

ARRHYTHMIA HEART DISEASE CLASSIFICATION USING DEEP  
LEARNING

ABDULKHALIQ ABDULKARIM FARAH

A project report submitted in partial  
fulfilment of the requirement for the award of the  
Degree of Master of Electrical Engineering



Faculty of Electrical and Electronic Engineering  
Universiti Tun Hussein Onn Malaysia

JANUARY 2020

## ACKNOWLEDGEMENT

### **In the name of Allah, the Most Gracious, and Most Merciful**

Alhamdulillah Praise be to Almighty Allah the only owner (Subhanahu Wa Ta'ala) who gave me the courage and patience to carry out this project requirement for the conferment of the Master Degree. Peace and blessing of Allah be upon his last prophet Mohammed (Sallulahu Alayhi Wassalam) and all his companions (Sahaba), (Razi-Allaho-Anhum) who devoted their lives towards the prosperity and spread of Islam.

I would like to express my sincere appreciation and heartfelt gratitude goes to my supervisor, DR Nor Suraya Hani Suriani for her kindness, constant endeavour, guidance, and the numerous moments of attention she devoted through out of this project. This thesis would not have been possibly finished without her encouragement and support.

My greatest thanks to my family, especially both my parents whose has given a lot of love, courage, sacrifice and support. Thanks also to all my friends and colleagues who give me ideas and support to me in order to complete this report. Thank you all for your kindness and generosity may Allah bless you all rewarding paradise Insha'Allah.

## ABSTRACT

Arrhythmia affects millions of people in the world. Sudden cardiac death is the cause of about half of deaths due to cardiovascular disease and about 15% of all deaths globally. About 80% of sudden cardiac death is the result of ventricular arrhythmias. Arrhythmias may occur at any age but are more common among older people. Arrhythmias are caused by problems with the electrical conduction system of the heart. Therefore, we have designed a model using supervised deep learning to classify the heartbeats extracted from an ECG into four (4) heartbeat classes which is normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB) and fusion beat, based only on the line shape (morphology) of the individual heartbeats.

The overall performance of the system resulted in a precision of 95.378%, a recall of 81.3035%, accuracy of 97.62% and an F1 score 84.6875%.



PTIA  
PERPUSTAKAAN TUNJUKKAN AMINAH

## CONTENTS

|                                    |            |
|------------------------------------|------------|
| <b>TITLE</b>                       | <b>i</b>   |
| <b>DECLARATION</b>                 | <b>ii</b>  |
| <b>ACKNOWLEDGEMENT</b>             | <b>iii</b> |
| <b>ABSTRACT</b>                    | <b>iv</b>  |
| <b>CONTENTS</b>                    | <b>v</b>   |
| <b>LIST OF TABLES</b>              | <b>ix</b>  |
| <b>LIST OF FIGURES</b>             | <b>x</b>   |
| <b>LIST OF ABBREVIATIONS</b>       | <b>xii</b> |
|                                    |            |
| <b>CHAPTER 1 INTRODUCTION</b>      | <b>1</b>   |
| 1.1 Introduction                   | 1          |
| 1.2 Problem Statement              | 2          |
| 1.3 Objectives                     | 2          |
| 1.4 Scope of Project               | 2          |
| 1.5 Thesis Outline                 | 3          |
|                                    |            |
| <b>CHAPTER 2 LITERATURE REVIEW</b> | <b>4</b>   |
| 2.1 Electrocardiogram              | 4          |
| 2.1.1 P wave                       | 5          |
| 2.1.2 QRS complex                  | 6          |
| 2.1.3 T wave                       | 7          |
| 2.1.4 PR-segment                   | 8          |
| 2.1.5 ST-segment                   | 9          |
| 2.1.6 QT-interval                  | 9          |
| 2.1.7 RR-interval                  | 9          |

|  |           |
|--|-----------|
| 2.1.8 PR-interval                            | 10        |
| 2.2 Heart Diseases                           | 12        |
| 2.2.1 Arrhythmia                             | 12        |
| 2.2.2 Sleep Apnea                            | 13        |
| 2.2.3 Coronary Artery Disease                | 14        |
| 2.3 Machine Learning                         | 15        |
| 2.3.1 Supervised Learning.                   | 15        |
| 2.3.2 Unsupervised Learning.                 | 16        |
| 2.3.3 Semi-supervised Learning.              | 17        |
| 2.3.4 Reinforcement Learning.                | 18        |
| 2.4 Classification Techniques                | 18        |
| 2.4.1 Deep Learning                          | 18        |
| 2.4.2 Deep Learning Architectures            | 19        |
| 2.4.3 Deep Learning Related Work.            | 19        |
| 2.5 Issues in ECG Classification             | 24        |
| 2.6 Summary                                  | 24        |
| <b>CHAPTER 3 METHODOLOGY</b>                 | <b>25</b> |
| 3.1 Flowchart                                | 25        |
| 3.2 Data Collection                          | 26        |
| 3.3 Pre-processing                           | 26        |
| 3.4 Model Building using Deep Learning Model | 27        |
| 3.5 Training Model using Deep Learning Model | 29        |
| 3.6 Prediction                               | 29        |
| <b>CHAPTER 4 RESULTS AND DISCUSSION</b>      | <b>31</b> |
| 4.1 Data Loading and First Insights          | 31        |
| 4.2 Correlation Matrix                       | 34        |
| 4.3 Data Standardisation                     | 35        |
| 4.4 Training and Validation Test             | 36        |

|   |           |
|---|-----------|
| 4.4.1 First Model                               | 36        |
| 4.4.2 Second Model                              | 37        |
| 4.4.3 Third Model                               | 38        |
| 4.5 Classification                              | 39        |
| 4.5.1 First Model                               | 39        |
| 4.5.2 Second Model                              | 40        |
| 4.5.3 Third Model                               | 41        |
| 4.6 Summary of the Classification Models        | 42        |
| <b>CHAPTER 5 CONCUSSION AND RECOMMENDATIONS</b> | <b>44</b> |
| 5.1 Conclusion                                  | 44        |
| 5.2 Recommendation for Future Work              | 45        |
| <b>REFERENCE</b>                                | <b>46</b> |



