

# **Sleep Stage Classification Using Time-Frequency Distribution of Bioradiolocation**

**MUHAMAD ADAM BIN JEMALI**



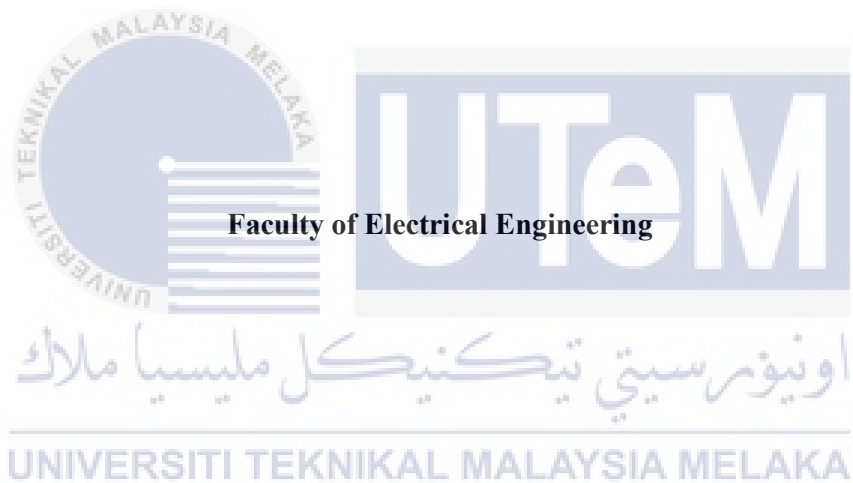
**BACHELOR OF ELECTRICAL ENGINEERING WITH HONOURS  
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**Sleep Stage Classification Using Time-Frequency Distribution of Bioradiolocation**

**MUHAMAD ADAM BIN JEMALI**

**A report submitted  
in partial fulfillment of the requirements for the degree of  
Bachelor of Electrical Engineering with Honours**



**UNIVERSITI TEKNIKAL MALAYSIA MELAKA**

**2021**

## DECLARATION

I declare that this thesis entitled “Sleep Stage Classification Using Time-Frequency Distribution of Bioradiolocation is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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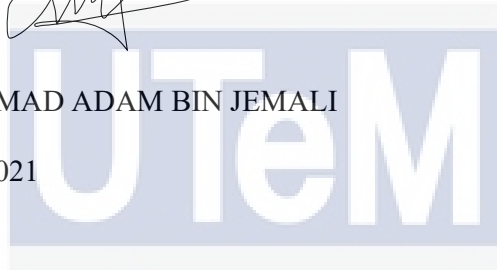
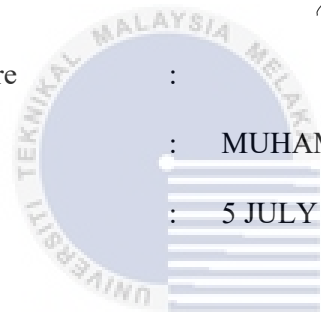


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## APPROVAL

I hereby declare that I have checked this report entitled “Sleep Stage Classification Using Time-Frequency Distribution of Bioradiolocation” and in my opinion, this thesis it complies the partial fulfillment for awarding the award of the degree of Bachelor of Electrical Engineering with Honours

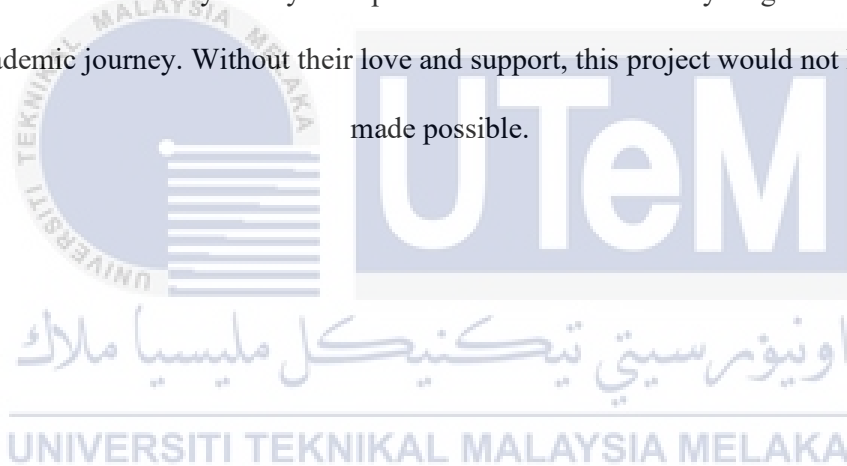
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## DEDICATIONS

This final year project report is dedicated to my beloved parents, Mr. Jemali Bin Marsidi and Mdm. Azimah Binti Abdul Halim who has been my constant source of inspiration with their endlessly love. They enlightened me with academic knowledge and gave me valuable advice whenever I needed it the most. I would like to thank my family and special friends who are always together with me in this academic journey. Without their love and support, this project would not have been made possible.



