

CLASSIFICATION OF ATRIAL FIBRILLATION USING SECOND ORDER
DYNAMIC SYSTEM WITH PATTERN RECOGNITION ALGORITHM

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DEDICATION

This thesis is dedicated to my parents, who taught me that the best kind of knowledge to have been that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

According to World Health Organization (WHO), an estimated 17.9 million people died from cardiovascular diseases (CVD) in 2019, representing 32 % of all global deaths. Of these deaths, 85 % were due to heart attack and stroke. The occurrence and prevalence of atrial fibrillation (AF) is growing worldwide. Limited tools are available to evaluate clinical outcomes and response to thrombolysis in stroke patients with AF. Therefore, this study analysed the ECG features of AF and the normal sinus rhythm signals for AF recognition. The first objective is to extract AF features using second-order dynamic system (SODS) algorithm. The following objective is to investigate the effect of windowing length towards AF classification. Next, to compare the two-pattern recognition machine learning support vector machine (SVM) and artificial neural network (ANN) on the accuracy, specificity, and sensitivity of AF classification. In this study, the ECG signals database from Physiobank included MITBIH Atrial Fibrillation Dataset and MITBIH Normal Sinus Rhythm Dataset are used. For signal pre-processing, butterworth filter are used to diminish the muscle noise and the features signals are extracted by using second order dynamic system. Multiple episodes of the windowing size 2s, 4s, 6s, 8s and 10s included in this design to evaluate the appropriate windowing size for AF signal processing. The pattern recognition machine learning SVM algorithm has higher accuracy compared to ANN accuracy of AF classification, which are having 100 % with 4s windowing size. In conclusion, the 4s windowing size having the highest detection rate in AF classification system.

ABSTRAK

Menurut Pertubuhan Kesihatan Sedunia (WHO), dianggarkan 17.9 juta orang mati akibat penyakit kardiovaskular (CVD) pada 2019, mewakili 32 % daripada semua kematian global. Daripada kematian ini, 85 % disebabkan oleh serangan jantung dan strok. Kejadian dan kelaziman fibrilasi atrium (AF) semakin berkembang di seluruh dunia. Alat terhad tersedia untuk menilai hasil klinikal dan tindak balas terhadap trombolisis dalam pesakit strok dengan AF. Oleh itu, kajian ini menganalisis ciri ECG AF dan isyarat irama sinus biasa untuk pengecaman AF. Objektif pertama adalah untuk mengekstrak ciri AF menggunakan algoritma sistem dinamik tertib kedua (SODS). Objektif berikut adalah untuk menyiasat kesan panjang tettingkap terhadap pengelasan AF. Seterusnya, untuk membandingkan mesin vektor sokongan pembelajaran mesin pengecaman dua pola (SVM) dan rangkaian saraf tiruan (ANN) pada ketepatan, kekhususan dan kepekaan klasifikasi AF. Dalam kajian ini, pangkalan data isyarat ECG daripada Physiobank termasuk MITBIH Atrial Fibrillation Dataset dan MITBIH Normal Sinus Rhythm Dataset digunakan. Untuk pra-pemprosesan isyarat, penapis butterworth digunakan untuk mengurangkan bunyi otot dan isyarat ciri diekstrak dengan menggunakan sistem dinamik tertib kedua. Berbilang episod saiz tettingkap 2, 4, 6, 8 dan 10 saat disertakan dalam reka bentuk ini untuk menilai saiz tettingkap yang sesuai untuk pemprosesan isyarat AF. Algoritma SVM pembelajaran mesin pengecaman corak mempunyai ketepatan yang lebih tinggi berbanding ketepatan ANN klasifikasi AF, yang mempunyai 100 % dengan saiz tettingkap 4 saat. Kesimpulannya, saiz tettingkap 4 saat mempunyai kadar pengesanan tertinggi dalam sistem pengelasan AF.

