Graph-based EEG Analysis

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***Abstract*—Electroencephalography (EEG) is a widely used non-invasive technique for monitoring brain activity, particularly valuable for the detection and analysis of epileptic seizures. Traditional approaches to EEG signal processing rely heavily on time-series models, often neglecting the spatial relationships between electrodes. In this project, we explore the application of graph-based neural networks for EEG seizure detection by leveraging the inherent spatial configuration of EEG electrodes. We use a subset of the Temple University Hospital EEG Seizure Corpus (TUSZ) and construct graph representations based on electrode distances to train both graph neural networks (GNNs) and conventional deep learning models. Through extensive experimentation and cross-validation, we compare the performance and interpretability of graph-based models against non-graph-based baselines. Our results indicate that while graph-based models provide interpretable insights into brain connectivity patterns, sequence-based approaches with handcrafted features currently achieve superior performance for seizure detection.**

I. Introduction

Epilepsy is a chronic neurological disorder marked by recurrent seizures, affecting nearly 50 million people worldwide. Despite medical advances, many patients remain treatment-resistant, underscoring the need for accurate and early seizure detection. Electroencephalography (EEG) is the primary non-invasive method for capturing brain activity via scalp electrodes, but its analysis is challenging due to high dimensionality, noise, and non-stationarity [1], [2].

Traditional EEG analysis methods, including Fourier transforms, wavelet decompositions, and deep learning models like RNNs and transformers, typically emphasize temporal dynamics while neglecting spatial interdependencies between channels. This oversight can limit the effectiveness of the model, as brain connectivity plays a crucial role in seizure manifestation.

To address this, we explore graph-based modeling where electrodes are nodes and their spatial or functional relationships form edges. This structure enables the use of Graph Neural Networks (GNNs), which are well-suited to non-Euclidean data. By incorporating spatial context, GNNs can potentially enhance both predictive accuracy and interpretability.

Using a subset of the Temple University Hospital EEG Seizure Corpus (TUSZ) [3], we compare graph-based and non-graph-based approaches under consistent preprocessing and training protocols, aiming to assess how spatial modeling impacts performance and complexity trade-offs. Our goal is to evaluate how graph structure influences learning outcomes and to identify the trade-offs between model complexity, accuracy, and interpretability. [1]

II. Related Work

Electroencephalography (EEG) has long served as a foundational tool for diagnosing and monitoring epilepsy, with automated seizure detection and classification emerging as core challenges in EEG analysis. Early methods focused on handcrafted features, such as statistical moments or frequency, domain characteristics, which were classified using traditional machine learning models like support vector machines and random forests. These approaches provided interpretability but often failed to generalize across different conditions.

With the rise of deep learning, more sophisticated models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied to raw or transformed EEG signals. CNNs trained on time–frequency representations (e.g., spectrograms, wavelet transforms) have demonstrated strong performance in learning local patterns [4], while LSTM and BiLSTM networks have been effective at modeling temporal dependencies [5]. However, these sequence-based models neglect spatial relationships between electrodes, which are essential for capturing functional brain connectivity.

To address this, Graph Neural Networks (GNNs) have been introduced for EEG analysis, where electrodes are modeled as graph nodes and inter-channel dependencies form edges [6]. Initial GNN studies relied on fixed adjacency matrices defined by physical distance or signal correlation, which limited their ability to capture dynamic and multi-dimensional interactions.

Recent work, such as NeuroGNN by Hajisafi et al. [7], introduced dynamic graph construction strategies that incorporate spatial, temporal, and semantic relationships. By adapting graph structure based on both anatomical and functional EEG features, NeuroGNN achieved state-of-the-art performance in seizure detection and classification tasks, highlighting the promise of more expressive GNN architectures.

In contrast to dynamic and multi-context graph approaches like NeuroGNN, our work begins with a simpler formulation based on a static, distance-based graph. We focus on evaluating the relative contributions of sequence-based and spatially informed models in a controlled setting, with an eye toward informing the design of more sophisticated node representations and graph structures in future work.

[1]Project Repository

III. Data Exploration

Understanding the characteristics of EEG data is crucial for developing effective seizure detection models. Our exploration of the Temple University Hospital EEG Seizure Corpus (TUSZ) dataset revealed several important patterns that informed our subsequent modeling choices and preprocessing strategies.

A. Dataset Composition and Class Distribution

The dataset consists of 12-second EEG segments recorded from 19 scalp electrodes following the standard 10–20 international system. Each segment is labeled as either seizure or non-seizure, creating a binary classification problem. A preliminary analysis revealed a significant class imbalance, with non-seizure segments substantially outnumbering seizure segments. This imbalance poses challenges for model training and necessitated the implementation of balancing strategies such as class-weighted loss functions and synthetic oversampling techniques.

