A Deep Learning Approach for Prediction of Epileptic Seizures Using EEG Signals

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ABSTRACT

Epilepsy is a brain disorder in which a patient undergoes frequent seizures. Around 30% of patients affected with epilepsy cannot be treated with medicines/surgical procedures. However, abnormal activity, known as the preictal state, starts some time before the seizure actually occurs. Therefore, it may be possible to deliver medication prior to the occurrence of a seizure if initiation of the preictal state is predicted before the seizure onset and it can also help in controlling the subsequent seizures. Electroencephalogram (EEG) signals are used to analyze the states of epileptic seizures which can be recorded by placing electrodes on scalp of subject known as scalp EEG signals or by implanting electrodes inside the brain on the surface called intracranial EEG signals. In this research, an epileptic seizure prediction method is proposed that predicts the start of preictal state before the seizure's onset using scalp and intracranial EEG. Proposed epileptic seizure prediction method involves three steps; (i) Preprocessing of EEG signals, (ii) Features extraction and (iii) Classification of preictal and interictal states. In this method, EEG signals are preprocessed using empirical mode decomposition followed by bandpass filtering and conversion of time domain signals into frequency domain using short time Fourier transform. Class imbalance problem is mitigated by generating synthetic preictal segments using generative adversarial networks. A three layer customized convolutional neural network is proposed to extract automated features and combined with handcrafted features to get a comprehensive feature set. To reduce the effect of curse of dimensionality, correlated features have been dropped from feature set using Pearson correlation coefficient and an optimal subset of features has been selected using particle swarm optimization. Feature set is then used to train an ensemble classifier that combines Support Vector Machine (SVM), Convolutional Neural Network (CNN) and Long Short Term Memory Units (LSTMs) using Model agnostic meta learning. CHBMIT scalp EEG and American epilepsy society-Kaggle seizure prediction challenge intracranial EEG datasets have been used to train and test the proposed method. An average sensitivity of 96.28 %

and specificity of 95.65 % with average anticipation time of 33 minutes on all subjects of CHBMIT has been achieved by proposed method. On American epilepsy society-Kaggle seizure prediction dataset, an average sensitivity and specificity of 94.2 % and 95.8 % has been achieved on all subjects. Results achieved by proposed method have been compared with the existing state of the art epileptic seizure prediction methods. Proposed method is able to achieve more than 3 % sensitivity, specificity and average anticipation time compared to existing methods.

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First and foremost, I thank God Almighty for enabling me to gain knowledge which bore fruit in the form of this dissertation as a success. I am thankful to my parents due to their continuous prayers and efforts, I have been able to achieve this milestone in my life. My wife Ayesha who encouraged and supported me during this whole period. My children Iraj and Ibrahim who showed patience during my work, especially Iraj who never disturbed me during my thesis due to which I was able to complete my work on time.

I am very thankful to my supervisor Prof. Dr. Shehzad Khalid who always provided guidance, mentorship and was always available despite his busy schedule. I am grateful to Dr. Imran Ahmed Siddiqi who showed keen interest in my thesis and highlighted some important changes in my thesis during internal defense and thankful to external and foreign examiners provided guidance in improving my thesis.

SYED MUHAMMAD USMAN

November 2021

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS AND ABBREVIATIONS

ANN	Artificial Neural Network
BLDA	Bayesian Linear Discriminant Analysis
CNN	Convolutional Neural Networks
CSP	Common Spatial Pattern Filter
DFT	Discrete Fourier Transform
EEG	Electroencephalogram
FFT	Fast Fourier Transform
GAN	Generative Adversarial Networks
GLCM	Gray Level co-occurrence Matrices
GMM	Gaussian mixture model
HVD	Hilbert Vibration Decomposition
iEEG	Intracranial Electroencephalogram
KNN	K-Nearest Neighbor Classifier
LDA	Linear Discriminant Analysis
LR	Gaussian mixture model
LSTM	Long Short Term Memory Unit
MAML	Model Agnostic Meta Learning
MLP	Multilayer Perceptron
OSP	Optimized Spatial Pattern Filter
PCC	Pearson Correlation Coefficient
PLV	Phase Locking Value
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
RF	Random Forest
RNN	Recurrent Neural Network
SNR	Signal to Noise ratio
STFT	Short Time Fourier Transform
SVM	Support Vector Machines

LIST OF NOTATIONS

α	Alpha frequency band of EEG signal
β	Beta frequency band of EEG signal
θ	Theta frequency band of EEG signal
δ	Delta frequency band of EEG signal
μ	Mean
σ_t	Standard Deviation
μ_t	Temporal Mean
σ_t	Temporal Standard Deviation
β_t	Temporal Skewness
K_t	Temporal Kurtosis
C_s	Spectral Centroid
σ_s	Spectral Standard Deviation
SK	Spectral Skewness
K_s	Spectral Kurtosis
λ_i	Lyaponov Exponent
$P(w)$	Power Spectral Density
$X(t)$	Input Signal
$X[k,l]$	Discrete Fourier Transform of signal
Obj^D	Objective Function
$r_y[n]$	Cross Correlation of signal $y[n]$
$\Phi(r)$	Approximate Entropy
y_k	Convolution of $x[n]$ with filter h_k
$\Delta W_l(t+1)$	Updated weight in hidden layer
z^i	Batch Normalization
$f(t)$	Forget Gate
$i(t)$	Input Gate
$C(t)$	Current State of LSTM
$o(t)$	Output of LSTM
$h(t)$	Weights of next layer of LSTM

APPENDIX A

Journal Publications

Cumulative Impact Factor = 18.499

1. **Syed Muhammad Usman**, Shehzad Khalid, Rizwan Akhtar, Zuner Bortolotto, Zafar Bashir, and Haiyang Qiu. "Using scalp EEG and intracranial EEG signals for predicting epileptic seizures: Review of available methodologies." Seizure Vol. 71 (2019): 258-269. **ISI Indexed [Impact Factor: 3.184]**

2. **Syed Muhammad Usman**, Shehzad Khalid, and Muhammad Haseeb Aslam. "Epileptic Seizures Prediction Using Deep Learning Techniques." IEEE Access 8 (2020): 39998-40007. **ISI Indexed [Impact Factor: 3.367]**

3. **Syed Muhammad Usman**, Shehzad Khalid, and Zafar Bashir. "Epileptic seizure prediction using scalp electroencephalogram signals ." Biocybernetics and Biomedical Engineering Vol. 41(1) (2021):211-220 **ISI Indexed [Impact Factor: 4.314]**

4. **Syed Muhammad Usman**, Shehzad Khalid and Sadaf Bashir. "A Deep Learning based Ensemble Learning Method for Epileptic Seizure Prediction." Computers in Biology and Medicine (2021): 104710. **ISI Indexed [Impact Factor: 4.589]**

5. **Syed Muhammad Usman**, Shehzad Khalid, Sohail Jabbar, Sadaf Bashir, Detection of preictal state in epileptic seizures using ensemble classifier, Epilepsy Research, Volume 178, (2021):106818,**ISI Indexed [Impact Factor: 3.045]**

CHAPTER 1
INTRODUCTION

Epilepsy is a disease, in which patients experience one or more seizures frequently due to disorder in the brain functionality. More than 65 million people [1] have been effected by this disease. Epileptic seizures can be categorized into two types including focal [2] and generalized [3] seizures. In focal seizures, abnormal activity starts during seizure due to disorder in neurons' functionality in a specific part of brain and are further divided into multiple categories including motor, sensory, autonomic and psychological seizures. Motor seizures cause abnormal movement of muscles or joints, whereas, in sensory seizures patient experiences pain or shocks. Autonomic seizures affect any organ's activity like heart rate or blood pressure and psychological seizures disturb the emotions or mood of subject.

In generalized seizures, abnormal activity of neurons spreads in the whole brain and is not limited to a specific region. These seizures are also categorized into absence, tonic, atonic, clonic, myoclinic and tonic-clinic. In the absence seizures, patient loses consciousness, whereas, in tonic seizures, a patient experiences stiffness in the muscles. Patients experience loss in muscle tone in atonic seizures and feel jerks in myoclonic seizures. Major causes of epilepsy are still not known. Due to stochastic nature of epileptic seizures, if a seizure occurs during driving, climbing stairs, walking, or swimming then it can lead towards serious accidents.

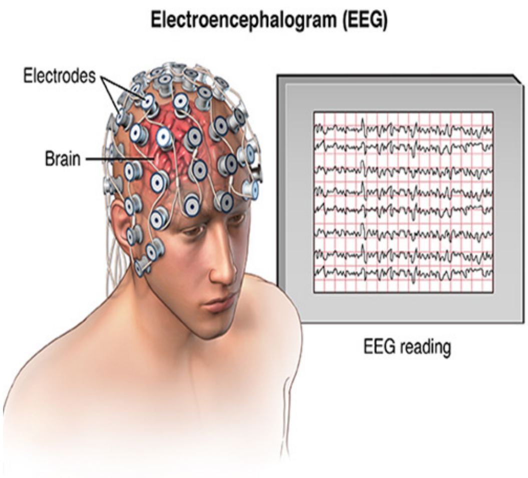
Patients affected from Epilepsy are treated with medicines [4] and in some cases with surgery [5]. Initially, medicines are used to control seizures and if medicines fail to stop seizures, then surgical treatment is provided, however, surgery is only beneficial in case of patients having focal epilepsy.

Focal seizures though treatable with surgery at early stage are converted into generalized seizures after some time. Patients with generalized epileptic seizures cannot be treated with surgery as there is no specific part of brain which is causing seizures. In more than 30 % of the cases, surgery and medicines are unable to control seizures [6], therefore, effective method to control epileptic seizures is to predict the onset of seizure few minutes before it occurs and control it with medication. Abnormal activity of the brain can be observed using Electroencephalogram (EEG) signals.

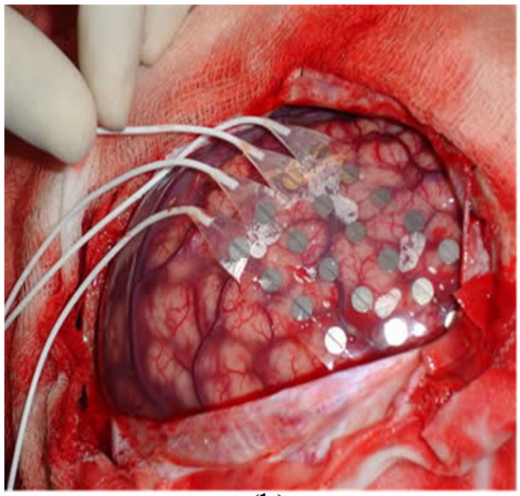
1.1 Electroencephalogram Signals

Electroencephalogram (EEG) is a test used to record the electrical activity inside the brain. These signals contain information that can be used for variety of applications including mind-controlled games [7], emotion recognition [8], Neuromarketing [9] and movement related potentials for stroke patients [10] depending upon the placement of electrodes. There is also a significant use of EEG signals in diagnosis and treatment of brain related diseases including Stroke [11], Alzheimer [12], Dementia [13], Parkinson [14], and Epilepsy [15]. In case of any neurological disorder, an abrupt change in the electrical signals inside the brain can be observed through EEG recordings. These signals can be recorded by placing electrodes on scalp or inside the skull of the subject called as scalp EEG and intracranial EEG (iEEG), respectively. The scalp EEG [16] is a non-invasive method to record electric potentials inside the brain produced due to electrical activity of neurons. Normally, it is measured by taking the difference in electrical potentials of two electrodes which are symmetrically arrayed after pacing electrodes on scalp of subject. In iEEG [17], electrodes are placed directly on the surface of the brain.

In scalp EEG signals acquisition, impedance is essentially checked before recording of these signals. Impedance is measure in $k\Omega$ using digital devices. EEG recordings with impedance value of 10 $k\Omega$ is considered as acceptable, however, recommended value is less than 5 $k\Omega$. In case if the impedance of electrodes falls below 100 Ω then it is not acceptable as it represents the short circuit between electrodes placed on the scalp of subjects. Normal use of gel or saline can lower the impedance, but excessive use is avoided to ensure that it does not reduce below the normal threshold level.



(a)



(b)

Figure 1.1: Electroencephalogram Signals Acquisition methods. a) Scalp EEG Signals Acquisition b) Intracranial EEG Signals Acquisition[1]

Figure 1.1 shows EEG signals acquisition from subjects using scalp and intracranial methods. Spatial distribution of electrodes plays a vital role in localizing the abnormality in the EEG signals. International 10-20 system is a standard method for placement of EEG electrodes on the scalp of subjects and an accuracy of 0.5 cm can be achieved with the help of this system. However, due to assumptions of anatomy of brain, it has been criticized. Spatial distribution of electrodes becomes important when there is dysfunction and anatomy of brain must be kept under consideration while placement of electrodes. Dipole localization is one of the methods for placement of electrodes for particular brain's anatomy in which electrodes are localized in spatial domain and placed on brain after mapping with the help of MR images.

[1] http://www.olavkrigolson.com/that-neuroscience-guy/archives/04-2016/

In the 10-20 electrodes positioning system on the cerebral cortex [18–20], the letters O, T, F, P and C stand for Occipital, Temporal, Frontal, Parietal and Central respectively. Each reading from the channel F_{p1} - F_7 gives the value of potential difference between the electrodes F_{p1} and F_7. All EEG channels indicate the potential difference measured between multiple electrodes from a specific region inside the brain. For example, the electrode positioned at F_{p1} - F_7 represents the neuron's activity originating from the frontal lobe of the left hemisphere. Even number with the alphabets denotes the brain's activity of right hemisphere, whereas, odd numbers represent the brain's activity of left hemisphere. The letter z refers to an electrode placed on the midline. Figure 1.2 shows the electrodes positions using 10-20 system.

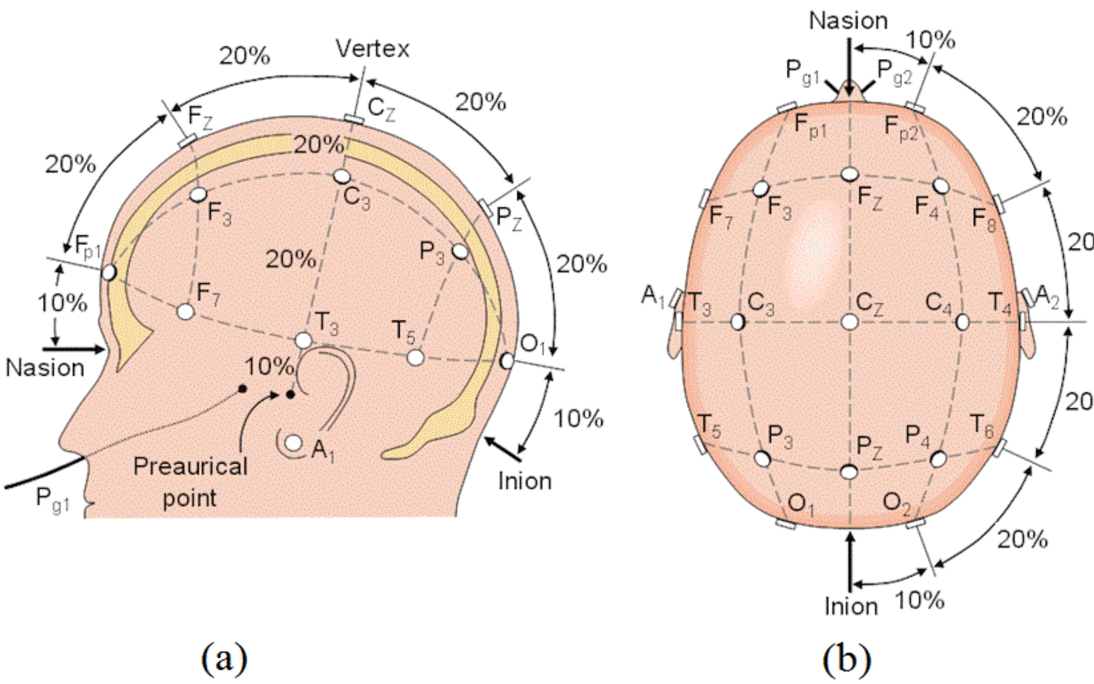


Figure 1.2: The international 10-20 system for placement of electrodes (a) left (b) above the head[2]

Researchers [21–26] have divided EEG into different bands in the frequency domain. These bands have different frequency ranges and represent the following activities.

- α band (8-14 Hz) shows the calmness of the brain.

[2]https://www.dreamstime.com/stock-photos-eeg-electrode-placement-image29444803

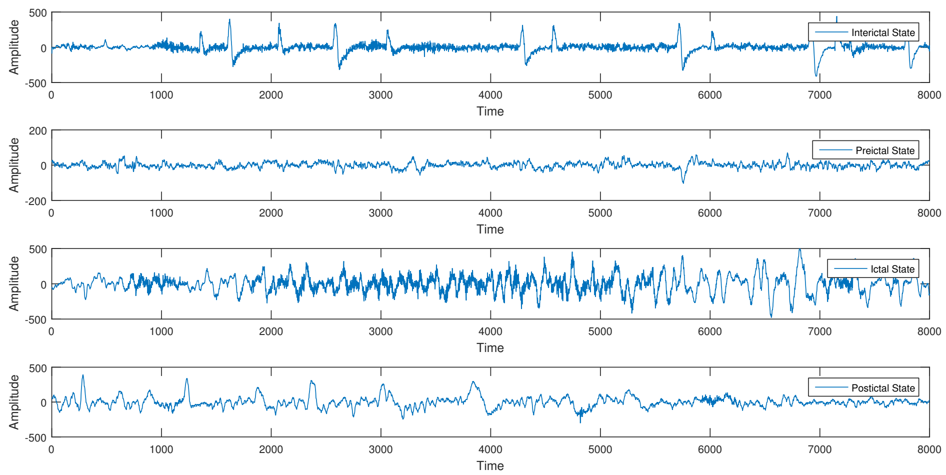


Figure 1.3: Thirty one seconds long Single Channel EEG signal with Four States of Epileptic Seizures; Interictal, Preictal, Ictal and Postictal.

- β band (14-30 Hz) represents the concentrated work of an occupied and busy brain.
- Θ band (4-8 Hz) reflects the excitement and shock.
- The δ band (1-4 Hz) describes sleep, relaxation and fatigue.

These frequency bands provide the information about normal and seizure state of a subject. Epileptic seizures consist of four different states [27] based on the occurrence of the seizure onset. These states include interictal [28], preictal [29], ictal [30] and postictal [31] state. Interictal state is the normal state in which brain functions properly without any interruption. An abnormal activity inside brain starts a few minutes before a seizure onset occurs. This abnormal activity is named as preictal state helps in predicting epileptic seizures. If preictal state is predicted few minutes before the onset, then the first seizure or any subsequent seizure can be controlled with the help of medicines or any other therapeutic measure before it occurs. However, there is no clear indication of start of this pre-seizure activity. Ictal state refers to the start of onset of a seizure and ends with the seizure. Postictal state starts after seizure ends and lasts for few minutes. Figure 1.3

shows thirty one seconds long Single Channel EEG signal with Four States of Epileptic Seizures; Interictal, Preictal, Ictal and Postictal.

Epileptic seizure detection [32] is a method for diagnosing whether patient had suffered with a seizure or not and it involves classification between ictal state with others. In epileptic seizure prediction [33] method, classification of preictal state and interictal state is involved to predict an upcoming seizure before it occurs. In this thesis, a seizure prediction method using intracranial and scalp EEG signals has been proposed. The aim of this research is to predict epileptic seizure by detecting the start of preictal state sufficient time before a seizure onset starts. This will help in controlling the first or subsequent epileptic seizure to improve the quality of life of an epilepsy patient. Machine learning and deep learning methods in combination with signal processing techniques help in predicting epileptic seizures using EEG signals.

1.2 Motivation

Epilepsy affects more than 1 % of the world's population while more than 30 % of epilepsy patients do not recover completely from epileptic seizures upon medication or surgical procedures. Epileptic seizures are sudden in nature; therefore, in many cases, patients get very marginal time with no obvious clinical symptoms before the seizure onset starts. Sometimes, they suffer from frequent seizures subsequently after first seizure ends. More than 80 % of the patients affected from epilepsy live in developing countries. Epileptic seizures upon occurrence limit the patient's life as it may cause accident and can lead towards serious injury. Medical staff in many small cities and rural areas of developing countries is not very well trained for analysis of EEG signals. Devices available in health facilities are not well equipped with automated detection technology and the diagnosis depends only on visual analysis of EEG signals.

Epileptic seizures are divided into two types including focal seizures which are limited to a specific part of brain and generalized seizures where the region responsible for seizures is unknown. In focal epilepsy, seizures can be treated with surgery and brain tissues responsible for producing seizures are removed, whereas, in generalized epilepsy, seizures cannot be treated with surgery as the region of brain responsible for generating seizures is unknown. In focal epilepsy, if subsequent seizures are not controlled, then these seizures are converted into generalized epilepsy which is difficult to control than focal epilepsy.

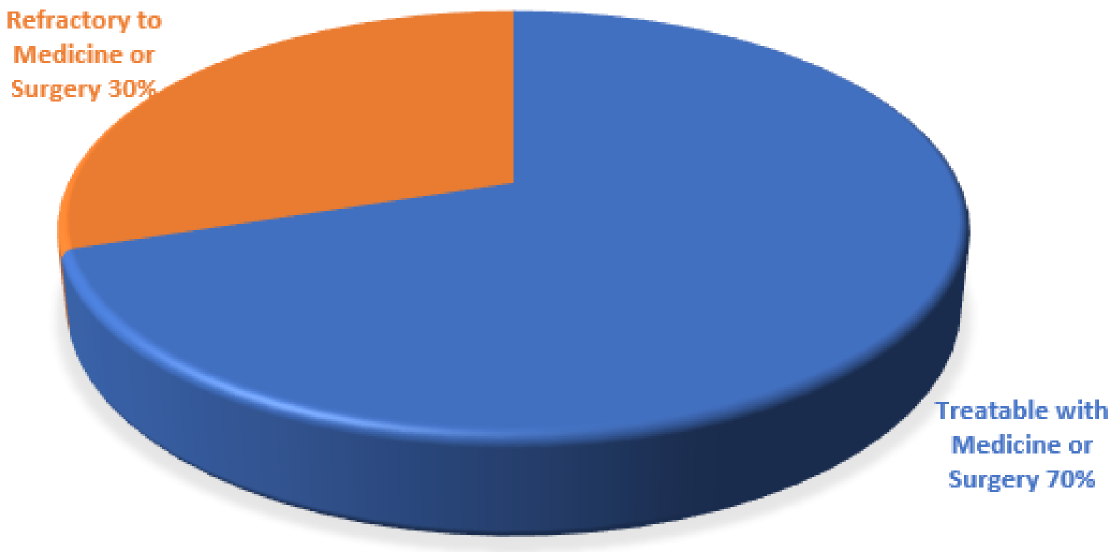


Figure 1.4: Epilepsy patients treatable with medication, surgery or non-treatable with both

Patients remain unconscious for few minutes to few hours after seizure ends making the life of patient very difficult. Figure 1.4 shows approximately 60% of epilepsy patients can be treated with surgery, 10% with medication and 30% cannot be treated with medication or surgery. These 30% patients are refractory to medication and their seizures cannot be controlled with medicines. Due to the stochastic nature of epileptic seizure, it could lead towards patient's injury while driving, swimming, walking on roadside or during exercise. Hence, limiting the life of a patient and disturbing the normal activities of daily routine. Therefore, it is extremely important to predict seizure onset before it occurs to control first or subsequent seizures. In many cases, patients suffer from multiple seizures with a delay of few minutes to few hours.

A method for accurate prediction of epileptic seizure could help in preventing the subsequent seizures using therapeutic interventions to control the seizures. It will reduce the chance of injury and will significantly improve the quality of life of epilepsy patients. This system will help medical staff to monitor and suggest preventive measures for controlling seizures in time. Rural areas of developing countries lack the availability of high quality health facilities, this system can be quite useful for treatment of epilepsy patients. The proposed method will help epilepsy affected patients in controlling the seizures upon successful prediction before the onset of a seizure starts.

1.3 Problem Statement

Patients affected from epilepsy experience one or more seizures frequently due to disorder in the brain functionality. Currently, more than 65 million people have active epilepsy worldwide. Epileptic seizures are sudden in nature; therefore, in many cases, patients get very marginal time with no obvious clinical symptoms before the seizure onset starts. Sometimes, they suffer from frequent seizures subsequently after first seizure ends. It is extremely important to control subsequent seizures of focal epilepsy, otherwise, it is converted into generalized epilepsy which cannot be treated with surgery. Existing epileptic seizure prediction methods are unable to achieve increased sensitivity, specificity and average anticipation time due to multiple factors including presence of noise in the EEG signals, low interclass variance between features and low performance of classifiers. Zhang et al [34] have achieved highest sensitivity of 92.9% with specificity of 87.04% using scalp EEG signals. Similarly, researchers [35–42] have obtained sensitivity ranges between 70-90% with specificity less than the sensitivity. In epileptic seizure prediction, it is very important to achieve increased sensitivity and specificity. Therefore, an epileptic seizure prediction system need to be developed to predict epileptic seizures before the onset of seizure using effective preprocessing, comprehensive feature set extraction and accurate classification between preictal and interictal states.

1.4 Epileptic Seizure Prediction

Prediction of epileptic seizures involves detecting the start of preictal state as early as possible to percent the first or subsequent seizures with medicines. Start of preictal state can be detected by performing classification between preictal and interictal state samples. A typical epileptic seizure prediction method involves four steps including acquisition of EEG signals, noise removal from EEG signals, feature extraction and classification. In the first step, EEG signals are recorded by placing electrodes on the scalp or on the surface of epilepsy effected patient's brain. After data acquisition, preprocessing of EEG signals is performed for noise removal to increase Signal to Noise Ratio (SNR) [43] and then features are extracted from both interictal and preictal states. In the last step, classification between interictal and preictal states is done to identify whether the EEG signals belong to preictal class or interictal. Upon successful detection of preictal state, an alarm is generated so that an upcoming seizure can be prevented before it occurs.

Preictal state can start 30 to 90 minutes before the ictal state. Researchers have considered 30, 60 or 90 minutes EEG signals before ictal state as preictal state to apply seizure prediction methods. Many researchers [34–42, 44–72] have proposed machine learning and deep learning methods for prediction of epileptic seizures using scalp and intracranial EEG signals. Some common preprocessing methods include filtering of the EEG signals in the time domain with bandpass Butterworth [42] and Notch filters [46]. Common Spatial Pattern (CSP) filter [73] and Optimized Spatial Pattern (OSP) filter [74] also provide a better signal to noise ratio when applied on EEG signals. Empirical Mode Decomposition (EMD) [35] is also quite useful to preprocess EEG signals as it gives intrinsic mode functions and by keeping low-frequency components, noise can be removed as high frequency components are prone to noise. In this way, increased signal to noise ratio can be achieved. Fourier transform [39] and Wavelet transform [35] can also be used to preprocess the EEG signals in order to make them suitable to feed in Convolutional Neural Networks (CNN) for automated feature extraction.

After noise removal, features are extracted, and suitable features are selected with high interclass variance and low intraclass variance [75] to form a feature set. Researchers [35, 36, 38, 44–48] have extracted hand-crafted features in both temporal and spectral domain to predict epileptic seizures. Temporal features include the first four statistical moments [76], entropy [77], approximate entropy [76], Hjorth parameters [78] and Lyapunov exponents [79]. Statistical moments include mean, variance, skewness and kurtosis in time domain EEG signals. In spectral features [80], power spectral density is computed to compute EEG signal's energy and then spectral centroid, variational coefficient, spectral skewness and spectral kurtosis is computed in frequency domain. After the evolution of deep learning algorithms, automated feature extraction using CNN has also been used by many researchers [39, 40, 49, 50, 61, 62] that have proved to be good as these features are extracted with class information provided along with data.

Classification between interictal and preictal states is performed after feature extraction from both preictal and interictal state EEG signals with the help of traditional classifiers or deep learning methods. Researchers have used Support Vector Machine (SVM) [35], Random forest [81], *k*-Nearest Neighbor (KNN) [82], Naïve Bayes [83] and Multi-layer Perceptron (MLP) [84] as machine learning classifiers to classify preictal and interictal states. Deep learning classifiers [85] including CNN [50], Recurrent Neural Networks (RNN) [86] and Long Short Term Memory Units (LSTM) [50] can also be used for classification of EEG signals to predict epileptic seizures. Figure 1.5 shows the flow diagram of proposed method for prediction of epileptic seizures.

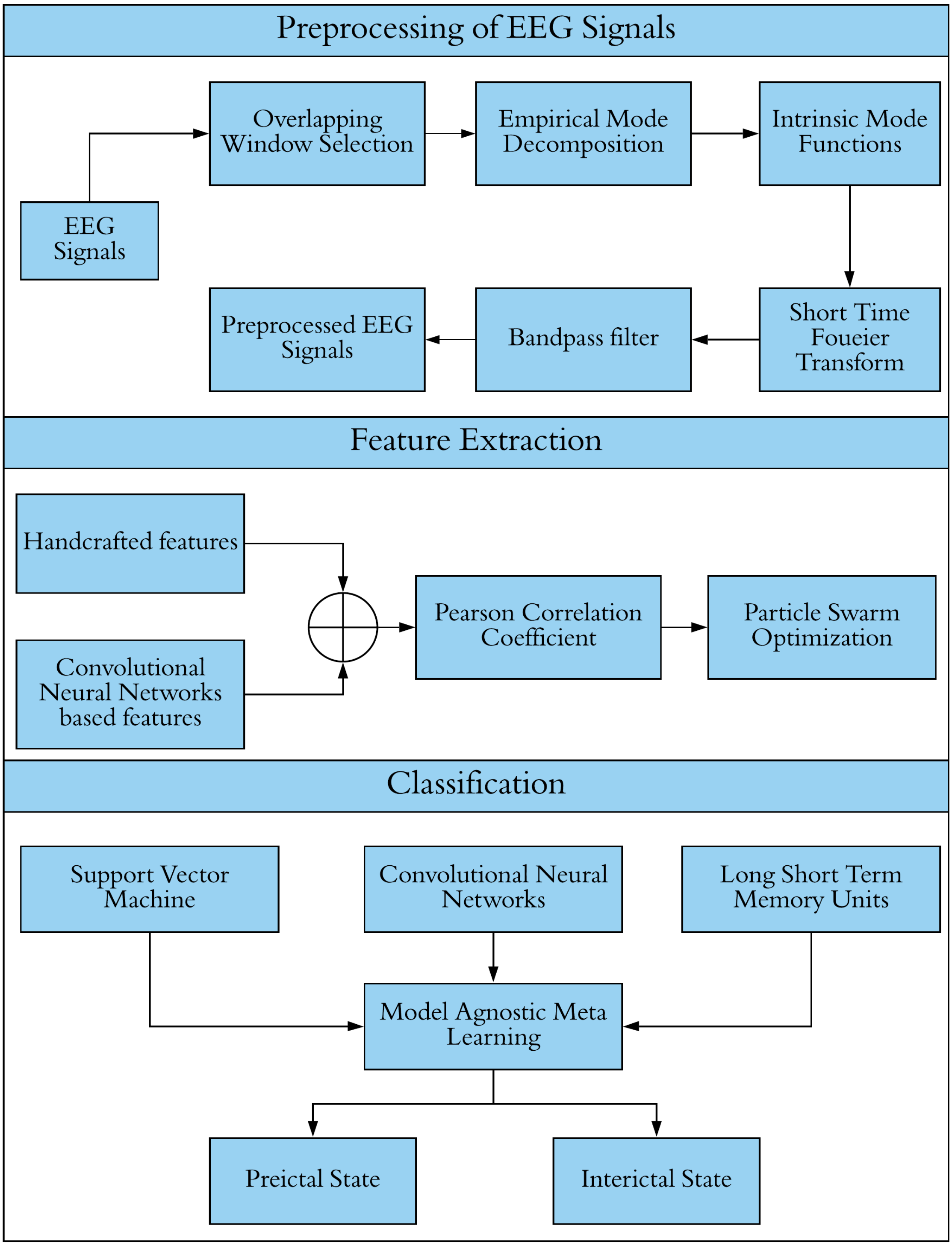


Figure 1.5: Flow Diagram of Proposed Methodology for Epileptic Seizure Prediction

In the first step of proposed method, EEG signals have been preprocessed to remove noise with the help of Empirical Mode Decomposition. These signals are then converted from time domain to frequency domain using Short Time Fourier Transform and Butterworth bandpass filter has been applied to remove power line noise. After noise removal, synthetic EEG segments of preictal states have been generated using Generative adversarial networks to mitigate the effect of class imbalance problem. After preprocessing, handcrafted features including statistical and spectral moments and automated features using CNN have been extracted for all channels of EEG signals for both preictal and interictal states. To reduce the curse of dimensionality effect, cross correlation between features have been computed using Pearson Correlation Coefficient (PCC) [87] and highly correlated features have been dropped from the feature set. Particle Swarm Optimization (PSO) [88] is then applied to select an optimal feature set. Preictal and interictal states have been classified using Model Agnostic Meta Learning (MAML) [89] by feeding output probabilities of SVM, CNN and LSTM. k-fold cross validation technique has been used to split the data into training and testing set.

Few datasets of EEG signals for humans and canine including scalp EEG dataset and intracranial EEG signals are publicly available. The proposed method has been applied on two datasets and obtained results have been compared with recent state of the art seizure prediction methods on same datasets. Features are extracted by dividing the samples into groups of multiple seconds known as windows, and are selected from a fixed length of EEG signals (one second to a few minutes).

1.5 Objectives

Classification between interictal and preictal states using EEG signals of epilepsy patients is a very challenging task for prediction of epileptic seizures. EEG signals are non-stationary in nature and it is very complex task to distinguish between interictal and preictal states. The objective of this research is to propose and validate an epileptic seizure prediction method that uses EEG signals and accurately classify interictal and preictal states with the help of deep learning techniques. The main objectives of this research are as follows:

- To remove different types of noise from scalp and intracranial EEG signals.
- To Mitigate the effect of class imbalance with the help of effective preprocessing techniques for EEG signals.
- To propose a lightweight architecture of CNN for automated feature extraction.
- To achieve increased sensitivity and specificity with low false alarms.
- To predict the epileptic seizures well before time with increased average anticipation time.

1.6 Contributions

Contributions of this research are as follows:

- Class imbalance problem has been mitigated by data augmentation using Geneartive Adversarial Networks.
- Noise removal in both time and frequency domain has been performed to remove all types of noise including power line, inter-electrode interference and noise added due to other artifacts.
- A three layer customized CNN with minimum number of training parameters.
- A comprehensive method for classification between preictal and interictal has been proposed.
- Proposed method has achieved increased sensitivity, specificity, and average anticipation time on all subjects. Existing methods have not achieved these three performance measures on all subjects of dataset and only reported results on selected subjects of dataset.

1.7 Thesis Organization

Remainder of the thesis is organized as follows:

- Chapter 2 provides the comparison between existing state of the art epileptic seizure prediction methods on scalp and intracranial EEG datasets. It also gives the analysis of existing methods in terms of classification performance and identifies limitations in the existing epileptic seizure prediction methods.

- Chapter 3 presents the proposed preprocessing method to increase Signal to Noise ratio of EEG signals for better prediction of epileptic seizures.

- Chapter 4 describes the set of extracted features in the proposed method including both handcrafted and automated features using deep learning methods. It also explains the formation of feature set by applying feature selection techniques and discusses the proposed classification methodology.

- Chapter 5 gives a detailed description of datasets used in this research and experimental settings and results achieved with state of the art seizure prediction methods.

- Chapter 6 concludes the thesis, presents contributions to literature and proposes future directions.

CHAPTER 2
LITERATURE REVIEW

Analysis of EEG signals has been used by many researchers for detection and prediction of epileptic seizures for more than two decades. Seizure detection [90] involves automated detection of onset of a seizure, whereas, seizure prediction [33] involves the detection of start of preictal class so that subsequent seizure may be prevented before it occurs. It is evident from EEG signal recordings of an epilepsy affected patient that there is a clear difference between ictal state and other states. Therefore, seizure detection is a relatively less complex problem than seizure prediction as there is overlapping of interictal and preictal states and very less difference in both states. Moreover, no annotations exist for the start of preictal states, therefore, increasing the complexity of prediction.