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LIST OF ABBREVIATIONS

AF	-	Atrial Fibrillation
AV	-	Atrioventricular node
WHO	-	World Health Organization
CVD	-	Cardiovascular Diseases
ECG	-	Electrocardiogram
DS	-	Dynamic System
SA	-	Sinoatrial node
SODS	-	Second Order Dynamic System
SODE	-	Second Order Differential Equations
STFT	-	Short-term Fourier Transform
SWT	-	Stationary Wavelet Transform
ASCII	-	American Standard Code for Information Interchange
Hz	-	Hertz

LIST OF SYMBOLS

μ	-	Forcing Input
ξ	-	Damping Coefficient
ω	-	Natural Frequency
p	-	Probability Value

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CHAPTER 1

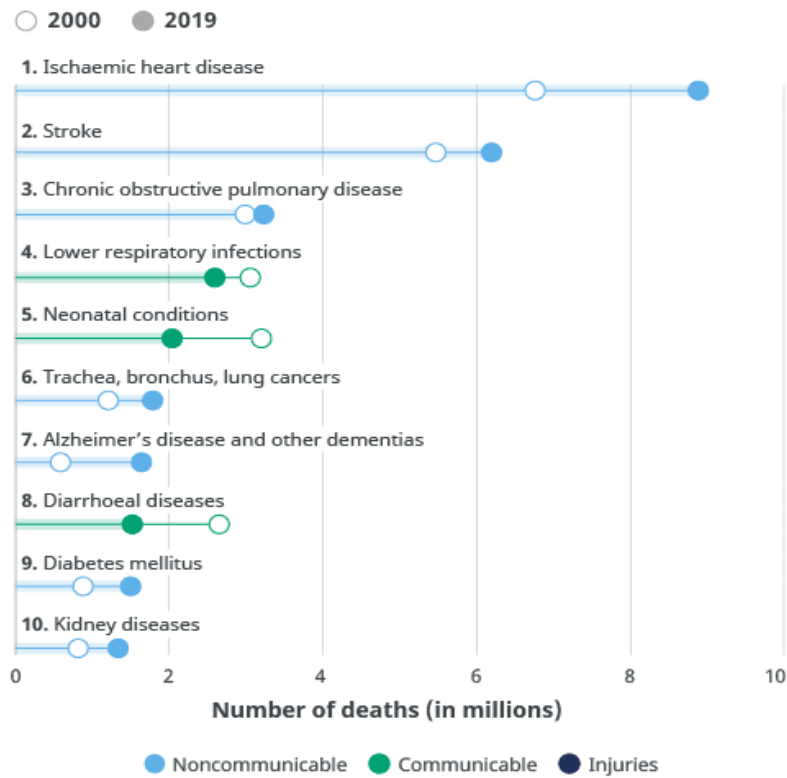
INTRODUCTION

1.1 Problem Background

Atrial Fibrillation (AF) is a condition of heartbeat that causes irregular, often abnormal fast heart rate, which can be understood as heart rate doesn't follow rhythm and not on pace. An adult's heart beats between 60 and 100 times per minute on average. An irregular heartbeat, sometimes referred to as an arrhythmia, is classified into two categories: bradycardia, or a heartbeat that is less than 60 beats per minute, and tachycardia, or a heartbeat that is greater than 100 beats per minute. AF can be brought on by cardiac arrhythmia, which are put on by irregular heartbeats. AF occurred when aberrant electrical impulses begin firing in the atria abruptly [1]. When the atrioventricular (AV) node becomes overloaded with electrical impulses that originate in the atria, it is causing the atria's muscle to fibrillate. The atria stop pumping blood to the ventricles because of the disorder. In the atrium, a blood clot may then develop and get dislodged as the ventricles contract.

According to the World Health Organization (WHO), estimates that 17.9 million individuals worldwide passed away from cardiovascular diseases (CVD) in 2019, accounting for 32 % of all death shows in Figure 1.1 [2].

Leading causes of death globally



Source: WHO Global Health Estimates.