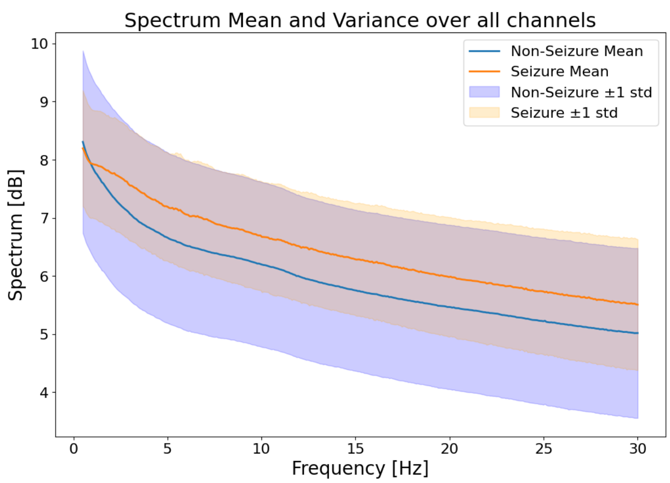

Fig. 1. Mean power spectral density comparison between seizure and non-seizure EEG segments across all channels, with shaded regions indicating ± 1 standard deviation.

B. Spectral Characteristics and Seizure Signatures

To understand the fundamental differences between seizure and non-seizure EEG patterns, we conducted a comprehensive spectral analysis across all channels. The frequency domain analysis provides insights into the power distribution characteristics that distinguish seizure activity from normal brain states.

Power Spectrum Differences: Seizure segments consistently exhibit higher power across most frequency ranges compared to non-seizure segments. This elevated power is particularly pronounced in the lower frequency bands (0-10 Hz), which correspond to the delta and theta frequency ranges commonly associated with pathological brain activity.

Low-Frequency Dominance: Both seizure and non-seizure signals demonstrate the expected pattern where power decreases with increasing frequency. However, seizure activity maintains higher absolute power levels across the entire spectrum.

Clinical Relevance: The observed spectral differences support the use of frequency-domain features in seizure detection algorithms. The elevated low-frequency power during seizures aligns with clinical observations of slow-wave activity and rhythmic discharges.

C. Implications for Model Design

These spectral characteristics directly guided our choice of features and model architectures. The clear distinction in frequency domain properties motivated the inclusion of Fourier-transform based approaches and the computation of Hjorth parameters, which capture both time and frequency domain properties.

IV. Preprocessing

A major challenge of the dataset was its inherent class imbalance, with non-seizure segments significantly outnumbering seizure segments. To address this, we experimented with two strategies. First, we evaluated the use of class-weighted loss functions during model training, which assigned a higher penalty to misclassified seizure samples to counteract their underrepresentation. Second, we tested the Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic seizure examples in the training set.

For models requiring frequency-domain inputs, we computed the Fast Fourier Transform (FFT) of each EEG channel, retaining only the magnitude spectrum between (0.5-30 Hz). In the case of feature-based approaches, Hjorth parameters (activity, mobility, and complexity) were computed for each electrode and frequency band and used as input features.

V. Sequence Based Methods

To establish a strong baseline for seizure detection and to identify the most informative features of EEG signals for classification, we implemented and compared four distinct sequence-based methods. These experiments were also intended to guide the design of node embeddings in our graph-based models by highlighting which temporal and spectral characteristics contribute most to performance. All approaches treat EEG as a multivariate time series and deliberately ignore spatial relationships between electrodes, focusing instead on capturing signal-level patterns relevant to seizure activity.

1) Hjorth Parameters: We first explored a classical feature-based approach using Hjorth parameters—activity, mobility, and complexity—which is often cited in literature as an important feature for EEG classification tasks [8]. These features were computed for each of the 19 channels and 5 frequency bands and then concatenated into one 285-dimensional feature vector. These feature vectors are then fed into the Random Forest model, which was chosen for its robustness and simplicity.

2) CNN in Time Domain: In the second approach, we trained a convolutional neural network (CNN) on raw, downsampled EEG time series. The CNN architecture was designed to extract local temporal patterns across channels and was followed by fully connected layers for classification.

3) Spectrogram and CNN: For each EEG segment, we compute a log-spectrogram for every channel using the Short-Time Fourier Transform (STFT). This process transforms the raw time-series EEG data into a 2D representation (frequency × time) for each channel, capturing both spectral and temporal information relevant for seizure detection. A simple Convolutional Neural Network is used as a model baseline.

4) BiLSTM in Frequency Domain: Lastly, we investigated a sequential model using a bidirectional LSTM (BiLSTM) applied to frequency-domain representations. For each segment, we computed the Fourier transform of each channel and used the magnitude spectra as the input sequence to the BiLSTM, allowing it to learn temporal patterns in the frequency domain.