**LIST OF TABLES**

|   |    |
|---|----|
| Table 2. 1: ECG Features and Their Normal Durations               | 11 |
| Table 2. 2: Summary of Deep Learning Related Work                 | 23 |
| Table 2. 3: Feature extraction methods for heartbeat segmentation | 24 |
| Table 4.1: Confusion Matrix                                       | 38 |
| Table 4.2: Confusion Matrix                                       | 39 |
| Table 4.3: Confusion Matrix                                       | 40 |
| Table 4.4: Summary of the classification model results            | 41 |
| Table 4.5: Comparison of heartbeat classification results.        | 42 |



## LIST OF FIGURES

|  |    |
|--|----|
| Figure 2. 1: The waveform of an ideal, normal ECG waveform with peaks labelled by P, Q, R, S and T[2].   | 5  |
| Figure 2. 2: Electrical activities of the heart are controlled by the sinoatrial (SA) node[2].   | 6  |
| Figure 2. 3: The sequence of muscle contractions follows after the firing of the electrical impulses form the sinoatrial (SA) node[2].   | 7  |
| Figure 2. 4: The ECG tracing is divided into two segments: PR segment and ST segment[2].   | 8  |
| Figure 2. 5: (a) A normal ST-segment in a normal ECG showing the base of the ST-segment remains relatively close to the isoelectric line. In normal ECG, the ST-segment moves into the beginning of the T wave. (b) ST-segment is elevated a above the isoelectric line, (c) and the ST-segment is depressed below the isoelectric line. Figure taken from [2] . | 10 |
| Figure 2. 6: the ECG tracing is divided into various intervals: PR-interval, RR-interval, and QT-interval[2].  | 11 |
| Figure 2. 7: Types of Arrhythmias.   | 12 |
| Figure 2. 8: Types of classification [19]  | 16 |
| Figure 2.9: Before clustering and after [19]   | 17 |
| Figure 3. 1: Project flowchart   | 24 |
| Figure 3. 2: Relu activation function  | 27 |



|  |    |
|--|----|
| Figure 3. 3: Deep Learning Model   | 27 |
| Figure 4. 1: QRS complex dataset   | 30 |
| Figure 4. 2: Distribution of classes   | 31 |
| Figure 4. 3: Heartbeat classes (a) Normal beat and Supraventricular ectopic beat (SVEB), (b) Ventricular ectopic beat (VEB) and Fusion beat                      | 32 |
| Figure 4. 4: Correlation matrix of features 79, 80, 78 and 77  | 33 |
| Figure 4.5: Heartbeat classes after standardisation (a) Normal beat and Supraventricular ectopic beat (SVEB), (b) Ventricular ectopic beat (VEB) and Fusion beat | 34 |
| Figure 4. 6: Loss and accuracy of the training and validation test   | 35 |
| Figure 4. 7: Loss and accuracy of the training and validation test   | 36 |
| Figure 4. 8: Loss and accuracy of the training and validation test   | 37 |



PTAA UTHM  
PERPUSTAKAAN TUNJUKKAN AMINAH

**LIST OF ABBREVIATIONS**

|      |                               |
|------|-------------------------------|
| ECG  | Electrocardiogram             |
| VEB  | Ventricular Ectopic Beat      |
| SVEB | Supraventricular Ectopic Beat |
| ANN  | Artificial Neural Network     |
| EMG  | Electromyography              |
| SA   | Sinoatrial                    |
| AV   | Atrioventricular              |
| HRV  | Heart Rate Variability        |
| CAD  | Coronary Artery Disease       |
| BMI  | Body Mass Index               |
| CNN  | Convolutional Neural Network  |
| MI   | Myocardial Infarction         |
| AF   | Atrial Fibrillation           |
| PPG  | Photoplethysmography          |
| DWT  | Discrete Wavelet Transform    |
| ReLU | Rectified Linear Unit         |
| SGD  | Stochastic Gradient Descent   |
| TP   | True Positive                 |
| TN   | True Negative                 |
| FN   | False Negative                |
| FP   | False Positive                |

# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Heart disease is the class of diseases that involve the heart or blood vessels (arteries and veins). Today, most countries face high and increasing rates of heart disease and it has become a leading cause of debilitation and death worldwide in men and women over age sixty-five and today in many countries heart disease is viewed as a “second epidemic,” replacing infectious diseases as the leading cause of death.[1]. To solve this and many other problems in the health sector related to heart diseases diagnosis, one must come up with a way to extract hidden information from enormous datasets that are collected in the past using electrocardiogram (ECG) which is low cost, non-invasive and effective test for heart disease analysis. Data mining and machine learning can be a solution by generating rules from those enormous datasets. Employing data mining and machine learning in the health sector has been rapidly gaining high importance around the world. The importance of health informatics has risen significantly in the recent years due to the need for a secured and efficient management of medical data. Health informatics also facilitates proper management, analysis and use of health-related data for the purpose of more efficient healthcare delivery.

The aim of this research is to classify heart diseases by using the data from kaggle website of MIT-BIH arrhythmia database containing 100000 beats from 22 recording into four heartbeat classes which is normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB) and fusion beat utilizing supervised deep learning technique.

## 1.2 Problem Statement

Heart Disease has become a common disease around the world. Most countries face high and increasing rates of heart disease or Cardiovascular Disease. Even though modern medicine is generating huge amount of data every day, little has been done to use this available data to solve the challenges that face a successful interpretation of echocardiography examination results.

Discovering the disease in its early stages may reduce the severity of heart disease. Computing technologies and machine learning tools can be used to assist physicians in diagnosing and predicting the disease so they can provide the necessary treatment and prevent the impact, including the possibility of death.

