Epileptic Seizure Prediction using Bandpass Filtering and Convolutional Neural Network

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Ethics Statement

Predicting an individual's disease only on the basis of a likelihood offered by a Neural Network Model may raise ethical concerns. As a result, we ensured the evaluation process was transparent and recommend seeking the advice of a medical professional before finalizing the result.

Abstract

Epilepsy, a chronic neurological disorder, causes seizure- a fast, uncontrollable electrical disturbance in the brain. Seizures that last for a long time might result in memory loss, weariness, photo sensitivity, paralysis, or death. The early diagnosis of seizures may assist reducing the severity of damage and can be utilized to aid in the treatment of epilepsy patients. Predicting seizures before they occur is a challenge that many researchers are working to overcome by monitoring the brain's activity; but achieving high sensitivity and precise prediction remains a barrier. Our objective is to predict seizure accurately by detecting the pre-ictal state that occurs prior to a seizure. We have used the CHB-MIT Scalp EEG Dataset for our research and implemented the research work using Butterworth Bandpass Filter and simple 2D Convolutional Neural Network to differentiate the pre-ictal and inter-ictal signals. We aim to propose a generalized approach for epileptic seizure prediction rather than patient-specific approach. We have achieved accuracy of 89.5%, sensitivity 89.7%, precision 89.0% and area under the curve (AUC) is 89.5% with our proposed model. In addition, we have addressed several researchers' seizure prediction models, sketched their core mechanism, predictive effectiveness, and compared them with our work. Our long-term goal is to develop an implantable device to with high accuracy and low errors that may effectively warn patients of oncoming seizures to initiate antiepileptic therapy so that those who are afflicted with the epilepsy can enjoy a healthy and risk-free life.

Keywords: Bandpass filter, Chronic neurological disorder, Convolutional neural network, CHB-MIT Scalp EEG Dataset, Deep learning, Epilepsy, Generalized model, Prediction, Seizure.

Dedication

With the hope that our thesis work may in one way or the other contribute to the people who are suffering and may endure from the complications of seizures.The most frequent cause of death from epilepsy is sudden unexpected death in epilepsy.We therefore would like to dedicate this thesis to the people who died prematurely by epilepsy and are suffering from this causal agent which may lead to death.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

$ANNs$ Artificial neural networks

BB Butterworth Bandpass

$CHB-MIT$ Children's Hospital Boston-Massachusetts Institute of Technology

CNN Convolutional Neural Network

CT Computerized tomography

$DTCWT$ Dual-tree complex wavelet transform

DWT Discrete wavelet transform

EDF European Data Format

EEG Electroencephalogram

ELM Extended Local Minimum

EMD Empirical mode decomposition

ES Epileptic seizure

FAR False alarm rate

FFT Fast Fourier transform

$fMRI$ Functional magnetic resonance imaging

$GRNN$ Generalized Regression Neural Networks

GTC Generalized tonic-clonic

KNN K-Nearest Neighbour

$LSTM$ Long short-term memory

MEG Magnetoencephalography

ML Machine Learning

PSD Power spectral density

$ReLU$ Rectified linear activation function

RNN Recurrent neural network

SNR Signal-to-noise ratio

SOP Seizure Occurrence Period

SPH Seizure prediction horizon

$STFT$ Short-time Fourier transform

SVM Support Vector Machine

$TanH$ Hyperbolic tangent function

Chapter 1

Introduction

1.1 Overview

Seizures have different signs and symptoms depending on the type. As a general guideline, signs, and symptoms include: rigid or stiffening movements such as jerking the arms and legs or stopping breathing, staring for short periods of time, appearing confused or in a haze, and rhythmic nodding of the head when there is a loss of awareness or consciousness, as well as periods of rapid eye blink and staring [1].

Not every seizure is epileptic. Brain cells interact by delivering regular electrical signals. Epileptic seizures, in contrast to other types of seizures, are triggered because of the dysfunction in the brain. The electrical storms in the brain are what cause seizures in people with epilepsy. These aberrant electrical signals might be localized to a certain area of the brain or they can be more widespread. Diabetes, for example, may trigger a seizure. Some other causes can be brain anomalies, low oxygen, brain injury, infection, stroke, brain tumor, etc [2].

Generalized seizures, focal seizures (previously called partial seizures), and epileptic spasms are three forms of epileptic seizures. A clinician can classify seizure/epilepsy types based on a patient's medical history, EEG results, and other supporting data. During focal seizures, a localized area of the brain is affected and it processes emotions and short-term memory, causing euphoria, anxiety, déjà vu, sensing taste and smell, hallucinations, etc. Generalized seizures begin with aberrant electrical activity in the whole brain, which may result in the loss of consciousness, whole-body stiffness, and rapid jerking movements. When generalized seizures become severe, they begin in bilaterally scattered neuronal networks. In generalized seizures, the most common kinds include generalized tonic-clonic seizures, myoclonic, as well as absence seizures and atonic seizures (GTC). There is no obvious impaired consciousness when people have myoclonic seizures because the movements are so rapid and transient ("lightning-fast"). Generalized myoclonic seizures or focal myoclonic seizures are both possible. When an atonic seizure occurs, there is a lack of muscle tone throughout the body, which can lead to a head drop or fall. The neuronal networks that generate focal seizures are restricted to one hemisphere of the brain. During a focal seizure, different areas of the brain exhibit distinct clinical signs and symptoms. Occipital lobes, can cause visual abnormalities, for example, can cause periodic clonic or tonic muscle activity; and the postcentral gyrus can cause sensory symptoms like paresthesia or a focal seizure that originates in the precentral gyrus. Auras, which are focused seizures in which the patient remains conscious and exhibits motor, sensory, autonomic, or psychic symptoms, can precede seizures on rare occasions. In the case of epileptic spasms, the cause is unknown. Extensive or quick flexing of the affected person's limbs will occur for a brief period of time. These muscle spasms can strike anyone of any age [3].

Seizures and epilepsy are diagnosed using a combination of history, physical examination, and laboratory testing [4]. Doctors may find it challenging to distinguish between seizure types. In order to appropriately diagnose a seizure and ensure that the therapies provided are effective, the doctor may request certain tests. A variety of factors can trigger a seizure, which includes migraine headaches, sleep deprivation, over working, hormonal changes, dehydration, high levels of psychological stress, etc. Other illnesses that can induce seizure-like behavior can be ruled out through lab tests. A spinal tap to rule out illness and a toxicology screening to look for drugs, poisons, or toxins are some of the procedures that may be conducted to check for electrolyte abnormalities in the blood. An electroencephalogram (EEG) can be used by doctors to detect a seizure. During a seizure, monitoring brain waves from an EEG test can help a doctor figure out what kind of seizure the patient is having. Imaging tests such as a C.T. scan or an MRI scan, which provide a clear image of the brain, can also be effective [5].

When it comes to Epileptic Seizure prediction research, there are various advantages to using EEG. Its inexpensive cost makes it ideal for epilepsy research because it can be used on a wide range of patients and can keep records of data for an extended period of time. More expensive and cumbersome equipment is needed for a number of different methods, such as fMRI or MEG.

EEG signals can be acquired by using headsets along with processed/stored with a sampling rate which ranges from 200 Hz to 5000 Hz following digitization. Neurologists apply specialized software to evaluate the signals that indicate the beginning and termination of seizures. Numerous researchers have presented seizure prediction algorithms based on deep learning and machine learning using strategies which are preprocessing, feature extraction, and classification. The first phase involves preprocessing the EEG data to remove noise and enhance the Signal-to-Noise Ratio (SNR) [6]. Among the preprocessing methods often used on EEG data in the time domain are bandpass Butterworth and notch filters [7], as well as notch filters in the frequency domain [8]. If you apply the common spatial pattern filter and the optimized spatial pattern filter on EEG data, you will see a significant increase in the signal-to-noise ratio [9]. It is also extremely effective for preprocessing EEG signals because it provides intrinsic mode functions and increases the signal-to-noise ratio by retaining low-frequency components. Empirical mode decomposition [10] can be used to generate intrinsic mode functions and increase the signal-to-noise ratio by retaining low-frequency components. Additionally, the Fourier and wavelet transformations may be used to preprocess EEG data in order to make it appropriate for input into convolutional neural networks [11], in order to enhance the precision of the outcomes. Feature retrieval is carried out once the noise has been eliminated, and relevant features with a big interclass variance and a small intraclass variance are selected [12]. For the objective of anticipating epileptic episodes, researchers retrieved unique temporal and spectral patterns. Following the growth of deep learning algorithms, various researches have utilized automatic feature extraction [13] using CNN, which has been shown to be effective due to the fact that these features are derived utilizing class information supplied alongside the data. After selecting 2 features, classification is carried out using the machine learning classifiers or deep learning techniques. SVM, Naive Bayes, Random forest, Multi-layer perceptron and KNN were used for classification. Classification may also be accomplished by the use of deep learning classifiers, such as RNN, LSTM, or CNN.

In this study, we present comprehensive findings of EEG data using freely accessible "CHB-MIT Scalp EEG Database." [14] The experimental campaign, which was confirmed using cross validation, demonstrates the high prediction capability with a very low false alarm rate of a couple of minute's prediction horizons after the seizure onset. Developing a model that has high accuracy and the lower false alarm rate for epileptic seizure is the goal of this study. For this rather than counting all the features, we will extract the features using the foremost significance and pre-process EEG signals accordingly using Butterworth Bandpass Filter. Afterwards, we will use automated feature extraction instead of traditional handcrafted feature extraction and utilize CNN along with several functions to classify the data to differentiate the pre-ictal and the inter-ictal state.

1.2 Usefulness/Importance:

Epilepsy may affect anyone at any time. Epilepsy affects both men and women of all races, ethnic origins, and ages, and it affects both children and adults. In the United States alone, the yearly expenditures associated with epilepsy are projected to be $15.5 billion dollar in direct medical bills as well as missed or reduced earnings and productivity, according to the Epilepsy Foundation [15]. Despite the fact that the vast majority of people who suffer with epilepsy have full and active lives, there is an elevated risk of death or substantial disability connected with the condition. Some anti-seizure drugs, which are also used to treat mania and bipolar illness, having suicidal thoughts or acting on such ideas may increase your likelihood of having them, according to some study. At this time, there are no drugs or other treatments that have been proven to be effective in the prevention of epilepsy. In certain circumstances, the risk factors that contribute to epilepsy can be reduced or eliminated altogether.

Epilepsy is mostly treated pharmacologically, with surgical intervention being used only in rare cases. Antiepileptic medicines, on the other hand, have their limitations and are unsuccessful in around 20–30 percent of patients, and surgery is not always an option. In this situation, being able to predict the commencement of epileptic seizures (like detecting a pre-ictal state) is crucial in order to intervene and prevent an oncoming seizure or to decrease seizure-related harm from occurring.

Doctors often focus on the symptoms of the condition that can be controlled by standard or alternative therapies, with the goal of improving people's overall quality of life. However, if this illness is detected early enough, it may be controlled. In order to do so, we are analyzing the "CHB-MIT Scalp Dataset"[14] in order to forecast indications as soon as we possibly can. Being able to distinguish between distinct stages of epileptic seizure states may be helpful in treating the seizures at different stages. Even though there have been several classifications developed so far, medical professionals are nonetheless concerned as to why and how this particular pattern identified the casualties. Thus, medical professionals would be able to provide their patients with valuable information regarding their current health status as well as the grounds behind the forecasts provided by various classifications.

1.3 Current scenario and Motivation

It is estimated that there are around 50 million individuals suffering with epilepsy in the globe, with almost 80 percent of those persons living in third-world nations. Epilepsy affects around 150,000 people each year, according to recent studies [15]. Because epileptic seizures are unpredictable events, they have an impact on the daily lives of those who suffer from them, causing sudden fatalities and heightened emotional stress.

A comprehensive research on the application of Machine Learning algorithms for epilepsy seizure prediction has yet to be published, despite the fact that several articles specifically address epilepsy seizure prediction utilizing EEG information. For example, Mormann et al.[16] reviewed the seizure evolution forecasting systems from the 1970s to 2006 and examined the crucial problems associated with seizure prediction technique. Gadhoumi et al. [17], for example, provided a thorough discussion of appropriate methodologies for the epileptic seizure prediction, as well as a thorough analysis of the statistical significance of the forecast's findings. In a recent publication, Kuhlmann et al.[18] provided a concise overview of epileptic seizure prediction advances. They came to the conclusion that these developments in standard statistical assessments are setting the framework for the creation of ES prediction tools, and they altered current criteria to make this development more feasible. Because it gives thorough answers to concerns such as why machine learning techniques are necessary for the epileptic seizure prediction, this research is unique in that it is the first of its kind, how relatively newer techniques such as deep learning are proving to be extremely useful for Epileptic Seizure prediction, and discusses future research directions in this area.

Epileptic seizures are common in both developing and industrialized nations in Asia, and they are associated with age, gender, socioeconomic and cultural background, among other factors. There are a lot of risk factors for epileptic seizures, and the social and economic consequences of this condition are yet unclear. Because of the consequences of epileptic seizures, they have become a significant socioeconomic burden in several populated nations. In these nations, the function of nursing staff management has been debated for quite some time. Some countries in South Asia are likewise worried about the occurrence of epileptic seizures. There is relatively little information available about the number of people who suffer from epileptic seizures in the third world nations.

The identification of Epileptic Seizure is now in its infancy stage in the third world nations. Consequently, patients and their families are continually presented with a wide range of issues as a result of their condition. The amount of money available for performing epileptic seizure research is restricted. In order to train models in the near future, we are working on a recent dataset "CHB-MIT Scalp EEG Dataset" [14]. Using it will allow us to train the models using a data set based on Epileptic Seizure patients in these countries.

1.4 Research Objective

Patients with epilepsy are at an increased risk of injury. These arise as a result of the fact that seizures may strike suddenly and without notice, leaving the patient defenseless. If epileptic seizures can be anticipated, patients may be relieved the sufferings the seizures cause. Researchers are working to enhance medical care via the use of AI, Neural Networks, and Machine Learning approaches. The following are the paper's objectives:

1. The goal of this study is to make people more aware of epilepsy. We have included a comprehensive description of Epileptic Seizures, including its phases, symptoms, and various methods for predicting and detecting seizure start in advance. With this knowledge, people will feel more comfortable discussing this sickness, since although Epileptic Seizure is prominent in many instances in Bangladesh, people often do not pay enough attention to minimizing the disease's prevalence.

2. The specific objective of this research is to provide an approach that is generalizable rather than patient-specific and capable of accurately predicting seizure with high accuracy and a low computational complexity. This will provide a solution recommendation that may be applied to a wide range of patients.

3. Our objective is to identify features that separate inter-ictal and pre-ictal states using automated feature extraction. We aim to present an approach for seizure prediction that combines minimal feature engineering with convolutional neural networks.

4. Our approach aims to assist people in predicting Epileptic Seizure in its earliest stages, so that when the initial stage, pre-ictal, is detected, patients and others can take necessary precautions to avoid or prepare for the final stage of Epileptic Seizure, and to assist the patient in dealing with it.

5. We want to provide insight from a larger perspective, by reviewing the most recent seizure prediction techniques, sketching their background and primary process, and assessing their predictive ability. Numerous seizure prediction algorithms and gathered information have shed light on epilepsy and the fundamental processes behind seizure generation.

6. Our objective is to give information on publicly accessible EEG datasets for analyzing patterns and predicting seizure the onset. With advancements in technol-

ogy and a rise in the number and quality of accessible EEG channels, it has become more vital to uncover patterns that may incorporate all available EEG channels for signal processing that extracts all available valuable information.

7. Additionally, by introducing future challenges in the detection of epileptic seizures, the methods we are using will be able to detect and predict risk factors for epileptic seizures, while also providing a better opportunity for researchers, making it extremely valuable for rapid discovery and treatment.

8. Our long-term goal is to build an implanted device capable of effectively alerting patients in advance of an oncoming seizure attack and also producing seizure prediction time adequate to initiate triggering antiepileptic treatments.