Figure 1.1 Graph of the leading causes of death globally in year 2019 [2]

Heart attacks and strokes were responsible for 85 % of these fatalities. Rheumatic heart disease, coronary heart disease, and cerebrovascular disease are among the disorders known together as "CVDs," which are conditions that affect the heart and blood systems. [3]. According to Department of Statistics Malaysia, ischemic heart diseases remained as main causes of death in Malaysia which the continued to be the leading in Malaysia cause of mortality, accounting for 17.0 % of the 109,155 deaths that were medically verified in year 2020 shows in figure 1.2 [4].

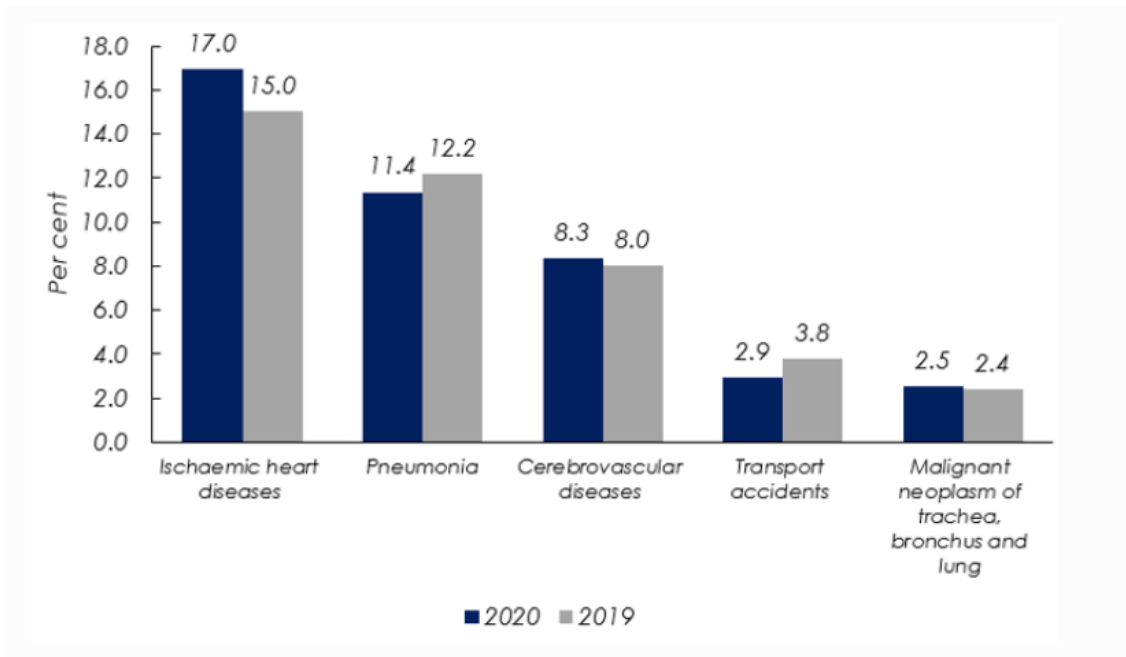


Figure 1.2 Statistics on Causes of Death, Malaysia, 2021 [4]

The risk of stroke from AF is increased by heart disease and high blood pressure. Ischemic stroke and haemorrhagic stroke are the two main types of strokes. Ischemic stroke, which is caused by a blood vessel rupture and bleeding, are both types of strokes. The risk of stroke from AF is increased by cardiovascular disease and high blood pressure. One of the most typical kinds of heart failure, AF has a significant death rate. Eight million individuals worldwide suffer with AF, which occurs in more than 70 % of cases without the patient's knowledge [5]. Unhealthy food, lack of exercise, cigarette use, and problematic alcohol use are the most significant behavioural risk factors for heart disease and stroke. The impacts of behavioural risk factors might manifest in people as elevated blood pressure, elevated blood glucose, elevated blood lipids, as well as overweight and obesity. It is possible to evaluate each of these intermediate risk factors in a primary care setting, and they all point to an elevated risk of consequences including heart attacks, strokes, and heart failure.

