ARTIFICIAL INTELLIGENT BASED ARRHYTHMIA IDENTIFICATION VIA SINGLE LEAD ECG RECORDING

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ARTIFICIAL INTELLIGENT BASED ARRHYTHMIA IDENTIFICATION VIA SINGLE LEAD ECG RECORDING

by

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List of Abbreviations

ACC	American College of Cardiology
AHA	American Heart Association
AF	Atrial Fibrillation
ANN	Artificial neural network
AV	ECG signal of Controlled Atrial Fibrillation
BP	back propagation
Bpm	beats per minute
CE	Cross Entropy
CVD	cardiovascular disease
ECG	Electrocardiogram
ESC	European Society of Cardiology
MF	morphological filters
MLP	multilayer perceptron
PPV	peak-to-peak and Variance Reckoning
RMSSD	square root of the mean squared differences of successive NN intervals
SA	Sinus Atrial
SDNN	standard deviation of the normal-to-normal, NN, interval
TH	threshold

PENGESANAN ARITMIA BERDASARKAN KECERDASAN UNTUK SALURAN TUNGGAL ECG

Abstrak

Elektrokardiogram (ECG) mewakili aktiviti elektrik jantung kita. Ia mengandungi pelbagai maklumat mengenai status hati kita seperti gangguan jantung atau aritmia. ECG telah menjadi alat diagnostik yang paling asas untuk menganalisis jantung serta pemantauan bagi masalah jantung. Pada zaman ini, aritmia ialah penyakit hati yang paling biasa, ia menunjukkan gejala yang kurang jelas manakala mempunyai kesan paling besar kepada mangsa. Walaupun banyak kajian yang telah dilakukan dalam pengesanan aritmia, pengesanan masih bermasalah kerana ia hanya berlaku secara berkala. Matlamat utama kajian ini adalah untuk membina satu algoritma berasaskan rangkaian neural yang dapat mengklasifikasikan jenis-jenis ECG ritma. Pada peringkat pertama, isyarat ECG yang dikelaskan kepada isyarat yang bising atau isyarat yang bersih. Hanya isyarat ECG yang bersih akan dimasukkan peringkat kedua untuk mengklasifikasikan kepada Aritmia atau Normal Sinus. Ciri-ciri yanf berbeza akan diekstrak dan dimasukan ke dalam rangkaian neural MLP untuk tujuan latihan rangkaian. Pada peringkat pertama, 6 ciri-ciri telah dipilih sebagai input dan 15 neuron di lapisan tersembunyi telah digunakan. Dan pada peringkat kedua, 4 ciri-ciri telah dipilih sebagai input dan 40 neuron lapisan tersembunyi yang telah digunakan. Ketepatan akhir sebanyak 83.3% telah dicapai pada peringkat latihan dengan menggunakan 300 data latihan. Markah prestasi setinggi 0.7076 telah dicapaicapai apabila 8528 data telah dimasukkan ke dalam rangkaian neural yang habis dilatih. Secara kesimpulannya, ciri-ciri sesuai telah dikenal pasti dan rangkaian neural ketepatan yang tinggi telah dibangunkan dalam kajian ini.

ARTIFICIAL INTELLIGENT BASED ARRHYTHMIA IDENTIFICATION VIA SINGLE LEAD ECG RECORDING

Abstract

Electrocardiogram (ECG) represents the electrical activities of our heart. It provides various information about our heart status such as cardiac disorder or arrhythmia. ECG has become the most common diagnostic tool in heart analysis as well as in monitoring for cardiac problem. In the past century, arrhythmia has become the most common heart disease, showing the least symptoms while having the greatest effect toward the victims. Despite the plenty of studies that have been done in Arrhythmia detection, it problematic as Arrhythmia may only happen periodically. The main goal of this study is to develop an artificial neural network based algorithm which is able to classify the ECG rhythm. At the first stage, the ECG signal is classified into noisy ECG and clean ECG. Only clean ECG signal will be fetched into the second stage to be classified into Arrhythmia or Normal Sinus rhythm. Different features have been used in both stages and been fetched into trained MLP neural network for classification purpose. At first stage classification, 6 features have been selected as input and 15 number of neurons in hidden layer have been used. Meanwhile at the second stage, 4 features have been selected as input and 40 numbers of hidden layer's neuron has been used. Final accuracy of 83.3% has been achieved during the training stage by using 300 training data. Final score of 0.7076 (Perfect score = 1) has been achieved when the 8528 data has been fetched into the developed neural network. In conclusion, suitable features have been identified which are average and standard deviation of heart rate and R-peak amplitude. Finally, a high accuracy neural network has been developed in this study.

CHAPTER 1

INTRODUCTION

1.1 Background

In the past few centuries, there has been a widespread interest in the study of ECG, known as electrocardiogram, a recording of electrical activities of heart by placing electrodes at specific points throughout the body. It has been utilized in medical field's research as well as biotechnology study. Through ECG interpretation, which is one of the most powerful tool in medicine, various diseases, or abnormalities such as Arrhythmia, Myocardial Infraction and Ventricular Hypertrophy can be detected. But this interpretation can only be done if one acquired considerable experience in analyzing ECG signal and correlating and in categorizing ECG reading with the physiology and status of the patient [1].

This thesis explores the method for signal processing of ECG signal in an attempt to develop methods for Arrhythmia classification. This study includes signal preprocessing which is the extraction of feature through the identification of R peak, as well as analyzing the parameter involved in Arrhythmia and lastly, classifying of the ECG signal into 1) Normal sinus rhythm, 2) Arrhythmia, 3) Too noisy to be classified.

This chapter introduces the characteristic of electrocardiogram (ECG), a record of the bio data associated with the contraction of heart muscle as well as the most common heart disease which is Arrhythmia together with the motivation behind this study.

1.2 Problem Statement

Mobile healthcare application, wireless hospital and portable tele-monitoring have been common nowadays which enable the bio-signal acquisition process to be done without any medical specialist or doctors' supervision.