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## ABSTRACT

The quality of life is significantly affected by sleep problems. The categorization of sleep stages and method used in quantify the quality of sleep remains unresolved question in the area of sleep research. The time-domain and frequency-domain based methods are not appropriate for sleep stage categorization due to the presence of low frequency signals. This study therefore was carried out to classify and evaluate sleep stages using Bio-radiolocation (BRL) data based on time-frequency distribution (TFD) method and compare with different classifier. A total of 16 signals data from 8 samples were segmented into 4 sleep stages using time-frequency spectrum as RMS voltage. The sleep stage classification was then compared with the different classifiers of Simple Vector Machine (SVM), K-nearest neighbor (KNN) and Ensemble classifiers. Results showed that the KNN model demonstrate the highest accuracy of 96.9% in classifying the sleep stages using TFD method compared to other classifiers. The experimental results presented from this study showed the proposed approach is effective in increasing the accuracy of the sleep stage detection using BRL data.

## ***ABSTRAK***

Kualiti hidup sangat dipengaruhi oleh masalah tidur. Pengkelasan tahap tidur dan kaedah yang digunakan dalam mengukur kualiti tidur masih menjadi persoalan yang tidak dapat diselesaikan dalam bidang penyelidikan tidur. Kaedah berdasarkan domain masa dan frekuensi tidak sesuai untuk mengkelaskantahap tidur kerana terdapatnya isyarat berfrekuensi rendah. Oleh itu, kajian ini dijalankan untuk mengklasifikasikan dan menilai tahap tidur menggunakan data Bioradiolokasi (BRL) berdasarkan kaedah taburan frekuensi masa (TFD) dan membandingkannya dengan kaedah pengkelasan yang berbeza. Sebanyak 16 data isyarat dari 8 sampel dibahagikan kepada 4 peringkat tidur menggunakan spektrum frekuensi masa sebagai voltan RMS. Klasifikasi tahap tidur kemudiannya dibandingkan dengan pengelasan yang berbeza iaitu *Simple Vector Machine* (SVM), *K-nearest neighbor* (KNN) dan *Ensemble*. Hasil kajian menunjukkan bahawa model KNN menunjukkan ketepatan tertinggi 96.9% dalam mengklasifikasikan tahap tidur menggunakan kaedah TFD berbanding dengan pengelasan lain. Hasil eksperimen daripada kajian ini menunjukkan kaedah pengkelasan yang digunakan adalah berkesan dalam meningkatkan ketepatan pengesanan tahap tidur menggunakan data BRL.

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## LIST OF SYMBOLS AND ABBREVIATIONS

BCG	-	Ballistocardiograph
BRL	-	Bioradiolocation
NREM	-	Non- Rapid Eye Movement
PSG	-	Polysomnography
REM	-	Rapid Eye Movement
KNN	-	K- Nearest Neighbor
SVM	-	Support Vector Machine



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# CHAPTER 1

## INTRODUCTION

### 1.1 Research Background

Bioradiolocation is a remote detection and recording of radar limb and organ movement for biological objects. The method reliably enables breathing and movement to be recorded during sleep. Continuous microwave bioradiolocation is an effective contactless tool for the monitoring of breathing activity. These active systems emit a single frequency, a low-power electromagnetic wave reflected by the human chest. The difference in phase between the incident and the reflected signals enables the respiratory rate to be estimated and monitored. Using this bioradiolocation will reduce the contactless from a human body, so the data can be obtained faster than other techniques that need to use multiple devices attached to the body. It is a new technology to be used in future studies and use for other applications. This research presents a method for classifying wakefulness, REM, light, and deep sleep based on the analysis of respiratory activity and body motions acquired by a bio radar using time-frequency distribution. The method was validated using data of 8 subjects without sleep-disordered breathing who underwent a polysomnography study in a sleep laboratory. The results might be useful for the development of discreet systems for long-term sleep monitoring at home, which might be helpful for diagnostics, prevention, and management of sleep disorders and improve sleep quality.