As AF is crucial to public fitness as it represents enormous morbidity, mortality, and fitness costs [6]. Few methods are introduced on AF treatment which including the medication, therapy which need to reset the heartbeat rhythm and catheter procedures to block faulty heart signals. AF can be temporary at first, however

many sufferers have a markedly modern disorder with a growth in frequency and length of attacks. It also crucial to public fitness as its debts for enormous morbidity, mortality, and clinical costs. Although AF can be temporary at first, many sufferers have modern disorder with growing frequency and length of episodes. As a result, to address the excess risk of AF, cost-effective preventative approaches and long-term treatment methods are requiring.

According to a study of the literature, only ventricular tachycardia (VT) and ventricular fibrillation (VF) signals for ECG signals have yet to be subjected to the extraction technique of ECG feature based on second-order dynamic system (SODS). All the research in the literature review employed with different windowing size of ECG for processing, but no one used the SODS method. To find the shorter windowing length that may enable greater AF detection, several windowing lengths were applied in this investigation. As a result, SODS feature selection methods and AF signal properties were also studied.

Finally, the normal sinus rhythm (NSR) and AF properties of the human heart were outlined. The traits matched the appropriate feature that was derived from the ECG data using the SODS approach. Several windowing lengths for ECG signals were evaluated, and the windowing length with the highest detection rate was selected using machine learning algorithms for pattern recognition. The windowing length determined the quickest amount of time required to process the ECG data accurately. Additionally, the method for the chosen feature was changed to incorporate the windowing length.

After that, the algorithm was mapped into a particular module to limit the scope or resource requirements at an earlier stage in building the algorithms for use in hardware design. Furthermore, none of the research had used second-order differential equations (SODE) in hardware design, according to a survey of the literature. As a result, analysing the SODS algorithm began with the module created for hardware design.

1.2 Problem Statement

AF is a main factor for irregular heartbeats, especially if a human is close to 65 years of age. Around 60% of AF patients are between 65 and 85 years of age [7]. The high mortality associated with AF is attributed to life-threatening cardiovascular complications, non-vascular causes, stroke, and haemorrhage. For all those who severely affect the patient's standard of living [8]. Therefore, early detection and early prevention of AF are essential [8]. However, a significant proportion of patients with AF are asymptomatic and paroxysmal, making it difficult to achieve a rapid diagnosis [7].

As the occurrence and prevalence of AF increases worldwide, most of the clinically useful information in the ECG signal is available in the time intervals and amplitudes determined by the characteristics of the ECG signal. The ECG feature extraction algorithm is also useful in detecting heart problems known as arrhythmias, including tachycardia, bradycardia, heart rate variability, and more [9]. Beat detection is used to identify heart rhythms and identify arrhythmias while additional processing is performed to detect irregular beats. For rapid diagnosis and appropriate treatment, it is important to develop appropriate methods that can monitor asymptomatic AF patients. Several techniques have been proposed to detect the electrocardiographic features, but limited tools for assessing clinical outcomes and responses to predict AF [10, 11, 12]. As early identification, and prediction of AF, as well as available treatments which to limit the occurrence and severity of AF, have important therapeutic and societal importance.

Currently, research on AF detection is often restricted in its usefulness. Various techniques for automated identification of AF have been developed, include random forests, decision trees, support vector machines, convolution neural networks, and recurrent neural networks. The early approaches relied mostly on feature extraction. Therefore, the characteristics of the research are scarce. In recent years, more and more characteristics have been chosen to increase identification accuracy and overall robustness [13, 14].

By referring to the literature review, SODS features extraction technique is not yet proven by any study for the relation with. According to the SODS method for identifying human heart behaviour, the behaviour of the human heart might be investigated. Additionally, the precision and appropriateness for AF pre-determination might be advantageous to the improvement of healthcare. Furthermore, AF recognition system of specific module design, such as System-on-a-chip (SoC), can increase patient and outpatient mobility.

