Network Machine Learning Report - Group 13

Elias Panner
elias.panner@epfl.ch
Sciper: 402620

Veit Weidinger
veit.weidinger@epfl.ch
Sciper: 404080

Manuel Westermann
manuel.westermann@epfl.ch
Sciper: 402357

Maximilian Spannring
maximilian.spannring@epfl.ch
Sciper: 403969

***Abstract*—This report describes the semester project of the Network Machine Learning course in spring semester 2025. In a group of four, we were exploring graph-based methods for epileptic seizure detection in EEG data. The used dataset comprises 75 patients from the Temple University Hospital EEG Seizure Corpus (TUSZ) with multiple EEG sessions per patient and 19 electrodes per measurement. We employed *EEGNet*, a convolutional neural network architecture specifically designed for processing EEG data, and extended it with a transformer to further improve the results. In addition to that, we tested *NeuroGNN* and *Bi-LSTM* for comparison. The final results show that *NeuroGNN* achieves the best overall performance on the validation set, whereas *EEGNet + Transformer* attains the highest accuracy on the test set.**

***Index Terms*—EEG analysis, epileptic seizure detection, machine learning, graph-based methods, GCN, GNN, EEGNet, Transfomer, NeuroGNN, Bi-LSTM.**

I. Introduction

Epilepsy is a widespread neurological disorder affecting approximately 50 million people worldwide, making it one of the most common neurological diseases globally. This condition causes significant human harm when not recognized early enough to initiate appropriate treatment, particularly as delayed diagnosis can lead to preventable complications and reduced quality of life. Current clinical practice relies heavily on manual electroencephalogram (EEG) analysis, a process that typically requires 2-4 hours per recording session for trained neurologists to complete. This labor-intensive approach creates substantial bottlenecks in clinical workflows and delays critical treatment decisions.

An electroencephalogram (EEG) provides continuous monitoring data and serves as the primary tool for tracking neuronal activity patterns associated with epileptic seizures. However, the complexity and volume of EEG data present significant challenges for manual interpretation. Automated detection systems have the potential to reduce diagnosis time, representing a transformative opportunity to improve patient outcomes while reducing clinical burden. Current automated analysis approaches for EEGs range from traditional signal processing techniques such as Fourier transformations and wavelet decompositions to modern deep learning architectures including recurrent neural networks (RNNs) and transformers.

Li et al. [3], Abadal et al. [4], as well as Tian and Zhang [5], among many others, have demonstrated the practicability and effectiveness of employing Graph Neural Networks (GNNs) for epilepsy detection in their work. These graph-based approaches show particular promise for capturing the complex spatial and temporal relationships inherent in multichannel EEG data. Thus, this project investigates the interpretability and performance of graph-based methods for EEG seizure detection through a comprehensive comparison of graph neural networks (GNNs) with conventional, non-graph-based approaches.

II. Background

A. EEGNet [1]

EEGNet is a compact convolutional neural network architecture designed specifically for processing EEG signals.

Initially, the model implements a set of 2D convolutional filters along the time axis. The filter length is set to half the sampling rate of the data. The resulting feature maps represent the EEG signal at various bandpass frequencies. Next, depthwise convolution is used to learn spatial filters for each temporal filter. This enables the extraction of frequency-specific spatial features. Batch normalization is applied along the feature map dimension, followed by an exponential linear unit (ELU) to introduce nonlinearity into the model.

Subsequently, the model uses a separable convolution, consisting of a depthwise convolution followed by pointwise convolutions. This allows the network to learn to summarize individual feature maps over time and combine them optimally.

B. EEGNet + Transformer [2]

This method extends the EEGNet architecture with a transformer module, to capture long term sequential information. The transformer treats each feature map from the separable convolution as an input token, where the embedding dimension is equal to the feature map dimension. To encode positional relationships, the model adds a learnable token at the beginning of each temporal feature map. The resulting embeddings are then passed through a transformer decoder.

C. NeuroGNN [6]

NeuroGNN is a dynamic GNN framework that dynamically constructs graphs to encapsulate evolving spatial, temporal, and semantic information between EEG electrodes and brain regions. The generated NeuroGraph is passed through a GNN block to update the node embeddings. Subsequently, the information is aggregated through hierarchical pooling, prior to the implementation of a Multi-Layer Perceptron (MLP) for detection.

The node feature generation consists of a temporal and semantic stream, which are concatenated to create the node feature matrix. The temporal stream aggregates the information from the electrodes to six meta regions. Subsequently, the additional channels are concatenated to the input channels. The updated representation is next passed through a bidirectional gated recurrent unit (BGRU). The final representation is composed of the concatenated hidden states from the forward and backward passes. The semantic stream captures the relationship between nodes and meta nodes using a language model. Given a set of textual descriptions, the language model outputs an embedding vector that is used as a semantic embedding.

