Automated Deep Neural Network Approach for Detection of Epileptic Seizures

By

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Abstract

In this thesis, I focus on exploiting electroencephalography (EEG) signals for early seizure diagnosis in patients. This process is based on a powerful deep learning algorithm for times series data called Long Short-Term Memory (LSTM) network. Since manual and visual inspection (detection) of epileptic seizure through the electroencephalography (EEG) signal by expert neurologists is time-consuming, work-intensive and error-prone and it might take a couple hours for experts to analyze a single patient record and to do recognition when immediate action is needed to be taken. This thesis proposes a reliable automatic seizure/non-seizure classification method that could facilitate the identification process of characteristic epileptic patterns, such as pre-ictal spikes, seizures and determination of seizure frequency, seizure type, etc. In order to recognize epileptic seizure accurately, the proposed model exploits the temporal dependencies in the EEG data. Experiments on clinical data present that this method achieves a high seizure prediction accuracy and maintains reliable performance. This thesis also finds the most efficient lengths of EEG recording for highest accuracies of different classification in the automated seizure detection realm. It could help non-experts to predict the seizure more comprehensively and bring awareness to patients and caregivers of upcoming seizures, enhancing the daily lives of patients against unpredictable occurrence of seizures.

Acknowledgment

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Chapter 1

Introduction

In this thesis, I focus on the development of a Deep Neural Network model to improve the accuracy of seizure detection by electroencephalogram (EEG) signals. This introductory chapter sets the general context of this research. First, we start with the research motivation, by a brief description of the problems and the necessary background information about epilepsy to understand the scope of the problem that is going to be addressed in this research. Then, the objective of the research is presented. This chapter ends with an overview of the thesis organization.

1.1 Motivation

Diagnosis of diseases through manual analysis of highly complex medical data is not only time-consuming but also error prone. Development of machine learning and pattern recognition enable scientists to provide new approaches to automate and facilitate some parts of these labor-intensive work partially. This progress not only proliferates across health care research areas but also multidisciplinary studies like brain-computer interface also take advantage of this approach.

Brain-computer interface is the emerging field of this research that integrates multifarious disciplines including neuroscience and computer science. This field of research mainly studies the brain function and neural electrical activity of neurons by analysis of the electroencephalography

(EEG). The EEG signal has become a standard method for learning about brain functionality and neural electrical activity of neurons [ARC12a].

The extracted knowledge from the brain can be applied to a wide range of applications, including to stop a driving car once the braking intent comes to the driver's mind, it can be used to enable disabled people to control their wheelchair, or it can be used for diagnosis of lies in court among other things. There are vast applications which are driven from EEG signals, either for disabled people or healthy people, all of which refer to brain computer interfaces (BCIs). In the health care realms, scientists try to investigate and analyze different abnormalities within the brain signals to detect the diseases and understand their causes. Today's state of the art technology enables diagnosis with help from machine learning (ML) and deep learning techniques to automate what had previously been done by experts while consuming large amount of time.

The neuroscience experts analyze EEG signals and characteristics of brain states. This is done by brain signal processing that aims to understand different complex states of the brain when brain responses are different at a specific time point between two states. Comparing these different states of the brain is called "univariate analysis". In fact, this method decodes an individual's cognitive or perceptual responses of human beings [HUL19].

However, it requires a lot of work because it is quite hard to extract meaningful information and find an individual feature of interest from high-dimensional, noisy EEG data and signals may become redundant in EEG data when they describe different things and intrinsically correlate to each other. In addition, in some cases, including in diseases, we have access to a limited number of samples in neuroimaging, this constrains researchers' ability to build an ideal model with many of parameters and factors. Electroencephalography (EEG) is a key component in the evaluation of epilepsy. Epilepsy is placed as one of the most common diseases after migraine in the world according to the World Health Organization's figures [ENG12]. The EEG provides important information about background EEG and epileptiform discharges, and it is required for the diagnosis of specific electroclinical syndromes [NOL04]. This thesis aims to diagnose this common neurological disease epilepsy through EEG signals with use of a deep neural network algorithm.

1.2 Epilepsy And Epileptic Seizures

According to the latest World Health Organization (WHO) statistics [ENG12], about 50 million people worldwide suffer from epilepsy. It could be considered a life-threating peril for epileptic patients in their daily lives and restrict them from many activities such as acquiring and using a driving license. Patients with epilepsy are socially discriminated due to negative public attitudes and misconceptions of the disease. In fact, epilepsy is a neurological condition which might lead to two or more unprovoked seizures and appearance of abnormal behaviors of brain activities over a 24-hour day period.

Epilepsy causes could be the result of brain injury, brain tumors, infections, nutritional deficiencies, calcium metabolism disorders, etc. Since neurons produce electrochemical impulses, they influence on other neurons that generate thoughts, movements, and feelings. In seizures, sudden changes in the electrical functioning of the brain in the cortex would disturb the normal pattern of neuronal behavior, causing strange emotions and behaviors, muscle spasms, loss of consciousness and other abnormalities. These abnormalities appear in the form of rapid spiking waves on the EEG recording. Therefore, electroencephalography (EEG) plays an important role for accurate diagnosis and classification of different forms of epilepsy, and it also aids in recognizing mechanisms which lead to seizures in epileptic disorders.

The unpredictable nature of epilepsy limits a human's perception and behavior result in the patients and their family suffering from low quality of life and self-esteem. Hence, it has drawn the attention of many researchers from different disciplines to predict and detect epileptic seizures before its occurrence and take appropriate measures to minimize its aftermath.

Analysis and research about seizures and epilepsy began in 1970 [MER70]. Manual seizure detection is time-consuming analysis of signals since they are violated by various artefacts and they encompass different components and epochs (periods) such as inter-ictal EEG, spikes, etc; hence differentiating them from each other requires specific expertise. The seizure occurrence pattern might change over time for each patient and this pattern may be different from one person to another person as well.

To facilitate the diagnosis and consequently the treatment of epilepsy, this research's goal is to develop an automated and robust method that can identify the epileptic EEG signals during seizure activity and during seizure-free time.

1.3 Objectives

Available treatments against seizure can be medication, surgery, and electric stimulation. Drugs try to neutralize the excessive neuronal activity associated with a seizure. Epilepsy surgery may reduce the number of seizure attacks and the long-term risk of brain damage. But neither of them can completely improve the quality of life of epileptic patients. Since brain surgery, has its own serious risks, including paralysis, speech issues, memory problems, loss of motor skills, and in some cases might lead to even more seizures and almost 30% of the patients who are drug-resistant to epilepsy suffer from drug refractory epilepsy; therefore, these are not final solutions to epilepsy [LAR16].

Alternative approaches for seizure treatment could be electric stimulation before the seizure occurrence or warning devices that could be designed to alert of the upcoming seizures if there is some efficient way to predict seizures. These options are highly dependent on early prediction of the seizure.

Recent research demonstrates that epileptic seizures are not unpredictable, recent investigations have demonstrated that seizures do not strike at random and (EEG) could be used as a tool for forecasting epileptic seizure attacks. Hence, the EEG can play a significant role in providing information to identify the occurrence patterns that indicate upcoming seizures.

Detection of epileptic seizures based on machine learning has become one of the hottest topics over the last decade and researchers have proposed several methods to develop EEG-based seizure prediction methods. However, there is still a lot of space to improve and build a robust seizure detection system with a time series EEG signal achieved from the brain. The problem with classical methods applied, like machine learning, is that these types of problems still involve a highly manual feature engineering and feature extraction from raw time series data and, which requires strong expertise in the field and makes this approach tricky.

The deep learning approach has been proposed to handle these limitations, addressing the complex problems. I propose utilizing a powerful deep neural network structure, for timeseries data from a category of recurrent neural network (RNN) called Long Short-Term Memory networks (LSTM), to extract the temporal dependencies in EEG signals.

Long Short-Term Memory networks (LSTM) provides a cutting-edge approach on challenging identification problems with little or no data feature engineering for time series data. In fact they do not need specialists to handle input features manually. The proposed model can learn internal relation embedded within the time series data. Then it generalizes the relation in the given dataset with automated engineered features and obtain satisfactory performance. Since deep learning algorithms are equipped with sophisticate backpropagation system which is enabled to learn and extract temporal and spatial dependencies in EEG data by using gradient descent .

This dissertation also reviews different approaches that have been used by over 20 previous research works on epileptic seizures and identify what is the best approach for preprocessing, which has good performance in the algorithm and provides better accuracy results.

1.4 Organization Of Thesis

The reminder of the thesis is organized as follows. Chapter 2 exposes the reader to the background concepts regarding epilepsy and the methods used to predict seizures by a brief literature review and discussion of previous research. This will provide the appropriate background information, along with their performance results. In Chapter 3, the data used for this project is described then the proposed approach for robust seizure diagnosis is explained elaborately. In

Chapter 4, I present the experiments and analysis of our model and discuss the obtained results and then compare the merits from different perspectives. Finally, Chapter 5 summarizes the contribution of this research and suggests future directions.

Chapter 2

Background Concepts

This chapter provide required principal concepts regarding epilepsy. All previous approaches used to predict seizures in literature review are discussed by their merits and demerits.

2.1 Epilepsy And Epileptic Seizures

Analysis and research about seizure and epilepsy began in 1970. Epilepsy is one of the most common diseases, after migraine headaches in the world according to the latest WHO statistics [ENG12]. An epileptic seizure is characterized by the occasional and recurrent occurrence of seizures due to excessive and disorderly discharging of neurons from a physiological perspective. This abnormal discharge, arising from neurons can fire as many as 500 times a second or faster than normal (1–100 μV) in localized areas of the brain. This might happen only occasionally in some people or hundreds of times a day for others. When seizures occur, abnormalities in the form of rapid spiking waves appear on the EEG recording. We can categorize abnormal activities in the EEG signals into ictal (during an epileptic seizure) and interictal (between seizures) which is discussed elaborately in section 2.3. To facilitate the diagnosis and treatment of epilepsy or neurological disease, this research's goal is to develop methods that can identify the epileptic EEG signals during seizure activity and during seizure-free time.

2.2 EEG Signals In The Brain

There are almost 100 billion nerve cells called neurons. All neurons have the same properties and hold electrical charge of brain and can transfer them as messages in long form. Neurons contain three components including cell body (soma), axon and dendrites as shown in Figure 2-1.

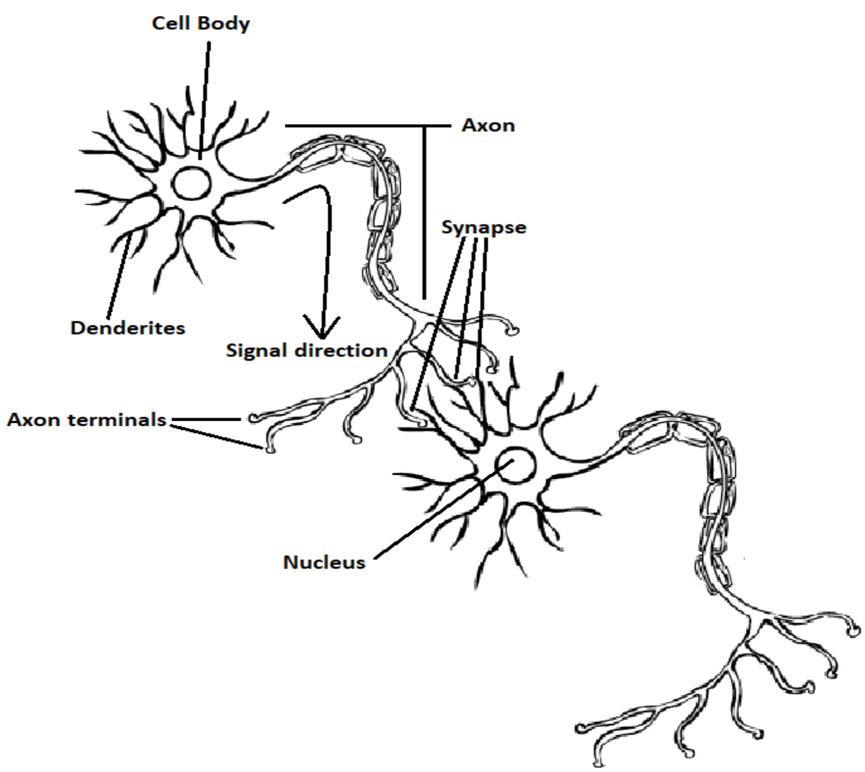

Figure 2-1. Simple Structure of a neuron

As Figure 2-1 shows, that the central part of the cell is the cell nucleus, and it is responsible for maintaining electrical charges. The long and narrow part of the neuron, axon, links the nucleus to the dendrites which contain many receivers. Whenever an ion pumps out through the axon, the rapid change of ions cause electrical signals to pass to adjacent dendrites through the connected axon. In fact, alteration of ionic charges leads to a voltage generation on the inside and outside of the cell membrane of the neuron. These neurons emit chemicals named neurotransmitters.

As Figure 2-2 illustrates, when electrochemical activates neurons, current flows are generated and then contributed to the surface. For the sake of simplicity, when a neuron becomes excited it passes electrochemical impulses incoming from the dendrites along the axon to communicate with other neurons in the brain. The brain, also, can be divided into three main parts, the cerebrum, the cerebellum, and the brain stem (Figure 2-3).

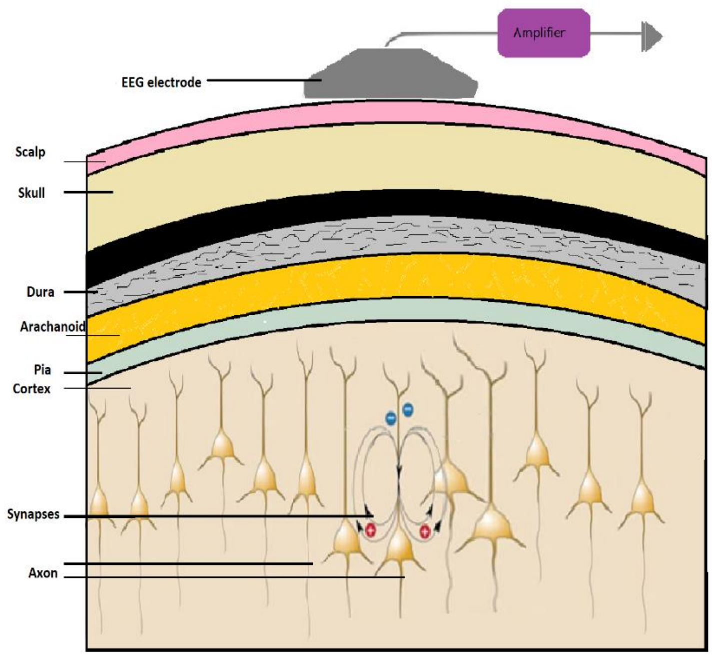

Figure 2-2. Illustration of the way how EEG electrode measures the signal through layers of tissue [KER19]

Each part of brain is responsible for specific activity. Based on this definition, cerebrum is the biggest and the most significant part of brain because it handles emotions, motor functions, thoughts, and movements. The cerebrum, itself, can be divided into four lobes on each the right and left hemisphere. The lobes are identified as frontal, parietal, occipital and temporal. These lobes are in charge of a variety of bodily functions. For instance, the temporal lobe is responsible for processing auditory information and with the encoding of memory. The outer layer of the cerebellum is the cerebral cortex. The cerebellum is one of the few sensory areas in the brain which controls motor function, sensory perception, co-ordination of voluntary muscle movements, fine motor skills, posture, and balance regulation. Cerebral cortex plays a significant role in EEG recordings due to its surface position. The EEG are recordable on the scalp from the cerebral cortex (surface of the cerebrum) in active neurons as Figure 2-3 presents it.

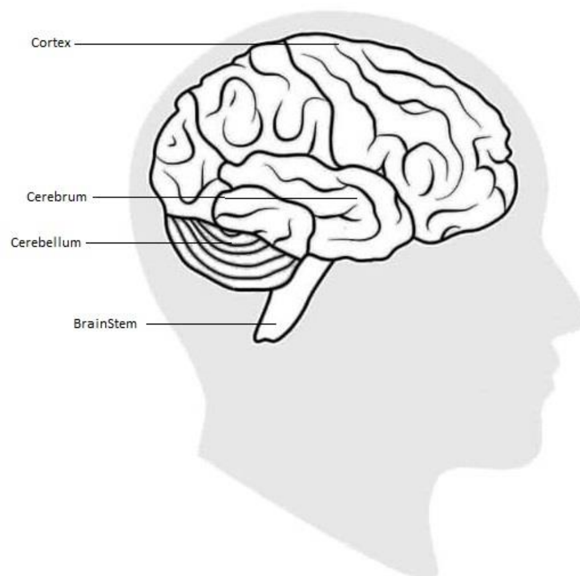

Figure 2-3. Different section of the brain

2.3 Characteristics And Nature of EEG Signals

Electroencephalography (EEG) is considered as a measurement for recording of the electricity activity of neurons in the brain and play a significant role in brain and neurological disorder studies and diagnosis such as brain tumor, brain damage from head injury, stroke, and sleep disorders. It is also applicable to resolving diagnosis and assessment of abnormalities and disturbance which arise from attention disorders and learning problems. The EEG originated from the German term “elektrenkephalogramm”. In 1924, for the first time, German neuropsychiatrist named Hans Berge recorded an EEG from the human brain to demonstrate electrical currents engendered in the brain.

Recording EEGs requires the placement of a few plates, called electrodes. Electrodes can be placed either along the scalp (non-invasive) or in direct contact with the brain (invasive). The electrodes are able to detect tiny electrical charges that result from the activity of the brain cells.

Intracranial EEGs can be recorded through implanting electrodes in the brain during surgery. This method is normally considered during brain surgery on an epileptic patient to identify seizure location and seizure boundary. It has an advantage over scalp EEG in that it is able to seize low voltages of brain signal along with a whole range of brain activities precisely since specialists implant the electrodes on the surface of the brain to record brain activities from the cerebral cortex. This intracranial/invasive EEG (iEEG) does not involve skull and scalp to weaken the electrical brain signal anymore, therefore, it can enhance distortion and amplify-signals and track the changes in the brain much better. Scalp EEG records electrical activities of the brain through electrodes which are placed with temporary glues on different locations of the surface of the scalp or the head of the patient. This acquired EEG recordings involve many factors which interfere with seizure recordings such as noise or filtering from the skull and scalp due to a large distance between neurons inside the skull and the electrodes. This method is a preferable measurement to record EEG signals than intracranial EEG or other devices like fMRI or MEG which require bulky and immobile equipment and cost millions of dollars.

