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Graph Neural Networks with Data Augmentation for Single-Channel EEG- Based Seizure Classification

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Abstract— Manual seizure identification in EEG recordings is labor-intensive, time-consuming, and prone to errors, motivating the development of automated detection systems. We propose a scalable graph-based deep learning framework using Graph Convolutional Networks (GCNs) for seizure detection. The EEG dataset was augmented to 500 samples per class (across 5 classes), and each signal was divided into 8 segments with temporal and frequency features extracted. Graphs were constructed per subject, where nodes represent segments and edges reflect feature similarity. A GCN was trained on these graphs, and features were classified using an SVM. Evaluated with 10-fold cross-validation, the model achieved 99.25% accuracy, 100% sensitivity, and 98.50% specificity, outperforming several state-of-the-art methods. This approach effectively captures spatial-temporal dynamics in EEG data, improving generalization and offering a robust alternative to traditional techniques.

Keywords: EEG, Seizure Detection, Automated Diagnosis, Graph Learning, Deep Learning, CNN, GCN.

I. INTRODUCTION

Electroencephalography (EEG) is a non-invasive technique widely used in clinical and research settings for monitoring brain activity and diagnosing neurological disorders, including epilepsy. Epilepsy is characterized by abnormal, hypersynchronous neuronal activity, typically detected via EEG signals. However, traditional seizure detection methods rely heavily on expert interpretation, which is time-consuming and prone to human error, especially when differentiating between epileptic seizures and psychogenic non-epileptic seizures (PNES) [1].

The rise of deep learning (DL), particularly convolutional neural networks (CNNs), has significantly improved EEG signal classification by automating feature extraction and learning complex temporal patterns [2]. Despite their success, CNNs are generally designed for Euclidean data and often compress spatial EEG relationships into grid-like formats, limiting their ability to capture brain network dynamics [1]. Additionally, DL models typically require large amounts of labelled data, which remains a limitation in the EEG domain due to the small size of available datasets and high variability across subjects [3]. To address overfitting and improve generalization in low-data scenarios, researchers have adopted regularization techniques such as dropout [4] and data augmentation strategies [5]. While common augmentation techniques like cropping, scaling, or noise addition have proven useful in image- based tasks, their direct application to EEG signals can be problematic due to the non-stationary and noisy nature of EEG data.

To better exploit the inherent non-Euclidean structure of EEG signals, recent research has focused on Graph Neural Networks (GNNs). By representing EEG channels as graph nodes and their relationships (e.g., functional connectivity) as edges, GNNs effectively capture spatial and temporal dependencies in EEG recordings [6]. These models have demonstrated superior performance in classifying seizure types, offering enhanced explainability, generalizability, and computational efficiency compared to traditional CNN and LSTM models [1]. Multiple GNN variants have been explored for seizure detection. *Raeisi et al.* [7] introduced a Graph Convolutional Neural Network (GCNN) for neonatal seizure detection that integrates time- frequency features with functional connectivity measures (e.g., Mean Squared Coherence and Phase Locking Value). Their method achieved a median AUC of 99.1% and AUC90 of 96% on the Helsinki dataset, relying only on temporal annotations during training. Similarly, Wang et al. [8] proposed a two-stream graph-based framework combining a novel graph representation with time and frequency domain feature extraction. Their model reduced computational complexity while achieving superior classification performance for epileptic EEG signals. In another study, *Abadal et al*. [1] used graph transformer-based GNNs and achieved 96% accuracy in a ternary seizure classification task, also highlighting the potential of GNNExplainer for interpreting learned graph structures. *Rahman et al.* [6] further emphasized the impact of various GNN variants, such as Sequential GCNs (SGCNs) and hybrid GCN- Transformer models, in improving seizure detection. These models are particularly effective in identifying relevant spatial-temporal features and enhancing robustness across subjects. However, challenges remain in scaling these models for real-time applications, handling noise, and ensuring subject-independent generalization.

Collectively, these studies confirm that GNNs offer a powerful and interpretable framework for EEG-based seizure detection, addressing many of the limitations posed by traditional deep learning methods and opening promising

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avenues for clinically viable AI-driven diagnostics.