The node adjacency matrix is generated by fusing the semantic and temporal embeddings with the pairwise euclidian distance of the electrodes. The semantic similarity is calculated using a cosine similarity function on the determined semantic embeddings. To determine the spatial similarity, the following procedure is undertaken: first, the Euclidian distances among the EEG-electrodes are calculated; second, the average distances between meta node pairs and meta nodes with normal node pairs are determined. Then, a Gaussian kernel with a thresholding is applied to calculate the similarity scores. The temporal embeddings are passed through a multi-head attention layer, creating temporal similarities.

The combination of the semantic and spatial similarities is given as:

$$S_{Gate} = (1 - \alpha)S_E + \alpha S_D$$

where α is a learned parameter, $\alpha \in [0, 1]$. The result is than combined with the temporal similarities through an element-wise dot-product.

$$S' = S_{Gate} \odot S_t$$

Afterwards, thresholding is applied to S' to get the final adjacency matrix.

III. Method

A. Data

We utilized a subset of the Temple University Hospital EEG Seizure Corpus (TUSZ) [9] comprising data from 75 patients (50 for training, 25 for testing). The dataset contains continuous EEG recordings sampled at 250 Hz from 19 electrodes positioned according to the 10-20 system. EEG signals, measured in mV, were segmented into non-overlapping 12-second windows and labeled as either normal brain activity or seizure episodes for supervised learning. We are using a ratio of 80% of the labled data for training and 20% for validation. We observed a class imbalance in the dataset: Out of 12993 training data points, 10476 described non-seizure data while 2517 described seizures. This is illustrated in Figure 1.

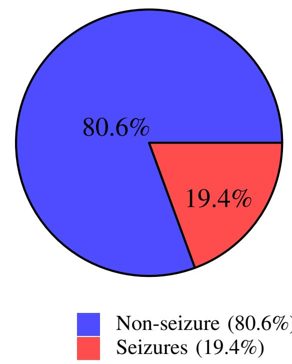

Fig. 1. Training dataset shows severe class imbalance with seizures representing less than 20% of samples

B. EEGNet + Transformer

We decided to implement EEGNet followed by a transformer, as this model is a lightweight design with fewer parameters, intended for mobile applications. The model could therefore potentially be better trained given the limited amount of training data.

To evaluate further improvements, we implemented an efficient channel attention (ECA) [12] block, that is applied consequatively to the EEGNet, but before the transformer. This block implements a lightweight attention block, aiming to enrich the learned represenions. The combination of EEGNets with ECA has first been introduced by [8], but without subsequent transformer.

C. Graph-based approaches

A downside of CNN based approaches is, that they neglect the spatial and functional relationships between the electrodes. [7] Therefore, we decided to evaluate GNNs, which could capture the relationship between the electrodes better.

We implemented a Graph Convolutional Network, followed by a bidirectional LSTM. The adjacency matrix is constructed using the Euclidean distances between the electrodes.

However, this approach only captures the spatial relationships between the electrodes, but ignores the temporal and semantic correlations. This fundamental limitation is addressed by NeuroGNN, which combines the information from all three domains to create a dynamic NeuroGraph.

IV. Results

A. Metrics

In order to determine the success of our models, we used four different metrics - accuracy, precision, recall and F1-score. [11]

- Accuracy is defined as

$$\frac{true\ positives + true\ negatives}{all\ classifications},$$

describing the number of currect classifications. It is heavily influenced by class distriution. This is important for our evaluation as our training data set is quite imbalanced. III-A

- Precision is defined as

$$\frac{true\ positives}{true\ positives + false\ positives},$$

determining, how many predictions out of all positive ones were correct.

- Recall is defined as

$$\frac{true\ positives}{true\ positives + false\ negatives},$$

descibing how many positive our model actually catched.

- F1-score is defined as the harmonic mean between precision and recall:

$$2\frac{recall \cdot precission}{recall + precission}.$$

There exists also a more general F_β-score that applies weights, valuing either precision or recall more than the other.

Since we do not want to miss seizures under any circumstance, a high recall is more important than the precission.