The scalp EEG is the most convenient, wearable, and affordable device. Therefore, it is more common for epilepsy detection and treatment to use the scalp EEG. The international 10–20 placement electrode system is defined to describe and apply the location of electrodes on scalp regarding the EEG exam. The International 10–20 placement electrode system was developed to maintain standardized testing methods in order to ensure the naming and location of electrodes is consistent across laboratories.

In EEG measurements, we measure voltage changes resulting from ionic current within the brain neurons. The amplification of an EEG signal varies from 1o to 100 µV in a normal adult in EEG scalp recordings.

Each scalp EEG electrode is connected to an amplifier (one amplifier per pair of electrodes). The electrical signals from the brain are converted into wavy lines on a computer screen to record the results. Figure 2-2 illustrate the configuration of how electrodes are placed on the scalp and EEG signals are recorded. Depending on the application of EEG, the number of electrodes could change from 1 to 256, referring to the channel which records the signal from each pair of electrodes. In fact, EEG signals in channels are the difference between the voltage of two electrodes. Figure 4 illustrates that each channel is a result of two electrodes.

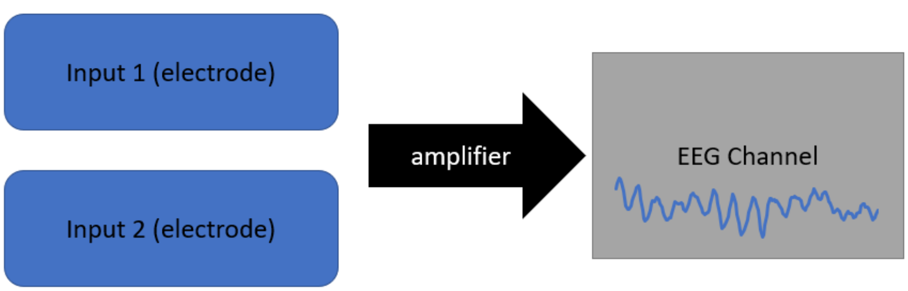

Figure 2-4. An EEG Channel

Frequency is also considered one of the significant factors for abnormality diagnosis in medical applications through the EEG scalp and it confirms the presence of abnormal electrical activity, giving information regarding the type of seizure disorder, and disclosing the location of the seizure focus. Signal sampling by EEG measurement is typically done by frequency. In fact, frequency counts the number of occurrences of repetitive activity in the unit of time with Hertz (Hz) which is the number of cycles in a second. The Amplitude changes from one state to another state like sleep and wakefulness and even from one person to another. Therefore, we can divide frequency from low to high into five various categorizations such as 0.5–4 Hz (delta, d), 4–8 Hz (theta, h), 8–13 Hz (alpha, a), 13–30 Hz (beta, b) and >30 Hz (gamma, c). For example, Delta is mostly found by infants and deep sleep stages of normal adults and Gamma is related to a stressed, happy, or aware person. The higher frequency is more likely to represent abnormalities of brain activities like seizure in measurement of EEG.

EEG abnormalities indicate dysfunction of the brain, and it would appear in a specific state of the person. EEG abnormality can be split into epileptiform pattern activity and non-epileptiform pattern abnormalities based on frequencies and intensity of abnormality. Epileptiform indicates high frequency with sharp waves and spike. This EEG signal focuses on seizures. Non-epileptiform abnormalities are shown with change in rhythmic EEG signal which are driven from a demonstrable structural lesion which leads to focal cerebral dysfunction. Diagnosis of these abnormalities with a wide range of neurological conditions of EEG signal need analysis of the EEGs.

After amplifying, the signal is filtered. Since there are artefacts that can contaminate EEG data. High-pass filtering is used to remove slow artefacts like movement, while low-pass filtering is also employed to remove higher frequency artefacts such as electromyographic signals. The most common types of artefacts that change EEG recordings could originate from the excitation of eyeball muscles like eye blinking or driven from bad contact between electrodes and skin. The frequency and amplitude of the artefact is dependable to the amplitude of the cortical signals. It is very likely to record electrical signals originating from other sources rather than cerebral.

In the analysis of the epileptic seizure EEG recordings, different stages of an epileptic seizure are identified: Pre-Ictal, Interictal State**,** Ictal State and Post-Ictal State. They are displayed in Figure 2-5. Description of each stage could differentiate them from each other.

(a) Pre-ictal State: A pre-ictal state shows up during a time period before the occurrence of a seizure and can last from minutes to days. Not everyone experiences something at this stage of a seizure. It could be visually apparent or undisguisable. However, it will reflect transformation in the underlying signals and could be considered as a precursor of seizures within a specific range of values in clinical use as a warning system.

(b) Ictal State: The ictal state is a change in EEG signals during a seizure. During this time, actual physical changes will appear in the person’s body.

(c) Interictal State: It is referred to the stage between two following seizure onsets. It is worth mentioning that the number of epileptogenic neurons, cortical region, and the span of seizure can be changed even for the same patient over time.

(d) Post-Ictal State: This state refers to the state after the occurrence of a seizure.

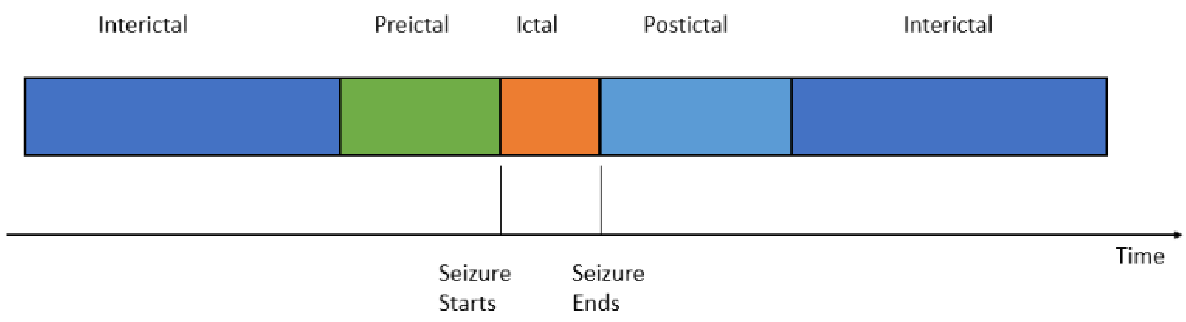

Figure 2-5. Different brain states of an epileptic patient

Seizures are the result of transient, paroxysmal, and synchronous discharges of groups of neurons in the brain. This desynchronization of electrical charge is apparent in electro decremental seizures which can be considered conversion of the preictal to the ictal state, by gradual transition from chaotic waveforms. However, an increased amount of spike in EEG signal would not indicate the severity of seizure. Mostly, the onset of seizure is characterized by abrupt changes in frequency of the EEG. During occurrence of the seizure. the amplitude increases and the frequency drops. The diagnosis of epileptiform activity and epileptic disorder requires a specific expert since it may vary within each epilepsy syndrome overtime.

The role that EEG signals play in an accurate diagnosis of abnormalities and neurological disorders is becoming more and more crucial for specialists and physicians. EEG signals are used for diagnosis of many mental and brain neuro-degenerative diseases like, dementia, Alzheimer, Parkinson, migraines, neuroinfectious, sleep disorders and traumatic disorders of the nervous system. EEG data contains a large amount of information, requiring a computer-aided analysis system for accurate classification of abnormality of the EEG recording to detect brain diseases.

2.4 Objectives Of EEG Analysis

An efficient classification technique helps to distinguish EEG segments to reach a better understanding of the cognitive processes in the decision making about a person's health. The principal step is how to represent and classify the elaborated raw EEG signals for further analysis; for this purpose, we need to extract useful features related to the occurrence of seizure embedded in the raw EEG data and then classify EEG segments based on the extracted features. Usually, classification refers to an algorithm procedure for dedicating a given piece of input data into one of the given numbers of categories. The main purpose of classification is to assign class and labels based on the extracted features and observation of datasets into a specific problem. The classification algorithm that maps the input data to a category is called classifiers. With help of training sets, the classifier learns how to identify the class correctly and how to identify the related relationship between extracted features and labels correctly. This will be discussed more in Chapter 3.

Classical approaches to these kinds of problems is through training machine learning models which involves the manual feature extraction from time series data. This engineering and feature extraction requires strong expertise in the field and will be reviewed in the next section. In fact, machine learning is driven from artificial intelligence and takes advantage of computational and statistical methods along with data and experience to improve performance on certain tasks and then generalize the result to build the model based on examples and experiments.

However, development of machine learning led to the emergence of state-of-the-art approaches on challenging recognition tasks called deep learning.

The deep learning method does this task through artificial neural networks within several layers with increasing levels of complexity. This neural network is also equipped with an automated feature extraction process which is independent from human manipulation and knowledge that reduces the time and requisite mastery of knowledge to develop an algorithm significantly. This dissertation introduces a novel deep recurrent neural network architecture that takes advantage of deep learning and artificial neural network to improve detection of a seizure. The deep learning algorithms can learn from temporal and spatial dependencies in Electroencephalogram (EEG) data.

2.5 Related Works

Previous sections provided background material and information on EEG , epilepsy and epileptic seizures and introduces the objectives and contribution of this thesis. In this section, research and works which have been done on EEG-based detection of epileptic seizure are reviewed from different perspectives, including signal processing used by traditional machine learning methods and then the deep learning classification methods.

Almost all proposed research on EEG-based detection systems commonly go through the same procedures to provide efficient and precise EEG classification: EEG data acquisition, EEG pre-processing (including different types of artifacts removal range from range muscle activities, eye-blinks, to white environmental noise), and EEG feature extraction and selection.

EEG signals are considered the main source for detection and prediction of epilepsy through monitoring brain activity; but EEG signals can be easily corrupted by eye-movements, blinks, cardiac signals, and muscle noise. Different filtering and noise reduction methods are used to lessen the impact of these various sources of noise and artifacts. Signal preprocessing refers to the filtering of the artifacts and it is considered a crucial procedure in processing of raw biomedical signals. There are a few processing methods including band-pass filter, wavelet filter, finite impulse response filter, and adaptive filter to clean the biomedical data [HUS19]. This processing also normalizes the data in order to compare it with other recordings from other subjects; otherwise, the vitiated data and outliers would diminish the performance of the algorithm and subsequently reduce accuracy of the model.

2.5.1 Machine Learning Approach

In the machine learning approach, feature extraction and selection is another mandatory step in assisting to make pre-ictal and interictal stages discernible. The main features in EEG signals could be in the time-domain, frequency domain and time-frequency domain.

Figure 2-6 briefly overviews the general procedures in machine learning techniques that have been used to solve the problem of epileptic seizure detection.

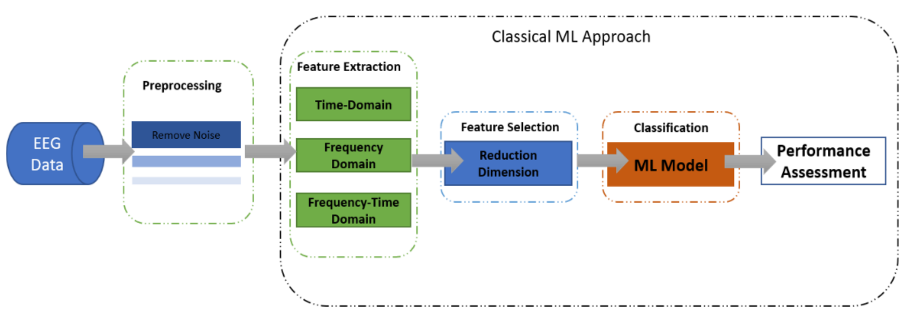

Figure 2-6. Process classification of Epilepsy by using EEG data

Time-domain methods calculate the correlation between statistical parameters and Electroencephalographic (EEG). In fact, it links physical time interpretation and conventional spectral analysis. Linear Prediction (LP), Component Analysis Principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) are the main methods for time domain EEG analysis. The Linear Prediction estimate value is based on a linear combination of the past output value with the present and past input value. PCA is developed to transform the high-dimensional data (in case of epilepsy high dimensional feature vectors) to a low-dimensional data. The independent component analysis (ICA) decomposes high-dimensional data into statistically linear independent components while LDA is used for dimension reduction of feature sets by finding linear combinations of feature vectors.

Gutman [GOT79] is considered as one of first founders of seizure diagnosis based on EEG signals. He considered time-domain analysis and then deployed 60 Hz as a digital filter to remove artefact from both EEG and iEEG signals to distinguish the normal and epileptic patterns recorded from 20 epileptic patients. The study [SHA16] on the CHB-MIT EEG dataset examined extracted features based on the mean and minimum values of EEG signal energy in successive one second EEG epochs. Then, by using a linear classifier, accuracy of 99.81% was achieved in classification tasks.

The nonlinearity and chaotic nature of EEG signals led the researchers to propose using nonlinear-based techniques. This method adds more complexity to the interpretation of EEG signals. To carry out nonlinear EEG analysis, many useful nonlinear parameters such as Lyapunov Exponent, Correlation Dimension, and entropies like Approximate Entropy and Sample Entropy have been proposed. In the study done by Acharya et al [ARC12b], they utilized EEG-based features including approximate entropy, sample entropy, and phase entropy to demonstrate different features of EEG signals and then built a Fuzzy Sugeno Classifier (FSC) and obtained seizure detection accuracy of 99.40%. Kollialil et al. [ELD13] also exploited entropy features in EEG signal energy as an attribute to EEG activities with the support vector machine (SVM) classifier to reach classification accuracy of 99.66%. In a study, conducted by Dash et al., they utilized the traditional entropy features in least square SVM (LSSVM) classifier to achieve an accuracy of 82.22% [DAS20].

In [ANT12], Dalton et al. used the same long-term EEG recordings of CHB-MIT database and examined different time domain features of EEG signals, including the mean, standard deviation, zero-crossing rate, entropy, and root means square (RMS) to detect seizure. They found the RMS was the most impressive feature that can be used to identify seizure from non-seizure activities. Results showed an average sensitivity and specificity of 91% and 84% for seizure classification.

In brief, time domain-based feature of EEG signals are widely used in real-time detection of epileptic seizures since they are computationally simple and sensitive to different artefact and intra patient variants. The frequency features of EEG signals could provide clearer perception and more descriptive information than time domain features. Various techniques have been used to extract features based on frequency of EEG signal to detect seizure from non-seizure.

During occurrences of epileptic seizure, sudden change in the frequency of EEG signals happen which can be assessed by using frequency-domain methods. Fourier transform (FT), moving average (MA), auto-regression (AR), and auto-regressive moving average (ARMA) are commonly used frequency-domain methods. In [HEB13], the authors also developed a single channel and patient-specific EEG-based seizure detection method with the help of Discrete Fourier transforms in a single channel and then Frequency-moment improved sensitivity of automated seizure detection to 91% and a false positive rate of 0.02per hour.

Frequency-domain approaches obtain acceptable result to detect seizure from non-seizure automatically for long term EEG signals on a large scale. However, they have their own constraints with identifying precise frequencies at a particular time instance Besides, time-based features are needed for visual interpretation of EEG recordings. Therefore, the researchers attempt to combine both time and frequency domain attributes of EEG signals to achieve more robust and reliable detection to overcome these constraints and obtain multi-resolution to decompose sub-band signals by feeding the EEG signal through filter banks [HUS19].

Short-time Fourier transform (STFT) and wavelet transform are powerful time frequency tools to extract discernible features from chaotic nature of signals like brain signals. The wavelet transform performs better in terms of frequency resolution compared to the short-time Fourier transform when the signal is changing in time. The wavelet transform can determine where and in what scale frequency changes occur by decomposing the signal into sub-bands and extracting features from these sub-bands. However, finding the optimal mother wavelet with the number of decomposition levels to extract distinguishable features of seizure through EEG activities is challenging.

Nilchi et al. [NIL10] in their research, took advantage of features from both time domain and frequency domain and then fetched into an MLP to categorize the EEG signal into normal (healthy), seizure-free interval (inter-ictal), and seizure interval (ictal). Their research obtained accuracy of 97.5% with of 0.095% for the variance. Ayoubian et al. [AYO13] used other features including the relative energy, number of peaks and wavelet entropy to improve accuracy of seizure detection by a sensitivity of 72% and a false detection rate of 0.7 per hour. The sample entropy was also used in [SON10] as a representative EEG feature to detect epileptic seizures. The features were fed into the extreme learning machine (ELM) and led to sensitivity, specificity, and classification accuracy of 97.26%, 98.77%, and 95.67%, respectively.

Furthermore, the researchers of [LIU12] proposed wavelet-based seizure detection method on a large dataset of 509 hours from 21 epileptic patients. The EEG data were first analyzed using wavelet transform to extract the effective features and classified and tested by using a SVM classifier. This method achieved a sensitivity of 94.46% and a specificity of 95.26% with a false detection rate of 0.58 per hour.

Polat et al.[POL07] proposed an innovative seizure detection method using both wavelet and Hilbert transforms. Mean, maximum, minimum, standard deviation, and average power were also extracted. They demonstrated that the features extracted from the Hilbert transform coefficients along with K-nearest neighbor (KNN) classifier achieved an average sensitivity and specificity of 100% for both. This is a superior seizure detection rate compared to the result obtained from wavelet coefficients.

In [NIK12], Niknazar et al. used the Daubechies 4 mother wavelet (Db4) to decompose the EEG recordings into five levels: the alpha, beta, delta, theta, and gamma EEG rhythms. Then, by exploiting a subset of statistical features and by using an error-correcting output coding (ECOG) classifier; they achieved an accuracy of 98.67%.

The research [PAN10] done by Panda et al. features were extracted through five-level wavelet decomposition and then fed into SVM classifier. They determined that energy values were the remarkable features that could achieve the highest seizure detection accuracy with 91.20%. In other research [UZZ12], the authors used different features including relative energy and normalized coefficient of variation (NCOV). Results attained were 83.60% accuracy, 100% sensitivity, 91.80% specificity, and 86.70% precision.

Another time-frequency analysis tool that is commonly used for seizure occurrence detection is the Empirical Mode Decomposition (EMD). Compared to short time Fourier and wavelet transforms, EMD does not require any prior fixed basis for analyzing chaotic time-series signals like EEG signals [HUA98]. EMD is a nonlinear signal decomposition algorithm which transforms time-series signals into a set of components called “intrinsic mode functions (IMFs)” keeping the features of the original signals. IMFs compromise statistical features though. Therefore, IMFs are used by numerous seizure detection methods to distinguish seizure and non-seizure EEG activities. Eftekhar et al. [EFT08] take advantage of applying EMD to both EEG and ECG signals in order to detect seizure. Their results were comparable to those of the existing time-frequency methods. It proved that EMD with a sufficient number of decomposition levels could surpass all previous wavelet-based methods regarding seizure detection accuracy and reliability.