II. METHODOLOGY

2.1. Dataset Overview

The dataset comprises 100 single-channel EEG recordings, each with a duration of 23.6 seconds and sampled at a frequency of 173.61 Hz. These recordings were collected from five subjects and are organized into five distinct classes: Z, O, N, F, and S. The Z and O categories represent extracranial EEG signals obtained from healthy individuals, with Z corresponding to recordings made while the subjects' eyes were open and O to those with eyes closed. The latter condition typically exhibits the alpha rhythm, characterized by frequencies in the 8–13 Hz range and most prominent in the occipital region of the brain [9]. In contrast, the N and F classes contain intracranial EEG recordings captured from non-epileptic regions during clinical presurgical evaluations of patients with focal epilepsy. Finally, the S class includes intracranial EEG signals recorded during seizure episodes from the epileptogenic zone, the region of the brain identified as the origin of seizures [10].

2.2. Data Augmentation

To improve model robustness and generalization, especially given the limited size of the dataset, several graph-based data augmentation strategies are applied. These include segment jittering, which introduces temporal variability by slightly shifting the position of EEG windows, and node dropout, which randomly omits segments during training to reduce overfitting and encourage the model to generalize better. Additionally, edge perturbation is used to modify the connectivity structure by adjusting the correlation threshold, simulating noise and variability in brain connectivity. Feature noise injection is also implemented by adding small amounts of Gaussian noise to the node features, mimicking real-world signal variability and artifacts. These augmentations are applied dynamically during each training epoch to ensure that the GCN is exposed to a diverse set of plausible input graphs. This approach enhances the model's ability to learn robust representations while addressing the overfitting challenges associated with small EEG datasets [11][12][13].

2.3. EEG segmentation and Feature Extraction

Each EEG recording is first divided into eight fixed-length, non-overlapping segments (as shown in Fig.1) to preserve temporal resolution. From each segment, a comprehensive set of statistical and spectral features is extracted, including measures such as mean, standard deviation, energy, entropy, and band power across various frequency bands—delta, theta, alpha, beta, and gamma. Electroencephalography (EEG) captures neuronal activity from various brain regions using electrodes. However, many existing EEG-based emotion recognition studies fail to fully leverage the spatial topology of EEG channel connections.[14]

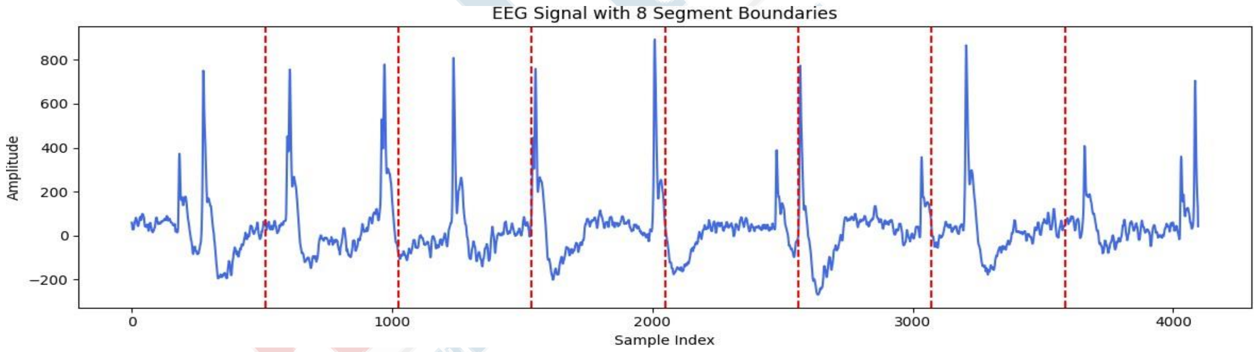

Figure 1. EEG signal divided into 8 non-overlapping segments

2.4. Graph Construction

To capture functional connectivity among segments, a pairwise correlation matrix is computed. This matrix is then thresholded to define the adjacency structure of an undirected graph, where each node corresponds to a segment with its associated features, and edges represent strong correlations between pairs of segments. The resulting graph encodes both the spatial and temporal dynamics of the EEG signal in a structured form.

