Epilepsy Period Analysis and Classification

Dynamical Processes in Complex Networks

Instructor: Chittaranjan Hens

Team 3: Network Explorers

Rhythm Aggarwal (2021101081), Khushi (2021101017), Pranjali Bishnoi (2021101038)

1 Base Line Model

Epilepsy is a chronic neurological disorder characterized by recurrent seizures, which are abnormal electrical activities in the brain. Electroencephalography (EEG) is a widely used non-invasive technique for monitoring brain activity and diagnosing epilepsy. However, accurate and automated detection of epilepsy from EEG signals remains a challenging task due to the complex and dynamic nature of brain signals. In recent years, graph signal processing (GSP) has emerged as a promising approach for analyzing brain signals, including EEG data. GSP leverages the underlying connectivity structure of the brain, represented as a graph, to model the interactions between different brain regions. This enables the detection of subtle changes in the brain network topology that may indicate the presence of epilepsy. The method for epilepsy detection in seizure patients can be broadly sub-divided into six subsections:

1. Band selection
2. Time-Frequency analysis
3. Windowed graph learning
4. Seizure Classification
5. Node selection
6. Network metrics trend analysis

In our study we used the analysis pipeline to process the EEG data to learn the graph structure from windowed data and save the result required for analysis and visualizations. We also observed network metrics like clustering coefficients, betweenness and eigenvector centralities to study the graphs for using in our project.

2 Introduction

Despite advancements in EEG-based epilepsy detection, accurate and automated diagnosis remains challenging due to the complex nature of brain signals. This study builds upon the baseline model by introducing innovative methodologies aimed at enhancing epilepsy detection and prediction.

Our analysis and prediction pipeline integrate two major methods:

1. Giant cluster distribution and giant component analysis: We analyze the distribution of giant clusters and identify significant brain network components at each window, providing insights into the functional connectivity changes during epileptic episodes.

2. Diffusion model simulations: We simulate diffusion models like SIS, SIR, and SIZ on the graph networks derived from EEG signals. This modeling approach allows us to capture the dynamic changes in brain functional connectivity, aiding in the characterization of epileptic activity.

By leveraging these novel techniques, we aim to improve the accuracy and efficiency of epilepsy detection, ultimately contributing to early diagnosis and personalized treatment strategies for epilepsy patients.

3 Objective

The objectives of this study are:

1. Analyze the cluster distribution during the pre, during, and post-epilepsy periods. This analysis aims to determine if the number of clusters increases or decreases and to identify the formation of giant components, providing insights into the changes in brain network connectivity during epileptic activity.

2. Simulate diffusion models such as SIR (Susceptible-Infectious-Recovered), SIS (Susceptible-Infectious-Susceptible), and SIZ (Susceptible-Infectious-Zombie) on graphs at each time window representing the pre, during, and post-epileptic periods. The goal is to study the infected probability of each node in the graph, elucidating the spread and dynamics of epileptic activity within the brain network.

3. Utilize the infected probability of each node at each time window obtained from diffusion model simulations and apply clustering algorithms such as Kmeans and neural network classifiers for classifying between the three epileptic periods. This approach aims to improve the accuracy of identifying distinct phases of epileptic activity based on network dynamics captured by the diffusion models.

We try to show consistency in results from the above mentioned analysis and prediction methods.

4 Methodology

4.1 Cluster Distribution Analysis

Cluster distribution analysis is a technique used to study the distribution of clusters within a graph network during different periods, such as pre, during, and post-epileptic activity. The methodology involves the following steps:

1. Graph Construction: EEG data is converted into graph representations, where nodes represent brain regions, and edges represent functional connectivity between regions.

2. Time Windowing: The EEG data is segmented into time windows corresponding to the pre, during, and post-epileptic periods.

3. Giant Component Identification: The presence of a giant component in the graph, representing a significant cluster of interconnected nodes, is examined. This component can provide insights into the overall connectivity and stability of the brain network during epileptic activity.

4. Cluster Dynamics: Changes in the number of clusters, size of clusters, and the formation of giant components are analyzed across different time windows, shedding light on the dynamic changes in brain network organization during epileptic episodes.

Cluster distribution analysis allows us to characterize the spatial organization of brain network connectivity and assess how it evolves during epileptic activity, contributing to a deeper understanding of epilepsy-related changes in brain function.