B. Validation Results

TABLE I
VALIDATION METRICS OF THE THREE DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1-score
NeuroGNN	0.90458	0.86119	0.60437	0.71028
EEGNet + Transf.	0.87803	0.75833	0.54274	0.63268
GCN + Bi-LSTM	0.86615	0.70968	0.52381	0.60274

By comparing the three different models on the validation data split, we observed that *NeuroGNN* is the overall best performing model, archieving the highest scores across all considered metrics. The recall (0.60437) however still resides in a modest area, meaning that around 40 percent of true positives are missing. We see that *NeuroGNN* archieves a good balance between detecting true positives and avoiding false positives, as indicated by the precision score.

EEGNet + Transformer has a lower F1-score (0.63268) and a lower recall (0.54274) with a solid precision (0.75833), meaning that the model is rather conservative and only finds around half of the positives. However, its accuracy (0.87803) is rather high and nearly on the same level as *NeuroGNN*, indicating that the model is still a valid option when weighing the avoidance of false positives higher than detecting all positives.

For *GCN + Bi-LSTM*, we obtained the lowest F1-score (0.60274) with inferior scores for precision (0.70969) and recall (0.52381), only the accuracy (0.86615) is on a promising level. Overall, this means that the model detects less true positives and more false positives.

C. Hyperparameter optimization

We conducted parameter sweeps to further optimize the performance of the EEG-Net in combination with the transformer model. Figure 2 shows the validation accuracy for selected hyperparameter configurations. In the conducted sweeps, adjustments were made to the kernel size and the number of filters for the initial convolutional layer. This layer performs a bandpass filtering of the input to extract frequency features. [1] Therefore, an increase in the number of filters results in an increase in the number of extracted features. Suprisingly, the algorithm becomes very unstable for 128 feature maps with a kernel of size 32. However, it has been demonstrated that increasing the kernel size by a factor of two can mitigate this effect.

D. Efficient Channel Attention

While enriching the learned representation, we noticed that efficient channel attention is not increasing the validation accuracy. A possible reason for this is, that the channel already contain a strong representation through the CNN-Layers.

E. Test Results

TABLE II
TEST ACCURACY FOR THE THREE MODELS, DETERMINED BY THE KAGGLE BOARD

Model	Test Accuracy
NeuroGNN Public	0.74754
NeuroGNN Private	0.49152
EEGNet + Transf. Public	0.82944
EEGNet + Transf. Private	0.81803
GCN + Bi-LSTM Public	0.80584
GCN + Bi-LSTM Private	0.7288

Looking at Table II, we observe significant differences in model generalization. The NeuroGNN model exhibits severe overfitting with accuracy dropping from 74.75% to 49.15%, approaching random performance on the private dataset. We also observe that the performance is worse than indicated in the original paper. [6] Possible reasons for this might be a larger split in the training data in the original model and/or optional pre-training steps with self-supervised learning.

In contrast, the EEGNet + Transformer architecture demonstrates excellent generalization with minimal performance degradation from 82.94% to 81.80% (1.1 percentage points), while GCN + Bi-LSTM shows moderate overfitting (7.7 percentage point drop). The severe overfitting in NeuroGNN likely stems from its complex multi-context architecture learning dataset-specific correlations rather than generalizable seizure patterns, whereas the simpler EEGNet + Transformer approach learns more robust features. From a clinical deployment perspective, EEGNet + Transformer emerges as the most reliable candidate due to its consistent performance across datasets.

V. Conclusion

Our experiments have shown, that its possible to detect seizures with a high accuarcy. However the generalization to new patients still remains an active challenge. While NeuroGNN achieved superior validation performance (90.46% accuracy, 0.71 F1-score), its severe overfitting on the private test set (accuracy dropping from 74.75% to 49.15%) demonstrates fundamental generalization issues. In contrast, EEGNet + Transformer shows good generalization to unseen patients. This consistency makes it the most suitable candidate for clinical deployment, where reliability across diverse patient populations and recording conditions is paramount. Our hyperparameter analysis revealed that certain configurations cause severe training instability, while the addition of Efficient Channel Attention provided no performance benefits.

This study demonstrates that in medical applications, sophisticated architectures do not guarantee superior real-world performance. Simpler, more robust approaches may be preferable for clinical deployment. While machine learning methods show promising results in EEG-seizure detection, the performance still needs to be improved to meet real-world certification standards.

References

[1] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," *Journal of Neural Engineering*, vol. 15, no. 5, p. 056013, Jul. 2018.

[2] Y. Zhu and D. Wang, "Automated Seizure Detection using Transformer Models on Multi-Channel EEGs," in *2023 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI) (IEEE BHI 2023)*, Oct. 2023, pp. 21.

[3] Z. Li, K. Hwang, K. Li, J. Wu, and T. Ji, "Graph-generative neural network for EEG-based epileptic seizure detection via discovery of dynamic brain functional connectivity," *Scientific Reports*, vol. 12, no. 1, p. 18998, Nov. 2022.

