NeuroGraph: Spatio-Temporal Graph Models for Wearable Seizure Forecasting

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Note: I'll use 'We' multiple times in this proposal as it's natural and accepted in research works and papers, but really, I'm mentioning myself.

Abstract. Seizures are well-known as volatile neurological episodes where the individual experiencing the episode faces a period of delirium, confusion, and even loss of consciousness. While Electroencephalography (EEG) remains the gold standard for monitoring, the transition from a normal state of neurological activity (interictal) to that of a seizure (ictal) state involves complex, non-linear shifts in neurological connections that are incredibly challenging to detect in real-time. We introduce NeuroGraph, a novel framework that treats the brain as a dynamic topological structure rather than a static structure. By implementing Spatio-Temporal Graph Neural Networks (ST-GNNs), we capture the connectivity between channels over time, along with the first reinforcement learning (RL) agent to introduce personalized thresholding. NeuroGraph achieves high-sensitivity forecasting results up to 30 minutes in advance (pre-ictal state). Evaluated on a subset of the MIT-CHB dataset, NeuroGraph achieves an accuracy of 90.7%, sensitivity of 90.2%, specificity of 90.8%, and AUC-ROC of 0.96, in a forecasting task to detect seizures 30 minutes in advance. The model also preserves the result under a 1.6x parameter reduction, while maintaining a cosine similarity within weight matrices of 0.9993, which demonstrates and validates the potential of deploying a complex graph-based deep learning model on resource-constrained wearable hardware.

Idea. Unlike traditional approaches to treat the brain as a set of 22 isolated sensors observing an event. We differentiate from this standard by treating the brain as a dynamic graph where the 'edges' (connections) between brain regions are just as important as the actual signals being

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reported. By learning how the brain's topological structure changes over time, we can detect the pre-ictal state before physical symptoms.

1. **Problem**: Seizure prediction tasks have the goal to distinguish interictal and preictal EEG segments with sufficient buffers to enable intervention early. However, this problem is multifaceted.

- Standard deep learning models treat EEG channels independently or assume spatial relationships to be insignificant. Recent literature resolves this issue and showcases that including some synchronization feature for all the recorded EEG channels is necessary to push the field forward
- Generic or low-dimensional models fail to account for the variability present between different patients. Something that is a 'normal' neurological spike for one person may be the exact neurological activity of someone else's seizure
- Graph Neural Networks (GNNs) are the intuitive approach given the medium of the data. However, GNNs are inherently expensive computationally due to the depth of the network, and the cost to evaluate repeated node connections (i.e., for an n-node graph, the number of interactions is (n)(n+1)/2). So while they may achieve high state-of-the-art results, these models aren't effectively usable for wearable microcontrollers or edge AI inference applications.

2. **Current Work**: Qiu et al. (2023) introduced LightSeizureNet, which addresses the real-time seizure detection problem by classifying interictal vs ictal EEG recordings using an ultra-lightweight Convolutional Neural Network (CNN), which they optimized for wearables. They had a clear interest in optimizing for and emphasizing efficiency

