Analysis of Seizure and its Types Based on Deep Learning using Multichannel EEG

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By

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Contents

Certificate of Approval

This is to certify that the thesis entitled "**Analysis of Seizure and its types Based on Deep Learning using Multichannel EEG"** submitted by **Debaleena Chakraborty (Roll No. 1901056)** to Indian Institute of Information Technology Guwahati, is a record of bona fide research work done under my supervision and I consider it worthy of consideration for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering at Indian Institute of Information Technology Guwahati.

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3. I have followed the guidelines provided by the Institute in writing the thesis.
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Debaleena Chakraborty

Abstract

Classification of seizure type is an important stage in the clinical process of examining people who have seizures. Classification of seizure actually dictates the course of treatment of a patient with seizure. Automated detection of seizure type may aid in illness comprehension and is crucial for prognosis. Thus, in this work a three-class classification problem and a six- class classification problem has been proposed in order to classify different seizure types using convolutional neural network (CNN). For this purpose, two types of methods have been used to provide inputs to the deep learning models. In the first method, phase synchronization matrices have been generated and in the second method, fuzzy recurrence plots have been generated. In both these methods, the present work, suggests a CNN based framework. In the first method, EEG data has been classified into three different types of seizures namely absence seizure, complex partial seizure and myoclonic seizure. In the second method, EEG data has been classified into six different seizure types which includes focal non-specific, generalized non-specific, complex partial, tonic-clonic, myoclonic and absence seizure. First, the collected EEG data was converted into segments which were then converted to mean phase coherence matrices. These mean phase coherence matrices in turn were converted into images which were fed as inputs to the CNN model. Results from the present work shows that a classification accuracy of 83.30% could be achieved using the phase synchronization method. In addition, the EEG data was also used to calculate fuzzy recurrence plots which were given as input to a CNN model. This method has also shown reasonable accuracy and therefore needs further tuning to improve upon the accuracy.

Chapter 1

Introduction

This chapter briefly introduces the problem undertaken in this project work by taking a quick look into the epilepsy in general and seizure in particular. It also presents the importance of automatic detection of seizure type and the machine learning methods used for classification of seizure type.

1.1 Epilepsy and Seizure

The brain is responsible for controlling different organs of human body and also happens to be the most amazing and complicated part of the human body. The neural activities in human brain starts as early as from the seventeenth to twenty-third week of prenatal development and from this early stage, it keeps on generating electrical signals throughout life which represents both the brain function and the whole body status.

Neurological diseases are the diseases of the central and peripheral nervous system. Hundreds of millions of people worldwide are affected by neurological disorders. These disorders can be broadly divided into non-communicable, communicable and injury related neurological disorders. Figure 1 shows the types of neurological disorders. Epilepsy is one of the most prevalent non communicable neurological disorders and has affected more than 65 million people worldwide second only to stroke. Epilepsy is a sudden and recurrent brain malfunction which is a disease reflecting an excessive and hypersynchronous activity of the neurons within the brain and people with epilepsy have recurrent seizures.

1.2 Classification of Different Types of Seizure

Seizures are caused by a disturbance in the electrical activity in the brain's neurons. The seizures generally occur randomly and impair the normal brain functions. Ictal state refers to the time frame during which a seizure takes place. Pre-ictal state is the period of time between 30 and 90 minutes prior to the start of the seizure. Postictal is referred to the period a few seconds after seizure. The interictal state is the normal state of brain, it starts after postictal state and ends before the pre-ictal state.

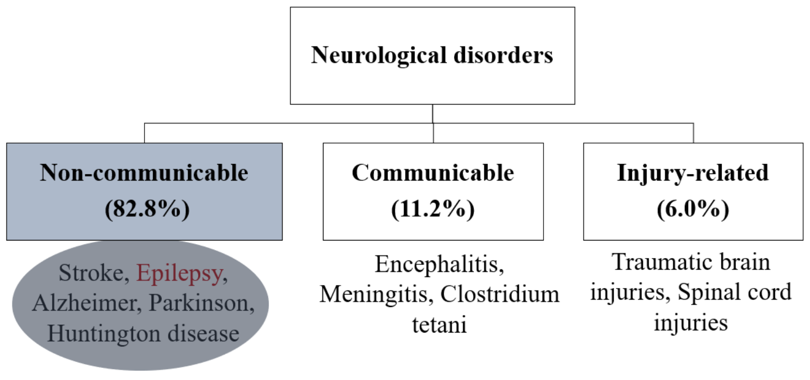


Fig.1.1 Classification of Neurological Disorders
[https://www.hindustantimes.com/india-news/cases-of-stroke-headache-epilepsy-more-than-doubled-in-last-30-years-in-india-lancet-study-101626243838382.html]

Seizures are divided into three major groups viz. generalized onset seizure, focal onset seizure, and unknown onset seizure. The focal seizures can start in one area or group of cells on one side of the brain and are further classified into simple partial and complex partial seizures based on generation in regions of the brain. Interestingly, generalized seizures affect both sides of the brain or a group of cells at the same time and are classified based on motor and non-motor symptoms into absence, tonic, atonic clonic, tonic-clonic, and myoclonic seizures. Table 1.1.shows some different types of seizures along with their description.

Table 1.1 Some seizure types and their description

Seizure Type	**Description**
Focal Non-Specific Seizure (FNSZ)	Seizures which begin in one area of the brain
Generalized Non-Specific Seizure (GNSZ)	Seizures which affect both sides of the brain
Complex Partial Seizure (CPSZ)	Partial Seizures during unconsciousness
Absence Seizure (ABSZ)	Absence discharges observed on EEG; the patient loses consciousness for a few seconds.
Tonic-Clonic Seizure (TCSZ)	At first stiffening and then jerking of a body
Myoclonic Seizure (MYSZ)	Seizures are brief, shock-like jerks of a muscle or a group of muscles

1.3 Detection of Epileptic Seizure

There are several techniques to record brain activities for in-depth analysis of epileptic seizures. Among them, electroencephalogram (EEG) is relatively simpler and takes less setup time. In addition, it is also portable and efficient to record brain signals. With the aid of headsets, EEG signals can be recorded/processed with sample rates ranging from 200 Hz to 5000 Hz. EEG is a multichannel signal, i.e., EEG signals are collected from different electrodes (corresponding to different channels) connected to the scalp. The electrodes are strategically placed at specific locations on the scalp to capture the electrical signals generated by the brain. The number and placement of the electrodes used in an EEG recording can vary depending on the type of information being sought and the purpose of the recording. Figure 1.2 is a representative figure showing the placement of electrodes in the scalp of the human head and the corresponding EEG signal recorded through computer software. With the aid of specialized software, a neurologist annotates these signals to indicate the beginning and end of seizures. However, extracting the features from the EEG signal is extremely important to accurately detect the seizure type. Feature extraction is complicated by the existence of noise and artifacts in the EEG data. Advent of different machine learning methodologies has therefore opened up new avenues in research in automatic and accurate seizure predictions. However, handcrafted features are not suitable for accurate