Heart failure and disease has become the world's number one killer in the recent centuries. An estimated 17.7 million people died from CVDs in 2015, representing 31% of all global deaths [2]. It is possible for a mobile device to aid in delivering quality healthcare to middle and low-income population around the world via ECG signal acquisition and interpretation by a professional in diagnosing CVD with present computing power and machine learning ability.

Among various types of CVD, Arrhythmia showed the least symptom while it has the greatest effect towards the victims [12]. Arrhythmia is a kind of disease which shows abnormal heartbeats which may cause changes in blood pressure and may lead to paralysis, stroke, or even sudden death. Abnormal heart rhythms and others accompanying cardiac symptoms often occur in a transient manner and therefore are difficult to detect, the result obtained when running the test at a one point in time may inaccurate as the patient may suffer future symptoms which were unable to be detected.

Arrhythmia which is defined as "tachyarrhythmia, is characterized by predominantly uncoordinated atrial activation with consequent deterioration of atrial mechanical function" by the American College of Cardiology (ACC), the American Heart Association (AHA), and the European Society of Cardiology (ESC) [3]. Among different rhythm of Arrhythmia, Atrial Fibrillation is the most common sustained cardiac arrhythmia, occurring in 1-2% of the general population [7]. Despite the plenty studies that have been done in Arrhythmia detection, AF detection remained a problem as it may only happen periodically. AF detection can be done via two methods, which are the atrial activity analysis and ventricular response analysis [4]. Each method contributes different advantages and disadvantages. In the first method, atrial activity analysis provides high accuracy given that the ECG signal which produces small noises with high resolution while ventricular response analysis based in prediction of inter beat duration which makes it more suitable for real time and automatic AF detection.

Therefore, an arrhythmia detection algorithm is important in interfacing with mobile healthcare devices, allowing more detail diagnostic to be done without an expertise.

1.3 Objective of Research

The objectives of this project are 1) To identify suitable features for neural network classification and 2) To develop an artificial neural network to classify the type of ECG rhythm.

This project focus on the development of a front-end ECG feature extraction system as well as arrhythmia detection algorithm by using artificial intelligent. The system is able to extract the basic feature from a single lead ECG recording (between 30s and 60s in length) and then identify which category the patient will be referred to. The ECG recordings are categorized into 3 classes which is normal sinus rhythm, arrhythmia, or too noisy to be identify.

The machine learning artificial intelligent network is done via the benchmark data provided by MIT-Physionet which consist of 8528 ECG recording.

1.4 Scope of Research

The goal of this research is to build a high accuracy Arrhythmia detection artificial intelligent based algorithm. This project will only cover the software development part which is the basic ECG feature extraction and Arrhythmia detection. Matlab is used throughout the process including artificial intelligent machine learning to classify the type of Arrhythmia. In this study, 8528 single lead ECG recording benchmark data provided by MIT-BIH is used throughout the data preprocessing and neural network training stage [21]. The limitation of this work will be entirely based on Matlab configuration as below.

- Maximum 40 number of neurons in hidden layer will be used.
- The neural network will be re-trained for maximum of 10 times to prevent over-train.

1.5 Thesis Outline

This thesis consists of five main chapters that are explain in detail about the artificial intelligent based Arrhythmia classification via single lead ECG recording from signal preprocessing until neural network based ECG classification.

The first chapter is the introduction of the research which gives an overview of the project as well as brief explanation on the motivation behind this study. This chapter includes the problem statement, objective, and scope of research.

The second chapter, which is the literature review, extends the progress of selected published work related to ECG signal processing, as well as classification of Arrhythmia classification via artificial intelligent. It contains the detail background information of ECG, theories as well as the methods used and ended with a summary of the chapter.

The third chapter describes the methodologies involve in the study as in explanation of software, selected method of artificial intelligent as well as design procedure throughout the study. This chapter also explain in detail about the method on identifying different peak in an ECG signal.

In chapter four, all the detail information about the result will be recorded follow by the discussion and explanation of the result acquired. Other than this, the performance of the algorithm will be presented in the end of this chapter. The final chapter will discuss the conclusion of the Study as well as the future works as in potential follow up and development. Overall project work and achievement will be summarized at this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The philosophy and theory of heart's electrical activity and electrocardiography will be explained in section 2.2. Section 2.3 will discuss about the most common cardio vascular disease, which is Arrhythmia in detail and the relationship in ECG signal. In the next section, 2.4 will explain about the various method been used in current published work in rhythm classification. Section 2.5 will discuss about the classifier used in this research which is artificial neural network (ANN). Finally, this chapter is summarized in section 2.6.

2.2 Philosophy and theory of heart's activity and electrocardiography

2.2.1 Overview

Electrography was introduced by Einthoven back in 1902. Electrography is the technique of recording the electrical signal generated by our heart [8]. This recording is called electrocardiogram (ECG), the most popular diagnostic system used in cardiovascular diseases detection. The output of the recording gives a plot of voltage as a function of time. The ECG is most frequent used technique for measuring the heart activity in Cardiology, which is a composite recording of different types nodal and myocardial action potentials generated during activation and deactivation as well as the resulting magnitude and orientation of dipoles created in myocardium [9].

The main responsibility of heart is to pump blood to different body parts. The heart consists of 2 upper chamber (right and left atrium) and 2 lower chamber (right and left ventricle). The right ventricle receive blood from right atrium and pumps through the pulmonary arteries to the lung where it absorbs oxygen and drop off carbon dioxide. The left ventricle receives oxygenated blood from left atrium and pumps it through aorta then to the rest of the body. The middle tissue which separate the right and left chamber called interventricular septum [10]. Figure 2.1 below shows the cross-section diagram of a human heart.