4.2 Diffusion Models Fitted on Graphs

1. **SIS**: In the SIS (Susceptible-Infectious-Susceptible) model, nodes in the graph represent individuals, and edges represent potential transmission pathways between them. The model simulates the spread of infection by assigning probabilities of infection and recovery to each node based on its connections in the graph. By fitting the SIS model on graphs, we can analyze how infections spread over time, identify critical nodes that contribute most to transmission, and understand the dynamics of epidemic outbreaks within the network.

$$s \to i \quad \text{with parameter } \beta \quad \text{(infection rate)}$$
$$i \to r \quad \text{with parameter } \gamma \quad \text{(recovery rate)}$$

$$\frac{ds}{dt} = \gamma i - \beta s i$$
$$\frac{di}{dt} = \beta s i - \gamma i$$

$$s + i = 1 \quad \text{(Constant)}$$

2. **SIR**: In the SIR (Susceptible-Infectious-Recovered) model, nodes in the graph represent individuals, and edges denote potential transmission pathways between them. This model divides the population into three compartments: susceptible (S), infected (I), and recovered (R). The SIR model simulates the spread of infection by transitioning individuals from the susceptible to the infected compartment, and from the infected to the recovered compartment, based on certain parameters.

   The transition from susceptible to infected occurs with a rate determined by the infection rate parameter β. This parameter represents the likelihood of an interaction between susceptible and infected individuals resulting in transmission. The infected individuals recover from the infection at a rate governed by the recovery rate parameter γ. Once recovered, individuals are assumed to be immune and cannot be infected again.

Mathematically, the SIR model is described by the following system of ordinary differential equations:

$$\frac{ds}{dt} = -\beta si$$
$$\frac{di}{dt} = \beta si - \gamma i$$
$$\frac{dr}{dt} = \gamma i$$
$$\frac{ds}{dt} + \frac{di}{dt} + \frac{dr}{dt} = 0$$
$$s + i + r = 1$$

where s, i, and r represent the fractions of susceptible, infected, and recovered individuals, respectively. The equations govern how these fractions change over time.

3. **SIZ**: The SIZ model is an epidemiological compartmental model that extends the classic SIR model to incorporate an additional compartment, zombified (Z), representing individuals who have been infected and transformed into a non-recoverable state. In the context of a graph, nodes represent individuals, and edges denote potential transmission pathways between them.

   Susceptible (S): Individuals who are susceptible to the infection and can become infected upon contact with infectious individuals. Infectious (I): Individuals who are currently infected and can transmit the infection to susceptible individuals. Zombified (Z): Individuals who have been infected and transformed into a non-recoverable state, representing the irreversible consequences of the infection.

   The dynamics of the SIZ model are governed by a set of ordinary differential equations (ODEs) that describe how the fractions of individuals in each compartment change over time.

$$\frac{ds}{dt} = -\beta si + \gamma z$$
$$\frac{di}{dt} = \beta si - \alpha i$$
$$\frac{dz}{dt} = \alpha i - \gamma z$$

   where s, i, and z represent the fractions of susceptible, infected, and zombified individuals, respectively. The equations govern how these fractions change over time.

In our study, each node in the graph corresponds to a specific brain region or electrode, and the edges represent the functional connectivity between these regions based on EEG data. The Diffusion models are fitted on EEG data by assigning probabilities of seizure propagation to each brain region based on its connectivity with neighboring regions. We conducted 100 iterations of each model for each window of the EEG data to capture the dynamics of seizure propagation within the brain network.

4.3 Clustering and Classification Pipeline

After conducting simulations of diffusion models on the graphs, we obtain the infected probability of each node at each time window for all patients. We then utilize a clustering algorithm like K-means to cluster similar state vectors together, creating clusters based on the nodes' infected probabilities. This clustering process allows us to analyze the distribution of clusters and examine how it correlates with the simulations of diffusion models.

1. Clustering with K-means: We apply K-means clustering to the state vectors obtained from the diffusion model simulations. By experimenting with different numbers of clusters, we analyze the cluster distribution and assess how it aligns with the dynamics captured by the diffusion models across pre, during, and post-epileptic periods.

2. Neural Network Classification: Using the same data, we build a neural network-based classifier to classify each node vector of a time window into one of the three windows: pre, during, and post-epileptic activity. The classifier learns from the features extracted from the state vectors and predicts the corresponding period for each node vector.

3. Evaluation and Model Refinement: We evaluate the performance of the neural network classifier and compare its classification results with the clustering method. Based on the best-fitting model, we adjusted the number of classes in the classifier to improve the alignment with the results from the clustering analysis.