### 1.2 Motivation

Sleep is a basic need of a human being. Currently, there is least research on the sleep stage based on the time-frequency distribution. There are three pattern stages of sleep that are REM, light and deep sleep. But somehow, not all people can make it to the deep sleep stage. Nowadays, more and more people face a sleep disorder problem.

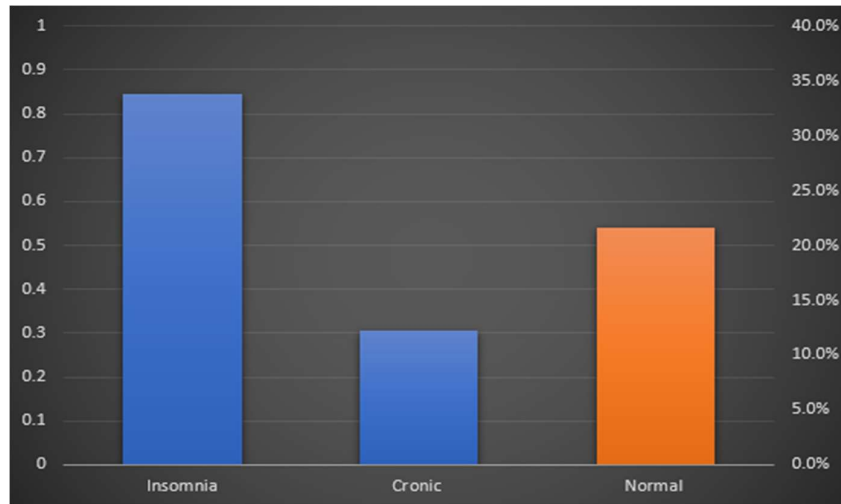


Figure 1.1 Epidemiology of Insomnia in Malaysian Adults: A Community-Based Survey in 4 Urban Areas

Research made by Zailinawati et al. conducted in 2008 stated that insomnia prevails as the most serious concern of sleep disorder with as high as 33.8% [1]. This research will reveal what kind of sleep stage can be produced from the signal for further studies using time-frequency distribution.

### 1.3 Problem statement

The condition of sleep pattern is different based on its frequency stages. Time-domain & frequency-domain based techniques are not suitable for the sleep stage classification because Low frequency signals and Using time-domain is hard to determine sleep stage condition. Different types of data reduce the quality of the classifier, requiring the search for the most accurate classifier for the bioradiolocation signal. Combination of time & frequency domain may be possible to classify sleep stages



## 1.4 Objective

The objective of this study is to:

1. To analyze sleep stages using Bio-radiolocation (BRL) data based on time-frequency distribution (TFD)
2. To classify sleep stages which are wake, light, deep and REM based on bioradiolocation signal.
3. To compare the sleep stages classification performance using various classifiers

## 1.5 Scope project

This project is focusing on the simulation of bioradiolocation signals from previous sleep research. The bioradiolocation signal needs to develop with advanced methods and gradually follow the procedures. The bioradiolocation features are extracted by using time-frequency distribution, and the details on the movements involved need to be collected. This project will also determine the best classifier to be used in a bioradiolocation signal application. The bioradiolocation signal will be simulated using MATLAB.

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## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Introduction

The sleep stage classification has many techniques, for example, the polysomnography (PSG) technique, which is intensive and costly. Thus, it cannot be applied in screening tools. Another technique is the cardiorespiratory technique. In addition, there are two non-contact methods that are the Bioradiolocation (BRL) and Ballistocardiograph (BCG) [1] use. Bioradiolocation provides more comprehensive sleep stage data. Frequency – distribution

#### 2.2 Bioradiolocation

Bioradiolocation refers to bio radar. It can be used for the detection of a human behind a wall obstacle. It is a method of detection using radar without any attachment to the biological object. It is also can be used for the detection motion of organ and limb, thus enable breathing and respiratory activity to be registered during sleep. Bio radiology has a distant and contactless existence as its major feature [2]

#### 2.3 Sleep stages

In 2015, research came out with the 'golden standard' for sleep stage classification. Overall, there consist of 4 stages. [3]