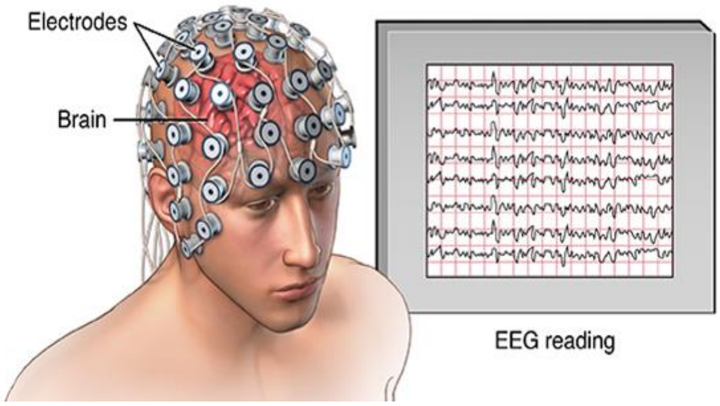


Fig 1.2 EEG data acquisition
[https://sipl.eelabs.technion.ac.il/projects/examination-of-tms-effect-using-eeg-signal/]

and authentic seizure prediction because the EEG data not only varies between patients but for the same patient, it also varies over time. It is therefore essential to have an automatic feature extraction and an efficient method to learn those features to accurately predict the seizure types.

1.4 Machine Learning and Deep Learning in EEG

Machine learning often including training and testing refers to a combination of learning from data and data clustering or classification/prediction. In most of the applications, it is combined with some signal processing techniques to extract the best discriminating data feature prior to taking learning and classification steps. The emerging machine learning techniques such as deep neural networks are also capable of feature learning which could potentially be used for automatic feature extraction from EEG signals. Machine learning techniques could be advantageously used in processing of EEG signals in epileptic seizures, because

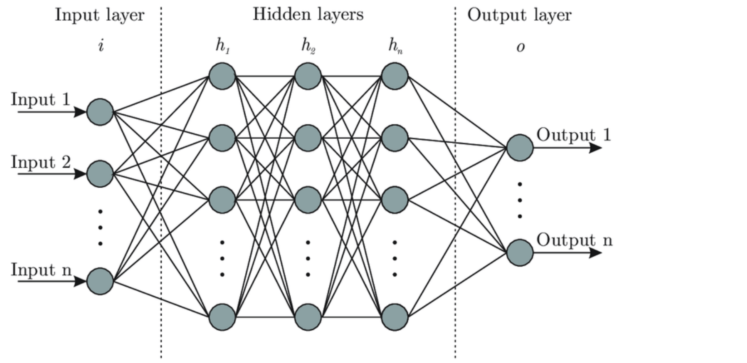


Fig. 1.3 Artificial Neural Network

[https://www.google.com/search?q=ANN&rlz=1C1CHBD_enIN860IN862&source=lnms&tbm=isch&sa=X&ved=2ahUKEwifkNvaktH-AhWS2wGHZTSAvsQ_AUoAXoECAEQAw&biw=1440&bih=732&dpr=1#imgrc=1ANMwvwfON5Dam]

1. It could accommodate the dynamic nature of EEG signals rapidly changing with time and from patient to patient.
2. Increasing data from healthy and diseased person enables training of machine learning system for detecting of epileptic seizures.

However, many machine learning algorithms do not perform efficiently when the number of features or the input samples are high and also there is a limited time to perform the classifications.

Among different techniques, artificial neural network (ANN) is a technique which attempts to mimic the human brain for decision making. ANNs are supervised non-linear machine learning algorithm constructed by cascading chains of decision units used to recognize non-linear and complex function. A shown in the Fig., ANN consists of input and output layers and a number of hidden layers. Each layer contains a number of neurons which performs a nonlinear operation on its input. Efficacy of ANNs depends upon the number of layers and number of neurons and often requires a very large number of layers and neuron for certain problems. As a result, even with a few training data, producing a generalized automatic system with consistent performance is a difficult challenge.

With the development of powerful computers and access to local and remote memory clusters as well as cloud, deep neural network (DNN) has become widely popular. These DNNs have large number of neurons and layers and hence more ability to learn, more scalable and further processing capability on their layers. Therefore, unlike conventional ANNs, DNNs can process large data in real time. Deep learning algorithms using DNNs allow computational models composed of multiple processing layers to learn data representations with multiple abstraction levels. Such deep learning algorithms' ability to learn features automatically is thus opening up new avenues of research in prediction and classification of seizures. Deep learning approaches provide characteristics that are more distinct and resilient than handcrafted features. One of the main differences between deep learning and traditional machine learning is the type of algorithms used. While traditional machine learning algorithms often use linear models and hand-crafted features to learn from data, deep learning algorithms use artificial neural networks to automatically learn features and patterns from the data. Another key difference is the amount and complexity of the data that can be handled. Deep learning algorithms are capable of processing large and complex datasets, such as images or audio, which would be difficult or impossible for traditional machine learning algorithms to handle. DNNs are therefore used with EEG signals in many important areas such as

- Classification of sleep stages and pattern
- Detection and classification of onset of seizure
- Characterizing attention deficiency

Therefore, deep learning algorithms could be advantageously used for processing of EEG signal for prediction and classifications of seizures.

Chapter 2

Motivation

This chapter discusses some of the important works reported in literature which are pertaining to the present work and then the motivation of undertaking the present work has also been explained.

2.1. Some Important Literatures

Schachter and Sirven [1] described in details the causes of seizures due to the disturbance in the electrical activity in the brain's neurons.

Fisher *et al.* [2], and S Scheffer *et al.* [3] provided a detailed classifications of epileptic seizures where seizures are divided into three major groups viz. Generalized Onset Seizure, Focal Onset Seizure, and Unknown Onset Seizure. The focal seizures can start in one area or group of cells on one side of the brain and are further classified into simple partial and complex partial seizures based on their generation in regions of the brain.