Tafreshi et al. [TAF08] also used EEG IMFs to define delegate features for recognition of seizure patterns. Then MLP classifier tested efficiency of this approach on a Freiburg EEG dataset with 90.69% classification accuracy.

To recapitulate, of all proposed models of machine learning, SVMs [HUS18] are the most commonly and successfully used classifier in machine learning to distinguish seizure from non-seizure and more investigations are required to optimize the performance of the time-frequency analysis tool for efficient and robust detection of epileptic seizures. It is worth mentioning that all the existing ML methods are hand-crafted feature extraction techniques which are implemented in specific domains. These domain-based methods also have their own challenges such as interpatient and intra-patient variabilities of seizure. Since EEG data is non-stationary and its statistical features regarding occurrence of seizure are different from one patient to the next patient. Furthermore, their vulnerability against different artifacts change over time for the same patient, which can leave a negative effect on the performance of seizure detection systems.

2.5.2 Deep Learning Approach

Deep learning is a subset of machine learning, having similar functionality but proposed to handle the limitations and iron out the problems of machine learning. It can figure out patterns more precisely from large scales of data by processing and feeding the information into a multi-layer hierarchical network via the input units. It simulates the neural jobs that exist in the human. In fact, they constitute a network of algorithms called artificial neural networks. The artificial neural network model is comprised of multiple layers and each layer consists of nonlinear modules that work collaboratively to process raw data and reach a desired result. These multiple layers extract significant features and examine or analyze them for the output result. Generally higher layers amplify features of the input that are significant to discriminate major variations from minor ones. Due to its high performance, the number of applications built on DL techniques has increased significantly.

Convolutional neural network (CNN) and recurrent neural network (RNN) are the most used algorithms for epileptic seizure prediction. Both take advantage of the connectivity pattern of neurons existing in the brain. The convolution function of a CNN is just like a filter with weights for extracting the features from multi-dimensional input data. While the RNNs are concentrated to find logical sequences in the input series of data. The output of each hidden layer passed to the next layer and is also fed back to itself. In fact, the present output is a result of a current moment and history. What makes RNNs architecture different from CNN is that RNN considers both current input and previous input due to memory logic inside the RNN algorithm while CNNs only consider the current input. RNNs are the better choice for time series data like EEG signals while CNN could be a good choice for data with multiple dimensions, like image classification.

The building of a machine learning model for seizure detection requires optimized feature vectors obtained from traditional signal processing methods to train the classifier and achieve the highest accuracy. It not only requires expert feature extraction but also takes a lot of time to handle the presence of noise and artifacts in data which makes the procedure more complex and time consuming.

While deep learning algorithms automatically learn features through different layers and provide encouraging result in ES prediction, features learned through DL models are more distinguishing and stable than hand-crafted features [GEO20].

In [SAM18], a convolutional neural network model was proposed for both feature extraction and classification to separate preictal segments from interictal ones. This approach obtained sensitivity of 81.4%.

Isabell et al. [ISA18] used Intracranial Electroencephalography (iEEG) data from ten patients. First, they trained a deep learning classifier to distinguish between preictal and interictal signals. After testing the classifier, the prediction system was tuned to prioritize sensitivity. The proposed system achieved mean sensitivity of 69% and mean time in warning of 27%. In this work, they reported mean performance which is averaged three independent runs.

Ramy Hussain et al. [HUS19] analyzed human iEEG data and proposed a pre-processing method for reducing the data size and converting the time-series iEEG data into an image-like format to be used as inputs to convolutional neural networks (CNNs). They then implemented a seizure prediction algorithm with cooperative multi-scale CNNs for automatic feature learning of iEEG data. They achieved an 87.85% sensitivity and 0.84 AUC (Area Under the Curve) on average as a performance measure of the prediction algorithm. In fact, AUC is used as the measure to assess the ability of a classifier to distinguish between classes. The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes. For example, AUC = 100%, then the classifier is able to perfectly distinguish between all the Positive and the Negative class points correctly.

Tsiouris et al. [TSI18] proposed a long short-term memory (LSTM) for the prediction of an epileptic seizure. They analyzed the performance of different architectures of LSTM for random input segment sizes ranging from 15 min to 2 h. They compared the performance of three architectures of LSTM by feature vectors of EEG segments as input to LSTM, where the feature vector consists of various features from the time domain, frequency domain, and local and global measures from graph theory. The best performance of their experiment achieved 99.28% sensitivity for a 15-minute pre-ictal period, 99.35% sensitivity for a 30-minute pre-ictal period, 99.63% sensitivity with a 60-minute pre-ictal period, and 99.84% sensitivity with a 120-minute pre-ictal period. However, feature engineering needed for these results was very complex.

2.5.3 EEG Feature Classification

The primary goal of this research is to focus on accurate identification of patient status, if patients experience seizure or not, and then make caregivers aware, take appropriate action and medication on time and help patients. Previous works on seizure detection can be categorized as a binary classification (normal vs. ictal) problem and ternary class (normal vs. interictal vs. ictal) problem.

We can also look at the published work related to EEG-based epileptic seizure detection from a classification perspective and used datasets. Based on the University of Bon’s dataset, most of the studies on diagnosis of seizure are binary classification systems (normal vs. ictal).

Classifications are built on patterns of EEG signal taken from epileptic patients during experiencing active seizures (set E) and the normal EEG signals taken from healthy subjects (set A) or any other normal and non-seizure brain activities class like sets B, C and D.

The research, done by Nikolaou et al. [NIC12] focused on entropy-based features for classification of A-E cases and ABCD-E. The accuracy of 93.55% and 86.1% were respectively attained. The authors in [ULL16] considered an A-E class combination and then applied pyramidal one-dimensional convolution neural network (P-1D-CNN) to achieve an accuracy of 100% as a result.

In [SHO09], the (SVM) classifier was used to discriminate between seizure and non-seizure. They developed models with two post-processing steps to enhance the temporal precision and the robustness of the system on a large clinical data set of 267 hours of EEG data from 17 full-term newborns with seizures. They achieved an average detection rate of ~89% with one false seizure detection per hour. Gandhi et al., [GAN11] applied a probabilistic neural network (PNN) in combination with SVM on class combination of ABCD-E to achieved accuracy of 95.44%.

EEG cross-correlation coefficients [SUR09] were used to extract three statistical features which the authors fed into the support vector machine (SVM). They yielded an average accuracy of 95.96% to identify seizure. Similar research was completed by Nicoletta et al. [NIC12]. They used entropy to extract feature from EEG signals then applied SVM to distinguish healthy and ictal EEG epochs with an accuracy of 93.80% for binary classification.

Three-class EEG classification is another seizure detection problem type which separates normal EEGs taken from healthy subjects, Inter-ictal EEGs taken from epileptic patients throughout seizure-free intervals, and Ictal EEGs recorded from epileptic patients while experiencing active seizures. This kind of classification (ternary classification) problem is more sophisticated compared to previous (binary) classification problem. This type of classification considers the EEG recordings from C and D sets as separate third of class - Inter-ictal- to identify alternation of EEG patterns to predict occurrence of seizure. This classification problem is also involved in topology of seizure occurrence in the brain, which could be significant in terms of automated seizure detection.

Numerous research and different methods have been used in this category of seizure detection problems. Next, I list a few recent research works done on the same dataset which I used for this research as it relates to my approach for classification.

Acharya et al. [ARC12a] studied the normal, interictal, and ictal activities in EEGs. They decomposed the dataset from Bonn University into wavelet coefficients by applying Wavelet Packet Decomposition (WPD) and used eigen values from the resultant wavelet coefficients using Principal Component Analysis (PCA). By testing different supervised classifiers, they obtained 99% classification accuracy using the Gaussian Mixture Model (GMM) classifier.

Other work [RAJ12] developed a model for the automatic detection of normal, pre-ictal, and ictal conditions. Entropy features like Approximate Entropy (ApEn), Sample Entropy (SampEn), Phase Entropy 1 (S1), and Phase Entropy 2 (S2) were extracted then fed into different classifiers including Fuzzy Sugeno Classifier (FSC), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Probabilistic Neural Network (PNN), Decision Tree (DT), Gaussian Mixture Model (GMM), and Naive Bayes Classifier (NBC). They achieved highest accuracy of 98.1% by Fuzzy classifier.

N. Ilakiyaselvan et al. in [ILA2020] used reconstructed phase space (RPS) representation of the signal to deal with seizure detection as a binary classification (normal *vs*. ictal) problem and ternary class (normal *vs*. interictal *vs*. ictal) problem. While the university of Bonn dataset contains 4097 samples, they used segments of 510 samples to build their models. Their classification accuracy of the model for the binary classes was (98.5±1.5) % and (95±2) % for the ternary classes.

Similar research was done by Ubeyli who achieved an accuracy of 99.30% classification. They implemented multiclass support vector machine (SVM) and trained on the extracted features through eigenvector methods [ELF20]. In addition, Ramy Hussain et al., also develop a ConvLSTM Network to achieve 100% classification accuracy and 100% specificity for three-class EEG classification problems by using segments of 2048 samples from the University of Bonn dataset to build their models [HUS19].

Chapter 3

Data and Methods

This chapter discusses the empirical dataset that has been used for this study. It then describes the methodology which is proposed to detect the occurrence of seizures.

3.1 Computer-aided analysis system

The role that the EEG signals play in an accurate diagnosis of abnormalities and neurological disorders is becoming more and more crucial for specialists and physicians. While EEG signals are used for diagnosis of many mental and brain neuro-degenerative diseases such as dementia, Alzheimer, Parkinson's, migraine, sleep disorders and traumatic disorders of the nervous system (e.g., brain trauma, autism, etc.), the main application of EEG signal is for epilepsy. Since EEG data contains a large amount of information which varies from patient to patient, its analysis is time consuming. A computer-aided analysis system not only facilitates diagnosis expediently, it also makes the procedure an automatic neurophysiological assessment for accurate detection of abnormalities from EEG signals.

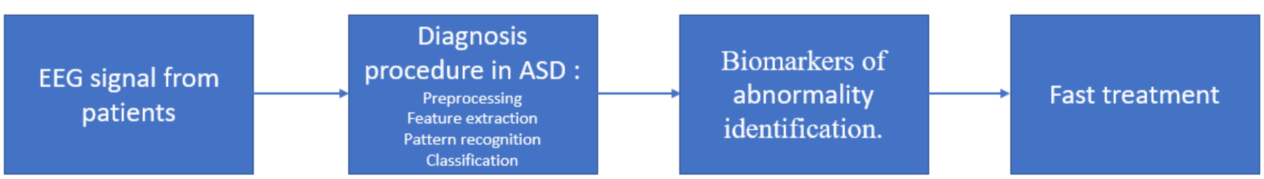

Figure 3-1.The procedure of automated seizure detection (ASD)

This thesis postulates a computer-aided analysis system that automate EEG-based seizure diagnosis as depicted in Figures 3-1. It demonstrates the required stages of diagnosis. At the beginning, the acquisition of the EEG signal from the patient is done by a clinician. Then the pre-processing stage is required. It includes removing noise that will diminish the complexity and computation time of algorithms and enhance the functioning of the classifier and the efficiency of feature extraction as biomarkers of disease identification. Then depending on the classification algorithm, specific feature extraction is required. After building the model based on the extracted features, the system can recognize the pattern of occurring seizure as seizure biomarkers. As a result, a fast and efficient treatment can be used for epileptic patients.

3.2 Dataset

The seizure detection experiments done in this dissertation is based on the benchmark clinical EEG dataset provided by Bonn University, Department of Epileptology, Germany, [AND01]. This is an open-source and widely used epileptic EEG dataset for epileptic seizure detection research.

It consists of EEG data from five different sets denoted as A, B, C, D, and E. Each set includes 100 single-channel EEG recoding signals recorded from a single subject separately for 23.6 seconds by using the standard 10-20 placement system for EEG electrode placement [AND01] for data acquisition.

Sets A and B contain normal EEG signals recorded from five healthy subjects who were awake and relaxed. Set A recorded EEG signals of the brain from the subjects whose eyes were open and Set B recorded signals when the patients' eyes were closed. Sets C, D and E were taken from five epileptic patients. EEG signals in set C are related to seizure-free intervals and recorded with electrodes placed in the brain epileptogenic zone, while set D signals are recorded from the hippocampal formation of the opposite hemisphere of the brain in seizure-free period. Set E captured EEG signals from five epileptic patients while experiencing active seizures. Sample EEG signals of five EEG classes are shown in Figure 3-2.

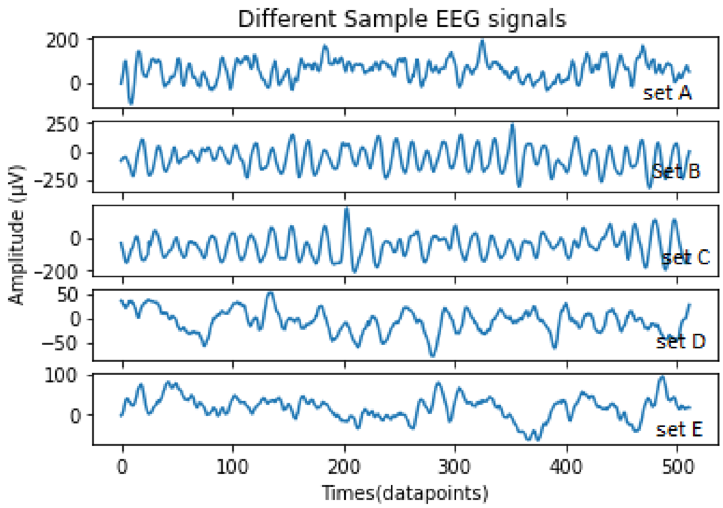

Figure 3-2. Sample EEG signals of five EEG classes

The detailed dataset is shown in Appendix A, Table 1.

3.2.1 Raw Data Preprocessing

Each EEG signals provided by the Bonn Dataset had been sampled at a rate of 173.6 Hz and then digitized by using a 12-bit analog-to-digital converter. All EEG used the same 128-channel amplifier system that fed into a band-pass filter with cut-off frequencies of 0.53Hz and 40Hz to remove artefacts from the EEG data. Datasets under this study encompass 500 EEG signals and each one is the recording of electrical activities of subjects for 23.6 second and the total number of data points in each EEG signal, d, is equal to 4096.

Each recording data includes 4096 data points, which I divide into segments of different length of datapoints from 1 to 4096, to not only generate many instances from one record but also to find the efficient length of recording to attain the highest accuracy in seizure classification. These segments form the basis for all further processing.

The EEG segmentation, particularly in this study, could resolve the need for a large number of labeled data samples to build a valid model. It is quite challenging to obtain sufficient well-labeled data for training deep neural networks in real-life applications, particularly for cases like seizures. Data segmentation aids deep neural networks to access more training samples while it also improves the performance of the deep learning network in the experiments. Moreover, segmentation facilitates the process of finding the dependencies between consecutive EEG data-points in each EEG channel signal. Since EEG recordings are non-stationary signals which don't have any stable statistical features over time. The EEG segmentation slides a signal recording into several segments with common temporal and spectral features. The different size of segmentation in this study experiments demonstrate which length is the most optimal length to capture the features efficiently.

3.3 EEG Classification

An efficient classification technique helps to distinguish EEG segments and reach a greater understanding of cognitive processes in the decision making of a person's health. The main step is to determine how to represent and classify the elaborated raw EEG signals for further analysis. For this purpose, the optimal segmentation is required to extract useful features from raw EEG data and then do the classification based on the extracted features. Usually, classification refers to an algorithm procedure for dedicating a given piece of input data into one of the given numbers of categories. The main purpose of classification is to assign class or labels to observation of the dataset based on the found and extracted features and in a specific problem.

The classification algorithm (classifier) maps input data to a category with help of training sets. The classifier learns how to identify the class correctly. This study focusses on analysis of EEG signal recordings. Measuring brain signals through EEG recording allows us to obtain collection of relevant properties of the brain signals from a large amount of data. In the classification realm, there are also two types of classification: supervised classification and unsupervised classification. In supervised classification, observations or set of data are labeled to relating class labels. In unsupervised classification, observations are not labelled or assigned to a known class.

Supervised classification is the most common approach in biomedical research, and this is the approach that has been used in this study. Supervised classification is done on a set of training dataset, consisting of a set of instances, which have been labelled with the correct output.

There are pairs of samples in the given training dataset that can be expressed as D = $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$. $x_1, x_2, \ldots, x_n$ are the observations and $y_1, y_2, \ldots, y_n$ are the class labels of the observations. The aim of classification is to find the accurate transformation between the feature space X and the class label space Y, i.e. f: X → Y. The class space has a finite number of elements, i.e. y ∈ {1, 2,…, K}. For example, in the binary classification, there are two classes that refers to the target and non-target classes. These classes are shown as Y = {0, +1}. For ternary classification, there are three classes, they are shown as Y = {0, +1 ,+2}.

3.4 Artificial Neural Networks Approach

Artificial Neural Networks (ANNs) are a learning-based algorithm, inspired by the anatomy of the brain and its learning procedures. Figure 3-3 depicts the similarities between the real (left) and the artificial (right) neurons. The artificial neuron constitutes a basic computational unit. The real, or biological, neuron gets information from axon terminals through dendrites from several other neurons. After processing, the neuron will pass the output through its axon terminals into other neurons. In fact, the structure of a synapse permits a signal to be passed between neurons. In the artificial neural model, the data received from other neurons are called the inputs (e.g. x) and the synapses are considered with the weights in ANNs (e.g. w). All the information received by one neuron can then be considered into one value by using equation 3-1.

$$n = \sum_t (w_t x + b) \qquad \text{Equation 3-1}$$

b is a constant and intrinsic to each neuron, called bias. Then the value of n is then the argument of the below function in Equation 3-2.

$$a = f(n) \qquad \text{Equation 3-2}$$

To produce a, the output of the neuron. The function f is also intrinsic to each neuron, called the activation function. and it can take many forms. Sigmoid , relu and Softmax are some of the widely used activation functions.

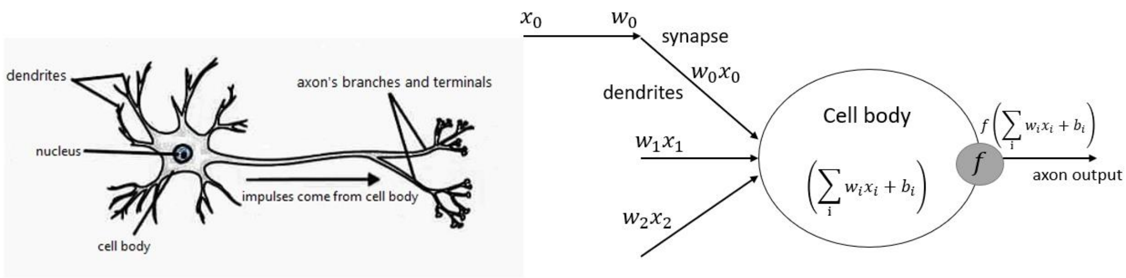

Figure 3-3. Biological neuron(left), Artificial neuron(right) [SEP97]

3.4.1 Deep Neural Networks

Deep learning Models use artificial neural networks (ANNs) that derive from perceptron's model inspired by the brain and its processes. As discussed in Section 2.5.2, there are several types of ANNs, from which CNNs and RNNs, can be highlighted. All of them have some common principles.

