CHAPTER 1
INTRODUCTION

1.1 Background

World Health Organization (WHO) states that epilepsy, as one of the most common chronic neurological diseases in the world, has attacked more than 50 million people in the world [1]. Epilepsy damages the cells in human brain and results peculiar behaviours and concentration loss due to some abnormalities of neurons activity in the brain [2], [3]. The occurrence of more than two seizures abruptly and lasts for several minutes with varying severity is one of the symptoms in epilepsy that increases the threat of critical injuries [4], [5]. Furthermore, patients with epilepsy have the potential to experience more side effects from mental disorders to sudden death [6]. Early prediction of seizures has a major impact on the quality of life in epileptic patients. However, until now, seizure prediction is still manually undertaken. Manual prediction has a high possibility of misinterpretation because it is only based on a self-prediction of the symptoms that appear which might increase the injuries [7], [8]. Thereby, automatic prediction of epileptic seizures is highly necessary to avoid the harm to the patients.

Epileptic seizures on the brain signals of people with epilepsy can be analyzed using the recordings of various instruments, but the most common is the electroencephalogram (EEG) [9]. EEG records the electrical activity of brain signals with a number of electrodes attached to the scalp [10]. By analyzing the EEG signals, previous studies discovered that the occurrence of seizures show a specific process before clinical changes within several minutes to hours [11]. This process is considered as pre-ictal condition. There are three other states of condition of epileptic patients, such as ictal, postictal, and interictal which is the time where seizure occurs, after seizure occurred, and between two seizures occur, respectively [12]. In this study, the epileptic seizures were predicted by detecting pre-ictal states on the recorded EEG signal.

The development of seizure prediction system has been started since the 1970s using machine learning (ML) and focuses on feature extraction [13]. Fuzzy logic, fractal analysis, and entropy are among most popular methods. Fuzzy logic and fractal analysis have succeeded in compiling the simplest form of EEG signals [14]–[16]. Meanwhile, entropy analysis outstands other methods in handling the high level of complexity of the EEG signals [4]. There are many entropy calculations, such as Shannon entropy (ShEN), Renyi entropy (REN), and permutation entropy (PE). In the previous study, the application of entropy in seizure prediction have worked on one scale only so it has not fully represented the dynamic of EEG signals [17]. Then, a new method has been developed, namely multiscale entropy (MSE) [18]. MSE considers correlations on several spatial-temporal scales of the time series so that it is easier to distinguish every seizure state [19]. In [20], several combinations of MSE have been proposed for the classification of lung sounds and achieved higher accuracy than entropy. However, MSE has not met the complexity criteria because of its unstable features [21]. Singh et al. [17] and Azami et al. [22] showed that the use of multiscale dispersion entropy (MDE) and multiscale fluctuation-based dispersion entropy (MFDE) were able to overcome the shortcomings of MSE. They implemented coarse-graining (CG) process in MDE and MFDE which resulted significantly different feature values and led to more accurate seizure prediction. However, CG still employs fixed frequencies resulting a non-adaptive system to various forms of signals [23].

In this study, seizure prediction is performed automatically using ML for the short-term and long-term dataset. Long-term dataset is able to capture more information so that the prediction results become more precise. Previous studies have successfully detected seizures on the short-term and long-term dataset, such as the Bonn University and CHB-MIT dataset [6], [16]. Therefore, this study continued to work on seizure prediction using Bonn University dataset and Temple University Hospital EEG Seizure Corpus (TUSZ), which is one of the largest open EEG datasets. The proposed feature extraction method is fluctuation-based dispersion entropy (FDE) since it is able to estimate the dynamic variability of signal fluctuations, so it is suitable for epilepsy prediction based on EEG signals [22]. FDE is combined with a multiscale empirical wavelet transform (EWT) approach to span multiple scales and get more information adaptively. Then, compare its performance with empirical mode decomposition (EMD). This prediction system ends with the classification of pre-ictal states by SVM.

1.2 Problem Identification

This study focuses on the multiscale-based feature extraction stage for automatic epileptic seizure prediction which is convenient to be implemented on dataset of EEG signal recordings with long duration and high accuracy values. The problem identification in this study is elaborated in the following points.

1. The EEG signal has multiscale component which provides more information so that the multiscale methods are developed. However, it cannot be concluded that the use of EWT as a multiscale method that uses an adaptive scaling function is able to predict seizures more accurately in the long-term EEG dataset.
2. Previous research has shown that the use of the FDispEn multiscale method with coarse-graining has been successfully implemented for biological problems using ECG signals and produces more stable and discriminative entropy values [22]. However, the use of multiscale FDispEn with EWT to analyze long-term EEG recordings has not been proven to be reliable.