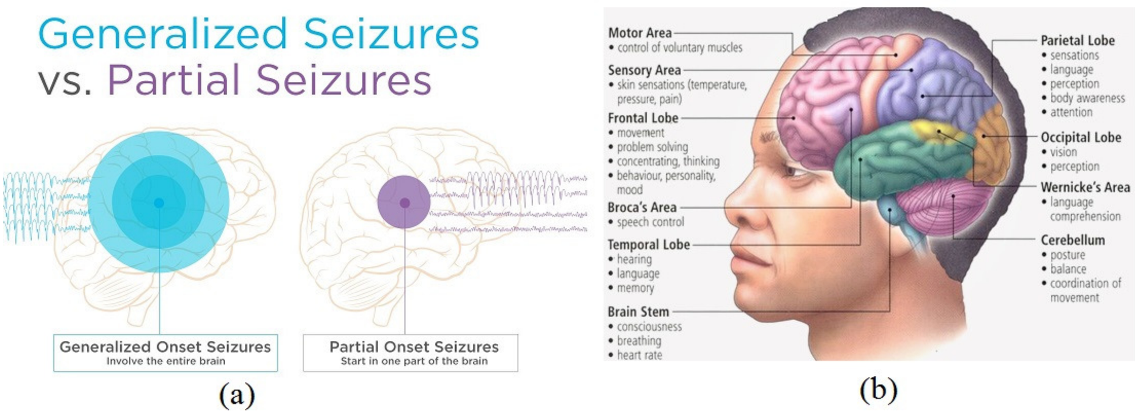


Figure 2.1: a) Generalized vs Focal Epilepsy b) Regions of brain and responsibility of each part[1]

[1] https://www.humanbrainfacts.org/basic-structure-and-function-of-human-brain.php,https://twitter.com/NeuroPace/status/910435887179227137/photo/1

Seizures can be categorized as generalized and focal seizures depending on the region of brain that causes the seizures. Figure 2.1 shows the difference between generalized and focal/partial [91] seizures. It also specifies the regions including motor, sensory,broca area, frontal, temporal, occipital and parietal lobe along with functions performed by these regions of brain. In generalized epileptic seizures [92, 93], there is no known specific part of brain which is responsible for generating seizures. Surgical treatments cannot be provided to patients affected from generalized epilepsy and can only be treated with regular medication. However, excessive use of medication for controlling seizures is not much effective and it may have many side effects on patient's health. Therefore, generalized seizures need to be predicted using scalp EEG signals so that medication can be provided to control the first seizure or subsequent seizures before they occur.

Focal seizures can be treated with the help of surgery. Tissues are removed from the specific region of brain which is responsible for seizures. This is an invasive method and it is very difficult to localize a specific region of brain for surgical treatment. If focal seizures are not timely controlled then these seizures are converted into generalized seizures which cannot be treated with the surgery. Therefore, it is extremely important to predict these focal seizures with the help of scalp or intracranial EEG signals.

A typical epileptic seizure prediction method involves acquisition of scalp or intracranial EEG signals from epilepsy affected patients, preprocessing of EEG signals for noise removal to increase SNR of EEG signals, feature extraction and classification. In this chapter, existing state of the art epileptic seizure prediction methods proposed by researchers in recent years using both scalp and intracranial EEG datasets are compared. Analysis of these methods is performed to identify the research gaps in the the existing epileptic seizure prediction methods.

2.1 Seizure Prediction Methods using Scalp EEG signals

Accurate prediction of epileptic seizures has always remained a challenge due to low SNR in EEG signals acquired from the scalp or brain's surface of epilepsy affected patient, comprehensive feature set extraction and classification between preictal and interictal classes with increased true positive rate and decreased false positive rate. In case of scalp EEG signals, problem of low SNR is very common due to interference between multiple electrodes as the placement of electrodes is also not on the surface of brain, power line noise, eye blinking, interference of heart rate and electrical activity generated in movement related cortical potentials. Feature extraction also remains a challenge as there is no clear distinction between preictal and interictal states and no these states are not annotated.

In recent years, many researchers [34–42, 44–54] have proposed different machine learning and deep learning methods for prediction of epileptic seizures. These methods consist of preprocessing of scalp EEG signals for noise removal to increase SNR of EEG signals for better characterization of preictal and interictal states. Preprocessing is followed by feature extraction to form a feature vector for classification between preictal and interictal states. Publicly available dataset of scalp EEG signals recorded from multiple subjects has been used by these methods to train and validate the epileptic seizure prediction methods. Seizure prediction methods on CHBMIT [94] dataset proposed in recent years have been compared and research gaps have been identified after analysis of these methods. Preprocessing, feature extraction and classification steps have been compared separately followed by detailed analysis based on sensitivity, specificity and average anticipation time.

2.1.1 EEG Preprocessing Techniques

EEG signals are prone to noise due to power line noise [95], inter-electrode interference [96], movement related cortical potentials [96], Electrocardiogram [97], and blinking eyes [98]. All these factors decrease Signal to Noise Ratio (SNR) [99] of EEG signals, leading to less accurate classification between interictal and preictal states. Therefore, accurate epileptic seizure

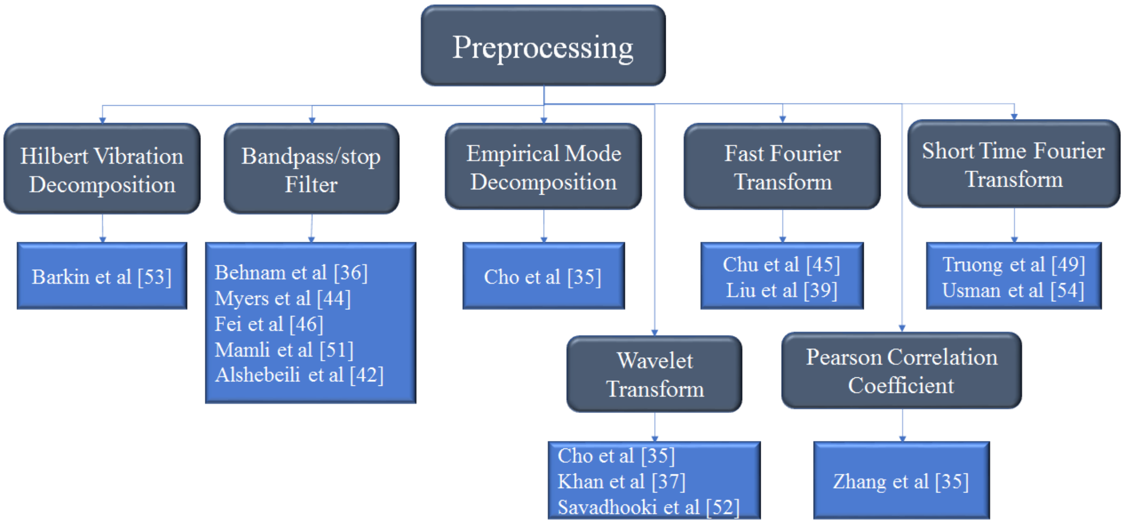


Figure 2.2: Preprocessing techniques for Epileptic seizure prediction methods using scalp EEG signals

prediction remains a challenge. Researchers have proposed different techniques to remove noise from scalp EEG signals so that SNR can be increased. These techniques include Bandpass/ Band-stop filtering [36], Wavelet transform [52], Discrete Fourier Transform (DFT) [100], Fast Fourier Transform (FFT) [101], Short Time Fourier Transform (STFT) [102], Pearson Correlation Coefficient (PCC) [34], Hilbert Vibration Decomposition (HVD) [53] and Empirical Mode Decomposition (EMD) [35]. Figure 2.2 provides multiple preprocessing techniques used by researchers for predicting epileptic seizures in recent years. Preprocessing for noise removal is essential step for accurate classification. Existing methods that have employed little or no preprocessing have not achieved better results in terms of sensitivity, specificity and average anticipation time.

Behnam et al. [36] proposed low pass filter to remove the noise that is incurred in the EEG signals due to interference between multiple biological signals. Myers et al [44] have also used bandpass filter to increase the SNR of EEG signals. In [46], authors have preprocessed EEG signals with bandpass filter of 0.5 to 45 Hz to remove the noise artifacts due to interference between channels and power line. Mamli et al [51] eliminated power line noise of 50 Hz with the help of 10^{th} order Notch filter [103]. Alshebeili et al [42] have computed derivatives, median and mean and variance after applying bandstop filter as preprocessing of EEG signals to reduce the effect of noise. Pearson Correlation Coefficient (PCC) [104] matrices have been extracted by Zhang et al [34] to assess the synchronization between multiple channels of scalp EEG signals.

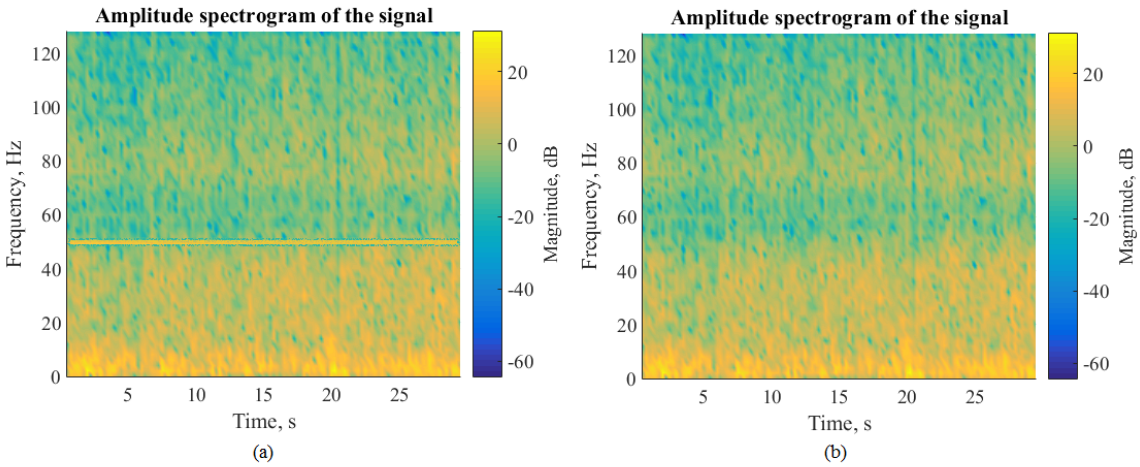


Figure 2.3: (a) Spectrogram of EEG signal with power line noise (b) Spectrogram of EEG Signal after removal of power line noise

Researchers [39, 45] have converted EEG signals from time domain to frequency domain and to remove noise in frequency domain signals using Fast Fourier Transform (FFT) [105]. Due to non-stationary [106] and non-linear [107] nature of EEG signals, researchers [49, 54] proposed STFT [108] so that SNR can be increased using short intervals of EEG signals instead of computing Fourier transform by passing the EEG signals for long duration. With the assumption that EEG signals remain stationary in short interval of time, this STFT has performed better in some cases. Figure 2.3 illustrates the spectrogram of EEG signal converted into frequency domain with power line noise and after removal of power line noise. Suitable combination of different preprocessing techniques for removing all types of noise while keeping the important information of EEG signals can be useful in effective seizure prediction. There exists class imbalance between preictal and interictal states samples as very few minutes of recordings consist of preictal state. This problem has been ignored in recent epileptic seizure prediction methods which affects the overall performance of these methods.

Class imbalance problem exists in the EEG signals that are recorded for epilepsy patients due to a smaller number of samples of preictal as compared to interictal state segments. In some cases, the ratio between preictal to interictal is 1:10 that affects the classification accuracy adversely. Researchers have proposed multiple data augmentation techniques to reduce the effect of class imbalance using geometric transformations, noise addition, oversampling, mixing Intrinsic mode functions (IMFs), synthetic data generation using Generative adversarial networks (GANs) using CNNs and Recurrent GANs. Wang et al [109] have added Gaussian noise in the EEG signals with different variance to increase the samples of EEG signals. Authors have compared the classification accuracy with and without data augmentation and have achieved significant increase in the accuracy when the data augmentation is performed. Zhang et al [110] have proposed a method for EEG data augmentation by mixing IMFs extracted by applying empirical mode decomposition. Classification results have been reported on the real and synthetic data separately and have obtained same accuracy on both EEG signals. GANs using recurrent neural network layers have been proposed for synthetic EEG signals generation by Abdelfatteh et al [111] GANs with LSTM layers have been used for data augmentation by Harada et al [112] GANs have better performance for data augmentation of EEG signals than other techniques.

2.1.2 EEG Feature Extraction Methods

Extracting features with increased inter-class and low intra-class variance for preictal and interictal classes has been a challenging task for predicting epileptic seizures. In recent years, many researchers [34–42, 44–54] have proposed multiple methods for feature extraction using both handcrafted as well as automated features with the help of deep learning techniques. These features include statistical moments in time and spectral moments in

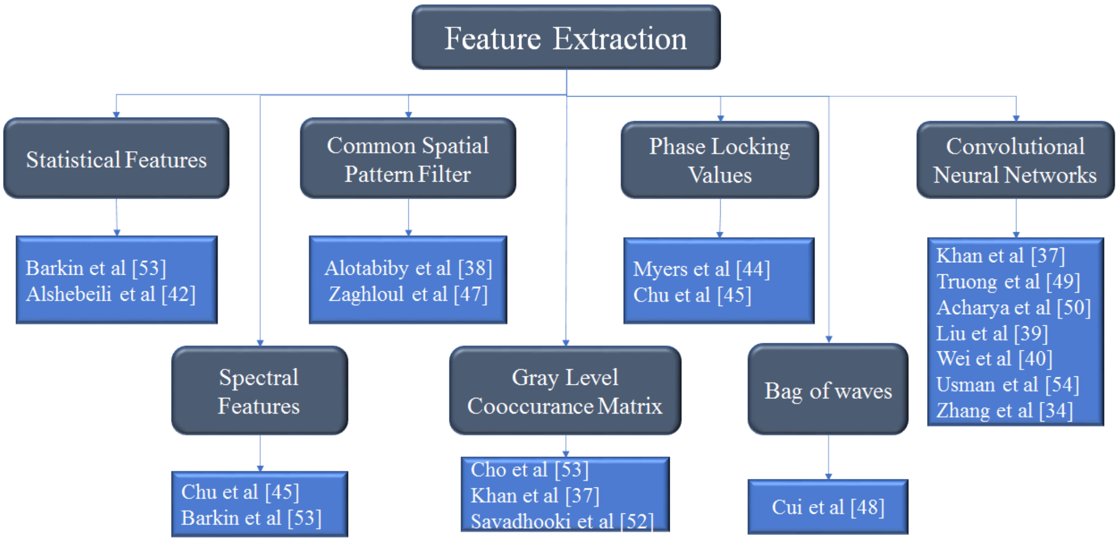


Figure 2.4: Feature extraction techniques for Epileptic seizure prediction methods using scalp EEG signals

frequency domains, univariate/ multivariate features, entropy, approximate entropy, sample entropy, Hjorth parameters [113] including activity, mobility and complexity, derivatives, histogram-based features, and pdf bins. All these handcrafted features have achieved good results in terms of sensitivity and specificity but with the evolution of deep learning methods for feature extraction that include use of CNN [114], RNN [115], LSTM [116], autoencoders [117] and RCNN [118], deep learning based features have gained so much attention of researchers. In these automated methods of feature extraction, one of the most effective factors is their ability to extract features while keeping the respective class under consideration. Such methods provide high interclass variance in extracted features which ultimately lead towards better classification of different states of seizures. Figure 2.4 categorizes the commonly used feature extraction techniques for epileptic seizure prediction method on scalp EEG dataset in recent years.

Barkin et al [53] have extracted mean, variance, skewness, kurtosis [119], sample entropy [120] and power spectral density (PSD) [121] as features for prediction of epileptic seizures. Alshebeili et al [42] have used derivative, local mean, variance and median as features for classification between interictal and preictal states. Another important feature extraction method is combining the multiple channels of EEG signals to get a single surrogate channel. Alotaiby et al [38] proposed Common Spatial Pattern (CSP) [73] filtering to extract features from scalp EEG signals. Frequency bands including α (8 Hz to 12 Hz), β (12 Hz to 30 Hz), γ (30 Hz to 60 Hz) and θ frequency (4 Hz to 8 Hz) are useful in categorizing states of epileptic seizures. Figure 2.5 illustrated the feature extraction process that involves noise removal and extraction of skewness and kurtosis from denoised EEG signal.

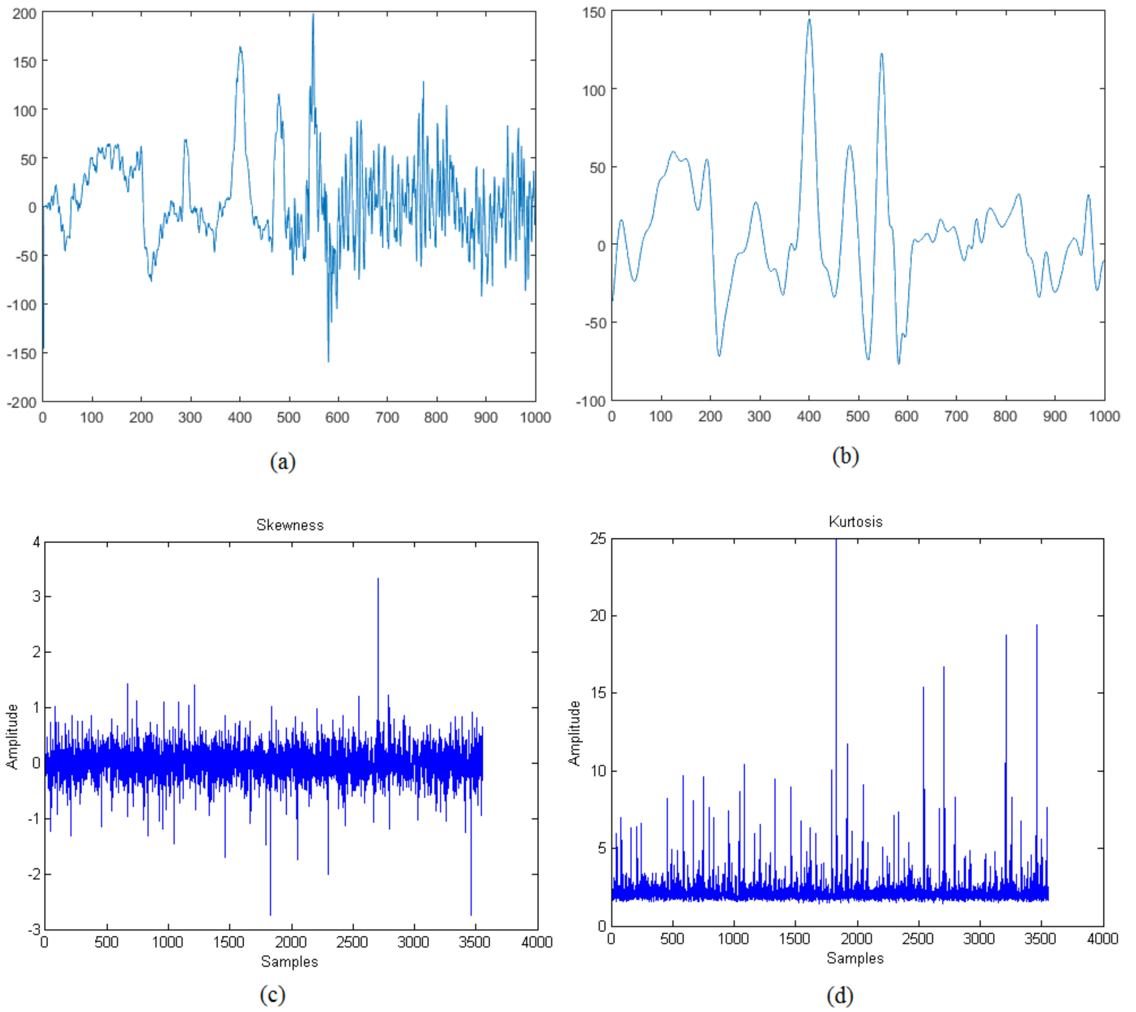


Figure 2.5: Illustration of feature extraction process (a) Single Channel EEG signal (b) EEG signal after noise removal (c) Plot of Skewness from denoised EEG signal (d) Plot of Skewness from denoised EEG signal

Myers et al [44] and Chu et al [45] have extracted Phase locking values (PLV) [122] for these frequency bands as features to distinguish between interictal and preictal classes. Mamli et al [51] proposed Gray Level Co-occurrence Matrix (GLCM) [123] as features. Cui et al [48] have performed automated feature extraction using Bag of Waves method. Many researchers [34,39,40,49,50,54] in recent years have used different variants of CNN for automated feature extraction of preictal and interictal classes for epileptic seizure prediction.

Barkin et al [53] have extracted statistical moments including standard deviation (σ), skewness (β_t) and kurtosis (K_t) which can be computed through following equations.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \tag{2.1}$$

$$\beta_t = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^3 \tag{2.2}$$

$$K_t = E\left[\left(\frac{x_i-\mu_t}{\sigma_t}\right)^4\right] \tag{2.3}$$

Where, x_i is the EEG signal and N is the number of samples. Spectral features are frequency domain features and include spectral centroid, variational coefficient, and spectral skewness. These features can be computed easily with the help of power spectral density. Power spectral density [124, 125] is computed as follows:.

$$P(w) = \sum_{n=1}^{N} r_y[n]e^{-jwn} \tag{2.4}$$

Where, r_y denotes autocorrelation of the signal x_n. Chu et al [45] have extracted spectral features including spectral centroid, variational coefficient, and spectral skewness can be computed by following equations.

$$C_s = \frac{\sum_w wP(w)}{\sum_w P(w)} \tag{2.5}$$

$$\sigma_s^2 = \frac{\sum_w (w - C_s)^2 P(w)}{\sum_w P(w)} \tag{2.6}$$

$$\beta_s = \frac{\sum_w ((w - C_s)/\sigma_s)^3 P(w)}{\sum_w P(w)} \tag{2.7}$$

Fei et al [46] have proposed Lyapunov exponents as features which are useful in determining the aperiodic behavior of signals. Assume that $||\delta x_i(0)||$ and $||\delta x_i(t)||$ are the distances of two points in i^{th} direction. Then the Lyapunov exponent [126] can be computed as:

$$\lambda_i = \lim_{t \to \infty} \frac{1}{t} log_2 \frac{||\delta x_i(t)||}{||\delta x_i(0)||} \tag{2.8}$$

Hjorth parameters [113] include mobility and complexity, which are useful for the classification of EEG signals. Hjorth activity can be defined as variance of EEG signal in time.

$$Activity = var(t) \tag{2.9}$$

$$Mobility(y(t)) = \sqrt{\frac{Activity(\frac{dy(t)}{dt})}{Activity(y(t))}} \tag{2.10}$$

$$Complexity(y(t)) = \frac{Mobility(\frac{dy(t)}{dt})}{Mobility(y(t))} \tag{2.11}$$

Automated features have been extracted in existing seizure prediction methods using different architectures of convolutional neural networks. Multiple convolutional layers with varying filter size and number of filters have been proposed in existing methods for extracting automated features from preictal and interictal states. However, to extract features from CNN, EEG signals are converted into images with the help of Fourier or wavelet transform. CNN extracts features keeping class information under consideration, whereas, handcrafted features do not consider such information while feature extraction. Number of trainable parameters, layers, filter size and total number of filters for each convolution layer are important factors that need to be optimized in CNN for effective feature extraction.

Khan et al [37] have proposed CNN architecture of seven convolutional layers for automated feature extraction from EEG signals. Acharya et al [50] and Wei et al [40] have used five convolutional layers to extract features using CNN. Liu et al [39] have extracted features from two CNNs of five layers in each CNN. They have used time series signals as input in first CNN and frequency domain signals for second as input to CNN. Truong et al [49] and Zhang et al [34] have proposed a solution for prediction of epileptic seizures and have extracted features using three layer convolutional neural network architecture.

2.1.3 EEG Classification Models

Classifier selection is one of the key steps in classification of EEG signals for preictal and interictal classes. Researchers have used multiple machine learning and deep learning-based classifiers for prediction of epileptic seizures for classification between multiple states of seizures using EEG signals. Accurate classification between preictal and interictal state is extremely important as it leads towards effective prediction of epileptic seizures. Machine learning classifiers include Linear Discriminant Analysis (LDA) [127], Bayesian classifier [128], K nearest neighbor (KNN) [129], Thresholding [130], Extreme Learning Machine (ELM) [131], Support Vector Machine (SVM) [132], Artificial Neural Network (ANN) [133], Multilayer Perceptron (MLP) [84], Convolutional Neural Networks (CNN) [50] and Long Short Time Memory Units (LSTM) [134].

Figure 2.6 presents classifiers used by researchers in recent years for classification of preictal and interictal classes to predict epileptic seizures using scalp EEG signals. SVM has been widely used for the classification of EEG signals. Other classifiers that can be used include the k-nearest neighbor classifier and the Gaussian mixture model (GMM) [135]. CNNs consist of fully connected layers after convolution layers for classification and are

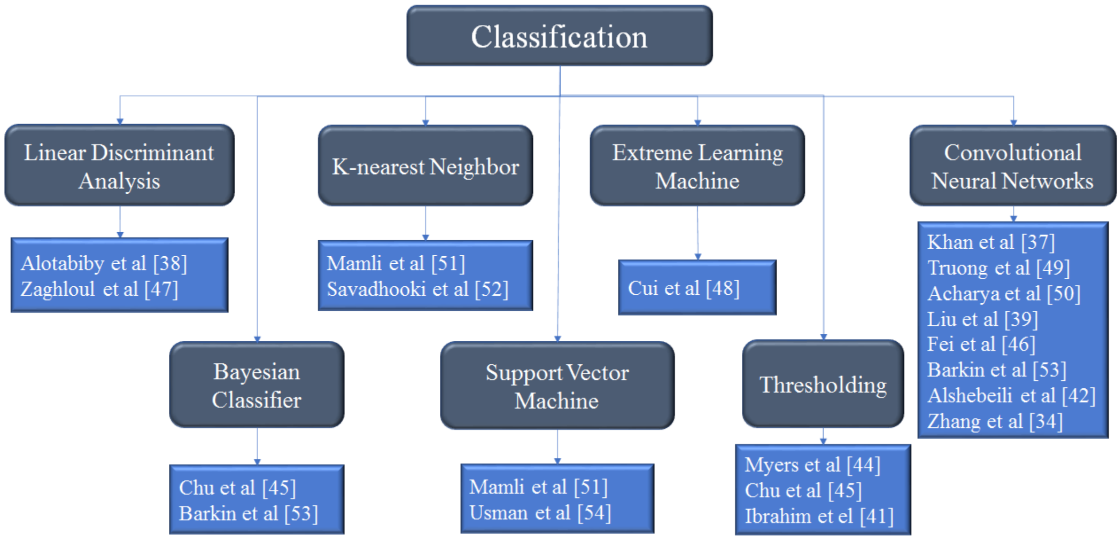


Figure 2.6: Classifiers for Epileptic seizure prediction methods proposed by researchers in recent state of the art methods on scalp EEG signals

also considered very useful for classification. SVM and CNN perform well in classification between multiple states of seizures. Gaussian Mixture Models (GMM) [136], Logistic Regression (LR) [137], and Random Forest (RF) [138] have also been used by researchers.

Alotaiby et al. [38] and Zaghloul et al. [47] have proposed classification using Linear Discriminant Analysis (LDA) and achieved average classification performance. Researchers [51, 52] have performance classification using *k-NN* classifier. Bayesian classifier has been applied by Barkin et al. [53] for classification between interictal and preictal classes. Thresholding is also a useful method to classify multiple classes of epileptic seizures, however, threshold selection is an empirical problem. Myers et al. [44] and Chu et al. [44, 45] have used specific thresholds for each patient for classification between two classes. This threshold is patient specific as researchers do not find a particular threshold which can be applied on all patients, therefore, it limits the use of threhold for classification.

Extreme learning machine has been used by Cui et al. [48] for classification. SVM is also widely used classifier and linear decision boundary is good for classification between epileptic seizure classes. Chu et al. [45] , Mamli et al. [51] and Usman et al. [54] have achieved good results of epileptic seizure prediction with SVM. Many researchers have selected deep learning based classifiers for classification between interictal and preictal states of epileptic seizures. Fei et al. [46], Barkin et al. [53] and Alshebeili et al. [42] classified preictal and interictal states using MLP. Researchers [37,39,49,50] have used CNN for classification which is quite similar to MLP with fully connected layers. LSTM has also been proved as good classifier by recent methods [40] in terms of sensitivity and specificity.

2.2 Analysis of Existing Seizure Prediction Method using Scalp EEG Signals

State of the art epileptic seizure prediction method proposed by researchers in recent years have been compared. All these methods have been evaluated based on sensitivity, specificity, and average anticipation time. Sensitivity measures the true positive rate and specificity is the true negative rate, whereas, average anticipation time is the detection time of start of preictal state of a seizure to predict the upcoming seizure. Table 5.17 presents a comparison between state of the art epileptic seizure prediction methods using scalp EEG signals proposed by researchers in recent years. A typical seizure prediction involves three steps including preprocessing of EEG signals for noise removal, feature extraction to get distinct features for preictal and interictal classes and classification between these states. Objective of an effective epileptic seizure prediction method is to achieve increased sensitivity, specificity, and average anticipation time. Without preprocessing of EEG signals, researchers are unable to achieve the desired results. Researchers [38,47,48] have ignored preprocessing of EEG signals due to which they have achieved considerably poor results. Zaghloul et al. [47] have not preprocessed EEG signals and could achieve only 71% sensitivity and 14.5 seconds average anticipation time, however, authors have not reported specificity.

Table 2.1: Comparison of Existing Epileptic Seizure Prediction Methods Using Scalp EEG Signals

State-of-the-art Methods	**Preprocessing of EEG signals**	**Features**	**Classification**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time**
Cho et al. (2016) [35]	EMD, Wavelet transform	PLV	SVM	80.54	80.50	-
Behnam et al. (2016) [36]	Bandpass filter	Histogram based features	Bayesian classifier	86.56	80.53	6.64 sec.
Myers et al. (2016) [44]	SD, Bandpass filter	PLV	Threshold	76.8	90	-
Chu et al. (2017) [45]	FFT	Spectral features	Threshold	86.67	86.67	45 min.
Khan et al. (2017) [37]	DWT	CNN	CNN	87.8	85.8	-
Fei et al. (2017) [46]	Bandpass filters	Lyapunov exponent, Fourier Transform	ANN	89.5	89.75	-
Alotaiby et al. (2017) [38]	-	CSP	LDA	89	61	68.7 min.
Zaghloul et al. (2017) [47]	-	CSP	LDA	71	-	14.5 sec.
Cui et al. (2018) [48]	-	Codebooks Construction, Bag of waves Segments	ELM	70.5	75	1 min.
Truong et al.(2018) [49]	STFT	CNN	CNN	81.2	84	-
Acharya et al.(2018) [50]	Z-score normalization	CNN	CNN	88	90	-
Liu et al.(2019) [39]	FFT	CNN	CNN	91.5	79.5	5 min.
Wei et al.(2019) [40]	Multichannel Fusion	CNN	LSTM	91.88	86.13	21 min.
Ibrahim et al.(2019) [41]	Derivatives and statistical moments	PDF bins	Threshold	90.3	85.2	22.63 min.
Mamli et al.(2019) [51]	Bandpass Filter	GLCM	KNN,SVM	90.6	97.4	-
Savadkoohi et al. (2020) [52]	Wavelet transform	Fourier Transform	KNN	90.06	97.4	-
Barkin et al.(2020) [53]	HVD	Statistical, Spectral Moments	MLP	89.8	90.1	-
Alshebeili et al.(2020) [42]	Band limiting filter	Statistical features	MLP	88	87.8	
Usman et al.(2020) [54]	STFT	CNN	SVM	92.7	90.8	21 min.
Zhang et al.(2020) [34]	PCC	CNN	PLV	92.9	87.04	15 min.

Alotaiby et al. [38] have achieved 89% sensitivity with 61% specificity without using preprocessing step. Specificity is also important in seizure prediction methods as false positive could also affect patient's health adversely upon medication to control the seizure which is not going to occur actually. Similarly, Cui et al [48] have obtained sensitivity and specificity of 70.5 % and 75 % respectively with average anticipation time of 1 minute. It is also due to non-preprocessing of EEG signals. Significant increase in sensitivity and specificity has been observed in the methods proposed by researchers who have preprocessed EEG signals. Common techniques for preprocessing of scalp EEG signals include Bandpass/ Bandstop filter [139], Wavelet transform [140], Fast Fourier transform [102], Short Time Fourier transform [108], Wavelet transform [141], Empirical Mode Decomposition [142], z-score normalization [143], Hilbert Vibration Decomposition [53], and multichannel fusion to form a surrogate channel.

Feature extraction step in epileptic seizure prediction method is equally important like preprocessing with the focus to extract features that discriminate preictal and interictal classes. Researchers have proposed both handcrafted as well as automated feature extraction techniques for seizure prediction. Handcrafted features include Phase locking values from different frequency bands of EEG signals, statistical and spectral moments, lyapunov exponents, PDF bins, gray level co-occurrence matrix and Fourier transform based features.

Automated features have also been extracted in multiple methods using CNN. Researchers have used proposed different architectures of CNN for automated feature extraction. Cho et al. [35] and Myers et al. [44] have extracted phase locking values from different frequency bands of EEG signals and have achieved sensitivity of 80.54 % and 76.8 % respectively. Chu et al. [45], Barkin et al. [53] and Alshebeili et al. [42] have attained sensitivity of 86.68 %, 89.8 % and 88 % with specificity ranges between 86-91 % using statistical and spectral features. Bag of waves features have been used by Cui et al. [48] to achieve sensitivity and specificity of 70.5 % and

75 % respectively. Khan et al. [37], Truong et al. [49], Acharya et al. [50], Liu et al. [39], Wei et al. [40] and Zhang et al. [34] have used CNN for automated feature extraction and have achieved sensitivity and specificity in ranges between 80-92 % and 80-90 %. Analysis of these feature extraction methods concludes that epileptic seizure prediction methods that have extracted automated features using CNN, statistical and spectral features are successful in achieving high sensitivity as well as specificity. It is due to the fact that these techniques extract features with high interclass variance which have the ability to distinguish between multiple classes with increased sensitivity and specificity.

Classification is the last step in seizure prediction methods and the most important step as the sensitivity and specificity are computed based on the classifier performance. Researchers have used Linear Discriminant Analysis, $K-$Nearest Neighbor, Threshold, Support Vector Machine, Artificial Neural Networks, Extreme Learning Machine and Convolutional Neural Network. Comparison of epileptic seizure prediction method shows that SVM, CNN and ANN performs better in terms of sensitivity, specificity and average anticipation time for classification between preictal and interictal classes.

Comparison of the recent state of the art epileptic seizure prediction method shows that preprocessing of EEG signals is a mandatory requirement for classification of EEG signals with high sensitivity and specificity. Both handcrafted and automated features can be extracted in the feature extraction step, however, it has been observed that automated features outperform than handcrafted features. A combination of both these features can be useful but not used by researchers in existing methods. Feature selection also helps in reducing the affect of curse of dimensionality which is also missing in the existing techniques. Multivariate features must be extracted, and classification must be done with the help of CNN or SVM as these two classifiers give better detection provided that preprocessing and features extraction have been done in an effective manner, however, there is a tradeoff between sensitivity, specificity, and average anticipation time. It has been seen that methods with a greater anticipation time results in increased false alarms, which is not effective in real life application and could have adverse effects on a patient's health. Therefore, an optimal setting need to be chosen to get a better sensitivity and average anticipation time with minimum false alarms. Comparison of these classifiers shows that CNN and SVM performed better for scalp EEG signals in terms of sensitivity, specificity and average anticipation time.

2.3 Seizure Prediction Methods using intracranial EEG signals

Seizures that occur due to generalized epilepsy can be predicted with the help of non-invasive scalp EEG signals. In generalized epilepsy, region that causes epileptic seizures is unknown, whereas, in case of focal epilepsy, a specific region of brain causes seizures. These regions include frontal lobe, temporal lobe, parietal lobe, and occipital lobe. To detect focal epilepsy, a non-invasive method of recording EEG signals is used in which electrodes are implanted on the surface of specific region of brain after performing surgery known as intracranial EEG, however, intracranial EEG signals are useful locating only the focal epilepsy and does not work well in case of generalized epilepsy. The process of epileptic seizure prediction remains the same as in case of scalp EEG signals that involves preprocessing of EEG signals, feature extraction and classification between preictal and interictal states. State of the art methods proposed by researchers in recent years have been compared to predict epileptic seizures using intracranial EEG signals.

2.3.1 EEG Preprocessing Techniques

EEG signals are prone to different types of noise including power line noise, interference between multiple electrodes, electrical signals generated by brain for other actions like movements, vision, heart rate variations, speech signals and eye movement. Intracranial EEG signals are affected by all these types of noise that lead towards decreased SNR of EEG signals, therefore, preprocessing of iEEG signals to increase the SNR for prediction of epileptic seizures remains a challenge. Another problem with associated with noise removal is that useful information for seizure prediction must be retained while preprocessing. Multiple techniques including Bandpass/ bandstop filtering, local mean decomposition, empirical mode decomposition, wavelet transform, fast Fourier transform and Short time Fourier Transform have been propsoed by researchers to increase SNR of intracranial EEG signals. Another problem which is faced by researchers is class imbalance between preictal and interictal class data. To deal with this imbalanced data problem, researchers have used Synthetic Minority Over Sampling (SMOTE) [144] in the preprocessing step. Figure 2.7 enlist some the preprocessing techniques for epileptic seizure prediction method on scalp EEG dataset proposed by researchers in recent years.