This study will opt to further concentrate on analyze AF signals the traits to lower the causes of AF and lower the mortality rate from embolic stroke. It happens when the blood is clotted in the heart during AF which mobile to the brain and block the blood stream. There are two types of ischemic stroke, which are embolic and thrombosis which embolic and thrombosis are Therefore, in considering of the problems, the aim and objective of this study can be determined into two part which is software part as using SODS system for ECG signal feature extraction and hardware part of machine learning recognition for ECG signal classification.

1.3 Scope of study

The scope of this study will be focusing on DSP learning and machine learning ECG signal classification. There are several scopes of study to accomplish the objective of the study. In this study, the electrocardiogram (ECG) signals database had selected from Physiobank ECG archive database. Two type of the ECG signal, MITBIH Atrial Fibrillation Dataset (AFDB) and MITBIH Normal Sinus Rhythm Database (NSRDB) will be used in this study. For each of the database, 12 ECG records with 2s, 4s, 6s, 8s and 10s windowing length are used in this study.

The SODS are used in this study for ECG signal pre-processing and feature extraction stage. The dynamic concept theory which is to distinguish the type of ECG signals for pre-processing. In this extraction stage, SODS algorithm was used, which is to extract the three main features for ECG signals distinguish. Three features will be analyses for each the ECG signals which is natural frequency, ω , damping

coefficient, ζ and forcing input, μ . There are total of six features that will be normalised and extracted for the data analysis purpose.

Next, validate the ECG signal extracted data with statistical analysis (t-test) and analyze, classify the signal using MATLAB. Not only that, the study of an extracted features which need an appropriate windowing into multiple episodes. Continue with finding a suitable windowing size for AF database processing. Next, two pattern recognition machine learning algorithm ANN and SVM are introduced and used for the ECG recognition system. Last, compare the classification result between SVM and ANN in terms of sensitivity, specificity, and accuracy with different windowing length.

1.4 Objectives

Based on the problem statement, the implementation of AF classification system enables to classify the heart rate of a person in the shortest possible time and prescribe with more accurate result or report in time for timely treatment and avoid serious diseases that may result in a long time. While need to compare the accuracy of the AF signal classification system using the pattern recognition machine learning.

The first objective which is to extract AF features using second-order dynamic system (SODS) algorithm. The second objective is to investigate the effect of windowing length towards AF classification, to find the suitable windowing length. For the third objective which is to compare the two-pattern recognition machine learning (SVM and ANN) on the accuracy of AF classification.

1.5 Thesis Organization

There are five chapters consists in the thesis, each of the chapter has its own role to play to present the study. In general, this project starts in the field of complementary medicine which the study on the AF signal classification system.

Specifically, this project is devoted to the development of recognition to AF signal to establish a classification system as a classification tool to verify its performance in terms of accuracy, sensitivity, and specificity.

Chapter 1 includes the problem background, research problems, research goals, and research objective. This chapter address research issues and some research gaps. These shortcomings provide impetus for our research. This research aims to classify the in the research on the performance of the tongue segmentation algorithm in terms of the sensitivity, accuracy to develop a reliable system tool to classify the AF ECG signal.

Chapter 2 discussed were mainly focus on literature review of several important previous studies that have been conducted the signal classification system. This provides an impetus for narrowing the research gap in this research field. The literature review covers the previous important research from the ECG AF signal classification system which including the pre-processing, feature extraction, machine learning algorithm that implement and the classification analysis.

Chapter 3 discussed the methodology and the review of the implementation for ECG signal classification system. First the data acquisition, pre-processing me including pre-processing, feature extraction, machine learning algorithm, and the result analysis.

Next for chapter 4 included all the signal extraction result and simulation result for this study. In this chapter, it introduces the ECG signal classification system on the pre-processing, feature extraction, machine learning algorithm, and the result analysis by comparing classification system.

Lastly, the chapter 5 concludes the research findings, contributions, and recommendations of some idea for future works. The study references and appendix are also included in at the end of the report.

1.6 Summary

This chapter summarised the motivation of the study. The problems of statement was presented to define the objectives for the study. Moreover, the scope of the study was explained for restricting the study. Additionally, the significance of the study was included to summarise the contributions of the study. Finally, the thesis organisation was mentioned.

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