Classifying the outcome of a disease is one of the most interesting and challenging tasks in which to develop data mining applications. Classification systems with a high precision of heart diseases screening and classification will help in decreasing the workload for healthcare personnel in the process of the early detection of heart diseases. Therefore, this thesis intends to utilize the latest technologies, focusing on deep-learning Neural Networks approach, in data mining science to produce model that can assist physicians in the process of classifying of heart diseases.

## 1.3 Objectives

- ❖ To identify the features of normal and abnormal heartbeats.
- ❖ To design heartbeat classification model based on Deep Neural Networks.
- ❖ To validate the performance of proposed framework on various measures.

## 1.4 Scope of Project

- ❖ The tools that have been used in this project.
  - The method used in this project is deep learning technique to classify heart beats.
  - Python software is used for this project.

- Data that have been used for this project is collected from kaggle website of MIT-BIH Arrhythmia database.
- The classification of four (4) heartbeat classes which is normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB) and fusion beat.
- The performance measures are Accuracy, Precision, Recall Score and F1 Score.

## 1.5 Thesis Outline

Chapter one gives information related to the aims of the project.

Chapter two provides full comprehensive literary works review on heart disease detection using deep learning method , and Also the reader will gain knowledge about the electrocardiograms, heart diseases, machine learning types and deep learning architectures.

Chapter three summarizes the steps taken to design the project.

Chapter four discusses the classification results of the deep neural network and lastly is the conclusion and future recommendation.

## CHAPTER 2

### LITERATURE REVIEW

This chapter reviews some necessary background on electrocardiograms and deep learning method. First, the electrical phenomena aspects of the heart are presented in order to understand how the familiar “waves” observed in an ECG arise. Then we will discuss the common types of heart diseases.

Secondly, types of machine learning and the classification algorithm of deep learning method, deep learning architectures and their literary works review on previous studies are presented in this chapter.

#### 2.1 Electrocardiogram

The electrocardiogram (ECG) is a time-varying electro-cardiac signal that represents the electrical activity of the human heart. It is obtained using surface electromyography (EMG), where electrodes are attached to the surface of the skin in close proximity to the human heart. It is a non-invasive procedure that is widely used in hospital settings to measure and diagnose abnormal rhythms of the heart. The ECG signal measured from the patient, results in a periodic waveform with multiple apexes called the PQRST-complex. Figure 2.1 shows and ideal PQRST-complex waveform.

The apexes in the PQRST-complex are labelled with P, Q, R, S and T, which are commonly used in medical ECG terminology. Each apex results from ionic current exchanges in the heart causing muscle contraction and relaxation. All the muscle contractions and relaxations in the heart begin at the sinoatrial (SA) node, which is a specialized cell that regulates the heartbeat. (See Figure 2.2).the SA node produces electrical impulses, which spread radially throughout the whole heart. As the electrical

impulses traverse through the heart, different muscle groups in the heart contract in a sequential manner to produce the PQRST-complex waveform. The order of muscle contractions is shown in Figure 2.3.

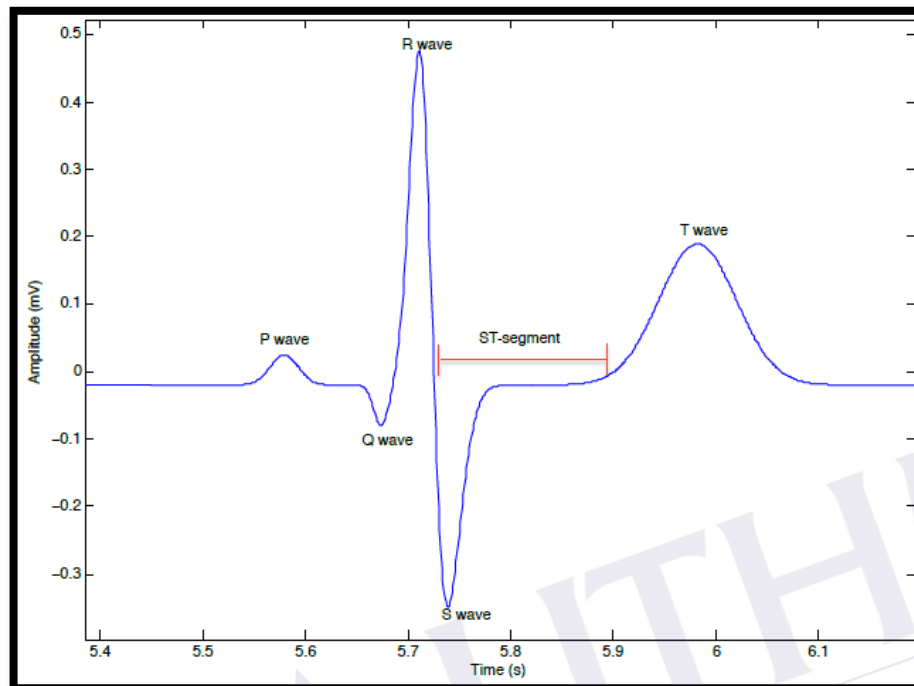


Figure 2. 1: The waveform of an ideal, normal ECG waveform with peaks labelled by P, Q, R, S and T. The ST segment defines the interval from the beginning of the S wave to the beginning of the T wave[2].

In Figure 2.3, the atria contraction produces the P wave and the ventricle contraction produces the QRS complex and the T wave.

### 2.1.1 P wave

The electrical impulses produced by the SA node first propagate to the right atrium then the left atrium (see Figure 2.2). Depolarization of the right atrium produces a small-voltage deflection away from the baseline. The plateau of the P wave represents the completion of the right atrial contraction and beginning of the left atrial contraction; the left atrium contraction finishes at the end of the P wave. In other words, the P wave is produced by the contraction of the right and left atria (see Figure 2.3).

The P wave is a small, smooth, rounded deflection that precedes the spiky-looking QRS-complex. The duration from the end of the P wave to the beginning of the Q wave represents the necessary physiologic delay to allow the left and the right ventricles to prepare for contraction. To achieve this necessary delay, the electrical impulses pass through multiple parts of the heart: the AV node, the bundle branch, and the Purkinje network (see Figure 2.3). This delay is a natural delay mechanism to allow the ventricles to be filled with blood.