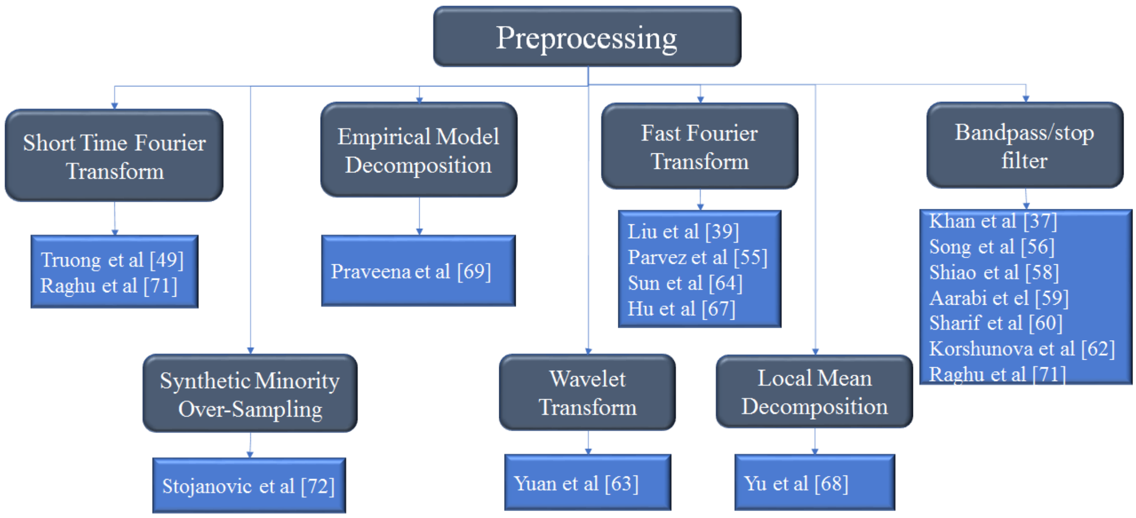


Figure 2.7: Preprocessing techniques for Epileptic seizure prediction methods using intracranial EEG signals

Shiao et al. [58] have used bandpass filter to split the EEG signals into different frequency bands to compute the power of each band for further process of feature extraction and classification. Aarabi et al. [59] and Song et al. [56] have used bandpass filter to eliminate high frequency components in the EEG signals with the assumption that useful information for epilepsy prediction is present in low frequency component. Aarabi el al. [59] have also applied another bandpass filter to remove the effect of power line noise. In [60], authors have separated alpha, beta and gamma frequency bands using bandpass filtering and then removed power line noise with a bandstop filter.

Similarly, Korshunova et al. [62] have also applied bandpass filter with 0.1 to 180 Hz and then extracted different frequency bands.

Khan et al. [37] have applied low pass filter of 128 Hz to remove high frequency components from EEG signals. Bandpass filter at 0 to 44 Hz has been used for noise removal by Raghu et al. [71] In addition with low pass filter, Praveena et al. [69] have also extracted intrinsic mode functions using Empirical Mode Decomposition (EMD). Yu et al. [68] and Yuan et al. [63] have proposed Local Mean Decomposition and wavelet transform respectively as preprocessing of iEEG signals. Many researchers [39, 55, 64, 67] have used Fast Fourier Transform in the preprocessing step for seizure prediction, whereas, due to non-stationary nature of EEG signals, some researchers [49, 71] have proposed Short Time Fourier Transform (STFT) as preprocessing. Comparison of existing epileptic seizure prediction methods using intracranial EEG signals shows that without preprocessing, researchers are unable to achieve better sensitivity and specificity. Fourier transform and bandpass/ bandstop filtering are useful for preprocessing of EEG signals and have proved to achieve increase SNR of EEG signals.

In existing seizure prediction methods using iEEG signals, preprocessing has been done for noise removal, however, no single method consists of combination of preprocessing techniques suitable for increasing the robustness of seizure prediction method. Class imbalance problem between preictal and interictal state also reduces the effectiveness of seizure prediction method. Except synthetic minority oversampling technique, no method to reduce the effect of class imbalance is used by recent methods.

2.3.2 EEG Feature Extraction Methods

Feature extraction is the most important step in the seizure prediction system due to its primary role in classification between preictal and interictal states. Without extracting features with high interclass variance and low intraclass variance, accurate classification is not possible. Due to very high significance of features in predicting epileptic seizures, researchers have attempted to extract features from multiple techniques using iEEG signals. These features include both handcrafted as well as automated from deep learning methods. Handcrafted features can be further categorized into time and frequency/spectral domain. Time domain features include statistical moments, fuzzy rules [145], entropy based and univariate linear features, whereas, frequency domain features include power spectral density and spectral moments. Automated features include features that have been extracted using multiple variants of CNN. Figure 2.8 shows feature extraction techniques for epileptic seizure prediction method using intracranial EEG dataset proposed by researchers in last few years.

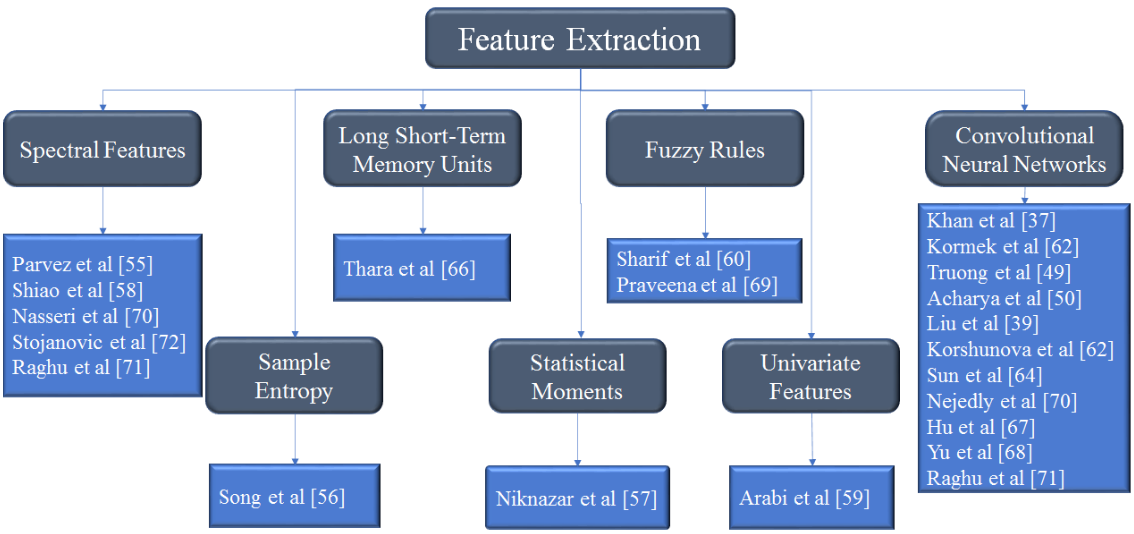


Figure 2.8: Feature extraction techniques for Epileptic seizure prediction methods using intracranial EEG signals

Niknazar et al. [57] have used an overlapping window to extract multiple patterns from all channels of EEG signals as features. Aarabi et al. [59] have extracted six features from EEG signals including both univariate and bivariate linear/non-linear features. To avoid the outliers and noise artifacts, Song et al. [56] have extracted sample entropy as feature for classification between preictal and interictal states. Signal's power [146] from six bands in frequency domain, FFT and cross correlation has been extracted as features by authors in [58]. FFT has also been used by Parvez et al. [55] to extract features including phase correlation, discrete cosine transform and energy concentration ratio. Stojanovic et al. [72] have extracted non-negative matrix factorization as features for epilepsy prediction. Researchers [60, 69] have also proposed fuzzy rules for classification between preictal and interictal states. Many researchers [37, 39, 49, 50, 61, 62, 64, 65, 67, 68, 71] propose use of CNN for feature extraction and Thara et al. [66] have used LSTM for extracting features from EEG signals.

Univariate features [147] in time, frequency domain and automated features using CNN have been extracted by most of the researchers in recent state of the art seizure prediction methods on intracranial EEG signals. Different architectures of CNN have been proposed by researchers with varying number of convolution layers. Extracting features with high interclass variance that will distinguish preictal and interictal classes is a major challenge due to non-stationary nature of EEG signals. Another problem which has been ignored in many existing methods is Curse of dimensionality. It arises due to large number of features and can be resolved with effective feature selection. Highly correlated features in the feature set do not contribute in increasing the classification accuracy and also lead towards curse of dimensionality problem. In automated feature extraction using CNN, selection of convolutional layers with optimal number of trainable parameters still remains a challenge for seizure prediction methods. Increase in number of convolutional layers results to increase in complexity of the CNN architecture and processing time is also increased.

In recent epileptic seizure prediction methods using intracranial EEG signals, researchers have not proposed any method that combines the both automated as well as handcrafted features to form a feature vector. There are many handcrafted and automated feature extraction techniques that provide high interclass variance between preictal and interictal state including. These techniques include univariate feature extraction and different variants of CNN. A combination of these handcrafted and automated features can also help in getting better decision boundary for classification between preictal and interictal states. Korshunova et al [62], Sun et al [64] and Hu et al [67] have proposed two layer convolutional neural network for automated feature extraction with different size and number of filters. Nejedly et al [65] have used three convolutional layers for feature extraction from intracranial EEG signals. Raghu et al [71] have applied pretrained models for feature extraction and have obtained maximum accuracy with the help of Inception v3.

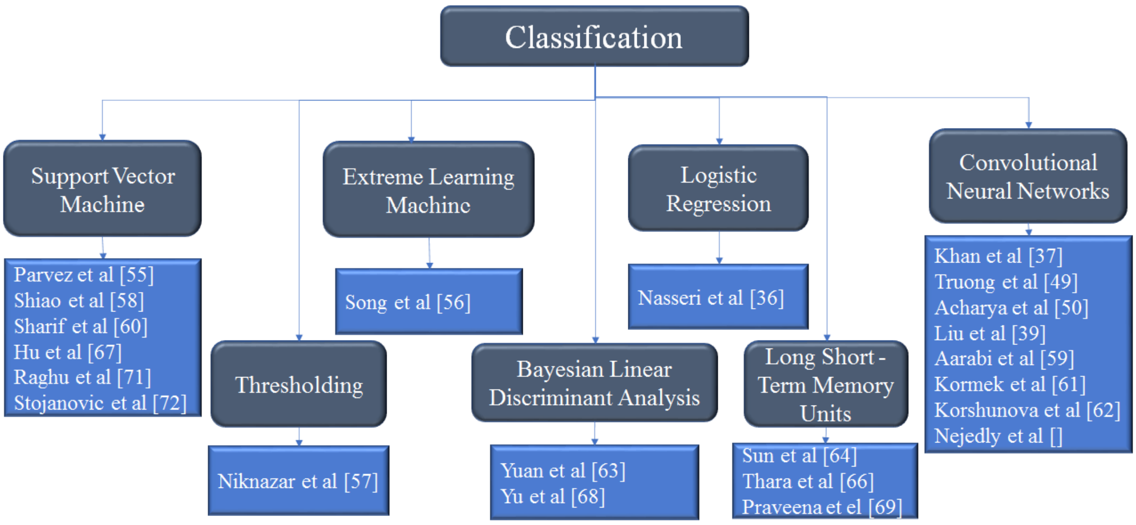


Figure 2.9: Classification method for Epileptic seizure prediction methods using intracranial EEG signals

2.3.3 EEG Classification Models

Accurate classification after extracting features from iEEG signals is necessary for prediction of epileptic seizures. Researchers have proposed variety of machine learning and deep learning approaches for classification between preictal and interictal states. Machine learning classifiers used by researchers in recent years for epileptic seizure prediction include

Thresholding, Bayesian Linear Discriminant Analysis (BLDA) [148], Logistic Regression and SVM. Deep learning-based classifiers used in recent studies include Extreme Learning Machine [131], Artificial Neural Networks [149, 150], CNN, Recurrent Neural Networks and Long-Short Term Memory Units. Figure 2.9 shows the commonly used classification methods for epileptic seizure prediction method using intracranial EEG dataset.

Researchers [55, 58, 60, 67, 71, 72] have used SVM with multiple kernels for classification on iEEG dataset to get good accuracy on the iEEG dataset. Yuan et al. [63] and Yu et al. [68] have used BLDA as classifier. Niknazar et al. [57] and Nasseri et al. [70] have used thresholding and logistic regression for classification between preictal and interictal classes. Song et al. [56] have classified preictal and interictal classes using Extreme learning machine. Researchers [64, 66, 69] have used Recurrent Neural Networks and LSTM for classification. Fully connected layers are used for classification in CNN similar to Multilayer perceptron. Many researchers [37, 39, 49, 50, 61, 62, 65] have used CNN for classification between preictal and interictal for prediction of epileptic seizures using iEEG signals.

Machine learning and deep learning classifiers have achieved good results in terms of sensitivity and specificity. Epileptic seizure prediction methods on intracranial EEG signals have been evaluated on these measures and average anticipation time is not considered as the iEEG dataset does not have any information of continuous recordings of each patient. Support Vector Machine [151, 152], Long Short Term Memory Units [153, 154] and Convolutional Neural Networks [155, 156] have achieved greater classification sensitivity and specificity compared with other classifiers.

Niknazar et al [57] could achieve only 63.75 % sensitivity using thresholding for classification. No specific threshold can be applied for classification between preictal and interictal states due to non-stationary nature of EEG signals. SVM has been used for classification by Shiao et al [58], Sharif et al [60], Hu et al [67], Raghu et al [71] and Stojanovic et al [72]. All these methods have been able to achieve an average sensitivity and specificity of more than 80 %. LSTM has also proved to be good classifier for intracranial EEG signals in methods proposed by Thara et al [66] Praveena et al [69]. An average sensitivity of 89 % has been obtained with LSTM in these methods. It has been concluded that SVM and LSTM perform better for classification between preictal and interictal states in intracranial EEG signals. However, simple classifiers have not been able to classify with greater accuracy due to non-stationary nature of EEG signals. Researchers have not employed any ensemble classifier in the existing methods. These methods have been compared and analyzed for identification of research gaps in these methods.

2.4 Analysis of Existing Seizure Prediction Method using intracranial EEG Signals

In this thesis, state of the art epileptic seizure prediction method on intracranial EEG signals proposed by researchers in recent years have been compared. All these methods have been evaluated based on sensitivity and specificity. Sensitivity measures the true positive rate and specificity is the true negative rate. Average anticipation time has not been reported by researchers in methods of intracranial EEG signals. Table 5.19 compares state of the art epileptic seizure prediction methods using intracranial EEG signals proposed by researchers in recent years. Epileptic seizure prediction method using intracranial EEG signals consists of three steps like scalp EEG methods including preprocessing of EEG signals, feature extraction and classification between preictal and interictal states. Niknazar et al [57] and Kornek et al [61] have not preprocessed EEG signals and as as result obtained low sensitivity and specificity. Preprocessing of intracranial EEG involves noise removal to increase SNR of EEG signals and reducing class imbalance problem by increasing preictal class samples.

Stojanovic et al [72] have proposed Synthetic Minority Oversampling

(SMOTE) for increasing the samples of preictal class so that class imbalance problem can be minimized. For noise removal researchers have proposed Bandpass filtering, Fast Fourier Transform, Wavelet Transform, Discrete Fourier Transform, Local Mean Decomposition, z-score normalization and Empirical Mode Decomposition. Song et al [56], Shiao et al [58], Aarabi et al [59], Sharif et al [60], Korshunova et al [62], Khan et al [37] and Raghu et al [71] have applied bandpass filter to remove noise from iEEG signals for increasing SNR and have achieved more than 80 % sensitivity.

STFT has been applied by Truong et al [49] and Raghu et al [71] for conversion of iEEG signals from time domain to frequency domain. Praveena et al [69] have achieved sensitivity of 89.8 % using Empirical Mode Decomposition for noise removal. Both handcrafted and automated features have been extracted in recent epileptic seizure prediction methods. Handcrafted features include Signal energy, sample entropy, statistical/spectral moments, Lyapunov exponent and fuzzy rules. Automated features have been extracted using Convolutional Neural Network and Long Short Term Memory Units. Parvez et al [55], Song et al [56], Niknazar et al [57], Araabi et al [59], Praveena et al [69], Nasseri et al [70] and Stojanovic et al [72] have extracted handcrafted features for seizure prediction and achieved the maximum sensitivity of 89 %.With the help of CNN, reseachers have obtained approximately similar results as compared to handcrafted features. Therefore, it has been concluded that both handcrafted and automated features are useful for seizure prediction using iEEG signals. In order to achieve increased sensitivity and specificity than existing methods, we need a customized CNN architecture that will provide increased sensitivity using reduced number of training parameters. Feature selection is also useful to enhance the effectiveness of feature set, however, no recent method employed feature selection technique for seizure prediction.

Table 2.2: Comparison of Existing Seizure Prediction Methods using intracranial EEG Signals

Method	**Preprocessing**	**Features**	**Classifier**	**Sensitivity (%)**	**Specificity (%)**
Parvez et al. (2016) [55]	FFT	Signal Energy	SVM	89	64
Song et al. (2016) [56]	Bandpass Filter	Sample Entropy	ELM	86.75	83.80
Niknazar et al. (2016) [57]	-	Statistical features	Thresholding	63.75	67
Shiao et al. (2016) [58]	Bandpass filter	PSD, FFT, Cross correlation	SVM	81.8	74.6
Aarabi et al. (2017) [59]	Butterworth filter	Correlation dimension, Lyapunov exponent, Nonlinear interdependence	Rule-based decision-making	86.7	88.9
Sharif et al. (2017) [60]	Chebyshev filter	Fuzzy rules	SVM	91.8	92
Kornek et al. (2017) [61]	-	CNN	CNN	69	70
Korshunova et al. (2017) [62]	Bandpass Filter	CNN	CNN	-	80.75
Khan et al. (2017) [37]	Bandpass Filter	CNN	CNN	87.8	85.8
Acharya et al. (2018) [50]	Z-score normalization	CNN	CNN	88	96
Yuan et al. (2018) [63]	Wavelet transform	Diffusion distance	Bayesian linear discriminant analysis	85.11	92
Truong et al. (2018) [49]	STFT	CNN	CNN	75	79
Sun et al. (2018) [64]	DFT	CNN	RNN	80	78
Nejedly et al. (2019) [65]	z-score normalization	CNN	CNN	79	82
Liu et al. (2019) [39]	FFT	CNN	CNN	83	82
Thara et al. (2019) [66]	Bandpass filtering	LSTM	LSTM	89.1	90
Hu et al. (2019) [67]	FFT	CNN	SVM	86	87.5
Yu et al. (2020) [68]	Local mean decomposition	PCA+CNN	Bayesian linear discriminant analysis	87.7	75
Praveena et al. (2020) [69]	Low Pass Filter, EMD	Univariate features	LSTM	89.8	91.2
Nasseri et al. (2020) [70]	Data Segmentation	Spectral features	Logistic Regression	88	88
Raghu et al. (2020) [71]	Bandpass filter, STFT	CNN	SVM	87	88
Stojanović et al. (2020) [72]	SMOTE	Time domain, Spectral Features	SVM	80	82

Classifier selection is equally important step like feature extraction in epileptic seizure prediction using intracranial EEG signals. Niknazar et al [57] proposed threholding for classification but could only get 63.75 % sensitivity as no single threshold can be applied to classify between multiple states of seizure. Parvez et al [55], Shiao et al [58], Sharif et al [60], Hu et al [67], Raghu et al [71] and Stojanovic et al [72] have used Support Vector Machine for classification between interictal and preictal states. With SVM, classification sensitivity ranges 80-91.8 % and maximum specificity of 88 % has been achieved. CNN is also proposed for classification by researchers including Kornek et el [61], Korshunova et al [62], Khan et al [37], Acharya et al [50], Truong et al [49], Nejedly et al [65] and Liu et al [39]. Sensitivity and specificity achieved from CNN varies between 69 % to 88 %. This variation in classification sensitivity is due to different architecture and number of layers/neurons in the fully connected layers of CNN. Thara et al [66] and Nasseri et al [70] have proposed Long Short Term Memory Units for classification between interictal and preictal states of iEEG signals. Sensitivity of 89 % has been obtained in both methods.

Noise is added into intracranial EEG signals from different sources that include inter electrode interference and noise due to MRCP or ECG signals. Therefore, noise removal is necessary in case of these signals like in scalp EEG signals. Absence of preprocessing in existing seizure prediction that have used intracranial EEG dataset have not achieved good sensitivity and specificity. On the other hand, use of bandpass/bandstop filter could not remove noise that has been added due to inter electrode interference. Therefore, preprocessing that combines different techniques to remove all these types of noise is necessary. Comparison of existing methods shows that Empirical Mode Decomposition and Fourier Transform provide better Signal to Noise ratio, however, class imbalance problem has not been addressed in recent epileptic seizure prediction methods. Both handcrafted and automated features can be used for classification between preictal and interictal states. CNN with less number of convolutional layers have been able to achieve better results. Features extracted from CNN are dependent on number of convolution layers and filter size proposed in different methods. It has been observed that feature selection techniques have not been proposed in existing methods. Similarly, reducing number of trainable parameters used by CNN also remains a challenge for reducing the processing time for effective prediction of epileptic seizures. In classification, CNN, LSTM and SVM have classified preictal and interictal states with greater sensitivity and specificity.

2.5 Research Gaps

For this research, analysis of epileptic seizure prediction methods has been performed using scalp and intracranial EEG signals comprehensively and following research gaps in existing methods have been found.

1. Existing seizure prediction methods are patient-specific, therefore, method need to be evaluated on all subjects of the dataset which is missing in many cases.
2. Class imbalance that limits the performance of prediction methods has not been addressed in existing literature.
3. EEG signals are prone to different types of noise, therefore, noise removal need to be done for all types of noise including power line, inter electrode interference and noise due to other artifacts.
4. Both handcrafted and automated features help in extracting features to distinguish between preictal and interictal states, however, feature selection is required from both these types of features.
5. There is lack of comparison between number of parameters of deep learning classifiers. These parameters need to be minimized so that processing time can be reduced.

2.6 Summary

Epileptic seizures can be predicted using scalp EEG or intracranial EEG signals. A typical seizure prediction method involves recording of EEG signals, preprocessing of EEG signals for noise removal, feature extraction and classification between interictal and preictal states. Multiple methods have been proposed by researchers in recent years based on both scalp and intracranial EEG signals. This chapter provides a comparison between existing seizure prediction methods on both scalp EEG as well as intracranial EEG signals and identifies the research gaps in these methods. Analysis of existing state of the art methods have showed that without effective preprocessing, comprehensive feature set and accurate classification, epileptic seizures cannot be predicted with increased sensitivity. There are many research gaps in the existing methods in all three steps. In preprocessing, combination of any technique is not used by many studies to ensure the increased SNR of EEG signals. No method in scalp EEG signals have proposed any technique to mitigate the effect of class imbalance problem for epileptic seizure prediction methods. Researchers have propsosed few methods for data augmentation of EEG signals for movement related EEG and emotion recognition. GANs have performed well for augmentation in these methods. A comprehensive feature set also need to be formed by combining both handcrafted and automated features which is missing in the existing methods. Similarly, classification has also been kept simple in the existing methods.

CHAPTER 3
PREPROCESSING OF EEG SIGNALS

Epileptic seizure prediction involves preprocessing of EEG signals noise removal, feature extraction and classification between preictal and interictal states. The proposed epileptic seizure prediction method can be applied on both scalp as well as intracranial EEG signals for accurate and in-time prediction of focal and generalized seizures. Proposed methodology consists of preprocessing of EEG signals for noise removal and synthetic data generation for class with less segments, feature extraction and classification using ensemble classifier.

3.1 Overview of Preprocessing Methodology

EEG signals are prone to noise due to power line [157, 158], inter-electrode interference [159, 160], movement related cortical potentials [161–163], electrocardiogram [97, 164, 165], and effect of blinking eyes [166]. All these factors reduce Signal to Noise Ratio (SNR) [167] of EEG signals that lead towards decrease in classification accuracy between interictal and preictal states. Therefore, preprocessing method has been proposed that involves noise removal including power line noise, inter-electrode interference and noise inducted due to other artifacts. Another problem is preictal to interictal samples ratio i.e. very few samples of preictal state are available in the existing datasets as compared to interictal which leads to class imbalance problem and as a result limits the classification performance. In the proposed method, synthetic data has been generated for preictal class to mitigate the effect of class imbalance between preictal and interictal classes.

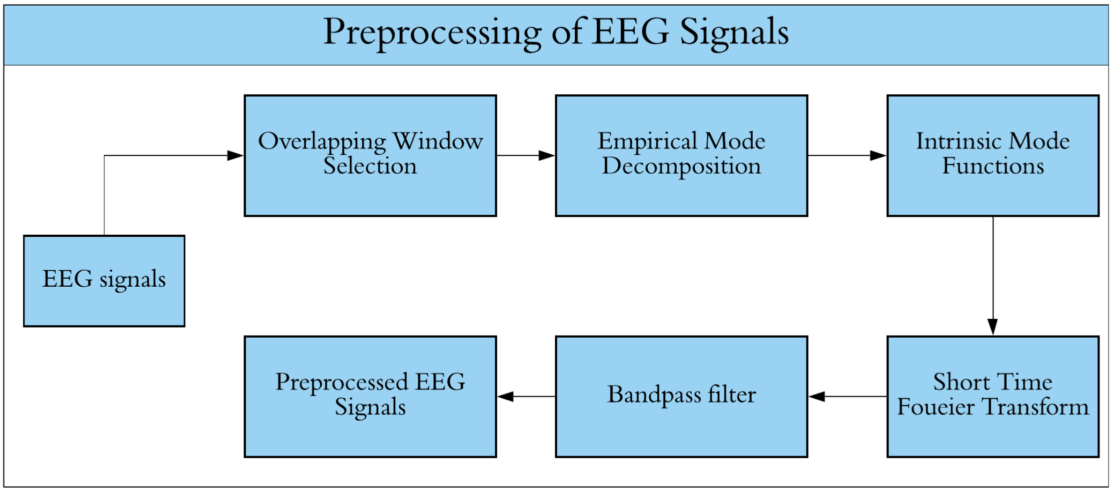


Figure 3.1: Flow Diagram for Preprocessing of EEG Signals

Figure 3.1 shows the flow diagram of the proposed preprocessing method for noise removal from EEG signals. EEG signals recorded from scalp or surface of patient's brain are preprocessed to increase the SNR of EEG signals. These signals with increased SNR are more robust for epileptic seizure prediction. In the first step, EEG recordings have been divided into fixed length segments with the help of an overlapping/sliding window of 30 seconds with an overlap of 15 seconds. Figure 3.2 represents three time steps of overlapping window of 30 seconds.

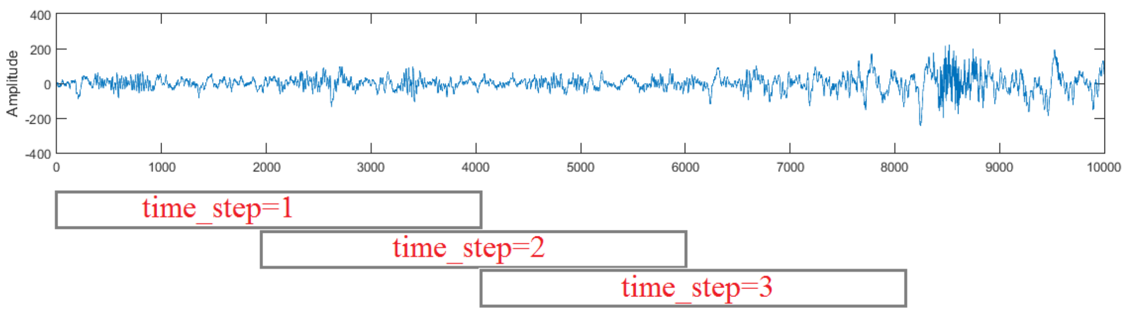


Figure 3.2: Overlapping window selection for EEG Signals with time step representing each window

Empirical Mode Decomposition (EMD) [168–174] has been applied on segments of both preictal and interictal classes for extraction of Intrinsic

Mode Functions (IMF). Hurst exponent is computed and IMFs with value of exponent less greater than 0.5 have been removed. EMD performs better denoising of EEG signals than low pass filters [9, 175–177] as the important information of EEG signals required to distinguish between multiple states is retained and greater SNR is achieved using EMD, however, it does not remove the power line noise that affects the EEG signals at 50-60 Hz.

To remove the power line noise, time domain EEG signals are first converted into frequency domain and then band-stop filter is applied to remove power line noise at 50-60 Hz. Time domain EEG signals can be converted into frequency domain using Discrete Fourier Transform (DFT) [178], Fast Fourier Transform (FFT) [102] or Short Time Fourier Transform (STFT) [179, 180]. EEG signals recorded from epilepsy patients are non-stationary and frequency changes abruptly in different states of seizures. Therefore, STFT has been used to convert EEG signals into frequency domain as it takes a window of EEG signals and convert it into frequency domain. It assumes that the signal is stationary for short interval of time. STFT performs better than DFT and FFT as EEG signals are stationary only for a few seconds window.

3.2 Noise Removal in Spatial Domain

Empirical Mode Decomposition (EMD) [181] decomposes the time domain signal into multiple signals based on frequency components called Intrinsic Mode Functions (IMF). EMD has been applied on all channels of EEG signals using overlapping window of 30 seconds with an overlap of 15 seconds. Signal to Noise ratio is computed for each extracted IMF and only those IMFs that give greater SNR are kept while others are ignored. Figure 3.3 shows the single window of EEG signal passed to EMD and corresponding denoised signal obtained after IMF selection. Analysis of these figures shows that high frequency component has been removed and information required for multiple states of seizures has been retained which is necessary for classification between interictal and preictal states.

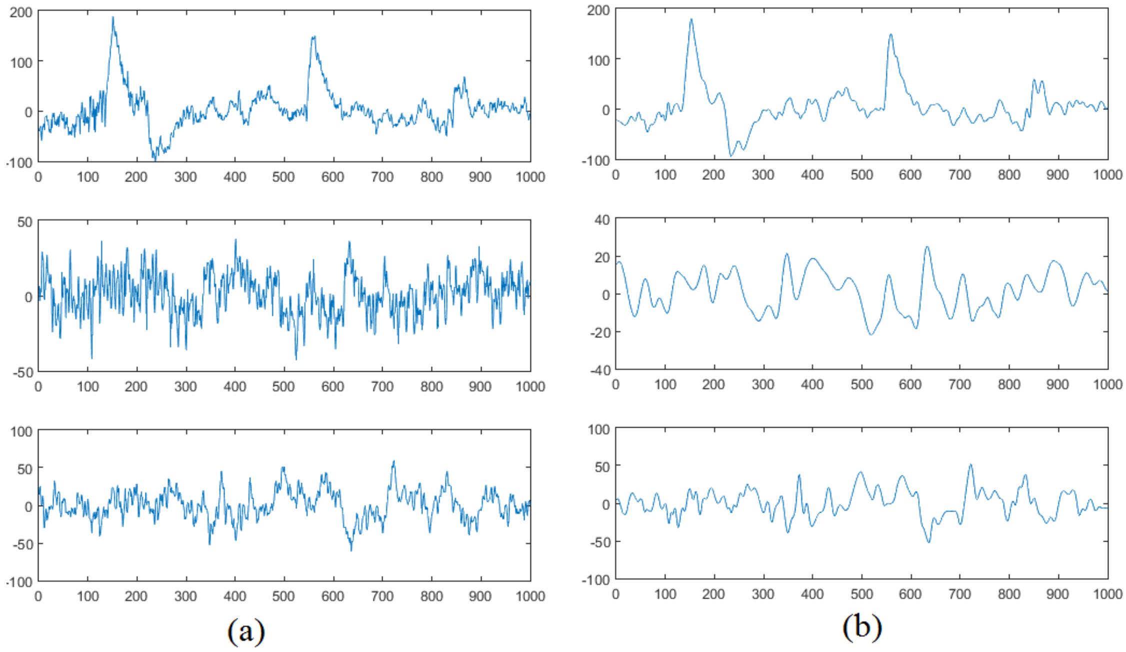


Figure 3.3: (a) 1-Channel of EEG signal before applying EMD (b) Denoised Signal after applying Empirical Mode Decomposition

Assume $X(t)$ be the window of an EEG signal, an IMF is extracted from the signal provided it satisfies following conditions:

1. Total number of peaks must be same as total number of zero crossings.
2. At any time in the signal, mean value of local maxima and minima must be zero.

Algorithm 1 [181] is a standard algorithm for IMF extraction that has been used in this research to extract IMFs from the input signal $X(t)$.

Algorithm 1: IMF Extraction

Input: $X(t)$
Output: IMF
1 Apply up-sampling between positive and negative peaks for generating envelopes $max(t)$ and $min(t)$;
2 Calculate average between minima and maxima $m(t)$;
3 Extract $y_1(t)$=$X(t)-m(t)$;
4 Check whether $y_1(t)$ is an IMF by applying two conditions ;
5 Repeat step 1 to step 4 till IMF is confirmed.

Signal to Noise ratio is calculated for each IMF and then decision is taken based on SNR of that IMF whether to keep that IMF or not. All

IMFs with greater SNR are kept and combined to form a denoised EEG signal. To deal with non-stationary EEG signals, three approaches can be used including Fourier Transform, Wavelet transform and Empirical Mode Decomposition. Fourier analysis assumes that EEG signals are stationary for specific non-overlapping window on which Fourier transform has been applied. Moreover, to localize the state of seizure from EEG signal, a short window size must be used for Fourier transform.

The shortcomings of Fourier analysis have been removed in wavelet transform which can be used for the same purpose but still ther is a problem while interpreting signal's information in low frequencies. A change that occurs in low frequency cannot be localized by wavelet transform. Moreover, wavelet transform interprets linear signals and easily localized for stationary and linear signals, whereas, in epileptic seizure prediction, EEG signals are considered as non-linear and non-stationary in nature. Therefore EMD has been used in the proposed method for denoising of EEG signals instead of Fourier Transform or Wavelet Transform to achieve better SNR of EEG signals.

3.3 Noise Removal in Frequency Domain

Scalp and intracranial EEG signals are non-stationary and not localized in time domain, however, frequency domain analysis gives better characterization of these signals. Fast Fourier Transform and Discrete Fourier Transform can be used to convert EEG signals into frequency domain for analysis but due to non-stationary nature of these signals, both discrete Fourier transform and wavelet transform do not represent the changes in short duration. Therefore, Short Time Fourier Transform (STFT) [182] has been used for analyzing the frequency spectrum of EEG signals for overlapping window of short duration. EEG signals of both preictal and interictal states have been segmented using an overlapping window of 30 seconds with an overlap of 15 seconds and these segments have been used as input to STFT. Figure 3.4 shows the Spectrogram obtained from STFT.

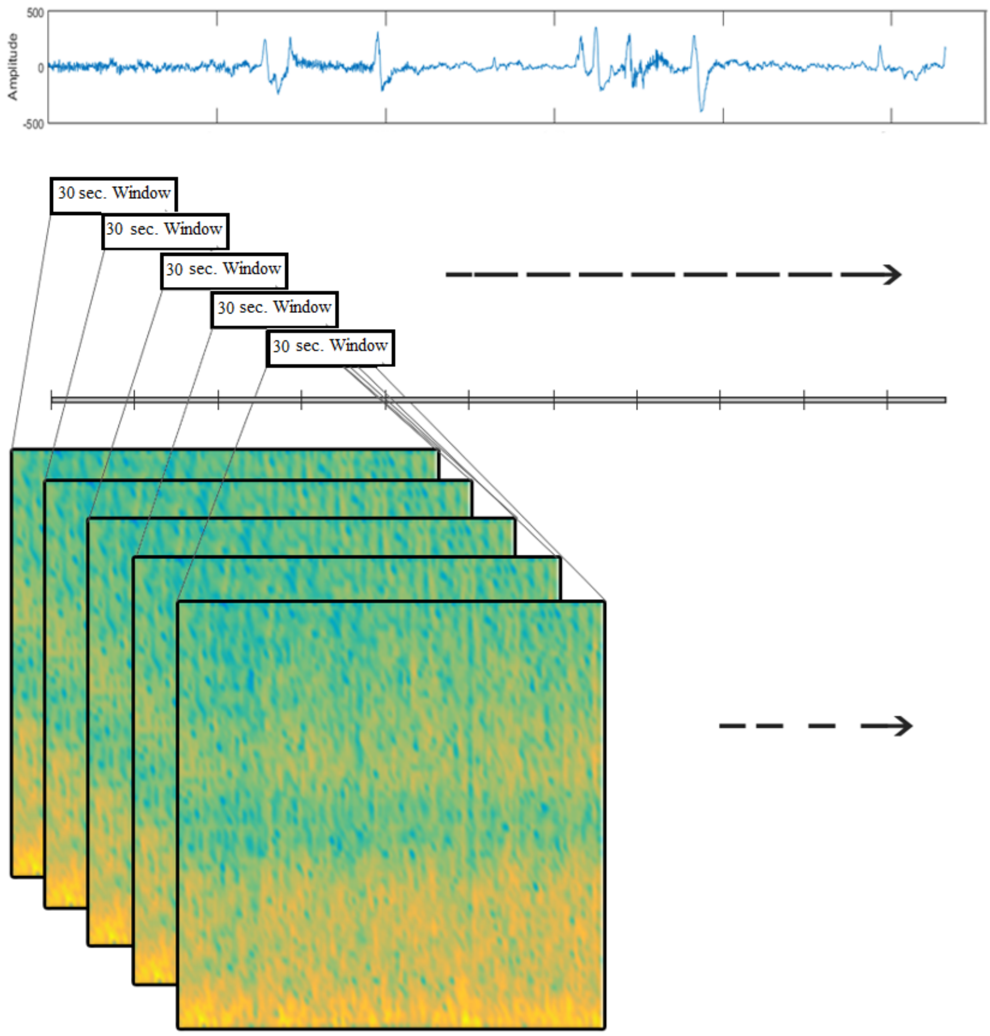


Figure 3.4: Spectrogram obtained from STFT after Converting time domain signal into frequency domain with 30 seconds of overlapping window with an overlap of 15 seconds.

