data consist of n data expressed as (x_1, y_1), (x_2, y_2), …, (x_m, y_m), LS-SVM will find the optimal separating hyperplane to separate these class through the formula in Equation (2.7).

$$(w, b, \alpha, \xi) = \frac{1}{2}\|w\|^2 + \frac{c}{2}\sum_{i=1}^{m}\xi_i{}^2 - \sum_{i=1}^{m}\alpha_i\left\{y_i[(wx_i) + w_0] - 1 + \xi_i\right\} \qquad (2.7)$$

where x_m is the training data value, y_m is the label of training data, w is the weight vector, b is the vector for bias term, α is the vector for Lagrangian multipliers, ζ is the vector for slack variable and c is the regularization parameter.

2.4.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a supervised learning machine that used to provide effective solutions for many complex modeling problems (J. Zhang et al., 2017). Training dataset needed to be stored in tuples so that ANN algorithm can be applied for data training. The weight of ANN algorithm needed to be adjusted so that the mean squared error between the network's prediction and actual target value can be minimized (Vijayarani et al., 2015).

ANN use a set of processing neurons which are interconnected and can be considered as a directed graph in which each neuron i executes the transfer function f_i expressed in Equation (2.8) (J. Zhang et al., 2017).

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j - \theta_i\right) \tag{2.8}$$

where y_i is the output of neuron i, f_i is the transfer function, x_j is the jth input to the neuron, w_{ij} is the connection weight between neurons i and j and θ_i is the threshold bias of neuron. Vijayarani et al. (2015) had developed a pseudo code for ANN which shown in Table 2.8.

Table 2.8: Pseudo code for ANN (Vijayarani et al., 2015)

(1)	while terminating condition is not satisfied {
(2)	for each training tuple ***X*** in *D* {
(3)	for each input layer unit *j* {
(4)	$O_j = I_j$;
	// *Oj* is the output of an input unit, I_j is the actual input value
(5)	for each hidden or output layer unit *j* {
(6)	$I_j = \sum_i w_{ij}O_i + \theta_j$; // w_{ij} is the connection weight between neurons i and j
(7)	$O_j = \frac{1}{1+e^{-1}j}$;
(8)	for each unit *j* in the output layer {

Table 2.8 (continue): Pseudo code for ANN

$Err_j = O_j(1 - O_j)(T_j - O_j)$; // Err_j is the error, T_j is the target value

for each unit j in the hidden layers, from the last to the first hidden layer {

$Err_j = O_j(1 - O_j)\sum_k Err_k w_{jk}$

for each weight w_{ij} in *network* {

$\Delta w_{ij} = (l) Err_j O_i$; // Δw_{ij} is the weight increment between neurons i and j

$w_{ij} = w_{ij} + \Delta w_{ij}$;}

for each bias θ_j in *network* {

$\Delta\theta_j = (l) Err_j$; // $\Delta\theta_j$ is the bias increment

$\theta_j = \theta_j + \Delta\theta_j$;}

} }

A simple experiment had been conducted by Vijayarani et al. (2015) to test the accuracy measure and execution time for SVM and ANN algorithm. A total of 583 testing data were used for both SVM and ANN algorithms. The results are tabulated in Table 2.9. SVM algorithm has a lower accuracy as compared to ANN algorithm. However, the execution time for SVM algorithm is shorter compared to that for ANN algorithm.

Table 2.9: Comparison between SVM and ANN algorithms (Vijayarani et al., 2015)

Algorithms	Correctly Classified Instances (%)	Incorrectly Classified Instances (%)	Execution Time (s)
SVM	76.32	23.68	3.22
ANN	87.70	12.30	7.26

2.5 Algorithm for Face Detection

Before a set of images were trained for face recognition purpose, face detection is necessary to ensure its high accuracy of result. There are a few types of algorithm can be used for face detection. The most two common algorithms used are Haar Cascade (Cuimei, Zhiliang, Nan, & Jianhua, 2017) and Multi-task Cascaded Convolutional Network (K. Zhang, Zhang, Li, & Qiao, 2016).

2.5.1 Haar Cascade Algorithm

Haar Cascade is an open source algorithm developed by Open Source Computer Vision Library (OpenCV) used to detect human face. The Haar-like in Haar Cascade can be divided into three types, namely edge features, line features and center-surround features. These features are illustrated as shown in Figure 2.13. Haar Cascade is utilized with rejection cascade to achieve good performance. Rejection cascade composed of a series of decision trees trained on features from faces and non-faces. Figure 2.14 showed the principle working of rejection cascade (Cuimei et al., 2017).

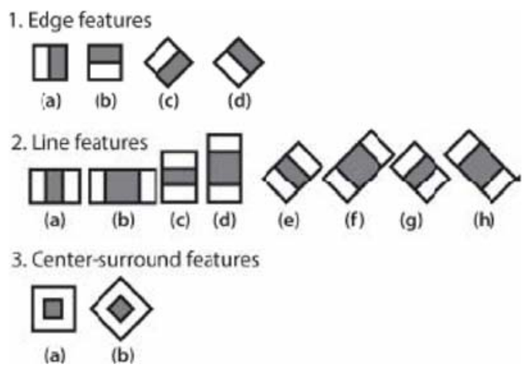


Figure 2.13: Haar Cascade features (Cuimei et al., 2017)

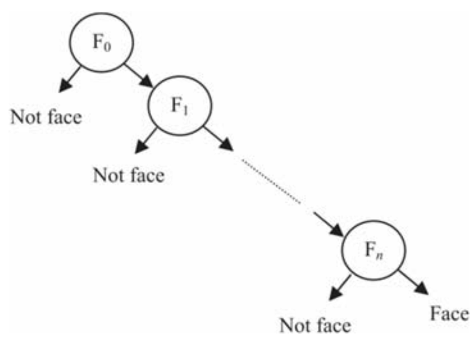


Figure 2.14: Rejection cascade in Haar Cascade (Cuimei et al., 2017)

Shimomoto, Kimura, and Belém (2015) used Haar Cascade algorithm to identify face elements, such as eyes, nose and mouth on face. Before the algorithm was used to find the face elements, skin segmentation was applied on the image to obtain the skin area. From the skin segment found in the image, the presence of eyes, nose and mouth are verified together with a few geometric restrictions to ensure for correct results. The image result obtained by Shimomoto et al. (2015) was shown in Figure 2.15 with eyes