1.5 Thesis Outline

There is a total of seven chapters to this thesis. An epileptic seizure prediction model is the primary objective of this thesis, which aimed to build a model that could predict the probability of a patient having a seizure relying on their indicators. We aim to build the best possible model with not only higher accuracy but also with better explanation with includes providing graphical explanations for analysis. The present chapter provides a detailed overview to introduce the epileptic seizure and its symptoms, available diagnosis, EEG signals descriptions followed by the usefulness/importance of this research, the motivation and objectives to the thesis at hand. Furthermore, a brief explanation of the present condition of the Epileptic Seizure in the globe and how our study will be of great assistance in the medical field is included.

Chapter 2 reviews the earlier research and the current research direction in seizure prediction, describing and evaluating a variety of different methodologies and notable works. Researchers' notable accomplishments in the field of Epileptic Seizure are discussed in detail in Chapter 2. Additionally, the absence of current methodologies was over-viewed.

Chapter 3 provides more details about the techniques presented in later chapters. It also combines all the proposed methods together and presents a comprehensive study. Chapter 3 discusses the background analysis of Epilepsy seizure prediction on different stages, followed by details about EEG and scalp EEG. Later on, a visual overview of CNN models and Activation functions is provided in this chapter.

In Chapter 4, we discussed the data collection process and the dataset we will be working with. We went into great detail about our observations on raw EDF files. Seizures that begin before the scalp EEG shows signs of rhythmic activity can be predicted using data from other physiological indicators in Chapter 4.

Furthermore, in Chapter 5, we explained our model implementation using preprocessing and CNN. We've also provided some details on our test and training datasets. This chapter describes a computationally efficient data-driven approach to seizure prediction, using CNNs and factor graph inference. It is demonstrated that the proposed algorithm can capture temporal correlation at reduced complexity and our approach can achieve a better performance compared to prior works.

Chapter 6 presents the results, evaluating the process of noise and outlier removal, performing statistical analysis of the computed patterns, discussing the separation of the patterns belonging to different classes, and analyzing the classification results. When a seizure is predicted, this Chapter demonstrates how the procedures described in Chapters 4 and 5 were incorporated into a real-time system in response.

Chapter 7 is the concluding chapter of the thesis that highlights the findings corresponding to studies detailed in each chapter as well as strengths and limitations of our proposed technique. It also describes future research directions in seizure prediction and classifications.

Chapter 2

Literature Review

2.1 Related Works

As technology advances, there has been significant improvement in the treatments of neurological diseases. The ability to detect, predict, and classify epileptic seizures has vastly increased in recent years. Although the terms "seizure detection" and "seizure prediction" sound similar, they have different meanings. Researchers over the years have developed advanced techniques for correction, prediction, and early detection, and the classification of seizure attacks. All the epileptic seizure detection, prediction and classification process is completed analyzing the neural signals [19]. Epileptic seizure detection is the process of detecting the occurrence of seizure while having one. The seizure prediction involves an early forecast of seizure onset, that is, recognizing the possibilities of getting a seizure. Seizure classification is to spot which sort of seizure has occurred by analyzing the region of the brain that has been affected.

Using categorization, doctors can distinguish between pre-ictal, inter-ictal, and final seizure stages in epileptic seizure forecasting. For the most part, scientists have relied on classifiers based on Machine Learning and Deep Learning. In addition to K-nearest neighbor and other traditional classifiers for classification, there are also Extreme Learning Machines, Convolutional Neural Networks, Linear Discriminant Analysis, Generalized Regression Neural Networks (GRNN), Domain matching, and Artificial Neural Networks for classification [20].

Among the strategies used in early studies on the epileptic seizure prediction in the 1970s were linear feature extraction techniques [21]. However, despite the fact that these approaches were developed in the 1980s, the introduction of non-linear methodology made their use of feature extraction more straightforward owing to the non-linear structure of EEG data [22]. It was also used to identify ES throughout this decade, in combination with the detection of epilepsy-related EEG patterns, including pre-ictal and ictal patterns as well as inter-ictal patterns. In 1998, Salant et al. [23] presented an early seizure prediction. Drogenlen et al., amended this prediction in 2003 [24] and it is now trusted. The Kolmogorov entropy was used to predict ES occurrence 2–40 minutes before the trial started. In 2002, on the basis of multi-day EEG recordings supplied by many epileptic centers, the first worldwide symposium on Epileptic Seizure prediction was held. This dataset has since been studied 8 in depth [25]. In 2003, Mormann et al., revealed that before the seizure onset, the phase synchronization utilized to predict the seizure onset for certain EEG channels decline. [26].

Throughout the first decade of the twenty-first century, studies using enormous volumes of EEG data cast doubt on the accuracy of the previous century's observations. When the researchers used large and hitherto untapped data sets, they discovered that the outcomes of previous studies could not be duplicated. Preprocessing reduces noise from EEG signals, and achieving high sensitivity and specificity requires a high SNR (signal-to-noise ratio). Using bandpass Butterworth filters to filter EEG signals in the temporal domain [27] is a standard preprocessing approach. Preprocessing EEG signals using the Fourier transform [28] [29] [30] and wavelet transform [29] can also be utilized to make them acceptable for feeding into convolutional neural networks (CNN). Recent research [28] [29] [30] indicates that preprocessing raw EEG data into a time-frequency domain matrix achieves a conversion rate of between 75% using the wavelet transform [29] and 95% using the short-time Fourier transform (STFT). Because it can catch short-term variations, the stochastic Fourier Transform produces superior preprocessing results for EEG signals. Usman (2021) Demonstrated using Butterworth bandpass filters that the CHB-MIT scalp EEG dataset [14] has 90.8% specificity and 92.7% average sensitivity, followed by STFT. [27]

The use of Convolutional Neural Network (CNN) is prevalent in predicting a typical seizure in many types of research [27] [28] [29] [30] following preprocessing for feature extraction from refined data. To eliminate noise from EEG recordings, researchers utilized empirical mode decomposition [28] and three-layer Convolutional Neural Networks. The resulting images are flattened to form a feature vector after applying these three layers of CNN. The study's sensitivity rate was 95%.

Medical image analysis and bioelectric signal processing are two examples of where deep learning is now being used. It outperforms classic feature extraction and machine learning approaches in the areas of pattern identification and picture recognition. EEG seizure detection is increasingly relying on deep learning methods, notably convolutional neural networks (CNN). Troung and colleagues detected epileptic episodes, utilizing EEG and 13-layer depth CNN with an accuracy rate of 88 percent [30] . EEG characteristics were extracted and identified using CNN and SVM algorithms in another study [29]. Seizures may be detected with an accuracy of 86.25 percent using this approach. The sensitivity (i.e., the probability of detection) is taken into account while measuring classification performance. Ozcan et al., classified the EEG data with 89% accuracy using CNN [19], whose findings were reported in NeuroImage. Using a CNN architecture with six convolutional layers, Khan et al. [31] were able to extract features from EEG wavelets with an 87.8% sensitivity rate.

Additionally, Hjorth parameters, statistical moment, and spectral band power were used in this work [19]. When these features were created independently for each EEG channel, the moving window analysis revealed an accuracy rate of 85.7% including a 0.096 percent/h false prediction rate. Using the CHB-MIT database [14], as recommended in another study, allows for a certain level of artifact tolerance without the need for filtering techniques [32]. So, even without preprocessing, they suggested 9 method for feature extraction utilizing the fast Fourier transform (FFT) achieves 100 percentage accuracy, but falls short of reaching an exceptionally low false alarm rate (FAR). In a study published in the Journal of Biomedical Research, to extract features from EEG signals, researchers used signal decomposition representations based on EMD and DWT approaches which enabled them overcoming the non-linearity and non-stationary nature of EEG signals while achieving a 100% accuracy rate [20].

Extracted data must be categorized in order to be assigned to the inter-ictal, preictal, or ictal states. To classify the retrieved feature, support vector machines [27], RNN [28], k-nearest neighbor, Random Forest, convolutional networks, and the machine learning algorithms and deep learning approaches were used. We can see that studies that use SVM to extract features produce better outcomes in terms of sensitivity and preciseness. This technique separates data into two groups drawing a line between them, and it is part of supervised machine learning. Ansari's research [33] suggests that using a small number of set features is preferable. The study used a single-feature long short-term memory (LSTM) to attain an accuracy of 95.71%.

Chapter 3

Background Analysis

3.1 Epileptic Seizure Prediction

The typical method for identifying Epileptic Seizure activity in the brain is to analyze EEG signals. EEG recordings are an essential diagnostic tool for evaluating whether or not a patient has Epileptic Seizure. EEG data may be utilized to determine the phases of an epileptic seizure as well as the features of each episode throughout the pre- and post-seizure periods. Numerous researchers [28] [29] [30] [19] [31] have analyzed the association between EEG synchronization patterns and seizures, indicating that the pre-ictal state, ictal state, inter-ictal state, and post-ictal state may be distinguished.

(i) Pre-ictal State: This is the period of time before the seizure; typically, 30 to 90 minutes before to the onset of the seizure. Mood swings, anxiety, feeling light-headed, trouble sleeping, difficulty staying focused, experiencing a sense of déjà vu, nausea, and headache are some of the symptoms that might occur. It is not always visible. Alterations in the basic signals are used to predict seizures. To be therapeutically effective in a warning system, a pre-ictal condition must be detected early enough to reduce time spent in false alarm [18].

(ii) Ictal State: A shift in electroencephalogram (EEG) data that occurs during a seizure is referred to as the ictal state. This is the state of seizure itself. In this state, the person's brain experiences an electrical storm. Until the brain stimulation stops, autonomic nervous system control movements that tend to continue rapidly and rhythmically.

(iii) Inter-ictal State: This state is the interval between the onsets of two consecutive seizures. The quantity of cortical area, epileptogenic neurons, and seizure length may all be varied in the same person.

(iv) Post-Ictal Condition: This is the final state, the typically lengthy period of recovery after a seizure has occurred. The length of time it takes for a person to recover to normal depends on the severity, type, and location of the seizure in their brain.

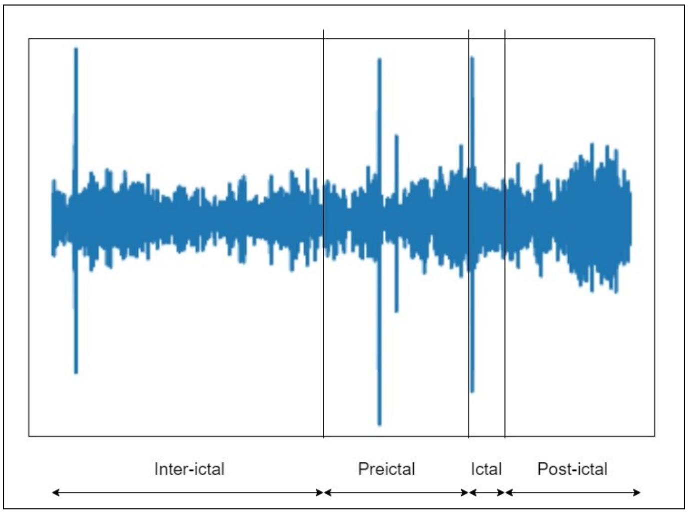

Figure 3.1: Four Stages of seizure

The epileptic seizure prediction process mainly includes dataset collection, pre-processing of data, feature extraction, classification, and post-processing of all parts of the epileptic seizure prediction process to validate the result [10]. Recognizing neurological diseases prior to time will relieve the load on healthcare providers, policy-makers, and also the medical system itself. The prognosis of a chronic nerve condition will advance research while also improving the quality of life for patients [17].

In general, pre-processing data entails cleansing and removing unnecessary material from raw data to make it more useful and acceptable. The term "pre-processing" refers to the process of reducing undesirable noise from EEG signals in order to obtain superior brain signals. Preprocessing EEG data is required for numerous reasons. First, the signals picked up by the scalp are not always precise representations of the brain's signals, since spatial information is lost. Second, EEG data tends to be noisy, which might mask weak EEG signals. Moreover, blinking or muscle movement may taint data and distort images. Noise is removed in this stage to enhance the signal-to-noise ratio in the EEG signal. Artifacts are eliminated from the primary signal during pre-processing to identify the artifact-free signal. To filter the data in this procedure, band-pass filter is used [27].

The importance of feature extraction in this study cannot be overstated. After pre-processing, Feature Extraction removes irrelevant characteristics from the improved data. So, in order to reduce the enormous amount of data, feature extraction and selection could also be used to reduce the complexity of the classification system and increase the computation of machine learning algorithms. The signals' statistical moments in the time domain, frequency domain moments, entropy, approximate entropy, Hjorth parameters, Lyapunov exponents, phase angle, the amplitude, and power spectral density are all extracted by researchers [31]. Automated feature extraction for EEG signal is an emerging part of research. Manual approaches for extracting features need a lot of time and effort since they are based on theory. Automated EEG signal feature extraction can save time, effort, and complexity. With automation, the process of extracting features becomes more efficient.

Classification is the process of classifying things into groups or classes based on their shared characteristics. When it comes to distinguishing between a seizure and a non-seizure state, this is a critical first step. In order to classify test data using the training data of several classifiers, classification is used. Data sets are used to train a classifier's parameters. By modeling the relationship between classes and attributes, a trained classifier may identify new instances in an unknown testing dataset. Classification of EEG data using traditional classifiers has shown promising results. However, the general feature extraction method's classification impact is unstable as data changes. Feature extraction and classification may be performed separately using CNN-based classification. When faced with varying sampling frequencies or varying sample data lengths, it tries to get excellent and consistent classification results.

3.2 EEG Signals

In diagnostic and therapeutic uses, the electroencephalogram (EEG) has been widely utilized to capture the electrical activity of the human brain. Multichannel recordings of electrical activity produced by groups of neurons in a brain are made from scalp EEG recordings. Due to its low cost and non-invasive nature, EEG is an extensively utilized noninvasive neuro-diagnostic tool globally. In 1929, Hans Berger, a German psychiatrist, devised EEG, a non-invasive functional imaging technology for gaining a better understanding of the brain that enables clinicians to establish a neurological diagnosis and plan future neurosurgical operations [4].

To detect seizure diseases such as epileptic seizures and stress-related disorders, depending on their severity, EEG is used. An EEG uses small metal discs known as electrodes which are connected to the scalp which is a painless and safe test to detect electrical activity in the brain [9]. Even as we sleep, electrical impulses carry signals between our brain cells, and this creates wavy lines on an EEG recording. The brain cells have specific wave patterns when we are awake or asleep, but when a person experiences a seizure, the wave patterns shift [28].

EEG electrodes are placed on a patient's scalp to record scalp EEG signals, or electrodes can be implanted into the brain to monitor intracranial EEG signals. A patient's scalp is considered to be divided into four different lobes- frontal, parietal, temporal, and occipital. The EEG electrodes are placed in those parts of the crown of the skull. The numbers and names of these channels are employed in the data analysis. Neuronal activity evident in the scalp EEG is constrained in its occurrence and features because of the principles of EEG generation. For example, the left hemispheric frontal lobe is represented in the channel "FP1 - F7". This is how we may identify the kind of seizure, such as Localized, Myclonic, or Generalized, as well as its severity. Any time a seizure occurs, the brain's electrical activity changes rapidly, and this can be detected in scalp EEG recordings as a sudden redistribution of spectral shifts. EEG results may suggest seizure activity was not happening at the time of the test, if they appear normal.

EEG monitors brain electrical activity in two ways: amplitude and frequency. This includes Delta (up to 4 Hz) and Theta (from 4 to 8 Hz), as well as Alpha (from

8 to12 Hz), Beta (from 12 to 26 Hz), and Gamma (from 26 to 100 Hz). The four sub-bands namely -1 (from 30 to 50 Hz), -2 (from 50 to 75 Hz), -3 (from 75 to 100 Hz), and -4 (from 100 to 128 Hz) comprise of the band. It is avoided that the 60 Hz power line noise and harmonics are used in the spectral power calculations [19]. During an Epilepsy Seizure attack, EEG plays an efficient role to study the brain functional anatomy [12].