Assume $x[n]$ be an EEG signal recorded from subject's scalp or surface and $x_l[t]$ represents the extracted segment from the signal using overlapping window $w[t]$ can be computed using following equation [183].

$$x_l[t] = w[t]x[t + lH] \tag{3.1}$$

$t \in \{1,....,T\}$ is starting time of the overlapping window, $T \in \mathbb{N}$ is the length of the window which is 30 seconds, $l \in \mathbb{N}$ is the frame number and $H \in \mathbb{N}$ is the hop size. Fourier transform for each frame $x_l[t]$ can be computed using the equation as follows:

$$X[f,l] = \frac{1}{T}\sum_{t=1}^{F} x_l[t]e^{-j2\pi\frac{tf}{F}} \tag{3.2}$$

Where, $f \in \{1,....,F\}$ is the index of frequency bin and $F \in \mathbb{N}$ is the size of DFT. The input sequence of DFT $x_l[t]$ has been interpolated with zero padding as $F > T$. $X[f,l]$ is the extracted STFT of EEG signal frame $x[n]$ and represents the local time frequency behavior of the signal around the time index lH and the frequency bin k. After converting time domain EEG signals into frequency domain with STFT, power line noise has been removed by applying 4^{th} order Butterworth Bandpass filter with pass bands of 0-40 Hz. and 65-130 Hz. For interictal class samples, spectrogram obtained from STFT is fed into Convolutional Neural Network (CNN) for feature extraction, whereas, spectrogram of preictal state samples is passed into Generative Adversarial Networks (GAN) [184] for generation of synthetic preictal state samples followed by feature extraction using CNN.

3.4 Mitigation of Class Imbalance Problem

In scalp and intracranial EEG recordings of existing datasets, preictal state data is very less as compared to interictal state data due to fewer number of seizure occurrences in specified time of recording these signals. It leads toward class imbalance problem between preictal and interictal state which in some cases can be 1:10 samples. Classification performance is adversely affected due to class imbalance problem as classifier may be over-trained for interictal class and under-trained for preictal class. Previously, only a few researchers have used Synthetic Minority Oversampling technique (SMOTE) [185] for dealing with class imbalance issue. In SMOTE, an overlapping/sliding window approach is used to increase the samples of particular class.

Wang et al [109] have added Gaussian Noise with zero mean for augmentation of EEG signals. Zhang et al [110] have applied empirical mode decomposition on EEG signals for extraction of IMFs and then these IMFs are swapped to generate new samples of EEG signals. Luo et al [186], Lashgari et al [187] and Abdelfattah et al [111] have proposed Generative Adversarial networks for generating synthetic EEG signals that have improved the classification performance. Based on the results achieved from GAN have been better compared with 1D oversampling.

An overlapping window of 30 seconds with an overlap of 15 seconds for both preictal and interictal states by assuming that the desired information might be available in any time step. This approach has not only increased the samples of preictal states but also increased for interictal state. The problem of class imbalance remains the same as the ratio of preictal to interictal samples is same. To deal with this problem, 1D EEG signals are first converted into 2D signals with the help of STFT and then synthetic data has been generated using Generative Adversarial Networks (GAN) [111] for preictal class only so that samples of class with fewer examples can be increased. With the help of GANs, proposed method has been able to generate synthetic preictal class data almost equal to the existing preictal data.

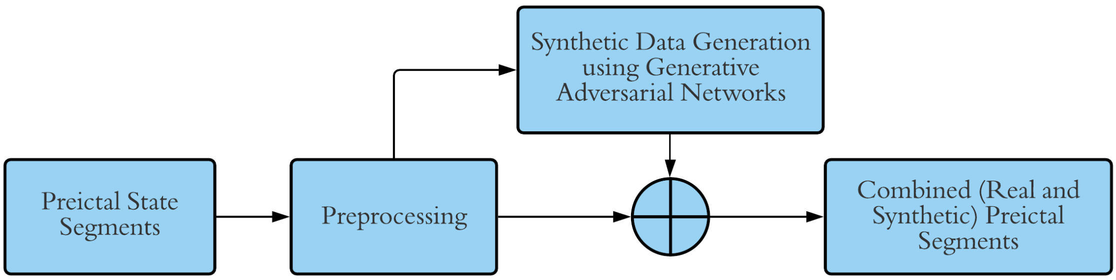


Figure 3.5: Generation of Preictal States Samples of EEG Signals with Generative Adversarial Networks.

In the proposed method, synthetic preictal state samples have been generated with Generative Adversarial Networks. Figure 3.5 shows the flow diagram of synthetic data generation for preictal state. Initially, preprocessing techniques have been applied on preictal state for noise removal to increase the SNR. Preprocessed preictal segments are then fed into the discriminator of GANs. Meanwhile, random noise is passed as input to generator for generating synthetic samples. Output of generator is compared by discriminator using original preprocessed preictal sate samples. In the next iteration generator updates its parameters to minimize the loss function. The process repeats for 100 iterations and then synthetic samples are combined with original segments to increase the ratio of preictal to interictal samples and then used as input for feature extraction.

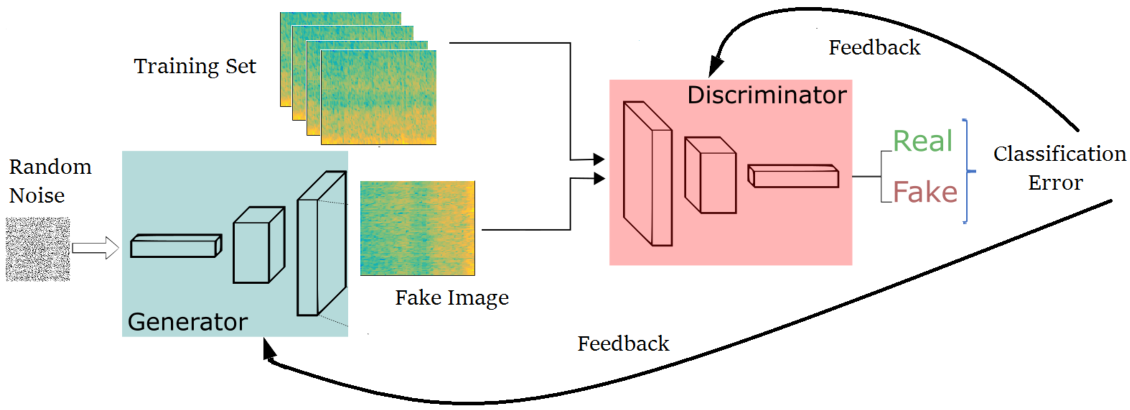


Figure 3.6: Block diagram of Generative Adversarial Networks for generation of preictal segments

GAN comprises of generator that generates the synthetic data and discriminator that differentiate between the real and synthetic data. Figure 3.6 shows Block diagram of Generative Adversarial Networks for generation of preictal segments. The goal is to estimate the distribution of real preictal class data so that new synthetic data of same distribution can be generated and optimize the performance of generative. After the estimation of distribution of real data, GAN tries to maintain the Nash Equilibrium of game theory. Generator creates a distribution of synthetic data after estimating the distribution of real data while discriminator determines whether the data is received from real segments or synthetic from generator. To achieve Nash equilibrium state, both participants need to optimize their abilities of generating and discriminating the data. Samples which are real but classified as synthetic and vice versa are known as adversarial samples. Table 3.1 and 3.2 provides the summary of number of parameters required in each layer of the proposed generator and discriminator.

Table 3.1: Summary of proposed GAN's discriminator

Layer	**Output Shape**	**Parameters**
Input	(64,112,1)	0
Conv2D	(32,56,32)	832
LeakyReLU	(32,56,32)	0
Dropout	(32,56,32)	0
Conv2D	(16,28,64)	18496
Zeropadding	(17,30,64)	0
LeakyReLU	(17,30,64)	0
Dropout	(17,30,64)	0
Batch Normalization	(17,30,64)	256
Conv2D	(9,15,128)	73856
LeakyReLU	(9,15,128)	0
Dropout	(9,15,128)	0
Batch Normalization	(9,15,128)	512
Conv2D	(9,15,256)	295168
LeakyReLU	(9,15,256)	0
Dropout	(9,15,256)	0
Flatten	(34560)	0
Dense	(1)	34561
Total parameters		423681

Table 3.2: Summary of proposed GAN's generator

Layer	**Output Shape**	**Parameters**
Input	(100)	0
Dense	(57344)	5791744
Reshape	(16,28,128)	0
Batch Normalization	(16,28,128)	512
Upsampling	(32,56,128)	0
Conv2D	(32,56,128)	147584
Activation	(32,56,128)	0
Batch Normalization	(32,56,128)	512
Upsampling	(64,112,128)	256
Conv2D	(64,112,64)	73792
Activation	(64,112,64)	0
Batch Normalization	(64,112,64)	256
Conv2D	(64,112,1)	577
Activation	(64,112,1)	0
Total parameters		6017977

Figure 3.5 shows original preictal state segments and synthetic preictal state segments generated using GANs. Objective of discriminator is to minimize the loss function cross entropy similar to traditional sigmoid based classifiers. Objective function [188] for generator can be described

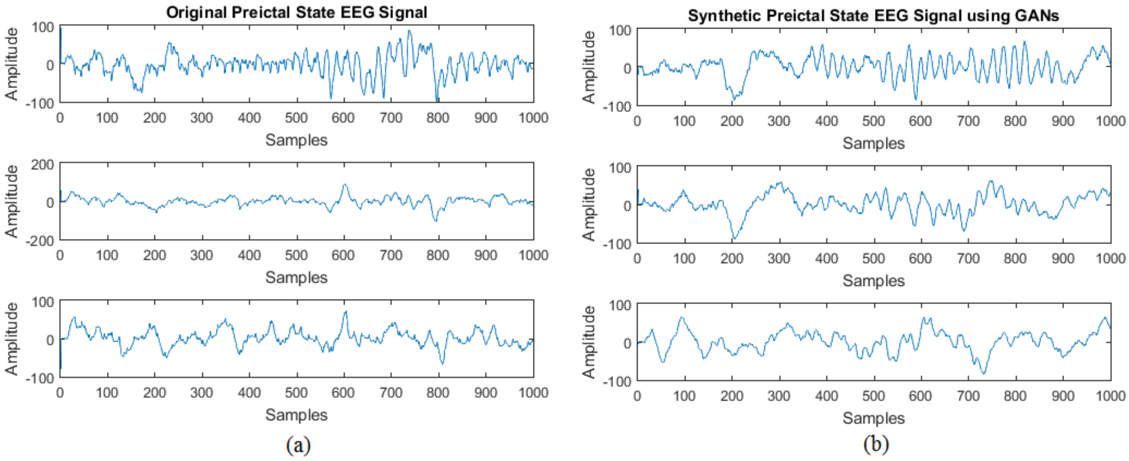


Figure 3.7: a) Original preictal state samples recorded from scalp of subjects b) Synthetic preictal state segments generated using GANs

as follows:

$$Obj^D(\theta_D,\theta_G) = -\frac{1}{2}E_{x\sim pdata(x)}[logD(x)] - \frac{1}{2}E_{z\sim p_z(z)}[log(1-D(g(z)))] \tag{3.3}$$

where D and G denote discriminator and generator respectively. x represents the real preictal data sampled with distribution p_{data}, z is sampled from the normal distribution p_z and E represents the expectation.

Discriminator is trained with both real preictal data distribution p_{data} and generated synthetic data distribution by generator p_g. Due to this, it is different from traditional classification methods. Objective function of the generator is to minimize the loss and can be computed as follows:

$$Obj^D(\theta_D,\theta_G) = -\frac{1}{2}\int_x p_{data}(x)log(D(x))dx - \frac{1}{2}\int_z p_z(z)log(1-D(g(z)))dz \tag{3.4}$$

For any $(m,n) \in \mathbb{R}^2 \setminus \{0,0\}$ and $y \in [0,1]$

$$mlog(y) - nlog(1-y) \tag{3.5}$$

Therefore, given generator G, the objective function achieves its minimum value at

$$D_G^* = \frac{p_{data}(x)}{p_{data}(x) + p_g(x)} \tag{3.6}$$

D_G^* gives the optimal solution for discriminator D. Discriminator of GAN computes the ratio between probability densities between original and generated preictal data.

3.5 Summary

The proposed epileptic seizure prediction method involves three steps i.e. preprocessing of EEG signals, feature extraction and classification between interictal and preictal states. Preprocessing of scalp and intracranial EEG signals being the key step in epileptic seizure prediction method has been used to increase the signal to noise ratio so that better characterization of interictal and preictal states can be achieved. Proposed method involves noise removal in both time and frequency domain followed by synthetic data generation of preictal states. Noise removal is necessary for increasing signal to noise ratio of EEG signals, whereas, generating synthetic EEG signals of preictal states is required to mitigate the class imbalance problem.

EEG signals have been divided into segments using an overlapping window of 30 seconds with an overlap of 15 seconds. Empirical mode decomposition has been applied on these segments of both preictal and interictal states for noise removal to increase SNR of EEG signals followed by bandpass filter to remove power line noise. Time domain EEG signals have been converted into frequency domain with the help of short time Fourier transform. To mitigate the effect of class imbalance between preictal and interictal states EEG signals, proposed method consists of synthetic data generation of preictal state using generative adversarial networks.

CHAPTER 4
FEATURE EXTRACTION AND CLASSIFICATION OF EEG SIGNALS

Preprocessing of EEG signals involves noise removal and mitigating the affect of class imbalance problem by generating synthetic data for preictal class. After preprocessing of EEG signals, handcrafted and automated features have been extracted followed by feature selection methods for formulation of feature vector. Classification between preictal and interictal states is then performed using this feature vector for prediction of epileptic seizures. In the proposed method, mean, variance, skewness, kurtosis, spectral centroid, variational coefficient, spectral skewness, spectral kurtosis and approximate entropy have been extracted as handcrafted features. A customized three-layer Convolutional Neural Network (CNN) has been proposed for automated feature extraction. Proposed method then combines both handcrafted and automated features. Both filter and wrapper based methods have been used for feature selection. Feature vector obtained after selection is then passed to train an ensemble classifier and validated using k-fold cross validation.

4.1 Feature Extraction

For accurate classification between interictal and preictal states of EEG signals, effective feature extraction is necessary. Both the handcrafted as well as the automated features extracted through deep learning are useful. Therefore, the proposed method combines both handcrafted and the automated

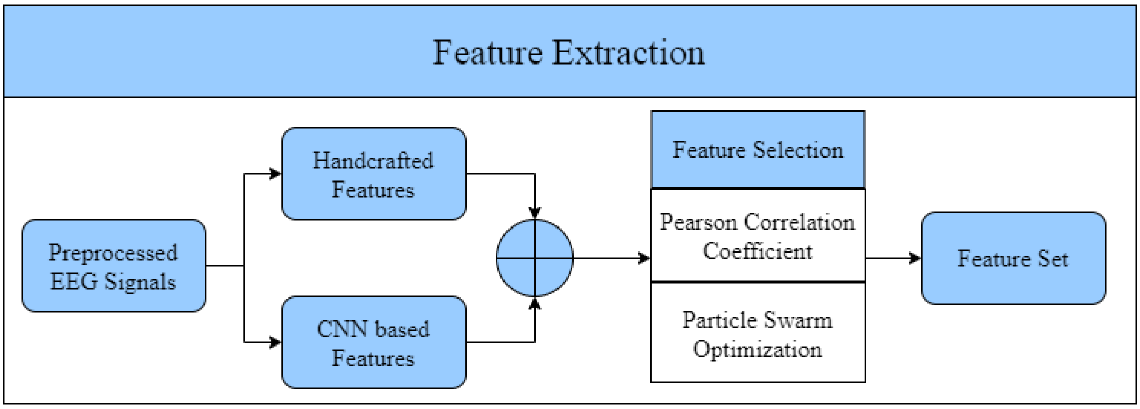


Figure 4.1: Flow Diagram of Proposed Feature Extraction Method

features followed by feature selection techniques to form a comprehensive feature set which is required to predict epileptic seizures with high accuracy. Figure 4.1 shows the flow diagram of proposed feature extraction methodology. Researchers have used two common feature extraction approaches. In the handcrafted feature extraction approach, features are extracted irrespective of the class of EEG signals, whereas, the automated feature extraction which is performed with the help of Convolutional Neural Networks [189] keeps class information under consideration while extracting features. This fact motivates the use of different CNN architectures for effective feature extraction.

In the proposed method, after preprocessing of EEG signals, both handcrafted and automated features have been extracted followed by feature selection to get a comprehensive feature vector. Handcrafted features include temporal and spectral features. Mean, variance, skewness, kurtosis and approximate entropy have been extracted as temporal features, whereas, spectral features include spectral centroid, variational coefficient, spectral skewness and spectral kurtosis. A three layer customized architecture of Convolutional Neural Network has been proposed to extract the automated features from preictal and interictal class data. Both handcrafted and automated features are then combined to form a single feature vector. These features consist of correlated features and dimensionality is high that can lead towards curse of dimensionality problem [190]. To minimize the curse of dimensionality, feature selection techniques [191] including Pearson Correlation Coefficient (PCC) [192] and Particle Swarm Optimization (PSO) [193] have been applied for feature selection to get a comprehensive feature set.

4.1.1 Handcrafted Features

In the proposed method, both time and frequency domain features from all channels of EEG signals have been extracted which distinguish between interictal and preictal states. Time domain features include mean, variance, skewness, kurtosis and approximate entropy, whereas, spectral moments including spectral centroid, variational coefficient, spectral skewness and kurtosis have been extracted. These features have been extracted by applying 30 seconds overlapping window with an overlap of 15 seconds on the preprocessed EEG signals obtained after applying EMD. Denoised signals using EMD give increased SNR, therefore, handcrafted features extracted from these preprocessed signals exhibits greater interclass variance. Spectral analysis [194] of IMFs obtained when EMD is applied on EEG signals in the preprocessing step provides useful information. Spectral analysis provides useful features for epileptic seizure prediction as change in behavior can be observed in different frequency bands of preictal and interictal states. Similarly, time domain features also distinguish between both states of epileptic seizures.

Figure 4.2 illustrates statistical features extracted for preictal and interictal states. Temporal mean computes the average in time domain from EEG signals, whereas, variance gives the variation in the distribution of EEG signals in time domain. Skewness measures the symmetry between multiple samples of EEG signals and kurtosis detects the abrupt changes in the time domain EEG signals. Approximate entropy captures the sharp changes of EEG signals in time domain. All these properties make these features valuable for classification between preictal and interictal states. In the same way, spectral moments are also quite useful for classification

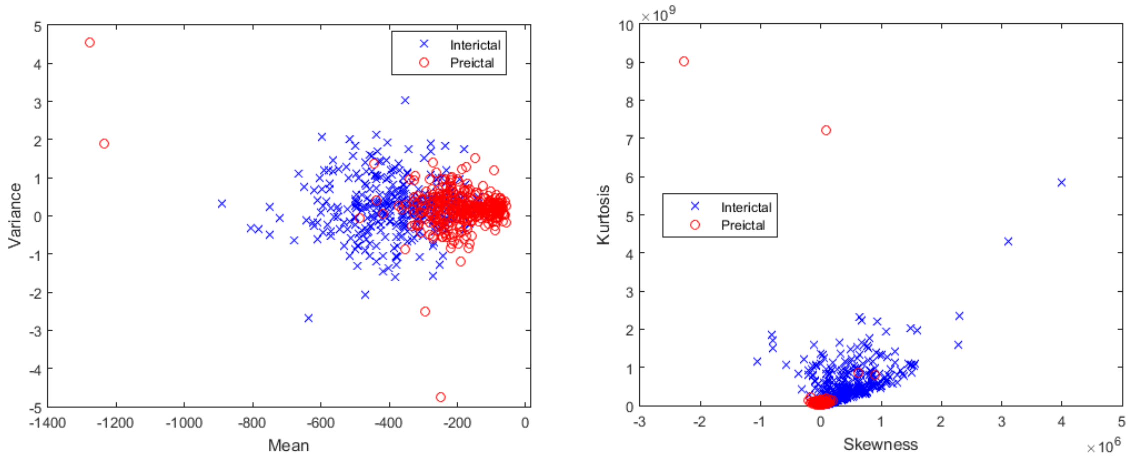


Figure 4.2: a) 2D plot of Mean and Variance b) 2D plot of Skewness and Kurtosis

as the abrupt changes can also be observed in different frequency bands. Proposed method combines these temporal and spectral features to develop a handcrafted feature vector.

In the proposed method, after extracting different features including Hjorth parameters, Lyapunov exponent, Phase locking values, statistical, spectral moments, entropy and approximate entropy. However, features that have provided better classification results have been selected for formation of feature set. These features include statistical, spectral moments and approximate entropy and have been computed as features from IMFs obtained after applying EMD on the scalp and intracranial EEG signals. Description of all handcrafted feature used in this study is as follows:

1. *Mean* (f_1) computes the average of EEG segment from the IMFs. Equation 4.1 computes the mean from IMFs.

$$\mu_t = \frac{1}{N}\sum_{i=1}^{N}(x_i) \tag{4.1}$$

where N is the length of IMF, t is EEG segment and μ mean of IMF.

2. *Variance* (f_2) measures the deviation of EEG segment from local mean. Following equation describes the formula for computing vari-

ance from IMF obtained after applying EMD to EEG signals.

$$\sigma_t^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu_t)^2 \tag{4.2}$$

3. *Skewness* (f_3) provides the information about abrupt changes in the EEG signals. It is zero in case of symmetric signal. Skewness β_t can be computed as follows:

$$\beta_t = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_i - \mu_t}{\sigma_t} \right)^3 \tag{4.3}$$

where N represents is the output samples obtained from EMD after denoising, μ denotes the mean and σ is the standard deviation.

4. *Kurtosis* (f_4) identifies the peaks in the EEG signals. Kurtosis of IMF can be computed using following equation.

$$K_t = E\left[\left(\frac{x_i - \mu_t}{\sigma_t} \right)^4 \right] \tag{4.4}$$

5. *Spectral Centroid* (f_5) is the mean of EEG signal in frequency domain. Due to abrupt change in preictal state which can be observed in frequency domain, spectral centroid is a useful feature.

$$C_s = \frac{\sum_w wP(w)}{\sum_w P(w)} \tag{4.5}$$

where $P(w)$ is power spectral density of w^{th} frequency bin in the spectrum and can be computed as follows:

$$P(w) = \sum_{n=1}^{N} r_y[n] e^{-jwn} \tag{4.6}$$

$$r_y[n] = E(y[m] + y[m+n]) \tag{4.7}$$

6. *Variational Coefficient* (f_6) determines the variance of EEG segments from mean in frequency domain. Since the spectral variation in

the IMFs is different for preictal and interictal states in EEG signals, therefore it can be used for their characterization. This variation can be calculated as follows: where C_s is the spectral centroid

$$\sigma_s^2 = \frac{\sum_w (w - C_s)^2 P(w)}{\sum_w P(w)} \tag{4.8}$$

7. *Spectral Skewness* (f_7) is the 3^{rd} spectral moment and measures the symmetry of EEG segment. Spectral skewness changes positive or negative based representing the symmetry in frequency distribution for EEG signals.

$$\beta_s = \frac{\sum_w \left(\frac{w-C_s}{\sigma s}\right)^3 P(w)}{\sum_w P(w)} \tag{4.9}$$

8. *Spectral Kurtosis* (f_8) is the 4^{th} spectral moment and provides the information about the impulsiveness of EEG signal.

$$K_s = \frac{\sum_w \left(\frac{w-C_s}{\sigma s}\right)^4 P(w)}{\sum_w P(w)} \tag{4.10}$$

9. *Approximate Entropy* (f_9) measures the fluctuations in the EEG signals.

$$\Phi(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} log C_i^m(r) \tag{4.11}$$

All these features f_1 to f_9 have been extracted for all channels of EEG signals using 30 seconds segments of both preictal and interictal states obtained with non-overlapping window. Datasets used in in this study consist of 16 and 23 channels. These features from all channels have been concatenated to form a feature vector. Therefore, in case of 16 channels, feature vector consists of 144 features and for dataset with 23 channels, dimension of feature vector is 207.

4.1.2 Feature Extraction Using CNN

In this method, features are extracted keeping the class of EEG signals under consideration. Improved results can be achieved as these features have low intraclass variance and high interclass variance [195].

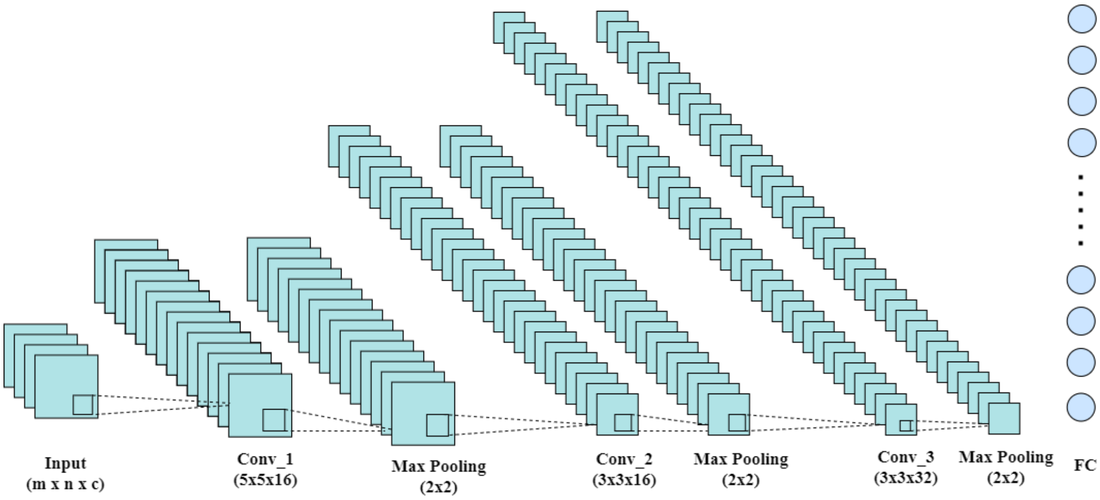


Figure 4.3: Proposed 3-layers CNN architecture for automated feature extraction

In this study, a customized three-layer convolutional neural network architecture for feature extraction from scalp EEG signals has been proposed. Figure 4.3 shows CNN architecture used for feature extraction. CNN gets input of mxnxc which is obtained by converting time domain signals into the frequency domain using STFT, where m,n represent rows and columns of input matrix and c denotes number of channels for EEG signals. STFT has been applied on 30 seconds overlapping window with an overlap of 15 seconds EEG signals to get the exact 64x112 signals. c is 23 for scalp EEG dataset, whereas, it has value of 16 for intracranial EEG dataset. First layer of CNN consists of convolution with 16 filters of 5x5 followed by activation layer with leaky ReLU [196] as activation function. Max-pooling [197] and Batch Normalization [198] is performed after convolution to reduce the feature map and increase the training process. In the second layer, 16 filters of 3x3 are applied following by activation layer, max pooling and batch normalization. In the last layer, 32 filters of 3x3 are used followed by activation layer, max pooling and batch normalization. Leaky ReLU has been used instead of simple Relu to avoid vanishing gradient problem [199]. Batch normalization has been applied to speed up the training process. After using these three layers of CNN, resultant images are flattened to get feature vector of 1x3584. Table 4.1 provides the summary of our proposed CNN model.

Table 4.1: Summary of Proposed CNN Model

Layer	**Output Shape**	**Parameters**
Conv2D	(64,112,16)	9216
LeakyReLU	(64,112,16)	0
Max Pooling	(32,56,16)	0
Batch Normalization	(32,56,16)	64
Conv2D	(32,56,16)	2320
LeakyReLU	(32,56,16)	0
MaxPooling	(16,28,16)	0
Batch Normalization	(16,28,16)	64
Conv2D	(16,28,32)	4640
LeakyReLU	(16,28,32)	0
Max Pooling	(8,14,32)	0
Batch Normalization	(8,14,32)	128
Flatten	(3584)	0
Total parameters		16432

CNN [189] consists of convolution with suitable filter size followed by activation function, pooling and batch normalization. If x_n represents the input signal and h_k filter, convolution can be performed using the following equation.

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n} \tag{4.12}$$

During back-propagation [200] weights/bias for all the layers can be computed following equations.

$$\Delta W_l(t+1) = -\frac{x\lambda}{r} W_l - \frac{x}{n}(\frac{\partial C}{\partial W_l}) + m\Delta W_l(t)) \tag{4.13}$$

$$\Delta B_l(t+1) = -\frac{x}{n}(\frac{\partial C}{\partial B_l}) + m\Delta B_l(t) \tag{4.14}$$

Where, W represents weights for layer l and B bias. x, n, m and t are regularization parameters [201]. Max pooling is generally used for downsampling and reducing feature map. Batch normalization helps in reducing the training time. Assume that z_i represents output of neuron then batch normalization can be performed using the following equations.

$$\mu = \frac{1}{m}\sum_i z^i \tag{4.15}$$

$$\sigma^2 = \frac{1}{m}\sum_i (z^i - \mu)^2 \tag{4.16}$$

$$z^i_{norm} = \frac{(z^i - \mu)}{\sqrt{\sigma^2 + \varepsilon}} \tag{4.17}$$

$$z^i = \gamma . z^i_{norm} + \beta \tag{4.18}$$

Where, μ, σ represents mean and standard deviation respectively. γ and β are trainable parameters.

4.2 Feature Selection

Comprehensive feature set extraction is very important for accurate classification. High dimensional feature set with increased number of features may cause curse of dimensionality problem [202]. In this problem, due to increased number of features the classifier lead towards poor generalization as feature set might contain many correlated features. Another problem is to process the high dimensional feature set. To minimize the affect of these problems, variety of feature selection techniques to decrease the dimension of feature set have been used by researchers including filter [203–205], wrapper [206–208] and embedded based methods [209, 210].

In the proposed method, a two-step approach for feature selection has been used. In the first step, correlation between all features using Pearson Correlation Coefficient (PCC) is computed and correlated features with greater value of correlation than specific threshold have been dropped from the feature set to reduce it's dimension. In the second step, Particle Swarm

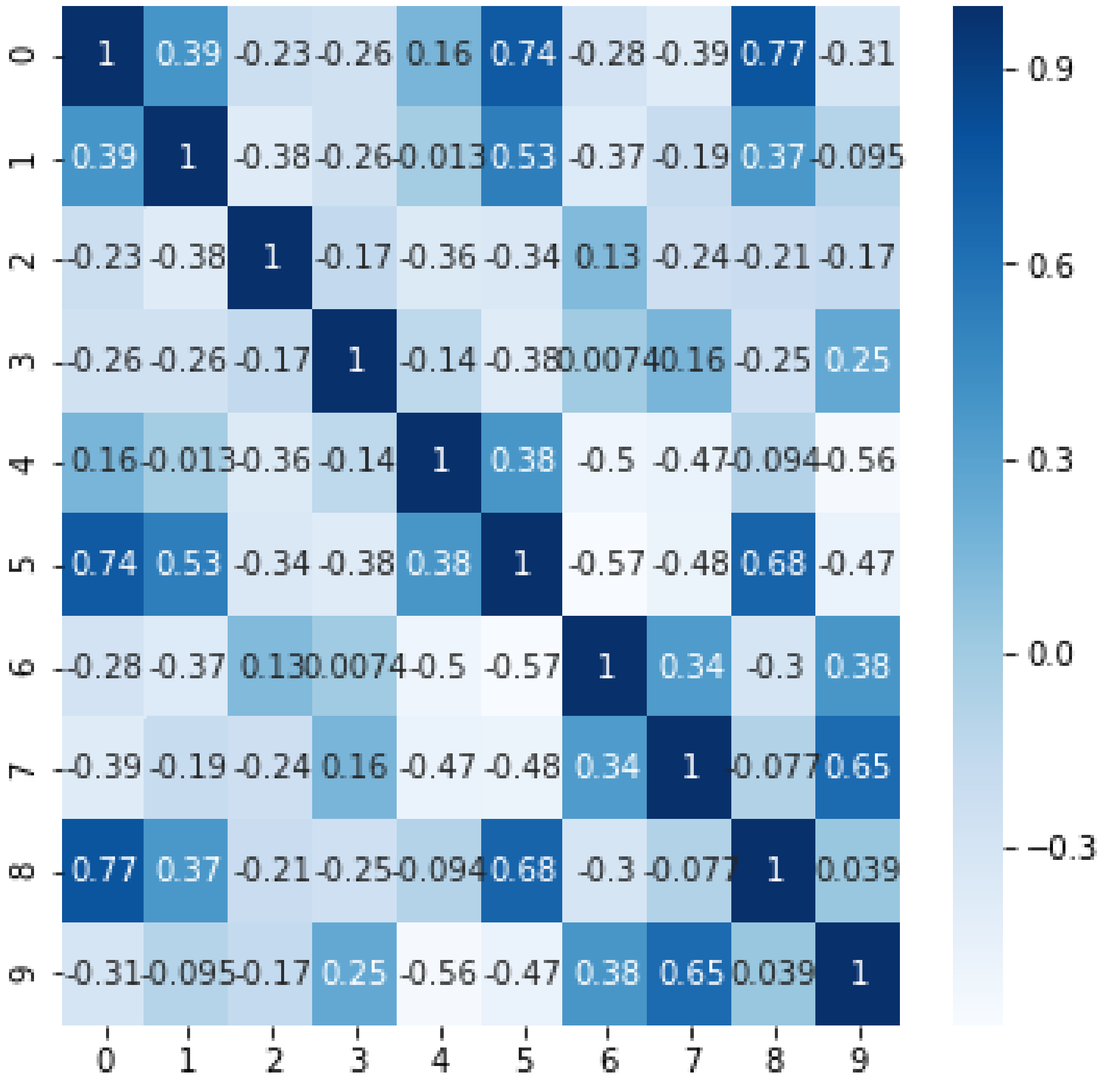


Figure 4.4: Heatmap of Cross Correlation of ten randomly selected features

Optimization (PSO) have been used for further reduction and to get a optimal feature set for classification between interictal and preictal states.

Figure 4.4 shows the heatmap of Cross Correlation of ten randomly selected features. If correlation between two features is more than a specific threshold say 0.5 or -0.5 in negative side, then it shows that features are either positive or negative correlated. In either case, both these features do not add any useful information for classification between preictal and interictal state rather increases processing power and lead towards curse of dimensionality. Correlated features add redundancy and do not help in increasing classification accuracy for prediction of epileptic seizures. PCC helps in finding correlation between same features across multiple channels so that highly correlated features may be dropped to reduce the effect of curse of dimensionality.

Pearson Correlation Coefficient measures the correlation between different features and based on threshold highly correlated features have been dropped to select a feature set with less redundant features. Assume that X and Y be the two distinct features, then correlation between these features can be computed as follows:

$$Corr = \frac{\sum_i (x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum_i (x_i - \bar{x}_i)^2}\sqrt{\sum_i (y_i - \bar{y}_i)^2}} \tag{4.19}$$

Although feature reduction after computing Pearson Correlation Coefficient helps in feature selection, yet an efficient algorithm wrapper based method is needed to get a comprehensive feature set for epileptic seizure prediction. Evolutionary computing techniques have proved to provide optimal solutions for feature selection. Particle Swarm Optimization (PSO) is a recent and more robust optimization technique than Genetic Algorithms. It is less expensive and consume less time in finding optimal solution. PSO reduces the feature set by selecting the optimal feature set which increases the classification performance with minimum number of features. To achieve this, PSO considers the features as multi-objective problem and gets subset of feature set. After applying PSO, a subset consisting of 500 features have been selected from the feature set for classification between preictal and interictal state.

PSO is an evolutionary computing technique proposed in 1995 by Kennedy and Eberhart. It is motivated with the bird flocking or fish schooling behaviors with the basic principle that the knowledge can be optimized like social interactions and not by individual behavior. According to the solution provided by PSO, every solution can be expressed as particle in swarm. Every particle in a search space has a particular position that can be expressed with a vector $y_i = (y_{i1}, y_{i2}, ..., y_{iD})$ having D dimension for search space.

Particles search optimal solutions in the search space with a velocity $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$. While moving in the group particles update positions based on their own and neighbor's experience. p_{best} represents the best position of particle that it had previously and g_{best} is the best position achieved by the population. Based on these two parameters i.e; p_{best} and g_{best}, PSO updates the velocity and it's position to find the optimal solution using equation as follows:

$$x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1} \tag{4.20}$$

$$v_{id}^{j+1} = w * v_{id}^{j} + c_1 * r_1 * (p_{id} - x_{id}^{j} + c_2 * r_2 * (p_{gd} - x_{id}^{j}) \tag{4.21}$$

Where, j denotes the j^{th} iteration of evolution process, d represents the d^{th} dimension in the search space with $d \in D$. w denotes the weight of velocities, c_1 and c_2 are constants of acceleration, whereas, r_1 and r_2 are uniformly distributed random values between [0, 1], p_{id} and p_{gd} represents the elements of p_{best} and g_{best} in the d^{th} dimension. Figure 4.5 shows the scatter plot of randomly selected handcrafted and machine learned features from the feature set selected after applying PSO.