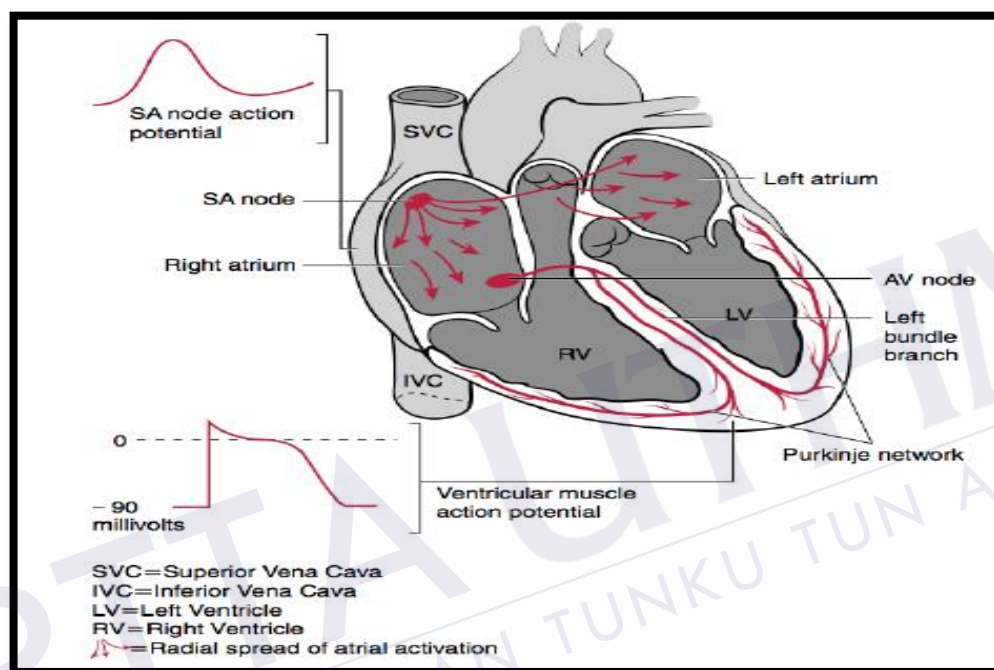


Figure 2. 2: Electrical activities of the heart are controlled by the sinoatrial (SA) node. The electrical impulses fired by the SA node spread radially outward to the atria and the atrioventricular (AV) node. The AV node relegates the current from the SA node down the left bundle branch to the ventricular muscles and Purkinje network [2].

### 2.1.2 QRS complex

The QRS-complex reflects the rapid depolarization of the right and left ventricles, and marks the beginning of the ventricle contraction. The ventricles have a large muscle mass compared to the atria, so the QRS complex has a much larger deflection than the P wave. The wave is composed of the Q wave, R wave and S wave, and is used as a landmark to estimate the heart rate of a patient by tracking the RR interval. The RR interval is the interval from the R peak of one ECG waveform to the R peak of the next ECG waveform. The RR interval indicates the interval between successive heartbeats



and determines the heart rate. The RR interval often contains other valuable information, such as the types of arrhythmia that might be present in a patient [2].

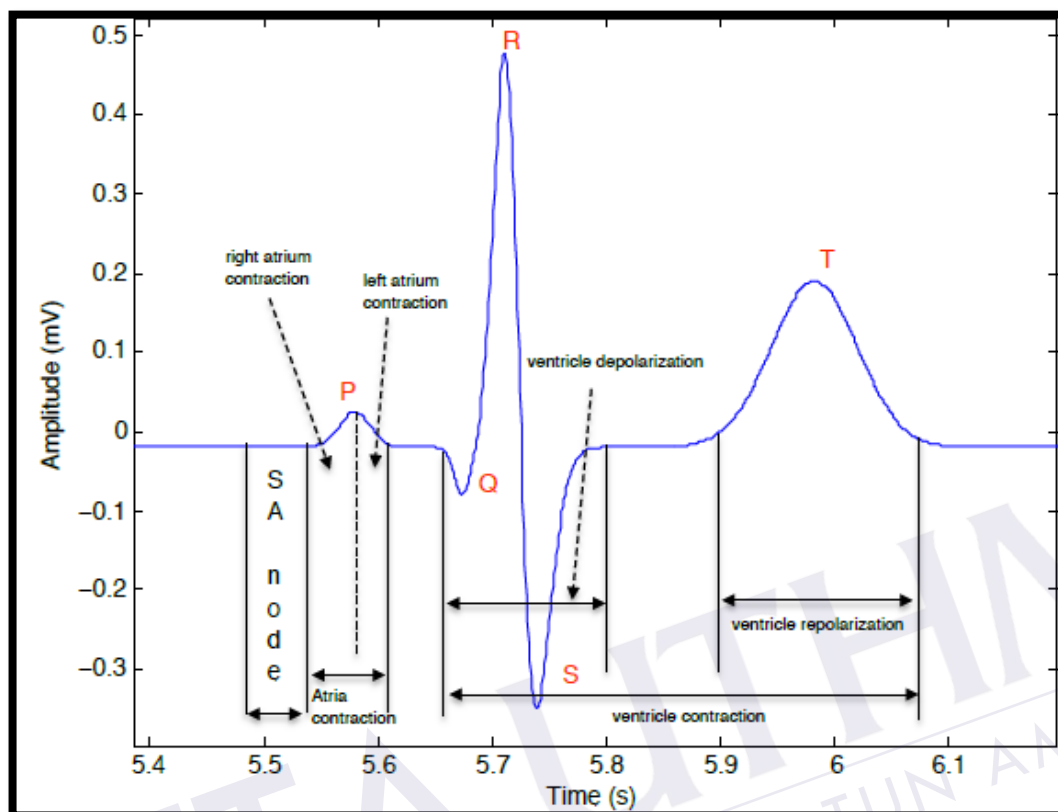


Figure 2. 3: The sequence of muscle contractions follows after the firing of the electrical impulses from the sinoatrial (SA) node[2].

