

VENTRICULAR ARRHYTHMIAS CLASSIFICATION BASED ON DEEP  
LEARNING ALGORITHM

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## **DEDICATION**

This project report is dedicated to parents who had always supported me, friends and seniors whom had gave me guidance and advise.

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I would like to express my greatest thanks to my family whom had enabled me to complete this project without any worry on family issues. I would also like to thank my fellow friends, peers for their honest feedback, cooperation and support which had helped me to get results of better quality.

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## ABSTRACT

Cardiac arrhythmia is a group of conditions in which the heartbeat is irregular, where it can be too fast or too slow. This happens when electrical impulses that coordinate the heartbeat fail to work in a correct manner. Some of these diseases show no symptoms, but ECG (electrocardiogram) can help to diagnose as it extracts the rhythmic information of the heart and heartbeat. This information is important, and it can distinguish the cardiac condition of the patient. Some of these diseases can cause serious condition to the patient if not treated immediately, for instance, Ventricular Fibrillation can result in loss of consciousness and even death in the matter of minutes. Due to limitation in the availability of doctors or cardiologist, machine can help to perform ECG interpretation task. Deep Learning (DL), which is a subset of Machine Learning (ML), does not require human intervention as the nested layers in the neural networks put data through hierarchies of different concepts, which eventually learn through their own errors, is suitable to perform such task. This project aimed to have ECG data extraction to classify the cardiac arrhythmias using deep learning approach for Premature Atrial Contraction, Atrial Tachycardia, Atrial Flutter, Atrial Fibrillation, Premature Ventricular Contraction, Ventricular Tachycardia, Ventricular Fibrillation and Normal Sinus Rhythm. In this project, the final classifying model has achieved an average accuracy of 94.52 across 6 cardiac arrhythmias. All ECG information will be selected from a few databases such as MIT-BIH arrhythmia database, Creighton University Ventricular Tachyarrhythmia Database, Intracardiac Atrial Fibrillation Database, Long-Term AF Database, MIT-BIH Atrial Fibrillation Database, MIT-BIH Normal Sinus Rhythm Database and MIT-BIH Supraventricular Arrhythmia Database. All these databases have annotated ECG files by cardiologist annotators. These ECG data will have to go through pre-processing to remove noises such as the baseline wanders and powerline interference. After that, the ECG data will be broken down into segments of PQRST where it will serve as the input data for the deep learning model. Step segmentation process and CNN deep learning are both done in Python with TensorFlow package for deep learning model and SciPy and NumPy packages for signal processing.