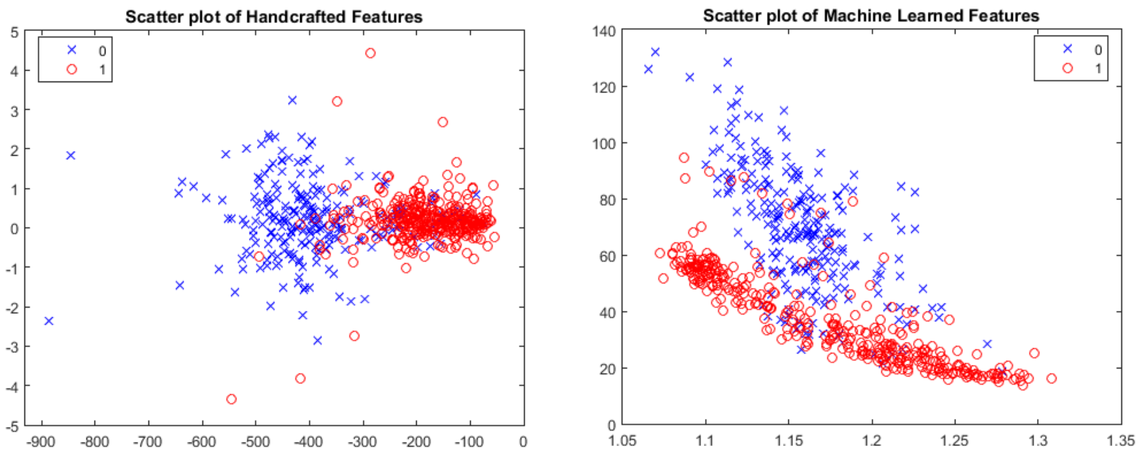


Figure 4.5: Scatter Plot of Randomly Selected Handcrafted and Automated Features

4.3 Classification

After feature extraction and selection of a feature set, classification is performed between interictal and preictal states using Model Agnostic Meta Learning (MAML) classifier. In the propsoed method, MAML receives output from three different classifiers including SVM, CNN and LSTM. Output probabilities of both classes are same that were obtained while training the CNN for automated feature extraction with fully connected layers. The main idea behind using ensemble classification using MAML is to train the classifier with a smaller number of training examples without overfitting with the help of probabilities of classes obtained from three different classifiers. Figure 4.6 shows the flow diagram of proposed classification method.

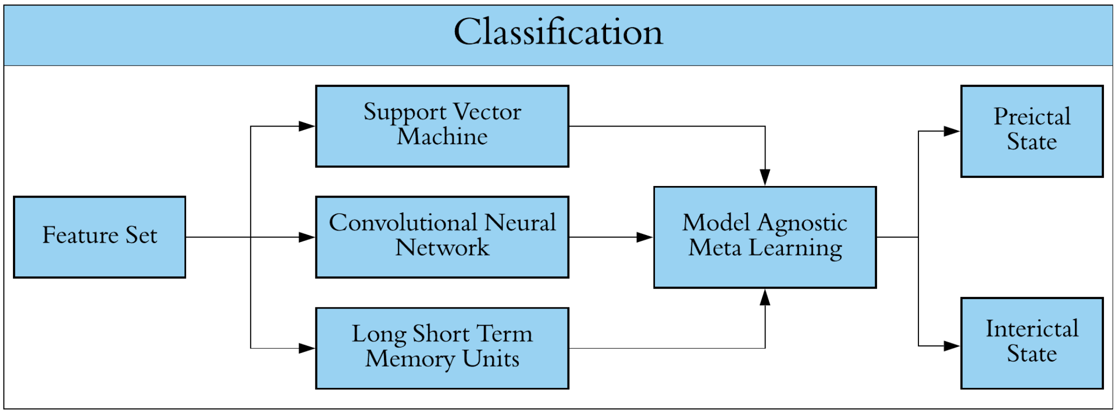


Figure 4.6: Flow diagram of proposed classification methodology

After extracting feature set by combining handcrafted and automated features followed by feature selection techniques, it is then passed to three different classifiers including support vector machine, convolutional neural networks and long short term memory units. SVMs [211] can be divided into two types i.e; linear and non-linear SVM [212]. If we have data which is linearly separable then we can easily find support vectors and with the help of slope and intercept we can draw a decision boundary. These are called linear SVM. Generally, we cannot classify data with the help of linear boundary as data may not be linearly separable. Therefore, SVM maps the data into higher dimensional space so that data is easily separable. Kernel trick is used for this purpose. Some commonly used kernels include multilayer perceptron [213], linear and Gaussian kernels. In this work, we have used linear SVM to classify interictal state and preictal state.

CNN consists of fully connected layers for classification after convolution layers which are used for feature extraction. Propose method uses two hidden layers with 512 and 256 neurons in layer 1,2 and two neurons in output layer with Softmax activation function. It is the same experiment which was performed for automated feature extraction. It gives probabilities of both classes which are fed into MAML for final classification result.

$$E = \frac{1}{2}\sum_{d=1}^{m}(T^{(d)} - O^{(d)})^2 \tag{4.22}$$

$$O^{(d)} = w_0 + w_1 x_1^d + w_2 x_2^d + ... + w_n x_n^d \tag{4.23}$$

$$\Delta w_i = \Delta w_i + \eta(t - o)x_i \tag{4.24}$$

$$w_i = w_i + \Delta w_i \tag{4.25}$$

Recurrent Neural networks have been used for classification in this proposed method. A variant of recurrent neural networks known as Long Short Term Memory Units (LSTMs) [214] has been used to classify preictal and interictal states. Feature set obtained from CNN are converted into sequences with sequence length of 50 and fed into LSTMs for classification. LSTM consists of forget and input gates to store previous information or forget information. This information is passed from one cell to another by maintaining cell states. Implementation of forget ($f(t)$), input ($i(t)$) gates, weights of previous layer of LSTM (H_{t-1}) [215], cell states and new weights can be computed as follows:

$$f(t) = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{4.26}$$

$$i(t) = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{4.27}$$

$$\hat{C}(t) = tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{4.28}$$

$$C(t) = f_t * C_{t-1} + i_t * \hat{C}_t \tag{4.29}$$

$$o(t) = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{4.30}$$

$$h_t = o_t * tanh(C_t) \tag{4.31}$$

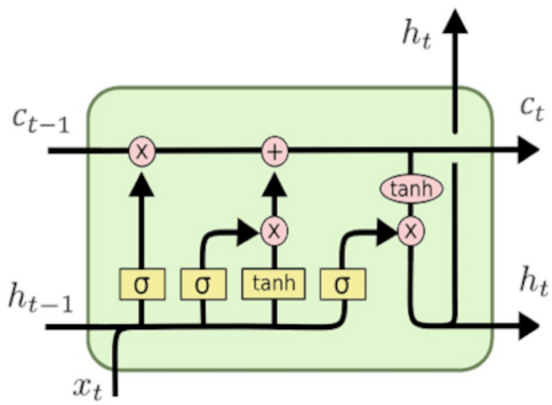


Figure 4.7: Architecture of Long Short Term Memory Units (LSTM) [1]

Figure 4.7 shows the repeating unit of LSTM. In this proposed method, LSTM consists of 256 neurons at input and two neurons at output for classification between preictal and interictal EEG patterns. Proposed method consists of 775,682 trainable parameters for classification using LSTM.

4.3.1 Ensemble Classification

An ensemble classification using LSTM based Model Agnostic Meta Learning has been proposed for classification between interictal and preictal

[1] https://neuronbits.com/en/blog/2020/11/17/lstm-architecture//

states to predict epileptic seizures. In few shot meta learning approach, a model is trained with very small training data and is expected to classify test examples with an increased accuracy. MAML is a technique used for few shot learning and has been applied as ensemble classifier with probabilities of three different classifiers fed as input to MAML for both preictal and interictal classes.

Few shots learning is supervised by machine learning method that takes the output of any machine /deep learning classifier as input with a goal to classify preictal and interictal states with increased accuracy. Algorithm 2 and 3 explains Model Agnostic Meta Learning and Model Agnostic Meta Learning for Few Shot Learning.

Algorithm 2: Model Agnostic Meta-Learning

Input: $d(\tau)$:distribution of tasks
Input: α,β: step size
random initialization of θ;
while not completed;
Sample batch for tasks $\tau_i \sim d(\tau)$;
for all τ_i do ;
Evaluate $\Delta_\theta \zeta_{\tau_i}(f_\theta)$ with respect to K examples

Algorithm 3: Model Agnostic Meta Learning for Few Shot Learning

Input: $d(\tau)$:distribution of tasks
Input: α,β:step size hyperparameters
random initialization θ;
while not completed **do**;
Sample batch for tasks $\tau_i \sim d(\tau)$;
for all τ_i **do** Sample n datapoints $D = x^{(i)}, y^{(j)}$ from τ_i , Evaluate $\Delta_\theta \zeta_{\tau_i}(f_\theta)$ using Δ and ζ_{τ_i};
Compute parameter θ with gradient descent: $\theta_i^{'}$=θ-$\alpha\Delta_\theta \zeta_i f_\theta$ from τ;
Sample the data points $D_i^{'} = x^{(j)}, y^{(j)}$ from τ_i;
meta update;
end for;
Update $\theta \leftarrow \theta$ -$\beta \Delta_{\theta \sum_{\tau_i \sim p(\tau)}} \zeta_{\tau_i}(f_{\theta_i^{'}})$;
end while;

In Algorithm 2, α is the step size with value 0.01, β is meta step size which is meta learned and the model parameters are updated using stochastic gradient descent. It describes the model agnostic meta learning in which a meta learner is trained using set of tasks. Loss function is computed for while training the meta learner with these tasks and objective is to minimize the loss function. Algorithm 3 presents the few shot learning in which few batch tasks are considered from the all tasks and gradient is updated for few samples only to optimize the objective function. It is an extension of MAML and its purpose is to train the meta learner using only few tasks instead of all the training data. A small subset of the tasks is used to train the meta learner. Gradient is updated to train the meta in few iterations. Multilayer perceptron with two hidden layers of 256, 64 neurons and an output layer with 2 neurons has been used as meta learner. In the proposed method, probabilities received from three classifiers SVM, CNN and LSTM have been used as input to MAML. Output of MAML determines the interictal and preictal class.

4.4 Summary

After preprocessing of EEG signals, feature extraction and classification between preictal and interictal state segments is required for epileptic seizure prediction. In the proposed method, both handcrafted and automated features have been extracted from both preictal and interictal state segments of scalp and intracranial EEG signals. Approximate entropy and statistical moments including mean, variance, skewness and kurtosis have been extracted in time domain. A customized three layer architecture of convolutional neural network has been proposed to extract automated features. These handcrafted and automated features are then combined and feature selection techniques have been applied to reduce the effect of curse of dimensionality and increase the processing time.

Cross correlation between all features have been computed using Pearson correlation coefficient and features with correlation greater than 0.5 have been dropped from the feature set. An optimal feature set has been then selected by using Particle swam optimization. Feature set is then passed to three different classifiers including support vector machine, convolutional neural networks and long short term memory units to get probabilities of preictal and interictal classes as output. These probabilities have been used as input to ensemble classifier to get the class label as final output. LSTM based model agnostic meta learning has been used as ensemble classification technique.

CHAPTER 5
RESULTS AND DISCUSSION

In biomedical signal processing applications, accuracy, sensitivity, and specificity are important performance measures. Therefore, the proposed method has been trained on scalp and intracranial EEG signals' datasets for epileptic seizure prediction. k fold cross validation has been applied to validate the results obtained from the proposed method. In this chapter, detailed description of datasets, performance measures and experimentation results have been presented. Results obtained on scalp and intracranial EEG signals' datasets have been compared with recent state of the art epileptic seizure prediction methods.

5.1 Datasets

To train and evaluate the performance of epileptic seizure prediction methods, datasets are the necessary requirement. In this study, two publicly available datasets including scalp EEG dataset and intracranial EEG dataset have been used. These datasets consist of several hours EEG recordings of patients affected from epilepsy. Following subsections provide necessary background information and details of the aforementioned datasets.

5.1.1 CHBMIT Scalp EEG Dataset

Children Hospital Boston and Massachusetts Institute of Technology (CHB-MIT) collaborated to collect EEG dataset for patients affected from epileptic seizures which were non-controllable with medication. 22 subjects were monitored for several days without any type of medication for controlling seizures. It includes 5 male and 17 female subjects. EEG signals have been recorded using 10-20 international system of electrodes placement on scalp of subjects. All EEG recordings have been renamed with chb01 to chb22 prefix not to disclose the original patient's information and saved in European Data Format (EDF) files after digitizing the signals at 256 Hz. These files contain 644 recordings with mostly one hour recording in each file. Each file is annotated with start and end of ictal state. Preictal state is considered as 20 minutes before ictal state, whereas, interictal state is considered few hours before onset of seizure and atleast one hour after seizure end. Summary of each subject is provided in a separate file of all subjects. Table 5.1 provides detail of all subjects for CHBMIT datasets including age, sex, total number of seizures and length of recordings in Hours.

Table 5.1: Patient-wise Details of Subjects Data of CHBMIT Dataset

Patient	**Sex**	**Age**	**No. of Seizures**	**Length of Record (Hrs)**
Chb01	Female	11	7	41
Chb02	Male	11	3	35
Chb03	Female	14	6	38
Chb04	Male	22	3	43
Chb05	Female	7	5	39
Chb06	Female	1.5	6	24
Chb07	Female	14.5	3	19
Chb08	Male	3.5	5	29
Chb09	Female	10	4	18
Chb10	Male	3	6	31
Chb11	Female	12	3	39
Chb12	Female	2	6	24
Chb13	Female	3	12	35
Chb14	Female	9	5	39
Chb15	Male	16	14	46
Chb16	Female	7	10	19
Chb17	Female	12	3	21
Chb18	Female	18	6	36
Chb19	Female	19	3	30
Chb20	Female	6	5	29
Chb21	Female	13	4	33
Chb22	Female	9	3	34

Table 5.2: Summary of CHB-MIT Dataset

Type	Subjects		Channels	Sampling Rate	Seizures	Recordings (Hrs.)
	Male	Female				
Scalp EEG	5	17	23	256 Hz	198	644

Summary of CHB-MIT dataset is presented in Table 5.2. Scalp EEG signals have been recorded using 23 electrodes and sampled at 256 Hz. The dataset consists of total 198 seizures and recordings of each subject have been divided into one hour long sessions which in few cases are upto four hours.

5.1.2 American Epilepsy Society and Kaggle Seizure Prediction Challenge Intracranial EEG Dataset

In this study, intracranial EEG signals have also been used to validate the proposed epileptic seizure prediction method. This dataset was recorded by American Epilepsy Society in collaboration with Kaggle for seizure prediction challenge few years ago. Table 5.3 shows the summary of American Epilepsy Society Seizure Prediction Challenge Dataset. Intracranial EEG dataset recorded for the competition is a publicly available dataset. It comprises of EEG recordings from 5 Canine and 2 Human subjects. EEG signals from dogs were recorded using 16 electrodes implanted inside the brain's surface of subjects and sampled at 400 Hz. for dogs. EEG signals have been recorded for long period of time spanning from several months to year.

Table 5.3: Summary of American Epilepsy Society Seizure Prediction Challenge Dataset

Type	Subjects		Channels	Sampling Rate	Seizures	Recordings (Hrs.)
	Canine	Human				
Intracranial EEG	5	2	16	400/5000 Hz	198	458/21.3

EEG data from Human subjects have been recorded where patients undergone surgery to get electrodes implanted on the brain surface to locate the region affected from epilepsy. In such cases, sampling rate has been kept at 5000 Hz. for human subjects. Dataset contains interictal and preictal segments of iEEG signals. EEG segments for more than one week after the seizure onset have been considered as interictal segments for dogs and atleast four hours before a seizure takes place is considered as interictal for human subjects. Similarly, segments which are five minutes before each seizure are saved as preictal segments in both dogs and human cases.

5.2 Performance Measure

In classification problems, accuracy is considered as one of the most important performance measure for evaluating the method. However, in problems that involve high importance of correct classification of one class than other class, sensitivity is considered as key measure that reflects the true performance of method on positive class. In this research, detection of preictal class is extremely important and it has less occurrences as compared to interictal class. Preictal class is considered as positive class, therefore, sensitivity is more important than specificity and accuracy while evaluating the proposed method. Sensitivity measures the True Positive Rate (TPR) which is correctly classified preictal state samples, whereas, specificity gives the True Negative Rate (TNR)and measures correctly classified interictal state segments. Accuracy, sensitivity and specificity can be defined through following equations.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5.1}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{5.2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{5.3}$$

Where, TP is true positive, which is correctly classified preictal class examples, TN is true negative, that denotes correctly classified interictal class examples. Similarly, FP is false positive, an interictal class predicted as preictal, and FN is false negative, which is preictal class predicted as interictal. In epileptic seizure prediction methods, the preictal state is considered to be positive class and the interictal state as a negative class. It is extremely important that a proposed method must predicts a preictal class correctly so that preventive measures can be taken to control the seizure and at the same time it is also equally important that the method avoids misclassification of interictal class as preictal. Therefore, upon evaluation, a seizure prediction method must achieve high sensitivity as well as specificity. Average anticipation time and Receiver Operating Characteristic (ROC) curve analysis are also useful performance measures. Average anticipation time is computed as the difference between the actual onset of the seizure and detection of first few samples of preictal state. With increased average anticipation, greater is the margin to control the upcoming seizure with medication. ROC curve analysis gives the performance of the seizure prediction method in terms of sensitivity and false alarm rate. Performance of the proposed method has been evaluated based on sensitivity, specificity, average anticipation time and ROC curve analysis.

5.3 Results of Proposed Method on Scalp EEG dataset

The proposed epileptic seizure prediction method involves three steps that include preprocessing of EEG signals for noise removal to increase SNR of signals, feature extraction and classification between interictal and preictal classes. Accuracy, sensitivity, specificity, and average anticipation time have been computed from multiple experiments by varying the techniques in each step of seizure prediction method. Multiple combinations of different techniques for all three steps have been tried in experimentation and results obtained from each experiment have been presented. All these experiments are patient dependent and training/testing has been done for each patient separately. 2000-3000 samples of interictal state and 200-500 samples of preictal states have been obtained after windowing for each subject.

5.3.1 Performance Evaluation of Preprocessing Techniques

Preprocessing is an important step in seizure prediction method as it reduces noise and other artifacts in the EEG signals to increase the SNR which is quite useful in accurate classification between different states of seizures. In the proposed method, multiple preprocessing techniques have been applied on EEG signals to increase SNR and remove power line noise. These methods include Bandpass filtering, Short Time Fourier Transform (STFT), Empirical Mode Decomposition (EMD) and synthetic data generation using Generative Adversarial Networks (GAN).

Table 5.4: Performance Evaluation of Epileptic Seizure Prediction Method with no preprocessing, time/frequency domain feature extraction and Classification using SVM

Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time (minutes)**
chb01	78.19	75.00	78.65	2
chb02	76.67	52.78	78.33	5
chb03	82.19	73.06	83.59	7.5
chb04	76.53	68.15	77.36	6.5
chb05	80.60	70.56	81.99	5
chb06	79.72	73.06	80.69	4.5
chb07	78.51	61.85	80.14	5
chb08	71.60	68.33	72.04	6.5
chb09	73.33	68.89	73.79	7
chb10	76.33	72.22	77.06	8
chb11	70.36	68.44	70.50	5.5
chb12	74.64	80.19	61.33	8.5
chb13	74.93	76.79	74.56	9
chb14	73.27	69.29	75.09	2
chb15	76.03	75.89	76.19	4
chb16	67.08	72.78	64.64	5
chb17	69.48	72.89	69.06	8
chb18	75.89	69.17	76.92	11.5
chb19	63.72	48.15	64.75	25.5
chb20	71.19	73.06	70.90	5
chb21	70.82	60.74	72.02	5
chb22	66.82	67.41	66.75	6
Average	**74.00**	**69.03**	**73.93**	**6.9**

In the first experimental setup, EEG signals have not been preprocessed to assess the performance of baseline feature extraction technique and classification algorithm. Time/frequency domain features have been extracted and SVM is trained for classification between preictal and interictal states. Accuracy, sensitivity, specificity and average anticipation time is computed to assess the performance of the experimental setup. Table 5.4 shows the performance indicators of all subjects of CHBMIT scalp EEG dataset. It is observed from the achieved results that without preprocessing of EEG signals, an epileptic seizure prediction method is unable to achieve better results on almost all subjects. In this experimental setting, no subject is able to get more than 80% sensitivity and accuracy. With this experimental settings, an average accuracy of only 74%, sensitivity and specificity of 69.03% and 73.93% with standard deviations of 0.73,0.71 and 0.56 has been achieved respectively. An average anticipation time of only 6.9 minutes could be achieved with this experimental setting. Highest ancitpation time of 25.5 minutes has been achieved on subject chb19 but with very low sensitivity of 48.15% and specificity of 64.75% which depicts that without preprocessing epileptic seizure prediction method could not achieve good results. It shows the significance of preprocessing of EEG signals to enhance performance of epileptic seizure prediction method.

After analysis of results obtained from first experimental setup, it is concluded that without preprocessing of EEG signals, it is not possible to achieve better results in terms of all evaluation measures. Therefore, in the 2^{nd} experimental setup, bandpass filter has been applied to remove high frequency components and power line noise at 50 Hz. from the EEG signal. To apply bandpass filter, first the EEG signals have been converted into the frequency domain by using Short Time Fourier Transform on 30 seconds overlapping window with an overlap of 15 seconds of preictal and interictal segments. Multiple window sizes have been applied to segment both preictal and interictal states signals including overlapping and non-overlapping window. An overlapping window of 30 seconds with overlap of 15 seconds has been selected as it gives optimal results in terms of accuracy, sensitivity and specificity. 4^{th} order Butterworth filter with pass band frequencies from 0 Hz. to 40 Hz. and 60 Hz. to 130 Hz. has been

Table 5.5: Performance Evaluation of Epileptic Seizure Prediction Method with Bandpass filtering, time/frequency domain feature extraction and Classification using SVM

Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time (minutes)**
chb01	83.33	82.50	83.45	2.5
chb02	85.22	66.67	86.51	6
chb03	89.48	87.50	89.79	9
chb04	80.99	82.59	80.83	8
chb05	85.19	81.67	85.68	6
chb06	81.06	83.61	80.69	5.5
chb07	83.50	81.48	83.70	6
chb08	85.13	81.67	85.59	8
chb09	80.58	78.89	80.76	8.5
chb10	88.28	91.56	87.70	10
chb11	82.79	80.00	83.00	7
chb12	87.32	89.81	81.33	10
chb13	89.98	86.42	90.69	11
chb14	84.38	85.05	84.07	2.5
chb15	86.90	88.89	84.76	5
chb16	85.42	86.67	84.88	6
chb17	84.00	80.00	84.50	10
chb18	90.11	86.67	90.64	14
chb19	87.77	62.96	89.41	31
chb20	84.68	86.67	84.37	7
chb21	85.41	73.33	86.84	7
chb22	87.94	83.33	88.46	7
Average	**85.43**	**82.18**	**85.35**	**8.5**

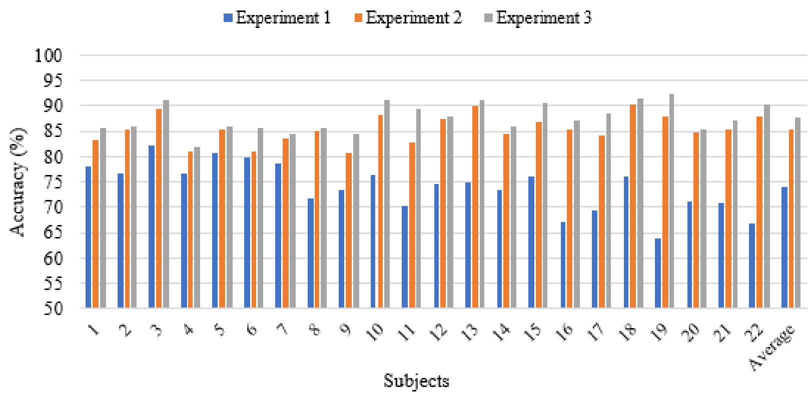
used to remove high frequency components and power line noise.

Feature extraction and classification has been kept same as in first experiment. Table 5.5 provides the performance evaluation of Epileptic Seizure Prediction Method with Bandpass filtering, time/frequency domain feature extraction and Classification using SVM. With this experimental setting, an average accuracy of 85.43%, sensitivity of 82.18% and specificity of 85.35% with standard deviation of 0.69, 0.78 and 0.62 respectively has been obtained on all subjects. Therefore, it is concluded by comparing results of both experiments that with preprocessing there is significant improvement in the performance of seizure prediction method. Average anticipation time has also been improved and this experimental setup hasbeen able to achieve average prediction time of 8.5 minutes. This fact motivates to improve the preprocessing of EEG signals and compute the SNR so that more accurate results could be achieved for epileptic seizure prediction.

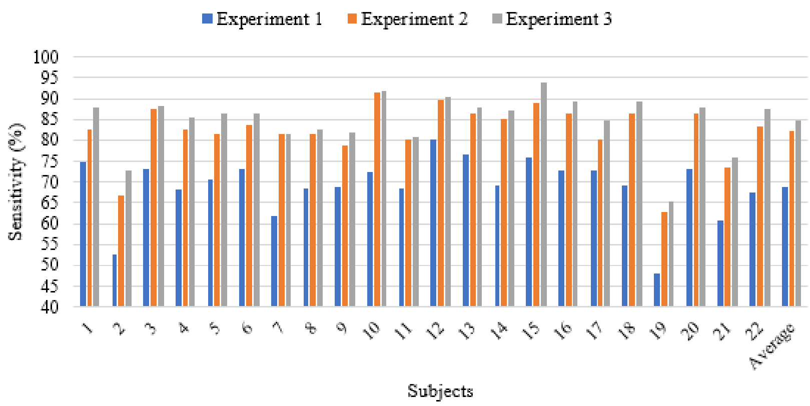
Comparison of experimental results achieved from first two experiments which are shown in Table 5.4 and 5.5 motivate to further improve preprocessing of EEG signals to get better classification results as removal of noise artifacts is inevitable for achieving better accuracy. Therefore, in the 3^{rd} experiment Empirical Mode Decomposition (EMD) along with Bandpass filtering is used to increase the SNR of the EEG signals. Only Bandpass filter has shown good performance for noise removal, however, by simply applying bandpass filter for removing high frequency components from EEG signals is not effective as it may result in losing information useful for classification of related to specific class. Therefore, in this experimental setup, EMD has been used for removing high frequency components by combining Intrinsic Mode Functions (IMFs) obtained from low frequency EEG signals.

Feature extraction and classification have been kept same as in first two experimental settings. Table 5.6 shows the results obtained after applying this method on all subjects of CHBMIT scalp EEG dataset. An average accuracy of 87.66%, sensitivity of 84.78% and specificity of 87.44% with standard deviation of 0.82, 0.89 and 0.75 respectively has been achieved which is higher than previous approaches. An average anticipation time has also increased upto 10.47 minutes. Maximum average anticipation time of 38% has been obtained on subject chb19 but with sensitivity of only 65%.

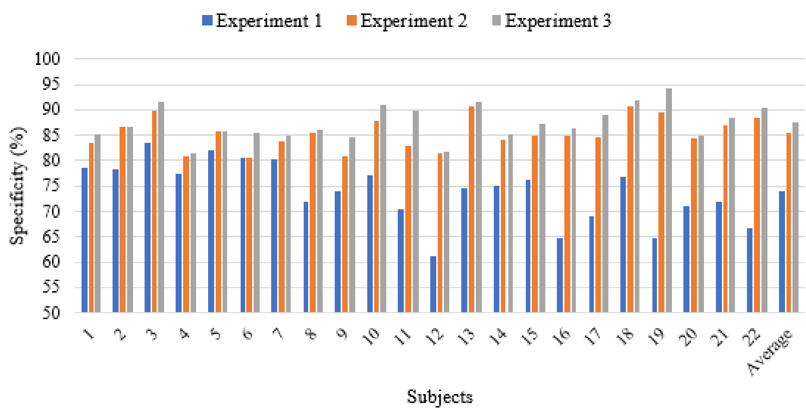
With these preprocessing methods, highest accuracy, sensitivity and specificity have been achieved than previous experimental settings. Therefore, it has been concluded that EMD followed by Bandpass filtering after converting EEG signals into frequency domain gives better classification results. Figure 5.1a, b and c shows the bar charts of results achieved on all subjects of CHBMIT dataset by varying preprocessing methods and keeping same feature extraction and classification. Figure 5.1c describes that greater accuracy, sensitivity and specificity has been achieved when EEG signals are preprocessed using EMD followed by bandpass filtering.



(a)



(b)



(c)

Figure 5.1: Comparison of a) Accuracy b) Sensitivity and c) Specificity achieved on CHBMIT scalp EEG dataset after applying three different approaches by keeping fixed feature extraction and classification, and varying preprocessing techniques; 1) No preprocessig 2) Bandpass filtering as preprocessing 3) EMD and Bandpass filtering as preprocessing of EEG signals

Table 5.6: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, time/frequency domain feature extraction and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
chb01	85.45	87.78	85.12	3
chb02	85.83	72.78	86.74	8
chb03	91.22	88.33	91.67	12
chb04	81.91	85.56	81.56	10
chb05	86.00	86.67	85.91	8
chb06	85.57	86.39	85.45	7
chb07	84.52	81.48	84.82	8
chb08	85.69	82.50	86.11	1
chb09	84.40	81.85	84.66	11
chb10	91.01	91.78	90.87	13
chb11	89.32	80.89	89.95	9
chb12	87.97	90.56	81.78	13
chb13	91.00	87.90	91.62	14
chb14	85.84	87.07	85.28	3
chb15	90.63	93.89	87.14	6.5
chb16	87.17	89.17	86.31	8
chb17	88.54	84.89	89.00	13
chb18	91.44	89.17	91.79	18
chb19	92.37	65.19	94.17	38
chb20	85.39	88.06	84.97	9
chb21	87.06	75.93	88.38	9
chb22	90.19	87.41	90.50	9
Average	**87.66**	**84.78**	**87.44**	**10.47**

Therefore, it is evident from the results obtained by varying different preprocessing methods that EMD along with bandpass filtering provides better SNR of EEG signals which lead towards better classification of interictal and preictal states.

5.3.2 Evaluation of Feature Extraction methods

Feature extraction is the most important step for prediction of epileptic seizures. Therefore, after evaluating the performance of different preprocessing approaches, both handcrafted as well as automated features have been extracted to form a comprehensive feature vector. Feature selection techniques have also been applied to remove the correlated features on the basis of Pearson correlation coefficient between them and Particle swam optimization algorithm has been applied to get features with increased inter-class variance for preictal and interictal states. Feature selection provides robustness of epileptic seizure prediction method against curse of dimensionality. Comparison between results obtained from different feature extraction methods by keeping the same preprocessing and classification has been presented.

In the first experiment for selection of feature set, preprocessed EEG signals are used for feature extraction. Automated features that distinguish between interictal and preictal classes have been extracted using Convolutional Neural Networks (CNN). While evaluating the performance of preprocessing techniques, time/frequency domain handcrafted features have been extracted, therefore, in this experiment automated features have been extracted using CNN and the performance classification performance of automated feature has been compared with handcrafted features.

Table 5.7 presents the evaluation of epileptic seizure prediction Method with EMD and Bandpass filtering for noise removal, time/frequency domain feature extraction and Classification using SVM. An average accuracy, sensitivity and specificity of 91.72%, 92.69% and 90.80% with standard deviation of 0.53, 0.52 and 0.59 respectively and average anticipation time of 21 minutes have been obtained with this experimental setting. A significant increase in performance measures has been observed from comparison of Table 5.6 and 5.7. It shows that keeping preprocessing and classification same, automated features extracted using CNN gives better classification accuracy than handcrafted features. This is due to the fact that CNN extract features by keeping class information under consideration. In handcrafted features, class information is not kept that leads to reduced inter-class variance in features.

Both handcrafted features and automated extracted from CNN have been combined in a feature vector and it's performance has been then evaluated. Table 5.8 presents results achieved by keeping the same preprocessing and classification setting and combining both handcrafted and automated

Table 5.7: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, feature extraction using CNN and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
chb01	92.08	97.50	91.31	23.5
chb02	93.55	72.22	95.04	18.5
chb03	95.30	95.28	95.30	21.5
chb04	88.35	91.48	88.04	22
chb05	92.75	96.67	92.20	23.5
chb06	90.57	97.78	89.51	25
chb07	87.95	90.74	87.68	19.5
chb08	93.07	96.11	92.67	21.5
chb09	93.81	88.89	94.32	19
chb10	96.67	98.00	96.43	18
chb11	93.01	84.44	93.65	35.5
chb12	93.99	96.30	88.44	23.5
chb13	93.05	95.06	92.65	12.5
chb14	92.70	93.94	92.13	15.5
chb15	91.38	98.89	83.33	19
chb16	92.58	97.50	90.48	32
chb17	88.69	86.67	88.94	21
chb18	87.59	95.83	86.32	22
chb19	92.46	81.48	93.19	32.5
chb20	88.19	96.67	86.87	12.5
chb21	87.61	92.22	87.06	12
chb22	92.43	95.56	92.08	12
Average	**91.72**	**92.69**	**90.80**	**21**

features. It is evident that combination of both kind of features is useful in getting better classification results.

In the next experiment, Pearson Correlation Coefficient has been used to compute the cross correlation between features. In cases where correlation is high, such features have been dropped from the feature set to reduce the size of the feature vector. Features with high correlation values are redundant in feature vector, take more memory to store during training and gives no benefit in achieving good results. Therefore, in this experiment feature vector has been reduced by selecting features after computing PCC. Table 5.9 shows the results achieved by preprocessing of EEG signals through EMD and Bandpass filtering, feature selection using PCC after combining both handcrafted and automated features extracted through CNN and classification with SVM. It can be concluded by analyzing the results

Table 5.8: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (Minutes)
chb01	91.70	96.94	90.95	23.5
chb02	94.57	76.67	95.81	18.5
chb03	95.63	94.17	95.85	21.5
chb04	92.94	93.70	92.86	22
chb05	92.27	95.28	91.86	23.5
chb06	90.64	95.28	89.96	25
chb07	88.78	92.96	88.37	19.5
chb08	93.79	97.50	93.30	21.5
chb09	94.47	87.41	95.19	19
chb10	95.05	95.78	94.92	18
chb11	94.15	87.11	94.68	35.5
chb12	92.16	95.00	85.33	23.5
chb13	93.29	93.58	93.24	12.5
chb14	94.29	93.33	94.72	15.5
chb15	91.21	96.89	85.12	19
chb16	92.17	95.28	90.83	32
chb17	88.99	93.33	88.44	21
chb18	87.67	93.33	86.79	22
chb19	93.52	75.56	94.71	32.5
chb20	88.15	93.06	87.39	12.5
chb21	86.82	88.52	86.62	12
chb22	92.70	97.04	92.21	12
Average	**92.04**	**92.17**	**91.33**	**21**

that feature selection has improved the classification accuracy of the method.

Particle Swarm Optimization (PSO) has also been used to get an optimized feature vector with low intra-class and high inter class variance for two classes of EEG signals. 500 features have been obtained by applying PSO to get final feature vector with automated features dominated in the final feature set. Therefore, by keeping the experimental settings of previous experiment and further feature selection with the help of PSO, epileptic seizure prediction method has been able to achieve very good results in terms of sensitivity, specificity and accuracy of seizure prediction system. Table 5.11 provides the performance evaluation of epileptic seizure prediction method with feature vector formation by feature selection using PCC and PSO.

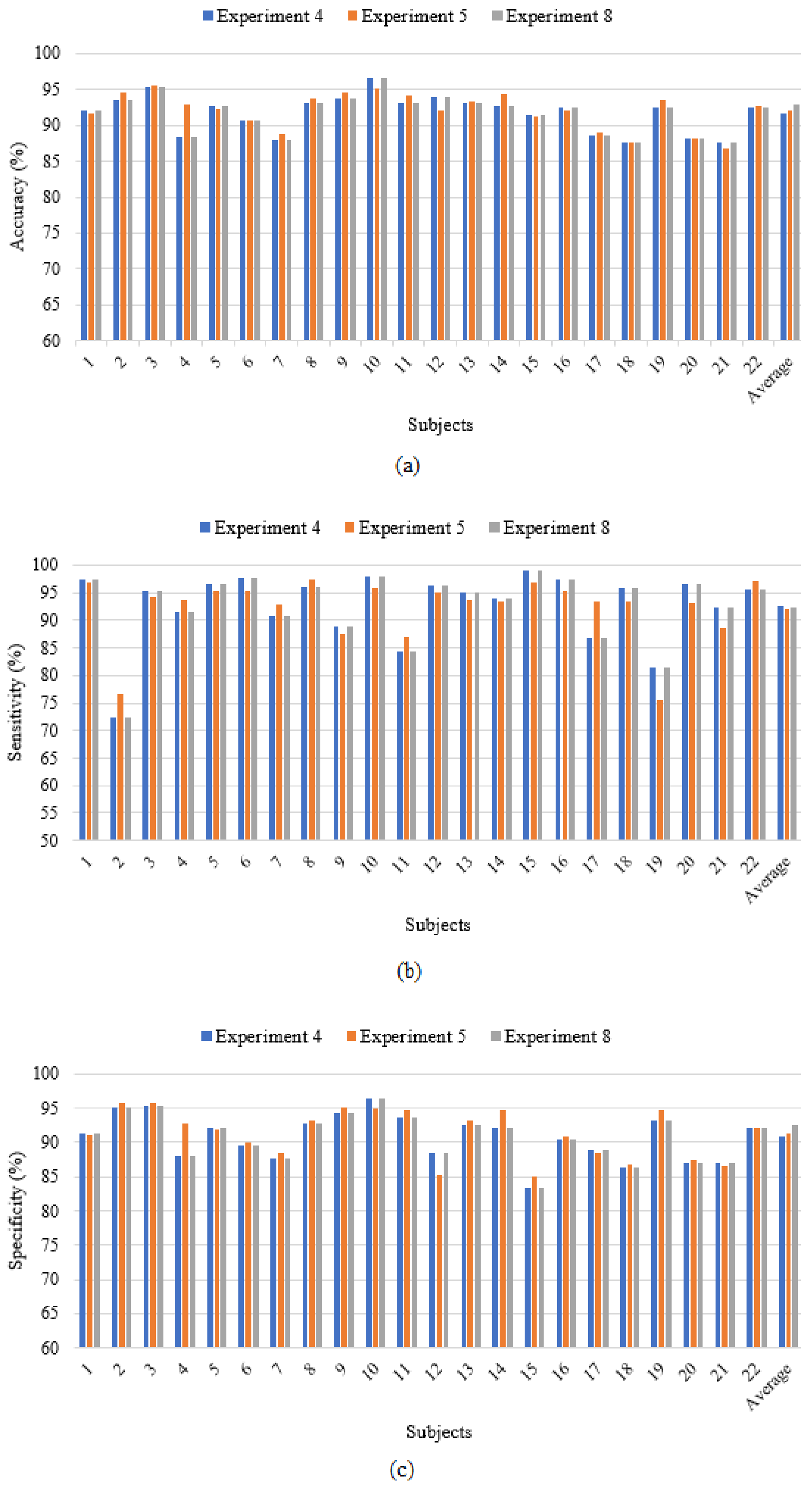


Figure 5.2: Comparison of a) Accuracy b) Sensitivity and c) Specificity achieved on CHBMIT scalp EEG dataset after applying three different approaches by keeping preprocessing using EMD and Bandpass filtering, classification with SVM, and varying feature extraction methods; 1) Automated feature extraction with CNN 2) Feature selection using Pearson Correlation 3) Feature selection using Pearson Correlation and Particle Swarm Optimization.