### 2.1.3 T wave

The T wave depicts the electrical recovery and repolarization of the ventricles, and marks the end of the contraction of the ventricles. It is typically a round, approximately semi-circular shaped wave, which deflects slightly above the baseline. The T wave follows each QRS complex. The time-separation between the QRS complex and the T wave is typically constant for normal ECG traces and is also known as the ST segment.

Using the five basic waves as landmarks, the ECG tracing is divided into various segments and intervals. An ECG segment is defined as the period between the ends of one wave to the start of the next wave (see Figure 2.4). For example, the PR-segment begins at the end of the P wave and ends at the beginning of the Q wave. An ECG interval (not to be confused with an ECG segment) includes one segment and one or more waves (see Figure 2.6). Thus, the PR-interval starts at the beginning of

the P wave and ends at the onset of the QRS-complex. Each segment and interval displayed in Figure 2.4 and Figure 2.6 has its own characteristics and clinical significance, which are discussed in the following subsection.

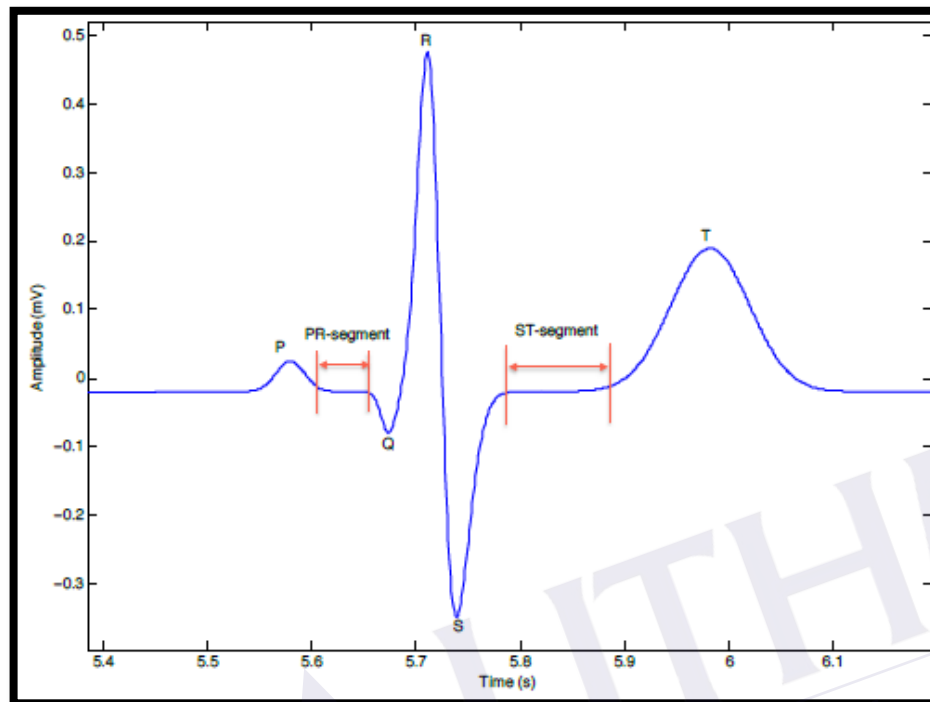


Figure 2. 4: The ECG tracing is divided into two segments: PR segment and ST segment[2].

#### 2.1.4 PR-segment

The PR-segment starts from the end of the P wave to the beginning of the successive Q wave. It appears as a flat, horizontal tracing on the ECG tracing. The duration of the segment represents the delay of the electrical impulse at the AV node where the electrical current traverses down the bundle of branches to the ventricles. Under both normal and abnormal ECG activities, the baseline of the PR segment remains constant and is approximately the same amplitude level as the isoelectric line. The isoelectric line is equivalent to the baseline of the entire ECG wave, which is typically at 0mV. The amplitude of the PR segment is used to measure the amplitude of the isoelectric line. The portion of the ECG tracing following the T wave and preceding the next P wave could also be used to measure the isoelectric line.

### 2.1.5 ST-segment

The ST-segment starts from the end of the QRS-complex to the beginning of the succeeding T wave. This is the period of slow depolarization of the ventricles after the contractions of the left and right ventricles. In normal individuals, the baseline of the ST-segment typically remains close to the isoelectric line. The baseline of the ST-segment also curves rapidly into the ascending limb of the T wave from the end of the S wave as in Figure 2.5(a); it should not form a horizontal line nor a sharp angle with the start of the T wave like Figure 2.4. In abnormal cardiac activities, the baseline of the ST-segment is abnormally elevated or depressed from the isoelectric line as shown in Figure 2.5(b) and 2.5(c). For cardiac arrhythmia analysis, elevation of the ST-segment indicates myocardial infarction, while depression of the ST-segment is typically associated with hypokalaemia or digitalis toxicity.

### 2.1.6 QT-interval

The QT-interval (see Figure 2.6) is the time from the beginning of the Q wave to the end of the T wave. The interval reflects the amount of time for ventricle depolarization and repolarization. If the interval is abnormally prolonged or shortened, there is a risk of developing ventricular arrhythmia. In certain cases, a prolonged QT-interval could lead to a life-threatening cardiac arrhythmia known as ventricular tachycardia, which in turn can lead to death of the patient.

### 2.1.7 RR-interval

The RR-interval (see Figure 2.6) is measured from one peak of the R wave to the next peak of the R wave. The RR-interval reflects the heart rate of a patient, the RR-interval varies over time as a consequence of the general physiological and psychological condition of the patient. The variations in the RR-interval is also known as heart rate variability (HRV). Both research and clinical studies have indicated the HRV contains valuable information about the various types of arrhythmia that might be present in a

patient [3]. For instance, the HRV can be used to predict the survivability of a patient after a heart attack [3] .