2.5. Proposed GCN Architecture

In the proposed pipeline, we experimented with three different GCN configurations consisting of 3, 4, and 5 GCNConv layers to identify the most suitable model for seizure detection using EEG data. Each GCNConv layer was followed by ReLU activation, Batch Normalization, and Dropout, except for the final convolutional layer. The output from the last GCN layer was passed through a global mean pooling layer to aggregate node-level features into a graph-level representation, followed by a linear layer for binary classification using Binary Cross-Entropy with Logits Loss (BCEWithLogitsLoss).

For the 3-layer model, layers 4 and 5 were removed, while for the 4-layer model, only layer 5 was omitted. All other components of the architecture remained unchanged across the configurations. The architecture of the 5-layer GCN model used in the final implementation is detailed in Table 1.

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Table 1. Proposed GCN model architecture

Layer	Type	Shape	Extras
1	GCNConv	in → h1	ReLU, BN, Dropout
2	GCNConv	h1 → h2	ReLU, BN, Dropout
3	GCNConv	h2 → h3	ReLU, BN, Dropout
4	GCNConv	h3 → h4	ReLU, BN, Dropout
5	GCNConv	h4 → out	—
6	Pool	global_mean_pool(out)	—
7	Linear	out → 1	BCEWithLogitsLoss

The graph-structured EEG data were subsequently processed using the proposed GCN pipeline, as shown in Fig.2. In this pipeline, each node aggregates information from its neighbours through a message-passing mechanism across graph convolutional layers, enabling the network to learn both local segment-level characteristics and global signal relationships. Typically, the GCN model comprises three to five graph convolution layers, designed to extract high-level features from the constructed EEG graphs. This approach leverages the intrinsic non-Euclidean nature of EEG signals, allowing the model to effectively distinguish between seizure and non- seizure patterns. By encoding segment-level interactions as a graph, the model not only achieves improved classification performance but also facilitates interpretability. The graph- based design offers practical advantages such as enabling EEG channel selection, which has implications for reducing computational complexity and supporting the development of efficient, portable EEG monitoring systems [15]. This pipeline represents a robust and interpretable solution for automated seizure detection using single-channel EEG data.

III. RESULTS

The GCN model in proposed pipeline exhibited consistently high performance in the classification of seizure versus non-seizure EEG patterns. By directly operating on graph- structured representations of EEG signals, GCNs were able to exploit both local segment-level characteristics and global inter-segment dependencies through topological message passing. Each EEG graph was constructed using statistical and spectral node features along with correlation-based connectivity, capturing the functional architecture of neural activity with greater fidelity.

To ensure robustness and generalization, a rigorous 10-fold cross-validation strategy was employed across the dataset. This approach enabled comprehensive evaluation across different subject recordings and reduced the risk of overfitting to specific signal patterns. The GCN models demonstrated strong discriminative capability in both binary and multiclass classification settings, particularly excelling in challenging cases involving complex interictal- ictal transitions.