Table 5.9: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient for feature selection and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
chb01	93.58	87.50	94.44	24
chb02	93.91	73.33	95.35	18
chb03	95.63	94.72	95.77	22.5
chb04	92.84	93.70	92.75	20.5
chb05	93.93	96.94	93.51	21.5
chb06	92.45	96.11	91.91	24
chb07	89.47	92.96	89.13	19
chb08	94.93	95.83	94.81	21.5
chb09	94.60	89.26	95.15	12.5
chb10	97.21	96.67	97.30	16
chb11	96.98	89.33	97.55	2
chb12	93.07	94.44	89.78	13.5
chb13	95.21	96.79	94.90	12.5
chb14	91.43	91.11	91.57	15.5
chb15	90.57	97.78	82.86	16
chb16	94.25	88.61	96.67	32
chb17	91.06	92.89	90.83	21
chb18	90.26	94.72	89.57	22
chb19	95.40	82.96	96.23	32.5
chb20	90.62	95.28	89.90	12.5
chb21	87.76	91.11	87.37	12
chb22	94.68	95.56	94.58	12
Average	**93.18**	**92.16**	**92.82**	**18.3**

Figure 5.2 compares the performance of epileptic seizure prediction methods on scalp EEG signals by varying feature extraction techniques and keeping fixed preprocessing and classification. It shows that automated features performs better in terms of classification accuracy, sensitivity and specificity as compared to handcrafted features. Figure 5.2 also describes the performance of seizure prediction method with optimal feature set. Both handcrafted and automated features have been combined and then correlated features have been dropped after computing Pearson correlation coefficient. Particle swarm optimization has been used for further selection of features to get a comprehensive feature set.

Table 5.10: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Particle Swarm Optimization for feature selection and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (Minutes)
chb01	93.13	95.00	92.86	24
chb02	94.57	72.22	96.12	19.5
chb03	96.11	93.06	96.58	23.5
chb04	91.78	92.22	91.74	21.5
chb05	93.08	96.39	92.63	22.5
chb06	91.56	97.50	90.69	23.5
chb07	88.25	89.63	88.12	20
chb08	93.50	96.67	93.07	21.5
chb09	93.92	88.15	94.51	14.5
chb10	97.24	97.33	97.22	17.5
chb11	93.60	86.67	94.11	18
chb12	93.73	94.81	91.11	13.5
chb13	94.60	95.80	94.36	15.5
chb14	91.62	92.73	91.11	15.5
chb15	90.52	98.33	82.14	16.5
chb16	94.67	89.17	97.02	32
chb17	90.52	94.22	90.06	21
chb18	87.30	95.83	85.98	22
chb19	94.71	81.48	95.59	32.5
chb20	88.45	96.67	87.18	12.5
chb21	87.25	90.00	86.93	12
chb22	92.66	94.44	92.46	12
Average	**92.40**	**92.20**	**91.89**	**19.6**

5.3.3 Evaluation of Classifier Performance using Scalp EEG Signals

After preprocessing of EEG signals and feature extraction, classification of preictal and interictal segments is performed. Three different experiments have been performed for classifier selection in this phase. Classification using SVM has been already done to finalize the preprocessing and feature extraction phases. Now, in this phase, empirical mode decomposition and bandpass filtering has been used for preprocessing followed by combined feature set extraction and selection using PCC and PSO. Multiple classification approaches have been used that include classification through CNN, LSTM and ensemble classifier using Model Agnostic Meta Learning (MAML) using all three classifiers including SVM, CNN and LSTM.

Table 5.11: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient and Particle Swarm Optimization for feature selection and Classification using SVM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
chb01	92.08	97.50	91.31	24
chb02	93.55	72.22	95.04	19.5
chb03	95.30	95.28	95.30	21.5
chb04	88.35	91.48	88.04	22.5
chb05	92.75	96.67	92.20	19.5
chb06	90.57	97.78	89.51	23
chb07	87.95	90.74	87.68	18
chb08	93.07	96.11	92.67	20.5
chb09	93.81	88.89	94.32	14.5
chb10	96.67	98.00	96.43	18.5
chb11	93.01	84.44	93.65	12.5
chb12	93.99	96.30	88.44	18.5
chb13	93.05	95.06	92.65	16.5
chb14	92.70	93.94	92.13	21
chb15	91.38	98.89	83.33	23
chb16	92.58	97.50	90.48	28
chb17	88.69	86.67	88.94	19.5
chb18	87.59	95.83	86.32	18.5
chb19	92.46	81.48	93.19	26
chb20	88.19	96.67	86.87	12.5
chb21	87.61	92.22	87.06	12
chb22	92.43	95.56	92.08	14
Average	**92.93**	**92.25**	**92.46**	**20 min**

In the first experiment of this phase, classification has been done with the help of CNN. It uses fully connected layers for classification after feature extraction and two neurons at output layer for class identification. In this experimental setting, CNN consists of two fully connected layers with 512 and 256 neurons in each layer followed by output layer with 2 neurons and softmax activation function. Classification component of CNN is same like an ANN will fully connected layers. Table 5.12 shows the results obtained from this experimental setting. An average accuracy of 91.67%, sensitivity of 89.31% and specificity of 91.42% with standard deviation of 0.51, 0.54 and 0.53 respectively has been obtained with this experimental setup. Average anticipation time of 22.7 minutes has been obtained with this method. Comparison of the classification results obtained from CNN and SVM as classifiers, there is decline in all performance measures obtained in this method except slight increase in average anticipation time. It is observed after the analysis of results that SVM gives better classification accuracy as compared to CNN. This is due to the fact that CNN uses simple fully connected layers as of ANN which do not perform better than SVM.

Table 5.12: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient and Particle Swarm Optimization for feature selection and Classification using CNN

Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time (minutes)**
chb01	93.13	94.44	92.94	26.5
chb02	93.66	69.44	95.35	21.5
chb03	93.96	90.28	94.53	23.5
chb04	92.48	88.52	92.86	23
chb05	92.51	92.22	92.55	21.5
chb06	89.82	89.17	89.92	21.5
chb07	89.24	89.26	89.24	18.5
chb08	96.18	91.94	96.74	21
chb09	92.30	83.70	93.18	20
chb10	95.08	91.56	95.71	19
chb11	92.95	84.00	93.62	15.5
chb12	90.20	91.67	86.67	19.5
chb13	93.09	89.88	93.73	17.5
chb14	91.24	91.11	91.30	21.5
chb15	89.60	97.33	81.31	23.5
chb16	93.17	88.61	95.12	32
chb17	90.07	92.89	89.72	31
chb18	86.78	95.00	85.51	29
chb19	95.03	80.74	95.98	28
chb20	87.71	94.17	86.70	21
chb21	87.02	88.15	86.89	22
chb22	91.61	90.74	91.71	23
Average	**91.67**	**89.31**	**91.42**	**22.7**

In the 2^{nd} experimental setting, LSTM has been used for classification. Table 5.13 compares the results obtained from seizure prediction method that include preprocessing of EEG signals using EMD and Bandpass filtering, feature selection with PCC and PSO and classification between interictal and preictal states using LSTM. An average accuracy of 92.98%,

Table 5.13: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient and Particle Swarm Optimization for feature selection and Classification using LSTM

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
chb01	92.59	95.14	91.87	30
chb02	92.86	82.78	94.26	25
chb03	90.95	94.72	89.79	27
chb04	88.24	92.59	87.39	26.5
chb05	89.20	96.39	87.21	25
chb06	90.22	93.61	89.23	25
chb07	92.91	91.85	93.12	22
chb08	95.73	94.72	96.00	24.5
chb09	91.19	86.67	92.12	23.5
chb10	96.70	94.00	97.66	22.5
chb11	94.88	94.22	94.97	19
chb12	95.71	96.67	91.11	23
chb13	96.74	95.06	97.40	21
chb14	94.20	96.77	91.85	25
chb15	97.23	99.00	93.45	27
chb16	95.96	93.06	98.45	35.5
chb17	90.98	96.89	89.50	34.5
chb18	90.85	90.00	91.11	32.5
chb19	96.15	85.19	97.60	31.5
chb20	89.03	94.72	87.26	24.5
chb21	91.63	89.26	92.19	25.5
chb22	91.56	92.96	91.25	26.5
Average	**92.98**	**93.01**	**92.49**	**26.2**

sensitivity of 93.01% and specificity of 92.49% with standard deviation of 0.48, 0.49 and 0.52 respectively has been achieved with this method. Results obtained from this classification method shows that there is some improvement in classification accuracy with LSTM compared with ANN and are comparable to the results achieved from seizure prediction method with SVM as classifier. The average anticipation time is also increased compared with SVM. 26.2 minutes prediction time is observed with this experimental setting.

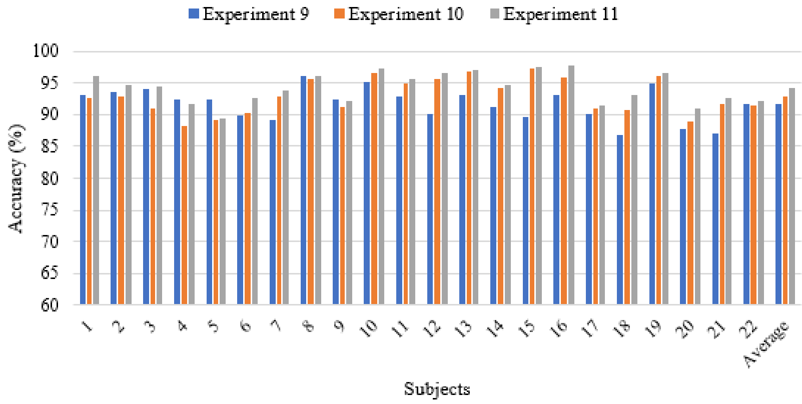
In the 3^{rd} experiment of classifier selection, an ensemble classifier of SVM, CNN and LSTM is proposed using Model Agnostic Meta Learning (MAML) classification method. Output of all classifiers in the form of

Table 5.14: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient and Particle Swarm Optimization for feature selection and Classification using Ensemble Classifier

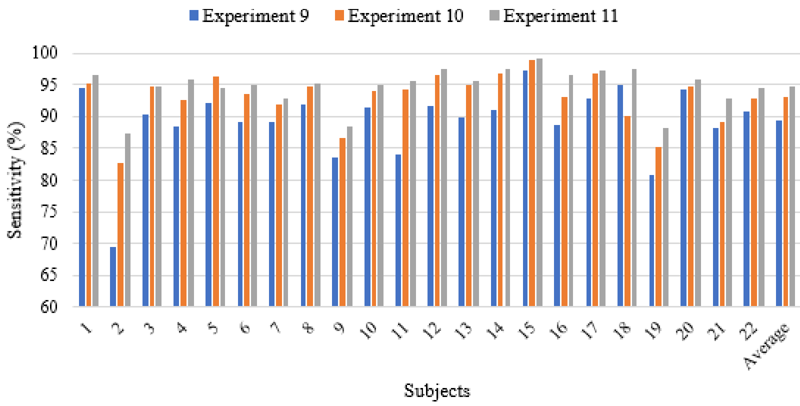
Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time (minutes)**
chb01	96.02	96.67	95.83	33.5
chb02	94.69	87.22	95.74	34.5
chb03	94.58	94.72	94.53	30.5
chb04	91.76	95.93	90.94	30
chb05	89.38	94.44	87.98	35.5
chb06	92.61	95.00	91.91	28.5
chb07	93.70	92.96	93.84	28.5
chb08	96.05	95.28	96.26	28
chb09	92.11	88.52	92.84	31.5
chb10	97.22	94.89	98.06	29
chb11	95.60	95.56	95.60	32.5
chb12	96.48	97.41	92.00	26.5
chb13	97.16	95.56	97.79	24.5
chb14	94.83	97.58	92.31	28.5
chb15	97.54	99.22	93.93	30.5
chb16	97.76	96.67	98.69	39
chb17	91.60	97.33	90.17	38
chb18	93.17	97.50	91.84	36
chb19	96.67	88.15	97.79	35
chb20	91.04	95.83	89.55	35.5
chb21	92.73	92.96	92.68	29
chb22	92.07	94.44	91.54	33.5
Average	**94.31**	**94.72**	**93.72**	**31.72**

probabilities has been fed into MAML to obtain the final classification output. Table 5.14 presents that an average accuracy of 94.31%, sensitivity of 94.73% and specificity of 93.72% with standard deviation of 0.53, 0.56 and 0.53 respectively has been achieved with this ensemble classification method. Average anticipation time of all subjects is also 31.7 minutes with this experimental setup. It shows that there is significant improvement in classification accuracy, sensitivity, specificity and anticipation time of epileptic seizure prediction method. Therefore, it is concluded that ensemble classifier gives the optimal classification performance compared to result achieved from individual classifiers.

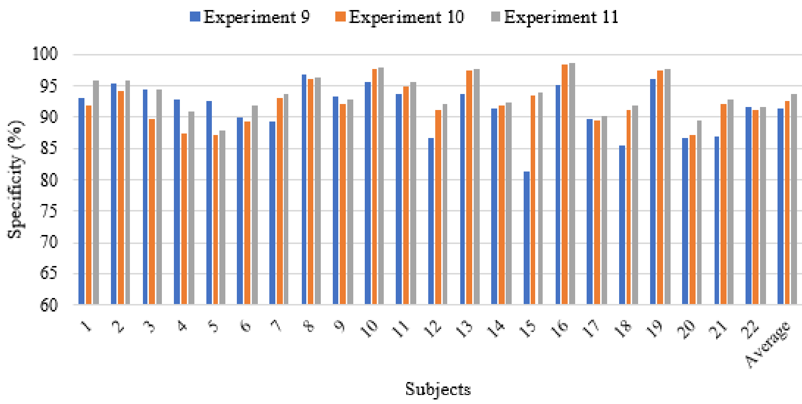
Results achieved from different classifiers have been presented in figure



(a)



(b)



(c)

Figure 5.3: Comparison of a) Accuracy b) Sensitivity and c) Specificity achieved on CHBMIT scalp EEG dataset after applying different approaches of classification by keeping preprocessing using EMD and Bandpass filtering, feature selection using PCC and PSO from both handcrafted and CNN extracted features, and varying classification methods; 1) Classification using CNN 2) Classification using LSTM 3) Classification using ensemble learning.

5.3. Highest accuracy, sensitivity, specificity and average anticipation time has been obtained from ensemble classifier, whereas, LSTM and SVM has performed as classifier compared to CNN which uses fully connected layers like ANN.

Table 5.15: Evaluation of Epileptic Seizure Prediction Method with EMD and Bandpass filtering for noise removal, synthetic preictal segments generation using GAN, combined feature set having both Handcrafted and CNN based features, Pearson Correlation Coefficient and Particle Swarm Optimization for feature selection and Classification using Ensemble Classifier

Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Average Anticipation Time (minutes)**
chb01	98.80	98.75	98.81	34.5
chb02	97.14	96.11	97.29	35.5
chb03	97.42	95.97	97.86	31.5
chb04	97.03	96.67	97.10	31
chb05	95.34	95.69	95.24	36.5
chb06	94.06	95.83	93.54	29.5
chb07	94.76	95.37	94.64	29.5
chb08	96.49	96.25	96.56	33.5
chb09	94.15	90.93	94.81	32.5
chb10	97.75	96.00	98.37	30
chb11	96.26	96.22	96.26	33.5
chb12	97.55	98.33	93.78	27.5
chb13	97.54	96.17	98.09	28.5
chb14	95.46	98.08	93.06	29.5
chb15	98.18	99.00	96.43	31.5
chb16	98.08	97.08	98.93	40
chb17	93.38	95.78	92.78	39
chb18	93.73	97.92	92.44	37
chb19	97.66	90.74	98.58	36
chb20	93.91	99.31	92.23	36.5
chb21	94.72	96.48	94.30	30
chb22	93.67	95.37	93.29	34.5
Average	**96.05**	**96.28**	**95.65**	**33.06**

Table 5.15 presents the results obtained using this method for epileptic seizure prediction method. k-fold cross validation method has been used for train test splitting using 10-fold validation. An average accuracy, sensitivity and specificity of 96.05%, 96.28% and 95.65% with standard deviation of 0.48, 0.51 and 0.53 respectively has been achieved. Average anticipation time of 30.7 minutes has also been achieved with this method. This experiment combines the best technique of all phases with an addition of

resolving class imbalance problem using Generative Adversarial Networks (GAN). Preictal segments are very less compared with interictal segments. In most of the subjects, ratio of preictal and interictal is 1:10 that makes the classification problem difficult and lead towards over-fitting issue to to less training data of preictal class. Effect of class imbalance has been mitigated by generating synthetic preictal segments using GAN which generates synthetic segments by estimating the distribution of original preictal class segments.

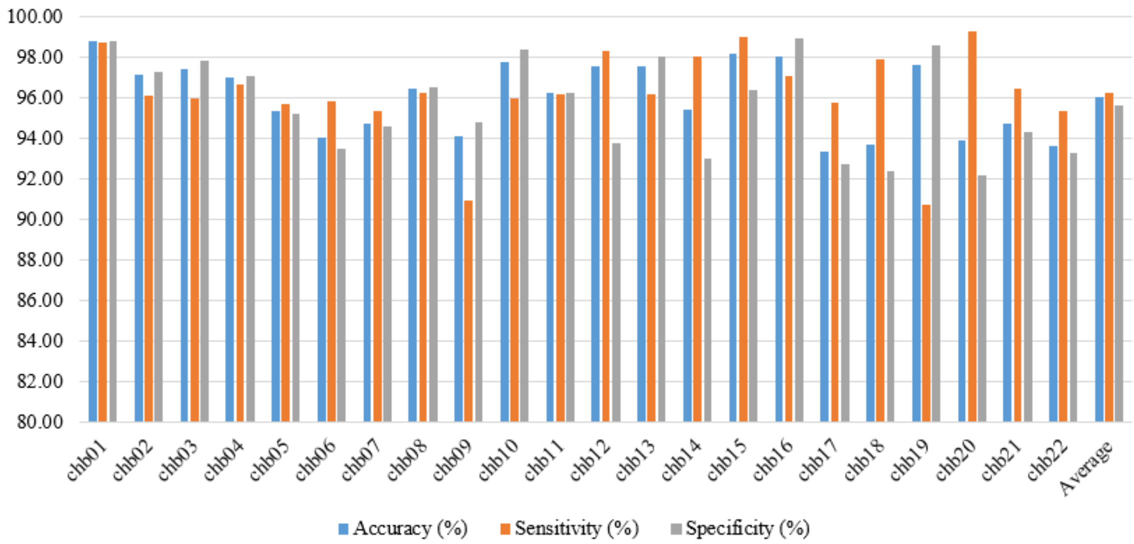


Figure 5.4: Performance evaluation of proposed method, Classification using ensemble learning after adding synthetic data generated using GANs.

Performance of the proposed method on all subjects in terms of accuracy, sensitivity and specificity is shown in figure 5.4. This experimental setting gives highest accuracy and sensitivity with low false positive alarms and increased average anticipation time. Table 5.16 compares the results achieved by varying experimental settings for prediction of epileptic seizures using scalp EEG signals. Different experiments include multiple combinations of preprocessing, feature extraction and classification of interictal and preictal states. These experiments have been evaluated based on accuracy, sensitivity, specificity and average anticipation time. On the basis of performance, method has been improved to get optimal results.

Table 5.16: Comparison of results achieved from epileptic seizure prediction method using different experiments

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Average Anticipation Time (minutes)
Handcrafted features, SVM	74.00	69.03	73.93	6.9
Bandpass filter, Handcrafted features, SVM	85.43	82.18	85.35	8.5
EMD, Bandpass filter, Handcrafted features, SVM	87.66	84.78	87.44	10.47
EMD, Bandpass filter, CNN based features, SVM	91.72	92.69	90.80	21
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, SVM	92.04	92.17	91.33	21
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PCC, SVM	93.18	92.16	92.82	18.3
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PSO, SVM	92.40	92.20	91.89	19.6
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PCC and PSO, SVM	92.93	92.25	92.46	20
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PCC and PSO, CNN	91.67	89.31	91.42	22.7
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PCC and PSO, LSTM	92.98	93.01	92.49	26.2
EMD, Bandpass filter, Combination of both Handcrafted and CNN based features, feature selection using PCC and PSO, Ensemble classifier	94.31	94.72	93.72	31.72
EMD, Bandpass filter, Synthetic data generation using GAN, Combination of both Handcrafted and CNN based features, feature selection using PCC and PSO, Ensemble classifier	96.05	96.28	95.65	33.06

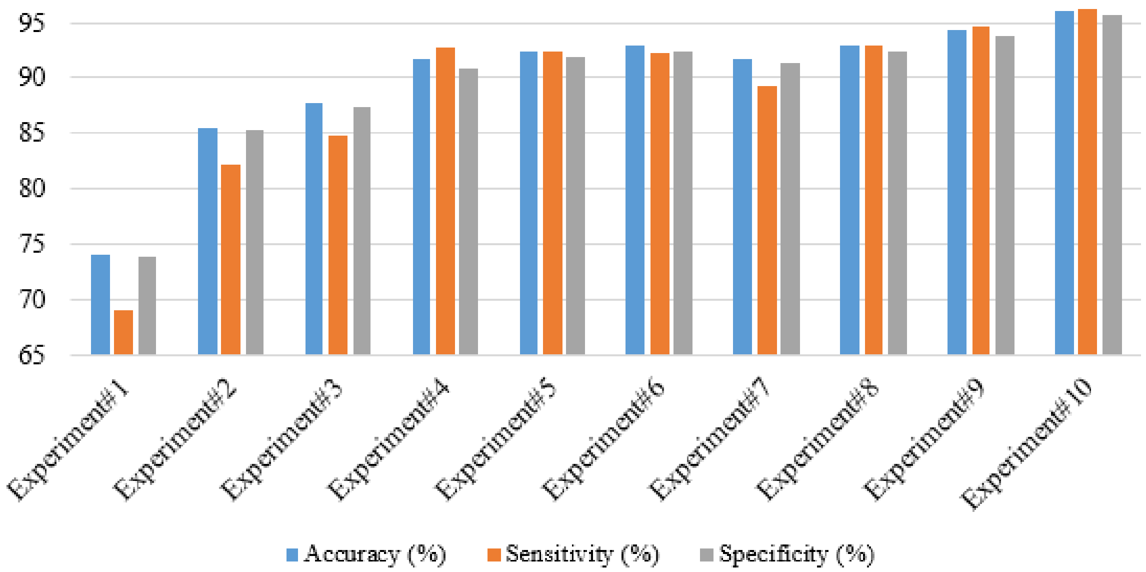


Figure 5.5: Comparison of results achieved from epileptic seizure prediction method using different experiments

Preprocessing of EEG signals have been decided based on the results obtained from first three experiments. Figure 5.5 compares the performance of different experiments performed in this research. In the 1^{st} experiment, handcrafted features have been extracted from scalp EEG signals without preprocessing and classification is done using SVM. EEG signals have been preprocessed in the 2^{nd} experiment using bandpass filtering to remove high frequency components from the signals followed by handcrafted feature extraction and classification using SVM. Comparison of these two experiments shows that there is significant improvement in results achieved from preprocessed signals. In the $3^{r}d$ experiment, due to motivation of previous experiment, preprocessing of EEG signals is further improved and these signals are preprocessed using empirical mode decomposition followed by bandpass filter. However, feature extraction and classification has been kept same as in previous experiments. Further increase in accuracy, sensitivity, specificity and average anticipation time has been observed with this experimental setting. Similarly, in experiment 4 to 6, feature extraction techniques have been varied by keeping same preprocessing and classification. Combination of both handcrafted and automated features followed by feature selection using Pearson correlation coefficient and particle swarm optimization has proved to give better classification results.

Experiment 7 to 9 have been performed by keeping the preprocessing and feature extraction fixed and changing the classifiers for classification between preictal and interictal states. In 7^{th} experiment, preictal and interictal states have been classified using LSTM and it achieves results comparable to classification with SVM in experiment#5. An ensemble classifier is proposed in this method that takes probabilities from SVM, CNN and LSTM as input and generates output class using few shot MAML. Experiment#9 shows that this ensemble classifier has been able to achieve 94.31% accuracy, 94.72% sensitivity, 93.72% specificity with standard deviation of 0.46, 0.48 and 0.51 respectively. An average anticipation time of 31.72 minutes on all subjects of scalp EEG dataset.

Preictal segments are very few as compared to interictal class segments due to very less number of seizures present in the recordings of EEG signals that lead towards class imbalance problem for classification of interictal and preictal classes. Experiment#10 mitigates the effect of class imbalance problem by synthetic data generation for preictal class using generative adversarial networks. Better results have been achieved with the experimental setting of previous experiment and adding more segments which are synthetically generated using GANs. An average accuracy of 96.05%, sensitivity of 96.28%, specificity of 95.65% with standard deviation of 0.53, 0.56 and 0.54 respectively. An average anticipation time of approximately 33 minutes have been achieved on all subjects of CHBMIT scalp EEG dataset using this experimental setting. This increased average anticipation time has been achieved due to better performance of classifier. Once the classifier is trained with preictal and interictal class samples, a complete session of EEG recordings is then passed to detect the preictal state samples. Upon successful detection of 5 consecutive samples of preictal state, the sample is marked as start of preictal state. Time between onset of the seizure and start of preictal state is computed and represented as anticipation time. For implementation of the proposed method, time required to process each new test sample is 1 minute and 56 seconds for the final experimental setup. Figure 5.6 illustrates anticipation time in epileptic seizure prediction system. First window from the left represents the sample where preictal state is detected, whereas, second window represents onset of seizure. Difference between these window is computed which is anticipation or seizure prediction time.

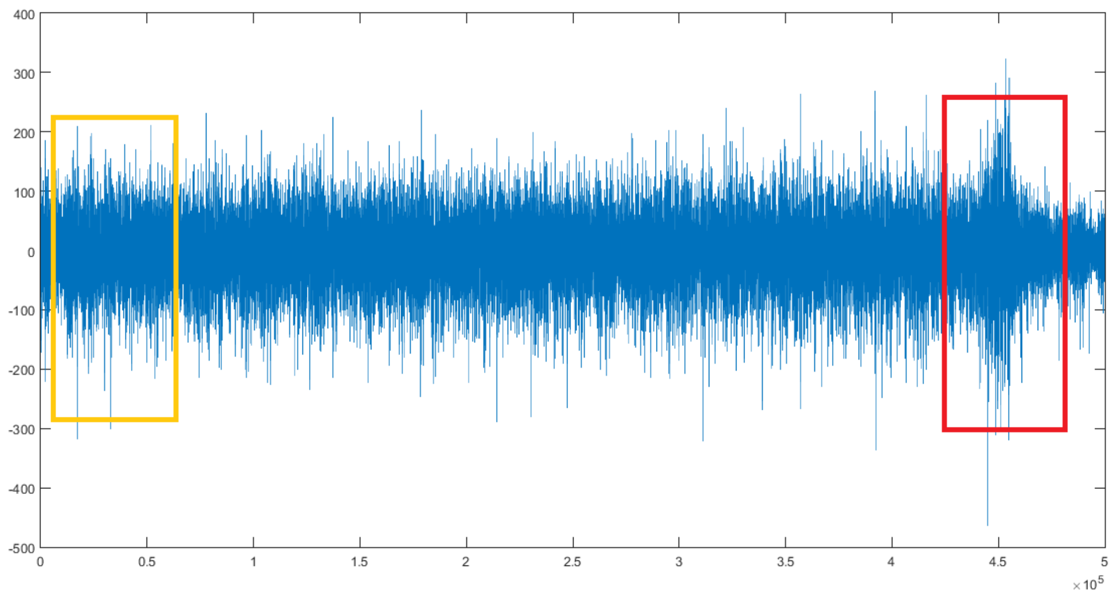


Figure 5.6: Illustration of anticipation time in epileptic seizure prediction system

Schelter et al [216] have proposed the method to compute the probability for alarm generation upon prediction of preictal state which has been used for statistical validation of the seizure onset and can be computed as follows:

$$P \approx 1 - e^{-FPR} \tag{5.4}$$

Probability to predict m seizures from total M seizures is computed as:

$$p = \sum_{i \geq m} \binom{M}{i} P^i (1-P)^{M-i} \tag{5.5}$$

p has been computed to each subject with FPR and m number of seizures predicted by the proposed method. It has been concluded that p is less than 0.05 in case of all subjects, therefore the proposed method performs better.

Results achieved from proposed method have been compared with the recent state of the art epileptic seizure prediction methods on scalp EEG dataset. Table 5.17 compares the sensitivity, specificity and average anticipation time achieved in recent state of the art epileptic seizure prediction methods on scalp EEG signals with the proposed method. Proposed method achieves better results from existing methods on the same dataset. Epileptic seizures need to be predicted well before the onset of seizure starts with increased accuracy, sensitivity and specificity. If a seizure prediction method achieves increased average anticipation time with decreased sensitivity and specificity then its performance is considered as low due to increased number of false alarms. Increased sensitivity with low specificity can also lead towards adverse effects as medication due to false alarm affects health of patient adversely.

Alotaiby et al. [38] have achieved average anticipation time of approximately 68 minutes, however, specificity of 64% has been obtained that shows the high false alarm rate which affects adversely on patient's health. Similarly, method proposed by Chu et al [45] is also able to predict epileptic seizure 45.3 minutes before onset of a seizure but could not achieve sensitivity and specificity of more than 86%. Seizure prediction method proposed by Liu et al [39] have obtained an average sensitivity of 91.5% but could achieve only 79.5% specificity. CNN has been used for feature extraction by Khan et al [37], Truong et al [49], Acharya et al [50], Liu et al [39], Wei et al [40] and Zhang et al [34], however, the proposed architecture of CNN requires less number of trainable parameters compared with existing methods.

Table 5.17: Comparison of Existing Epileptic Seizure Prediction Methods Using Scalp EEG Signals

State-of-the-art Methods	**Preprocessing of EEG signals**	**Features**	**Classification**	**Sensitivity (%)**	**Specificity (%)**	**Average Prediction Time**
Cho et al. (2016) [35]	EMD, Wavelet transform	PLV	SVM	80.54	80.50	-
Behnam et al. (2016) [36]	Bandpass filter	Histogram based features	Bayesian classifier	86.56	80.53	6.64 seconds
Myers et al. (2016) [44]	SD, Bandpass filter	PLV	Threshold	76.8	90	-
Chu et al. (2017) [45]	FFT	Spectral features	Threshold	86.67	86.67	45.3 minutes
Khan et al. (2017) [37]	DWT	CNN	CNN	87.8	85.8	-
Fei et al. (2017) [46]	Bandpass filters	Lyapunov exponent, Fourier Transform	ANN	89.5	89.75	-
Alotaiby et al. (2017) [38]	-	CSP	LDA	89	61	68.71 minutes
Zaghloul et al. (2017) [47]	-	CSP	LDA	89	-	14.5 seconds
Cui et al. (2018) [48]	-	Codebooks Construction, Bag of waves Segments	ELM	70.5	75	1 minute
Truong et al.(2018) [49]	STFT	CNN	CNN	81.2	84	5 minutes
Acharya et al.(2018) [50]	Z-score normalization	CNN	CNN	88	90	-
Liu et al.(2019) [39]	FFT	CNN	CNN	91.5	79.5	5 minutes
Wei et al.(2019) [40]	Multichannel Fusion	CNN	LSTM	91.88	86.13	21 minutes
Ibrahim et al.(2019) [41]	Derivatives and statistical moments	PDF bins	Threshold	90.3	85.2	22.63 minutes
Mamli et al.(2019) [51]	Bandpass Filter	GLCM	KNN,SVM	90.06	97.4	-
Savadkoohi et al. (2020) [52]	Wavelet transform	Fourier Transform	KNN	87.5	90.6	-
Barkin et al.(2020) [53]	HVD	Statistical, Spectral Moments	MLP	89.8	90.1	-
Alshebeili et al.(2020) [42]	Band limiting filter	Statistical features	MLP	88	87.8	19 minutes
Usman et al.(2020) [54]	STFT	CNN	SVM	92.7	90.8	21 minutes
Zhang et al.(2020) [34]	PCC	CNN	PLV	92.9	87.04	15 minutes
Proposed Method	**EMD, Bandpass filter GAN, STFT**	**CNN, Statistical and Spectral moments**	**Ensemble of SVM, CNN, LSTM**	**96.28**	**95.65**	**33 minutes**

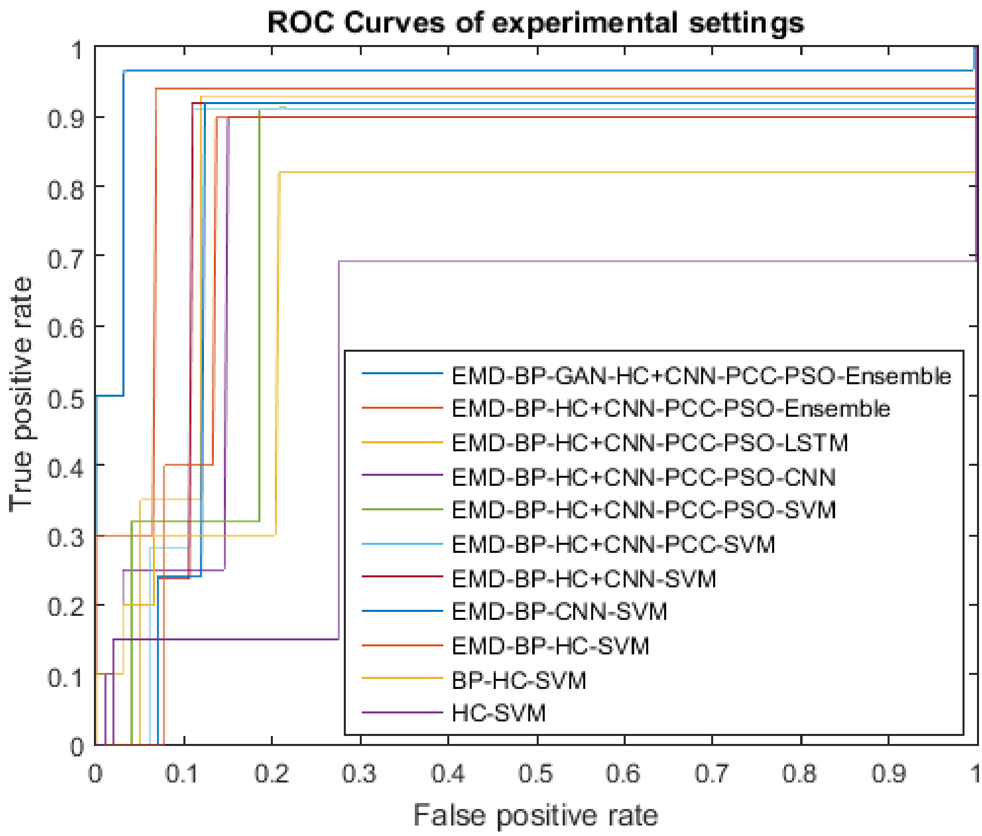


Figure 5.7: Comparison of ROC curves of different experiments performed

In comparison with existing methods, the proposed method have achieved an average sensitivity of 96.8 % with specificity of 95.565 % and an average anticipation time of 33 minutes on all subjects of CHBMIT scalp EEG dataset. Another important performance measure is Receiver Operating Characteristic (ROC) curve that shows the classification performance in terms of sensitivity vs false positive rate. This experimental setting include preprocessing of EEG signals using EMD, bandpass filtering and synthetic data generation using GAN, comprehensive feature set extraction and classification with ensemble classifier. Figure 5.7 provides a comparison of ROC curves of different experiments performed in this study. It has been observed that proposed method is able to achieve increased sensitivity with low false positive rate.

5.4 Results of Proposed Method on intracranial EEG dataset

The proposed method for prediction of epileptic seizures has also been applied on intracranial EEG signals. Dataset of intracranial EEG signals recorded by American epilepsy association for Kaggle competition has been used for training and validation of results obtained with the proposed method. Dataset consists of iEEG recordings of five canine subjects and two human subjects recorded at 400 Hz. and 5000 Hz respectively. There is no information present about start and end of epileptic seizure in this dataset, therefore, average anticipation time cannot be determined by proposed seizure prediction method as it requires annotation of seizure onset. However, sensitivity and specificity can be computed to evaluate the performance of proposed method. Table 5.18 presents the results achieved after applying proposed method on iEEG dataset. It has been observed that an average accuracy of 95.53%, sensitivity of 94.27% and specificity of 95.81% has been achieved on all subjects including canine and human.