Neurons can be stacked to form one layer of neurons in the neural network and the deep neural network embraces multiple layers of neurons. The most principal architecture of neural networks follows the architecture shown in Figure 3-4.

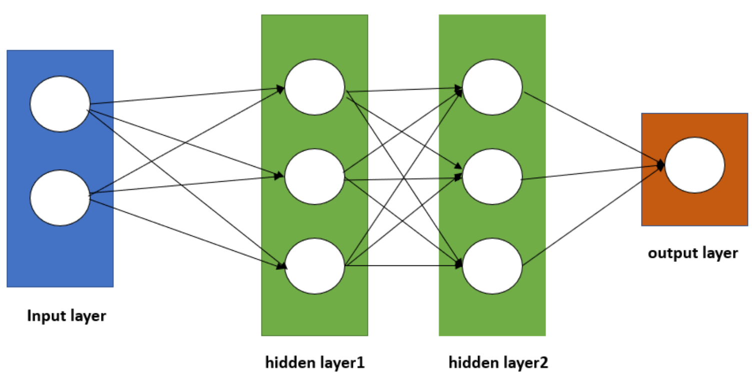

Figure 3-4. Architecture of neural network

In every ANNs, there is an input layer (blue), the middle layers (green) are called the hidden layers and the last layer (red) is the output layer that produces the final output of the network. An array p ∈ R_d is considered as an input, where d is the number of inputs (features). Formally, each layer j can be described by the following parameters.

- $w^j \in R^{s*r}$, where **s** is the number of neurons of the present layer and **r** is the number of neurons of the previous layer.
- W is the weight related to each neuron in each row.
- $b^j \in R^s$contains the bias
- f^j is the activation function.

Equation at layer j is:

$$a^j = f^j(\sum(w^{j-1}p + b^j\ \ ) = f^j(n^j) \qquad \text{, if j =1} \qquad \text{Equation 3-3}$$

$$a^j = f^j(\sum(w^{j-1}a^{j-1} + b^j) = f^j(n^j) \quad \text{, if j >1} \qquad \text{Equation 3-4}$$

Artificial Neural networks can be used for both regression and classification problems. In order to adjust the neural networks for classification problems, the number of neurons of the output layers has to be equal to the number of classes in the defined problem, therefore, each class is coordinated to one output neuron. In this study the adjustment has been set for binary and ternary classification. We can build classifiers by analyzing the outputs of the algorithm for a single pattern and values of outputs. The value of each output is significantly dependent on the activation function. In this dissertation, the SoftMax is proposed to be used. The value of an output neuron is the probability of a given pattern belonging to the class associated with it, this is why different activation functions are usually used in the context of classification such as sigmoid and Softmax .The Softmax function is shown by the equation of 3.5

$$\sigma(n)_j = \frac{e^{n_j}}{\Sigma_{j=1}^{k} \mathrm{e}^{n_k}} \qquad \text{Equation 3-5}$$

- For j=*1,...,*k and $n = (z_1, \dots, z_k) \in R^k$
- The Softmax function takes as input a vector z of K real numbers and normalizes it into a probability distribution consisting of K probabilities proportional to the exponentials of the input numbers. After applying Softmax, each component will be in the interval [0,1], and the components will add up to 1, so that they are considered as probabilities.
- Where $\sigma(n)_j$ is the probability of a pattern assigned to the class related with output neuron j, and K is the number of output neurons (classes).
- Softmax function $\sigma = R^k \to [0,1]^k$
- it applies the standard exponential function(e^{n_j}) to each element $n_j$of the input vector n and normalizes these values by dividing by the sum of all these exponentials; this normalization ensures that the sum of the components of the output vector is 1

3.4.2 Recurrent Neural Networks

Humans do not start their thinking and reasoning from scratch. It is usually based on previous experience and understanding. The whole concept behind deep learning is to try and mimic the human brain and to achieve a similar kind of function as the human brain by using different implementations of ANN and CNN. The main advantage of Neural Network is that the Neural Network (NN) with neurons connecting to themselves through time can learn from prior experience through epochs in extremely valuable and optimal way.

Although the results obtained in seizure detection by using such artificial neural methods have been promising, there is still some space for improvements. CNN-base models are looking for and learning the same pattern over the EEG signals obtained from different patients. However, the signature of the epileptic seizure varies across different patients and even for the same patient over time. A solution might be proposed to capture these features. But traditional neural network cannot satisfy this requirement, especially if we consider the recording of EEG signals for seizure detection. Because in order to understand what is going on currently, we need to know what happened at a previous point in the EEG recording, then decide and predict what is happening next at that point in the EEG recording. Based on the variation of EEG signal during time, we would be able to train our model and then predict if the seizure would happen or not. Recurrent neural network smooths this issue and enables the information flow to persist through networks by loops.

Recurrent Neural Networks (RNNs) are a subclass of Artificial Neural Networks with embedded loops in their architecture, as shown in Figure 3-5. This is the main reason that makes this algorithm suitable for sequential data, like the time series. The inner loops are able to pass information from one pattern to another pattern to learn temporal dependencies. The original version of RNN is called vanilla and is depicted with Equations 3-6 and 3-7. This network takes advantage of state h at each timestep t, and is a function of the current inputs x_t, the state from previous time step, h_{t-1}, along with weight matrices w and U. The algorithm can compute the output at any given time step with Equations 3-6 and 3-7.

$$h_t = f(wh_{t-1} + U_{x_t}) \qquad \text{Equation 3-6}$$

$$a_t = f(Vh_t) \qquad \text{Equation 3-7}$$

V is the weight matrix associated with the state h when computing the output. As seen in Equation 3-**7**.

The unrolled RNN in time looks like an ANN with many layers, while weights are shared across layers for the RNNs. In other words, recurrent neural network is not much different from normal neural network. It multiplies the same network, each network passing a message to their successor network. RNNs are cyclic directed graphs like that of Figure 3-5 which considers the present input and also past output to make decisions.

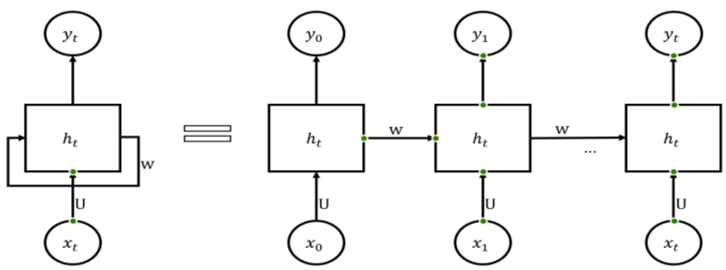

Figure 3-5. Architecture of a Recurrent Neural Network it shows a module is repeated and applied to the past outputs and present inputs

Past information is held in the network's hidden state (h_{t-1}), obtained by Equation 3-8

$$h_t = f(wh_{t-1} + U_{x_t}) \qquad \text{Equation 3-8}$$

Thus, h_t is a function of the current input, x_t, and of the previous hidden state, h_{t-1}, multiplied by weight matrices (w and U). The weight matrices determine how important the present and past states are, and they are applied to minimize the error by using an algorithm called Back Propagation Through Time (BPTT). BPTT is the application of the backpropagation training and supervised learning algorithm to recurrent neural network applied to sequence data like a time series. The general procedure of algorithm works on unrolling all input timesteps. In each time, a sequence of timesteps of input, one copy of the network, and one output are presented. Then, errors are calculated and accumulated for each time, The network is rolled back up and update the weights.

The mapping function, f, can be considered the logistic function, control gradients by BPTT. Since it calculates the errors for each time step, accumulating them. The update of the weights is done at the end, given w and U throughout the network. This process is repeated until the error is minimized. BPTT becomes slow when input sequences are comprised of thousands of timesteps, due to the hidden unit per time step and the same number of updates for each weight update. Sometimes, a high number of time steps is necessary for longer persistence in memory, and it may make the network very computationally expensive which is problematic which can lead the weights to vanish or explode, and make a slow learning and the model inefficient.

3.4.3 Vanishing Gradient Problem

In each timestep, the error is back propagated across all previous layers until the first layer. The act of back propagating from layer to layer refer to the multiplication of the derivatives of the activation functions of each layer. If we consider the sigmoid function as one common activation function, given by Equation 3-9.

$$\sigma(x) = \frac{1}{1+e^{-x}} \qquad \text{Equation 3-9}$$

The maximum value of the derivate of the sigmoid function occurs at 0.25, $F'(net) = 0.25$. Since the weights become updated by contribution of the weights located n time steps behind is proportional to $\left(\frac{d\sigma}{dx}\right)^n$ with the assumption that the sigmoid function is used in each layer and

$\max\left(\frac{d\sigma}{dx}\right)$= 0.25, we can conclude that the contribution from previous layers to update weights approaches zero as we go deeper in the neural network.

The derivative feature of this function in the process of updating weights in order to decrease error leads the output we expect from each cell to be different from what is achieved from the algorithm. Because every time the error and weight of neurons are multiplied and updated by this value, the resulting gradient will become smaller value every time. Therefore, the result of the update diverges from the actual result. This is called the Vanishing Gradient Problem [HOR98].

3.4.4 Long Short-Term Memory (LSTM)

As earlier discussed, the advantage of RRNs over other neural networks is that they can connect previous information to predict what is going on at a current point. This is done by learning or training neurons from reading and learning from previous data in the time series data. Traditional RRNs lead to a gap, between the needed information and the current task, which may grow, therefore RNNs become inefficient. Since the RNN is designed in a way that consider long term dependencies, we need more intelligent algorithm similar to human reasoning. If we aim to simulate neural networks to the human brain, it needs to take advantage of intelligence can pick appropriate parameters and relevant information for reasoning and addressing the problems carefully. In other words, some level of intelligence is needed to identify how much old information is needed to predict the current task.

Particular to times series data, the algorithm receives large amount of information as sequence of timesteps; but not all information may play a critical role in improving the efficiency of the algorithm in consecutive epochs. Therefore, by removing some part of the data from previous epochs the neurons would get valid and enough required information to learn. RRN cannot remove impractical data from data automatically. It just tries to adjust a small weight for them to diminish their contribution in building the model. Thus, neurons cannot adjust their contribution in the output result correctly. This method is computationally costly and might diminish the efficiency of the algorithm for learning. However, a solution to this problem is the Long Short-Term Memory (LSTM) architecture.

LSTM is an architecture with different cells that have the ability to remove or add information from previous cells to the current cell and adjust their contributions in the calculation for the result.

Sepp Hochreiter and J¨urgen Schmidhuber [SEP97] proposed an innovative and different RNN architecture capable of learning long-term dependencies to overcome the above mentioned problems. Figures 3-6 and 3-7 show the difference between traditional RNN and LSTM architectures. Figure 3.6 depicts traditional RNNs. As illustrated, the state $h_t$is a function of the previous state, h_{t-1}, and the current inputs like x_t.

The architecture of the Long Short-Term Memory (LSTM) is shown in Figure 3-6. The LSTM network is a modified version of RNN to avoid the long-term dependency. Similar to the recurrent neural network, the LSTM network is built based on the repetition of a chain of modules. LSTMs exploit more sophisticated modules through the same repetitive structure.

LSTM's architecture, with different cells, has the ability to remove or add information from previous cells to the current cell. Each LSTM unit has four layers: a memory cell, an input gate, an output gate and a forget gate, displayed in Figure 3-6, and listed by Equations 3-10 to 3-15.

The main difference between LSTM and RNN is that instead of just one type of state h_t passing information from one timestep to another, now there is another type of state named the cell state Ct. The cell state allows information to just flow along without changes, acting like a conveyor belt, if needed. It is also equipped with different gates which enable the neurons to decide how to use the data coming from previous neurons or just ignore them and even how much of that information is needed to be kept for improving efficiency of the algorithm. In this way, information can be removed or added to the cell state by means of structures called gates.

The LSTMs are represented mathematically, by Equations 3-10 to 3-15, which are explained below. The operator ◦ represents point-wise multiplication.

Regarding the computation of the cell state, there are two equations. The first one is responsible for removing information from the cell state, and the second one is responsible for adding information.

$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ // forget gate Equation 3-10

$i_t = \sigma(w_i . [h_{t-1}, x_t] + b_i)$ // input gate Equation 3-11

$\tilde{C}_t = tanh(Wc\, . [h_{t-1,} x_t] + b_c)$ // output gate Equation 3-12

$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t$ // cell Equation 3-13

$O_t = \sigma(w_0 . h_{t-1} x_t + b_0)$ //LSTM output Equation 3-14

$h_t = O_t{}^{\circ} \tanh(c_t)$ // FC layer Equation 3-15

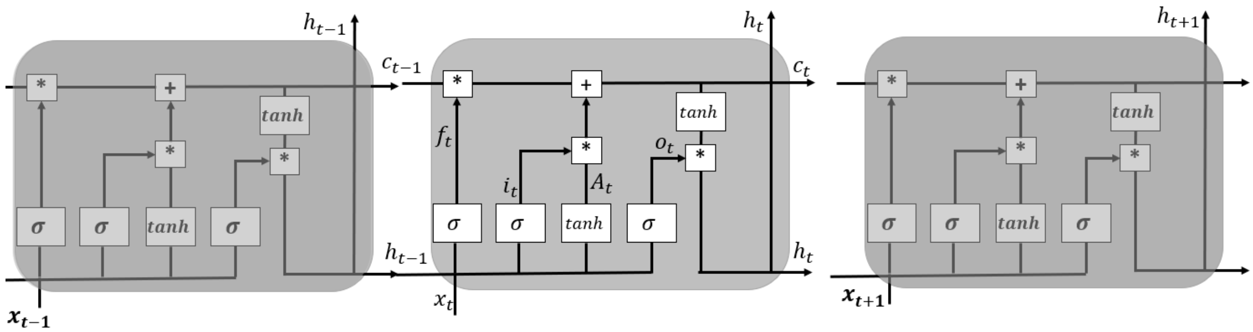

Figure 3-6. Representation of the repeating module in an LSTM

The cell state carries the flow of information through the network with the cell state being changed in each unit by its layers.

The forget gate decides how much of the previous hidden state, h_{t-1}has to be kept based on to $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$, which is also a function of the current input x_t. The activation function (e.g. sigmoid) could result in 0 and 1, with 1 meaning that all the information from the previous hidden state is kept.

The input gate performs an analogous decision, given by $i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$.

Concurrently, a vector of candidate values is added to the cell state, based on $\tilde{C}_t = tanh(Wc\, [h_{t-1,} x_t] + b_c)$. A hyperbolic tangent function is applied in this step, it has the same application as the sigmoid in the previous ones.

The cell state is then updated using $C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t$.

The output of each unit is given by the multiplication of the value at the output gate, calculated through $O_t = \sigma(w_0 h_{t-1} x_t + b_0)$ and the result of the application of the hyperbolic tangent to the previously calculated cell state. The resulting formula is $h_t = O_t \circ \tanh(c_t)$.

This output may exist for every unit. The network could be one to many or many to many. However, it is possible to have outputs for some units or just for one of them, depending on if the mapping is one to one or many to one. Having said that, there are variants of LSTM, such as the peephole LSTMs or different LSTMs architectures, which use a couple of forget and input gates.

3.4.5 Long Short-Term Memory (LSTM) For Classification

LSTM, like any other Deep Neural Networks, use the stochastic gradient descent optimization algorithm to be trained. Stochastic Gradient Descent (SGD) is an iterative optimization method for objective functions with suitable smoothness properties (e.g. differentiable or subdifferentiable). It is widely used in high-dimensional optimization problems because it reduces the computational burden by achieving faster iterations in trade for a lower convergence rate.

The optimization algorithm estimates the error for the current state of the model repeatedly. This requires the right choice of an error function, generally called a loss function, that can be used to estimate the loss of the model so that the weights can be updated to reduce the loss on the next evaluation or iteration.

Neural network models learn through mapping inputs to outputs in training sets (examples). The loss function must be matched with the framework of the predictive modeling problems which could be classification or regression. Further, the output layer also has to be appropriate for the chosen loss function.

3.4.5.1 Many To One Classification Model

This implementation is dealing with long-term EEG recordings which include sequence of timesteps as inputs. Finite sequence length from the data must be defined. At any timestep, t, we only back propagate the defined length through the sequence. This thesis considers different lengths of time from 1 to 4096 datapoint in 23.6 seconds for the sequence and assess the performance of the experiments. Figure 3-7 demonstrate the how sequence of the datapoints can be used to classification problems.

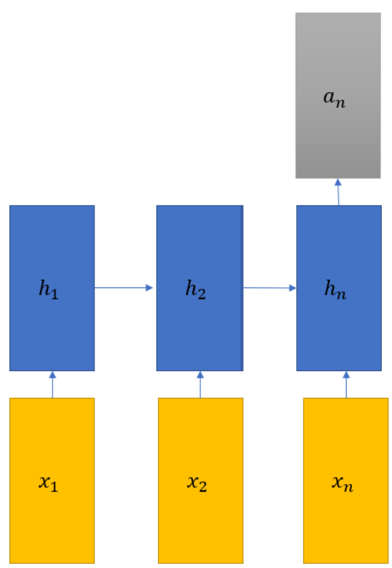

Figure 3-7. Many to one classification in ANN architecture

Figure 3-7 illustrates high level sequential classification. The top gray rectangle as output, the bottom yellow rectangles as representation of sequential input and the middle blue rectangles are states of network during training in different time steps are depicted.

In fact multi-class classifications are sub predictive modeling problems with more than two classes where each example can be as assigned as one class. The problem is often built as predicting an integer value, each unique integer value from 0 to (num_classes – 1) is assigned to a class. The problem is often implemented to predict the probability of the example belonging to each known class.

The loss functions that are appropriate for multi-class classification predictive modeling problems is cross entropy, which will be discussed in section 3.4.5.2.

This research applied deep learning to extract the discriminative EEG characteristics regarding to epileptic seizures. The proposed deep neural network includes 5 layers, including a Softmax layer. The EEG training sets were first fed into a LSTM layer with 100 cells to learn the short and long-term dependencies embedded in the EEG segment as input and between the different EEG signals belonging to the same and different signal recordings. Since the main job of LSTMs is to remember information for long periods of time(long sequence of datapoint), it is the best choice for processing long-term EEG signals. This is the main competitive advantage of the LSTM architecture over other neural network architectures.