Based on motor and non-motor symptoms, the generalized seizures which affect both sides of the brain or a group of cells at the same time and are again classified into absence, tonic, atonic clonic, tonic-clonic, and myoclonic seizures [1–3].

Hussain *et al.* [4] explained the limitations of the handcrafted features from EEG in detection of seizure types. They explained that because the EEG data vary from patient to patient and for the same patient the data vary from time to time, handcrafted features are not suitable for authentic seizure. Feature extraction is complicated by the existence of noise and artifacts in data and as a result, even with a few training data, producing a generalized automatic system with consistent performance is a difficult challenge.

2.2 Motivation of the Present Work

Most of the works reported till date focused on the seizures classification using EEG recordings. Indeed, in the accurate classification of seizure types, discriminative features among different seizure types needs to be well-defined, which is very challenging. It is very challenging to classify seizure types using EEG signals by traditional methods. Therefore, an automatic and accurate classification of seizure types is extremely important both for correct and timely treatment.

Traditional machine learning (ML) algorithms are not suitable because it depends on hand crafted features. Due to the non-stationary and non-linear characteristics of EEG signals, conventional ML techniques to study and detect the small variations and crucial distinguishing factors among various types of seizures are quite difficult. Currently, deep learning (DL) algorithms are extensively used in many proposed work to analyze epileptic seizures and different seizure types.

A few attempts at characterizing seizure types based on DL have been reported. In [5], 2D input images generated by spectrogram from EEG data was used as input to deep learning models and the data was classified into six different types of seizure.

Raghu *et al.*[6] employed four different CNN Models and also used 2D spectrogram images of EEG signals as input to these models and classified EEG data into eight different types of seizure.

In [7], the authors have used DL based epileptic seizure detection by generating 2D RP images of EEG signals for specific brain rhythms. Many such works have generated 2D images from EEG signals for several DL models --- stack-autoencoder, CNN, hybrid deep neural networks, and pre-trained deep neural networks to classify different seizure types.

EEG signals are complex in nature and use many channels for observation, which are fundamentally associated with one another. Thus it is important to find techniques that can be used to study the relation between EEG data acquired from different channels. For this purpose phase synchronization between different channels of EEG data may prove useful. Moreover, recurrence plots could also be suitable and advantageous choice for generating 2D input images from EEG as it considers recurrence characteristics including non-linearity and chaotic behavior of the time series.

This forms the motivation of undertaking the current work where an attempt has been made to classify EEG data into different types of seizures by taking into consideration the non-linear nature and recurrence characteristics of the EEG signal.

Chapter 3

Objective

This chapter presents the objectives of the present thesis with reference to the discussions on the literatures, summary of the literatures reviewed and the motivation presented in chapter 2.

3.1 Objectives of the Present Work.

Based on the literature review and the gaps discussed, the objectives of the present work has been laid down as two major objectives as

1. To classify seizure type using mean phase coherence matrices and deep learning models with the following

    - To segment the EEG data by using band pass filter
    - To evaluate the phase synchronization matrix from the segmented EEG date
    - To generate images from the phase synchronization matrix
    - To train a deep learning model using the generated image data for future prediction

2. To classify seizure type using fuzzy recurrence plots and deep learning models with the following

    - To segment the EEG data by using band pass filter
    - Using time delay embedding to calculate time delay, embedding dimension of each segment.
    - To generate Fuzzy recurrence plots
    - To train a deep learning model using the generated plots for future prediction

Chapter 4

Methodology

This chapter presents the different methodologies used in the present work. Starting with the filtering of the EEG data, the theoretical backgrounds of the different techniques like phase coherence matrices, fuzzy recurrence plots, and deep learning algorithm which have been used in the present study are discussed.

4.1 EEG Dataset and Pre-processing.

In this study, two data sets have been used viz.

1. **Publicly available EEG database contributed by the Temple University Hospital (TUH, v1.5.2).** Temple University EEG corpus is the largest free EEG data available till date for diagnosis of epilepsy and seizure types. It consists of data acquired during 2000 - 2013 using different EEG clinical settings for about 10,874 patients.
2. **CHB-MIT dataset.** This database comprises of 844-hour continuous EEG from 23 pediatric patients between age 1.5-19 who underwent scalp multi-channel EEG recording. It is the first pediatric EEG database available for epilepsy and seizure diagnosis. About 200 seizures were recorded in a universal bi-polar montage with about 24-27 EEG channels.

4.2 Segmentation of EEG Data

The band pass filter has been applied to extract the frequency band (5Hz – 30Hz) that mostly corresponds to seizures. The EEG signals have been segmented into different epochs. Each of the ictal, pre-ictal and post-ictal epochs is of the same duration. From the starting and ending time of the seizure (ictal period) specified in the database, the pre-ictal period is determined at a duration of 30 minutes (1800 seconds) before the ictal period and the post ictal duration is determined at a duration of 2 seconds after the seizure period. The segmentation of EEG data satisfies the primary demand of a deep neural network model of big and diverse variety of input data. Figure 4.1 shows a typical EEG data and the segmentation.

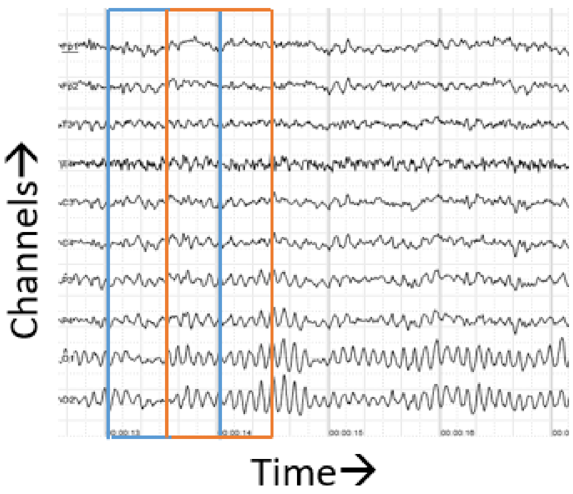


Fig 4.1. Segmentation of EEG Data

4.3 Phase Synchronization Matrices

Phase synchronization between two signals is the measure of the consistency of phase difference between them. The calculation of phase synchrony using analytic signals has numerous benefits over the conventional approaches [9]. The main advantages of using the analytic signal are that, given some real data represented by one function of time, we can determine two functions of time to better access meaningful properties of the signal. An analytical signal x_a (t) of a signal x(t) can be represented as

$$x_a(t) = \operatorname{Re} x(t) + \operatorname{Im} x(t) \qquad (4.1)$$

The imaginary part of $x_a(t)$ can be evaluated by taking its Hilbert transform as

$$\operatorname{Im} x(t) = HT\{x(t)\} = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(t)}{t-\tau} d\tau \qquad (4.2)$$