Table 5.18: Results achieved on American Epilepsy Association-Kaggle intracranial EEG dataset

Subject	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Dog 1	96.11	95.81	96.17
Dog 2	95.17	95.43	95.13
Dog 3	94.72	96.24	94.43
Dog 4	94.80	93.12	95.13
Dog 5	97.35	95.00	97.94
Human 1	94.96	92.08	95.53
Human 2	95.60	91.75	96.37
Average	**95.53**	**94.20**	**95.81**

These results show that proposed method is not only able to achieve better results on scalp EEG signals but also performs well on iEEG signals for predicting epileptic seizures. Figure 5.8 compares the accuracy, sensitivity and specificity obtained by proposed method on each subject. Highest accuracy has been achieved on subject#5, whereas, highest sensitivity and specificity have been achieved on subject#3 and 5 respectively. Average anticipation time cannot be computed on intracranial EEG dataset as there is no information about start and end of seizure is provided in this dataset, however, preictal and interictal state segments have been provided in separate files that help in computing sensitivity and specificity. Table 5.19 compares the recent state of the art methods on intracranial EEG signals with the proposed method in terms of sensitivity and specificity.

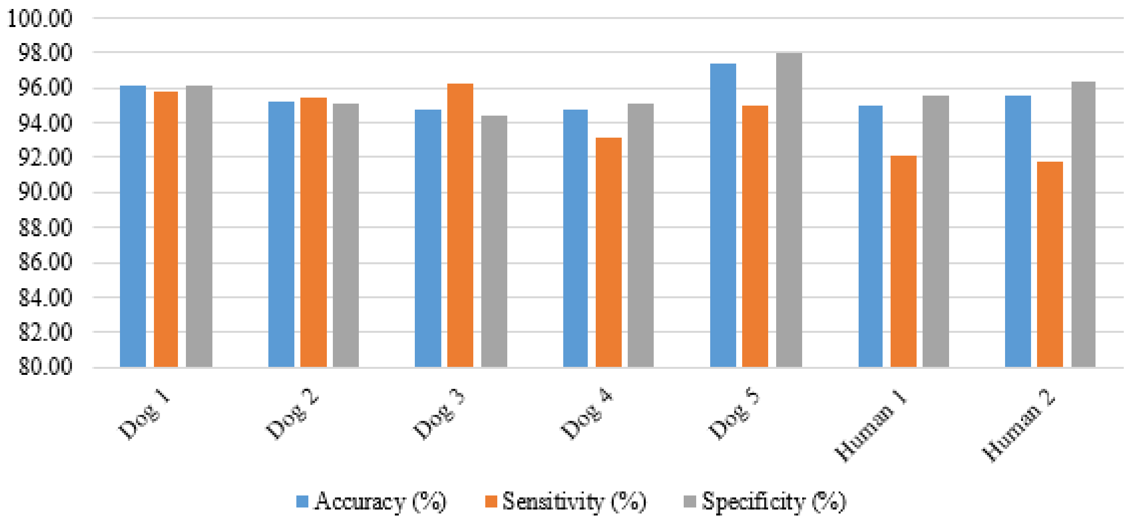


Figure 5.8: Performance evaluation of proposed method, Classification using ensemble learning after adding synthetic data generated using GANs on AES-Kaggle Seizure Prediction Challenge intracranial EEG signals

Niknazar et al [57] have achieved the lowest sensitivity of 63.75% as they have not preprocessed the iEEG signals. Similarly, an average sensitivity of 69% have been obtained by Kornek et al [62] without preprocessing of iEEG signals. Sharif et al [60] have obtained highest sensitivity and specificity of 91.8% and 92% in recent state of the art epileptic seizure prediction methods using iEEG signals. The proposed method has achieved increased average sensitivity of 94.2% with specificity of 95.8% which is greater than the existing methods. It is due to effective preprocessing, comprehensive feature set that combines both handcrafted and automated features followed by optimal feature selection and classification using ensemble classifier. Therefore, the proposed method gives optimal feature set by combining both handcrafted and automated features extracted using CNN. In the same way, ensemble classifier helped to achieve increased sensitivity with low false positives.

Table 5.19: Comparison of Existing Seizure Prediction Methods Using Intracranial EEG Signals

Method	**Preprocessing**	**Features**	**Classifier**	**Sensitivity (%)**	**Specificity (%)**
Parvez et al. (2016) [55]	FFT	Signal Energy	SVM	89	64
Song et al. (2016) [56]	Bandpass Filter	Sample Entropy	ELM	86.75	83.80
Niknazar et al. (2016) [57]	-	Statistical features	Thresholding	63.75	67
Shiao et al. (2016) [58]	Bandpass filter	PSD, FFT, Cross correlation	SVM	81.8	74.6
Aarabi et al. (2017) [59]	Butterworth filter	Correlation dimension, Lyapunov exponent, Nonlinear interdependence	Rule-based decision-making	86.7	88.9
Sharif et al. (2017) [60]	Chebyshev filter	Fuzzy rules	SVM	91.8	92
Kornek et al. (2017) [61]	-	CNN	CNN	69	70
Korshunova et al. (2017) [62]	Bandpass Filter	CNN	CNN	Not reported	80.75
Khan et al. (2017) [37]	Bandpass Filter	CNN	CNN	87.8	85.8
Acharya et al. (2018) [50]	Z-score normalization	CNN	CNN	88	96
Yuan et al. (2018) [63]	Wavelet transform	Diffusion distance	Bayesian linear discriminant analysis	85.11	92
Truong et al. (2018) [49]	STFT	CNN	CNN	75	79
Sun et al. (2018) [64]	DFT	CNN	RNN	80	78
Nejedly et al. (2019) [65]	z-score normalization	CNN	CNN	79	82
Liu et al. (2019) [39]	FFT	CNN	CNN	83	82
Thara et al. (2019) [66]	Bandpass filtering	LSTM	LSTM	89.1	90
Hu et al. (2019) [67]	FFT	CNN	SVM	86	87.5
Yu et al. (2020) [68]	Local mean decomposition	PCA+CNN	Bayesian linear discriminant analysis	87.7	75
Praveena et al. (2020) [69]	Low Pass Filter, EMD	Univariate features	LSTM	89.8	91.2
Nasseri et al. (2020) [70]	Data Segmentation	Spectral features	Logistic Regression	88	88
Raghu et al. (2020) [71]	Bandpass filter, STFT	CNN	SVM	87	88
Stojanović et al. (2020) [72]	SMOTE	Time domain, Spectral Features	SVM	80	82
Proposed Method	**EMD, Bandpass filter GAN, STFT**	**CNN, Statistical and Spectral moments**	**Ensemble of SVM, CNN, LSTM**	**94.2**	**95.8**

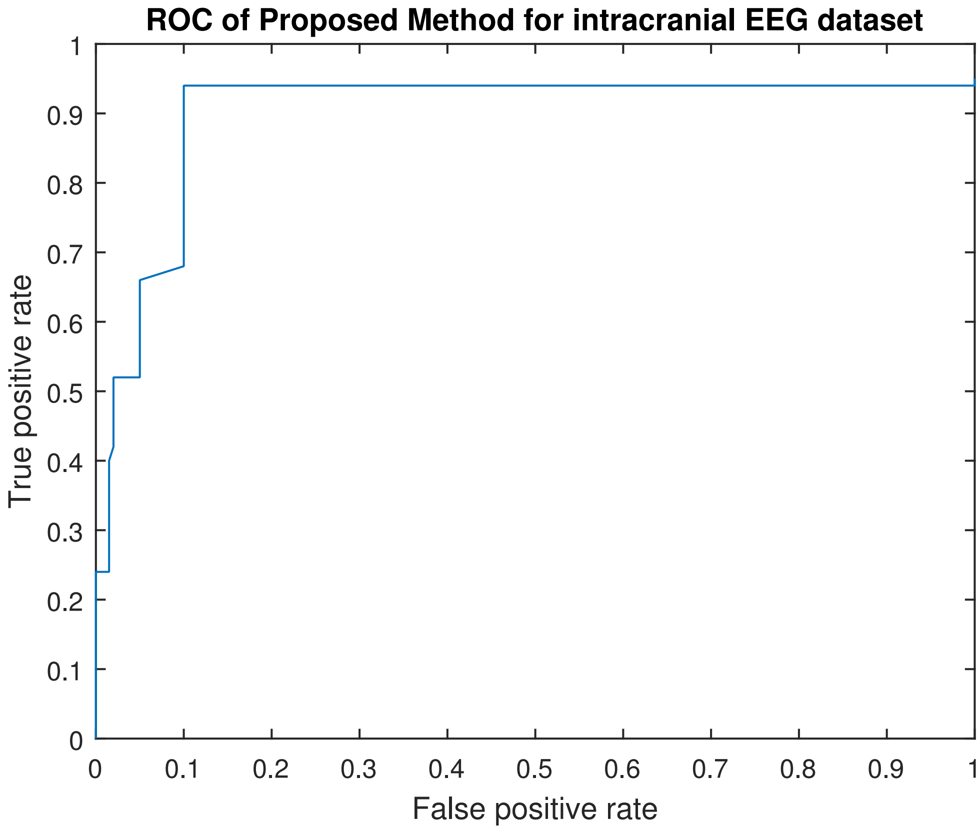


Figure 5.9: ROC curve of proposed method on intracranial EEG signals dataset

ROC curves of existing state of the art epileptic seizure prediction methods on intracranial EEG signals have been compared with the proposed method in figure 5.9. Proposed method is able to achieve high sensitivity with low false positive rate on dataset recorded by American epilepsy society-Kaggle for seizure prediction challenge. It is also evident from the ROC curves of the proposed method that the method has been able to achieve better prediction results.

5.5 Summary

EEG signals are divided into two types based on the data acquisition process including scalp in which electrodes are placed on scalp of subject, whereas, intracranial EEG in which electrodes are placed on the surface of subject's brain. Publicly available datasets have been used in this research of both scalp and intacranial EEG signals. CHBMIT dataset consists of scalp EEG recordings of 22 subjects recorded using 23 electrodes and sampled at 256 Hz. American epilepsy association-kaggle seizure prediction intracranial EEG signals dataset of 7 subjects including 5 canine and 2 human subjects has also been used in this study which has been sampled at 400 Hz. and 5000 Hz. for canine and human subjects respectively. Proposed method has been evaluated based on accuracy, sensitivity and average anticipation time. Results of these evaluation measures have been computed by varying techniques in all steps including preprocessing, feature extraction and classification to get better results. Experimental setting that gives optimal results have been compared with recent state of the art methods on both scalp EEG and intracranial EEG datasets. The proposed method performs better in terms of accuracy, sensitivity, specificity for both scalp and intracranial EEG datasets. It has also achieved greater average anticipation time for scalp EEG dataset. In case of intracranial EEG signals dataset, no information about the start and end of seizure is provided, therefore, it is not possible to compute the average anticipation time for intracranial EEG dataset. ROC curve analysis is also an important performance measure, ROC curves of both dataset shows that the proposed method also performs better than recent state of the art seizure prediction methods.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusion

A typical seizure prediction method consists of preprocessing of EEG signals, feature extraction and classification. In recent years, many researchers have attempted to predict seizures before the onset of seizure so that it can be prevented with medication. However, all of them have faced challenges in predicting epileptic seizures with increased sensitivity and specificity. These challenges include; effective preprocessing of EEG signals to remove noise from EEG signals, dealing with class imbalance problem due to very few preictal state data compared to interictal state and extraction of features that give high inter-class variance to help in accurate classification of preictal and interictal states.

Without preprocessing of EEG signals, researchers have been unable to achieve better classification results. Researchers have used HVD, FFT, STFT, Bandpass filtering, EMD and wavelet transform for preprocessing. However, it is evident from results that HVD, STFT and EMD performs better to increase Signal to noise ratio. Researchers have extracted both handcrafted features including univariate/multivariate features in time/frequency domain and automated feature extraction is done using CNN. It has been observed that features extracted using CNN gives better inter-class variance. Better classification results have been achieved using CNN and LSTM. From this comparison we have concluded that there are many gaps in preprocessing and feature extraction. In preprocessing, there is class imbalance issue between interictal and preictal data and a customized CNN architecture is required for feature extraction. These methods have been evaluated based on sensitivity, specificity, and average anticipation time. Preictal state is considered as positive whereas interictal as negative class.

Class imbalance problem is not addressed in existing methods. In the proposed method, preictal data has been generated using Generative Adversarial Networks to solve the class imbalance problem by synthetic data generation which has similar distribution as original data. It has been observed during experimentation that by applying low pass or bandpass filter, noise is removed but important information is also removed. Therefore, EMD is used to preserve the signals' information to get better characterization between preictal and interictal states. Another problem is class imbalance as there are very few sessions that contain preictal state. Synthetic Minority Over-sampling Technique (SMOTe) is used for dealing with class imbalance issue by increasing samples of preictal state by using overlapping window. SMOTe has been used for generating preictal state samples in the proposed method, it showed improvement on train data but reduced the performance of method on test data. This reduced performance might be result of over-fitting as similar samples of preictal state were used for training. GAN generates synthetic data without oversampling.

A three layer customized CNN to minimize learning parameters. LSTMs used in proposed method for classification helps in achieving increased average anticipation time of seizures as gates in LSTMs are useful in retaining information of previous samples. Significance of our work lies in the fact that our proposed method has achieved increased sensitivity, specificity, and average anticipation time on all subjects. Existing methods have not achieved these three performance measures on all subjects of dataset and only reported results on selected subjects of dataset. k fold cross validation has been applied in the proposed work to validate the results and performance of method. ROC curves analysis have also shown that our proposed method performs better compared to existing methods by achieving increased sensitivity with low false alarm rate.

6.2 Contribution

The main contributions of the thesis is as follows:

- Proposed method has achieved significant improvement in results due to noise removal from EEG signals.
- Class imbalance problem has been mitigated with the help of synthetic data generation using generative adversarial networks.
- Proposed method has been able to predict epileptic seizures on both scalp and intracranial EEG datasets. An average accuracy of 96.05 %, sensitivity of 96.28 % and specificity of 95.65 % has been achieved on saclp EEG dataset, whereas, on intracranial EEG dataset 95.53 %, 94.2 % and 95.81 % accuracy, sensitivity and specificity respectively has been obtained.
- A customized three layer architecture of convolutional neural network has been proposed with minimum number of existing parameters that existing architectures for epileptic seizure prediction methods. Total number of trainable parameters required in the proposed CNN architecture are very less compared to existing CNN architectures for feature extraction from EEG signals.
- An ensemble classifier has been proposed in this research which has not been used earlier in existing methods and it helps in achieving accurate classification between preictal and interictal states.

6.3 Future Directions

Deep brain electroencephalogram recordings are also used for prediction of epileptic seizures in which microelectrodes are placed inside the tissues of brain. In this study, scalp and intracranial EEG signals have been used to predict epileptic seizures. Deep brain EEG signals also provide EEG recordings with high signal to noise ratio and can be used in future for prediction of focal seizures. These signals can be used. Heart rate variability can also be used for prediction of epileptic seizures in combination with EEG signals as the heart rate changes before and during occurrence of epileptic seizures. Changes in the short term heart rate recordings can be observed during preictal state. In future, epileptic seizure prediction method can be improved by combining heart rate variability with EEG recordings. Proposed epileptic seizure prediction method can be implemented in real time environment where EEG signals can be directly processed in a controlled environment like hospital etc. An optimized system can or a seizure prediction device can be developed that takes EEG signals as input from subject's brain in real time, processes it and generates alarm upon prediction of an upcoming seizure.

In future, a portable and lightweight seizure prediction system can be developed by performing simple preprocessing using bandpass filtering, conversion of time domain signals into frequency domain with the help of Short Time Fourier Transform and feature extraction followed by classification using the proposed CNN architecture. Computational complexity can be computed in terms of arithmetic operations required for each module of seizure prediction system including preprocessing, feature extraction and classification for real time implementation of epilepsy perdiction. This system will use less resources and will be able to provide acceptable performance in terms of sensitivity and specificity. Hybrid Fourier transform can be applied in future to convert time domain EEG signals into frequency domain EEG signals so that both long term and short term frequency components can be preserved and used for better characterization of different states of epileptic seizures.

REFERENCES

[1] Man Mohan Mehndiratta and Swati Anil Wadhai. International epilepsy day-a day notified for global public education & awareness. *The Indian journal of medical research*, 141(2):143, 2015. Cited on p. 1.

[2] Nancy Foldvary, G Klem, J Hammel, W Bingaman, I Najm, and H Lüders. The localizing value of ictal eeg in focal epilepsy. *Neurology*, 57(11):2022–2028, 2001. Cited on p. 1.

[3] Andreas Schulze-Bonhage, Christoph Kurth, Astrid Carius, Bernhard J Steinhoff, and Thomas Mayer. Seizure anticipation by patients with focal and generalized epilepsy: a multicentre assessment of premonitory symptoms. *Epilepsy research*, 70(1):83–88, 2006. Cited on p. 1.

[4] Emilio Perucca and Torbjörn Tomson. The pharmacological treatment of epilepsy in adults. *The lancet neurology*, 10(5):446–456, 2011. Cited on p. 1.

[5] Nathalie Jetté, Josemir W Sander, and Mark R Keezer. Surgical treatment for epilepsy: the potential gap between evidence and practice. *The Lancet Neurology*, 15(9):982–994, 2016. Cited on p. 1.

[6] Wolfgang Löscher, Heidrun Potschka, Sanjay M Sisodiya, and Annamaria Vezzani. Drug resistance in epilepsy: clinical impact, potential mechanisms, and new innovative treatment options. *Pharmacological Reviews*, 72(3):606–638, 2020. Cited on p. 2.

[7] Alvin Khong, Lin Jiangnan, Kavitha P Thomas, and A Prasad Vinod. Bci based multi-player 3-d game control using eeg for enhancing attention and memory. In *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 1847–1852. IEEE, 2014. Cited on p. 2.

[8] Yisi Liu, Olga Sourina, and Minh Khoa Nguyen. Real-time eeg-based human emotion recognition and visualization. In *2010 international conference on cyberworlds*, pages 262–269. IEEE, 2010. Cited on p. 2.

[9] Mahendra Yadava, Pradeep Kumar, Rajkumar Saini, Partha Pratim Roy, and Debi Prosad Dogra. Analysis of eeg signals and its application to neuromarketing. *Multimedia Tools and Applications*, 76(18):19087–19111, 2017. Cited on pp. 2 and 46.

[10] Susan Aliakbaryhosseinabadi, Vladimir Kostic, Aleksandra Pavlovic, Sasa Radovanovic, Ernest Nlandu Kamavuako, Ning Jiang, Laura Petrini, Kim Dremstrup, Dario Farina, and Natalie Mrachacz-Kersting. Influence of attention alternation on movement-related cortical potentials in healthy individuals and stroke patients. *Clinical Neurophysiology*, 128(1):165–175, 2017. Cited on p. 2.

[11] Natalie Mrachacz-Kersting, Ning Jiang, Andrew James Thomas Stevenson, Imran Khan Niazi, Vladimir Kostic, Aleksandra Pavlovic, Sasa Radovanovic, Milica Djuric-Jovicic, Federica Agosta, Kim Dremstrup, et al. Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface. *Journal of neurophysiology*, 115(3):1410–1421, 2016. Cited on p. 2.

[12] Hamed Azami, Daniel Abásolo, Samantha Simons, and Javier Escudero. Univariate and multivariate generalized multiscale entropy to characterise eeg signals in alzheimer's disease. *Entropy*, 19(1):31, 2017. Cited on p. 2.

[13] Pholpat Durongbhan, Yifan Zhao, Liangyu Chen, Panagiotis Zis, Matteo De Marco, Zoe C Unwin, Annalena Venneri, Xiongxiong He, Sheng Li, Yitian Zhao, et al. A dementia classification framework using frequency and time-frequency features based on eeg signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(5):826–835, 2019. Cited on p. 2.

[14] Syed Aamir Ali Shah, Lei Zhang, and Abdul Bais. Dynamical system based compact deep hybrid network for classification of parkinson disease related eeg signals. *Neural Networks*, 130:75–84, 2020. Cited on p. 2.

[15] Ömer Türk and Mehmet Siraç Özerdem. Epilepsy detection by using scalogram based convolutional neural network from eeg signals. *Brain sciences*, 9(5):115, 2019. Cited on p. 2.

[16] Michel Le Van Quyen, Jacques Martinerie, Vincent Navarro, Paul Boon, Michel D'Havé, Claude Adam, Bernard Renault, Francisco Varela, and Michel Baulac. Anticipation of epileptic seizures from standard eeg recordings. *The Lancet*, 357(9251):183–188, 2001. Cited on p. 2.

[17] Neep Hazarika, Jean Zhu Chen, Ah Chung Tsoi, and Alex Sergejew. Classification of eeg signals using the wavelet transform. In *Digital Signal Processing Proceedings, 1997. DSP 97., 1997 13th International Conference on*, volume 1, pages 89–92. IEEE, 1997. Cited on p. 2.

[18] Richard W Homan. The 10-20 electrode system and cerebral location. *American Journal of EEG Technology*, 28(4):269–279, 1988. Cited on p. 4.

[19] Jaakko Malmivuo and Robert Plonsey. *Bioelectromagnetism. 13. Electroencephalography*, pages 247–264. 01 1995. Cited on p. 4.

[20] Terrence D Lagerlund, Frank W Sharbrough, Clifford R Jack Jr, Bradley J Erickson, Dan C Strelow, Kathleen M Cicora, and Neil E Busacker. Determination of 10–20 system electrode locations using magnetic resonance image scanning with markers. *Electroencephalography and clinical neurophysiology*, 86(1):7–14, 1993. Cited on p. 4.

[21] Wei-Long Zheng and Bao-Liang Lu. Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks. *IEEE Transactions on Autonomous Mental Development*, 7(3):162–175, 2015. Cited on p. 4.

[22] José Maltez, Lars Hyllienmark, Vadim V Nikulin, and Tom Brismar. Time course and variability of power in different frequency bands of eeg during resting conditions. *Neurophysiologie Clinique/Clinical Neurophysiology*, 34(5):195–202, 2004. Cited on p. 4.

[23] CM Michel, D Lehmann, B Henggeler, and D Brandeis. Localization of the sources of eeg delta, theta, alpha and beta frequency bands

using the fft dipole approximation. *Electroencephalography and clinical neurophysiology*, 82(1):38–44, 1992. Cited on p. 4.

[24] Hailong Liu, Jue Wang, Chongxun Zheng, and Ping He. Study on the effect of different frequency bands of eeg signals on mental tasks classification. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, pages 5369–5372. IEEE, 2006. Cited on p. 4.

[25] Jan C de Munck, Sonia I Gonçalves, R Mammoliti, Rob M Heethaar, and FH Lopes Da Silva. Interactions between different eeg frequency bands and their effect on alpha–fmri correlations. *Neuroimage*, 47(1):69–76, 2009. Cited on p. 4.

[26] Yu Zhang, Yu Wang, Jing Jin, and Xingyu Wang. Sparse bayesian learning for obtaining sparsity of eeg frequency bands based feature vectors in motor imagery classification. *International journal of neural systems*, 27(02):1650032, 2017. Cited on p. 4.

[27] PA Robinson, CJ Rennie, and DL Rowe. Dynamics of large-scale brain activity in normal arousal states and epileptic seizures. *Physical Review E*, 65(4):041924, 2002. Cited on p. 5.

[28] Louis St and K Erik. Minimizing aed adverse effects: improving quality of life in the interictal state in epilepsy care. *Current Neuropharmacology*, 7(2):106–114, 2009. Cited on p. 5.

[29] Samanwoy Ghosh-Dastidar, Hojjat Adeli, and Nahid Dadmehr. Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection. *IEEE transactions on biomedical engineering*, 54(9):1545–1551, 2007. Cited on p. 5.

[30] Ronald Schuyler, Andrew White, Kevin Staley, and Krzysztof J Cios. Epileptic seizure detection. *IEEE Engineering in medicine and Biology Magazine*, 26(2):74, 2007. Cited on p. 5.

[31] Robert S Fisher and Jerome J Engel Jr. Definition of the postictal state: When does it start and end? *Epilepsy & Behavior*, 19(2):100–104, 2010. Cited on p. 5.

[32] Alexandros T Tzallas, Markos G Tsipouras, and Dimitrios I Fotiadis. Epileptic seizure detection in eegs using time–frequency analysis. *IEEE transactions on information technology in biomedicine*, 13(5):703–710, 2009. Cited on p. 6.

[33] Leon D Iasemidis. Epileptic seizure prediction and control. *IEEE Transactions on Biomedical Engineering*, 50(5):549–558, 2003. Cited on pp. 6 and 15.

[34] Shasha Zhang, Dan Chen, Rajiv Ranjan, Hengjin Ke, Yunbo Tang, and Albert Y Zomaya. A lightweight solution to epileptic seizure prediction based on eeg synchronization measurement. *The Journal of Supercomputing*, pages 1–19, 2020. Cited on pp. 8, 9, 17, 18, 19, 20, 23, 25, 28, 30, 102, and 103.

[35] Dongrae Cho, Beomjun Min, Jongin Kim, and Boreom Lee. Eeg-based prediction of epileptic seizures using phase synchronization elicited from noise-assisted multivariate empirical mode decomposition. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(8):1309–1318, 2016. Cited on pp. 8, 9, 10, 17, 18, 20, 28, and 103.

[36] Morteza Behnam and Hossein Pourghassem. Real-time seizure prediction using rls filtering and interpolated histogram feature based on hybrid optimization algorithm of bayesian classifier and hunting search. *Computer methods and programs in biomedicine*, 132:115–136, 2016. Cited on pp. 8, 9, 10, 17, 18, 20, 28, and 103.

[37] Haidar Khan, Lara Marcuse, Madeline Fields, Kalina Swann, and Bülent Yener. Focal onset seizure prediction using convolutional networks. *IEEE Transactions on Biomedical Engineering*, 65(9):2109–2118, 2017. Cited on pp. 8, 9, 17, 20, 25, 27, 28, 30, 33, 35, 37, 39, 40, 41, 102, 103, and 107.

[38] Turky N Alotaiby, Saleh A Alshebeili, Faisal M Alotaibi, and Saud R Alrshoud. Epileptic seizure prediction using csp and lda for scalp eeg signals. *Computational intelligence and neuroscience*, 2017, 2017. Cited on pp. 8, 9, 10, 17, 20, 22, 26, 27, 28, 29, 102, and 103.

[39] Chien-Liang Liu, Bin Xiao, Wen-Hoar Hsaio, and Vincent S Tseng. Epileptic seizure prediction with multi-view convolutional neural networks. *IEEE Access*, 7:170352–170361, 2019. Cited on pp. 8, 9, 10, 17, 19, 20, 23, 25, 27, 28, 30, 33, 35, 37, 40, 41, 102, 103, and 107.

[40] Xiaoyan Wei, Lin Zhou, Zhen Zhang, Ziyi Chen, and Yi Zhou. Early prediction of epileptic seizures using a long-term recurrent convolutional network. *Journal of neuroscience methods*, 327:108395, 2019. Cited on pp. 8, 9, 10, 17, 20, 23, 25, 27, 28, 30, 102, and 103.

[41] Fatma Ibrahim, Saly Abd-Elateif El-Gindy, Sami M El-Dolil, Adel S El-Fishawy, El-Sayed M El-Rabaie, Moawaed I Dessouky, Ibrahim M Eldokany, Turky N Alotaiby, Saleh A Alshebeili, and Fathi E Abd El-Samie. A statistical framework for eeg channel selection and seizure prediction on mobile. *International Journal of Speech Technology*, 22(1):191–203, 2019. Cited on pp. 8, 9, 17, 20, 28, and 103.

[42] Saleh A Alshebeili, Ahmed Sedik, Basma Abd El-Rahiem, Turky N Alotaiby, Ghada M El Banby, Heba A El-Khobby, Mahmoud AA Ali, Ashraf AM Khalaf, and Fathi E Abd El-Samie. Inspection of eeg signals for efficient seizure prediction. *Applied Acoustics*, 166:107327, 2020. Cited on pp. 8, 9, 17, 19, 20, 21, 27, 28, 29, and 103.

[43] Arent de Jongh, Jan Casper de Munck, Sónia I Gonçalves, and Pauly Ossenblok. Differences in meg/eeg epileptic spike yields explained by regional differences in signal-to-noise ratios. *Journal of clinical neurophysiology*, 22(2):153–158, 2005. Cited on p. 9.

[44] Mark H Myers, Akshay Padmanabha, Gahangir Hossain, Amy L de Jongh Curry, and Charles D Blaha. Seizure prediction and detection via phase and amplitude lock values. *Frontiers in human neuroscience*, 10:80, 2016. Cited on pp. 9, 10, 17, 18, 20, 22, 26, 28, 29, and 103.

[45] Hyunho Chu, Chun Kee Chung, Woorim Jeong, and Kwang-Hyun Cho. Predicting epileptic seizures from scalp eeg based on attractor state analysis. *Computer methods and programs in biomedicine*, 143:75–87, 2017. Cited on pp. 9, 10, 17, 19, 20, 22, 23, 26, 28, 29, 102, and 103.

[46] Keling Fei, Wei Wang, Qiaoli Yang, and Shusen Tang. Chaos feature study in fractional fourier domain for preictal prediction of epileptic seizure. *Neurocomputing*, 249:290–298, 2017. Cited on pp. 9, 10, 17, 18, 20, 24, 27, 28, and 103.

[47] Zaghloul Saad Zaghloul, Nelly Elsayed, and Magdy Bayoumi. Early prediction of epilepsy seizures system based on artificial immune bci system. *International Journal of Computer Applications*, 975:8887, 2017. Cited on pp. 9, 10, 17, 20, 26, 27, 28, and 103.

[48] Song Cui, Lijuan Duan, Yuanhua Qiao, and Ying Xiao. Learning eeg synchronization patterns for epileptic seizure prediction using bag-of-wave features. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–16, 2018. Cited on pp. 9, 10, 17, 20, 23, 26, 27, 28, 29, and 103.

[49] Nhan Duy Truong, Anh Duy Nguyen, Levin Kuhlmann, Mohammad Reza Bonyadi, Jiawei Yang, Samuel Ippolito, and Omid Kavehei. Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram. *Neural Networks*, 105:104–111, 2018. Cited on pp. 9, 10, 17, 19, 20, 23, 25, 27, 28, 30, 33, 35, 37, 39, 40, 41, 102, 103, and 107.

[50] U Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, and Hojjat Adeli. Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals. *Computers in biology and medicine*, 100:270–278, 2018. Cited on pp. 9, 10, 17, 20, 23, 25, 27, 28, 30, 35, 37, 40, 41, 102, 103, and 107.

[51] Shamzin Mamli and Hashem Kalbkhani. Gray-level co-occurrence matrix of fourier synchro-squeezed transform for epileptic seizure detection. *Biocybernetics and Biomedical Engineering*, 39(1):87–99, 2019. Cited on pp. 9, 17, 18, 20, 23, 26, 28, and 103.

[52] Marzieh Savadkoohi and Timothy Oladduni. A machine learning approach to epileptic seizure prediction using electroencephalogram (eeg) signal. *Biocybernetics and Biomedical Engineering*, 2020. Cited on pp. 9, 17, 18, 20, 26, 28, and 103.

[53] Barkın Büyükçakır, Furkan Elmaz, and Ali Yener Mutlu. Hilbert vibration decomposition-based epileptic seizure prediction with neural network. *Computers in Biology and Medicine*, 119:103665,

2020. Cited on pp. 9, 17, 18, 20, 21, 23, 26, 27, 28, 29, and 103.

[54] Syed Muhammad Usman, Shehzad Khalid, and Muhammad Haseeb Aslam. Epileptic seizures prediction using deep learning techniques. *IEEE Access*, 8:39998–40007, 2020. Cited on pp. 9, 17, 19, 20, 23, 26, 28, and 103.

[55] Mohammad Zavid Parvez and Manoranjan Paul. Seizure prediction using undulated global and local features. *IEEE Transactions on Biomedical Engineering*, 64(1):208–217, 2016. Cited on pp. 9, 33, 35, 37, 39, 40, 41, and 107.

[56] Yuedong Song and Jiaxiang Zhang. Discriminating preictal and interictal brain states in intracranial eeg by sample entropy and extreme learning machine. *Journal of neuroscience methods*, 257:45–54, 2016. Cited on pp. 9, 32, 35, 37, 39, 40, and 107.

[57] Hamid Niknazar and Ali Motie Nasrabadi. Epileptic seizure prediction using a new similarity index for chaotic signals. *International Journal of Bifurcation and Chaos*, 26(11):1650186, 2016. Cited on pp. 9, 34, 37, 38, 39, 40, 41, 106, and 107.

[58] Han-Tai Shiao, Vladimir Cherkassky, Jieun Lee, Brandon Veber, Edward E Patterson, Benjamin H Brinkmann, and Gregory A Worrell. Svm-based system for prediction of epileptic seizures from ieeg signal. *IEEE Transactions on Biomedical Engineering*, 64(5):1011–1022, 2016. Cited on pp. 9, 32, 35, 37, 39, 40, 41, and 107.

[59] Ardalan Aarabi and Bin He. Seizure prediction in patients with focal hippocampal epilepsy. *Clinical Neurophysiology*, 128(7):1299–1307, 2017. Cited on pp. 9, 32, 33, 34, 39, 40, and 107.

[60] Babak Sharif and Amir Homayoun Jafari. Prediction of epileptic seizures from eeg using analysis of ictal rules on poincaré plane. *Computer methods and programs in biomedicine*, 145:11–22, 2017. Cited on pp. 9, 33, 35, 37, 39, 40, 41, 106, and 107.

[61] Isabell Kiral-Kornek, Subhrajit Roy, Ewan Nurse, Benjamin Mashford, Philippa Karoly, Thomas Carroll, Daniel Payne, Susmita Saha,

Steven Baldassano, Terence O'Brien, et al. Epileptic seizure prediction using big data and deep learning: toward a mobile system. *EBioMedicine*, 27:103–111, 2018. Cited on pp. 9, 10, 35, 37, 38, 40, 41, and 107.

[62] Iryna Korshunova, Pieter-Jan Kindermans, Jonas Degrave, Thibault Verhoeven, Benjamin H Brinkmann, and Joni Dambre. Towards improved design and evaluation of epileptic seizure predictors. *IEEE Transactions on Biomedical Engineering*, 65(3):502–510, 2017. Cited on pp. 9, 10, 33, 35, 36, 37, 39, 40, 41, 106, and 107.

[63] Shasha Yuan, Weidong Zhou, and Liyan Chen. Epileptic seizure prediction using diffusion distance and bayesian linear discriminate analysis on intracranial eeg. *International journal of neural systems*, 28(01):1750043, 2018. Cited on pp. 9, 33, 37, 40, and 107.

[64] Mingrui Sun, Fuxu Wang, Tengfei Min, Tianyi Zang, and Yadong Wang. Prediction for high risk clinical symptoms of epilepsy based on deep learning algorithm. *IEEE Access*, 6:77596–77605, 2018. Cited on pp. 9, 33, 35, 36, 37, 40, and 107.

[65] Petr Nejedly, Vaclav Kremen, Vladimir Sladky, Mona Nasseri, Hari Guragain, Petr Klimes, Jan Cimbalnik, Yogatheesan Varatharajah, Benjamin H Brinkmann, and Gregory A Worrell. Deep-learning for seizure forecasting in canines with epilepsy. *Journal of neural engineering*, 16(3):036031, 2019. Cited on pp. 9, 35, 36, 37, 40, 41, and 107.

[66] DK Thara, BG PremaSudha, and Fan Xiong. Epileptic seizure detection and prediction using stacked bidirectional long short term memory. *Pattern Recognition Letters*, 128:529–535, 2019. Cited on pp. 9, 35, 37, 38, 40, 41, and 107.

[67] Wenbin Hu, Jiuwen Cao, Xiaoping Lai, and Junbiao Liu. Mean amplitude spectrum based epileptic state classification for seizure prediction using convolutional neural networks. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–11, 2019. Cited on pp. 9, 33, 35, 36, 37, 40, 41, and 107.

[68] Zuyi Yu, Weiwei Nie, Weidong Zhou, Fangzhou Xu, Shasha Yuan, Yan Leng, and Qi Yuan. Epileptic seizure prediction based on local

mean decomposition and deep convolutional neural network. *The Journal of Supercomputing*, pages 1–15, 2018. Cited on pp. 9, 33, 35, 37, 40, and 107.

[69] Hirald Dwaraka Praveena, C Subhas, and K Rama Naidu. Automatic epileptic seizure recognition using relieff feature selection and long short term memory classifier. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–17, 2020. Cited on pp. 9, 33, 35, 37, 38, 39, 40, and 107.

[70] Mona Nasseri, Vaclav Kremen, Petr Nejedly, Inyong Kim, Su-Youne Chang, Hang Joon Jo, Hari Guragain, Nathaniel Nelson, Edward Patterson, Beverly K Sturges, et al. Semi-supervised training data selection improves seizure forecasting in canines with epilepsy. *Biomedical Signal Processing and Control*, 57:101743, 2020. Cited on pp. 9, 37, 39, 40, 41, and 107.