## ABSTRAK

Aritmia jantung adalah sekumpulan dengan keadaan di mana degupan jantung tidak teratur, sama ada ia boleh terlalu cepat atau terlalu perlahan. Ini berlaku apabila impuls elektrik yang menyelaraskan degupan jantung gagal berfungsi dengan cara yang betul. Sesetengah penyakit ini tidak menunjukkan gejala, tetapi ECG (elektrokardiogram) dapat membantu mendiagnosis kerana ia mengekstrak maklumat berirama jantung dan degupan jantung. Maklumat ini penting bagi membezakan keadaan jantung pesakit. Sesetengah penyakit ini boleh menyebabkan keadaan serius kepada pesakit jika tidak dirawat dengan serta-merta, contohnya, Ventricular Fibrillation boleh mengakibatkan kehilangan kesedaran dan juga kematian dalam masa yang singkat. Dengan sebab kekurangan doktor atau pakar kardiologi, mesin boleh membantu melaksanakan tugas tafsiran ECG. Deep Learning (DL), yang merupakan subset Machine Learning (ML), tidak memerlukan campur tangan manusia kerana lapisan bersarang dalam rangkaian saraf meletakkan data melalui hierarki konsep yang berbeza, yang akhirnya belajar melalui kesilapan mereka sendiri, sesuai untuk melaksanakan tugas sedemikian. Projek ini bertujuan untuk mendapatkan pengekstrakan data ECG untuk mengklasifikasikan aritmia jantung menggunakan Deep Learning bagi Premature Atrial Contraction, Atrial Tachycardia, Atrium Flutter, Atrial Fibrillation, Premature Ventricular Contraction, Tachycardia Ventricular, Fibrillation Ventricular dan Sinus Rhythm Normal. Dalam projek ini, modal pengkelasan terakhir telah mencapai ketepatan rata-rata 94.52 peratus pada 6 aritmia jantung. Semua maklumat ECG akan dipilih dari beberapa pangkalan data seperti pangkalan data Arrhythmia MIT-BIH, pangkalan data Ventricular Tachyarrhythmia Creighton, pangkalan data Fibrillation Intracardiac Fibrillation, pangkalan data Long-Term AF, pangkalan data Fibrillation MIT-BIH, pangkalan data Normal Sinus Rhythm MIT-BIH dan pangkalan data Supraventricular Arrhythmia MIT-BIH. Semua pangkalan data ini telah memberi fail ECG dengan anotasi oleh annotator kardiologi. Data ECG ini perlu melalui pra-pemprosesan untuk mengeluarkan bunyi seperti pengembara dasar dan gangguan talian kuasa. Selepas itu, data ECG akan dipecah menjadi segmen PQRST di mana ia akan berfungsi sebagai data input untuk model Deep Learning. Proses segmentasi langkah dan pembelajaran mendalam CNN kedua-duanya dilakukan dalam Python dengan pakej TensorFlow untuk model Deep Learning dan pakej SciPy dan NumPy untuk pemprosesan isyarat.

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## LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AFL	-	Atrial Flutter
AT	-	Atrial Tachycardia
AV	-	Atrioventricular
CNN	-	Convolutional Neural Network
ECG	-	Electrocardiogram
NSR	-	Normal Sinus Rhythm
VT	-	Ventricular Tachycardia
MA	-	Moving Averaging
LMS	-	Least Mean Square
BLMS	-	Block Least Mean Square
DLMS	-	Delay Least Mean Square
XLMS	-	Filtered-X Least Mean Square
NLMS	-	Normalized Least Mean Square
LM	-	Levenberg Marquardt
CFS	-	Correlation-based Feature Selection
IBPNN	-	Incremental Backpropagation Neural Network
SNR	-	Signal to Noise Ratio
PAC	-	Premature Atrial Contraction
PVC	-	Premature Ventricular Contraction
SN	-	Sinoatrial Node
VF	-	Ventricular Fibrillation
GPIO	-	General Purpose Input Output
DSP	-	Digital Signal Processor
ADC	-	Analog to Digital Converter
FPGA	-	Field Programmable Gate Array
RTL	-	Resister Transfer Level

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# CHAPTER 1

## INTRODUCTION

### 1.1 Problem Background

Ischemic heart diseases are the world's biggest killer globally according to World Health Organization [1]. It ranked first in the top 10 causes of death in lower-middle-income countries, upper-middle-income countries even for high-income countries in 2016 [1]. Ischemic is a condition whereby the blood flow is restricted or reduced in a part of the body. When blood flow is restricted, it indirectly causes the oxygen obtained by cells to be reduced as well.

The heartbeat begins when there is an electrical impulse moving through the sinoatrial node (SA). SA node can also be referred as the natural pacemaker of the heart as it initiates impulses for the heart to begin the contraction. For a normal sequence, the electrical impulse begins in the right atrium and it spreads throughout to the atria and to the atrioventricular (AV) node. Down from the AV node, the electrical impulses continue to travel down to a group of specialized fibres called the His-Purkinje system where it is connected to all parts of the ventricles. This exact route or routine must be followed in order for the heart to pump in a proper manner. As long as the electrical impulse is correctly generated and transmitted normally, the heart function normally and beats in a regular pace [2]. Cardiac arrhythmias mainly cause disruption in the electrical impulses of the heart [2].