As a first step in using EEG data to diagnose an illness or interpret brain activity for neuropsychological testing, one needs to use spectral information or extract the features from the raw data [34]. The raw data that we get from the EEG tests cannot be used for diagnosing because it is difficult to interpret the data from a single pair of EEG electrode pairs. So the EEG dataset is fed into the preprocessing phase. Then, feature extraction is used to reduce the dimension of the raw EEG signals [12], which is critical in extracting distinctive patterns from the raw data for consistent categorization. The selection of features is a crucial stage in classification [20]. Redundant features may overburden the system, preventing the best possible outcome. As a result, reducing the number of features will assist the classifier in learning more robustly and achieving good performance. ML-based classifier is trained using extracted features or processed raw data as input for automatic feature extraction. In order to identify different brain disorders, analyzing EEG data can assist in distinguishing between normal and abnormal brain activity [25]. Longer-duration EEG recordings are required for effective epilepsy prediction. Expert neurologists evaluate EEG signals collected over a period of days, weeks, or even months in order to pinpoint the source of epilepsy.

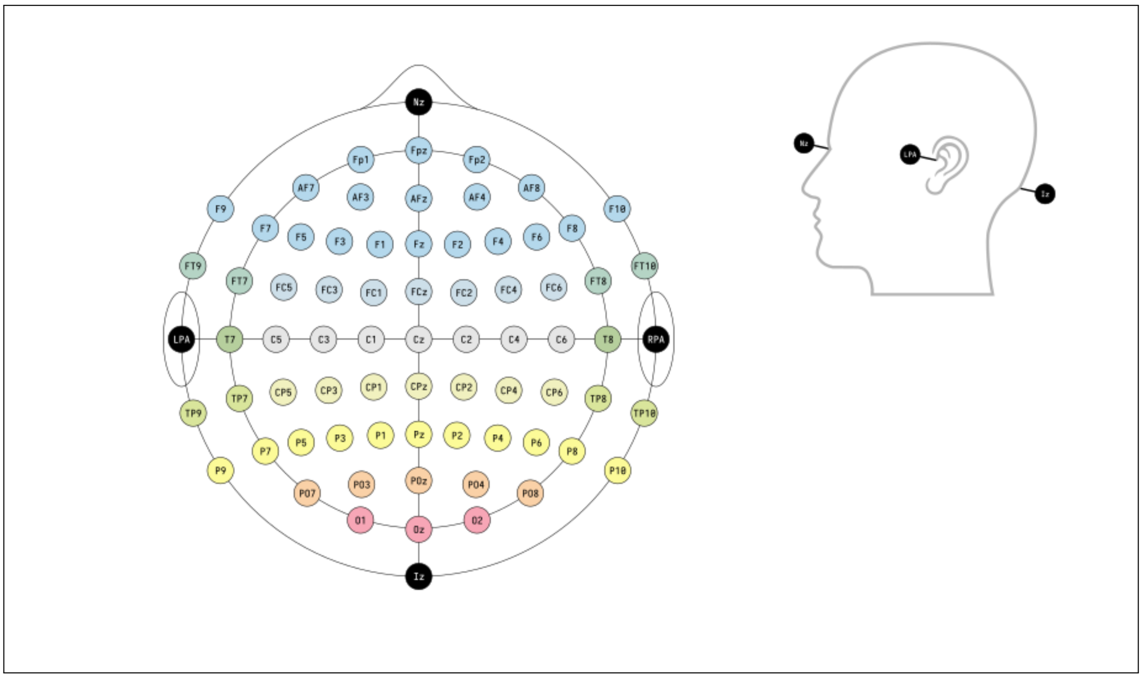

Figure 3.2: EEG Cap layout for scalp electrodes positions

3.3 Butterworth Bandpass Filter

Noise and artifacts contaminate measurements in the area of brain research, one of the most challenging issues. Examples of such sources include background noise, instrument noise, and internal signal sources that aren't relevant to the experiment. Noise may either conceal or complicate the accurate analysis of the intended signal. However, if the signal and interference are situated in discrete spectral parts of the spectrum, it may be possible to boost the SNR applying a filter to the data.

The Butterworth Bandpass filter is one of the most used frequency domain filters, also known as the maximally flat filter. Throughout its bandpass, it is a form of Active Filter that has a reasonably flat frequency response. Because the filter has a strong frequency roll-off feature, a magnitude function that changes monotonically with frequency, and a more linear phase response in the passband when compared to other traditional filters, it is more efficient.

In 1930, British scientist and engineer Stephen Butterworth first discussed the Butterworth filter in an article. As a result, the Butterworth filter was given its name [35]. Digital Butterworth filters and Low pass Butterworth filters are two examples of Butterworth filter types. Increasing the Butterworth filter order brings the wall response and filter closer together, which in turn brings up the number of cascaded stages in the design. This filter is to attenuate noise, remove artifacts and enhance target activity, making EEG recording analysis more accurate and precise. This filter aims to keep the unique frequency of the signal, and the information received from the clean EEG signal can be utilized for therapeutic applications, such as the detection of epilepsy, coma, brain damage and stroke amongst other things [35].

3.4 Convolutional Neural Network (CNN)

Neural networks are mathematical models that store knowledge via the use of brain-inspired learning mechanisms. Similar to the brain, the neural networks are composed of several neurons which are connected through numerous connections. In a variety of applications, neural networks have been used to simulate unknown relationships between various parameters using a huge number of samples [36]. Additionally, neural networks are increasingly being applied in medicinal applications. A Neural Network's fundamental an input layer, an output layer and one or more hidden layers are all components of architecture. As illustrated in the example below.

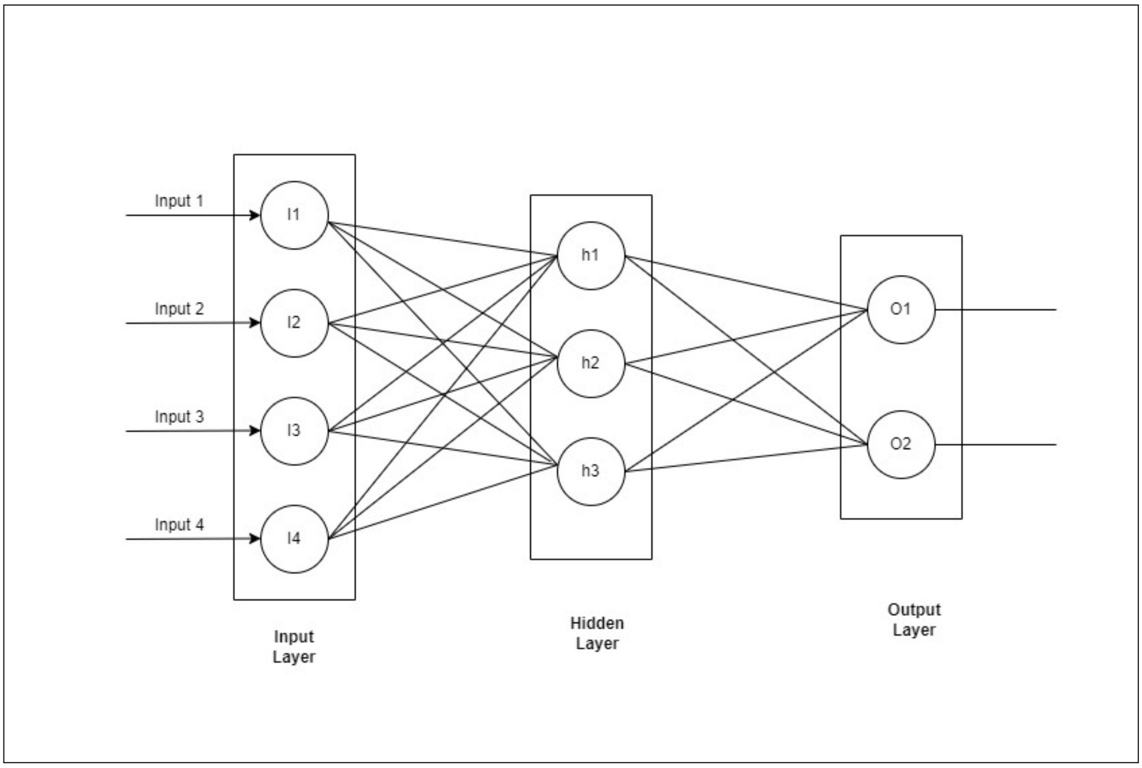

Figure 3.3: A simple 3-layered Neural Network

The data is transmitted to the input layer, which distributes it appropriately to the hidden layer (s). All calculations and conclusions are made here before they are sent to the output layer. The fact that neural networks usually include several hidden layers piled on top of one another characterizes deep learning.

Images were initially processed in pixels using a multi-layer architecture known as CNN. Traditional neural networks are not appropriate for image processing since the pictures must be entered as reduced-resolution bits [37]. But CNNs can be used for signal processing as well. Therefore, CNNs have their nodes, or neurons, organized more like the frontal lobe of the brain, which is responsible for visual stimuli processing in living beings. This way, the layers are organized in such a way that the entire image may be processed at once rather than separately. The neurons in the network's layers are organized in three dimensions, two of which are input dimensions, and the third of which is the activation volume.

CNNs are constructed with input and output layers and contain a number of layers that are hidden. Also, convolutional, fully connected and pooling layers are typically found in CNN's hidden layers. Before sending the output to the next layer, Convolutional layers convolutedly transform the input. Convolution replicates a single neuron's response to visual input. Pooling layers in convolutional networks forms one neuron in the succeeding layer by merging the output of neuron clusters in a single layer [38].The value obtained from the average of each cluster of neurons in the preceding layer is used in mean pooling. By progressively reducing the number of parameters, computations in the network as well as the spatial dimension of the depiction, and to minimize overfitting, we utilized a pooling layer.

3.4.1 Activation Functions

The activation functions of artificial neural networks (ANNs) are crucial in defining the output of deep learning models. Neural network output may be predicted using this tool. Each neuron in the network has a function that decides whether or not it should be active based on the information it provides to the model [39].

Deep Learning models' accuracy and computing efficiency are both determined by activation functions, which may make or break a large-scale neural network. Additionally, it has a significant impact on the neural network's capacity to and pace at which it can converge. Normalization can also be helped by the activation function [40]. The Activation function has a value that might be anything from 0 to 1 or from -1 to 1.

Sigmoid, for example, is a popular activation function that may be utilized in the output layer of binary classification. Using TanH in the network's lower levels is possible; This activation function is particularly easy to implement compared to other activation functions, such as ReLU, since it just activates neurons depending on the output, meaning that if the output goes below zero, the neurons are detached from the network [41]. In recent years, the ReLU (Rectified Linear Unit) has become the most common non-linear activation function. TanH and sigmoid functions are not included in this comparison. Several layers of neural networks, or deep neural networks, can be constructed using ReLU.

The ReLU equation indicates that the output of this method is the highest feasible value between 0 and the input value being utilized. The output equals to 0 when the input is negative; and when the input is positive, the output equals input. The rectified linear activation unit (ReLU) may be utilized in convolutional layers since it is compatible with layers. The pooling layer [38], sometimes referred to as the down-sampling layer, pools the output of the convolutional layer in order to retain higher-level representations. After convolutional and pooling layers, the signals are generally sent into fully connected layers for the purpose of classification [41].

CNNs clearly outperform traditional classifiers when it comes to evaluating large datasets. Parameter sharing is used to manage and decrease the number of parameters in convolutional layers of CNNs, a technique that CNNs employ. To avoid overfitting, a pooling layer is employed to gradually lower the spatial size of the network, as well as the number of parameters and computations [37]. CNN was fed with a multichannel time series based on signals in the time or frequency domain as the input layer.

Chapter 4

Dataset Analysis

We begin this chapter by describing how we acquired the dataset for our research. Then we'll dive deep into analysis of our selected dataset and it's features.

4.1 Data Acquisition

The term "data acquisition" refers to the process of gathering data from relevant sources prior to storing, cleaning, and preprocessing any data. It is the process of gathering relevant data from all acceptable sources and putting it into a machine-readable format so that the machine may be taught and become accustomed to the decision-making process. Our initial objective was to search for and retrieve publicly accessible EEG databases. Despite the fact that there are only a few open-access scalp EEG databases available, we will use the CHB-MIT Scalp EEG Database [14] from Children's Hospital Boston. The CHB-MIT Scalp EEG database [14] seemed to be the most trustworthy because it is one of the most widely used research resources for scalp EEG analysis The CHB-MIT Scalp EEG Database [14] is unique among databases in that it comprises raw EDF files of seizure and non-seizure recordings from persons of various ages, as well as a summary file. Due to the prevalence of raw EDF files in the database, it becomes easier to preprocess the raw files according to the purpose.

4.2 CHB-MIT Scalp EEG Dataset

The database contains scalp electroencephalograms of twenty-three patients with intractable focal epilepsy, nine of whom are men and seventeen of whom are women. Each case contains nine to twenty-four EDF files compiled from continuous EEG waves from the patients. Digitalized EEG signals contained in EDF files have exactly one-hour length. The bulk of files contain 23 channels in total. The data has a resolution of 16 bits and 256 samples per second sampling rate. This dataset contains a total of 198 seizures. It is possible to locate recordings labeled "chb_n", with the nth sample for the suitable subject denoted by the number n.

Table 4.1: The CHB-MIT EEG DATASET description.GENDER:Female(F) AND Male(M)

Case	Gender	Age	Number of seizure(s)
chb01	F	11	7
chb02	M	11	3
chb03	F	14	7
chb04	M	22	4
chb05	F	7	5
chb06	F	1.5	10
chb07	F	14.5	3
chb08	M	3.5	5
chb09	F	10	4
chb10	M	3	7
chb11	F	12	3
chb12	F	2	40
chb13	F	3	12
chb14	F	9	8
chb15	M	16	20
chb16	F	7	10
chb17	F	12	3
chb18	F	18	6
chb19	F	19	3
chb20	F	6	8
chb21	F	13	4
chb22	F	9	3
chb23	F	7	7

4.3 Observations on Raw EDF Files

The International 10 to 20 systems of EEG electrode placements and nomenclature were employed in order to obtain the EEG recordings. These groups of electrodes, which are twenty-one in number, are positioned on the scalp. In addition to the 21 electrodes of the 10-20 system, which is widely used around the world, it is also feasible to employ intermediate 10% electrode sites. The CHB-MIT Dataset [14] is comprised of a total of 23 channels: "FP1-F7", "FP2-F4", "F7-T7", "P3-O1", "P7-T7", "T7-P7", "T7-FT9", "F4-C4", "FP2-F8", "FP1-F3", "P7-O1", "F8-T8", "F3-C3", "T8-P8", "C3-P3", "FT9-FT10", "T8-P8", "P8-O2", "P4-O2", "CZ-PZ", "FT10-T8", "FZ-CZ". It shows the central, parietal, frontal, frontal polar, occipital, and occipital-temporal relationships. Cases chb01-chb11 and chb23 all had 23 channels, as determined by analyzing the dataset. Up to five "dummy" signals (marked as "–") were inserted between EEG readings in some situations, including chb12-chb19 and chb20-chb22, although these "dummy" signals can be ignored. While evaluating the dataset, it is discovered that channels in chb11-chb23 are altered many times. Channels between chb12 and chb23 have been altered at least three times. When the channels are changed, the difference between one electrode and a weighted average of electrodes in it's proximity changes as well.

Figure 4.1 which is of raw data of chb15_01 is a non-seizure file with a less generalized spike or poly-spike or a quicker wave discharge than 3-5 Hz in the EEG signals. We can see the insertion of 4 dummy signals marked as "-0", "-1", "-2", "-3" after the channels "P7-01", "P3-01", "CZ-PZ", "P4-02" respectively.