3.4.5.2 Loss Function

The loss function is used to measure the performance of the model during training on a deep learning problem. Its objective is always to minimize the loss, the function in fact minimizes the calculated error during the training. Its output is a probability value between 0 and 1. The lower the probability the better model we have. Its value is given by Equation 3-16

$$L = \sum_{i=1}^{N} \frac{1}{N} log(\hat{y}_i) \qquad \text{Equation 3-16}$$

where N is the number of samples and $\hat{y}_i$ is the probability, given by the network, that sample i belongs to its true class.

Since this application is a classification problem, I used the most important loss function called Cross-Entropy Loss. Cross-Entropy Loss is the loss function used for multi-class classification problems. Cross-entropy Loss increases as the predicted probability diverges from the actual label. where the output values are in the set {0, 1, 3, …, n}, and where each unique integer value is a representative class. Mathematically, it is the preferred loss function under the inference framework of maximum likelihood. Cross-Entropy assesses a score to summarize the average difference between the actual and predicted probability distributions for all classes in the problem. The score is minimized, and a perfect cross-entropy value is 0. Cross-entropy can be considered as the loss function in the Keras library which is used for LSTM implementation

3.4.5.3 Labelling

We considered seizure prediction as a two-class problem and as a three-class problem. In the two-class problem, every sample in a certain period preceding a seizure, called the Seizure

Occurrence Period (SOP), was labelled as pre-ictal while all the other samples are labelled as ictal which includes all the samples that belong to the interictal, ictal and postictal states. In the three-class problem, data are labeled pre-ictal, interictal and ictal.

3.4.5.4 Overfitting Control

The method which is used to avoid overfitting in this model is dropout. Dropout is an approach to reduce overfitting and regularization. Some neurons, in layers during training, are randomly ignored. In other words, each neuron has a probability of not being used for the output computation, having no contribution during the back propagation of the errors. It looks like a layer with a different number of nodes and connectivity to the prior layer. Since the weights are shared between the different architectures, they become regularized.

3.4.5.5 Optimizer

Adaptive Moment Estimation (Adam) was the optimization algorithm used to update the networks weights at each iteration. Adam is a method that computes adaptive learning rates for each parameter. It stores an exponentially decaying average of past gradients (first moment), and an exponentially decaying average of past squared gradients (second moment).

3.4.5.6 Fully Connected Layers

In fully connected layers, the last year responsible for preparing the processed data to produce the output is the Softmax layer. This layer can deal with all information from previous layers. Neurons in fully connected layers have connections to all the neurons from the previous layer, behaving like traditional multi-layer perceptron. The final layer must have the same number of units as the classes in the output, so for example the algorithm for binary classification would have 2 units in its last layer. In a binary case, the logistic function can be used to yield the probability of each class. The Softmax, a generalization of the Logistic function, is used in the last layer to perform multi-class classification.

3.4.6 High Level Implementation and Configuration of the Network

Figure 3-8 shows the high-level process of the proposed seizure detection system. At the beginning, each time-series EEG recoding is first split into smaller non-overlapping segments. These segments are then passed into the LSTM layers. The output of LSTM layers $\boldsymbol{y_i}$ is then fed into the fully connected Dense layer $\boldsymbol{h}$ to find the most prominent EEG features related to epileptic seizures. Finally, the Softmax layer completes the label predictions according to the features found in the previous layers.

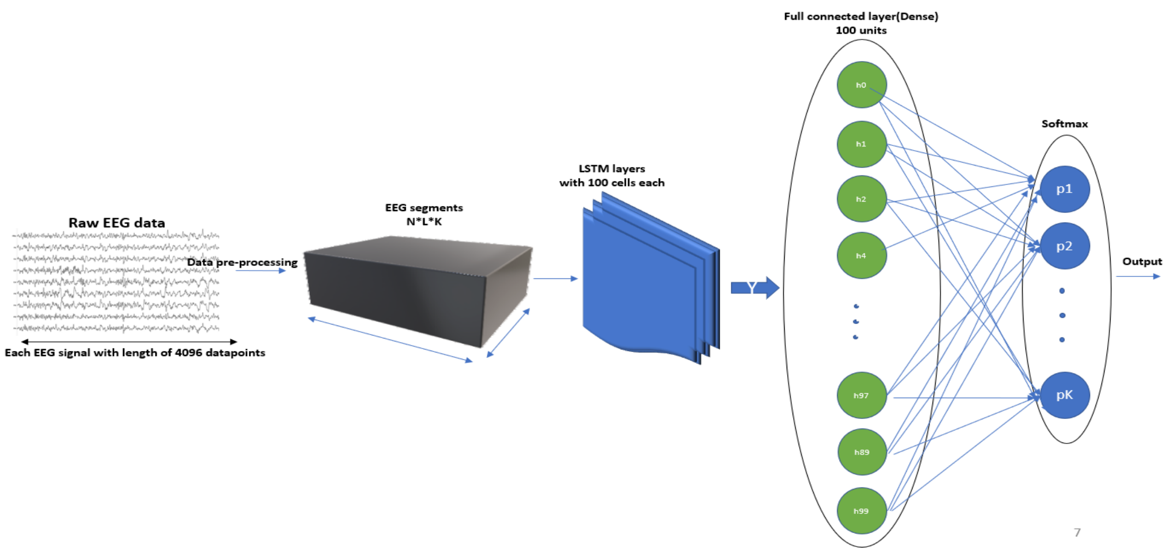

Figure 3-8. High level diagram of the proposed approach for seizure detection system

LSTM experiments on the EEG feature learning are conducted with the open-source library Keras. Keras is an open-source software library that provide a Python interface for artificial neural networks.

The total numbers of layers, including the number of LSTM cells and FC units were set to 3 layers containing 100 nodes and 100 units respectively. An FC unit is the fully connected layer placed after the LSTM layers. The “return sequence” was set to “True” so that all EEG segments are considered in the feature extraction process. The batch sizes were set to 64 and the network parameters converged after approximately 2000 iterations with 40 epochs. The implementation was derived in Python using Keras backend and underwent 4 hours training on an Intel(R)i7-8565U CPU@1.6HZ machine. Although the training of our end-to-end neural network model takes up to four hours, testing the trained model on new data takes less than a second. This fast-testing performance makes our model a perfect fit for the real-time processing of EEG signals in real-life and clinical applications.

Although very deep and complex neural network structures could be powerful enough to learn all the useful information required for detecting epileptic seizures, increasing the size of the network and introducing more parameters to capture would increase the risk of overfitting. To address the aforementioned issues, this study proposes a novel deep neural network architecture that uses LSTM cells from RNN to effectively exploit the temporal dependencies in time-series EEG signals along with dropout layers to resolve overfitting issues. A fully connected layer is used on top of the LSTM layer to capture the most prominent and discriminative EEG attributes associated with epileptic seizures. the pseudocode of the algorithm is described next.

Algorithm: Seizure Detection using Deep neural network (Long-Short-Term Memory).

Input: x→EEG signals;
Output: Trained LSTM model with optimal accuracy

Initialization: *d* 4096; *M* 2048;

Data preprocessing
K number of EEG classes; *K* = 2 *and* 3, for two-class, three-class, and detection problems.
EEG segment length change from $L \in \{2^0, 2^1, 2^2, , \cdots, 2^{12}$ *}and partitioning into segments*;
Procedure LSTM(**x**, K, LSTM)
while *t >M* **do**
$\boldsymbol{f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)}$ // forget gate
$\boldsymbol{i_t = \sigma(w_i. [h_{t-1}, x_t] + b_i)}$ // input gate
$\boldsymbol{\widetilde{C}_t = tanh(Wc\,. [h_{t-1,} x_t] + b_c)}$ // output gate
$\boldsymbol{C_t = f_{t^0} C_{t-1} + i_t \quad {}_0\, \widetilde{C}_t}$ // cell
$\boldsymbol{O_t = \sigma(w_0. h_{t-1} x_t + b_0)}$ // LSTM output
$\boldsymbol{h_t = O_{t^0}\, tanh(c_t)}$ //FC Layer
End
Compute *Pk* = *{P*1*, · · · , PK} //*softmax(**E**)
Find (max(*Pk*)) . class of highest probability
y˜ = Predicted class label

End

$\boldsymbol{x_t}$ and $\boldsymbol{y_t}$ *are* the LSTM input and output vectors respectively at time *t.* **σ**, **g**, and **h** are the point-wise activation functions. The logistic sigmoid **σ** (.) is used as the gate activation function and the hyperbolic tangent g(.) = h(.) = tanh(.) is used as the input and output activation function respectively. Denoted by the point-wise multiplication of two vectors $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$ are input and output vectors of the LSTM at time t. We then obtain the following weights for an LSTM layer:

- Input weights: $\boldsymbol{W_c}$, $\boldsymbol{W_i}$, $\boldsymbol{W_f}$, $\boldsymbol{W_o}$ ϵR
- Bias weights: $\boldsymbol{b_c}$, $\boldsymbol{b_i}$, $\boldsymbol{b_f}$, $\boldsymbol{b_o}$ ϵR

3.5 Summary

As previously described, EEG or Electroencephalography signals records the electrical activity of the brain neurons and is widely used to diagnose various brains problems. This data captured from the electrodes will be in time series form, and the signals can be classified into different classes related to occurrence of incidence. This thesis develop a Long Short-Term Memory network model (LSTM) for occurrences seizure based on the benchmark clinical EEG dataset provided by Bonn University. LSTM network model is a type of recurrent neural network that could to learn dependencies and then remember them over long sequences of input data. it is intended for use with data that is comprised of long sequences of data, up to 200 to 4000 time steps for different problems. This research performed different experiments described in Chapter 4 on different length of sequences of data on variant sets in the dataset to get highest accuracy of performance in order to automate the procedure of seizure detection.

Chapter 4

Performance Evaluation

In this Chapter, experimental results are reported. The same configuration of the LSTM algorithm with different sets for two classifications (binary and ternary) is implemented in Python. I use Python with different libraries including NumPy, Matplotlib, Pandas, Seaborn, Keras and Sklearn. .

In first part, the binary classification (normal vs. ictal) is implemented. Classifications are built on pattern of EEG signals taken from epileptic patients while experiencing active seizures (set E) and the normal EEG signals taken from healthy subjects (set A) or any other normal and non-seizure brain activities like sets B, C or D, which is considered as a different class combination.

In the second part, the three-class EEG classification is analyzed. It is another seizure detection problem type which separates normal EEG taken from healthy subjects, inter-ictal EEG taken from epileptic patients throughout seizure-free intervals, and ictal EEG recorded from epileptic patients while experiencing active seizures. This kind of classification problem is more sophisticated compared to the previous two-class problem. This type of classification considers the EEG sets C and D obtained from different epileptogenic brain zones, corresponding to the same class inter-ictal as separate class to identify alternation of EEG patterns. Since the EEG signals are recoded from different location of brain. This classification problem also involves localization and topology of seizure occurrence in the brain.

The performance of the proposed model is measured for each classification with a variety of different lengths of EEG signals. The experiments are organized to evaluate the performance of the LSTM algorithm and determine an optimal length of recording to achieve the highest performance accuracy.

4.1 Experimental System

All the experiments are performed on an ASUS ZenBook with a 2.53Ghz Inter Core i3 CPU, with 300 GB hard disk and 2.0GB of memory. The code is written in Python3.7 and run-on Windows 10 professional with 64-bit operating system.

4.2 Experimental Measurements

Experiments are conducted on the clinical dataset, described elaborately in Chapter 3. For this work, nineteen different combinations of classes were considered with different size segments for classifying them into being epileptic or non-epileptic. To evaluate the performance of the proposed LSTM based on deep learning approach, the performance was evaluated based on standard metrics like classification accuracy, sensitivity, specificity, precision, and F-score for all the binary and ternary classes as described below. Equation 4-1to 4-5 are their formulas

$$\text{Specificity(Spec)}= \frac{TN}{TN+FP} \qquad \text{Equation 4-1}$$

$$\text{Sensitivity(Sens)or Recall} = \frac{TP}{TP+FN} \qquad \text{Equation 4-2}$$

$$\text{Accuracy(Acc)}= \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Equation 4-3}$$

$$\text{Precision(Prec)}= \frac{TP}{TP+FP} \qquad \text{Equation 4-4}$$

$$\text{F Score}= \frac{2*Prec*Sens}{Prec+Sens} \qquad \text{Equation 4-5}$$

Here, TP refers to the number of predictions that are actually epileptic and predicted as epileptic class. FP indicates non-epileptic class predicted by the classifier as mistakenly epileptic. TN refers to actual non-epileptic class predicted as non-epileptic class while FN indicates epileptic and predicted wrongly as non-epileptic class.

First, the Tables 4-1 to 4-14 below show the classification Accuracy, Precision, and F1 score for 14 different binary class combinations. Likewise, in the second part, the performance of the model for ternary class combinations are presented in the Tables 4-15 to 4-19.

I analyze the performance of my proposed seizure detection approach under different segmentations and class combination conditions. The results are comparable to those of the other seizure detection methods that use the same dataset in [ILA2020], [HUS19] and [NIC12] .The detection performance was tested by using the metrics of sensitivity (Sens), specificity (Spec), classification accuracy (Acc), Precision (Prec) and fScore.

The experiments on the binary classification can be divided into two parts:

The first part of the two-class seizure detection problem is to distinguish between the normal EEGs obtained from healthy cases (sets A and B) and seizure EEGs recorded from epileptic patients while experiencing active seizures (set E). It refers to A-E (Table 4-1) and B-E experiments (Table 4-2) respectively. Furthermore, any non-seizure activities (Inter-ictal EEG sets C or set D and seizure activities (set E) are tested separately as well. Experiments on C-E, D-E sets are demonstrated on the Table 4-3 and Table 4-4 respectively.

In the second part of binary classification, any combination of classes related to non-seizure activities (sets A, B, C, or D) are considered for classifying the segments into being epileptic/non-epileptic conditions. It refers to experiments AB-E (Table 4-5), AC-E (Table 4-6), AD-E (Table 4-7), BC-E (Table 4-8), BD-E (Table 4-9), CD-E (Table 4-10), ABC-E (Table 4-11), ABD-E (Table 4-12), BCD-E (Table 4-14) and ACD-E (Table 4-14).

Taking this into account that each EEG set (A, B, C, D and D) comprises 100 signals, this classification approach has an imbalanced class distribution in the dataset. Since the number of EEG samples belonging to the seizure class(E) is significantly lower than the number of EEG samples of the non-seizure class.

The traditional machine learning approaches of seizure detection systems performed poorly for the imbalanced class distribution dataset, and they were inaccurate and prejudiced in the minority class. The proposed methods can decently handle this sort of classification troubles and overcome the imbalanced distribution in the dataset. Again, I assessed the performance in different terms of precision, fScore, and classification accuracy values. The seizure detection results achieved by the proposed are reported in the Tables 4-1 to 4-19. They provide evidence of improvement of the proposed approach over the state-of-the-art methods, by achieving and maintaining the topmost performance of over 98.00% for each of the precision, fscore, and classification accuracy in different length for each classification problems.

Table 4-1-Performance measures of binary class of A-E

A-E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	87.3	87.4	89.1	92.1	95.0	100	98.7	99.7	99.6	99.1	99.3	100	100
Precision *(%)*	75.7	74.8	78.2	90.2	90.1	100	97.6	99.3	99.3	99.3	98.7	100	100
F score *(%)*	87.3	87.2	78.2	92.1	95.1	100	98.8	99.6	99.6	94.4	99.3	100	100

Table 4-2-Performance measures of binary class B-E

B-E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	87.3	80.6	84.3	87.6	92.9	100	97.7	98.7	100	98.7	98.7	99.1	99.5
Precision *(%)*	74.7	61.2	68.5	75.2	85.9	100	95.6	97.5	100	97.7	97.5	97.2	98.2
F score *(%)*	87.3	80.6	84.2	87.6	92.9	100	97.8	98.7	100	98.8	98.7	98.6	98.6

Table 4-3-Performance measures of binary class C-E

C-E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	84.6	86.0	87.6	89.8	91.9	100	96.3	98.4	100	100	98.1	100	92.5
Precision *(%)*	69.3	72.0	75.3	80.0	83.7	100	95.7	96.8	100	100	96.2	100	91.8
F score *(%)*	84.6	86.0	87.6	90.0	91.8	100	96.3	98.4	100	100	98.1	100	94.9

Table 4-4-Performance measures of binary class of D-E

D-E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	82.1	84.2	84.3	87.6	88.9	100	93.2	96.1	100	96.2	95.6	93.7	97.5
Precision *(%)*	64.2	68.4	68.5	75.4	77.5	100	86.7	92.3	100	93.1	91.2	85.4	96.8
F score *(%)*	82.1	84.2	84.2	87.7	88.7	100	93.3	96.1	100	96.5	95.6	92.7	98.4

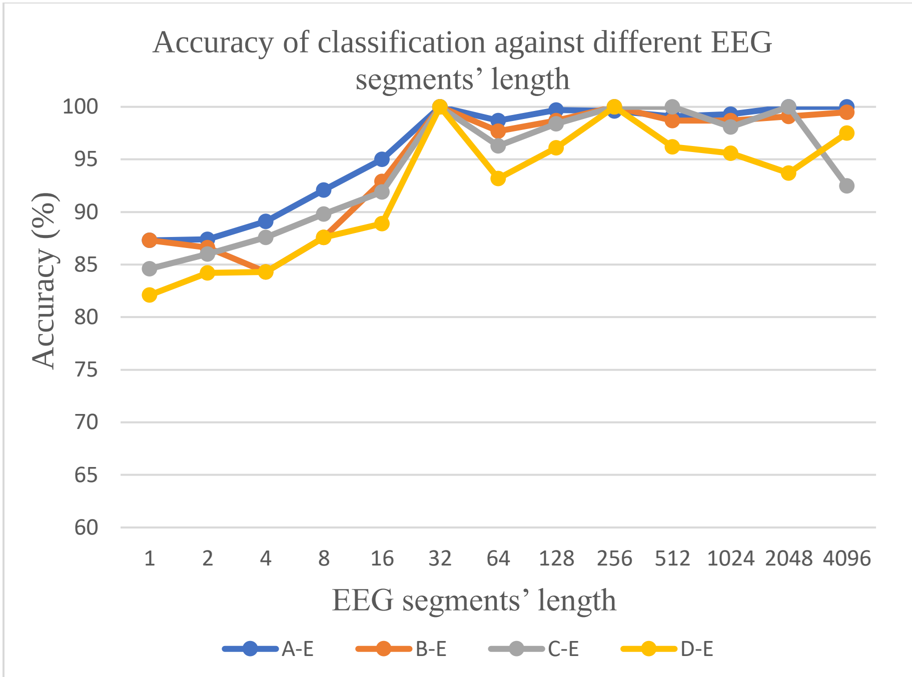

Figure 4-1. Accuracy Comparison of first part of binary classification in Seizure detection