Now, the instantaneous phase, $\phi_x(t)$ can be obtained by equation as

$$\phi(x) = \tan^{-1}\left(\frac{\operatorname{Im} x(t)}{\operatorname{Re} x(t)}\right) \qquad (4.3)$$

When mean phase coherence is used as a statistical measure for phase synchronization, a distinct difference in the degree of synchronization, was observed between the data corresponding to seizure free intervals and those corresponding to impending seizure. This clearly indicates an altered state of brain dynamics prior to seizure activity. The absolute value of mean phase coherence of two signals over a length *M* has been measured by

$$\phi_v = \left| \frac{1}{M} \sum_{k=1}^{M} e^{i} \left[\phi_x(t_k) - \phi_y(t_k) \right] \right| \qquad (4.4)$$

The value of ϕ_v varies between 0 to 1. The value close to 0 means less synchronization, whereas the value close to 1 exhibits the perfect synchronization between the two signals. Thus, using mean phase coherence, mean phase coherence matrices are constructed. The mean phase coherence matrices, has been transformed into 2D images by employing the *OpenCV* library of python. Next, images have been used as input for a deep neural network.

4.4 Recurrence Plots

Recurrence plots (RPs) are an advanced technique for analyzing nonlinear data. It is a representation (or graph) of a square matrix, in which the matrix's elements represent the occurrences of a dynamical system's states (each pair of columns and rows represents a particular pair of occurrences). Technically, the RP indicates all instances in which the dynamical system's phase space trajectory travels through nearly the same region of the phase space. A RP can be defined by:

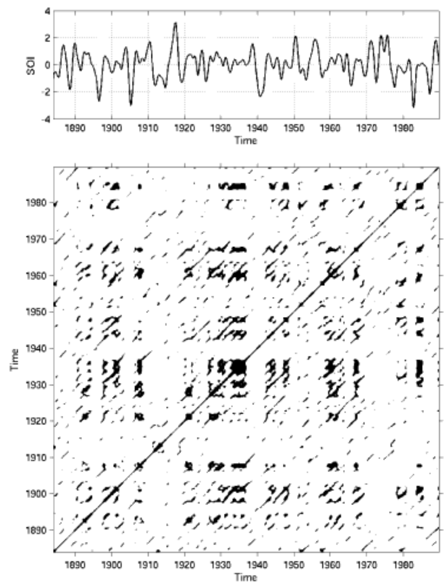


Fig. 4.2. Recurrence plot of a time series data

$$RM_{i,j}^{m,\varepsilon} = \begin{cases} 0 \; if \; \left\| \overrightarrow{x_i} - \overrightarrow{x_j} \right\| > \varepsilon_i \\ 1 \; if \; \left\| \overrightarrow{x_i} - \overrightarrow{x_j} \right\| \le \varepsilon_i \end{cases} \qquad (4.5)$$

where, *i,j* = 1,2,3,...N, N is number of sample points to be analyzed of xi and || || indicates the distance norms. Indeed, a valid recurrent point must lie inside a hypothetical sphere of radius ε cantered at xi and $RM_{i,j}^{m,\varepsilon}$ outputs are either 0 or 1. Figure 4.2 shows a time series and its corresponding recurrence plot.

4.5 Calculation of Fuzzy Recurrence plots

4.5.1 Time delayed embedding

Using the method or time-delayed embedding, a signal can be embedded into higher- dimensional space in order to study its dynamics [10]. This requires knowledge of two parameters: The delay parameter τ, and the embedding dimension parameter D. Two standard methods to estimate these parameters in one-dimensional time series involve the inspection of the Average Mutual Information (AMI) function and the False Nearest Neighbor (FNN) function.

Auto mutual information:

Fraser and Swinney (1986) devised a method to discover time delayed coordinates that are as independent from each other as possible in order to identify the best time delay for embedding a one-dimensional time series. The mutual information $I(x(t), x(t + \tau))$ between the original time series $x(t)$ and the time series $x(t + \tau)$ shifted by was used to quantify dependence. This is known as the auto mutual information or average mutual information because here the mutual information is computed for a time series and a time-shifted version of the same time series. The expression for the auto mutual information, which is a nonlinear generalization of the autocorrelation function, is given by Eqn (4.6)

$$I(x(t), x(t+\tau)) = \sum_{i,j} p_{ij}(\tau) \log\left(\frac{p_{ij}(\tau)}{p_i p_j}\right) \qquad (4.6)$$

Fraser and Swinney suggested using the location of the initial minimum of $I(x(t), x(t + \tau))$ as the ideal value of to generate coordinates for time delayed phase-space embedding that are as independent as possible. By using that specific value, the phase-space embedded signal's first coordinate, $y_1(t) = x(t)$, will be as minimally dependent on its second coordinate, $y_2(t) = x(t + \tau)$, etc., as possible. In reality, the AMI function might not have a local minimum but instead for instance, it may be a monotonically declining function of τ. As a consequence, other criteria, such as the lowest value of where the AMI function dips below the value of $1/e$, have been developed.. Figure 4.3 shows a plot between time lag of a time series data and the corresponding mutual information calculated.

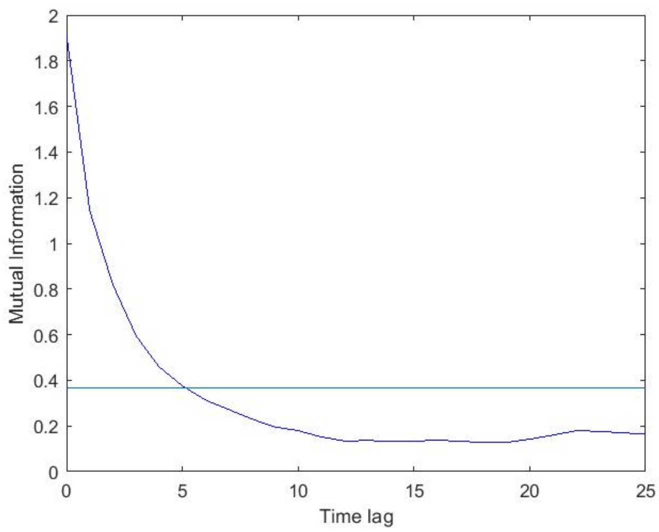


Fig. 4.3. Time lag vs Mutual Information

False Nearest Neighbor:

Using time-delayed surrogate copies of the original one-dimensional time series, Takens' theorem (Takens, 1981) states that higher dimensional dynamics of a signal can be created. To be more specific, we can create the following time series from the initial one- dimensional time series $x(t)$:

$$y(t) = (x(t), x(t+\tau), \ldots. x(t+(D-1)\tau)) \tag{4.3}$$

Here, t and τ are both numbers used to index the collected data, but by multiplying them by the sampling period, they can be expressed in real time. The AMI-approach outlined above can be used to estimate the time delay. Now that the original time series has been gradually embedded into higher dimensions, it is possible to estimate the embedding dimension D by observing the shift in the distance between nearby points in phase space.