1.3 Objectives

This study aims to design an epileptic seizure prediction system that is applicable to long-term EEG signal recordings dataset by optimizing the feature extraction process on the multiscale component of the EEG signal through the following steps.

1. Decompose the EEG signal with the multiscale component decomposition of the EWT.
2. Combine the method of FDispEn and EWT.
3. Compare the main methods with other methods that have been developed previously.

1.4 Problem Limitation

This research has problem limitations as follows.

1. The number of research objects used are 37 patients.
2. The type of epileptic seizure studied is Generalized Non-Specific Seizure (GNSZ).
3. The type of montage studied using TUSZ is the bipolar montage pair.

1.5 Hypothesis

In the process of developing an applicable automatic seizure prediction system, the features, that are able to distinguish each seizure condition in brain signals, are one of the significant components to generate high performance values. The non-stationary EEG signals are decomposed using a multiscale method with the EWT so that the decomposed signals become more stable and adaptive [24]. The features produced by FDispEn identify the fluctuations that occur to easily distinguish signals of pre-ictal condition from ictal and normal conditons in highly complex and irregular EEG signals [25]. The more unique the feature values are, the easier the classification is [26]. Therefore, the system is capable of producing higher performance values than the previous studies.

1.6 Research Methodology

Figure 1.1 shows the block diagram of this research. This research begins with a literature study of the dataset, namely TUSZ, and the methods used. Every dataset has various characteristics. Therefore, the characteristics of TUSZ must be mastered so that the methods used are adapted properly.

Pre-processing of the dataset is carried out to ensure that the EEG signals are clean from noise. After the EEG signals in TUSZ are clean from noise, the decomposition process is performed as the application of the multiscale concept. The decomposed EEG signals are further processed to obtain their feature values. Then, the features are classified so that the system can predict the pre-ictal conditions. The results of the classification stage are evaluated by calculating several parameters to see whether the seizure prediction system is well-run and applicable in real-time.

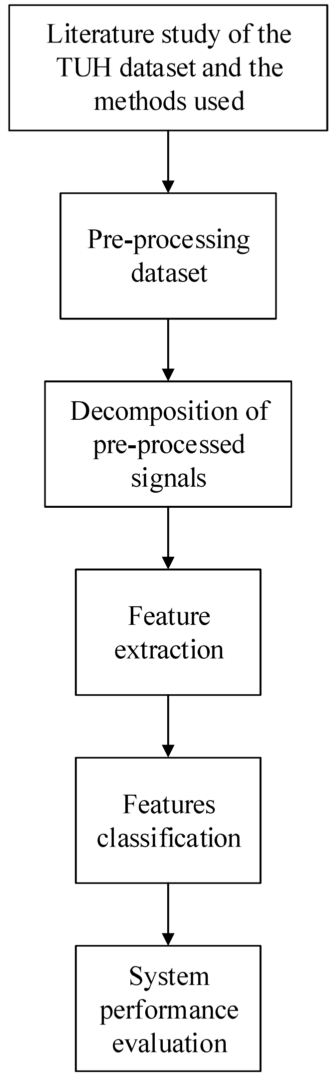

Figure 1.1 Block diagram of this research.

1.7 Research Method

This study uses two main methods which are described in the following points.

1. EWT for the multiscale approach.

   The wavelet transform acts as the multiscale approximation method in the decomposition stage of the EEG signal. There are many types of wavelet transforms that have been developed, such as EWT. EWT is an extension of EMD and discrete wavelet transform (DWT). If the signal is decomposed by DWT, not only the bandwidth, which acts as a scaling function, is fixed, but also the adjustment is hard to be performed as the shape of the signal changes. In addition, the use of EMD produces numerous modes so that the decomposed signals are more difficult to interpret [27]. On the other hand, EWT decomposition is adaptive by building a filter bank and acting as a bandpass filter [24]. EWT produces a more optimal total mode for signal interpretation [27].

2. FDispEn for the feature extraction.

   The difference of distribution pattern of brain signals recorded by EEG is troublesome to be seen because they fluctuate irregularly. In characterizing biomedical signals, FDispEn shows high potential [22]. The concept of FDispEn is to calculate features based on local signal fluctuations [25]. FDispEn is a suitable method to analyse the dynamic and nonlinearity of EEG signals because the complexity and irregularity are characterized well.