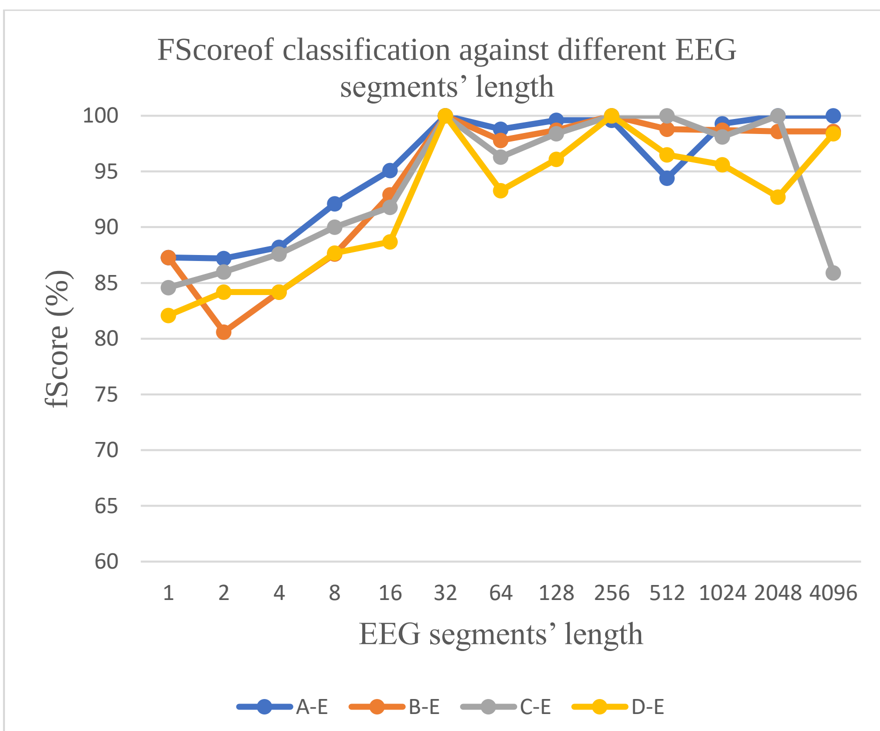

Figure 4-2. Fscore comparison of first part of binary classification in Seizure detection

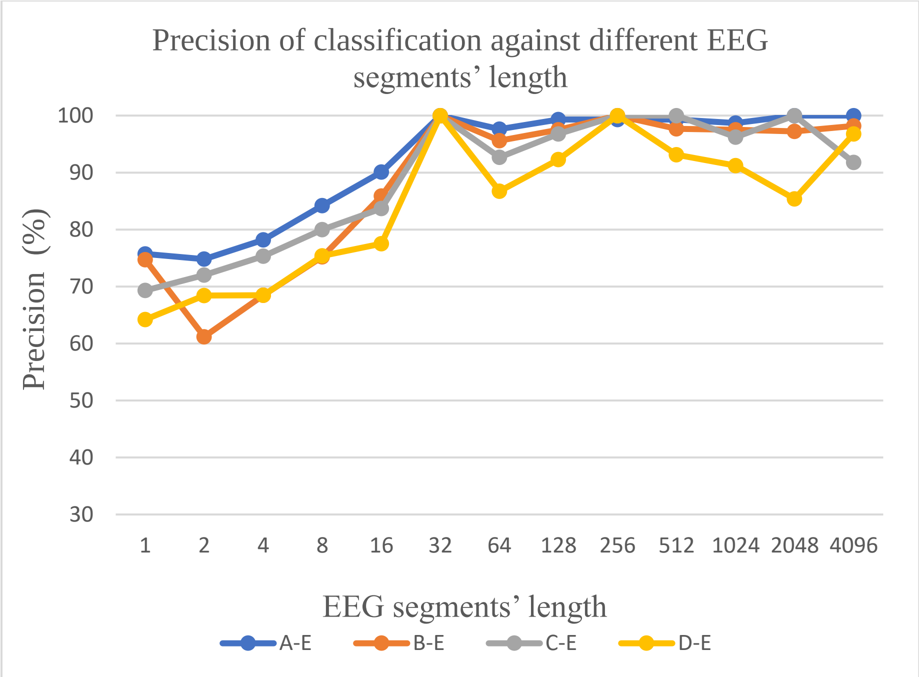

Figure 4-3. Precision comparison of first part of binary classification in Seizure detection

The Figure 4-1 to 4-3 and Tables 4-1 to 4-4 show the results for the first part of the binary experiments. The results achieved by the proposed method prove the model performs effectively on set A for seizure and non-seizure detection. However, when the lengths EEG signals are sliced into a segmentation with less than 32 datapoints (approximately less than 1 second of EEG recording) the accuracy and effectiveness of algorithm is diminished to almost 70. See Figure 4-1 to Figure 4-3 show this performance reduction.

Table 4-5-Performance measures of binary class of AB-E

AB - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	84.6	86.0	87.6	89.8	91.9	100	96.3	98.4	100	100	98.1	100	92.5
Precision *(%)*	69.3	72.0	75.3	80.0	83.7	100	92.7	96.8	100	100	96.2	100	91.8
F score *(%)*	84.6	86.0	87.6	90.0	91.8	100	96.3	98.4	100	100	98.1	100	85.9

Table 4-6-Performance measures of binary class AC-E

AC - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	87.1	89.1	90.1	90.5	94.3	95.9	98.0	98.5	99.1	98.9	99.5	97.5	97.5
Precision *(%)*	79.3	78.3	80.1	81.1	88.4	91.5	96.0	97.0	98.1	97.9	99.2	95.3	95.3
F score *(%)*	87.1	89.1	90.1	90.5	94.2	95.7	98.0	98.5	97.2	98.9	99.6	97.6	97.6

Table 4-7-Performance measures of binary class AD-E

AD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	87.3	88.3	89.4	90.6	92.3	93.9	96.1	97.3	97.7	97.5	95.0	97.5	98.0
Precision *(%)*	77.3	76.5	78.8	81.3	84.6	93.9	92.4	94.6	95.4	95.0	93.1	77.3	76.5
F score *(%)*	86.5	88.2	89.4	90.6	92.3	93.9	96.2	97.3	97.7	97.5	96.5	97.6	94.8

Table 4-8-Performance measures of binary class BC-E

BC - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	83.9	84.9	85.0	85.9	93.1	95.0	97.1	98.5	98.4	97.0	97.0	95.8	99.7
Precision *(%)*	70.7	71.9	71.1	71.9	86.2	90.2	94.2	97.0	96.8	94.1	94.5	92.1	99.4
F score *(%)*	84.6	85.9	84.1	85.9	93.1	95.1	97.1	98.5	98.4	97.0	97.2	96.0	99.8

Table 4-9-Performance measures of binary class BD-E

BD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	83.9	84.9	85.0	85.9	93.1	95.0	97.1	98.5	98.4	97.0	97.0	95.8	99.7
Precision *(%)*	70.7	71.9	71.1	71.9	86.2	90.2	94.2	97.0	96.8	94.1	94.5	92.1	99.4
F score *(%)*	84.6	85.9	84.1	85.9	93.1	95.1	97.1	98.5	98.4	97.0	97.2	96.0	99.8

Table 4-10-Performance measures of binary class CD-E

BD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	86.5	87.8	87.8	88.7	91.9	93.3	95.9	96.3	97.4	97.5	96.5	95.8	96.6
Precision *(%)*	73.0	75.6	87.4	77.5	83.8	86.3	91.9	92.7	94.7	95.0	95.0	92.1	93.3
F score *(%)*	86.5	87.8	86.7	88.7	91.9	93.1	95.9	96.3	97.4	97.5	97.5	96.0	96.6

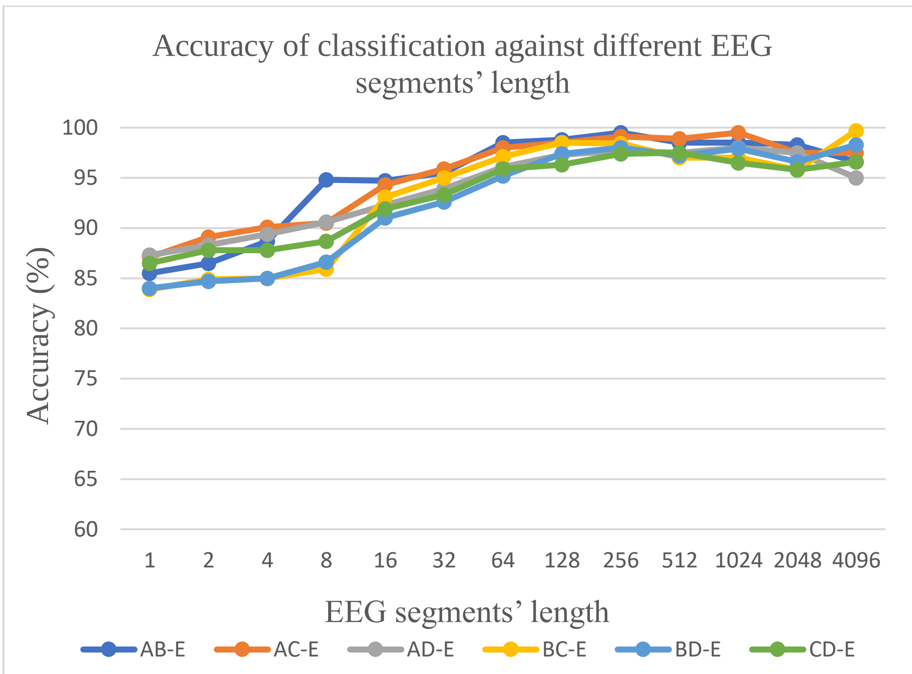

Figure 4-4. Accuracy comparison of second part of binary classification in Seizure detection

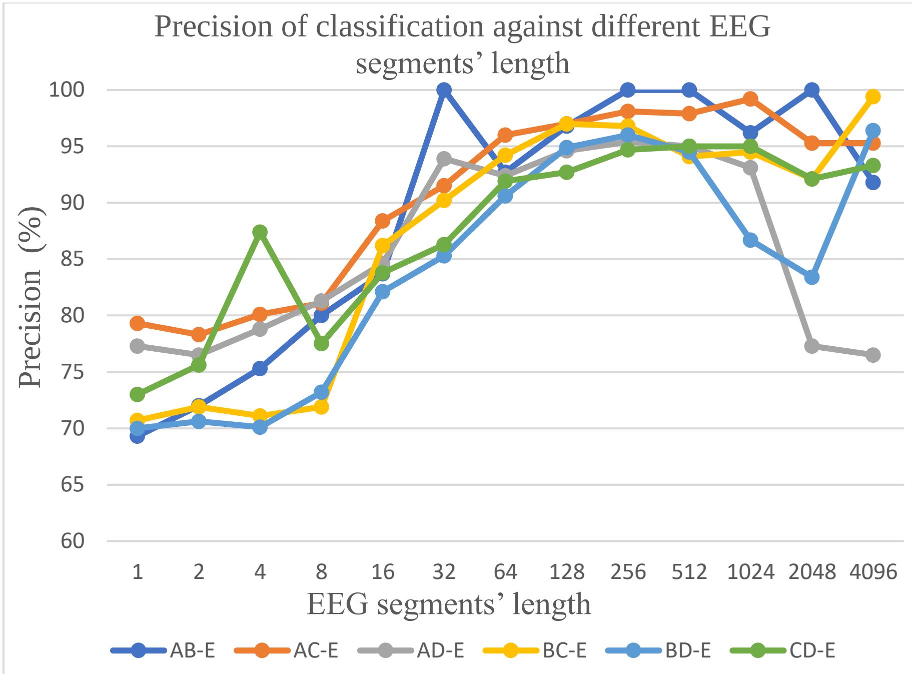

Figure 4-5. Precision comparison of second part of binary classification in Seizure detection

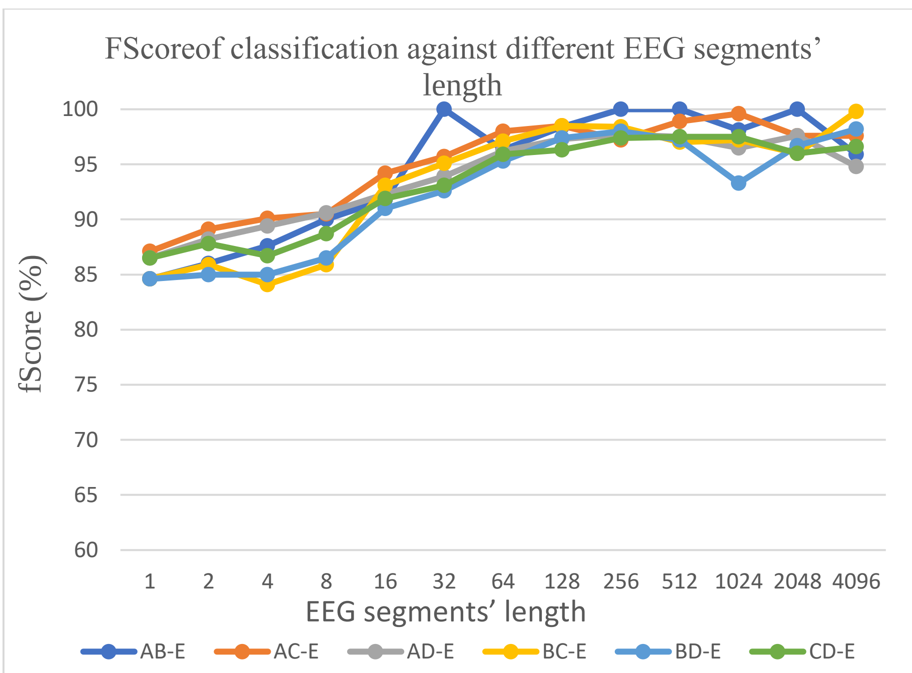

Figure 4-6. Fscore comparison of second part of binary classification in Seizure detection

Figures 4-4 to 4-6 and Tables 4-5 to 4-10 show the results for the second part of binary experiments when two sets are selected for non-seizure class. The results achieved by the proposed method on second part also prove that the model performs effectively on different combination of sets to seizure /non seizure classification. Similarly, the observations prove the length of the EEG segmentation plays a key role in the accuracy and effectiveness of algorithm.

Table 4-11-Performance measures of binary class ABC-E

ABC - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	86.8	89.3	90.8	92.0	94.6	96.4	98.0	98.1	99.1	99.5	95.9	93.7	93.7
Precision *(%)*	76.6	78.7	81.7	84.0	89.2	92.9	96.2	96.3	98.2	99.0	91.8	87.5	85.4
F score *(%)*	85.8	89.3	90.8	92.0	94.6	96.4	98.1	98.1	99.1	99.5	95.9	93.7	92.7

Table 4-12-Performance measures of binary class ABD-E

ABD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	87.8	88.5	89.7	91.1	93.4	95.3	96.7	98.2	98.2	95.6	98.4	95.6	88.7
Precision *(%)*	78.6	77.1	79.5	82.2	86.8	90.7	93.5	96.4	96.4	91.2	96.8	91.2	75.0
F score *(%)*	86.8	88.7	89.7	91.1	93.4	95.3	96.7	98.2	98.2	95.6	98.4	95.6	87.5

Table 4-13-Performance measures of binary class BCD-E

BCD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	89.8	88.3	89.4	91.1	93.1	94.8	96.5	98.5	97.6	96.0	95.9	96.8	93.7
Precision *(%)*	79.6	76.7	78.9	82.3	86.2	89.7	93.1	97.1	95.3	92.1	91.8	93.7	89.5
F score *(%)*	89.8	88.3	89.4	91.1	93.1	94.8	96.5	98.5	97.6	96.0	95.9	96.8	94.7

Table 4-14-Performance measures of binary class ACD-E

ACD - E													
	2^0	2^1	2^2	2^3	2^4	2^5	2^6	2^7	2^8	2^9	2^{10}	2^{11}	2^{12}
Accuracy (%)	88.8	89.8	91.2	92.3	93.9	95.0	96.5	98.2	98.5	95.3	97.8	96.2	92.5
Precision *(%)*	78.6	79.6	82.4	84.6	87.9	90.0	93.0	96.4	97.0	95.3	95.3	92.5	85.4
F score *(%)*	86.5	89.8	91.2	92.3	93.9	95.0	96.5	98.2	98.5	97.6	95.3	96.2	92.7

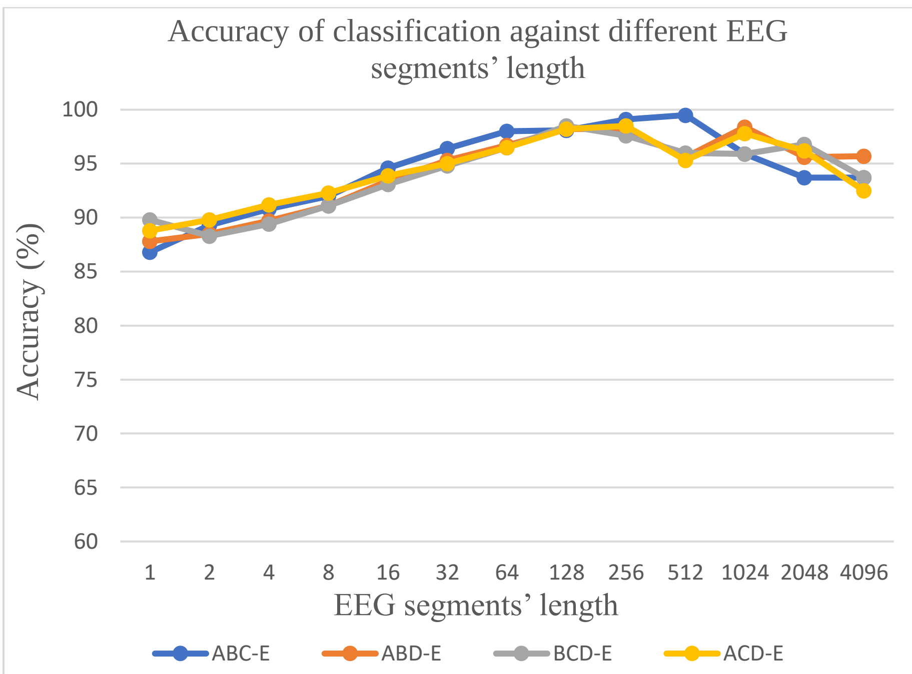

Figure 4-7. Accuracy comparison of third part of binary classification in Seizure detection