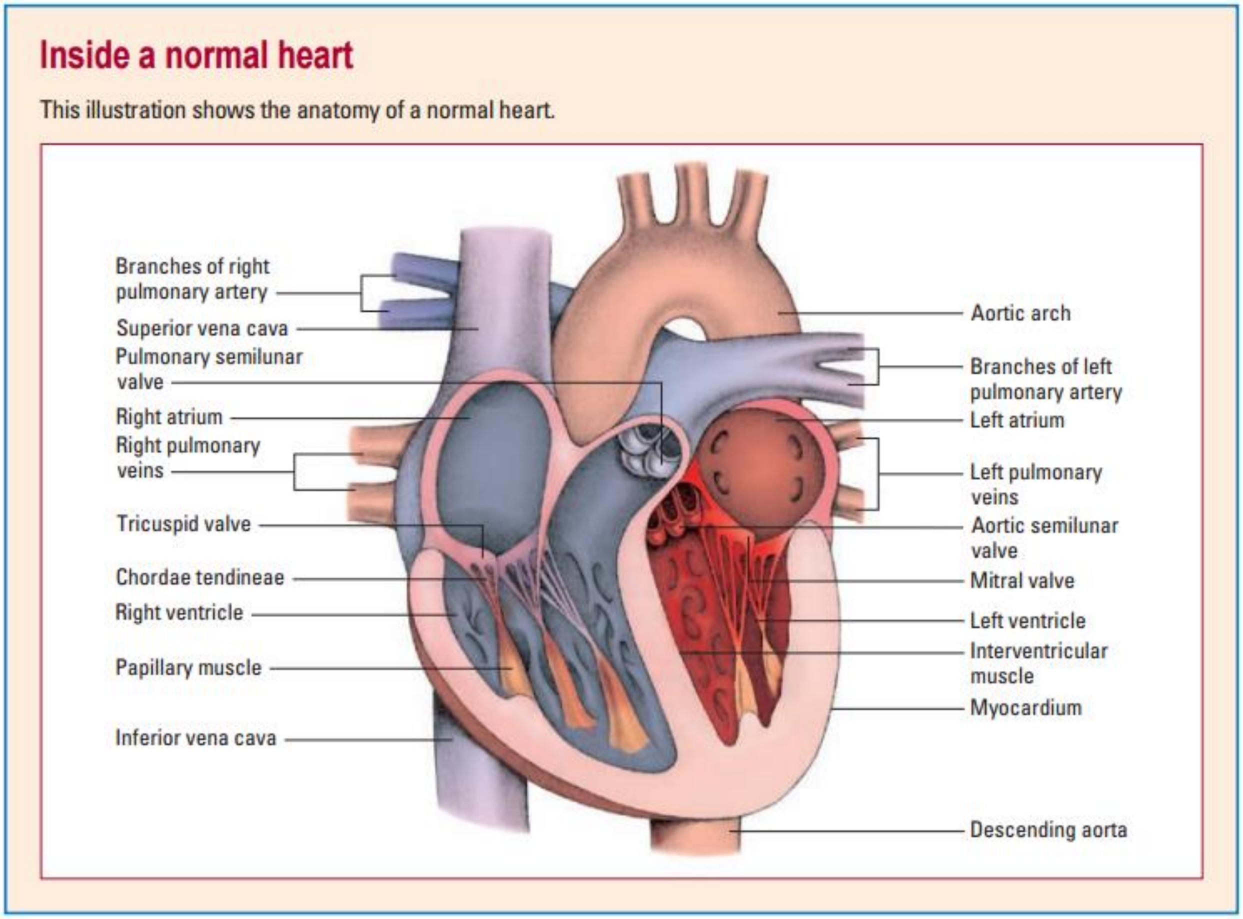


Figure 2.1: The cross-section diagram of a human heart [9]

2.2.2 Electrical activity of the heart

The heart can only pump blood after electrical impulses occurs. There are 4 characteristics of cardiac cells which happens during generation and transmission of electrical impulses.

i) Automaticity – The ability of cells (pacemaker cells) to initiate an impulse

ii) Excitability – Results when ion shift across cell membrane and indicate how well a cell respond to the electrical stimulus

iii) Conductivity – Ability of cell to transmit an electrical impulse to adjacent cardiac cell

iv) Contractility – How well the cell contract after receiving an electrical stimulus

Throughout the impulse transmission process, cardiac cells undergo depolarized and repolarized cycle. There are 5 phases in this cycle which is represented by a curve show in Figure 2.2. During phase 0, the cell receives an impulse from a neighboring cell and is polarized. Phase 1 is marked by early and rapid repolarization. Phase 2 which is the plateau phase is a period of slow repolarization [10]. Between the end of phase 2 and beginning of phase 3, the cardiac cell is in its absolute refractory period which is no stimulus can excite the cell. Phase 3, which is the rapid repolarization phase occur when the cells return to its original state. Only strong stimulus can depolarize the cell at the last half of this phase. The last phase is the resting period of the action potential which the cells is ready for another stimulus [10]. All this electrical activity is represented on an electrocardiogram.

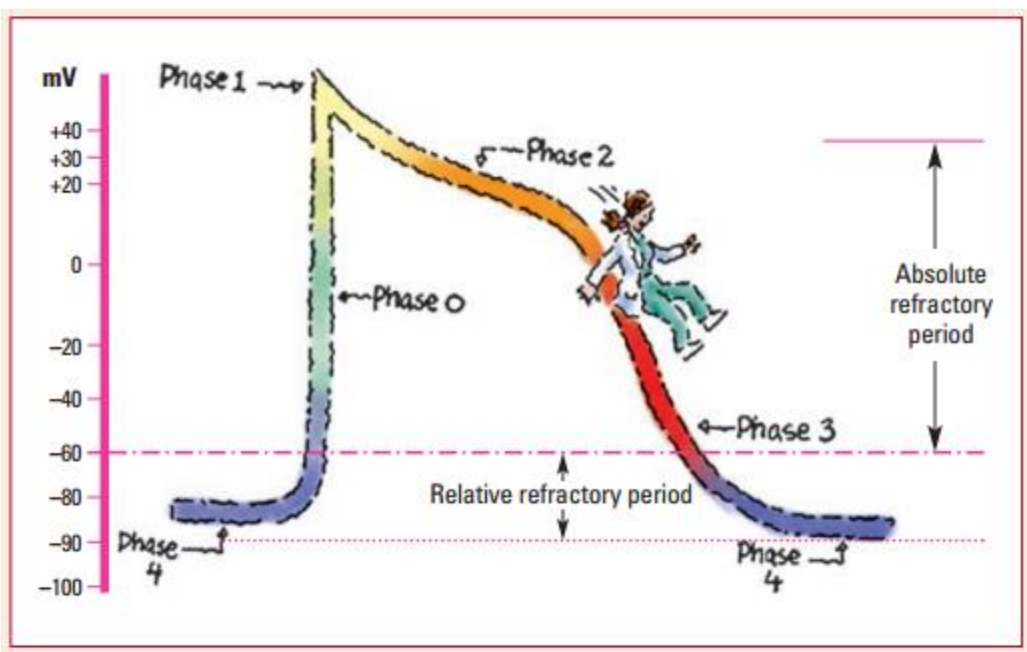


Figure 2.2: Action potential curve [10]