According to the following logic, Kennel et al. (1992) proposed the fundamental principle underpinning the estimation of embedding dimension using FNN. Assume two data points in the in the one-dimensional time series are close to one another (e.g., neighboring); in this case, they are neighbors. We can determine the distance between those neighbors based on the amount of their difference. The coordinates of those data points can be used to determine whether the separation between them has changed noticeably if the time series is first embedded once (i.e., into two dimensions) using a time delay. The neighbors are referred to as fake neighbors if embedding significantly increases the distance between them. This shows that more embedding of the data is required. The attractor's shape remains constant after embedding, indicating that the current embedding size is enough, and they are referred to as true neighbors if their distance does not change noticeably. This is possible for sequentially increasing embedding dimensions D, and we select a value for D at the point where the number of FNN drops to 0, the point at

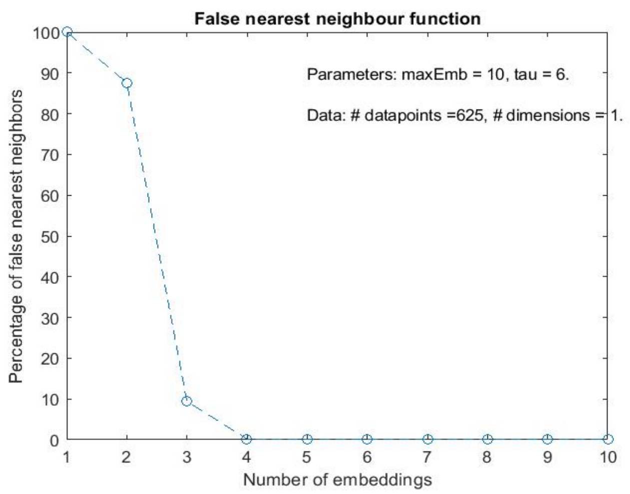


Fig. 4.4. No. of embeddings Vs % of false nearest neighbours

which subsequent embeddings have no effect on the number of FNNs, or the point just before the number of FNNs begins to increase once more. Fig 4.4 shows the number of embeddings of a time series data vs the percentage of false nearest neighbours.

4.5.2 Fuzzy recurrence plots

After calculating the time delay and embedding dimension of the EEG data, we calculate the phase space states of the data. The fuzzy recurrence plot can be calculated from the sets of phase space states as follows.

Let $X = \{x\}$, and $V = \{v\}$ be the sets of phase-space states and fuzzy clusters of the states, respectively. A fuzzy (binary) relation R from X to V is a fuzzy subset of $X \times V$ characterized by a fuzzy membership (characteristic) function $\mu \in [0, 1]$. This (fuzzy) grade of membership expresses the similarity or strength of relation of each pair (x, v) in R that has the following properties. The fuzzy clusters of the phase-space states can be obtained using the fuzzy c-means (FCM) algorithm.

The dynamic silhouette clustering index has been used to calculate the optimal number of fuzzy means clusters for a given data. The silhouette index (s(i)) is given as

$$S(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \quad (4.4)$$

where $a(i)$ is the average dissimilarity of the i^{th} object with all other objects in the same cluster and $b(i)$ is the average dissimilarity of the i^{th} object with all objects in the closest cluster. The time delay, embedding dimension and number of clusters is to be given as input to the fuzzy recurrent plot function to generate fuzzy recurrence plots.

4.6 Convolutional Neural Networks

A convolutional neural network (CNN or ConvNet) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data. A typical CNN architecture is structured as a series of stages. The first few stages are composed of two layers: convolutional and pooling layers. Units in a convolution layer are organized in feature maps, within which each unit is connected to local patches in the feature maps of the previous layer through a set of weights called a filter bank. The result of this local weighted sum is then passed through a non-linearity such as an ReLU (Rectified Linear Unit). The role of a convolutional layer is to detect local conjunction of features from the previous layer and the role of a pooling layer is to merge semantically similar features into one. Stages of convolution, non-linearity and pooling are followed by more convolutional and fully connected layers. The backpropagation operation is then used for weight optimization in a CNN as for multilayer ANN.

Chapter 5

Work Done

This chapter presents the details of the work done in the present study using the proposed methodology described in chapter 4.

5.1 Phase Synchronization Method to Classify Seizure Types

As discussed in the previous chapter, the segmented EEG data have been used to construct the 2D images using the mean phase coherence matrices using phase synchronization method. The constructed image is then fed to the deep neural network for classification and detection of seizure type.Figure.5.1 shows the pipeline of the proposed method for the classification of seizure types.