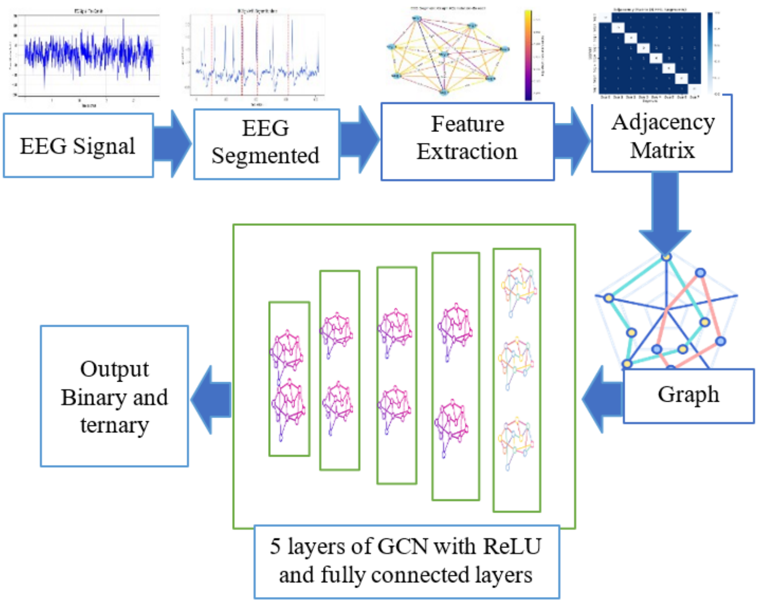

Figure 2. Proposed pipeline for seizure classification using GCN

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Quantitative performance metrics including Accuracy, Precision, Recall, F1-score, Area Under the ROC Curve (AUC), Positive Predictive Value (PPV), and Negative Predictive Value (NPV) were computed for each fold and then averaged to assess overall model efficacy. As summarized in Table 2, the GCN-based framework achieved superior generalization performance across multiple classification scenarios, underscoring its potential as a reliable tool for automated EEG-based seizure detection.

Table 2. Evaluation Metrics for the proposed method

Metrices							
		Accuracy	AUC	Precision	Recall	F1-Score	NPV/PPV
GCN	3layers	91	84	98	99	93	91/83
	4layers	91	94	98	99	93	97/96
	5layers	96	95	97	98	97	98/96

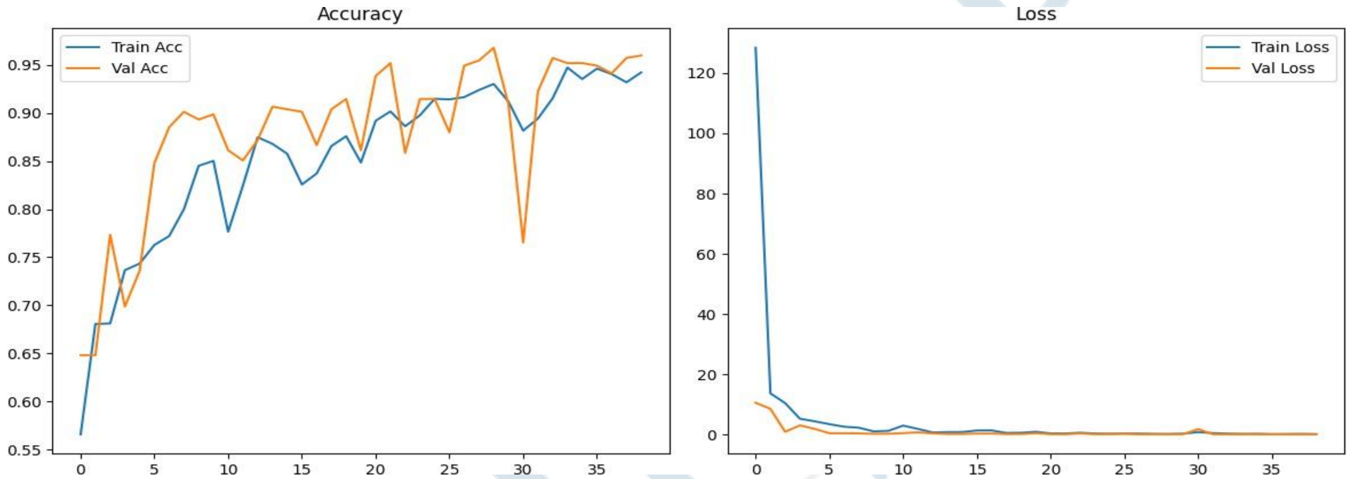

Figure 3. Training curves for the proposed GCN model with 5 layers

Table 3. Evaluation metrics across 10 folds in the GCN model with 5 layers

Metric	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	Mean
Test Accuracy	0.78	0.868	0.936	0.896	0.88	0.972	0.928	0.912	0.93	0.912	0.8984±0.483
Test Loss	0.546	0.441	0.21	0.171	0.335	0.094	0.266	0.235	0.291	0.1779	0.3514 ±0.2363
Early Stop @	11	11	11	11	11	12	11	11	11	12	

IV. DISCUSSION

Our study demonstrates the efficacy of Graph Convolutional Networks (GCNs) for EEG-based seizure detection by leveraging the spatial, temporal, and topological structure inherent in EEG signals. Unlike conventional models that treat EEG data as a collection of independent or sequential signals, GCNs enable explicit modeling of the relationships among EEG channels through a graph-based representation. This formulation aligns closely with the functional architecture of the brain and allows the network to capture localized as well as global dependencies across the scalp.