Table 2.1 shows the normal sleep phase consists of Non- Rapid Eye Movement (NREM) and Rapid Eye Movement (REM). This phase rotates clinically through the night [4]. N1 and N2 are represented as light sleep, N3 is deep sleep, and REM is different from light and deep sleep, where this stage is a smaller component of the average sleep period, also known as paradoxical sleep .[3]

Table 2.1 Sleep stage NREM and REM

Group	Stages
Wakefulness	Awake
NREM	N1, N2,
REM	REM

It is the principal occasion of dreams (or nights) and is related to the isolated and swift brain waves[5]. Normal sleep time of 90 minutes takes alternate NREM and REM sleep and 4-6 periods in decent sleep during the good night[6]. The complete cycle generally follows: N1 > N2 > N3 > REM. The sleep of a REM happens as a human wake from a deep sleep at stage 2 or 1, and there is a growing amount of deep sleep earlier at night during the two stages preceding a normal awakening. The ratio of REM sleep rises in both cycles. [7]

## 2.4 Feature extraction

Feature extraction is a process that reduces raw data to more manageable and useful information for processing. It is a key step to understand trends. Studies reveal that it is beneficial to minimize resources without wasting important resources. Feature extraction can be divided into three techniques which are the time-domain (TD), frequency domain (FD), and time-frequency domain (TFD). There is a particular form of function in each technique [8].

Time-domain features in bioradiolocation pattern recognition are easy and effective. The bioradiolocation power range is estimated by frequency distribution in frequency shape form. Meanwhile, the propagation of time-frequencies offers information that no time distribution or frequency domain features reachable [9].

### 2.4.1 Time – distribution

Time-domain analysis is defined when some amplitude is given to it as the output generated by the device. Therefore, the control system's time response defines the difference in the system's performance over time. In addition, the time domain often applies, in relation to time, as an environmental data analysis of spatial signals or time sequence[9]. The time-domain approach thus provides a bridge between the understanding of physical time and traditional spectral analysis. In the time domain, the value of the signal or function is understood to use those real numbers in the case of continuous-time or in the case of discrete-time at different specific instants [10]. Figure 2.1 shows the graph of time distribution.

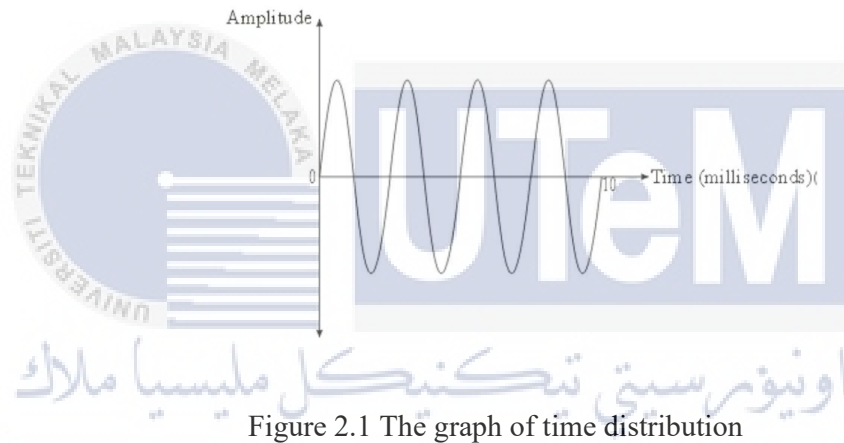


Figure 2.1 The graph of time distribution

### 2.4.2 Frequency distribution

A description of all distinct values in any vector and the number of times they appear is a frequency distribution. That is, a spectrum of frequencies explains how frequencies are scattered over values. For summarizing categorical variables, frequency distributions are often used. That is how so common values appear to have metric variables. This results in huge tables and charts that do not provide the data perspective. Histograms are the way to go in this situation since they visualize frequencies for importance periods rather than for each distinct value [11]. Figure 2.2 shows the graph of the frequency distribution.