[4] S. Abadal, P. Galván, A. Mármol, N. Mammone, C. Ieracitano, M. Lo Giudice, A. Salvini, and F. C. Morabito, "Graph neural networks for electroencephalogram analysis: Alzheimer's disease and epilepsy use cases," *Neural Netw.*, vol. 181, p. 106792, Jan. 2025.

[5] C. Tian and F. Zhang, "EEG-based epilepsy detection with graph correlation analysis," *Front. Med.*, vol. 12, p. 1549491, 2025.

[6] A. Hajisafi, H. Lin, Y. Y. Chiang, and C. Shahabi, "Dynamic GNNs for Precise Seizure Detection and Classification from EEG Data," in *Advances in Knowledge Discovery and Data Mining*, J. C. W. Lin, J. W. Huang, J. Pei, V. S. Tseng, X. Xie, and D. N. Yang, Eds. Singapore: Springer, 2024, vol. 14648, pp. 16.

[7] A. Demir, T. Koike-Akino, Y. Wang, M. Haruna, and D. Erdogmus, "EEG-GNN: Graph Neural Networks for Classification of Electroencephalogram (EEG) Signals," arXiv:2106.09135 [cs.LG], 2021. [Online]. Available: https://arxiv.org/abs/2106.09135

[8] X. Wu, Y. Chu, Q. Li, Y. Luo, Y. Zhao, and X. Zhao, "AMEEGNet: Attention-based multiscale EEGNet for effective motor imagery EEG decoding," *Frontiers in Neurorobotics*, vol. 19, 2025.

[9] V. Shah, E. von Weltin, S. Lopez, J. R. McHugh, L. Veloso, M. Golmohammadi, I. Obeid, and J. Picone, "The Temple University Hospital Seizure Detection Corpus," *Frontiers in Neuroinformatics*, vol. 12, Nov. 2018. [Online]. Available: https://doi.org/10.3389/fninf.2018.00083

[10] Powers, David. (2008). Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation. Mach. Learn. Technol.

[11] Z.-H. Zhou, "Model Selection and Evaluation," in *Machine Learning*. Singapore: Springer Singapore, 2021, pp. 25–55. [Online]. Available: https://doi.org/10.1007/978-981-15-1967-3_2

[12] Q. Wang, B. Wu, P. Zhu, P. Li, W. Zuo, and Q. Hu, "ECA-Net: Efficient Channel Attention for Deep Convolutional Neural Networks," arXiv:1910.03151 [cs.CV], 2020. [Online]. Available: https://arxiv.org/abs/1910.03151

VI. Appendix

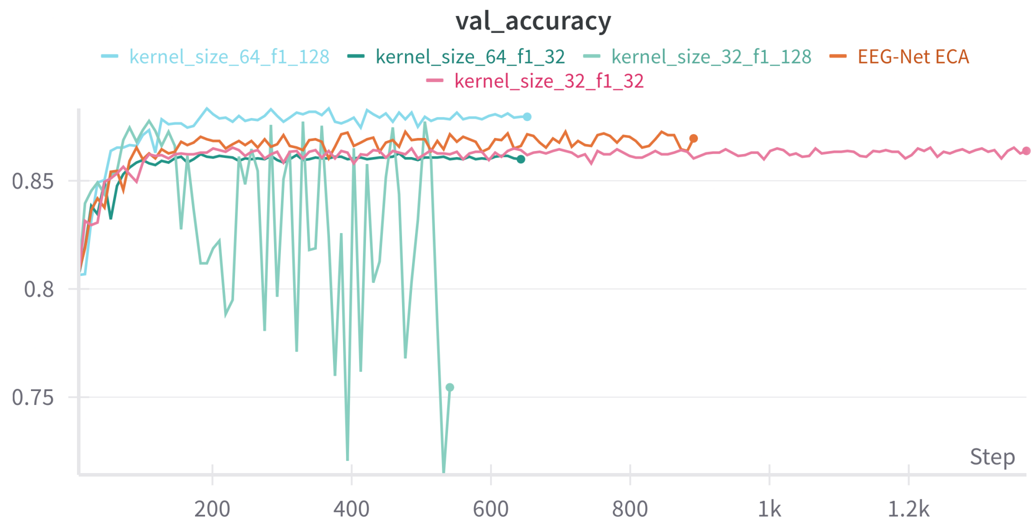

Fig. 2. Validation accuracy scores from different sweeps with the EEGNet + Transformer implementation. The swept parameters were kernel size, F1, and efficient channel attention(ECA).