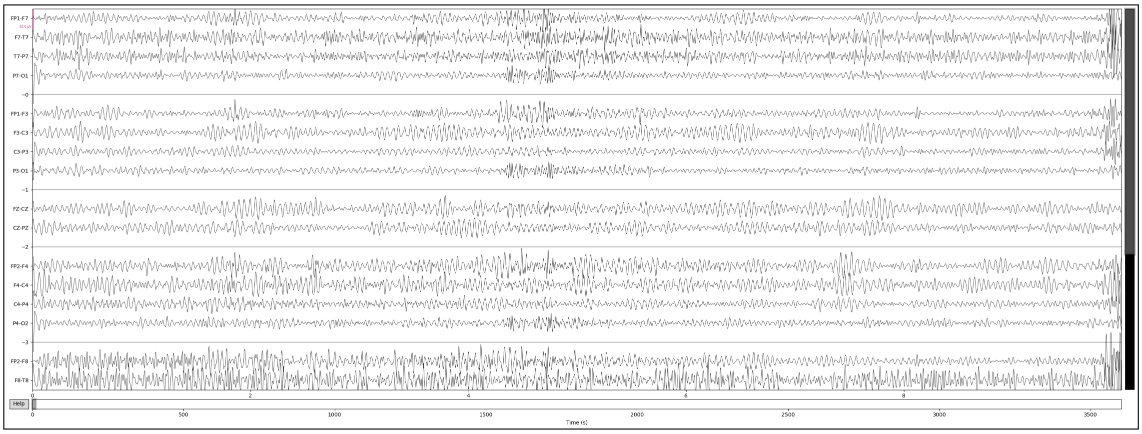

Figure 4.1: Raw non-seizure data of chb15_01

As seen in Figure 4.2 , even the cases of chb12 contain 4 dummy signals, as indicated in Figure 4.1 (marked "-"). A seizure attack is depicted in this image. In contrast to Figure 4.1, we can see continuous spikes at around 1600 seconds and again at 3400 seconds of in the first five channels in Figure 4.2. In focal epilepsy, it is also noticed that the seizure duration is short, even if the patient has multiple seizure attacks as shown in Figure 4.2.

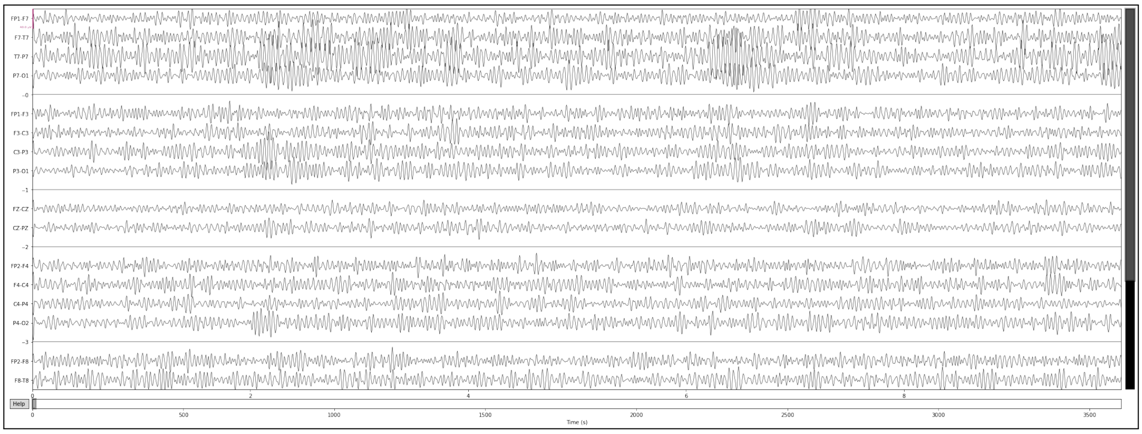

Figure 4.2: Raw seizure data of chb12_06

The power spectral density (PSD) per unit frequency of a signal describes the power of the signal as a function of frequency. PSD depicts the strength of related periodic signals. The PSD vs. Frequency graph of a non-seizure example is shown in Figure 4.3. It exhibits a sharp peak at $\sim$ 17 Hz, $\sim$ 34 Hz, indicating that noise is at its highest here, and because it's a harmonic signal, it will happen every 17 Hz or so as the power decreases.

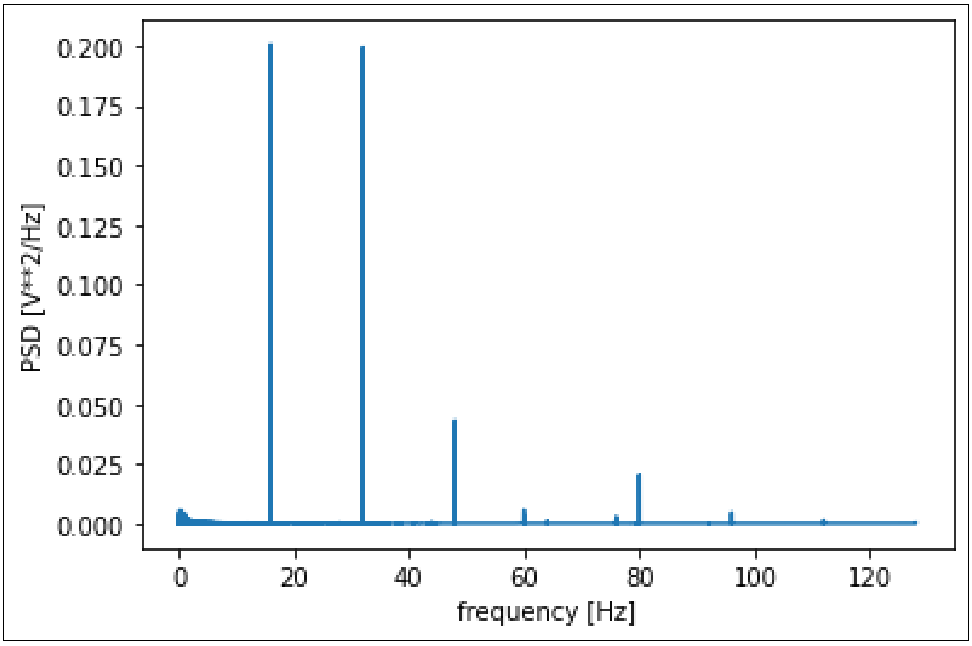

Figure 4.3: PSD of non seizure data of chb01_01

At ∼ 18 Hz and ∼ 35 Hz, the seizure case in Figure 4.4 exhibits the same characteristics of the noisy signal as the seizure case in Figure 4.3. Other frequency levels, such as 0 Hz, 50 Hz, 78 Hz. However, accumulate noisy signals as well in Figure 4.4. When we look at both the seizure and non-seizure PSDs, we can see that, the seizure one has a noisier signal than the non-seizure scenario.

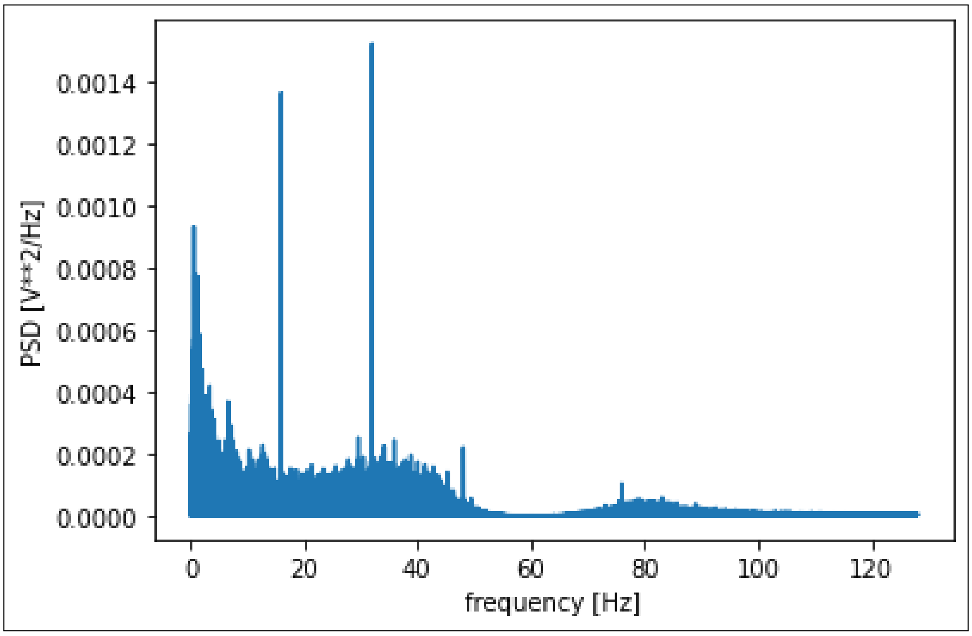

Figure 4.4: PSD of seizure data of chb07_13

Chapter 5

Model Implementation

5.1 Proposed Model

When it comes to computer-aided disease diagnosis, deep learning is now significantly contributing. For deep learning, there is no need for manual or expert based feature selection. Instead, raw data can be used to create an efficient optimal representation that incorporates that data. As a healthcare system, manual selection might be exhausting when dealing with a large number of patients with the same disease. The convolution neural network is distinct from the basic neural network in that it has 150 or more layers. This feature of CNN helps to cope with large datasets and enhance accuracy in several disciplines.

From Figure 5.1, We have a clear picture of the steps we need to take in order to make a reliable seizure prediction. To begin, we used the "CHB-MIT Scalp EEG Dataset" [14] to get our data and after this data acquisition process we have firstly analyzed the patients' seizure and non-seizure files thoroughly for better understanding. It took us a while to do the dataset analysis since we are new to the EDF format data. After analyzing the dataset, we figured out that we can focus on working with the first 10 patients and with 18 common channels. The findings on the common channel has helped us extensively in generalization of the model.

Right after selecting our desired cases and channels, we moved to the pre-processing part of our study. Since we are dealing with EDF file, it is very crucial to pre-process the signals. The pre-processing part took the longest time. Before pre-processing it was necessary for us to have a good understanding about the seizure signals. We had to have proper understanding about the inter-ictal, pre-ictal, ictal, post-ictal segments of the signals. The preprocessing of EEG signals is required to at least lessen the pre-ictal and ictal state imbalance complication, boost the SNR, and remove undesired artifacts. For preprocessing, the raw EEG data, we employ the Butterworth Bandpass filter with a cutoff frequency of 5-50 Hz [42]. Then we concatenate the ictal signals with the pre-ictal signals as 30 minutes time frame from the entire signal and define as pre-ictal/ictal signals [43], and cut off the rest of the data as inter-ictal signals. After successfully extracting inter-ictal and pre-ictal/ictal signals from the data signal, we finally got the shape of (12,1280) and got 35132 files in total that is fed to the CNN as input.

In computer vision and natural language processing, CNN is a well-known deep neural network architecture that has been widely used. We employed a ReLU function in conjunction with four convolution layers in our study. Following a batch normalization and max pooling layer, each convolution layer is made up of two conv2D layers. Following the convolution unit rather than using only Fully Connected (FC) layers which is most commonly used in the CNN models,in the goal of achieving greater precision, We opted to employ a Global Average Pooling (GAP) that creates a feature map for each category's associated classification task. By requiring correspondences between feature maps and categories, global average pooling has the benefit of making the convolution structure more native than fully connected layers. Thus, the feature maps may be simply understood as confidence maps for categories.

Additionally, overfitting at this layer is prevented since there is no parameter to optimize in global average pooling. A dropout unit with a rate of 0.4 was utilized after the GAP layer in order to use two dense (FC) layers. Each neuron in the dense layer gets information from all of the neurons in the layer preceding it due to the dense layer. Finally we used Sigmoid activation function the output layer which is also called a logistic function. We found that it is suitable for our proposed CNN model since we are using binary classification of data.

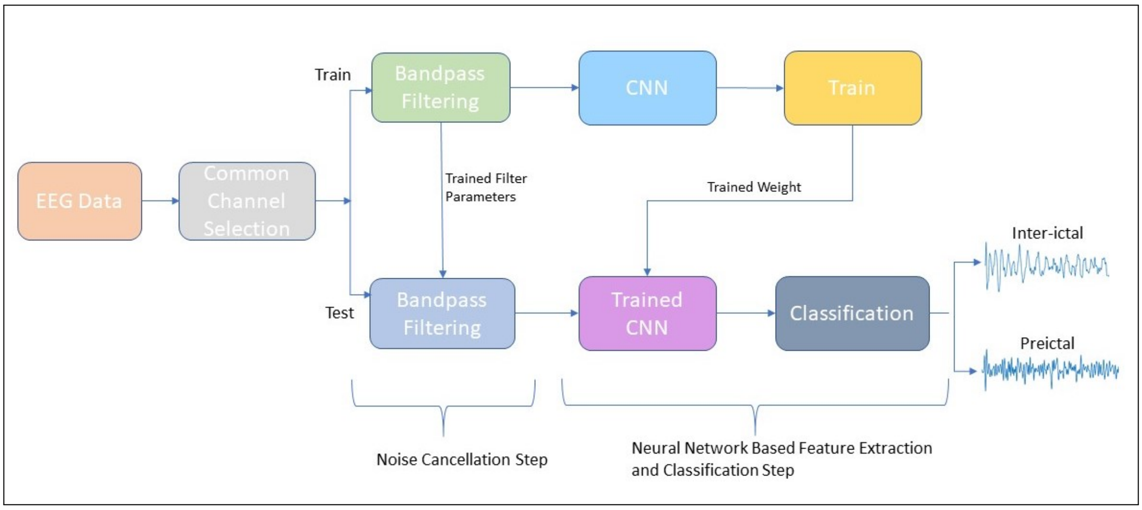

Figure 5.1: Proposed Model for Epileptic Seizure Prediction

5.2 Input Data

Originally, our data was saved in the edf format in the dataset. It's challenging to work with such a file format. Thus, we begin by reading the raw edf files using Python programming language's mne.io.read_raw_edf() function. Next, we used the Python's getdata() function to extract raw data from edf files and store it in a numpy.ndarray named edf_numpy. Because our goal is to develop a generic method for seizure prediction that can be applied to all patients, we chose the first ten cases, or a total of 55 seizure files, for our research. Additionally, we chose to deal with the common 18 channels because they are present in all cases. It's difficult to evaluate without identifying the common channels because the electrode used for each patient in numerous trials is different. The following are selected cases from all recordings, along with their associated channel names:

Table 5.1: Selected Cases and Channels as Input Data

	Cases and Channels	Description
Selected Cases	Cases from chb01-chb10 with seizure recordings only.	Due to the fact that not all electrode placements are identical and hardware issues caused in gaps between sequential edf files, during which the signals were not captured; in most cases, the intervals are 10 seconds or fewer, but occasionally there are substantially larger gaps.
Selected Channels	"FP1-F7","F7-T7","T7-P7","P7-O1","FP1-F3","F3-C3","C3-P3","P3-O1","FP2-F4","F4-C4","C4-P4","P4-O2","FP2-F8","F8-T8","T8-P8-0","P8-O2","FZ-CZ","CZ-PZ".	Additionally, this dataset includes up to 31 channels with dummy signals. However, upon the study of the data, we discovered that all patients utilize these common channels. As a result, we have narrowed our analysis to these common channels.

5.3 Pre-Processing

Pre-processing is critical in predicting epileptic seizures. To begin, we must import the following libraries: mne; pandas; numpy; matplotlib.pyplot; scipy; filtfilt, butter, and lfilter from scipy.signal; and stats from scipy. Following the selection of the ten cases and the common 18 channels, we proceeded to the pre-processing stage. We removed all channels except the common ones and placed them in edf_numpy, a 2D numpy array for our convenience. We employed the Butterworth Bandpass filter to remove the baseline and power line noise in selected cases. In comparison to other BBs, we chose a fifth-order BB since it provides a linear response. The frequency cutoff was between 5 Hz and 50 Hz because the irregular discharge associated with epilepsy seizures occurs primarily at frequencies between 5 and 50 Hz [42]. The low-cut and high-cut frequencies are 5 Hz and 50 Hz, respectively. Cutoff frequency is the frequency where the response is 3 dB lower than the passband's level, which is what determines the frequency of the filter's cutoff. Depending on the filter's design, all other frequencies will be attenuated once the cutoff frequency has been reached. These two frequencies were removed because they were deemed to constitute noise. As a result, we chose a frequency range of 5-50 Hz.