This pipeline enables us to analyze the temporal dynamics of epileptic activity based on the infected probabilities of brain network nodes, providing insights into the classification of different epileptic periods and their relationship with the underlying brain network dynamics.

5 Results

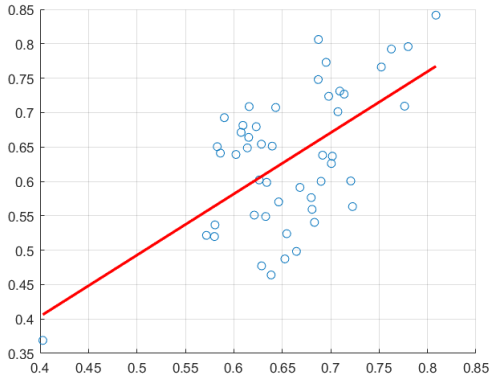

Figure 1: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-I with SIS Model Fitting

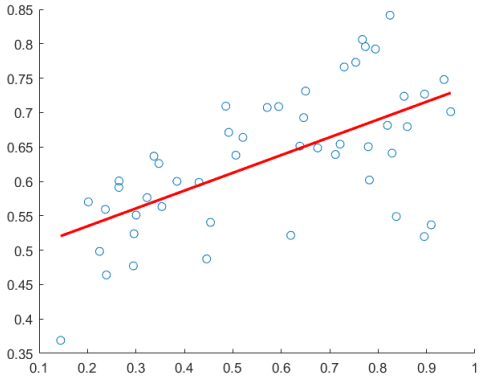

Figure 2: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-I with SIS Model Fitting

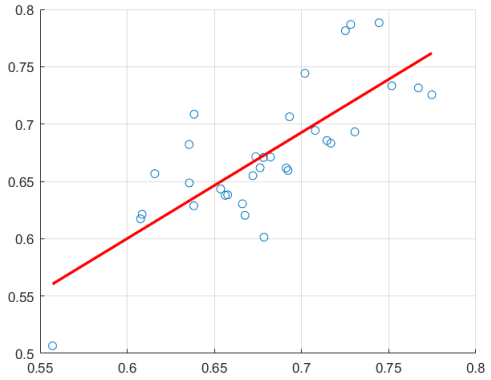

Figure 3: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-II with SIS Model Fitting

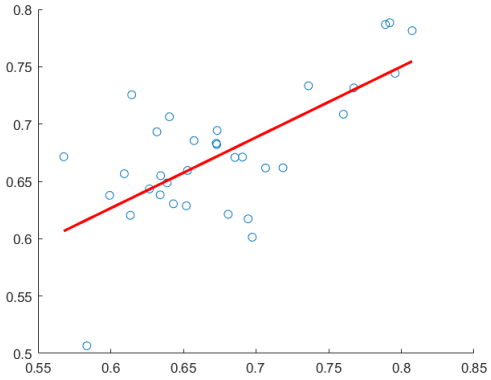

Figure 4: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-II with SIS Model Fitting

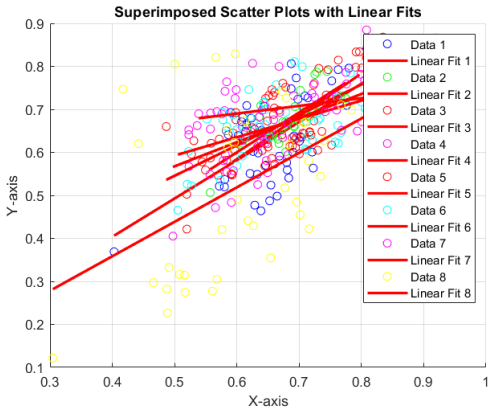

Figure 5: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in Seizure Patients with SIS Model Fitting

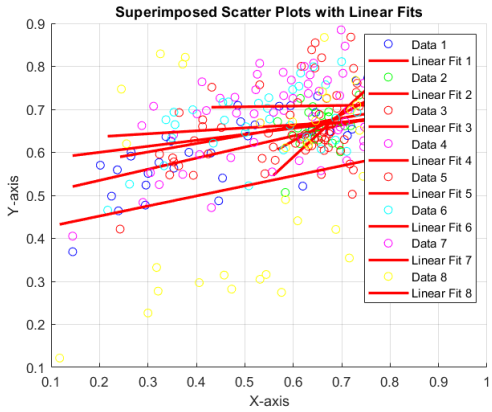

Figure 6: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in Seizure Patients with SIS Model Fitting