Cardiac arrhythmia is a group of conditions which the heartbeat is irregular be it too fast or too slow. It can occur when the electrical signals that control the heartbeat are blocked or delayed [3]. This is due to the nerve cells responsible to produce the electrical signals do not work properly or the electrical signals do not travel in a correct manner through the heart. It also can happen when another part of the heart could start to produce these electrical signals, disrupting the correct

electrical signal and heartbeat. Some of the cardiac arrhythmias are very dangerous and can cause sudden cardiac death [4]. This project will be targeting for Premature Atrial Contraction, Atrial Tachycardia, Atrial Flutter, Atrial Fibrillation, Premature Ventricular Contraction, Ventricular Tachycardia, Ventricular Fibrillation and Normal Sinus Rhythm. The model will cover classification of a variance of cardiac arrhythmia.

## 1.2 Problem Statement

- (a) ECG interpretation can only be done by cardiologist or doctors.

As some cardiac arrhythmias such as the Ventricular Fibrillation (VF) can be fatal if no proper medical treatment is provided immediately, it is vital that the exact condition to be determined immediately. As such, the number of patients with ratio to doctors is always large, and ECG interpretation can only be done by expert cardiologist or doctors, some patient that require immediate medical attention maybe neglected.

- (b) High time consumption and errors from human interpretation

ECG interpretation is no easy task, moreover interpretation can also come with human errors if there are no clear symptoms in the ECG signals. This result in error prone ECG interpretation and nevertheless it also consumes a lot of time [5]. Some cardiac arrhythmia conditions are timing critical, high time consumption of human ECG interpretation may cause the patient to suffer serious damage and even fatality.

- (c) Machine learning needs guided learning from human and may result in low accuracy. Unlike deep learning algorithm, machine learning does not have self-learning capability and need to be retrained through human intervention when the actual output was not the desire one. Deep learning has the capability to learn through their own errors and do not require human intervention

### **1.3 Objectives**

The objectives to be achieved in this project are:

1. To develop a deep learning model to classify 6 types of Cardiac Arrhythmias
2. To classify Atrial Flutter (AFL), Atrial Fibrillation (AF), Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF) and Normal Sinus Rhythm (NSR) using Deep Learning
3. Achieve classification accuracy of  $> 90\%$  for each Cardiac Arrhythmias through deep learning

### **1.4 Scope of Work**

A scope was defined to show what was the covered scope of this project and to allow the project to be completed within the allocated time frame. First, the deep learning classifier model will be developed using PYTHON with TensorFlow package, while the signal pre-processing will also be done using PYTHON with libraries such as Numpy, Scipy and Pandas.

The inputs of this project are datapoints of ECG retrieved from multiple databases. These databases are MIT-BIH arrhythmia database [6], Creighton University Ventricular Tachyarrhythmia Database [7], Intracardiac Atrial Fibrillation Database [8], Long-Term AF Database [9], MIT-BIH Atrial Fibrillation Database [10], MIT-BIH Normal Sinus Rhythm Database [8] and MIT-BIH Supraventricular Arrhythmia Database [11]. All these databases have annotated ECG files by cardiologist annotators. The output of the project is the accuracy of the classifier model classifying Premature Atrial Contraction, Atrial Tachycardia, Atrial Flutter, Atrial Fibrillation, Premature Ventricular Contraction, Ventricular Tachycardia, Ventricular Fibrillation and Normal Sinus Rhythm.



## **1.5 Thesis Outline**

This thesis consists of five chapters. Chapter 1 looks into the problem background, problem statement, objectives, scope of work and the thesis outline. Chapter 2 will be discussing about the fundamental overview and related research works to this project. Chapter 3 documents the complete research methodology, detailed explanation on the technique used and how are their implementation. Chapter 4 will be the results and discussion. Chapter 5 concludes the whole project.

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