Prior to algorithm implementation, the seizure prediction horizon must be determined. Seizure occurrence period (SOP) is an important factor to examine since it indicates the likelihood that a seizure will occur. The seizure prediction horizon (SPH) defined as the clinical intervention that is a minimum timeframe between the prediction of seizure and the start of SOP [43] . However, the prescribed pre-ictal horizon remains debatable. Seizure prediction facilitates the prediction of seizures ahead of their occurrence, allowing patients to get prompt and appropriate treatment. Unfortunately, by the time the ictal signal has been located, the ideal response time has elapsed. As a result, distinguishing the ictal state for epileptic seizure prediction makes no sense. So, we have incorporated them into the prediction time frame. For the sake of our experiment, we concatenate the ictal and preictal signals as 30 minutes pre-ictal/ictal signals (i.e. 30 minutes prior to the commencement of a seizure) for each patient's seizure. [43] After delimiting the pre-ictal/ictal signals, the remainder of the recording of the seizure files is referred to as the inter-ictal signals.

Following the specification of the BB cut off frequency, we begin filtering the 18 common channels, one by one using the BB Filter Algorithm and appending them in data_channel_filtered 2D numpy array. After retrieving the seizure end time, we separate the inter-ictal and pre-ictal/ictal signals by setting the pre-ictal/ictal signal files to 30 minutes or 1800 seconds and the rest of the file duration to the inter-ictal signal. We use the pre-ictal/ictal end time of each patient as the product of the sampling rate and seizure end time. As previously stated, the pre-ictal/ictal start time begins 1800 seconds earlier at the pre-ictal/ictal end time. Similarly, we define the inter-ictal start and end time as the seizure recording file start time and pre-ictal/ictal start time respectively.

If we take chb02_19 seizure case as an example which has a seizure end time at 3036 seconds of it's one-hour file recording. Traversing backwards from the ictal end time which is 3378×$sampling\_rate$ or 3378×256 or 864768 seconds, then pre-ictal/ictal start time will be (3378-1800)×256 or 403968 seconds.We can get the pre-ictal/ictal start time and end time by slicing the data_channel_filtered numpy array within range 403968 seconds and 864768 seconds. For inter-ictal part, it starts at 0 second that is the starting time of the file recording and ends at the starting of the pre-ictal/ictal start time at 403968 seconds.

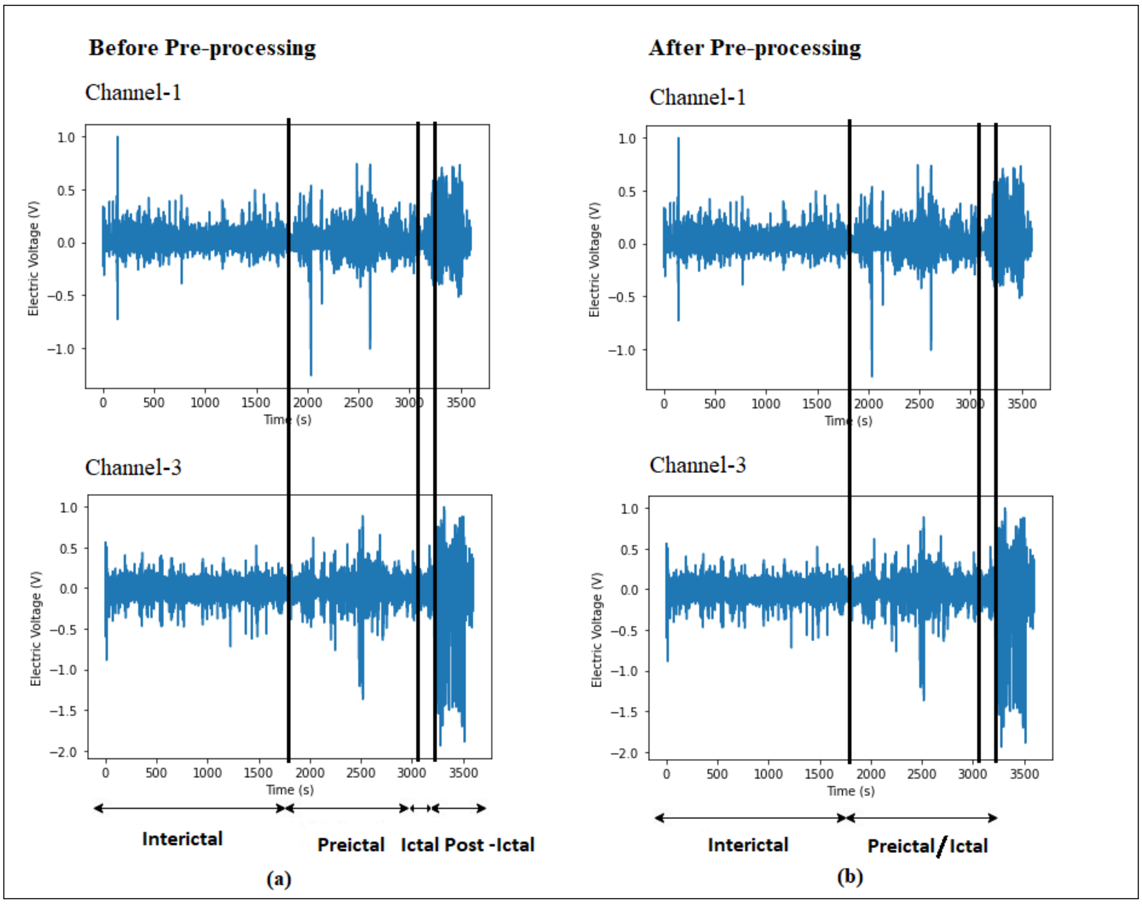

Figure 5.2: Raw Signal Data of chb02_19 seizure file (a) and Filtered Data of chb02_19 seizure file (b)

One of the challenges we ran into during pre-processing was that not all of the file recordings were exactly one-hour long. Cases like chb03_36, chb04_05, chb06_01, and chb10_31, for example, had longer records, so we cut off the standard 1800 seconds for the pre-ictal/ictal signal and used the rest of the data for the inter-ictal signal. Another issue we encountered was dealing with multiple seizures for the same recording. The recording in chb04_28, for example, is four hours lengthy and includes two seizure episodes. So, for the second seizure, we started trimming the pre-ictal/ictal and inter-ictal first. We cropped the inter-ictal period till the first seizure occurred. Finally, we set the pre-ictal/ictal period for 1800 seconds for the first seizure occurrence and trim the inter-ictal segment from the rest of the data as previously.The pre-ictal/ictal and inter-ictal signals split into five second signals [42] for binary classification trials and saved as numpy files.

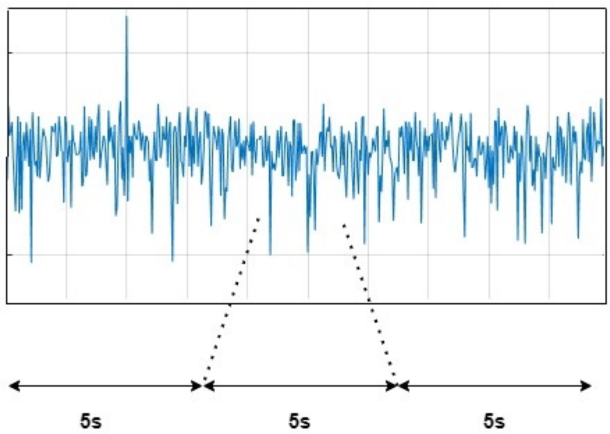

Figure 5.3: 5s Signal segmentation without overlapping

At the end of pre-processing we get a total of 35,132 numpy files and 14,269 pre-ictal/ictal files and 20,863 inter-ictal files. Finally, we get the shape of (18,1280) as the output of the pre-processing stage.

5.4 CNN as Automated Feature Extractor and Classifier

Due to its capacity to learn spatially invariant characteristics across many scales, CNNs have become the dominant approach in computer vision [44]. There have been significant advancements in the use of image processing techniques to the analysis of a wide variety of one- and two-dimensional structures for medical classification and prediction. Even when dealing with one-dimensional data and time series, CNNs are gaining popularity as a substitute for the more traditional Recurrent Neural Network approach (RNN). In comparison to RNNs, CNNs with wide receptive fields can also be trained significantly quicker, which enables them to outperform RNNs in the area of extended sequence analysis. Additionally, CNNs can only learn functions created by highly ordered convolutions, limiting their capacity to overfit in the absence of sufficient training data [44].

5.4.1 Initial Setup

We have used AMD Radeon RX 5600 XT GPU and i9-10850K processor. For the initial setup of out model, firstly we import the keras and layers from tensorflow. We used the classic 2D CNN model that takes input the formulated EEG signal samples. The samples were cropped with a 5s time-frame for both the inter-ictal and pre-ictal/ictal samples without overlapping. The samples have exactly 1280 elements in the time axis but only the selected 18 elements in the channel axis.

Since we have two categories of data, we use binary classification. The number of classes are 2 so we have used Label=0 for distinguishing inter-ictal and Label=1 for pre-ictal/ictal. There are 32 training samples in a batch size of 32, which we have chosen, and each iteration uses a different set of 32 training data. Then, for the training and validation datasets, we randomly divided our data into 80 percent and 20 percent of the samples, respectively, based on the target size.We filled our datasets for training and validation according to the percentages.

5.4.2 CNN Model Creation

In our proposed CNN Model we have kept the input shape same as our sample size (18×1280) to begin with in the input layer. We propose a model that includes four convolution layers and a 2D Global Average Pooling layer following the conv2d layers, excluding the input and output layers. The activation function for each of the CNN's convolution layers is a rectified linear unit (ReLU). A Batch Normalization layer and a 2D max-pooling layer follow each convolution layer. Figure 5.4 shows the kernel sizes for convolution kernels and max-pooling kernels.

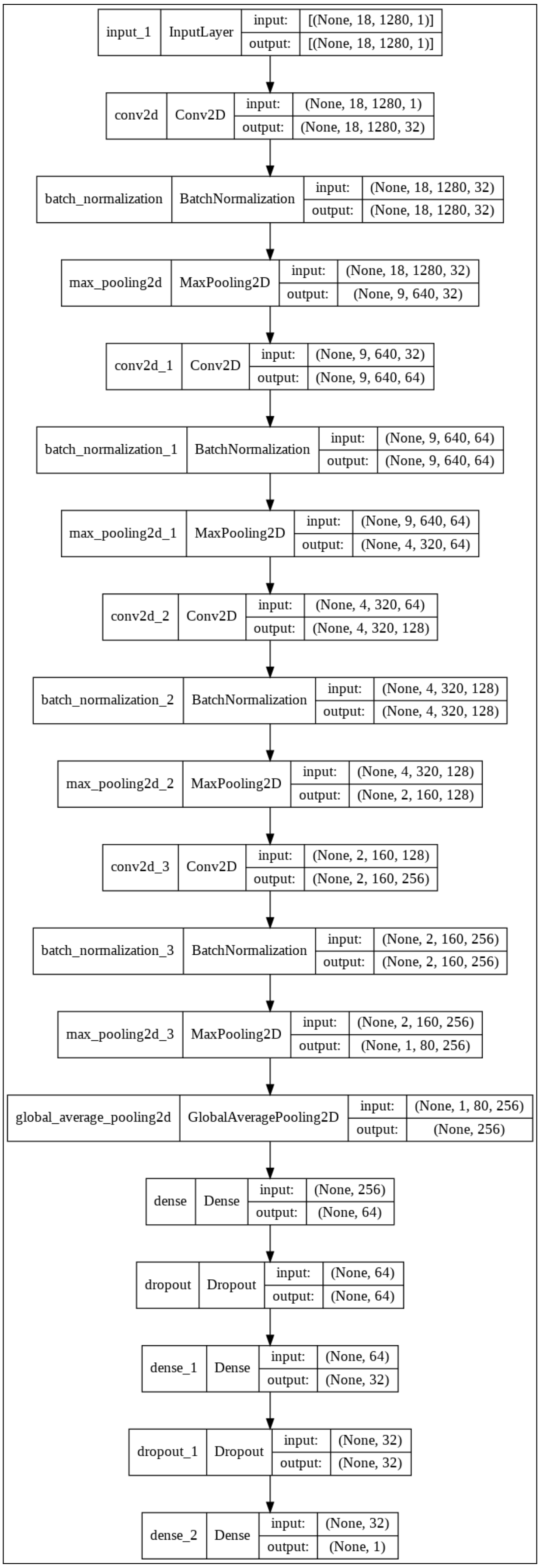

Figure 5.4: Summary of Proposed CNN Model

Convolutional Layers, Pooling Layers, and Fully-Connected Layers are used to construct ConvNet designs. These layers will be stacked to create a complete ConvNet architecture. Neurons in ConvNet layers are organized in three dimensions: width, height, and depth. In this context, “depth” refers to the activation volume’s third dimension. It is the primary building block of a Convolutional Network, which performs the majority of its computation. The output volume is controlled by three hyperparameters: depth, stride, and padding. The depth parameter specifies the number of filters to utilize; each filter looks for something unique in the input. Second, we defined the stride along which the filter slides. We utilized a stride of 1 to ensure that the filters leap one unit at a time as we move them. This results in spatially reduced output volumes. We set the padding=“same” so that the output size is the same as the input size which is convenient while training the model for when the stride is set to 1.

To normalize the output of the conv2d layer, we used a Batch Normalization layer. A transformation known as batch normalization is used to keep the output mean and standard deviation as near as possible to 0 and 1, respectively. Fit() normalizes the layer’s output based on the mean and standard deviation of the current batch of inputs during training.

The Max pooling 2D layer follows, and Max pooling is a discretization method based on samples. The goal is to down-sample to reduce the dimensionality of an input representation so that assumptions may be made about features. For example, we can see in our figure, for the first conv2D the input sample size is (18×1280) and batch normalization the output is fed into the Max pooling layer which takes it as input, reduces the dimension to (9×640). The sample size (9×640) is the again fed as input in to the next conv2D layer. The input is again fed into batch normalization layer and then the second layer of Max pooling 2D, which takes that as input and reduces that to (4×320) to provide the output. This is done in all the four layers. Thus, the number of kernels for the 4 convolution layers is 32, 64, 128, 256 respectively.

The convolution layers use a (3×3) convolution kernel and a (2×2) max-pooling kernel. The four convolution layers that we used each have 32, 64, 128, 256 kernels. After the 2D Global average pooling layer we used two Fully Connected layers (FC) of the ReLU activation function.Standard ReLU activation is returned by default: max(x, 0), which is the element-wise maximum value of 0 as well as the input tensor.