2.2.3 PQRST Terminology

In electrocardiogram interpretation, PQRST terminology is used to describe the waveform. The waves shown in ECG is due to the atria and ventricular depolarization and repolarization activity [11]. In ECG, PQRST peak happen due to different incident happening in our heart. Figure 2.3 shows the ECG waveform and the interval of electrical signal of the heart.

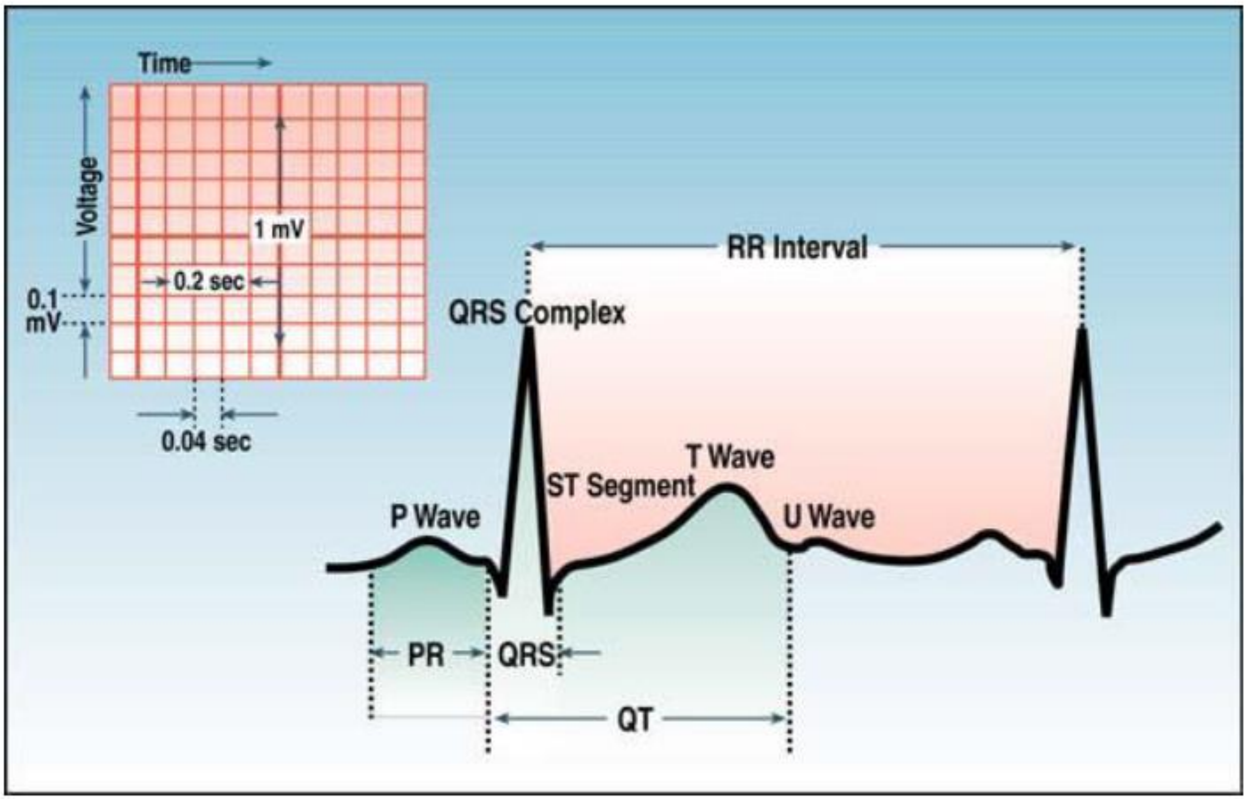


Figure 2.3: Illustration of ECG waves and intervals as well as standard time and voltage measures on ECG paper [11]

According to [1] and [11], the first deflection which is the P wave happens due to the depolarization of left and right atria, amplitude is low during atria repolarization. In a normal ECG, P wave is less than 2.5mm in amplitude (1.25mV) and less then 120ms in width. QRS complex happens after P wave which represents the depolarization and repolarization of ventricle. Typically, this complex consists of 3 deflection that reflect the current associated with right and left ventricle.

The first negative deflection in this QRS complex is the Q wave while the first positive deflection is called the R wave. Finally, the negative deflection after R wave is the S wave. It is then followed by the next positive deflection which is the T wave. In some ECG signal, Q and S wave may not be present. But irrespective of the number of wave present, they are called QRS complex.

PQ interval, which is the period between the P wave and the onset or QRS complex indicate the conduction time of impulse from atria to ventricle. The duration of QRS complex represent the time needed for the impulse to spread through the ventricles. The QT interval which starts from the beginning of QRS complex to the end of T wave represent the total electrical activity of ventricles. The period between the QRS complex and the T wave is the ST segment. ST segment is important in ventricular ischemia or hypoxia as it can become depressed or elevated if the patients suffer from these diseases. The most important information show in an ECG signal is the R-R interval which used to calculate the heart rate. Lastly the P-P interval is used to calculate the rate of atria or sinus cycle [1].