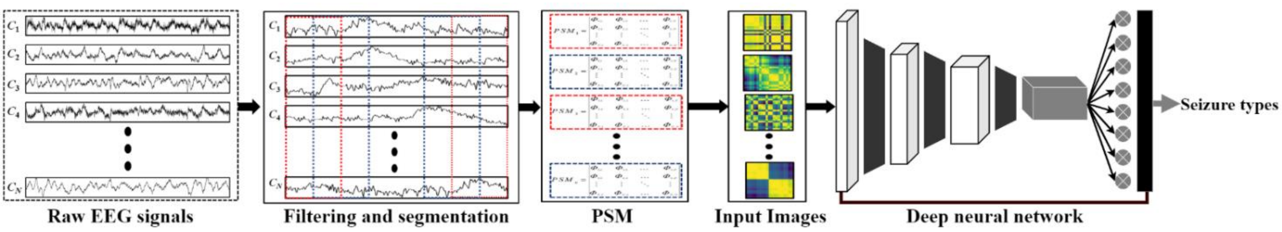


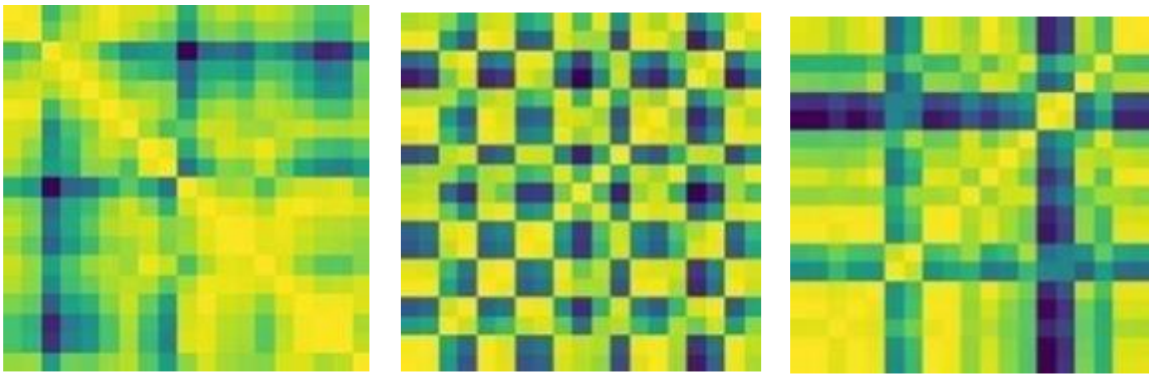
Fig. 5.1. The pipeline of proposed classification of seizure types based on deep neural network using multichannel EEG signals.

5.1.1 Calculation of mean phase coherence matrices

Mean phase coherence matrices have been calculated for epochs of 10 seconds with a 50% overlap between two consecutive segments. Since, 19 channels have been selected, each mean phase coherence matrix formed is of size 19×19. Table 5.1 shows a 6×6 part of a 19×19 mean phase coherence matrix for a particular epoch. The mean phase coherence matrices thus obtained, have been transformed into 2D images by employing the *OpenCV* library of python. Next, these images have been used as input for a deep neural network. Figure 5.1. shows examples of images generated for different seizure types.

	C1	C2	C3	C4	C5	C6
C1	1	0.9995	0.9982	0.9952	0.9893	0.9790
C2	0.9995	1	0.9994	0.9972	0.9918	0.9790
C3	0.9982	0.9994	1	0.9994	0.9950	0.9863
C4	0.9952	0.9972	0.9990	1	0.9983	0.9920
C5	0.9893	0.9918	0.9950	0.9983	1	0.9975
C6	0.9790	0.9819	0.9863	0.9920	0.9975	1

Table 5.1 Mean Phase Coherence Matrix



(a) Absence Seizure (b) Complex Partial Seizure (c) Myoclonic Seizure

Fig 5.1. Images generated from mean phase coherence matrices

5.1.2 Images generated as input to deep learning model

The proposed CNN pipeline having one input layer, three hidden layers, two affine layers and one output layer has been displayed in Fig.5.2. In addition, the batch normalization layer has been employed in each hidden layer to generate better stable input feature vectors and accelerate the training process [2-4]. Moreover, the max-pooling layer followed by the batch normalization layer in all the hidden layers has been engaged to reduce the dimension of feature vectors and computational burden. Next, to reduce the overfitting issue of the model, the dropout layer has been used in the last hidden layer and two affine layers. Additionally, L2 regularization has been used in the affine layers to reliably and smoothly extract the data features. The non-linear activation — rectified linear unit (ReLU) has been employed in the input, hidden and affine layers to determine whether or not to activate the neurons.

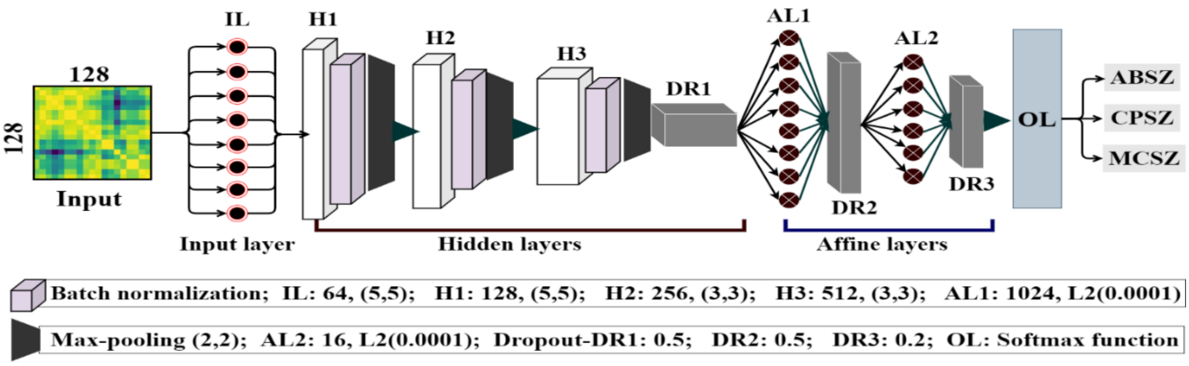


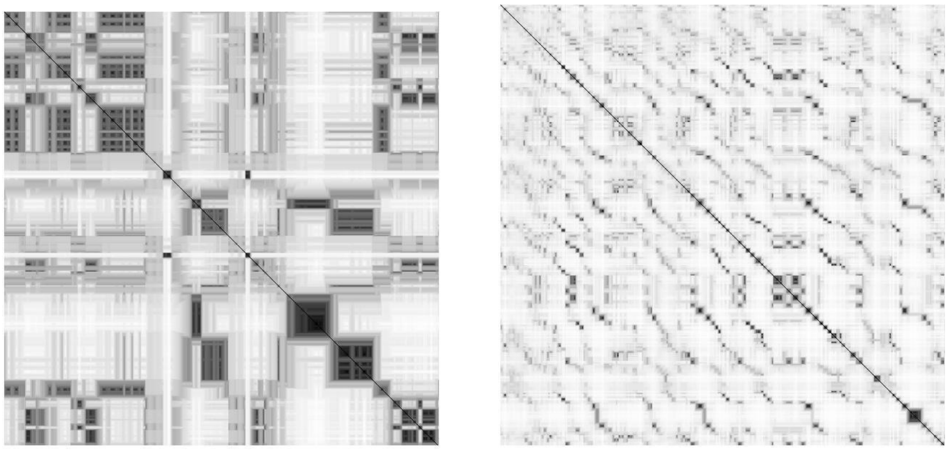
Fig. 5.2 The detailed description of designed framework of CNN model to classify seizure types.