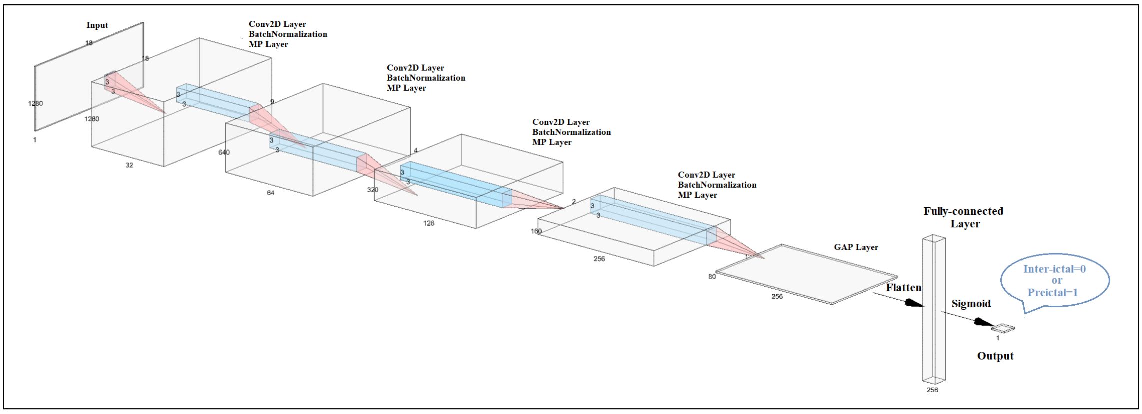

Figure 5.5: Proposed CNN Model for Seizure Prediction

For each of the input channels, the global average pooling block accepts a tensor of size $(input\_width) \times (input\_height) \times (input\_channels)$ and computes the average value of all values throughout the whole $(input\_width) \times (input\_height)$ matrix for each of the $(input\_channels)$. We then proceed to use two FC levels, each of which is deeply linked to the prior layer. Which means that the layer's neurons are connected to each neuron in the preceding layer at a dropout rate of 0.4.The output layer uses Sigmoid activation function for binary classification. Layers that are fully linked are prone to overfitting. We employed a regularizer with a dropout rate=0.4 to set the activations of dense layers to zero randomly during training. It has enhanced generalization capacity and substantially reduces overfitting.

5.4.3 Training parameters

For training our model we have used all patient data for generalization. We have used the callbacks API. Actions are carried out at different stages throughout the training process by this, and we have used the relevant methods of callbacks that will be called at each stage of training. After each epoch we have periodically saved our model to HDD. Then we have used the EarlyStopping and ReduceLROnPlateau class from Tensorflow to monitor the quantity of the training and stop training when a monitored metric has stopped working. In order to limit the learning rate, the factor parameter has been set to 0.1. So,

$$New\_learning\ rate = learning\ rate * Factor$$

The patience parameter is set to 10 for the EarlyStopping class which is the number of epochs that will be monitored before stopping the training when there is no improvement.While increased iteration during the training phase improves training accuracy, it also results in overfitting the training data. In order to avoid the CNN model from overfitting, we used earlystopping. When the error on the validation set starts to expand, the training is halted in this technique. Additionally, all prior iterations' network settings stay unchanged, as well as any errors in verification. Network settings are reset when the validation error rises over a certain threshold. The value of 5 is used for the ReduceLROnPlateau. We didn't change the metrics that keep track of things like recall, accuracy, and precision. After that, the model is compiled using the Adam optimizer, binary crossentropy as a loss, and the metrics were passed. Lastly, we run the model through 100 epochs of training. After 50 epoch it is found that the test set classification accuracy comes in at 89.5%, the Sensitivity is 89.7%, AUC is 89.5% and Precision is 89.0% .

5.4.4 Graphical Representation

Matplotlib was used to visualize the model's historical accuracy, AUC, precision, and sensitivity data. Accuracy is a metric used to assess the model's accuracy. Simply expressed, accuracy refers to the amount of true predictions provided by our model given the entire number of inputs. The Area Under The Curve (AUC) is used to quantify a classifier's ability to discriminate across classes. The greater the AUC, the more accurate the model is at classifying the classes. The precision metric indicates how accurate the model is at classifying samples as Positive. The precision goal is to correctly categorize all Positive samples as Positive and to avoid misclassifying a negative sample as Positive. Sensitivity is a benchmark that indicates how well a model predicts true positives for each available category. For each scenario, we preserved the epochs on the x axis and plotted only the accuracy, AUC, precision and sensitivity score during training and validation on the y axis.

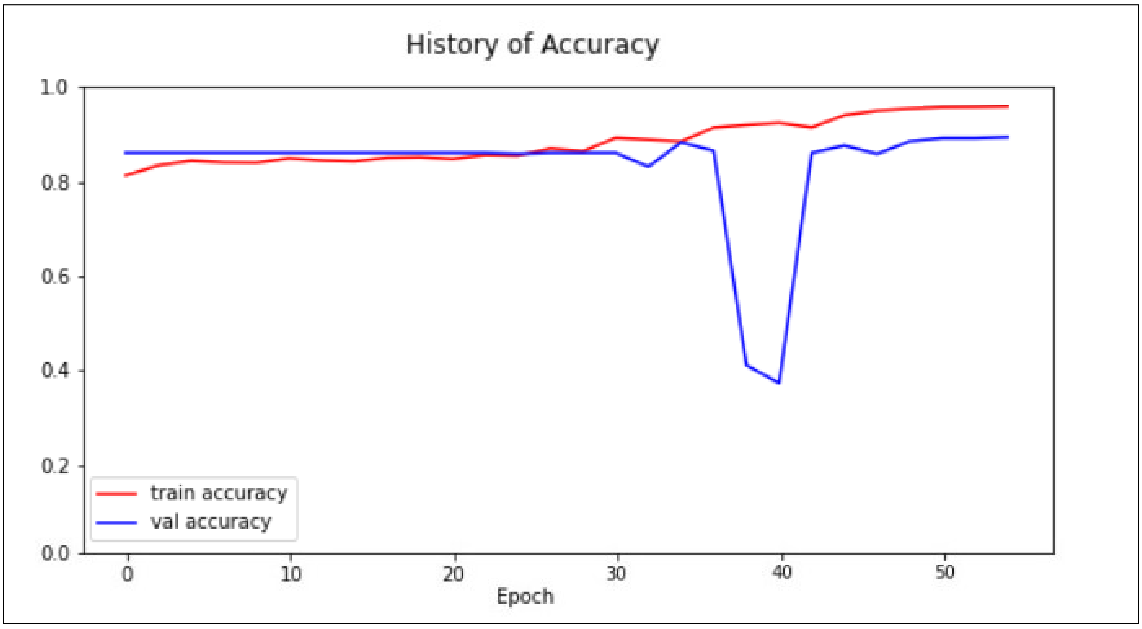

Figure 5.6: Visualization of accuracy of CNN Model

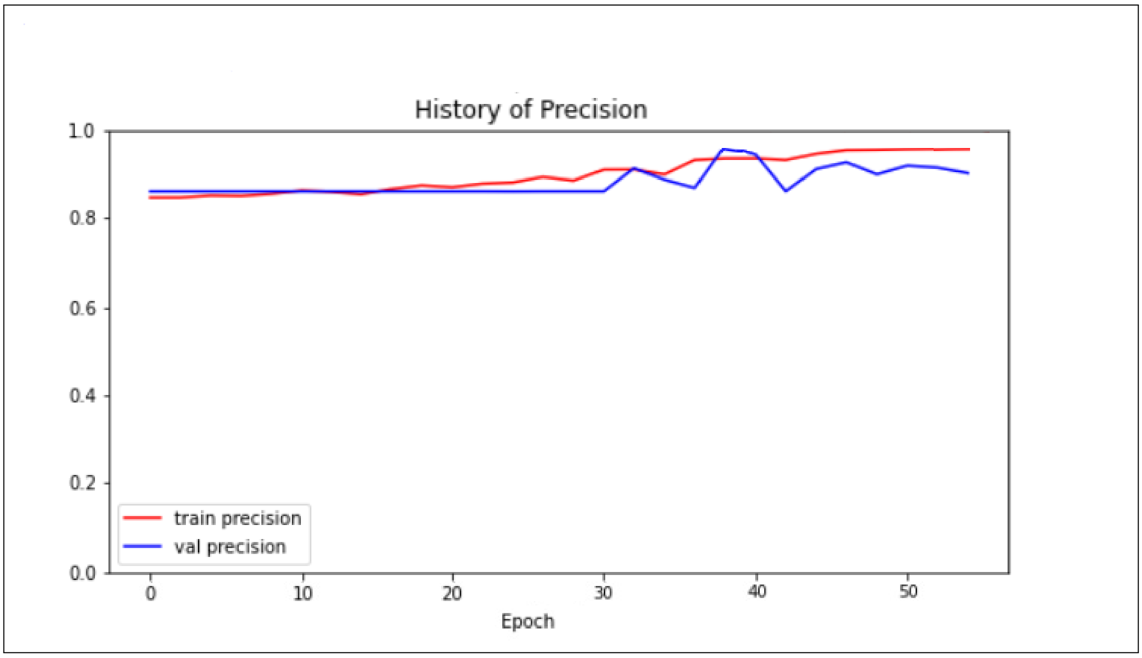

Figure 5.7: Visualization of precision of CNN Model

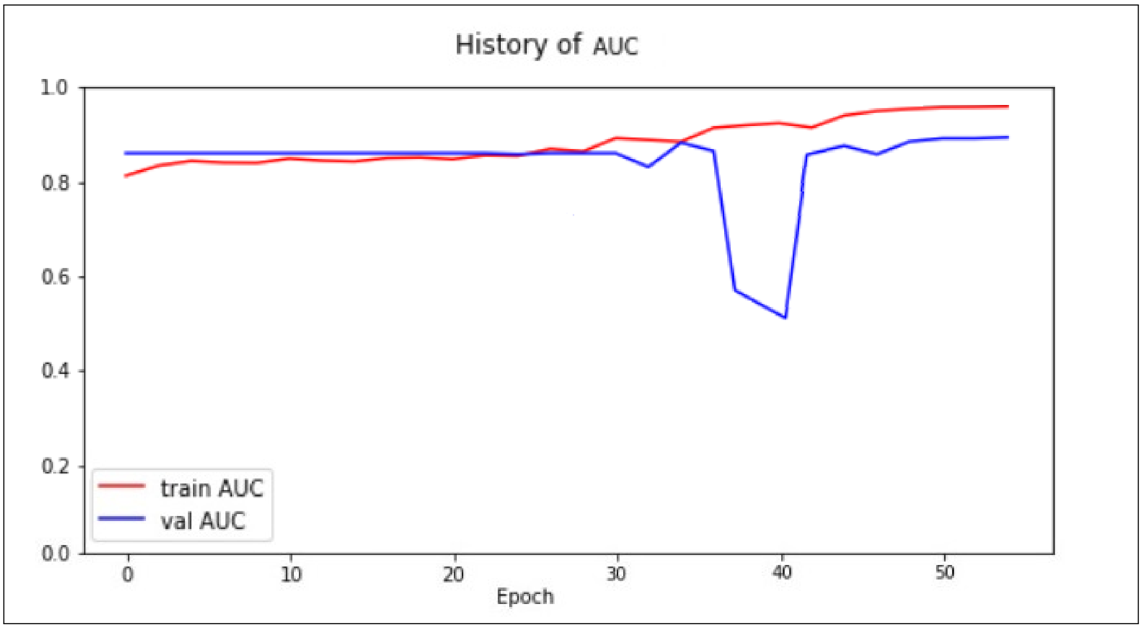

Figure 5.8: Visualization of AUC of CNN Model

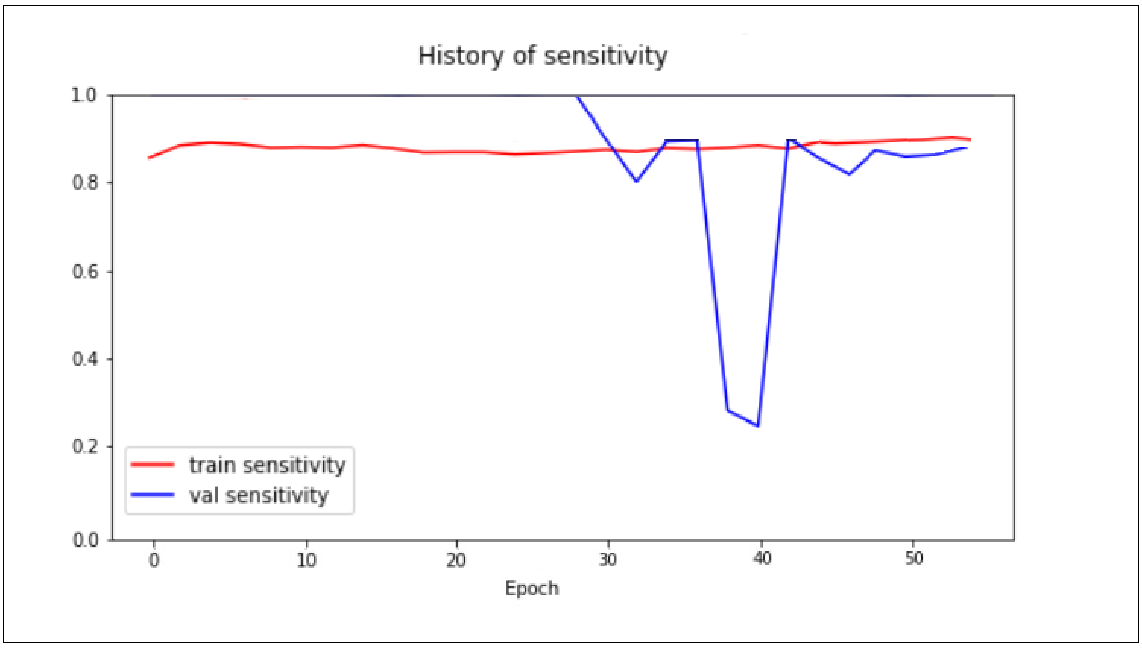

Figure 5.9: Visualization of sensitivity of CNN Model

Chapter 6

Experimental Result and Analysis

6.1 Performance Evaluation

Our work employs four evaluation criteria to assess algorithm performance: Accuracy, Sensitivity, area under the curve (AUC), and Precision.

Table 6.1: Patient wise Performance Evaluation of our proposed method

Patient No.	Accuracy	Sensitivity	AUC	Precision
01	0.92	0.94	0.92	0.93
02	0.89	0.88	0.90	0.89
03	0.90	0.91	0.88	0.87
04	0.90	0.87	0.87	0.90
05	0.89	0.89	0.89	0.90
06	0.88	0.92	0.91	0.91
07	0.89	0.87	0.90	0.93
08	0.90	0.89	0.89	0.89
09	0.90	0.91	0.90	0.85
10	0.89	0.89	0.89	0.83
Average	0.895	0.897	0.895	0.890

The table below illustrate the train and validation accuracy of the models using 70 and 30 epochs, respectively. Although the accuracy does not improve significantly with increasing epoch but rather degrades over time, we wanted to provide the findings for clarity.

Table 6.2: Associated Numerical Metric Score for proposed CNN

Train/Val	Epochs	Accuracy	Precision	AUC	Sensitivity
Train	70	0.855	0.907	0.837	0.879
Train	30	0.927	0.967	0.917	0.937
Validation	70	0.825	0.850	0.815	0.875
Validation	30	0.887	0.907	0.887	0.900

6.1.1 Comparison of evaluation metrics of 5s trial with 10s

From Figure 5.6 we can see that with a 5s trial of EEG signal data we achieve an accuracy of 89.5%. To compare the results of accuracy we implemented the proposed CNN model for a 10s trial as well. From figure 6.1 we see that the trial of 10s EEG signal data runs for 50 epochs and we reach an accuracy of 78.3%. So using a 5s trial provides 11.2% higher accuracy.