The first step in designing Automated Arrhythmia detection is to understand the acquisition of ECF signal. The most famous way in ECG signal acquisition is via 12 lead ECG signal. The term “lead” indicate the voltage different between 2 electrodes placed at different part of the body. In this study, the ECG signal used will be the single lead ECG recording.

2.3 Arrhythmia and ECG

From [12], Arrhythmia happens when the symptoms show irregular heart rhythm or rapid and sluggish heart beats. Most arrhythmia are harmless but some can be life threatening as well. Irregular heartbeats can affect the ability of heart to pump blood to our body which may cause damage to our body part or even brain. The speed and rhythm of the heart is controlled by an internal electrical system which the electrical impulses begin from a group of cells called sinus node (SA node), it travels through the right and left atrium and caused the atria to contract and pump the blood into ventricles. The electrical impulse thus moves down to a group of cells called atrioventricular node (AV node). Subsequent to that, the electrical impulse divide into 2 pathways which branches into right and left bundle of ventricle causing them to contract and pump blood into the lungs and other body parts.

There are several types of arrhythmia, which is Sinus Rhythm, Sinus Dysrhythmia, Atria Arrhythmia, Conduction Disturbance, Ventricular Arrhythmias, and ST changes [12]. In this study, we will be focusing on Atrial Fibrillation (a type of atria arrhythmia).

Atrial Fibrillation (AF) is characterized by a total disorganization of atrial activity without effective atrial contraction. The atrial rate is generally very fast which can reach up to 300-600 beats per minutes, but not all impulses are conducted to the ventricles. There are 3 types of AF, which is Controlled AF, Slow AF, and Rapid AF. Figure 2.4 below shows the ECG signal of Controlled Atrial Fibrillation which the rate varying from 50-95 beats per minutes with average of 75bpm. Figure 2.5 show the ECG signal of Slow Atrial Fibrillation which the rate varying from 26-45 beats per minutes with an average of 38bpm. And the next figure showed the ECG signal of Rapid Atrial Fibrillation which the rate varying from 112-250 beats per minutes which is an average of 160bpm.

Figure 2.4: ECG signal of Controlled Atrial Fibrillation [12]

Figure 2.5: ECG signal of Slow Atrial Fibrillation [12]

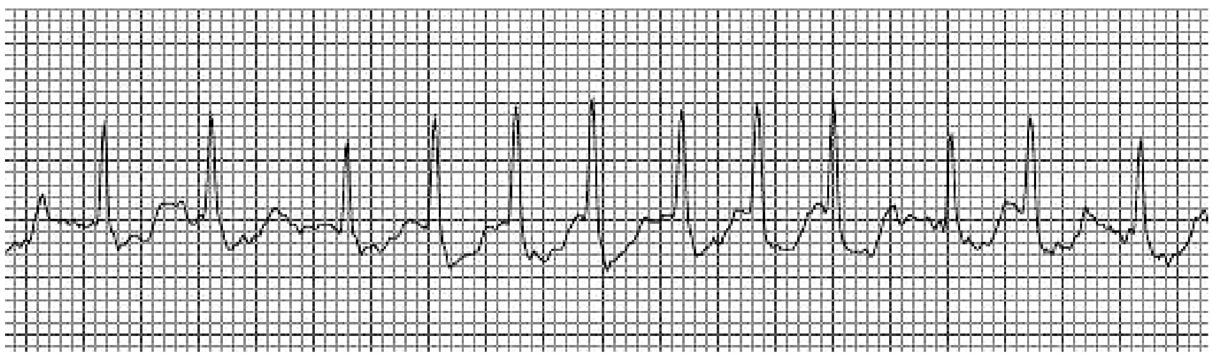


Figure 2.6: ECG signal of Rapid Atrial Fibrillation [12]

2.4 Review of Beat / Rhythm Classification

In the past centuries, a considerable amount of effort has been done globally in develop different method to analyze ECG signal automatically. Different algorithm has been invented to identify and classify different type of beats and rhythm for automatic arrhythmia detection. All the work done previously mainly consist of 2 parts which is feature extraction from the ECG signals and the classification method. A cardiologist interprets the ECG signal according to various interval through inspection on the PQRST peak which correspond to the P waves, QRS-complex, amplitude, and polarities. All these features have been originally included in an automatic ECG signal acquisition and analysis machine. More detailed analysis has to be done by a heart specialist or a professional doctor based on their understanding towards the disease. With this, diagnosis can only be done by expertise but those without the knowledge can never understand the condition of their heart. In order to solve this issue, researchers had come out with various solutions as from dealing with statistical parameter, frequency and time domain features or even more complex theory has been use on the feature extraction part. As for the classification part, some researchers used a simpler method which is classification according on a set of rules, while some use artificial intelligent, support vector machine, and K – which means the clustering method. In this section, studies that focus on automatic beat/rhythm classification are reviewed, mainly about feature extraction and the classification scheme.

One of the recent studies, which is the R peak detection algorithm, is performed by using double difference and RR interval processing [16]. At first, the filter ECG signal undergo doubled differential and different peak above the constant threshold of 3% of the maximum value is detected and selected as R peak. With the rule which states the maximum value of QRS region is 150ms, possibility of detection of several peaks in the same QRS region all the difference peaks within an interval of ±75ms of each selected difference peaks are eliminated. After identifying each region of QRS complex, the R-peak is located by selecting the maximum value within every QRS complex. In this method, noisy ECG data may produce false R peak and wrong RR interval will be computed. In order to solve this issue, R peak should be identified first instead of QRS complex. After the R peak is carefully selected according to specific decision rule, the only to locate the Q and S peak to identify the actual QRS complex.

According to [15], the authors used the threshold method to identify the R peak in the ECG signals. Two thresholding method has been used in this research which is the fixed threshold and variable threshold method. By using the first method which is the fixed threshold, some R peak might fail to be detected due to baseline changes in ECG signal. In order to solve this problem, the authors use variable threshold method which use the value corresponding to 55% of 4 data average except a highest from 5 R-peak detection. By using this method, the threshold value change accordingly from time to time which can allow all the R peak to be detected when the baseline shift to a lower value. By using this method, there might be chances which 2 consecutive R-peak to be detected when there are noises present. Therefore, in these studies, the minimum distance between 2 detected R peak has been included to prevent the false R peak detection.