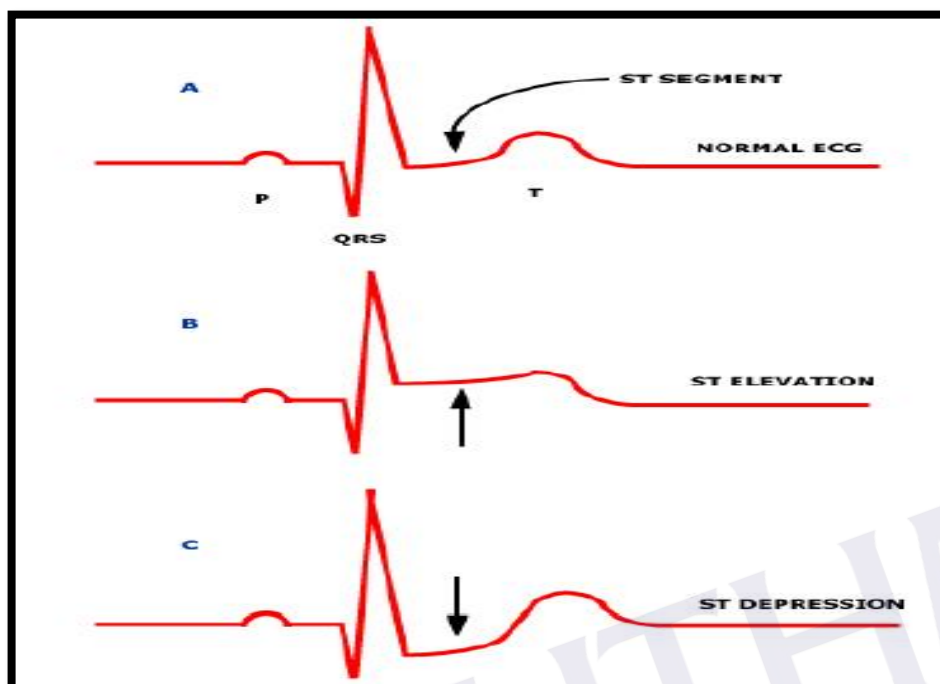


Figure 2. 5: (a) A normal ST-segment in a normal ECG showing the base of the ST-segment remains relatively close to the isoelectric line. In normal ECG, the ST-segment moves into the beginning of the T wave. (b) ST-segment is elevated a above the isoelectric line, (c) and the ST-segment is depressed below the isoelectric line.

Figure taken from [2] .

### 2.1.8 PR-interval

The PR-interval (see Figure 2.6) is measured form the beginning of the P-wave to the beginning of QRS-complex. This is the amount of time that is required by the electrical impulse to travel form the atria to permit the ventricular muscle to begin depolarize. The variations in the PR-interval indicates a first degree heart block.

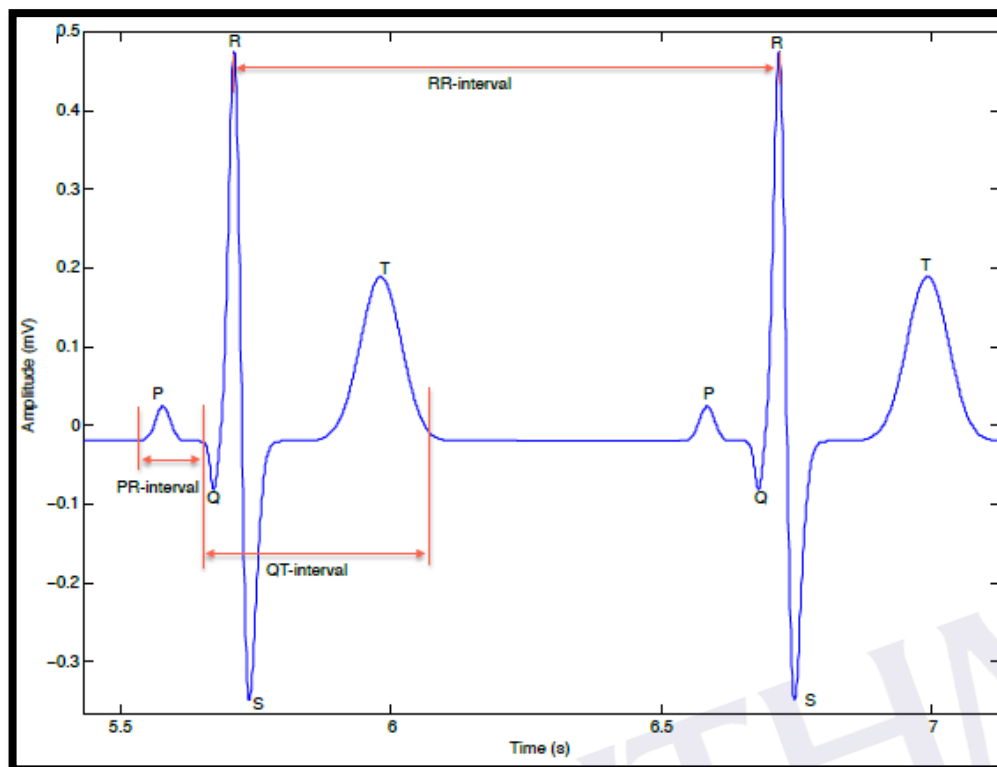


Figure 2. 6: the ECG tracing is divided into various intervals: PR-interval, RR-interval, and QT-interval[2].