[71] Shivarudhrappa Raghu, Natarajan Sriraam, Yasin Temel, Shyam Vasudeva Rao, and Pieter L Kubben. Eeg based multi-class seizure type classification using convolutional neural network and transfer learning. *Neural Networks*, 124:202–212, 2020. Cited on pp. 9, 33, 35, 36, 37, 39, 40, 41, and 107.

[72] Olivera Stojanović, Levin Kuhlmann, and Gordon Pipa. Predicting epileptic seizures using nonnegative matrix factorization. *PloS one*, 15(2):e0228025, 2020. Cited on pp. 9, 35, 37, 38, 39, 40, 41, and 107.

[73] Xinyi Yong, Rabab K Ward, and Gary E Birch. Robust common spatial patterns for eeg signal preprocessing. In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 2087–2090. IEEE, 2008. Cited on pp. 9 and 22.

[74] Benjamin Blankertz, Ryota Tomioka, Steven Lemm, Motoaki Kawanabe, and Klaus-Robert Muller. Optimizing spatial filters for robust eeg single-trial analysis. *IEEE Signal processing magazine*, 25(1):41–56, 2007. Cited on p. 9.

[75] Ling Guo, Daniel Rivero, Julián Dorado, Cristian R Munteanu, and Alejandro Pazos. Automatic feature extraction using genetic programming: An application to epileptic eeg classification. *Expert*

Systems with Applications, 38(8):10425–10436, 2011. Cited on p. 10.

[76] Vairavan Srinivasan, Chikkannan Eswaran, and Natarajan Sriraam. Approximate entropy-based epileptic eeg detection using artificial neural networks. *IEEE Transactions on information Technology in Biomedicine*, 11(3):288–295, 2007. Cited on p. 10.

[77] U Rajendra Acharya, Filippo Molinari, S Vinitha Sree, Subhagata Chattopadhyay, Kwan-Hoong Ng, and Jasjit S Suri. Automated diagnosis of epileptic eeg using entropies. *Biomedical Signal Processing and Control*, 7(4):401–408, 2012. Cited on p. 10.

[78] Florian Mormann, Thomas Kreuz, Christoph Rieke, Ralph G Andrzejak, Alexander Kraskov, Peter David, Christian E Elger, and Klaus Lehnertz. On the predictability of epileptic seizures. *Clinical neurophysiology*, 116(3):569–587, 2005. Cited on p. 10.

[79] Nihal Fatma Güler, Elif Derya Übeyli, and Inan Güler. Recurrent neural networks employing lyapunov exponents for eeg signals classification. *Expert systems with applications*, 29(3):506–514, 2005. Cited on p. 10.

[80] Syed Muhammad Usman, Muhammad Usman, and Simon Fong. Epileptic seizures prediction using machine learning methods. *Computational and mathematical methods in medicine*, 2017, 2017. Cited on p. 10.

[81] Eric Van Diessen, Willem M Otte, Kees PJ Braun, Cornelis J Stam, and Floor E Jansen. Improved diagnosis in children with partial epilepsy using a multivariable prediction model based on eeg network characteristics. *PloS one*, 8(4):e59764, 2013. Cited on p. 10.

[82] Wanpracha Art Chaovalitwongse, Ya-Ju Fan, and Rajesh C Sachdeo. On the time series k-nearest neighbor classification of abnormal brain activity. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 37(6):1005–1016, 2007. Cited on p. 10.

[83] A Sharmila and P Geethanjali. Dwt based detection of epileptic seizure from eeg signals using naive bayes and k-nn classifiers. *Ieee Access*, 4:7716–7727, 2016. Cited on p. 10.

[84] Umut Orhan, Mahmut Hekim, and Mahmut Ozer. Eeg signals classification using the k-means clustering and a multilayer perceptron neural network model. *Expert Systems with Applications*, 38(10):13475–13481, 2011. Cited on pp. 10 and 25.

[85] Oliver Faust, Yuki Hagiwara, Tan Jen Hong, Oh Shu Lih, and U Rajendra Acharya. Deep learning for healthcare applications based on physiological signals: A review. *Computer methods and programs in biomedicine*, 161:1–13, 2018. Cited on p. 10.

[86] Kostas M Tsiouris, Vasileios C Pezoulas, Michalis Zervakis, Spiros Konitsiotis, Dimitrios D Koutsouris, and Dimitrios I Fotiadis. A long short-term memory deep learning network for the prediction of epileptic seizures using eeg signals. *Computers in biology and medicine*, 99:24–37, 2018. Cited on p. 10.

[87] Roberto Vega, Touqir Sajed, Kory Wallace Mathewson, Kriti Khare, Patrick M Pilarski, Russ Greiner, Gildardo Sanchez-Ante, and Javier Mauricio Antelis. Assessment of feature selection and classification methods for recognizing motor imagery tasks from electroencephalographic signals. *Artif. Intell. Research*, 6(1):37–51, 2017. Cited on p. 12.

[88] Jingwei Too, Abdul Rahim Abdullah, Norhashimah Mohd Saad, and Weihown Tee. Emg feature selection and classification using a pbest-guide binary particle swarm optimization. *Computation*, 7(1):12, 2019. Cited on p. 12.

[89] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. *arXiv preprint arXiv:1703.03400*, 2017. Cited on p. 12.

[90] Yatindra Kumar, ML Dewal, and RS Anand. Epileptic seizure detection using dwt based fuzzy approximate entropy and support vector machine. *Neurocomputing*, 133:271–279, 2014. Cited on p. 15.

[91] JD Jirsch, E Urrestarazu, P LeVan, A Olivier, F Dubeau, and J Gotman. High-frequency oscillations during human focal seizures. *Brain*, 129(6):1593–1608, 2006. Cited on p. 16.

[92] Alexandros T Tzallas, Markos G Tsipouras, Dimitrios G Tsalikakis, Evaggelos C Karvounis, Loukas Astrakas, Spiros Konitsiotis, and

Margaret Tzaphlidou. Automated epileptic seizure detection methods: a review study. *Epilepsy-histological, electroencephalographic and psychological aspects*, pages 75–98, 2012. Cited on p. 16.

[93] Amy Loughman, Udaya Seneviratne, Stephen C Bowden, and Wendyl J D'Souza. Epilepsy beyond seizures: predicting enduring cognitive dysfunction in genetic generalized epilepsies. *Epilepsy & Behavior*, 62:297–303, 2016. Cited on p. 16.

[94] AL Goldberger, LAN Amaral, L Glass, JM Hausdorff, P Ch Ivanov, RG Mark, JE Mietus, GB Moody, CK Peng, and HE Stanley. Components of a new research resource for complex physiologic signals. *PhysioBank, PhysioToolkit, and Physionet*, 2000. Cited on p. 17.

[95] A Guruva Reddy and Srilatha Narava. Artifact removal from eeg signals. *International Journal of Computer Applications*, 77(13), 2013. Cited on p. 17.

[96] Denis Delisle-Rodriguez, Ana Cecilia Villa-Parra, Teodiano Bastos-Filho, Alberto López-Delis, Anselmo Frizera-Neto, Sridhar Krishnan, and Eduardo Rocon. Adaptive spatial filter based on similarity indices to preserve the neural information on eeg signals during on-line processing. *Sensors*, 17(12):2725, 2017. Cited on p. 17.

[97] A Garcés Correa, E Laciar, HD Patiño, and ME Valentinuzzi. Artifact removal from eeg signals using adaptive filters in cascade. In *Journal of Physics: Conference Series*, volume 90, page 012081. IOP Publishing, 2007. Cited on pp. 17 and 44.

[98] Mohd Shaifulrizal b Abd Rani et al. Detection of eye blinks from eeg signals for home lighting system activation. In *2009 6th International Symposium on Mechatronics and its Applications*, pages 1–4. IEEE, 2009. Cited on p. 17.

[99] Shivangi Agarwal, Asha Rani, Vijander Singh, and Alok Prakash Mittal. Eeg signal enhancement using cascaded s-golay filter. *Biomedical Signal Processing and Control*, 36:194–204, 2017. Cited on p. 17.

[100] Zhongde Wang. Fast algorithms for the discrete w transform and for the discrete fourier transform. *IEEE Transactions on Acoustics,*

Speech, and Signal Processing, 32(4):803–816, 1984. Cited on p. 18.

[101] Mehmet Akin. Comparison of wavelet transform and fft methods in the analysis of eeg signals. *Journal of medical systems*, 26(3):241–247, 2002. Cited on p. 18.

[102] M Murugappan and Subbulakshmi Murugappan. Human emotion recognition through short time electroencephalogram (eeg) signals using fast fourier transform (fft). In *2013 IEEE 9th International Colloquium on Signal Processing and its Applications*, pages 289–294. IEEE, 2013. Cited on pp. 18, 29, and 46.

[103] Syed Omer Gilani, Yasir Ilyas, and Mohsin Jamil. Power line noise removal from ecg signal using notch, band stop and adaptive filters. In *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, pages 1–4. IEEE, 2018. Cited on p. 18.

[104] Jacob Benesty, Jingdong Chen, Yiteng Huang, and Israel Cohen. Pearson correlation coefficient. In *Noise reduction in speech processing*, pages 1–4. Springer, 2009. Cited on p. 19.

[105] Mohammad Reza Arab, Amir Abolfazl Suratgar, and Alireza Rezaei Ashtiani. Electroencephalogram signals processing for topographic brain mapping and epilepsies classification. *Computers in biology and medicine*, 40(9):733–739, 2010. Cited on p. 19.

[106] Alexander Ya Kaplan, Andrew A Fingelkurts, Alexander A Fingelkurts, Sergei V Borisov, and Boris S Darkhovsky. Nonstationary nature of the brain activity as revealed by eeg/meg: methodological, practical and conceptual challenges. *Signal processing*, 85(11):2190–2212, 2005. Cited on p. 19.

[107] Rajendra Acharya, Oliver Faust, N Kannathal, TjiLeng Chua, and Swamy Laxminarayan. Non-linear analysis of eeg signals at various sleep stages. *Computer methods and programs in biomedicine*, 80(1):37–45, 2005. Cited on p. 19.

[108] Peter Kovacs, Kaveh Samiee, and Moncef Gabbouj. On application of rational discrete short time fourier transform in epileptic seizure classification. In *2014 IEEE International Conference on Acoustics,*

Speech and Signal Processing (ICASSP), pages 5839–5843. IEEE, 2014. Cited on pp. 19 and 29.

[109] Fang Wang, Sheng-hua Zhong, Jianfeng Peng, Jianmin Jiang, and Yan Liu. Data augmentation for eeg-based emotion recognition with deep convolutional neural networks. In *International Conference on Multimedia Modeling*, pages 82–93. Springer, 2018. Cited on pp. 20 and 50.

[110] Zhiwen Zhang, Feng Duan, Jordi Sole-Casals, Josep Dinares-Ferran, Andrzej Cichocki, Zhenglu Yang, and Zhe Sun. A novel deep learning approach with data augmentation to classify motor imagery signals. *IEEE Access*, 7:15945–15954, 2019. Cited on pp. 20 and 50.

[111] Sherif M Abdelfattah, Ghodai M Abdelrahman, and Min Wang. Augmenting the size of eeg datasets using generative adversarial networks. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–6. IEEE, 2018. Cited on pp. 20 and 51.

[112] Shota Haradal, Hideaki Hayashi, and Seiichi Uchida. Biosignal data augmentation based on generative adversarial networks. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 368–371. IEEE, 2018. Cited on p. 20.

[113] Seung-Hyeon Oh, Yu-Ri Lee, and Hyoung-Nam Kim. A novel eeg feature extraction method using hjorth parameter. *International Journal of Electronics and Electrical Engineering*, 2(2):106–110, 2014. Cited on pp. 21 and 24.

[114] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces. *Journal of neural engineering*, 15(5):056013, 2018. Cited on p. 21.

[115] Salma Alhagry, Aly Aly Fahmy, and Reda A El-Khoribi. Emotion recognition based on eeg using lstm recurrent neural network. *Emotion*, 8(10):355–358, 2017. Cited on p. 21.

[116] Xinmei Hu, Shasha Yuan, Fangzhou Xu, Yan Leng, Kejiang Yuan, and Qi Yuan. Scalp eeg classification using deep bi-lstm network for

seizure detection. *Computers in Biology and Medicine*, 124:103919, 2020. Cited on p. 21.

[117] Qin Lin, Shu-qun Ye, Xiu-mei Huang, Si-you Li, Mei-zhen Zhang, Yun Xue, and Wen-Sheng Chen. Classification of epileptic eeg signals with stacked sparse autoencoder based on deep learning. In *International Conference on Intelligent Computing*, pages 802–810. Springer, 2016. Cited on p. 21.

[118] Wonjun Ko, Jeeseok Yoon, Eunsong Kang, Eunji Jun, Jun-Sik Choi, and Heung-Il Suk. Deep recurrent spatio-temporal neural network for motor imagery based bci. In *2018 6th International Conference on Brain-Computer Interface (BCI)*, pages 1–3. IEEE, 2018. Cited on p. 21.

[119] Shang-Ming Zhou, John Q Gan, and Francisco Sepulveda. Classifying mental tasks based on features of higher-order statistics from eeg signals in brain–computer interface. *Information Sciences*, 178(6):1629–1640, 2008. Cited on p. 21.

[120] Jeng-Rung Huang, Shou-Zen Fan, Maysam F Abbod, Kuo-Kuang Jen, Jeng-Fu Wu, and Jiann-Shing Shieh. Application of multivariate empirical mode decomposition and sample entropy in eeg signals via artificial neural networks for interpreting depth of anesthesia. *Entropy*, 15(9):3325–3339, 2013. Cited on p. 21.

[121] Hadi Ratham Al Ghayab, Yan Li, Siuly Siuly, and Shahab Abdulla. Epileptic eeg signal classification using optimum allocation based power spectral density estimation. *IET Signal Processing*, 12(6):738–747, 2018. Cited on p. 21.

[122] Zhongmin Wang, Yue Tong, and Xia Heng. Phase-locking value based graph convolutional neural networks for emotion recognition. *IEEE Access*, 7:93711–93722, 2019. Cited on p. 22.

[123] Jiayuan He and Xiangyang Zhu. Combining improved gray-level co-occurrence matrix with high density grid for myoelectric control robustness to electrode shift. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(9):1539–1548, 2016. Cited on p. 23.

[124] CWNF Che Wan Fadzal, W Mansor, LY Khuan, NB Mohamad, Z Mahmoodin, S Mohamad, and S Amirin. Welch power spectral

density of eeg signal generated from dyslexic children. In *2014 IEEE REGION 10 SYMPOSIUM*, pages 560–562. IEEE, 2014. Cited on p. 23.

[125] Shiliang Sun and Changshui Zhang. Assessing features for electroencephalographic signal categorization. In *Proceedings.(ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.*, volume 5, pages v–417. IEEE, 2005. Cited on p. 23.

[126] Bartosz Swiderski, Stanislaw Osowski, and Andrzej Rysz. Lyapunov exponent of eeg signal for epileptic seizure characterization. In *Proceedings of the 2005 European Conference on Circuit Theory and Design, 2005.*, volume 2, pages II–153. IEEE, 2005. Cited on p. 24.

[127] Alan Julian Izenman. Linear discriminant analysis. In *Modern multivariate statistical techniques*, pages 237–280. Springer, 2013. Cited on p. 25.

[128] Hyun-Chul Kim and Zoubin Ghahramani. Bayesian classifier combination. In *Artificial Intelligence and Statistics*, pages 619–627, 2012. Cited on p. 25.

[129] Yong Xu, Qi Zhu, Zizhu Fan, Minna Qiu, Yan Chen, and Hong Liu. Coarse to fine k nearest neighbor classifier. *Pattern recognition letters*, 34(9):980–986, 2013. Cited on p. 25.

[130] MS Daud and J Yunus. Classification of mental tasks using de-noised eeg signals. In *Proceedings 7th International Conference on Signal Processing, 2004. Proceedings. ICSP'04. 2004.*, volume 3, pages 2206–2209. IEEE, 2004. Cited on p. 25.

[131] Nan-Ying Liang, Paramasivan Saratchandran, Guang-Bin Huang, and Narasimhan Sundararajan. Classification of mental tasks from eeg signals using extreme learning machine. *International journal of neural systems*, 16(01):29–38, 2006. Cited on pp. 25 and 37.

[132] P Bhuvaneswari and J Satheesh Kumar. Support vector machine technique for eeg signals. *International Journal of Computer Applications*, 63(13), 2013. Cited on p. 25.

[133] Ling Guo, Daniel Rivero, Jose A Seoane, and Alejandro Pazos. Classification of eeg signals using relative wavelet energy and artificial neural networks. In *Proceedings of the first ACM/SIGEVO Summit on Genetic and Evolutionary Computation*, pages 177–184. Elsevier, 2009. Cited on p. 25.

[134] Yingnan Sun, Frank P-W Lo, and Benny Lo. Eeg-based user identification system using 1d-convolutional long short-term memory neural networks. *Expert Systems with Applications*, 125:259–267, 2019. Cited on p. 25.

[135] Jing-Nan Gu, Hong-Tao Lu, and Bao-Liang Lu. An integrated gaussian mixture model to estimate vigilance level based on eeg recordings. *Neurocomputing*, 129:107–113, 2014. Cited on p. 25.

[136] Harikumar Rajaguru and Sunil Kumar Prabhakar. Logistic regression gaussian mixture model and softmax discriminant classifier for epilepsy classification from eeg signals. In *2017 International Conference on Computing Methodologies and Communication (ICCMC)*, pages 985–988. IEEE, 2017. Cited on p. 26.

[137] Abdulhamit Subasi and Ergun Ercelebi. Classification of eeg signals using neural network and logistic regression. *Computer methods and programs in biomedicine*, 78(2):87–99, 2005. Cited on p. 26.

[138] Damodar Reddy Edla, Kunal Mangalorekar, Gauri Dhavalikar, and Shubham Dodia. Classification of eeg data for human mental state analysis using random forest classifier. *Procedia computer science*, 132:1523–1532, 2018. Cited on p. 26.

[139] Aarti Sharma. Epileptic seizure prediction using power analysis in beta band of eeg signals. In *2015 International Conference on Soft Computing Techniques and Implementations (ICSCTI)*, pages 117–121. IEEE, 2015. Cited on p. 29.

[140] Katerina D Tzimourta, Alexandros T Tzallas, Nikolaos Giannakeas, Loukas G Astrakas, Dimitrios G Tsalikakis, Pantelis Angelidis, and Markos G Tsipouras. A robust methodology for classification of epileptic seizures in eeg signals. *Health and Technology*, 9(2):135–142, 2019. Cited on p. 29.

[141] M Kemal Kıymık, İnan Güler, Alper Dizibüyük, and Mehmet Akın. Comparison of stft and wavelet transform methods in determining

epileptic seizure activity in eeg signals for real-time application. *Computers in biology and medicine*, 35(7):603–616, 2005. Cited on p. 29.

[142] Azadeh Kamali Tafreshi, Ali M Nasrabadi, and Amir H Omidvarnia. Epileptic seizure detection using empirical mode decomposition. In *2008 IEEE International Symposium on Signal Processing and Information Technology*, pages 238–242. IEEE, 2008. Cited on p. 29.

[143] Rahul Sharma, Pradip Sircar, and Ram Bilas Pachori. A new technique for classification of focal and nonfocal eeg signals using higher-order spectra. *Journal of Mechanics in Medicine and Biology*, 19(01):1940010, 2019. Cited on p. 29.

[144] Dinghan Hu, Jiuwen Cao, Xiaoping Lai, Junbiao Liu, Shuang Wang, and Yao Ding. Epileptic signal classification based on synthetic minority oversampling and blending algorithm. *IEEE Transactions on Cognitive and Developmental Systems*, 2020. Cited on p. 32.

[145] Fatemeh Hasanzadeh, Mohsen Annabestani, and Sahar Moghimi. Continuous emotion recognition during music listening using eeg signals: A fuzzy parallel cascades model. *Applied Soft Computing*, page 107028, 2020. Cited on p. 34.

[146] Chungsong Kim, Jinwei Sun, Dan Liu, Qisong Wang, and Sunggyun Paek. An effective feature extraction method by power spectral density of eeg signal for 2-class motor imagery-based bci. *Medical & biological engineering & computing*, 56(9):1645–1658, 2018. Cited on p. 35.

[147] Moushmi Kar and Laxmikant Dewangan. Univariate feature selection techniques for classification of epileptic eeg signals. In *Advances in Biomedical Engineering and Technology*, pages 345–365. Springer, 2020. Cited on p. 35.

[148] Weidong Zhou, Yinxia Liu, Qi Yuan, and Xueli Li. Epileptic seizure detection using lacunarity and bayesian linear discriminant analysis in intracranial eeg. *IEEE Transactions on Biomedical Engineering*, 60(12):3375–3381, 2013. Cited on p. 37.

[149] Alberto Pliego Marugán, Fausto Pedro García Márquez, Jesus María Pinar Perez, and Diego Ruiz-Hernández. A survey of artificial neural network in wind energy systems. *Applied energy*, 228:1822–1836, 2018. Cited on p. 37.

[150] Cosmin Anitescu, Elena Atroshchenko, Naif Alajlan, and Timon Rabczuk. Artificial neural network methods for the solution of second order boundary value problems. *Computers, Materials and Continua*, 59(1):345–359, 2019. Cited on p. 37.

[151] Essam H Houssein, Asmaa Hamad, Aboul Ella Hassanien, and Aly A Fahmy. Epileptic detection based on whale optimization enhanced support vector machine. *Journal of Information and Optimization Sciences*, 40(3):699–723, 2019. Cited on p. 37.

[152] Katerina D Tzimourta, Loukas G Astrakas, Markos G Tsipouras, Nikolaos Giannakeas, Alexandros T Tzallas, and Spyridon Konitsiotis. Wavelet based classification of epileptic seizures in eeg signals. In *2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS)*, pages 35–39. IEEE, 2017. Cited on p. 37.

[153] Chen Lyu, Bo Chen, Yafeng Ren, and Donghong Ji. Long short-term memory rnn for biomedical named entity recognition. *BMC bioinformatics*, 18(1):1–11, 2017. Cited on p. 37.

[154] Xinmei Hu and Qi Yuan. Epileptic eeg identification based on deep bi-lstm network. In *2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT)*, pages 63–66. IEEE, 2019. Cited on p. 37.

[155] Felix Achilles, Federico Tombari, Vasileios Belagiannis, Anna Mira Loesch, Soheyl Noachtar, and Nassir Navab. Convolutional neural networks for real-time epileptic seizure detection. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 6(3):264–269, 2018. Cited on p. 37.

[156] Maria Hügle, Simon Heller, Manuel Watter, Manuel Blum, Farrokh Manzouri, Matthias Dumpelmann, Andreas Schulze-Bonhage, Peter Woias, and Joschka Boedecker. Early seizure detection with an energy-efficient convolutional neural network on an implantable microcontroller. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2018. Cited on p. 37.

[157] Sabine Leske and Sarang S Dalal. Reducing power line noise in eeg and meg data via spectrum interpolation. *Neuroimage*, 189:763–776, 2019. Cited on p. 44.

[158] Zhaojun Xue, Jia Li, Song Li, and Baikun Wan. Using ica to remove eye blink and power line artifacts in eeg. In *First International Conference on Innovative Computing, Information and Control-Volume I (ICICIC'06)*, volume 3, pages 107–110. IEEE, 2006. Cited on p. 44.

[159] Hans J Scheer, Tilmann Sander, and Lutz Trahms. The influence of amplifier, interface and biological noise on signal quality in high-resolution eeg recordings. *Physiological measurement*, 27(2):109, 2005. Cited on p. 44.

[160] German Rodriguez-Bermudez and Pedro J Garcia-Laencina. Analysis of eeg signals using nonlinear dynamics and chaos: a review. *Applied mathematics & information sciences*, 9(5):2309, 2015. Cited on p. 44.

[161] Tengjun Liu, Gan Huang, Ning Jiang, Lin Yao, and Zhiguo Zhang. Reduce brain computer interface inefficiency by combining sensory motor rhythm and movement-related cortical potential features. *Journal of neural engineering*, 17(3):035003, 2020. Cited on p. 44.

[162] Andreas Trøllund Boye, Ulrik Qvist Kristiansen, Martin Billinger, Omar Feix do Nascimento, and Dario Farina. Identification of movement-related cortical potentials with optimized spatial filtering and principal component analysis. *Biomedical Signal Processing and Control*, 3(4):300–304, 2008. Cited on p. 44.

[163] Chuang Lin, Bing-Hui Wang, Ning Jiang, Ren Xu, Natalie Mrachacz-Kersting, and Dario Farina. Discriminative manifold learning based detection of movement-related cortical potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(9):921–927, 2016. Cited on p. 44.

[164] Jan Sijbers, Johan Van Audekerke, Marleen Verhoye, A Van der Linden, and Dirk Van Dyck. Reduction of ecg and gradient related artifacts in simultaneously recorded human eeg/mri data. *Magnetic resonance imaging*, 18(7):881–886, 2000. Cited on p. 44.

[165] Sung Pil Cho, Mi Hye Song, Young Cheol Park, Ho Seon Choi, and Kyoung Joung Lee. Adaptive noise canceling of electrocardiogram artifacts in single channel electroencephalogram. In *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 3278–3281. IEEE, 2007. Cited on p. 44.

[166] Dirk Hagemann and Ewald Naumann. The effects of ocular artifacts on (lateralized) broadband power in the eeg. *Clinical Neurophysiology*, 112(2):215–231, 2001. Cited on p. 44.

[167] Georg Winterer and Daniel R Weinberger. Genes, dopamine and cortical signal-to-noise ratio in schizophrenia. *Trends in neurosciences*, 27(11):683–690, 2004. Cited on p. 44.

[168] Ram Bilas Pachori and Shivnarayan Patidar. Epileptic seizure classification in eeg signals using second-order difference plot of intrinsic mode functions. *Computer methods and programs in biomedicine*, 113(2):494–502, 2014. Cited on p. 45.

[169] Pablo Andrés Muñoz-Gutiérrez, Eduardo Giraldo, Maximiliano Bueno-López, and Marta Molinas. Localization of active brain sources from eeg signals using empirical mode decomposition: A comparative study. *Frontiers in integrative neuroscience*, 12:55, 2018. Cited on p. 45.

[170] Naveed ur Rehman, Yili Xia, and Danilo P Mandic. Application of multivariate empirical mode decomposition for seizure detection in eeg signals. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pages 1650–1653. IEEE, 2010. Cited on p. 45.

[171] Cristian Guarnizo and Edilson Delgado. Eeg single-channel seizure recognition using empirical mode decomposition and normalized mutual information. In *IEEE 10th INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING PROCEEDINGS*, pages 1–4. IEEE, 2010. Cited on p. 45.

[172] Varun Bajaj and Ram Bilas Pachori. Eeg signal classification using empirical mode decomposition and support vector machine. In *Proceedings of the International Conference on Soft Computing for Problem Solving (SocProS 2011) December 20-22, 2011*, pages 623–635. Springer, 2012. Cited on p. 45.

[173] Pramod Gaur, Ram Bilas Pachori, Hui Wang, and Girijesh Prasad. An empirical mode decomposition based filtering method for classification of motor-imagery eeg signals for enhancing brain-computer interface. In *2015 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2015. Cited on p. 45.

[174] Carlos Amo, Luis De Santiago, Rafael Barea, Almudena López-Dorado, and Luciano Boquete. Analysis of gamma-band activity from human eeg using empirical mode decomposition. *Sensors*, 17(5):989, 2017. Cited on p. 45.

[175] Kejian Guo, Xingang Zhang, Hongguang Li, and Guang Meng. Application of emd method to friction signal processing. *Mechanical Systems and Signal Processing*, 22(1):248–259, 2008. Cited on p. 46.

[176] Bo Luan, Mingui Sun, and Wenyan Jia. Portable amplifier design for a novel eeg monitor in point-of-care applications. In *2012 38th Annual Northeast Bioengineering Conference (NEBEC)*, pages 388–389. IEEE, 2012. Cited on p. 46.

[177] Lin Zhu, Haifeng Chen, Xu Zhang, Kai Guo, Shujing Wang, Yu Wang, Weihua Pei, and Hongda Chen. Design of portable multi-channel eeg signal acquisition system. In *2009 2nd International Conference on Biomedical Engineering and Informatics*, pages 1–4. IEEE, 2009. Cited on p. 46.

[178] MA Guevara, J Ramos, M Hernández-González, D Zarabozo, and Maria Corsi-Cabrera. Potencor: a program to calculate power and correlation spectra of eeg signals. *Computer Methods and Programs in Biomedicine*, 72(3):241–250, 2003. Cited on p. 46.

[179] Samir Ouelha, Sami Touati, and Boualem Boashash. An efficient inverse short-time fourier transform algorithm for improved signal reconstruction by time-frequency synthesis: Optimality and computational issues. *Digital Signal Processing*, 65:81–93, 2017. Cited on p. 46.

[180] Henry K Kwok and Douglas L Jones. Improved instantaneous frequency estimation using an adaptive short-time fourier transform. *IEEE transactions on signal processing*, 48(10):2964–2972, 2000. Cited on p. 46.

[181] Patrick Flandrin, Gabriel Rilling, and Paulo Goncalves. Empirical mode decomposition as a filter bank. *IEEE signal processing letters*, 11(2):112–114, 2004. Cited on pp. 46 and 47.

[182] Ye Yuan, Guangxu Xun, Kebin Jia, and Aidong Zhang. A multi-view deep learning method for epileptic seizure detection using short-time fourier transform. In *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, pages 213–222, 2017. Cited on p. 48.

[183] Hristo Zhivomirov. A novel visual representation of the signals in the time-frequency domain. *University Politehnica of Bucharest Scientific Bulletin Series C-Electrical Engineering And Computer Science*, 80(3):75–84, 2018. Cited on p. 49.

[184] Isaac A Corley and Yufei Huang. Deep eeg super-resolution: Upsampling eeg spatial resolution with generative adversarial networks. In *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pages 100–103. IEEE, 2018. Cited on p. 50.

[185] V Baby Deepa, P Thangaraj, and S Chitra. Mining rare event classes in noisy eeg by over sampling techniques. In *2010 International Conference on Innovative Computing Technologies (ICICT)*, pages 1–6. IEEE, 2010. Cited on p. 50.

[186] Yun Luo, Li-Zhen Zhu, Zi-Yu Wan, and Bao-Liang Lu. Data augmentation for enhancing eeg-based emotion recognition with deep generative models. *Journal of Neural Engineering*, 17(5):056021, 2020. Cited on p. 51.

[187] Elnaz Lashgari, Dehua Liang, and Uri Maoz. Data augmentation for deep-learning-based electroencephalography. *Journal of Neuroscience Methods*, page 108885, 2020. Cited on p. 51.

[188] Kunfeng Wang, Chao Gou, Yanjie Duan, Yilun Lin, Xinhu Zheng, and Fei-Yue Wang. Generative adversarial networks: introduction and outlook. *IEEE/CAA Journal of Automatica Sinica*, 4(4):588–598, 2017. Cited on p. 53.

[189] U Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, Hojjat Adeli, and D Puthankattil Subha. Automated eeg-based screening of depression using deep convolutional neural network. *Computer*

methods and programs in biomedicine, 161:103–113, 2018. Cited on pp. 57 and 63.

[190] Michel Verleysen and Damien François. The curse of dimensionality in data mining and time series prediction. In *International work-conference on artificial neural networks*, pages 758–770. Springer, 2005. Cited on p. 57.

[191] Germán Rodríguez-Bermúdez, Pedro J García-Laencina, Joaquín Roca-González, and Joaquín Roca-Dorda. Efficient feature selection and linear discrimination of eeg signals. *Neurocomputing*, 115:161–165, 2013. Cited on p. 58.

[192] Heba F Eid, Aboul Ella Hassanien, Tai-hoon Kim, and Soumya Banerjee. Linear correlation-based feature selection for network intrusion detection model. In *International Conference on Security of Information and Communication Networks*, pages 240–248. Springer, 2013. Cited on p. 58.

[193] Lin Shang, Zhe Zhou, and Xing Liu. Particle swarm optimization-based feature selection in sentiment classification. *Soft Computing*, 20(10):3821–3834, 2016. Cited on p. 58.

[194] M Akin and M Kemal Kiymik. Application of periodogram and ar spectral analysis to eeg signals. *Journal of Medical Systems*, 24(4):247–256, 2000. Cited on p. 58.

[195] Yakun Xie, Jun Zhu, Yungang Cao, Dejun Feng, Minjun Hu, Weilian Li, Yunhao Zhang, and Lin Fu. Refined extraction of building outlines from high-resolution remote sensing imagery based on a multifeature convolutional neural network and morphological filtering. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13:1842–1855, 2020. Cited on p. 62.

[196] Xiaohu Zhang, Yuexian Zou, and Wei Shi. Dilated convolution neural network with leakyrelu for environmental sound classification. In *2017 22nd International Conference on Digital Signal Processing (DSP)*, pages 1–5. IEEE, 2017. Cited on p. 62.

[197] Saad Albawi, Tareq Abed Mohammed, and Saad Al-Zawi. Understanding of a convolutional neural network. In *2017 International Conference on Engineering and Technology (ICET)*, pages 1–6. Ieee, 2017. Cited on p. 62.

[198] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pages 448–456. PMLR, 2015. Cited on p. 62.

[199] Hong Hui Tan and King Hann Lim. Vanishing gradient mitigation with deep learning neural network optimization. In *2019 7th International Conference on Smart Computing & Communications (ICSCC)*, pages 1–4. IEEE, 2019. Cited on p. 63.

[200] Rikiya Yamashita, Mizuho Nishio, Richard Kinh Gian Do, and Kaori Togashi. Convolutional neural networks: an overview and application in radiology. *Insights into imaging*, 9(4):611–629, 2018. Cited on p. 63.

[201] Li Wan, Matthew Zeiler, Sixin Zhang, Yann Le Cun, and Rob Fergus. Regularization of neural networks using dropconnect. In *International conference on machine learning*, pages 1058–1066. PMLR, 2013. Cited on p. 63.

[202] Elena A Allen, Erik B Erhardt, and Vince D Calhoun. Data visualization in the neurosciences: overcoming the curse of dimensionality. *Neuron*, 74(4):603–608, 2012. Cited on p. 64.

[203] Rich Caruana and Virginia R de Sa. Benefitting from the variables that variable selection discards. *Journal of machine learning research*, 3(Mar):1245–1264, 2003. Cited on p. 64.

[204] Daphne Koller and Mehran Sahami. Toward optimal feature selection. Technical report, Stanford InfoLab, 1996. Cited on p. 64.

[205] Jennifer L Davidson and Jaikishan Jalan. Feature selection for steganalysis using the mahalanobis distance. In *Media forensics and security II*, volume 7541, page 754104. International Society for Optics and Photonics, 2010. Cited on p. 64.

[206] Pavel Pudil, Jana Novovičová, and Josef Kittler. Floating search methods in feature selection. *Pattern recognition letters*, 15(11):1119–1125, 1994. Cited on p. 64.

[207] Patrenahalli M. Narendra and Keinosuke Fukunaga. A branch and bound algorithm for feature subset selection. *IEEE Computer Architecture Letters*, 26(09):917–922, 1977. Cited on p. 64.

[208] James Kennedy and Russell Eberhart. Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks*, volume 4, pages 1942–1948. IEEE, 1995. Cited on p. 64.

[209] Anne-Claire Haury, Pierre Gestraud, and Jean-Philippe Vert. The influence of feature selection methods on accuracy, stability and interpretability of molecular signatures. *PloS one*, 6(12):e28210, 2011. Cited on p. 64.

[210] Thomas Abeel, Thibault Helleputte, Yves Van de Peer, Pierre Dupont, and Yvan Saeys. Robust biomarker identification for cancer diagnosis with ensemble feature selection methods. *Bioinformatics*, 26(3):392–398, 2010. Cited on p. 64.

[211] James R Williamson, Daniel W Bliss, David W Browne, and Jaishree T Narayanan. Seizure prediction using eeg spatiotemporal correlation structure. *Epilepsy & Behavior*, 25(2):230–238, 2012. Cited on p. 68.

[212] Iftikhar Ahmad, Mohammad Basheri, Muhammad Javed Iqbal, and Aneel Rahim. Performance comparison of support vector machine, random forest, and extreme learning machine for intrusion detection. *IEEE Access*, 6:33789–33795, 2018. Cited on p. 68.

[213] SR Mousavi, M Niknazar, and B Vosoughi Vahdat. Epileptic seizure detection using ar model on eeg signals. In *2008 Cairo International Biomedical Engineering Conference*, pages 1–4. IEEE, 2008. Cited on p. 69.

[214] Ozal Yildirim, Ulas Baran Baloglu, Ru-San Tan, Edward J Ciaccio, and U Rajendra Acharya. A new approach for arrhythmia classification using deep coded features and lstm networks. *Computer methods and programs in biomedicine*, 176:121–133, 2019. Cited on p. 69.

[215] Marijn F Stollenga, Wonmin Byeon, Marcus Liwicki, and Juergen Schmidhuber. Parallel multi-dimensional lstm, with application to fast biomedical volumetric image segmentation. In *Advances in neural information processing systems*, pages 2998–3006, 2015. Cited on p. 69.

[216] Björn Schelter, Matthias Winterhalder, Thomas Maiwald, Armin Brandt, Ariane Schad, Andreas Schulze-Bonhage, and Jens Timmer. Testing statistical significance of multivariate time series analysis techniques for epileptic seizure prediction. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 16(1):013108, 2006. Cited on p. 101.