According to [13], two alternative algorithms for the detection of atrial fibrillation in five minutes long ECG signals have been proposed. The authors intended to use algorithm on mobile devices, therefore they have developed a low processing power techniques. Various features have been extracted for the ECG signals which is the QRS detection and the RR interval from the Tachogram Generation method. The two algorithms used in this paper are the PPV detector (peak-to-peak and Variance Reckoning. In this method, the classification is done by using specific decision tree based on threshold comparison. AF and non-AF is classified for each segment by thresholding the RR interval of 0.2s. The final classification part is determined by the variance and standard deviation of the RR interval. Generally, this method mainly classifies the brat rhythm into AF or non-AF by using the threshold value of RR interval and RR standard deviation. As stated in the symptoms of Arrhythmia, the symptoms may occur periodically or even one beat in few minutes. There for there might be some miss classification if the ECG signals is too shorts which less then 60s. The second method used in this study is still the PPV but with the assist of morphological filters (MF). Morphological filter is a process which locates their origin in the area of image processing and mainly the field of noise reduction but also to suppress specific signal structures. In this study, both method achieve high accuracy which is 80.1% for the first method and 88.3% for the second method. High accuracy can be achieved due to long duration of ECG signals which is 5 minutes.

In depth of recent studies, [14] RR-based featured is continued to be used for ECG classification. The analysis was done based on both time and time-frequency features. In this study, the time domain features were SDNN, RMSSD, pNN5 pNN10, pNN50 and the standard deviation of successive difference of all normal-to-normal RR intervals. For time-frequency analysis, short time Fourier transform and 18-time-frequency distribution were used to compute the power spectral density and 6 features were chosen for each case. Time domain measurement are extracted and several combinations between the extracted features are used to train a set of neural network. The result of this method had achieved 87.5% and 89.5% sensitivity respectively for each analysis while 90 and 93% accuracy respectively. This study is based on the analysis of RR-interval duration which only capable of detecting arrhythmia type that produce irregularities on RR-interval the HRV or the heart rhythm. Therefore, left and right buddle branch block could not be detected as they did not produce such symptoms.

2.5 Artificial Neural Network

2.5.1 Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP), represented in Figure 2.7 below is the most common used artificial neural network (ANN). Each circle represents a neuron, or a unit and weight is associate to each connection between each neuron. There are mainly 3 layers which is the input layer, hidden layer, and the output layer

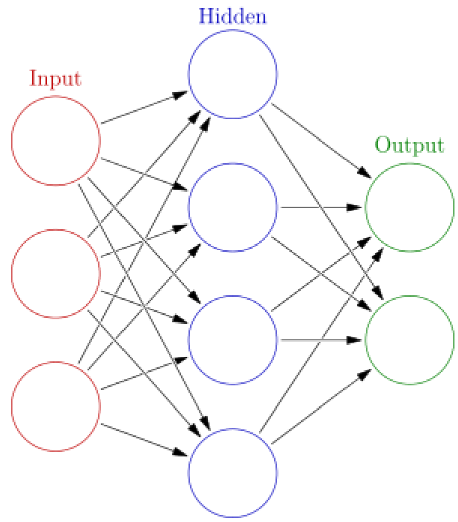


Figure 2.7: a multilayer perceptron with 3 neurons at the input, 4 neurons in the hidden layer and 2 in the output layer [16]

The structure of each neuron is represented by Figure 2.8 below. The sum of the input to the unit, γ is passed through a non-linear or activation function given by equation 1. The activation function can be any differentiable equation. The most common activation function used in ANN is given by equation 2.

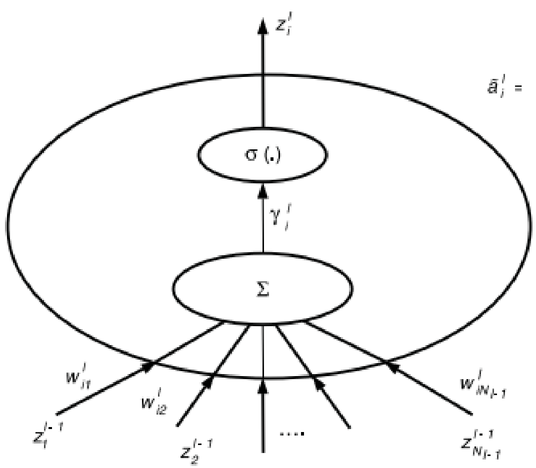


Figure 2.8: Basic architecture of a neuron with z_i inputs including one bias term [16]

The sum of the inputs is then passed through a nonlinear function activation function, σ.

$$\sigma(\gamma) = \gamma = \sum_{j=0}^{N} w_{ij}^{L} z_{j}^{L-1} \tag{1}$$

$$\sigma(\gamma) = \frac{1}{(1 + e^{-\gamma})} \tag{2}$$

The network is trained by feeding it a training pattern and adjusting the weight according to the desired target output. For each training pattern, k, a scalar measure of the error, E, is given by equation (3) and in the whole training system, equation (4) represents the deviation of the whole network from its ideal behavior.

$$E^{k} = |e^{k}|^{2} \tag{3}$$

$$E = \sum_{k=1}^{K} E^{k} \tag{4}$$

The formulae of the weight computation is given by equation (5), where n is the step size parameter and w is the weight.

$$w^{n+1} = w^{n} - \eta \nabla E \tag{5}$$

In practice, the computation of the gradient component is achieved by using the backpropagation (BP) method [16]. The error propagation network is constructed from the initial network by linearizing the nonlinear component and then reversing it. Once the training pattern is input into the network, the partial derivative of the difference between the output and the desired output is inserted to the error propagation network. The partial derivative is simply given by the product of the input correspond to the weight of the original network and in the backpropagation network. The training ends when the error is under predefined threshold or the maximum epoch is reach. Therefore, training the network could be a very lengthy process.