5.2 Fuzzy Recurrence Method to Classify Seizure Types

In addition to the phase synchronization method, fuzzy recurrence plot has also been used to classify the seizure type.

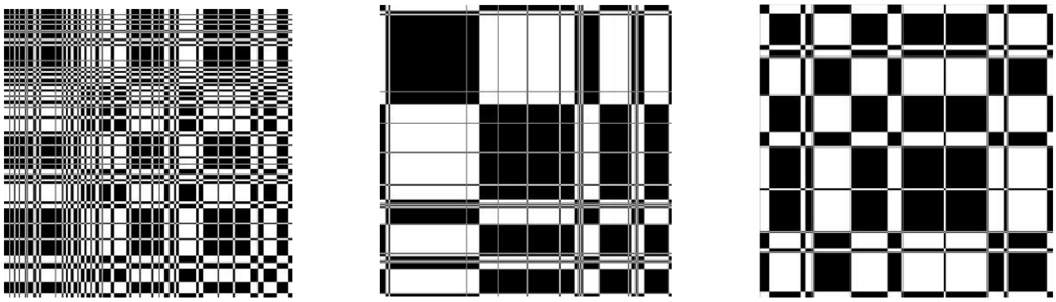
5.2.1 Generating fuzzy recurrence plots

Using the method of time delayed embedding, the EEG time series data is projected into higher dimensional space, which is then converted to a fuzzy recurrence plot. The time delay embedding dimension for each segment of data is generated using a MATLAB program. The optimal number of clusters for each segment was generated for the present data using the silhouette cluster index. Figure 5.3 shows fuzzy recurrence plots generated for some EEG data using the optimal number of clusters. However, for the present study, 2, 3 and 5 as the number of clusters have been used to generate the fuzzy recurrence plot. Figure 5.4 shows the fuzzy recurrence plots generated for the ictal, pre-ictal and post-ictal EEG data segment respectively taken from a single patient.



(a) Number of clusters: 8 (b) Number of clusters: 17

Fig 5.3. Fuzzy Recurrence Plots for some time series data



(a) Ictal (b) pre-ictal (c) pos-tictal

Fig 5.4. Fuzzy Recurrence plot for different EEG segments from the same patient

5.2.2 Fuzzy recurrence plots as input to deep learning model

The CNN pipeline proposed in the present work has one input layer, six hidden layers, four affine layers and one output layer and the same has been displayed in Fig.5.5. Moreover, the max-pooling layer in all hidden layers has been engaged to reduce the dimension of feature vectors and computational burden. Next, to reduce the overfitting issue of the model, the dropout layer has been used in five of the hidden layers and all the affine layers. Additionally, L2 regularization has been used in affine layers to reliably and smoothly extract data features. The non-linear activation — rectified linear unit (ReLU) has been employed in the input, hidden and affine layers to determine whether or not to activate the neurons. In future studies, the attention layers may also be introduced in the model to improve classification accuracy.

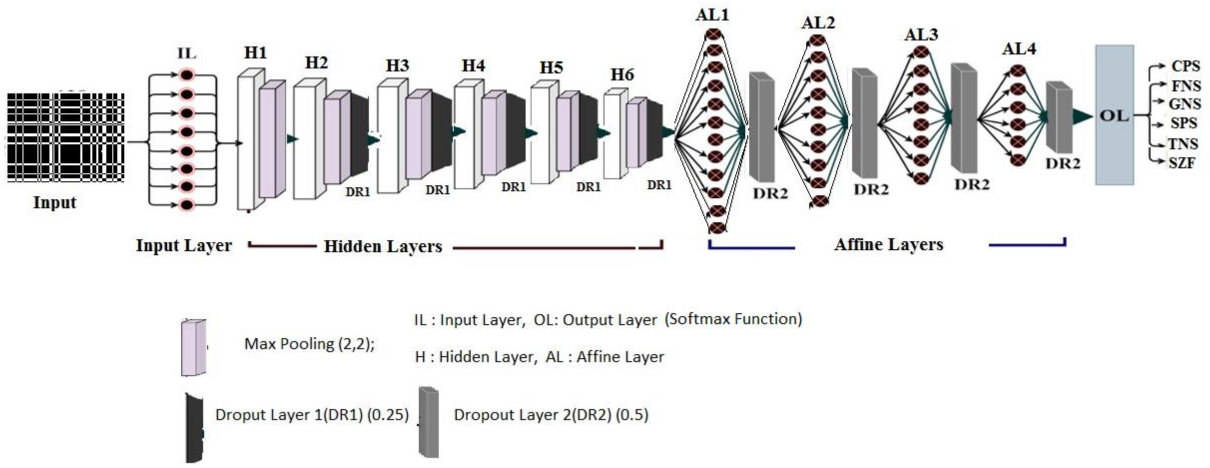


Fig. 5.5 The detailed description of designed framework of CNN model to classify seizure types

Chapter 6

Results and Discussions

In this chapter the results obtained using the methodologies discussed in chapter 4 and the proposed pipeline described in chapter 5 for detection and classification of seizure type have been presented and discussed in details.

6.1 Results from Phase Synchronization Method to Classify Seizure Types

In the study of classification of seizure types using phase synchronization and deep learning, data obtained from Temple University EEG dataset (TUH) have been used. Multiclass discrimination tasks along with 5-fold cross-validation(k_1, k_2, k_3, k_4, k_5) have been executed to classify seizure types. This is based on training on 80% of the data and testing with the remaining 20% data. The categorical cross entropy used as a loss function evaluates how the proposed CNN pipeline is modeling the data set. Experimental performances of the proposed method have been examined by calculating different performance metrics — as

$$A_c = \frac{TP+TN}{TP+FP+TN+FN} \qquad (6.1)$$

$$S_e = \frac{TP}{TP + FN} \qquad (6.2)$$

$$S_p = \frac{TN}{FP + TN} \qquad (6.3)$$

$$F1 = \frac{2TP}{2TP + FP + FN} \qquad (6.4)$$

Where accuracy A_c is the accuracy, S_e is the sensitivity, S_p is the specificity and $F1$ is the weighted $F1$-score. TP and TN depict the true positive and negative respectively, while FP and FN represent false positive and negative respectively. In the present work the values of the classification performance metrics obtained are as follows.