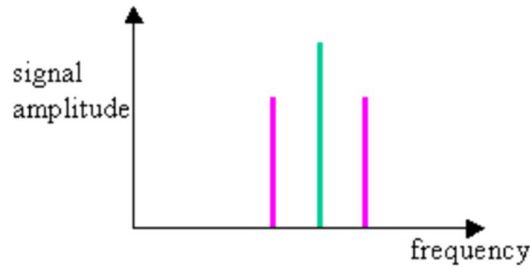


Figure 2.2 Graph of frequency distribution

### 2.4.3 Time-frequency distribution

Time-frequency analysis in signal processing is a series of techniques and methods used to classify and modify signals whose numbers differ in time, for which transient signals. It is a collection of methods and techniques used to classify and control signals whose figures, such as transient signals. It is a generalization and improvement of the study of Fourier, as the properties of the signal frequency vary over time. Since several signals of concern have evolving frequency characteristics, time-frequency analysis has a large variety of uses, such as voice, music, pictures, and medical signals. Whereas the Fourier transform method can be generalized to obtain the frequency spectrum of any locally integrable signal that is slowly increasing, this methodology involves a full explanation of the actions of the signal overall time. Indeed, points in the (spectral) frequency domain may be thought of as smearing details together from around the entire time domain [12]. Figure 2.3 shows the graph of time-frequency distribution.

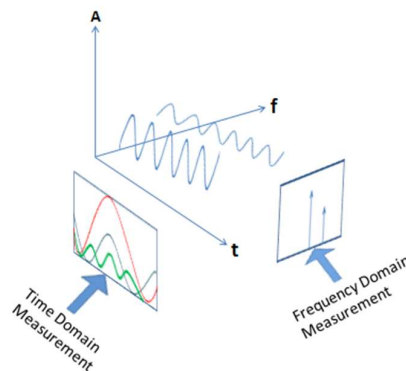


Figure 2.3 Graph of time-frequency distribution

## 2.5 Signal Classification

The data should be put into a classifier to plan, recognize, and estimate the different samples of data collected from the bioradiolocation signal. This classifier is designed to recognize a variety of different samples of bioradiolocation signal highlights. By feeding the classifier a preparatory set of successfully estimated data, the classifier will output the regulated data [13]. As shown in Table 2.2, there are many classification methods for bioradiolocation data, each with its own set of benefits and drawbacks advantage and disadvantage of various classifiers[14].

Table 2.2 feature extraction comparison

<b>Classifier</b>	<b>Advantage</b>	<b>Disadvantage</b>
Support Vector Machine (SVM)	It works very effectively when there is a clear delineation between classes.	Perform poorly as a result of increased noise
K-Nearest Neighbor (KNN)	Very simple implementation	Sensitive to noisy and missing data
Ensemble Bagged Tree	Straight forward	High in terms of computational time classifier for real-world use.

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## CHAPTER 3

### METHODOLOGY

#### 3.1 Introduction

The detailed methodology used to record the bioradiolocation signal and the classifier will be explained in this section. The study consists of three phases: signal pre-processing, signal processing, and classification of signals. The general structure of the analysis and the overview of the methodology is shown in Figure 5 and Figure 6, respectively.