2.5.2 Back Propagation training algorithm

Back propagation algorithm is the most famous Neural Network algorithm. [16] claimed that BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the back-propagation algorithm is used to compute the necessary corrections. The algorithm can be decomposed in the following four steps:

i) Feed-forward computation

ii) Back propagation to the output layer

iii) Back propagation to the hidden layer

iv) Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small. This is very rough and basic formula for BP algorithm. There is some variation proposed by other scientist but Rojas definition seem to be quite accurate and easy to follow. The last step, weight updates takes place throughout the algorithm.

From [17], Feed forward computation is a 2 steps process which the first step is getting the value of the hidden nodes and second step is using the value to compute value of the output. Once the error is known after the error calculation is done, it will be used for backward propagation and weight adjustment. First, the error is propagated from output to hidden layer where the learning rate and momentum are brought to equation. Before weights can be updated, rate of change needs to be found. This is done by multiplication of the learning rate, error value and node value.

At the back propagation to hidden layer stage, the error has to be propagated from hidden layer down to the input layer. Weight between input and hidden layer can be updated after the error in the hidden layer is known. Finally, the Weight is updated and algorithm is improved.

2.6 Summary

This chapter presents the basic knowledge of ECG system and also some known ECG processing method. Based on the literature review, it is seen that the PQRST waves of ECG signal is the result of a series of electrical activities of hearts. This chapter also incorporate with multiple Arrhythmia classification method. One of the best method used is neural network based classification. Different features shall be extracted for neural network training algorithm. We know that different feature extracted from the raw ECG signal is essential for the neural network during arrhythmia classification. Number of feature should not be too less and also not too much for the neurons in the MLP to identify the correlation between each class. Therefore, the feature extraction part is essential to train the neural network.

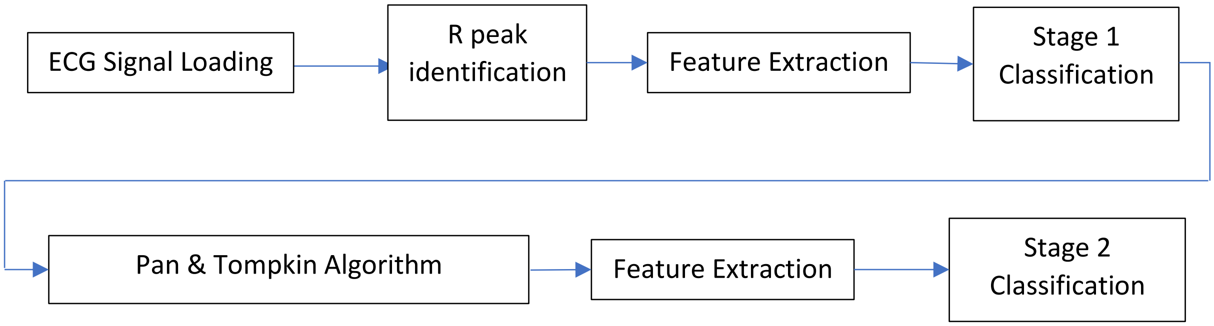
CHAPTER 3

METHODOLOGY

3.1 Introduction

This project basically consists of the development process of an ANN which is able to classify the type of single lead ECG recording into noisy, normal sinus and Arrhythmia. Neural network is the main part of this study as it allows the machine to learn to increase the accuracy as the database grows bigger. The overall process including ECG signal loading, signal pre-processing to extract feature for stage 1 classifier, signal pre-processing to extract feature for stage 2 classifier and finally a result will be generated which consist the name of the patients and the diagnosed rhythm. The methodology proposed in this thesis is schematized in Figure 3.1 below, encompassing the following steps: signal loading, 2 staged of ANN classifier and finally rhythm classification result. The detail explanation of each step will be discussed in the following section.

i)



ii)

Figure 3.1 i) Overall signal analysis flow chart
ii) Detailed stage 1 and stage 2 flow chart

3.2 Database

The single lead ECG recording used in this study is provided by MIT-BIH Physionet ECG database. The ECG recording is collected using the AliveCor device. The training set contains 8528 recording last from minimum 9 second to just over 60 seconds. The recordings were sampled at 300Hz and been through band pass filter by the AliveCor device. The data provided in MATHLAB V4 WFDB-compliant format (including a .mat file containing the ECG signal and a .hea file containing the waveform information. There are 4 classes in these 8528 ECG recordings, which are the normal rhythm, AF rhythm, other rhythm, and noisy recording. Table 3.1 below indicate the data profiling for the training set.

Table 3.1: Data profiling for the training set [21]

Type	recording	Time length (s)				
		Mean	SD	Max	Median	Min
Normal	5154	31.9	10.0	61.0	30	9.0
Arrhyth -mia	3328	33.5	12.1	60	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	**8528**	**32.5**	**10.9**	**61.0**	**30**	**9.0**

3.3 ECG Signal Processing

3.3.1 Header file's information retrieving process

A00058 1 300 18000 2014-04-16 07:04:56

A00058.mat 16+24 1000/mV 16 0 437 0 0 ECG

The information above is provided in the header file of an ECG signal. As shown as above, the first string represents the patient name, following by the number of signal and the sampling frequency. The example above shows the patient with the name "A00058", 1 ECG signal, Sampling frequency of 300Hz and 18000 samples recorded. The ECG signal is recorded on 16^{th} April of 2014, at the time of 07:04:56.

At the second row of the header file, it started with the filename then followed by the format which is 16-bit signal and the gain of the signal is 1000 and the unit used is mV, ADC resolution of 16 bits. Initial value in the signal (437) followed by the checksum, blocksize and the description.

3.3.2 Stage 1 Signal Classifier

In this stage, the raw signals are fetched into the program to classify the signals into 2 categories which are the signals that are too noisy to be classified and the signals that are clean enough for further classification. The signals which categorized as too noisy will be recorded in a text file which stated the patient's name and classified rhythm, "~" which represent too noisy data.