Table 2. 1: ECG Features and Their Normal Durations

| Feature | Description  | Duration |
|---------|--|----------|
| P       | The P wave is a small, smooth, rounded deflection that precedes the spiky-looking QRS-complex.               | 80ms     |
| QRS     | Normally begins with a downward deflection Q, a larger upwards deflection R and ends with a downward S wave. | 80-120ms |
| T       | Normally a modest upward waveform.   | 160ms    |
| PR      | The PR-segment starts from the end of the P wave to the beginning of the successive Q wave.                  | 50-120ms |
| ST      | The ST-segment starts from the end of the QRS-complex to the beginning of the succeeding T wave.             | 80-120ms |
| QT      | The QT-interval (see Figure 2.6) is the time from the beginning of the Q wave to the end of the T wave.      | 420ms    |
| RR      | The RR-interval is measured from on peak of the R wave to the next peak of the R wave.                       | 0.6-1.2s |

## 2.2 Heart Diseases

### 2.2.1 Arrhythmia

Arrhythmia is a problem of the heartbeat rhythm, which is the rate of beat is too slow or faster than normal. so the lower beat and faster beat are called bradycardia and tachycardia. Many factors can cause the change the heart beat like exercise, smoking, and heart failure and heart defects. Some drugs can change the heart rhythm which is if the person is taking medications. Symptoms of arrhythmias are: chest pain, shortness of breath, sweating, fast or slow heartbeat and light-headedness or dizziness [3]. The main types of arrhythmia which causes irregular heart beat is atrial fibrillation.

As shown in Figure 2.7, there are two groups of arrhythmias which has different patterns. The first group is bradycardia which is called morphological arrhythmia because of their single irregular heart rhythm, the other group is tachycardia called rhythmic arrhythmias which is created by a set of irregular heartbeats. so those irregular heartbeats helps us to classify into those two groups because it changes the morphology of the signal by using electrocardiogram to record.



Figure 2. 7: Types of Arrhythmias.

Some heartbeats can be difficult for human to classify and sometimes it takes several hours to do it and that is time consuming. In addition to that, it is important to analyse all heartbeats from Holter monitor because they carry a lot of information. Machine learning comes handy when classifying arrhythmias because of it is fast and analysing a large signals [4].

Arrhythmias are caused by a problem in the electrical system of the heart. Some causes of arrhythmias include: irritable heart cells, blocked signals, abnormal pathway and medicines [5].

### 2.2.2 Sleep Apnea

Sleep apnea is caused by a pause of breathing that lasts for about ten seconds and that may happen many times during sleep, if that happens it is called apnea. If that condition happens, the body will get less oxygen that effects the patient during the day in which he feels tired and dizziness[6].furthermore, it is dangerous for long-term because it will effect cardiovascular system and causes morbidity and mortality[7].

The most common risk factors that may cause sleep apnea are listed below [8]:

- obesity
- big neck size
- Male gender
- High blood pressure
- Family history

Sleep apnea and heart disease have been researched for many years and it showed that there is a link between them and sleep apnea increased the risk of having cardiovascular morbidity and mortality [9].it also discovered that sleep apnea increases the risk of sudden cardiac death as had been discussed in paper [10].when person's breathing pauses a hundred times at night and that causes the body gets less oxygen which results heartbeat to flutter. That is one of the conditions that causes sudden cardiac death [11]. Sleep apnea is dangerous a can cause sudden death if the person's feels that he is not breathing it is advisable to see a doctor.

### 2.2.3 Coronary Artery Disease

Coronary artery disease is affecting many people in the world, and it takes a lot many to cure this disease which worries the stakeholders in the healthcare [12].furthermore, to the money problems it causes, coronary artery disease has been named as one of the most causes of sudden death in the world [13] [14], which is dangerous and need to be controlled.

Coronary artery disease causes 7 million deaths on the planet. The plaque builds up in coronary arteries and other parts of the body [15] and that blocks the blood supply to that heart and after that heart will not get enough blood and that causes death. This plaque consist of calcium and other substances found in the arterial.

Coronary artery disease is affecting many people in the world, and it takes a lot many to cure this disease which worries the stakeholders in the healthcare [12].furthermore, to the money problems it causes, coronary artery disease has been named as one of the most causes of sudden death in the world [13] [14], which is dangerous and need to be controlled. The Figure 2.1 presents coronary artery disease and normal coronary artery disease.

As mention in section 2.2.1, arrhythmia is the change of heart rhythm which is also the first signs of coronary artery disease [15]. As time goes, the hurt fails to pump to blood and that causes heart failure and it also weakens the heart muscle.

To check if the person's has coronary artery disease is by checking blood pressure, body mass index, smoking and physical activity[15]. In addition to that, one of the diagnosis is if there is family history of having heart diseases and also age [15] [16].

In addition, if the patient is suffering from the disease, a doctor gives treatment regime [17].The treatment of coronary artery disease is expensive it involves analysing Hotler monitor which takes several hours and other diagnosis as mentioned above.

Coronary artery disease starts at early age, and plaques develops between the walls and stay with us for the most people however, early prevention will delay the disease which is greater benefit. Healthy eating and exercising will also delay the development of coronary artery disease and there is chance that can be regressed before it becomes CHD.



## REFERENCES

- [1] Nutrition Encyclopaedia, 2011. *Heart Disease*. [Online] Available at: <http://www.answers.com/topic/ischaemic-heart-disease> [Accessed January 2017].
- [2] Su A 2013 ECG Noise Filtering Using Online Model-Based Bayesian Filtering Techniques
- [3] American Academy of Sleep Medicine, 2016. *Sleep Apnea - Symptoms & Risk Factors*. [Online] Available at: <http://www.sleepeducation.org/essentials-in-sleep/sleep-apnea/symptoms-risk-factors> [Accessed 16 October 2016].
- [4] Luz', E. J. d. S., Schwartz, W. R., Cháveza, G. C. & Menotti, D., 2015. ECG-based heartbeat classification for arrhythmia detection: A survey. *Computer Methods and Programs in Biomedicine*, December, Volume 127, p. 144–164.
- [5] Mankar V R and Ghatol A A 2009 Design of Adaptive Filter Using Jordan/Elman Neural Network in a Typical EMG Signal Noise Removal *Adv. Artif. Neural Syst.* **2009** 1–9
- [6] K Derrer, D., 2014. *Sleep Apnea*. [Online] Available at: <http://www.webmd.com/> [Accessed 14 August 2016].
- [7] Caples, S. M., 2007. Sleep-disordered breathing and cardiovascular risk. *Sleep*, 30(3), pp. 291-303
- [8] American Academy of Sleep Medicine, 2016. *Sleep Apnea - Symptoms & Risk Factors*. [Online] Available at: <http://www.sleepeducation.org/essentials-in->

sleep/sleep-apnea/symptoms-risk-factors [Accessed 16 October 2016].