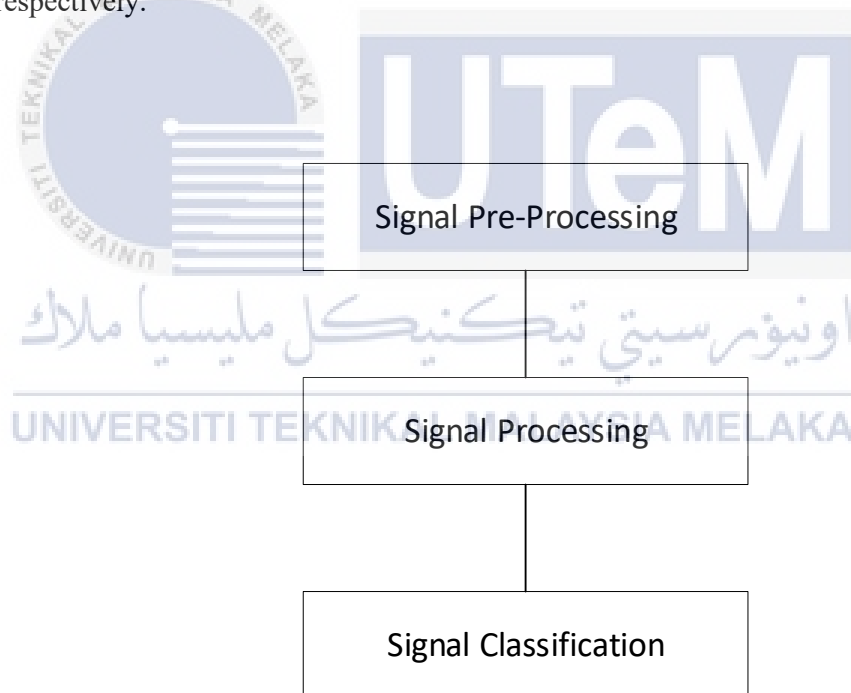


Figure 3.1 General Structure of methodology

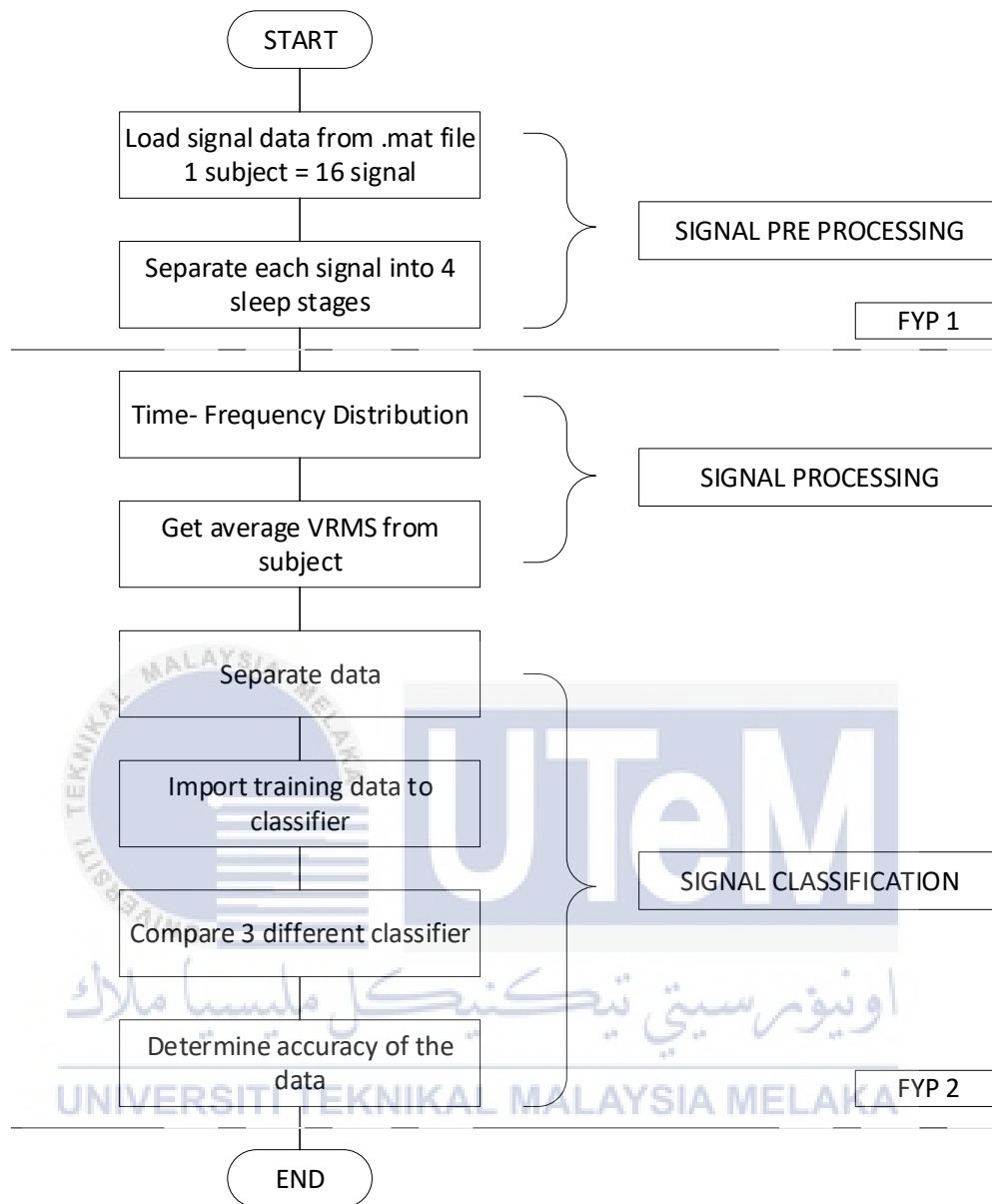


Figure 3.2 The overview of methodology

Table 3.1 shows the information about the individuals who took part in the study. The subjects who took part in the study are 8 subjects listed in the table. The ages of those who participated in the research ranged from 22 to 67 years old. Age on average is 44 years old. Females are defined by the letter "F," whereas males are defined by the letter "M."