3.3.2.1 R-peak Detection

The QRS-complex consist of 3 major components which is the Q-wave, R-wave, and S-wave. The R-wave is acquired simply by thresholding the amplitude of signal. In this research, variable thresholding is used to identify the R peak. The thresholding value is changed every second. The value is determined by the mean of the top 10% of the amplitude in every second. Q and S peak is identified by selecting the first point of deflection before and after the R peak detected. R peak can be detected by using the Matlab code below.

```
[~,locs_Rwave]=findpeaks(sortedVal,'MinPeakHeight',MeanThr,'MinPeakDistance',60);
```

Accuracy = % of correct R peak detected

Sensitivity = Number of R peak detected including false and correct R peak

The following detection rule is applied:

1. All peaks that precede or follow larger peaks by less than 200 milliseconds are ignored [22].

2. The peak is assumed to be a wrong R-peak if the amplitude of the R peak is smaller than half the maximum derivative of the previous detection [22].
3. The peak is assumed to be a wrong R-peak if the difference of the simultaneous Q and R peak is below 75% of R peak.
4. The peak is assumed to be a wrong R-peak if the difference of the simultaneous Q and S peak is below 75% of R peak.

3.3.2.2 Feature Extraction

After the R-peak has been detected and the location (x-coordinate) of r peak had been store. 6 parameters are extracted for 1st stage classifier which is:

- Mean and standard deviation of heart rate.

- Mean and standard deviation of R-peak's amplitude.

- Rate of fluctuation.

- Number of R-peak in 3 seconds.

3.3.3 Stage 2 Signal Classifier

In this stage, the signals which are clean enough for further classification are fetched into the program to classify into 2 categories which are Normal sinus rhythm and Arrhythmia. A text file which stated the patient name and classified rhythm will be generated at the end of this stage.

3.3.3.1 R-peak Detection (Pan and Tompkin Algorithm)

In this second stage of classification, Pan and Tompkin Algorithm has been used to identify the R peak in ECG signal. The flow chart below stated the flow diagram of this algorithm. At the end of this algorithm, the location of R peak can be detected in high accuracy.

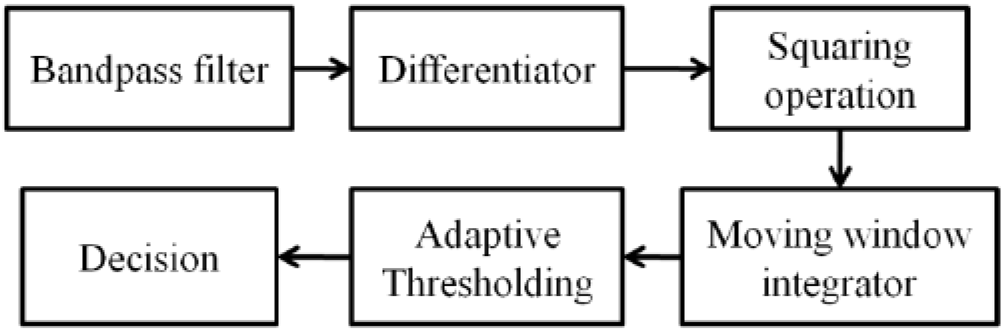


Figure 3.2: Block diagram of Pan Tompkins algorithm [19]

3.3.3.2 Feature Extraction and Normalization

After the R-peak had been detected, few parameters have been extracted for the classification purpose.

The parameter below has been extracted for classification purpose:

- Average heart rate

- Standard deviation of heart rate

The set of R-peak amplitude detected is normalized by scaling to the range [0, 1]. This operation is detailed in Equations below.

$$R_{scaled} = \frac{r - \min r}{\max r - \min r} \tag{5}$$

Where r is the amplitude of R-peak in raw ECG signal.

- Mean of Normalized R amplitude, R_{scaled}

- Standard deviation of Normalized R amplitude, R_{scaled}

- Mean of raw R amplitude

- Standard deviation of raw R amplitude

- Difference of the maximum raw R amplitude and min raw R amplitude

Different combination has been used to train the ANN and the combination which provide the highest accuracy has been selected.

3.4 Classifier (Artificial Neural Network)

The classifier used in this study has been discussed in the previous chapter which is one type of machine learning artificial intelligent, artificial neural network (ANN) which is also called as multilayer perceptron (MLP).

The network of the ANN classifier was constructed with just one hidden layer. Bias terms are included in the hidden and output layers. Figure 3.3 below simplify the topology of a network with N input features, HN hidden neurons and N1 number of outputs. In this ANN classifier, the input including the RR interval, RR interval standard deviation, mean and standard deviation of normalized and actual R-peak's amplitude, difference between maximum and minimum R-peak amplitude. For each classification task, multiple tests are performed to choose the most suitable number of neurons in the hidden layer. Scaled conjugate gradient backpropagation is used as the training function that update weight and bias. Backpropagation is used to calculate derivatives of performance perf with respect to the weight and bias variables X. Additionally, 15% of the training set was used as validation set. This is meant to avoid over fitting of the network, thus assuring a better generalization capability.

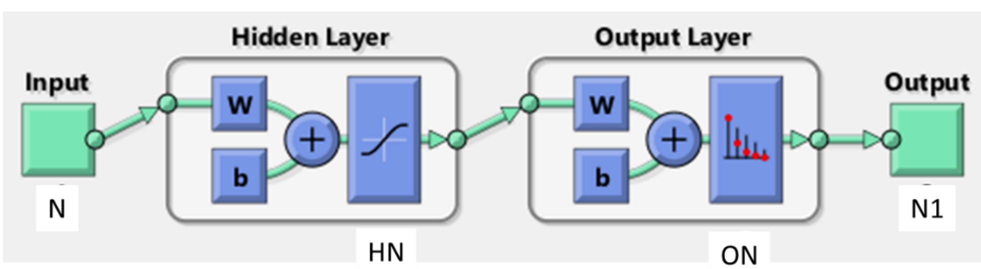


Figure 3.3: Example of the topology of a network with N input features, 10 hidden neurons and 4 outputs

Training stops when the condition bellows occurs:

- The maximum number or epochs is reached (1000 epochs).
- The maximum time is exceeded.