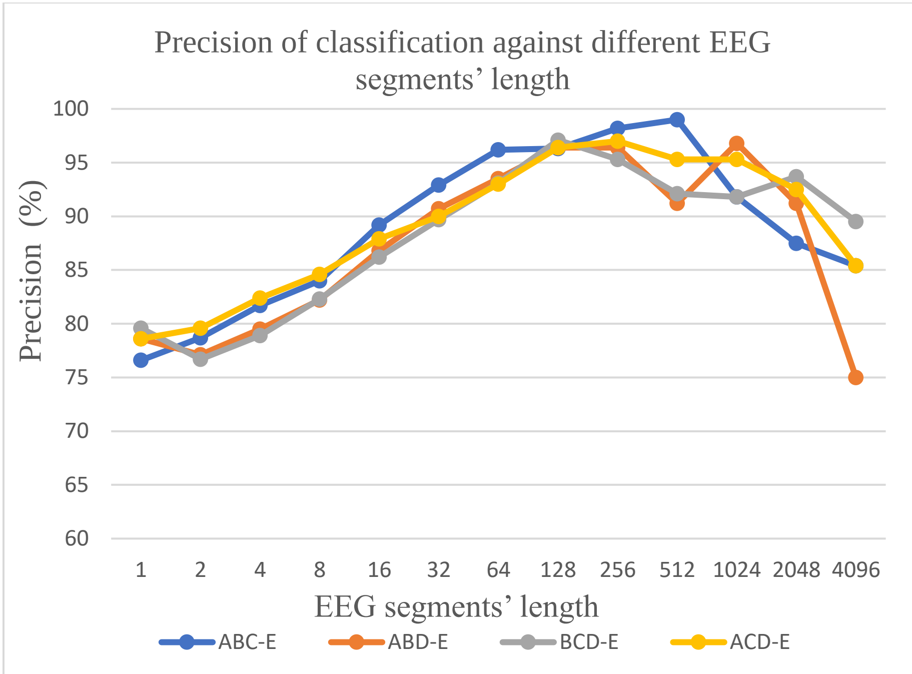

Figure 4-8. Precision comparison of third part of binary classification in Seizure detection

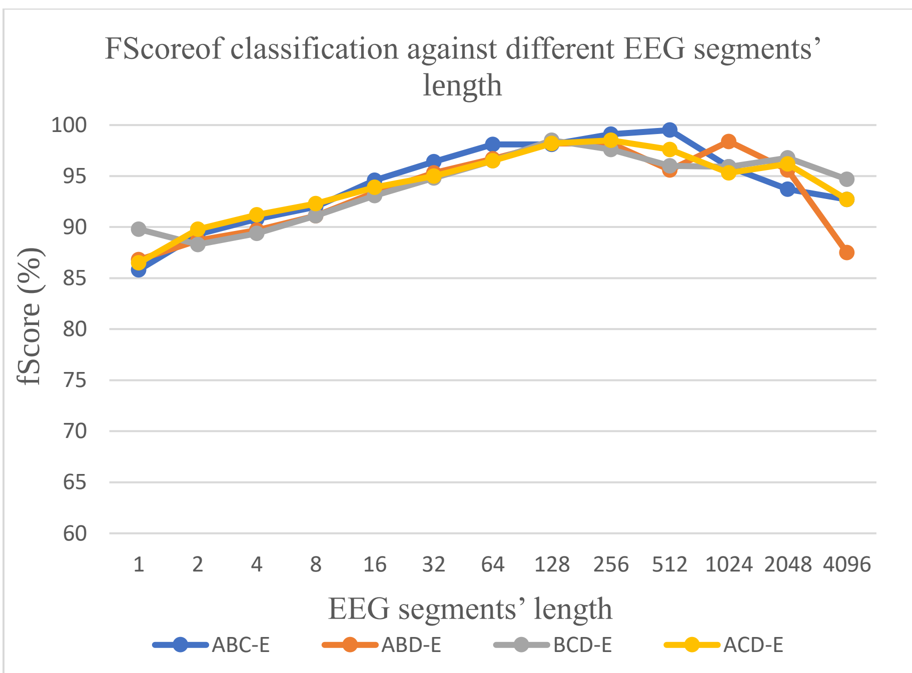

Figure 4-9. Fscore Comparison of third part of binary classification in Seizure detection

Figure 4-7 to 4-9 and Tables 4-11 to 4-14 also show the results for the second part of binary experiments when 3 sets are chosen for non-seizure class . The results achieved by the proposed method on second part of experiment for binary classification prove the model performs effectively as well on different combination of sets to seizure /non seizure classification. Length of EEG signals can play a significant role in the effectiveness of the model so that its accuracy and precision increase by growing the size of EEG recording from1 to 512 and then algorithm face a challenge to detect the seizure for recoding larger than 1024. Figure 4-7 shows this accuracy reduction. This can be due to the number of dependencies in long sequence of data. Since they increase as variables and dependencies in the LSTM algorithm and the algorithm faces problem to recognize their relation and to identify the biomarker of seizure. The other possible reason is the current number of layer and neurons in configuration of neural network in the algorithm are not adequate to capture and learn this complexity since the increasing the length, of EEG segmentation make us to consider more dependencies. But we have to bear in mind that increasing numbers of layers and neurons lead to cost memory and time cost in the implementation.

In the second part, this research also evaluated the capabilities of the proposed method to differentiate between three defined classes of EEG recordings: normal, inter-ictal, and ictal. Figures 4-11 to 4-12 and Tables 4-15 to 4-19 show the performance metrics achieved by the proposed method on ternary classification. The achieved results can compete with other existing method results previously reported on the same clinical EEG dataset [ILA2020] [HUS19] [NIC12]. The proposed approach results provide initial evidence that yields an improved precision, Fscore, and classification accuracy. The key reason for this classification improvement with the use of LSTM is to figure out the correlation between the EEG signals taken from different subjects and the dependencies among EEG segments of the same subject [HUS19]. This study also investigated the robustness of the proposed seizure detection approach in different segmentation sizes.

This deep recurrent neural network utilized on the experiments and presented a reliable EEG feature learning algorithm on ternary classification that can deal with different length of data for training and extracting the features. However, this research also shows that our deep learning model can effectively detect occurrence of seizure by capturing seizure feature in EEG recording when then length of the EEG signal meets the requirement.

Figure 4-1 to Figure 4-9 demonstrate the overall performance of the proposed approach when the length of recording is varied for different classes. It is clearly shown that in the proposed approach, the optimal length for extracting and training model is highly dependent on the data set. LSTM networks can effectively extract the most faithful and robust EEG representations pertinent to epileptic seizures.

Table 4-15-Performance measures of Ternary class AB-CD-E

AB-CD- E													
	$\mathbf{2^0}$	$\mathbf{2^1}$	$\mathbf{2^2}$	$\mathbf{2^3}$	$\mathbf{2^4}$	$\mathbf{2^5}$	$\mathbf{2^6}$	$\mathbf{2^7}$	$\mathbf{2^8}$	$\mathbf{2^9}$	$\mathbf{2^{10}}$	$\mathbf{2^{11}}$	$\mathbf{2^{12}}$
Accuracy (%)	50.5	62.3	69.2	74.9	81.9	85.8	91.5	94.6	97.1	97.1	85.0	80.5	81.0
Precision *(%)*	52.1	42.1	53.5	62.4	72.8	78.8	87.4	91.9	95.6	95.6	77.9	71.7	83.1
F score *(%)*	58.6	59.2	68.4	74.6	81.8	85.8	91.6	94.6	97.1	97.1	85.3	80.9	88.7

Table 4-16-Performance measures of Ternary class A-D-E

A-D- E													
	$\mathbf{2^0}$	$\mathbf{2^1}$	$\mathbf{2^2}$	$\mathbf{2^3}$	$\mathbf{2^4}$	$\mathbf{2^5}$	$\mathbf{2^6}$	$\mathbf{2^7}$	$\mathbf{2^8}$	$\mathbf{2^9}$	$\mathbf{2^{10}}$	$\mathbf{2^{11}}$	$\mathbf{2^{12}}$
Accuracy (%)	51.5	63.0	69.9	75.1	80.6	84.7	88.3	91.3	94.6	93.7	84.1	88.3	85.0
Precision *(%)*	55.1	67.5	54.4	62.7	71.1	76.9	81.5	86.9	92.0	90.6	76.8	82.8	77.9
F score *(%)*	50.6	59.8	68.5	74.7	80.6	84.6	87.6	91.2	94.6	93.7	84.5	88.5	85.2

Table 4-17-Performance measures of Ternary class A-C-E

A-C-E													
	$\mathbf{2^0}$	$\mathbf{2^1}$	$\mathbf{2^2}$	$\mathbf{2^3}$	$\mathbf{2^4}$	$\mathbf{2^5}$	$\mathbf{2^6}$	$\mathbf{2^7}$	$\mathbf{2^8}$	$\mathbf{2^9}$	$\mathbf{2^{10}}$	$\mathbf{2^{11}}$	$\mathbf{2^{12}}$
Accuracy (%)	65.2	64.0	69.7	75.2	80.7	84.9	88.0	91.3	93.1	94.7	91.6	94.1	91.6
Precision *(%)*	67.7	68.2	54.1	62.8	71.0	77.4	82.3	86.9	89.6	92.1	85.9	91.4	87.2
F score *(%)*	63.2	60.8	68.2	74.8	80.5	84.9	88.1	91.3	93.1	94.7	90.6	94.2	91.5

Table 4-18-Performance measures of Ternary class B-D-E

B-D-E													
	$\mathbf{2^0}$	$\mathbf{2^1}$	$\mathbf{2^2}$	$\mathbf{2^3}$	$\mathbf{2^4}$	$\mathbf{2^5}$	$\mathbf{2^6}$	$\mathbf{2^7}$	$\mathbf{2^8}$	$\mathbf{2^9}$	$\mathbf{2^{10}}$	$\mathbf{2^{11}}$	$\mathbf{2^{12}}$
Accuracy (%)	65.2	71.7	77.1	77.1	83.1	85.5	90.1	93.8	95.9	96.2	87.9	80.8	90.0
Precision *(%)*	47.7	57.3	65.6	65.6	74.6	78.3	85.4	90.6	93.9	94.5	74.1	81.8	86.2
F score *(%)*	63.2	70.5	76.6	76.6	82.9	85.5	90.2	93.7	95.9	96.3	80.4	815.	90.7

Table 4-19-Performance measures of Ternary class B-C-E

B-C-E													
	$\mathbf{2^0}$	$\mathbf{2^1}$	$\mathbf{2^2}$	$\mathbf{2^3}$	$\mathbf{2^4}$	$\mathbf{2^5}$	$\mathbf{2^6}$	$\mathbf{2^7}$	$\mathbf{2^8}$	$\mathbf{2^9}$	$\mathbf{2^{10}}$	$\mathbf{2^{11}}$	$\mathbf{2^{12}}$
Accuracy (%)	65.2	66.3	72.2	78.5	85.8	87.6	90.5	90.5	96.2	95.2	95.4	93.3	83.3
Precision *(%)*	48.7	48.8	58.1	67.7	78.8	81.5	85.8	85.8	94.3	92.8	91.8	89.8	78.8
F score *(%)*	63.2	64.0	71.3	78.1	85.8	87.6	90.5	90.5	96.2	95.2	94.5	93.2	85.6

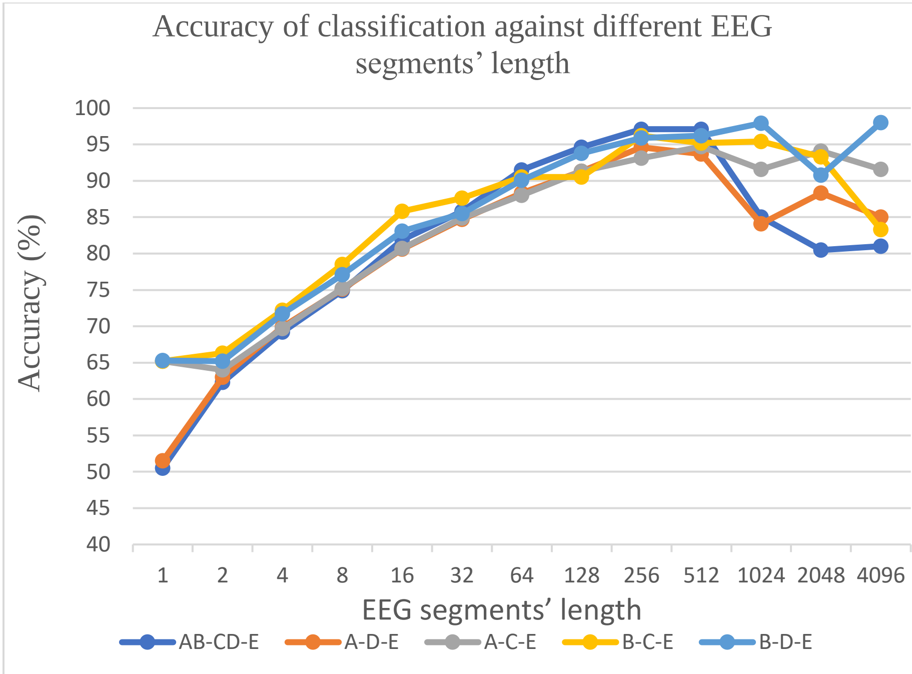

Figure 4-10. Accuracy comparison of ternary classification in Seizure detection

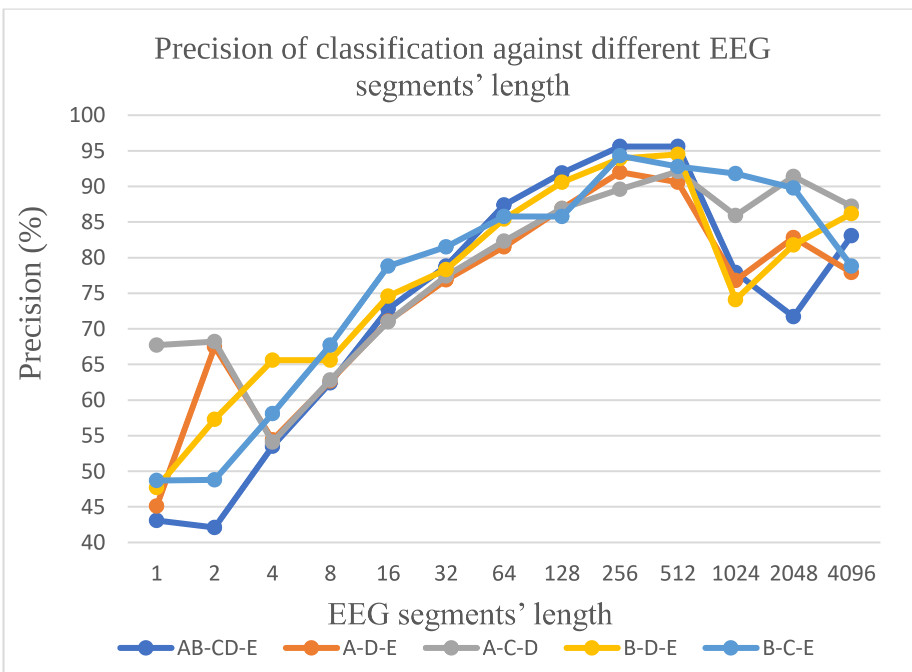

Figure 4-10. Precision comparison of ternary classification in Seizure detection

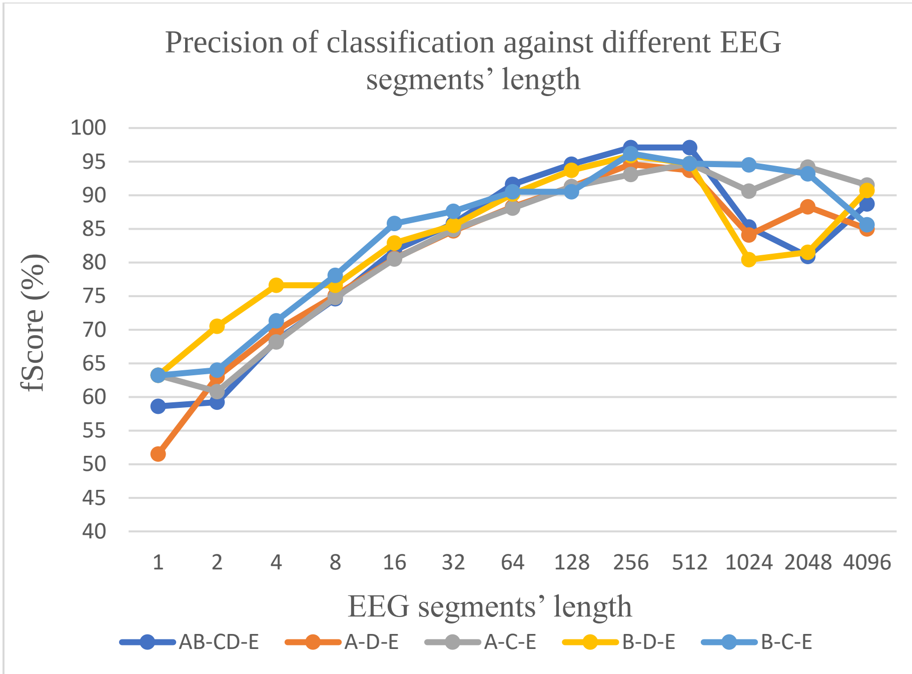

Figure 4-11. FScore comparison of ternary classification in Seizure detection

The last part of seizure detection experiment is dedicated to ternary classification. My research goal is to recognize normal EEG taken from healthy subjects, Inter-ictal EEG taken from epileptic patients throughout seizure-free intervals and Ictal EEG recorded from epileptic patients while experiencing active seizures. Five distinct set combinations are tested on different length recordings to determine the best combination and optimal length for effectiveness of the algorithm.

The results achieved by the proposed method on ternary classification demonstrate that the model has similar efficiency on 5 different combinations of sets. The performance of algorithm can be increased by incrementing the length of the recoding. It was found that 512 and 128 data points in segments are the most optimal lengths for a good effectiveness of seizure detection. The outcome from the experiment shows that for higher lengths of 512 datapoint (5 seconds) the algorithm faces a challenge to figure out the features automatedly.

Even though the three-class EEG classification is an intractable problem, particularly in small lengths of EEG recordings, the proposed method is proven to maintain high seizure detection results between 32 and 2048. For instance, it yields a classification accuracy larger than 94% when the length of EEG signals is 256 datapoints. The classification accuracy drops to 80.50% for shorter lengths of EEG recordings though. However, in realistic situations the length of recording would be more than large enough to be passed into algorithm, thus the proposed method could achieve a notable performance.

The corresponding matrices for both selected binary and ternary classes combinations related to the different length of EEG segments were investigated. The results indicate that the proposed system maintained a high performance for all class combinations of both binary and ternary classification. For example, on the cases with optimized length segments the accuracy is above 95%.