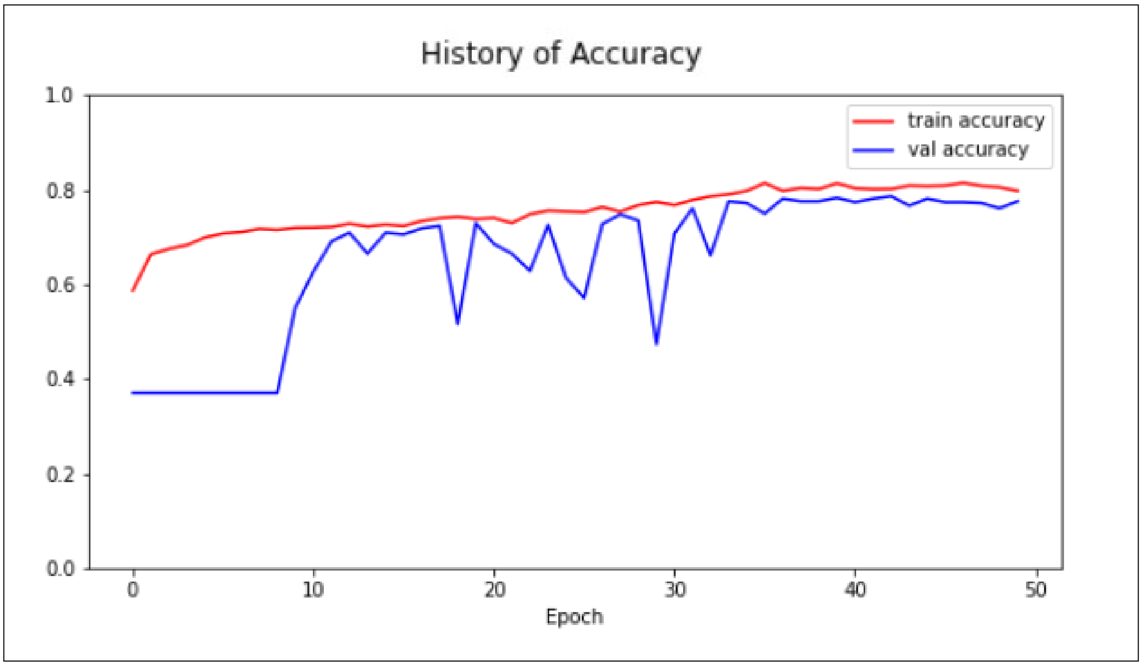

Figure 6.1: Visualization of Accuracy of CNN Model for a Window of 10s

From figure 5.9 we can see that with a 5s trial of EEG signal data we achieve an sensitivity of 89.7%. To compare the results of sensitivity we implemented the proposed CNN model for a 10s trial as well. From figure 6.2 we see that the trial of 10s EEG signal data runs for 50 epochs and we reach an sensitivity of 75.8%. So using a 5s trial provides 13.9% higher accuracy.

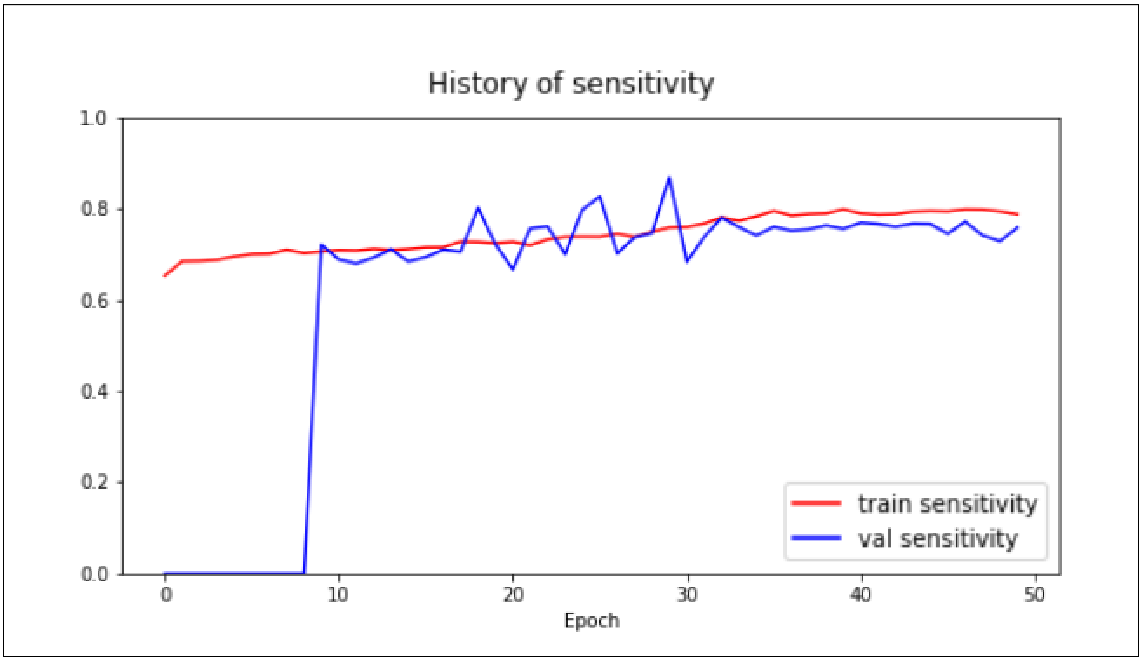

Figure 6.2: Visualization of Sensitivity of CNN Model for a Window of 10s

6.1.2 Comparison of evaluation metrics of 5s trial with 2.5s

From figure 6.3 we see that the trial of 10s EEG signal data runs for 25 epochs and we reach an accuracy of 82.6%. So using a 5s trial provides 6.9% higher accuracy.

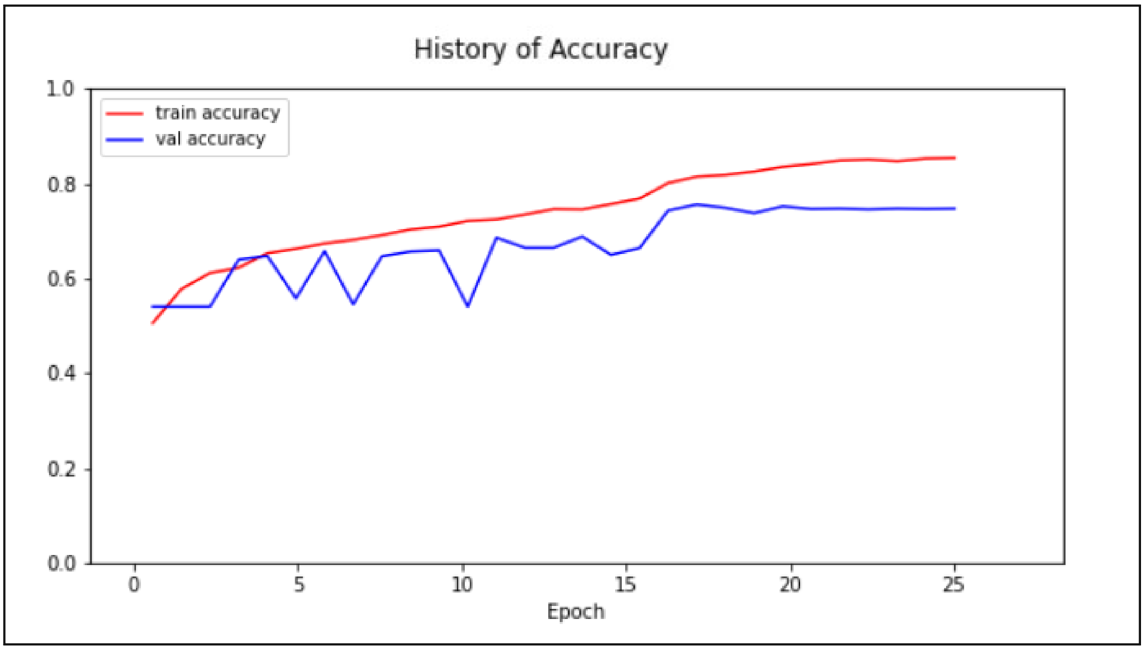

Figure 6.3: Visualization of Accuracy of CNN Model for a Window of 2.5s

From figure 6.4 we see that the trial of 10s EEG signal data runs for 25 epochs and we reach an sensitivity of 58.9%. So using a 5s trial provides 30.8% higher accuracy.

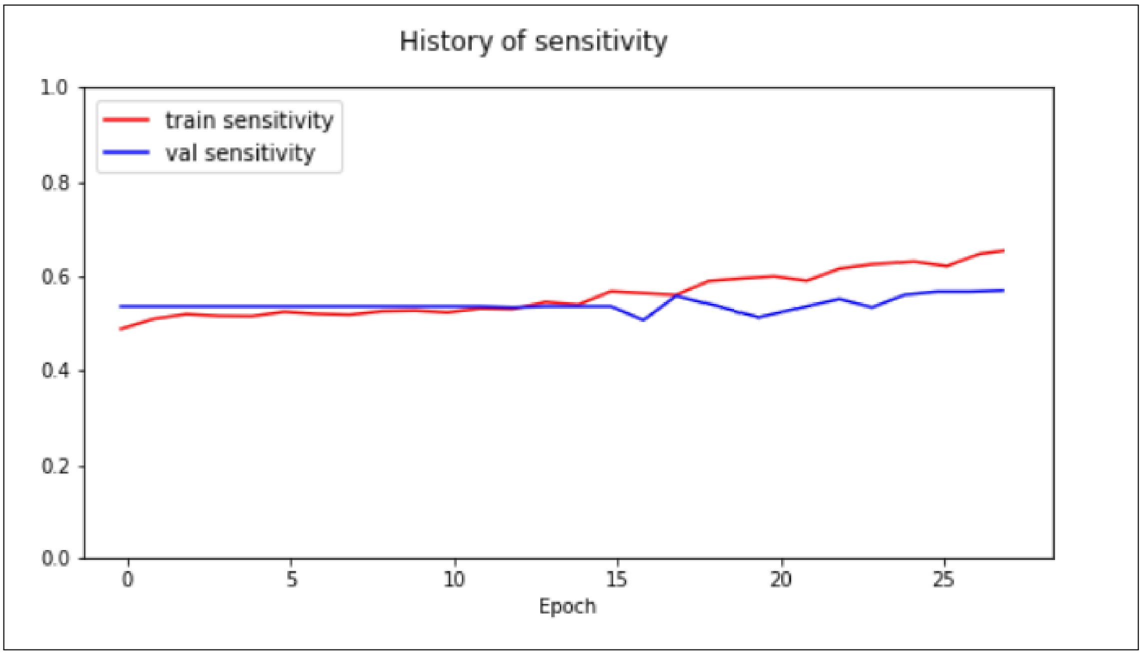

Figure 6.4: Visualization of Sensitivity of CNN Model for a Window of 2.5s

6.2 Comparison of our work to prior works

Table 6.3 shows that the performance of the proposed method in terms average sensitivity and accuracy is in comparison to some previous works using existing relevant methods.

Table 6.3: Comparison with previous work

Method	No. of patients	No. of seizures	No. of channels	Feature Extraction	Classifier	Sensitivity (%)	Accuracy (%)
Truong et al. [45]	13	59	23-31	Automated	2D CNN	89.1	-
Wang et al. [46]	7	42	23-31	Automated	Dilated 3D CNN	85.8	80.5
Ozcan et al. [19]	16	77	23-31	Spectral power, Statistical moments, Hjorth parameters	3D CNN	85.71	-
Liu et al. [47]	2	12	23-31	Automated	Multi-view CNN	91.5	85.5
This work	10	55	18	Automated	2D CNN	89.7	89.5

Comparing our work to the aforementioned papers in the table demonstrates that, despite the use of a simple 2D CNN model, our research outperforms state-of-the-art approaches. The major goal of our study was generalization of seizure prediction instead of patient based approach, so we considered the common 18 channels unlike Wang [46], Truong [45], Ozcan [19], Liu [47] who considered all channels. The idea of selecting the common channels has improved our evaluation metrics considerably. We have also shown the performance of our proposed model if we had worked with all the 23-31 channels.The idea of selecting the common channels has improved our evaluation metrics considerably.