- Accuracy, $A_{c=}$ 83.30%,
- Sensitivity, S_e = 91.43%,
- Specificity, S_p = 82.90% and
- Weighted F1-score, $F1$ = 83.03%

As mentioned earlier, only three types of seizures have been classified in this method and Fig. 6.1 (a) and (b) show receiver operator characteristic (ROC) curves for different types of seizures viz. ABSZ, CPSZ and MYSZ for *k1* and *k2* folds respectively. Similar trends have been obtained for other folds also. As could be seen from the Figs 6.1 (a) and (b) that the area under the curves (AUC) for all types of seizures is ≥ 84.0% showing that the proposed method could classify the seizure type satisfactorily.

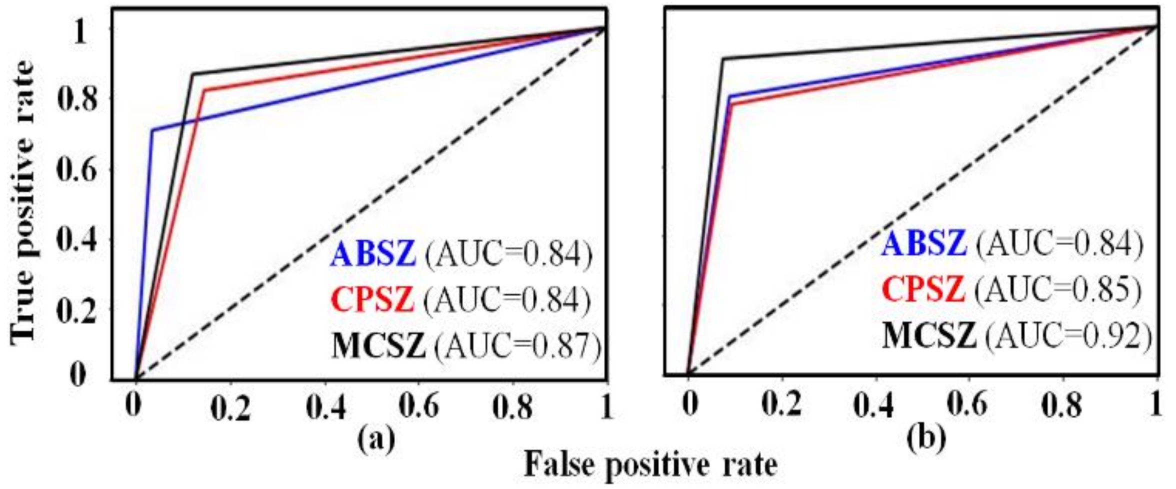


Fig 6.1 The ROC curves obtained by phase synchronization method for (a) k_1 fold, and (b) k_2-fold along with their respective area under curves for different seizure types

6.2 Results from Fuzzy Recurrence Plot Method to Classify Seizure Types

Using the Fuzzy Recurrence method, currently a classification accuracy of around 75% has been achieved. Efforts are still on to fine tune the proposed deep learning model further with an objective to increase the classification accuracy. It may be noted that in this method unlike the phase synchronization method, data from both the data set viz. Temple University EEG dataset (TUH) and CHB-MIT dataset have been used to achieve a better accuracy.

Chapter 7

Conclusion and Scope for Future Works

This chapter summarizes the present work with concluding remark.

In this work, The EEG data from the Temple University EEG dataset (TUH) and CHB-MIT dataset has been used. EEG data has been segmented and for each such segments. These segmented EEG data have been used in deep neural network following two methods. In the first method, phase synchronization method was used to construct the 2D images to be fed to the CNN for classification of the seizure type .In the second method, fuzzy recurrence plot has been used to classify the seizure type.

Using the phase synchronization the proposed model could classify the seizure types with a classification accuracy of 83.30 % along with the weighted F1-score of 83.03%, which is quite satisfactory. However using the fuzzy recurrence plots, a classification accuracy of approximately 75% could be achieved. Therefore, this model needs further fine tuning of the hyper parameters. Currently, efforts are on to achieve an improved accuracy.

In the future, attempts will be made at the following:

- Trying to achieve better accuracy by tuning the hyperparameters of our deep learning model.
- Graph Neural Networks (GNNs) could be tried to classify the seizure type from the same data as well as localization of the source of seizure.

Bibliography

[1] C. Schachter and J. I. Sirven. EEG, https://www.epilepsy.com/learn/diagnosis/eeg (2017, Dec)

[2] RS Fisher, JH Cross, JA French, N Higurashi "Operational classification of seizure types by the international leagueagainst epilepsy: Position paper of the ilae commission for classification and terminology." Epilepsia, vol. 58 4,pp. 522–530, (2017).

[3] IE Scheffer, S Berkovic, G Capovilla, MB Connolly, "Ilae classification of the epilepsies: Position paper of the ilae commission for classification and terminology." Epilepsia, vol. 58 4, pp. 512–521, (2017).

[4] R Hussein, MO Ahmed, R Ward, ZJ Wang, "Human Intracranial EEG Quantitative Analysis and Automatic Feature Learning for Epileptic Seizure Prediction." ArXiv abs/1904.03603 (2019).

[5] U Asif, S Roy, J Tang, S Harrer, "SeizureNet: Multi-spectral deep feature learning for seizure type classification," arXiv:1903.03232, (Sep. 2019.)

[6] Raghu; Natarajan Sriraam; Yasin Temel; Shyam Vasudeva Rao; Pieter L Kubben., "A convolutional neural network based framework for classification of seizure types". Annu Int Conf IEEE Eng Med Biol Soc. 2019 Jul;2019:2547-2550. doi: 10.1109/EMBC.2019.8857359. PMID: 31946416.

[7] Shankar, A., Dandapat, S., & Barma, S. "Seizure Types Classification by Generating Input Images With In-Depth Features From Decomposed EEG Signals For Deep Learning Pipeline". *IEEE Journal of Biomedical and Health Informatics* (2022).

[8] Roy, S., Asif, U., Tang, J., & Harrer, S. "Seizure type classification usingEEG signals and machine learning: Setting a benchmark". In *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)* (pp. 1-6). IEEE (2020, December).

[9] Shankar, A., Dandapat, S., & Barma, S. "Seizure Type Classification Using EEG Based on Gramian Angular Field Transformation and Deep Learning", In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 3340-3343). IEEE (2021, November).

[10] F Mormann, K Lehnertz, P David, CE Elger "Mean phase coherence as a measure for phase synchronization and itsapplication to the EEG of epilepsy patients, " Physica D 144, pp. 358-369, 2002

[11] Wallot, S., & Mønster, D. "Calculation of average mutual information (AMI) and false-nearest neighbors (FNN) for the estimation of embedding parameters of multidimensionaltime series in matlab". *Frontiers in psychology*, *9*, 16 (2018)..