This dissertation demonstrates the impact of the EEG segment length on the detection accuracy of epileptic seizures. The common assumption is that longer segment lengths lead to improvements on seizure detection accuracy. Although increasing the length of segment would seemingly increase seizure detection accuracy, it needs to be noted that there is maximum for achieving the highest accuracy. This is what the experimental results plots in Figures 4-1 to 4-11 show that increasing the length of the segment by 1024 would not assure an increment of seizure detection accuracy. The most optimized length for building a model and achieving the highest accuracy is dependent on sets of a general length between 128 and 1024 datapoints of EEG recording, which could increase effectiveness of detection and prediction of seizures in patients.

Besides accuracy, F1-score and precision were also measured. The reason for choosing accuracy is because it is mostly used measurement when the true positives and true negatives are more important for making dissection. F1-score is mostly used when classes are imbalanced, and the false negatives and false positives are crucial. Precision also assesses the ratio of correctly predicted positive observations to the total predicted positive observations.

We see that the proposed approach of using stacked LSTM based RNN models perform better than existing approaches reported in the literature [HUS19], [ELF20] [ILA2020] [RAJ12], [ARC12a]. For all binary classes with an accuracy of (98.5±1.5) %. For ternary class combinations, the proposed system has an accuracy of (95±2) % with finding the optimized length for building models based on observation and different experimental scenarios. These results can be considered as a guideline for future works to attain the highest accuracy.

4.3 Summary

Chaotic dynamical systems like EEG may evolve complex structures and neither fixed and long lengths of recording nor short lengths of recording could guarantee better accuracy as plots and tables demonstrated in Section 4.2.

The brain is a nonlinear dynamic system, and the EEG signals are modeled as time series chaotic data. The novelty of this study is the use of different length size of segments as input to the RNN model to research at which lengths could the algorithm achieved the highest accuracy, since the algorithm itself completely cannot handle this matter. We further employ different stacked LSTM layers for the seizure detection problem. We report an accuracy of (98.5±1.5) % (epileptic *vs.* non-epileptic) and (95±2) % (normal *vs.* interictal *vs.* ictal) which is higher than most existing results in the literature. This research highlight that the proposed approach can model the dynamic nature of the EEG signals. The deep LSTM model can accurately capture the features in the EEG signals and perform classification with high accuracy for 19 different class combinations. The outcome of the proposed system using EEG signals could be used in supporting physicians to detect epilepsy and may serve as a precursor to assist the neurologist in building models and classifying the epileptic states of patients with further research.

Chapter 5

Conclusion And Future Work

5.1 Conclusion

This thesis focuses on robust methods for detection and prediction of epileptic seizures. First, it described the importance of this issue to epileptic patients for their quality of life. Then, the influence of a variety factors including length of data segmentation and classification on prediction performance was analyzed through extensive experiments on real EEG data taken from normal people and patient with epileptic seizures.

To enhance the performance of the seizure detection system, a new recurrent neural network (RNN) configuration was proposed and implemented that was able to detect epileptic seizure patterns accurately. The developed RNN architecture utilized a long short-term memory (LSTM) architecture to capture both the low- and high-level representations of the EEG patterns. The goals of this study are to answer the questions: (a) how is it possible to improve the accuracy of detection to extract the temporal dependency in different combinations of classes considered for being epileptic/non-epileptic, (b) what is the optimal length to consider in the proposed deep learning approach to maintain a robust seizure detection performance, and (c) can the proposed deep neural system sustain robust seizure detection performance under changing length and shortage of data?

Extensive experiments on a real-world clinical dataset show initial evidence that the proposed approach can effectively recognize different seizure patterns by extracting a high level sequence of features recorded from several patients and can precisely differentiate between the seizure and non-seizure brain activities. Experimental results provided evidence that the proposed research algorithms obtain better classification and prediction accuracy compared to some studies reported in the literature for the utilized dataset. The proposed algorithms have the potential to be used in diagnostic clinical applications .

5.2 Future work

This dissertation is a step forward in the realm of epileptic seizure detection and prediction. There is still a lot that can be done regarding this problem as well as other deep learning approaches in the extended health field. It has showed what was already possible with the given available data and allowed us to identify limitations and perspectives about what is required to be done to make more robust models in future experiments. Since the EEG dataset used in this experiment was obtained from five healthy volunteers and five epileptic patients, the interpreting and generalizing of the results have been done cautiously. Further experiments require larger datasets to generalize our research results.

Larger EEG dataset, consisting of recorded electrical activity of many more patients, enable the deep neural network model to learn from the more diverse patterns of epileptic seizures across patients, and hence boost its communalization since the performance of deep neural networks improves as the size of training data increases.

Another suggestion is to access long-term EEG recording signals to extend research scope to identify the pre-seizure EEG activities and bring awareness to epileptic patients of upcoming seizures through learning different patterns of interictal, preictal, and post ictal. Moreover, since this proposed approach exploited the single-channel EEG data as univariate variable, multivariate and other neural networks, like convolution neural network with some adjustment can be used to exploit the spatial correlations between the EEG epochs from different channels on the scalp.

Even though EEG and invasive EEG signals are the main method to identify abnormalities and seizure occurrence, each has their own pros and cons that need to be considered. Although invasive EEG is assumed more reliable than scalp EEG for brain activity recording and achieving more accurate seizure prediction performance, the patients must carry the burden of brain surgery for implementation of electrodes and its side effects including cost of surgery and threat of infection. Broad, in-depth research is required to outweighed merits and demerits of both approaches for epileptic seizure detection and prediction.

There are other data collection technologies available to take advantage of the performance enhancement along with the patient undertaking less inconvenience. These technologies include accelerometer sensor, electromyography (EMG), electrocardiography (ECG), and electrodermal screening (EDS) in addition to EEG scalp. These technologies can provide complementary data that enhances the epileptic seizure detection and prediction

With the availability of large dataset that retain longer recordings of EEGs, beneficial algorithms can be developed to enable awareness for patients and care givers to give treatment a half hour before the onset of a seizure. potentially curing, but improving the patient's quality of life. There are still significant unknowns about epilepsy, but the results from recent and subsequent research strengthen the hope that one day the mysteries surrounding this disease will be unraveled and make life for family members and patients more enjoyable.

References

[AND01] Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state. *Physical review. E, Statistical, nonlinear, and soft matter physics*, *64*(6 Pt 1), 061907. https://doi.org/10.1103/PhysRevE.64.061907

[ANT12] Dalton, A., Patel, S., Chowdhury, A. R., Welsh, M., Pang, T., Schachter, S., OLaighin, G., & Bonato, P. (2012). Development of a body sensor network to detect motor patterns of epileptic seizures. *IEEE transactions on bio-medical engineering*, *59*(11), 3204–3211. https://doi.org/10.1109/TBME.2012.2204990.

[ARC12a] U Rajendra Acharya, Filippo Molinari, S Vinitha Sree, Subhagata Chattopadhyay, Kwan-HoongNg, and Jasjit S Suri. Automated diagnosis of epileptic EEG using entropies. *Biomedical Signal Processing and Control*, 7(4):401–408, 2012.

[ARC12b] U Rajendra Acharya, S Vinitha Sree, Ang Peng Chuan Alvin, and Jasjit S Suri. Use of principal component analysis for automatic classification of epileptic EEG activities in wavelet framework. *Expert Systems with Applications*, 39(10):9072–9078, 2012

[AYO13] Ayoubian, L., Lacoma, H., & Gotman, J. (2013). Automatic seizure detection in SEEG using high frequency activities in wavelet domain. *Medical engineering & physics*, *35*(3), 319–328. https://doi.org/10.1016/j.medengphy.2012.05.005

[DAL12] Anthony Dalton, Shyamal Patel, Atanu Roy Chowdhury, Matt Welsh, Trudy Pang, Steven Schachter, Gearoid ´ OLaighin, and Paolo Bonato. Development of a body sensor network to ´detect motor patterns of epileptic seizures. *IEEE Transactions on Biomedical Engineering*, 59(11):3204–3211, 2012.

[DAS20] Dash, D. P., & H Kolekar, M. (2020). Hidden Markov model based epileptic seizure detection using tunable Q wavelet transform. *Journal of biomedical research*, *34*(3), 170–179. https://doi.org/10.7555/JBR.34.20190006

[EFT08] Amir Eftekhar, Farah Vohra, Chris Toumazou, Emmanuel M Drakakis, and Kim Parker. Hilberthuang transform: preliminary studies in epilepsy and cardiac arrhythmias. In *2008 IEEE Biomedical Circuits and Systems Conference*, pages 373–376. IEEE, 2008.

[ELD13] E. S. Kollialil, Gopika Gopan K, Harsha A and L. A. Joseph, "Single feature-based non-convulsive epileptic seizure detection using multi-class SVM," 2013 International Conference on Emerging Trends in Communication, Control, Signal Processing and Computing Applications (C2SPCA), 2013, pp. 1-6, doi: 10.1109/C2SPCA.2013.6749374.

[ELF20] Elif Derya Ubeyli. Analysis of EEG signals by combining eigenvector methods and multiclass ¨support vector machines. *Computers in Biology and Medicine*, 38(1):14–22, 2008.

[ENG12] Mary Jane England, Catharyn T Liverman, Andrea M Schultz, and Larisa M Strawbridge. Epilepsy across the spectrum: Promoting health and understanding.: A summary of the institute of medicine report. Epilepsy & Behavior, 25(2):266–276, 2012.

[GAN11] Gandhi T, Panigrahi BK, Anand S A comparative study of wavelet families for EEG signal classification. Neurocomputing. 2011;74(17):3051–3057. doi: 10.1016/j.neucom.2011.04.029.

[GEO20] Georgiou, T., Liu, Y., Chen, W. et al. A survey of traditional and deep learning-based feature descriptors for high dimensional data in computer vision. Int J Multimed Info Retr 9, 135–170 (2020). https://doi.org/10.1007/s13735-019-00183-w

[GOT79] Gotman J, Ives JR, Gloor P Automatic recognition of inter-ictal epileptic activity in prolonged EEG recordings. *Electroencephalogr Clin Neurophysiol.* 1979;46(5):510–520. doi: 10.1016/0013-4694(79)90004-X.

[HEB13] Heba Khamis, Armin Mohamed, and Steve Simpson. Frequency-moment signatures: a methodfor automated seizure detection from scalp EEG. *Clinical neurophysiology : Official Journal of the International Federation of Clinical Neurophysiology*, 124(12):2317–27, Dec 2013.

[HOR98] Hochreiter, S. (1998). The Vanishing Gradient Problem During Learning Recurrent Neural Nets and Problem Solutions.. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 6, 107-116

[HUL19] Hu L, Zhang Z, editors. EEG Signal Processing and Feature Extraction. Springer Singapore; 2019; Available from: http://dx.doi.org/10.1007/978-981-13-9113-2

[HUS18] Hussain L. Detecting epileptic seizure with different feature extracting strategies using robust machine learning classification techniques by applying advance parameter optimization approach. *Cogn Neurodyn*. 2018;12(3):271-294. doi:10.1007/s11571-018-9477-1

[HUS19] Hussein R, Palangi H, Ward RK, Wang ZJ. Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals. *Clin Neurophysiol*. 2019;130(1):25-37. doi:10.1016/j.clinph.2018.10.010

[ISA18] Isabell Kiral-Kornek, Subhrajit Roy, Ewan Nurse, Benjamin Mashford, Philippa Karoly, Thomas Carroll, Daniel Payne, Susmita Saha, Steven Baldassano, Terence O'Brien, et al. Epileptic seizureprediction using big data and deep learning: toward a mobile system. *EBioMedicine*, 27:103–111, 2018

[JAN16] Eric Jang, Shixiang Gu, and Ben Poole. Categorical reparameterization with gumbel-softmax. *arXiv preprint arXiv:1611.01144*, 2016.

[KAM08] Azadeh Kamali Tafreshi, Ali M Nasrabadi, and Amir H Omidvarnia. Epileptic seizure detection using empirical mode decomposition. In 2008 IEEE International Symposium on Signal Processing and Information Technology, pages 238–242. IEEE, 2008

[KER19] In Levin, K. H., & In Chauvel, P. (2019). Clinical neurophysiology.

[LAR16] Larmuseau, Maarten, and Joni Dambre. Epileptic Seizure Prediction Using Deep Learning. 2016.

[LIU12] Yinxia Liu, Weidong Zhou, Qi Yuan, and Shuangshuang Chen. Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 20(6):749–755, 2012

[MER70] Merlis JK. Proposal for an international classification of the epilepsies. Epilepsia. 1970;11(1):114-119. doi:10.1111/j.1528-1157.1970.tb03873.x

[NIC12] Nicoletta Nicolaou and Julius Georgiou. Detection of epileptic electroencephalogram based on permutation entropy and support vector machines. Expert Systems with Applications, 39(1):202– 209, 2012

[NIK12] Mohammad Niknazar, SR Mousavi, B Vosoughi Vahdat, and M Sayyah. A new framework based on recurrence quantification analysis for epileptic seizure detection. *IEEE Journal of Biomedical and Health Informatics*, 17(3):572–578, 2013

[NIL10] A. R. Naghsh-Nilchi and M. Aghashahi, “Epilepsy seizure detection using eigen-system spectral estimation and multiple layer perceptron neural network,” Biomedical Signal Processing and Control, vol. 5, no. 2, pp. 147–157, 2010.

[NOL04] Nolan MA, Redoblado MA, Lah S, et al. Memory function in childhood epilepsy syndromes. J Paediatr Child Health. 2004 Jan-Feb. 40(1-2):20-7.

[NOR98] Norden E Huang, Zheng Shen, Steven R Long, Manli C Wu, Hsing H Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H Liu. The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, 454(1971):903–995, 1998.

[PAN10] R Panda, PS Khobragade, PD Jambhule, SN Jengthe, PR Pal, and TK Gandhi. Classification of EEG signal using wavelet transform and support vector machine for epileptic seizure diction. In *2010 International Conference on Systems in Medicine and Biology*, pages 405–408. IEEE, 2010

[POL07] Polat, K., & Günes, S. (2007). Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. *Appl. Math. Comput., 187*, 1017-1026.

[RAJ18] Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, and Hojjat Adeli. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in Biology and Medicine*, 100:270–278, 2018

[SAM18] Samuel Ippolito, and Omid Kavehei. Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram. *Neural Networks*, 105:104–111, 2018.

[SEP97] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*, 1735-1780.

[SHA16] Shanir, P. P. M., Khan, K. A., Khan, Y. U., Farooq, O., & Adeli, H. (2018). Automatic Seizure Detection Based on Morphological Features Using One-Dimensional Local Binary Pattern on Long-Term EEG. Clinical EEG and Neuroscience, 49(5), 351–362. https://doi.org/10.1177/1550059417744890

[SHO09] Shoeb AH. Application of machine learning to epileptic seizure onset detection and treatment[D]. Cambridge: Massachusetts Institute of Technology, 2009.

[SUR09] Suryannarayana Chandaka, Amitava Chatterjee, and Sugata Munshi. Cross-correlation aided support vector machine classifier for classification of EEG signals. *Expert Systems with Applications*, 36(2):1329–1336, 2009.

[TSI18] Tsiouris, K. M., Pezoulas, V. C., Zervakis, M., Konitsiotis, S., Koutsouris, D. D., & Fotiadis, D. I. (2018). A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals. *Computers in biology and medicine*, *99*, 24–37. https://doi.org/10.1016/j.compbiomed.2018.05.019

[ULL16] Ullah I, Hussain M, Qazi EUH, et al An automated system for epilepsy detection using EEG brain signals based on deep learning approach. *Expert Syst Appl.* 2018;107:61–71. doi: 10.1016/j.eswa.2018.04.021.

[UZZ12] Yusuf Uzzaman Khan, Nidal Rafiuddin, and Omar Farooq. Automated seizure detection in scalp EEG using multiple wavelet scales. In *Signal Processing, Computing and Control (ISPCC), 2012 IEEE International Conference on*, pages 1–5. IEEE, 2012

[ILA20] Ilakiyaselvan, N., Nayeemulla Khan, A., & Shahina, A. (2020). Deep learning approach to detect seizure using reconstructed phase space images. *Journal of biomedical research*, *34*(3), 240–250. https://doi.org/10.7555/JBR.34.20190043 *International Conference on Emerging Trends in Communication, Control, Signal Processing and Computing Applications (C2SPCA)*, pages 1–6. IEEE, 2013.

Appendix A Dataset Description

Table A-1. Description of the EEG database from University of Bonn

Dataset	Subject details	Patient status	Electrode type	Electrode placement	Duration (second)
Set A	Five healthy subjects (normal)	Awaken state with open eyes	Surface	International 10-20 system	23.6
Set B		Awaken state with eyes closed	Surface	International 10-20 system	23.6
Set C	Five epilepsy patients	Interictal (seizure-free)	Surface	Opposite to epileptogenic zone	23.6
Set D		Interictal (seizure-free)	Intracranial	epileptogenic zone	23.6
Set E		Ictal (seizure)	Intracranial	epileptogenic zone	23.6

Appendix B Softmax Function

The Softmax function, $h_\theta(x)$, is defined as follows:

$$h_\theta(x) = \begin{pmatrix} P(y = 1|x;\theta) \\ P(y = 11x;\theta) \\ \cdot \\ \cdot \\ \cdot \\ P(y = k|x;\theta) \end{pmatrix} = \frac{1}{\sum_{j=1}^{k} exp\left(\theta_j^T x\right)} \begin{pmatrix} ex_P(\theta_1^T x) \\ exp(\theta_2^T x) \\ \cdot \\ \cdot \\ \cdot \\ exp\,(\theta_K^T x) \end{pmatrix}$$ Equation B-1

$\theta_1, \theta_2, \cdot\cdot\cdot, \theta_k$are the softmax parameters. The "cross entropy" $J_{(\theta)}$ is the cost function that is often used with Softmax.

$$j(\theta) = \left[\sum_{i=1}^{N} \quad \sum_{K=1}^{N} \mathbb{L}\{y^{(i)} = k\} \log P(\,y^{(i)} = k|x^{(i)}\,;\theta\right]$$

$$= -\left[\sum_{i=1}^{N} \quad \sum_{K=1}^{N} \mathbb{L}\{y^{(\mathrm{i})} = k\} \log \quad \frac{exp(\theta)}{\sum_{j=1}^{k} exp\left(\theta_j^T x^{(\mathrm{i})}\right)}\right]$$ Equation B-2

$\mathbb{L}\,\{.\}$ is the "indicator function", it equals to 1 when the statement is true otherwise it is 0. The stochastic gradient descent is applied to minimize the cost function and to maximize the probability of the true class label [JAN16]