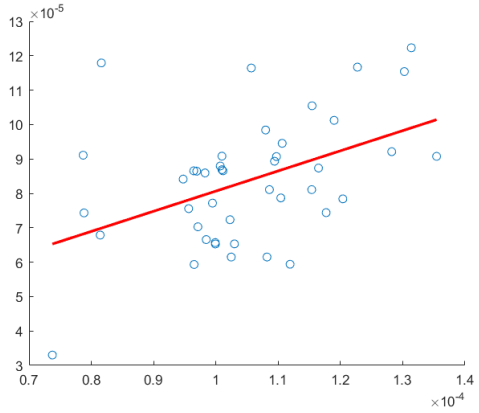

Figure 7: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-I with SIR Model Fitting

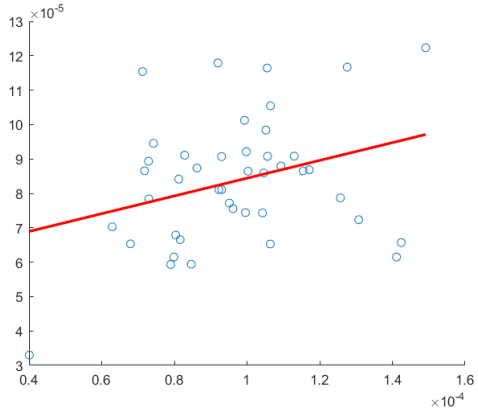

Figure 8: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-I with SIR Model Fitting

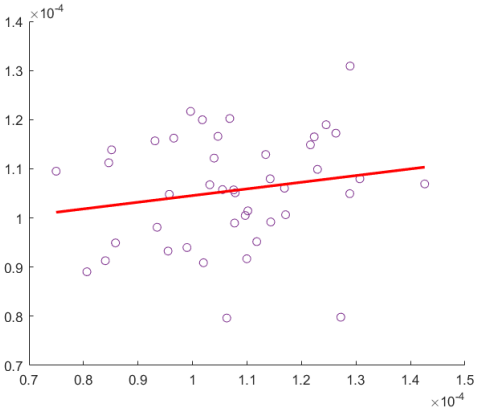

Figure 9: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-II with SIR Model Fitting

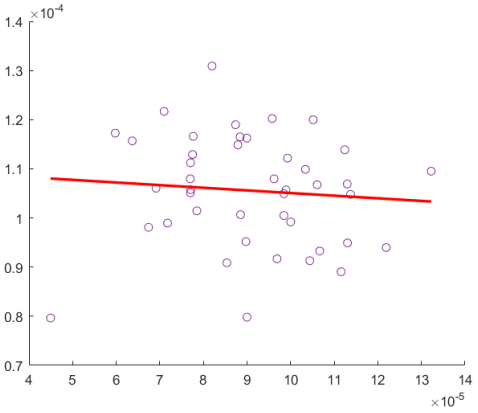

Figure 10: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-II with SIR Model Fitting

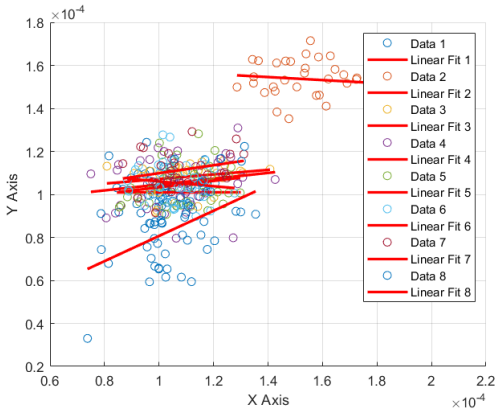

Figure 11: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in Seizure Patients with SIR Model Fitting

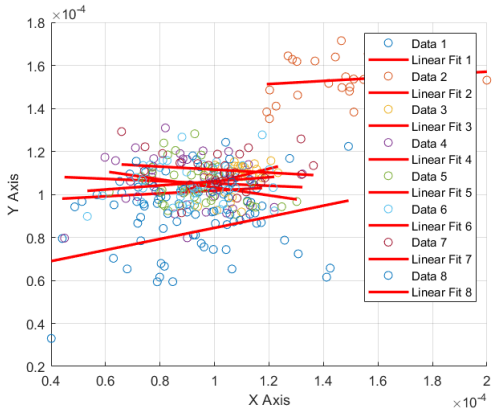

Figure 12: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in Seizure Patients with SIR Model Fitting