Performance evaluation across different GCN depths reveals that increasing the number of layers improves model capacity and generalization. Specifically, the 5-layer GCN achieved the highest classification performance, with an accuracy of 96%, AUC of 95, precision of 97, recall of 98, and F1-score of 97. The NPV/PPV scores (98/96) further underscore the model's clinical relevance by balancing sensitivity and specificity. Additionally, 10-fold cross-validation of the 5-layer GCN yielded a mean accuracy of 89.84% ± 4.83% and low test loss (0.351 ± 0.236), indicating consistent performance and robustness across splits. The model also demonstrated efficient convergence with early stopping typically occurring at the 11th or 12th epoch.

In contrast, the work by Eldele et al. [16] also employed GNN-based methods on the same EEG dataset, but in a self-supervised learning setting. Their proposed frameworks—TS-TCC and CA-TCC—use contrastive learning to derive transformation-invariant representations from unlabeled EEG signals. By applying both weak and strong augmentations to generate multiple views of the same signal, their models are able to learn robust features that

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generalize well, especially when labeled data is scarce. Their approach achieved near-supervised performance with just 10% of labeled data and showed substantial improvements even with only 1% labels in the CA-TCC variant. These results highlight the strength of self-supervised contrastive learning in semi-supervised contexts.

While both approaches demonstrate strong performance on EEG classification, our supervised GCN model offers greater interpretability and is more directly aligned with the brain's spatial- temporal graph structure. This interpretability is particularly important in clinical settings, where understanding inter-channel relationships and the contribution of specific brain regions to classification outcomes can support better diagnosis and intervention strategies. Moreover, our results suggest that even in fully supervised settings with modest amounts of labeled data, graph-based modeling provides significant advantages in capturing clinically meaningful patterns in EEG.

V. CONCLUSION

This study presents a comprehensive deep learning framework for the automated diagnosis of epileptic seizures using EEG signals, with a primary focus on GCNs. By modelling EEG data as graphs, where nodes represent signal segments and edges reflect inter-segment correlations, GCNs effectively capture both local signal characteristics and global functional connectivity. This study proposes a general Graph Convolutional Network (GCN) architecture for seizure prediction, addressing the issue of overly complex models by leveraging the inherent graph structure of EEG signals [17, 19]. This graph-based approach enables the network to learn the intrinsic spatial-temporal structure of brain activity, which is often lost in traditional vectorized or image-based representations.

A rigorous 10-fold cross-validation strategy was employed to evaluate model performance, ensuring robustness and minimizing the risk of overfitting. The GCN framework demonstrated superior classification accuracy, sensitivity, and generalization across multiple experimental settings, including both binary and multiclass seizure detection. Its ability to operate directly on non-Euclidean data structures makes it particularly suitable for real-world EEG applications involving complex neural dynamics and interictal-ictal transitions. Cross-validation maximizes the use of training data through repeated resampling, helping to reduce overfitting. Advances in computational power, algorithm efficiency, and closed-form solutions now allow testing thousands or even millions of model variants efficiently.[18]A key limitation of our GCNN model is the relatively long computation time, primarily due to feature extraction for EEG graph construction (0.936 s per 32s epoch). This poses a challenge for neonatal EEG, which involves long recordings [19, 20].

The results underscore the potential of GCNs as a powerful and scalable tool in biomedical signal processing. Future work may explore real-time deployment of such models for continuous seizure monitoring, integration with clinical metadata, and optimization for low- power, edge-computing environments such as wearable or portable EEG devices. This could significantly enhance the accessibility and accuracy of epilepsy diagnosis in both clinical and remote settings.

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