- [9] Duna, i. A., Mucsi, I., Juhász, J. & Novák, M., 2006. Obstructive sleep apnea and cardiovascular disease. *Orv Hetil.*, 147(48), pp. 2303-2311.
- [10] Apoor Gami, M. & Neil Sanghvi, M., 2013. *Journal of the American College of Cardiology*.
- [11] Eric Cohen, M., 2014. *Can Sleep Apnea Predict a Heart Attack?*. [Online] Available at: <http://www.everydayhealth.com/columns/eric-cohen-breathe-well-sleep-well/can-sleep-apnea-predict-a-heart-attack/> [Accessed 20 January 2017].
- [12] Kuulasmaa, K. et al., 2000. Estimation of contribution of changes in classic risk factors to trends in coronary-event rates across the WHO MONICA project populations. *Lancet*, 26 February, 355(9205), pp. 675-687.
- [13] Kuulasmaa, K. et al., 2000. Estimation of contribution of changes in classic risk factors to trends in coronary-event rates across the WHO MONICA project populations. *Lancet*, 26 February, 355(9205), pp. 675-687.
- [14] Genders, T. S. S., Steyerberg, E. W., Hunink, M. & Laule, M., 2012. Prediction model to estimate presence of coronary artery disease: retrospective pooled analysis of existing cohorts. *British Medical Journal*, Volume 344, pp. 1-13.
- [15] National Heart, L. a. B. I., 2016. *What Is Coronary Heart Disease?*. [Online] Available at: <http://www.nhlbi.nih.gov/health/health-topics/topics/cad> [Accessed 17 October 2016].
- [16] Foundation, B. H., 2015. *Risk Factors of Coronary Heart Disease*. [Online] Available at: <https://www.bhf.org.uk/heart-health/risk-factors> [Accessed 17 October 2016].
- [17] NHS, 2015. *Coronary heart disease - Diagnosis*. [Online] Available at:

<http://www.nhs.uk/Conditions/coronary-heart-disease/Pages/diagnosis.aspx>

[Accessed 17 October 2016].

- [18] American Heart Association, 2016. *Coronary Artery Disease - Coronary Heart Disease*. [Online] Available at: [http://www.heart.org/HEARTORG/Conditions/More/MyHeartandStrokeNews/Coronary-Artery-Disease---Coronary-Heart-Disease\\_UCM\\_436416\\_Article.jsp#.WANbfeV97IV](http://www.heart.org/HEARTORG/Conditions/More/MyHeartandStrokeNews/Coronary-Artery-Disease---Coronary-Heart-Disease_UCM_436416_Article.jsp#.WANbfeV97IV) [Accessed 16 October 2016].
- [19] [online] available at <https://www.guru99.com/supervised-vs-unsupervised-learning.html#7>
- [20] Zeiler M D and Fergus R 2014 Visualizing and understanding convolutional networks *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **8689 LNCS** 818–33
- [21] Hinton G, Deng L and Et. A 2012 Ieee Signal Processing Magazine [82] November 2012 82–97
- [22] De Brébisson A and Montana G 2015 Deep neural networks for anatomical brain segmentation *IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work.* **2015-Octob** 20–8
- [23] Dong B and Wang X 2016 Comparison deep learning method to traditional methods using for network intrusion detection *Proc. 2016 8th IEEE Int. Conf. Commun. Softw. Networks, ICCSN 2016* 581–5
- [24] Karthikeyan T and Kanimozhi V A 2017 Deep Learning Approach for Prediction of Heart Disease Using Data mining Classification Algorithm Deep Belief Network *Int. J. Adv. Res. Sci. Eng. Technol.* **4** 3194–201
- [25] Kim J, Kang U and Lee Y 2017 Statistics and deep belief network-based

cardiovascular risk prediction *Healthc. Inform. Res.* **23** 169–75

- [26] Acharya U R, Fujita H, Oh S L, Hagiwara Y, Tan J H and Adam M 2017 Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals *Inf. Sci. (Ny)*. **415–416** 190–8
- [27] Shashikumar S P, Shah A J, Li Q, Clifford G D and Nemati S 2017 A deep learning approach to monitoring and detecting atrial fibrillation using wearable technology *2017 IEEE EMBS Int. Conf. Biomed. Heal. Informatics, BHI 2017* 141–4
- [28] Chitra R and Seenivasagam V 2013 Heart Attack Prediction System using Cascaded Neural Network 223–8
- [29] Miao K H and H. J 2018 Coronary Heart Disease Diagnosis using Deep Neural Networks *Int. J. Adv. Comput. Sci. Appl.* **9** 1–8
- [30] S. M. Anwar, M. Gul, M. Majid, and M. Alnowami, “Arrhythmia Classification of ECG Signals Using Hybrid Features,” vol. 2018, 2018.
- [31] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, “ECG Heartbeat Classification : A Deep Transferable Representation.”
- [32] U.R Acharya, S. L. Oh, y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. San Tan, "A deep convolutional neural network model to classify heartbeats, " *Computers in biology and medicine*, vol. 89, pp. 389-396, 2017.
- [33] T. Y. Li and Z. Min, “ECG Classification Using Wavelet Packet Entropy and Random Forests,” *Entropy*, vol. 18(8), pp. 1–16, 2016.
- [34] R. Mark and G. Moody. (1997, May) MIT-BIH Arrhythmia Database. [Online]. Available: <http://ecg.mit.edu/dbinfo.html>
- [35] De Chazal P, O’Dwyer M and Reilly R B 2004 Automatic classification of

heartbeats using ECG morphology and heartbeat interval features *IEEE Trans.*

*Biomed. Eng.* **51** 1196–206