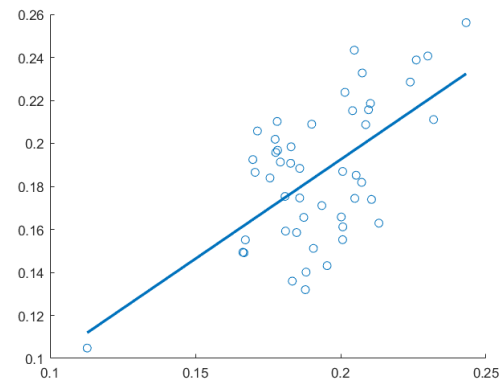

Figure 13: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-I with SIZ Model Fitting

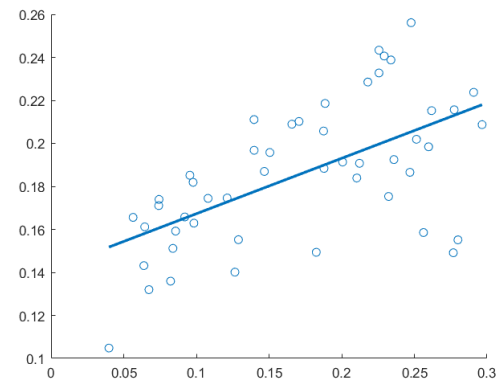

Figure 14: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-I with SIZ Model Fitting

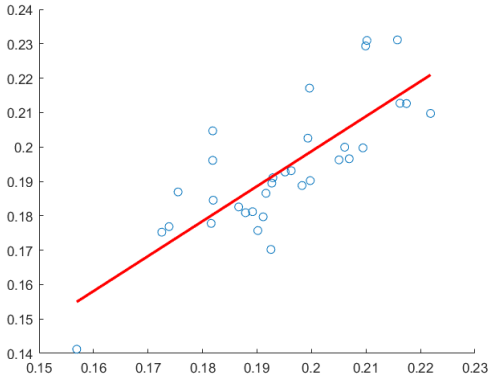

Figure 15: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in a Seizure Patient-II with SIZ Model Fitting

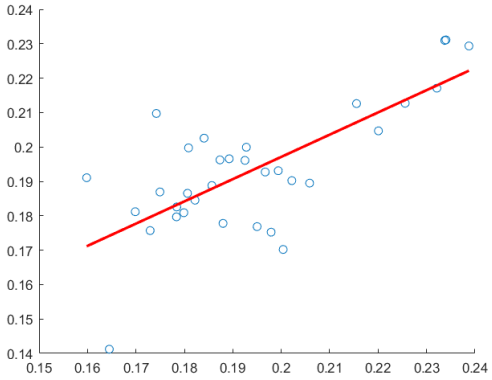

Figure 16: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in a Seizure Patient-II with SIZ Model Fitting

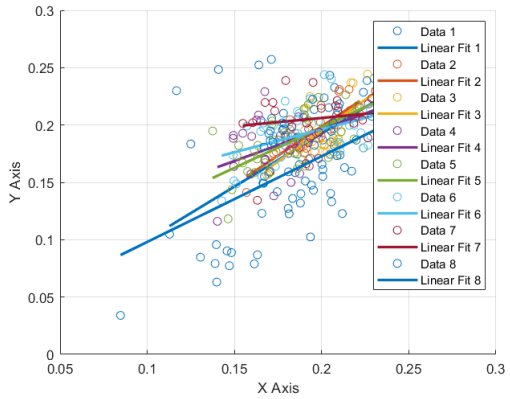

Figure 17: Correlation Analysis of EEG Signals Between Pre-Epilepsy and During-Epilepsy Phases in Seizure Patients with SIZ Model Fitting

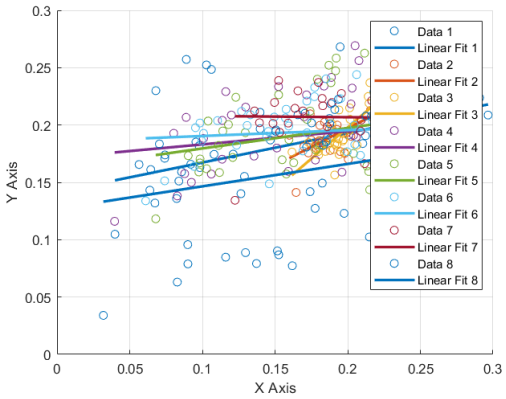

Figure 18: Correlation Analysis of EEG Signals Between During-Epilepsy and Post-Epilepsy Phases in Seizure Patients with SIZ Model Fitting