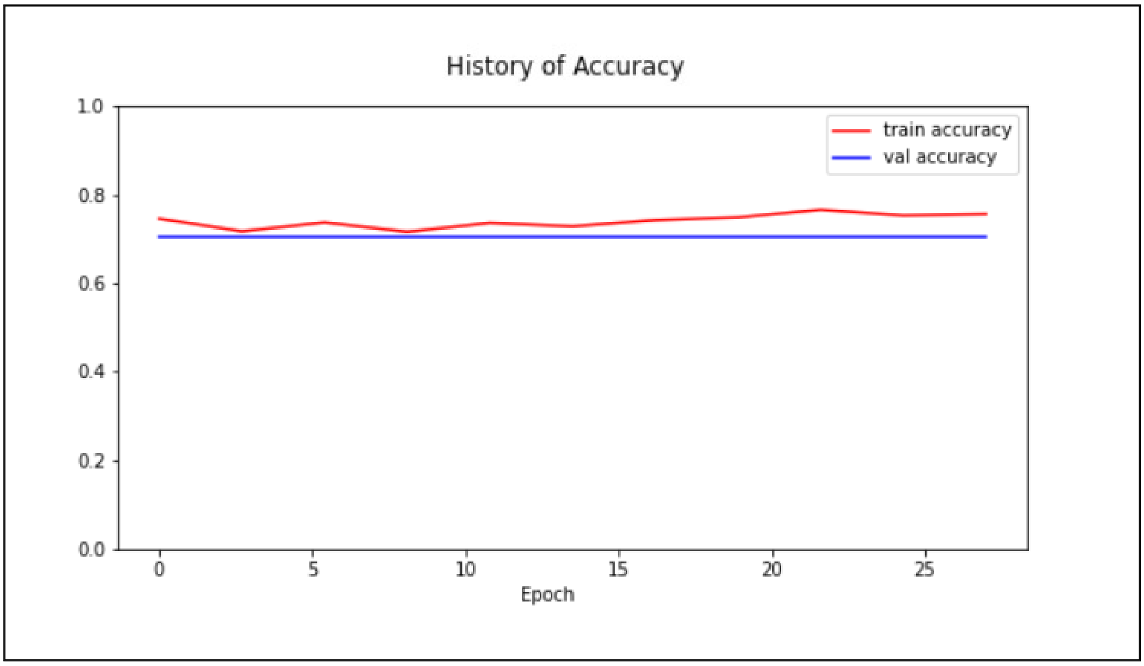

Figure 6.5: Visualization of Accuracy of CNN Model for 23 channels

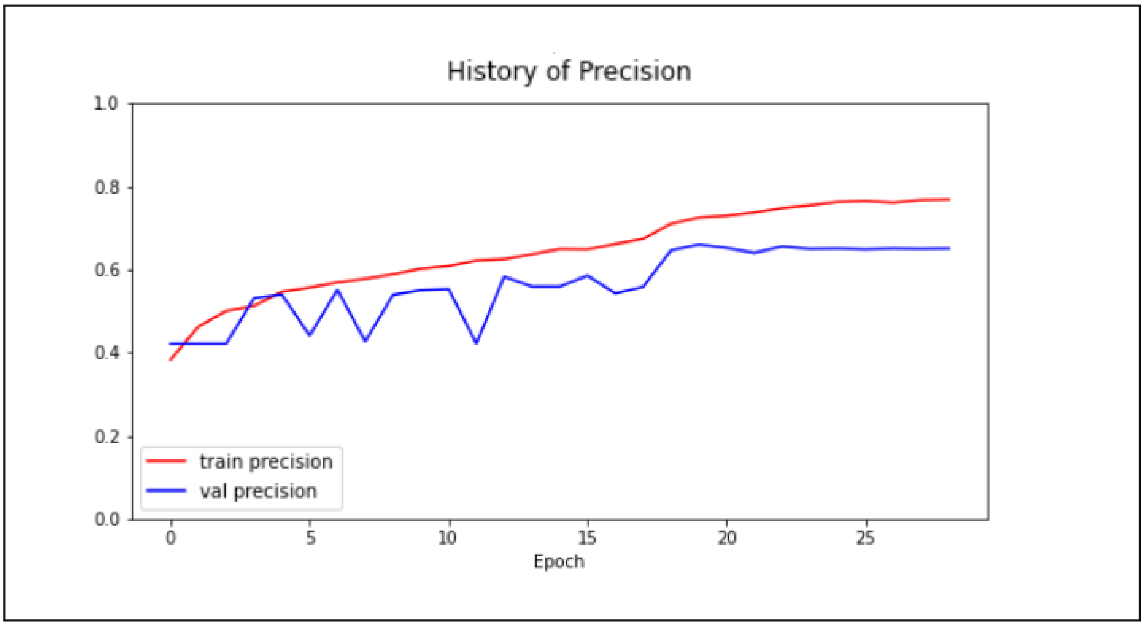

Figure 6.6: Visualization of Precision of CNN Model for 23 channels

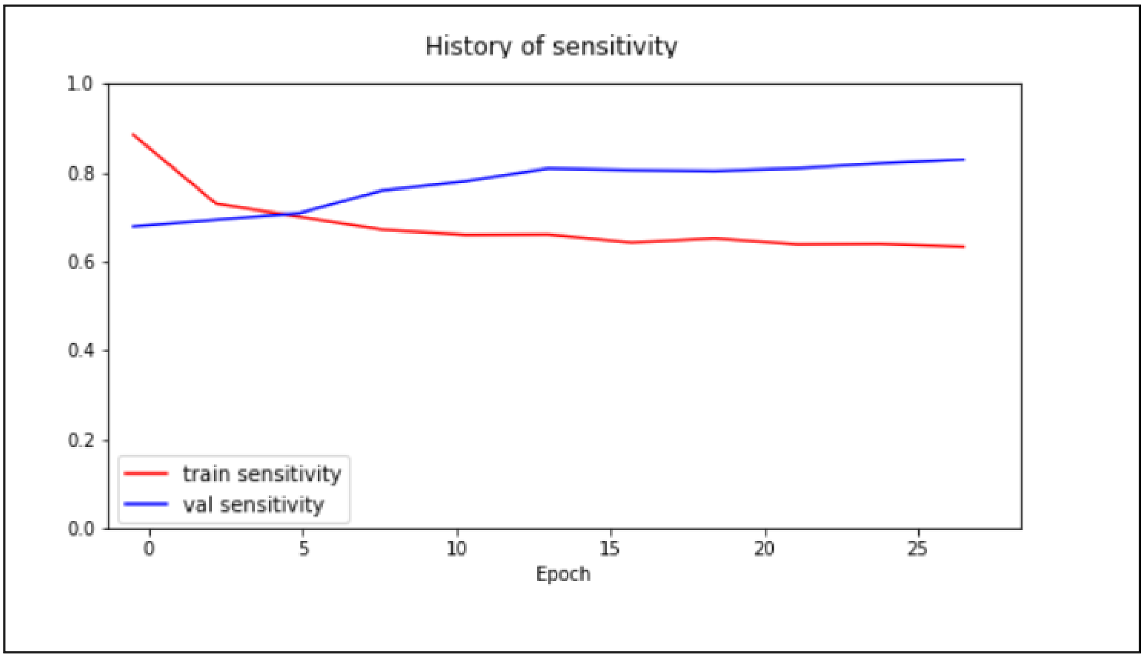

Figure 6.7: Visualization of Sensitivity of CNN Model for 23 channels

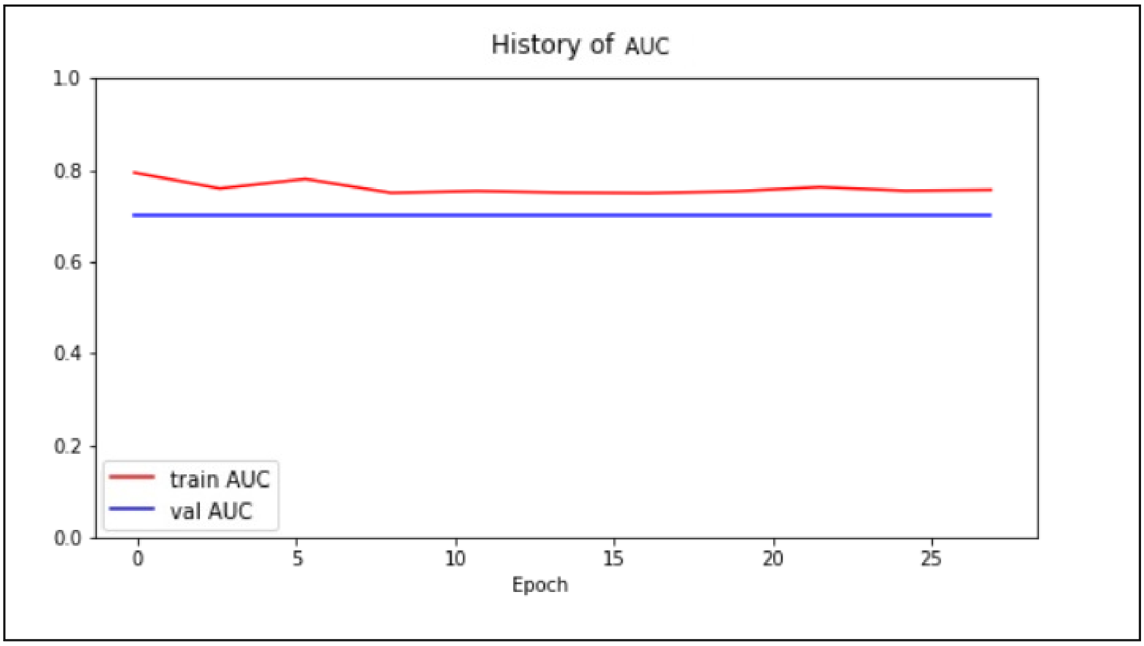

Figure 6.8: Visualization of AUC of CNN Model for 23 channels

Our proposed technique is suitable since no patient-specific engineering has been done available at a particular stage. We trained the entire dataset, and tested on each patient for generalizing the proposed model. We considered the mean of the evaluation metrics for the performance of our proposed model. Ozcan [19], Truong [45] have also proposed a generalizable approach for predicting seizure of individual patients. However, Liu [47] and Wang [46] have proposed patient-specific models.

Our 2D CNN Model, like Wang [46] , has a GAP layer, but unlike Ozcan [19], Truong [45], and Liu [47], does not include any flatten layer. In addition to dropout layers, Liu [47] employed the $\ell 2$ regularizer to prevent the model from overfitting; however, we overcame overfitting using GAP. We reduced the number of parameters in the model by using the GAP layer, which helps to reduce overfitting and improves performance. GAP layers perform a more drastic reduction in dimension, reducing a tensor with dimensions H$\times$ W$\times$ D to dimensions 1$\times$1$\times$ D. The one-dimensional GAP block accepts a two-dimensional tensor (data point channels) and computes the average of all values (data points) for each channel. GAP has reduced the amount of parameters, resulting in a model that is shallow and quick enough for real-time use.

Additionally, to train very deep neural networks we used batch normalization techniques such as Truong [45]. It standardizes inputs to each mini-batch layer. It has resulted in a significant reduction in the number of training epochs necessary for deep networks to be trained. However, Wang [46] , Ozcan [19], and Liu [47] did not utilize a normalizing procedure. The layer normalizes its output during testing by taking the mean and standard deviation of batches it encountered during training are calculated as a moving average.

In our study, the GAP layer is followed by two tightly linked layers with ReLU activation function, and then the GAP layer. A Softmax function, on the other hand, with only one FC layer with is implemented in Wang's proposed model [46].Truong [45] used two fully-connected layers using the sigmoid activation.

A fully connected layer in Liu's multi-view CNN has a different activation function than a convolutional layer, and that activation function is tanh. Only Wang [46] has used the activation function in the FC layer similar to our study. However, due to using different activation functions, the sensitivity and accuracy of the papers have affected and varied accordingly. In our study, the output layer uses Sigmoid Activation function instead of the typical Softmax function unlike Wang [46], Ozcan [19]. Truong [45] uses Sigmoid Activation function like us.

In Liu [47], they utilized stochastic gradient descent to optimize the model; in this case, we used Adam's optimizer. While Liu [47] utilized two convolutional layers, we used four. Due to a shortage of training data, initially, Liu [47] presented five convolutional layers comprised multi-view CNN that was susceptible to over-fitting. Reduced CNN architecture, to address this problem, with just two convolutional layers was employed afterwards.

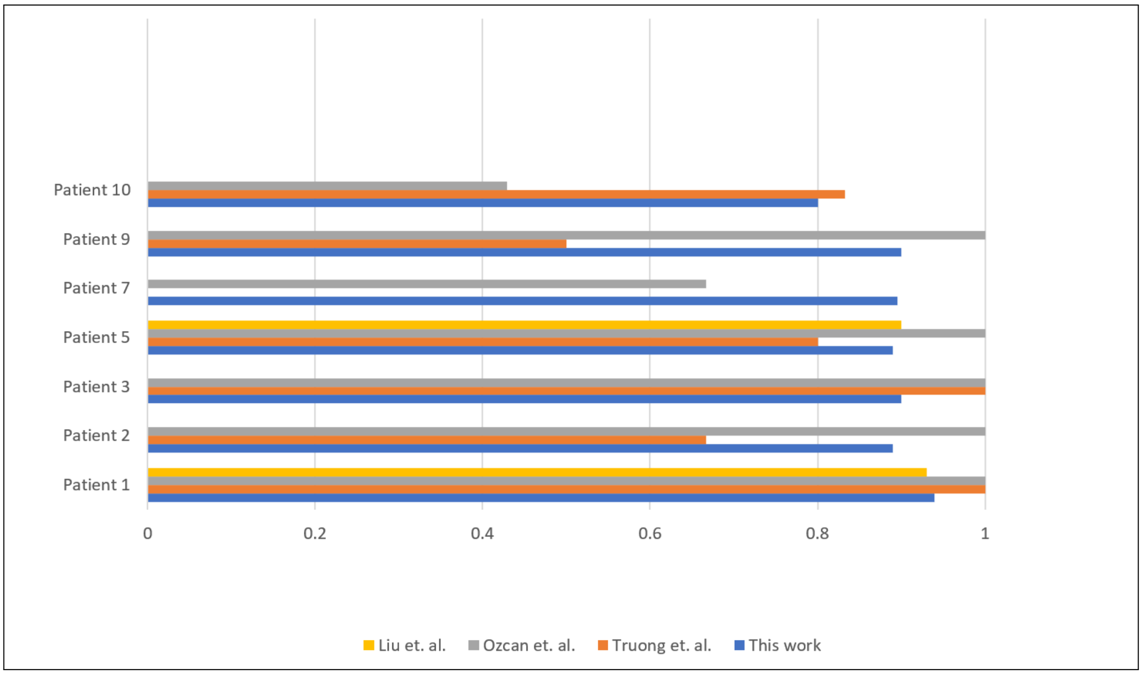

Figure 6.9: Sensitivity comparisons for individual patients among Ozcan et al., Truong et al., Liu et al., and this work.

Truong [45] utilized scalp EEG data without using any de-noising procedures other than the removal of the power line noise. They converted the raw EEG data to a 2D matrix with frequency and time axes using the Short-Time Fourier Transform. They efficiently reduced the power line noise in the frequency domain by removing components at 47–53 Hz and 97–103 Hz, as well as 0 Hz at the DC component. Ozcan [19] eliminated power line noise and harmonics at 60 Hz for his proposed model, by using frequency ranges 57-63 Hz and 117-123 Hz, which are not often employed in spectral power calculations. At 0 Hz, the DC component was likewise eliminated. We used BB for de-noising of scalp EEG.

Although our paper has worked with 10 patients but adequate data was generated from these patients, and GAP layer has reduced our overfitting significantly. According to Liu [47], there were only two individuals in the scalp database who had acceptable pre-ictal and inter-ictal sections. Even in the lack of training data for a complicated multi-view CNN model, they concluded that 5 convolutional layers are vulnerable to over-fitting when used in the absence of training data, so they used two convolutional layers. They believe that the classifier is unable to correctly separate the data points in the new space based on the retrieved attributes because the classifier does not have enough information.

We analysed that instead of using handcrafted feature extraction, we opted for an automated feature extraction process unlike Ozcan [19]. Ozcan [19] considered preserving the picture's spatial structure while analyzing the characteristics gathered from the EEG data. Seizures were successfully predicted utilizing cascade CNN and LSTM networks, using the multicolor image series acquired from multichannel EEG data, and this was done without involving the patient.

Chapter 7

Conclusion

7.1 Conclusion

In order for people with epilepsy to enjoy healthy and risk-free lifestyles, it is important that they have accurate seizure prediction. The aim of this thesis was to create, analyze, and medically evaluate a seizure prediction algorithm, which was accomplished through extensive research. Rather of focusing on a single patient, the paper's goal was to provide a solution that may be applied to many patients. Because our approach is primarily focused on the medical sector, it is vital for patients suffering from epileptic seizures to have more accuracy and fewer data loss than other patients. As demonstrated by testing with actual dataset "CHB-MIT Scalp EEG Database," [14] the computationally viable threshold-based technique described in the article is capable of identifying variations in synchronization that occur a few minutes before the onset of a seizure. When we used the models we provided to 10 patients in the dataset, we confirmed that they had an average accuracy of 89.7% and average sensitivity of 89.5%, according to our research. In the future, we believe that our findings will assist scientists in better understanding the role that model interpretation plays in predicting behavior patterns and find real-world solutions for the seizure prediction.

7.2 Limitations

Seizure prediction has always been a time-consuming operation that needs the use of reliable data as well as the expertise of an experienced interpreter to analyze the data. Because the data is in the form of a time series, the process of analyzing it has traditionally been done manually. Several strategies have developed in recent decades, but selecting a single methodology that gives excellent prediction has always been a difficult task, due to the vast amount of data that must be analyzed.

In order to get the information we need, we were unable to obtain patient data owing to the epidemic and accompanying possible health risks. There was also a restriction to share the patients' data locally, which prevented us incorporating local statistics and conditions into research.

Although the accuracy percentages we obtained from our training models were statistically significant, there is still opportunity for improvement because our initial aim was to attain values more than 90 percent, which represents a potential limitation.

Finding a prediction rate for generalized high epileptic seizures is still a challenge, which is another limitation. Each individual experiences an epileptic seizure in a different way. In order to accurately predict an epileptic seizure, it is necessary to consider the possibility that the same patient may experience several types of seizures. Patients may have abnormal brain activity only while they are having seizures, which make it difficult to anticipate when they will have another seizure.

However, to determine its overall effectiveness, the method should be extensively evaluated with a larger number of participants in a variety of clinical circumstances and age groups, owing to the fact that the "CHB-MIT scalp EEG dataset" [14] collection is comprised of young individuals mostly. One of the most significant limitations of many researches like this one, in which machine learning is applied to medical science, is the lack of data available for training the classifiers to begin with. While merely completing the EEG test, it is possible to identify patterns in the brain that are normal or abnormal [48]; nevertheless, this is a particularly important issue in seizure prediction.

It is also difficult to draw a boundary between how high accuracy has to be as well as when it can be applied in a detecting device that takes immediate action on the basis of the model. If the epilepsy symptoms are extremely severe, a tiny percentage of misinterpretation can be a risk worth taking in some circumstances.

7.3 Future Work

When compared to existing approaches, our suggested method combines feature extraction with CNN and classification with the use of a machine learning classifier to obtain higher sensitivity and specificity. Although there has been progress in many areas, there is still room for development. First and foremost, more data collection could be a promising avenue to pursue for future work. The increase in the amount of data points is critical to increase the accuracy of the classifiers, as a consequence, to better detect likely pre-ictal data.

Additionally, if the preprocessing is further improved, it has the potential to enhance the signal-to-noise ratio. We faced the class imbalance issue which was inherent in the dataset design. In future, we will work to improve the class imbalance problem by introducing artificial signals.

When employing machine learning and deep learning algorithms for feature extraction or classification, a huge number of parameters must always be studied in order for the system to function properly. As a result, additional research can be conducted in order to minimize the number of parameters. The approach we present can predict the occurrence of seizures in a specific patient. More study will be necessary in the future to develop approaches for predicting epileptic seizures that are not limited to a single patient.

To make the approaches even better, we will aim for a more hands-on approach to develop a system of alarm generators that draws on the decision function of the classifiers to provide automatic alerts. As a result of this implementation, algorithms could be trained on patient data obtained from the hospital system, and these algorithms could then be used to predict seizures based on real-time data recorded by the wearable's system acquisition.

In this work, for seizure prediction the EEG signals are focused; nevertheless, in the field of Brain Computer Interfaces, the signals are also extensively utilized, among the rest of the disciplines. As a result, one of the next objectives for our suggested approach is to apply it to these areas.

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