Among the four approaches, the Hjorth parameters achieved the highest performance, with an average F1 score of 0.7279 across five cross-validation folds (see Table I). However, since all three methods treat EEG channels independently and ignore spatial relationships across the scalp, they are inherently limited in capturing inter-regional brain dynamics. This limitation motivates the use of graph-based models, which are specifically designed to incorporate spatial structure into the learning process.

VI. Graph Construction

The construction of appropriate graph representations is crucial for the success of graph-based neural networks in EEG analysis. In this work, we explored three different approaches to define the adjacency relationships between EEG electrodes, each capturing different aspects of brain connectivity and spatial organization.

Distance-Based Adjacency Matrix: Our primary graph construction approach utilized the electrode distance matrix provided with the dataset, which encodes the Euclidean distances between electrodes based on their 3D coordinates in the standard 10–20 system. This spatial adjacency matrix $A_{spatial}$ was constructed by computing pairwise distances between all electrode positions, creating fully connected graphs where edge weights represent the physical proximity between electrodes. This approach assumes that spatially adjacent electrodes are more likely to exhibit correlated activity due to volume conduction effects and local neural connectivity.

Correlation-Based Adjacency Matrix: To complement the spatial information, we experimented with a functional connectivity approach based on temporal correlations between electrode signals. For each EEG segment, we computed the Pearson correlation coefficient between all pairs of electrode time series: $r_{ij} = \frac{\mathrm{cov}(X_i, X_j)}{\sqrt{\mathrm{var}(X_i)\mathrm{var}(X_j)}}$ where X_i and X_j represent the signal time series from electrodes i and j, respectively.

Pruned Distance-Based Adjacency: Recognizing that fully connected spatial graphs may introduce noise from distant electrode relationships, we also investigated a pruned version of the distance-based adjacency matrix. In this approach, we removed edges between electrodes that exceeded a certain distance threshold, effectively creating a sparse graph that preserves only local spatial relationships. This pruning strategy reduces computational complexity while focusing the model's attention on meaningful local interactions between neighboring electrodes.

VII. Graph Based Methods

To complement the sequence-based models and explicitly account for spatial dependencies between EEG electrodes, we implemented and compared two graph-based methods. These approaches treat the EEG as a graph signal, with nodes representing electrodes and edges encoding spatial relationships, allowing us to model inter-regional brain dynamics more effectively. Our goal was to evaluate whether incorporating spatial structure could improve classification performance and to assess the relative advantages of learned versus pre-defined node features.

1) ST-GCN with Filtered Signals: The first graph-based model we implemented was the Spatio-Temporal Graph Convolutional Network (ST-GCN) [9], which combines graph convolutions over spatial relationships with temporal convolutions over signal dynamics. We applied this model to both time-domain and frequency-domain representations of the EEG signals. In the time-domain implementation, each 12-second EEG segment was represented as a multivariate time series on the spatial graph. For the frequency-domain variant, we computed the Fourier transform of each electrode signal and used the magnitude spectra as input features. The ST-GCN model learned spatial and temporal patterns jointly from these filtered signal representations without relying on predefined features.

2) ChebNet with raw signals: The second approach was using ChebNet Graph Neural Network on the same spatial graph used in ST-GCN. These ChebNet layers perform localized spectral filtering on the EEG graph, allowing the model to capture spatial dependencies and interactions between electrodes. The key idea is to approximate the spectral graph convolution operation using a truncated expansion of Chebyshev polynomials, which allows for localized and computationally efficient filtering on graphs.

3) GAT with Hjorth Features: As an alternative to ST-GCN and ChebNet, we also implemented a Graph Attention Network (GAT) [10], which uses attention mechanisms to adaptively weight contributions from neighboring nodes during message passing. Unlike the previous two approaches, the GAT model operated on handcrafted Hjorth features—activity, mobility, and complexity—which were computed for each node (i.e., electrode) over each EEG segment. This setup allowed us to assess the utility of predefined features in a spatial context and evaluate how attention-based aggregation compares to fixed convolutional operations.

Among the three graph-based methods, ST-GCN achieved an average F1 score of 0.6600 across five cross-validation folds, while the GAT model slightly underperformed relative to ST-GCN with a score of 0.6452 (see Table II). These results suggest that end-to-end feature learning from raw signals remains effective, though the use of attention mechanisms and predefined features may offer better interpretability and flexibility in future extensions.

Overall, while graph-based models did not outperform the best sequence-based approach, they offer a principled way to incorporate spatial structure and have the potential to improve with more expressive graph architectures or dynamic connectivity estimation.

VIII. Results

We evaluated the performance of both sequence-based and graph-based models using 5-fold cross-validation. The primary metric used for comparison was the F1 score, which balances precision and recall, making it suitable for the imbalanced nature of seizure classification.