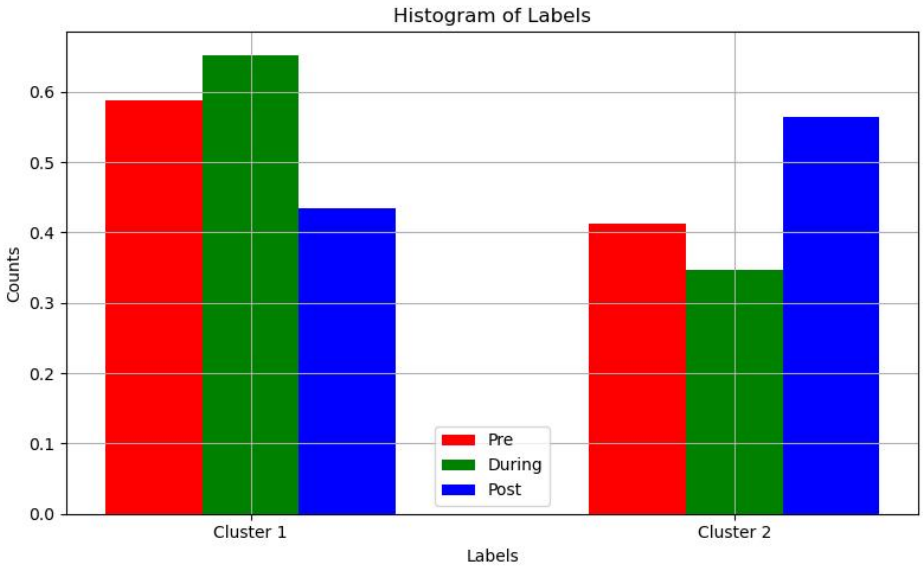

Figure 19: Visualization of EEG Signals for Pre, During and Post epilepsy for both cluster I and cluster II.

6 Conclusion

Our study has revealed that the dynamics during epileptic activity are more closely correlated with the pre-epileptic state than the post-epileptic state. Through our analysis using diffusion modeling on network graphs, clustering algorithms, and neural networks, we have drawn several key inferences and observations.

The clustering analysis based on K-means clustering showed that the clusters formed during epileptic activity exhibit similarities with the pre-epileptic state, indicating a certain level of continuity in brain network dynamics. This finding supports our hypothesis that the brain network undergoes significant changes leading up to and during epileptic events, which then stabilize to some extent in the post-epileptic period.

Additionally, our neural network-based classifier successfully classified nodes into pre, during, and post-epileptic periods with an accuracy of about 65%. The classification results were consistent with the observations from diffusion modeling and clustering analysis, further validating our hypothesis and highlighting the effectiveness of the proposed methodology.

In conclusion, our comprehensive approach combining diffusion modeling, clustering, and neural network classification has provided valuable insights into the temporal dynamics of epileptic activity and its correlation with pre and post-epileptic states. These findings contribute to a deeper understanding of epilepsy-related changes in brain network connectivity and pave the way for improved diagnosis and treatment strategies in epilepsy patients.

7 Future Works

In future research, several avenues can be explored to further enhance our understanding of epileptic activity dynamics and improve the efficacy of our methodologies:

1. **Node-Wise Analysis**: Conducting a node-wise analysis can provide deeper insights into the dynamics of specific brain regions during epileptic activity. For instance, selecting 3-4 nodes of interest and examining their infection pipelines, along with studying the nodes they influence, can elucidate localized network dynamics and their impact on overall brain network connectivity during epileptic episodes.

2. **Testing Various Diffusion Models**: While our study focused on diffusion models such as SIR, SIS, and SIZ, exploring other diffusion models can offer a broader understanding of brain network dynamics. Models like SEIR (Susceptible-Exposed-Infectious-Recovered), SEIRS (Susceptible-Exposed-Infectious-Recovered-Susceptible), and variations with different parameters can be tested to assess their suitability in capturing epileptic activity dynamics.

By pursuing these avenues, future research can advance our knowledge of epilepsy-related changes in brain connectivity and lead to the development of more robust and accurate methodologies for epilepsy detection and prediction.

References

[1] Electroencephalogram (EEG), PapersWithCode

[2] Dynamical processes in complex processes Class Slides

[3] Epilepsy Detection for EEG signals using Time-Frequency Analysis and Network Metrics