Table I summarizes the F1 scores obtained by each of the evaluated sequence-based methods, while Table II shows the score of graph-based methods.

TABLE I
F1 Scores of sequence based methods

Fold	BiLSTM	Hjort	CNN	Spectrogram
Fold 1	0.7421	0.8004	0.6907	0.7365
Fold 2	0.6791	0.6865	0.7035	0.6900
Fold 3	0.6545	0.6936	0.7314	0.7423
Fold 4	0.6801	0.7198	0.6975	0.7039
Fold 5	0.7525	0.7393	0.7174	0.6863
Average	0.7017	**0.7279**	0.7081	0.7118
Std Dev	0.0385	**0.0409**	0.0146	0.0234

TABLE II
F1 Scores of graph based methods

Fold	STGCN	ChebNet	GAT
Fold 1	0.6951	0.6426	0.6897
Fold 2	0.6570	0.5855	0.5750
Fold 3	0.6596	0.6187	0.6335
Fold 4	0.6140	0.5828	0.6922
Fold 5	0.6743	0.5679	0.6355
Average	**0.6600**	0.5995	0.6452
Std Dev	**0.0267**	0.0272	0.0432

In addition to quantitative evaluation, we investigated the interpretability of the graph-based models, with a focus on the GAT architecture. Figure 2 visualizes the top 10% of averaged attention-weighted edges learned by the GAT, comparing non-seizure (left) and seizure (right) states.

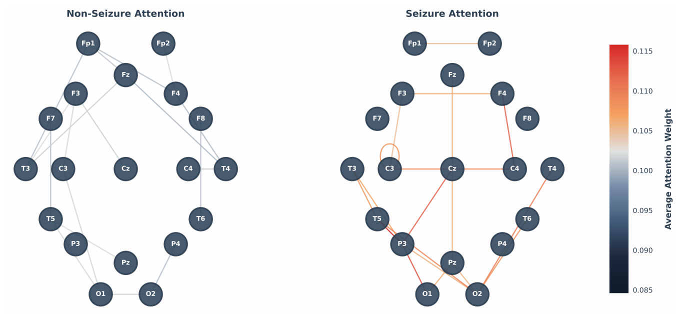

Fig. 2. GAT attention weights for the top 10% connections, highlighting distinct connectivity patterns in non-seizure (left) versus seizure (right) EEG segments

During non-seizure periods, the model assigns relatively low attention weights, with connectivity patterns appearing broadly distributed across electrodes. This suggests that under normal conditions, the GAT captures a more diffuse and weakly coupled network structure.

In contrast, seizure states reveal a marked increase in attention weights and the emergence of more centralized connectivity hubs. Notably, electrodes in central (C3, Cz, C4), parietal (P3, Pz, P4), and occipital (O1, O2) regions exhibit stronger and more focused interactions. These patterns highlight the model's ability to differentiate brain states through learned attention, offering promising avenues for interpretability and alignment with established neurological findings in seizure detection.

Beyond the interpretability insights and the results reported in Table II, we further evaluated the GAT model using pruned distance-based adjacency matrices to assess the impact of graph structure on performance. Specifically, we tested three configurations: a fully connected graph, a graph pruned to retain the top 50% of edges by distance, and a graph with no edges (i.e., isolating the nodes). The highest performance was observed with the half-pruned graph, achieving an F1 score of 0.64 ± 0.04, while the fully connected graph yielded the lowest score of 0.54 ± 0.04. Interestingly, the no-edge configuration performed slightly better (0.57 ± 0.07) than the fully connected case, suggesting that indiscriminate connectivity may dilute useful signal and that appropriate adjacency structure plays a critical role in model effectiveness.

IX. Conclusion

In this project, we investigated the potential of graph-based neural networks for EEG seizure detection, leveraging both spatial and temporal characteristics of EEG data. While traditional sequence-based models, particularly those using handcrafted Hjorth features, achieved the highest overall performance, our experiments demonstrated that graph-based models provide complementary insights by incorporating spatial relationships between electrodes.

Graph neural networks such as ST-GCN, ChebNet, and GAT allowed us to model inter-electrode dependencies and revealed interpretable connectivity patterns that align with known seizure dynamics. Although their performance did not surpass the best sequence-based baselines, attention-weight visualizations and pruning experiments with the GAT model highlighted the importance of meaningful graph structure for effective learning.

These findings underscore the value of integrating spatial context in EEG analysis and point toward promising directions for future work, including dynamic graph construction, multi-modal feature fusion, and the incorporation of neuroanatomical priors. Ultimately, graph-based models offer a flexible and interpretable framework that could enhance automated seizure detection systems in clinical settings.

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