over long-horizon forecasting. In contrast, NeuroGraph targets the prediction problem from the very beginning by modeling preictal dynamics up to 30 minutes in advance using the spatio-temporal structure of the graph instead of relying upon purely local temporal convolutions. The authors of Saadoon et al. (2025) formulate seizure prediction as a feature classification problem rather than relying on fixed preictal windows. They use STFT (Short-Time Fourier Transforms), a powerful signal-processing technique that analyzes how a signal's frequency content changes over time. This makes it an ideal technique for non-stationary signals for audio or speech, or in this case, for EEG spectrograms. They also adopted channel-correlation features using a CNN and Support Vector Machine (SVM) ensemble. They achieve high accuracies of 96.12%, 94.89%, and 94.21% over preictal windows of 10, 20, and 30 minutes. However, their methods rely on handcrafted features. NeuroGraph eliminates this step by learning the inter-channel connections across all of the EEG channels via ST-GNNs and using an adaptive, reinforcement-learning thresholding process. Kim et al. (2025) demonstrate the feasibility of short-horizon seizure predictions (1-7 minutes before the episode) using ConvLSTM models on neonatal EEGs. They prioritize improving the short-term resolution of trends they find within the data over long-term data trends. NeuroGraph goes beyond short-term horizon forecasting by targeting the longer preictal state. Li et al. (2025) present Spatio-Temporal Attention Networks (STAN) by using the attention mechanics that Vaswani et al. (2017) presented. They achieve strong sensitivity results with low false-alarms. Prasanna et al. (2021) surveyed the limitations that they noted with traditional seizure detection pipelines that depend directly on handcrafted time, frequency, and nonlinear features, as well as patient-specific tuning. We note these challenges and address them in the engineering NeuroGraph. Ji et al. (2022) formulate seizure predictions as a graph classification problem, and show that GCNs (Graph Convolutional Networks) are capable of preserving EEG spatial information while having the capability to reduce model size and energy consumption. Wei et al. (2024) continue on this model archetype by introducing adaptive functional connectivity (AFC). They address patient heterogeneity with adaptive learning of functional connectivity graphs instead of using predefined matrices for these thresholds. They can achieve a strong performance without raising the complexity significantly. Xiang et al. (2025) incorporate synchronization metrics and spatio-temporal attention to learn time-variant EEG features. Li et al. (2021) propose a patient-specific framework to make sense of the hierarchical graph structure using frequency bands and a variant of semi-supervised active learning to infer optimal preictal temporal patterns. This research shows the variability of the seizure onset dynamics. Zhengdao Li et al. (2022) developed a Graph-Generative Neural Net (GGN), which focuses on seizure detection by generating dynamic functional connectivity graphs. With these graphs, they can emphasize the interpretability aspect of seizure patterns.

3. **Solution**: To address the limitations of prior methods, NeuroGraph introduces a unified framework that features three main parts: dynamic graph encoding to get relative spatial patterns, reinforcement learning to personalize sensitivity thresholds, and ARSVD - Adaptive-Rank Singular Value Decomposition, as outlined in Cherukuri & Lala 2025, Low-Rank Matrix Approximation for Neural Network Compression.

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I. NeuroGraph treats the brain as a shifting graph topology, so just a large set of nodes with edges of varying importance. Similarly, brain regions have periods of synchronization and desynchronization (Herweg et al., 2018). For every 4-second interval in the EEG data, the model calculates how 'synchronized' every pair of electrodes is. We use the Pearson Correlation Coefficient (r), which compares the linearity of two signals. So if electrode 1 and electrode 2 were to rise and fall together, their r would be approximately 1. If they do opposite actions, then it would be approximately 0. A fully connected graph, one where every node can communicate with all the others, is expensive. Because that creates n(n-1)/2 operations, if there are n nodes. To reduce the number of ops, we apply a Top-K filter, which keeps only K connections for each electrode (the strongest K). For our purposes, we keep k=4. This creates a clean, sparse map for the brain's most important communication pathways. Then Spatio-Temporal Learning comes into play. Where a Graph Attention Transformer (GAT) looks at this map, and doesn't just average all the signals; it learns to weight which nodes to pay attention to via the attention mechanism. This is done through training and using the data to develop these weights. The Temporal aspect is accomplished by combining this with a Temporal Convolutional Network (TCN) that basically watches a movie of all the graphs and how the graphs' weights change over time. It looks for a specific sequence of repetition that typically happens during that preictal state (30 minutes before a seizure for our test).

II. A major flaw in generic models is that there is a kind of 'one-size-fits-all' sentiment. NeuroGraph completely solves this problem by using a Deep Q-Network (DQN) agent. Instead of following a simple comparative that if the risk is > 50%, then to alarm that there is a seizure is imminent, the RL agent learns to act as a sort of smart gatekeeper. The agent observes the model's confidence in its predictions over time (this is the state), specifically with: current confidence, variance - how stochastic the signal is, rate of change - how fast the signal is escalating. The agent is trained via a standard reward system, where it gets punished heavily for missing a seizure (false negatives), as those are **significantly** more dangerous than marking an imminent seizure as a fake alarm (false positives). Over time, it learns a personalized policy network, so that for each patient, it can dynamically adjust the continuous function (sensitivity) to maximize safety.

III. The third aspect of this is the Adaptive-Rank Singular Value Decomposition method, where, for brevity, it uses spectral entropy to approximate the optimal rank to compress a weight matrix. Conventional SVD-based methods use a fixed-rank truncation through all of their layers. For all technical details of the method, find the paper below -

IEEE paper: https://ieeexplore.ieee.org/document/11193154

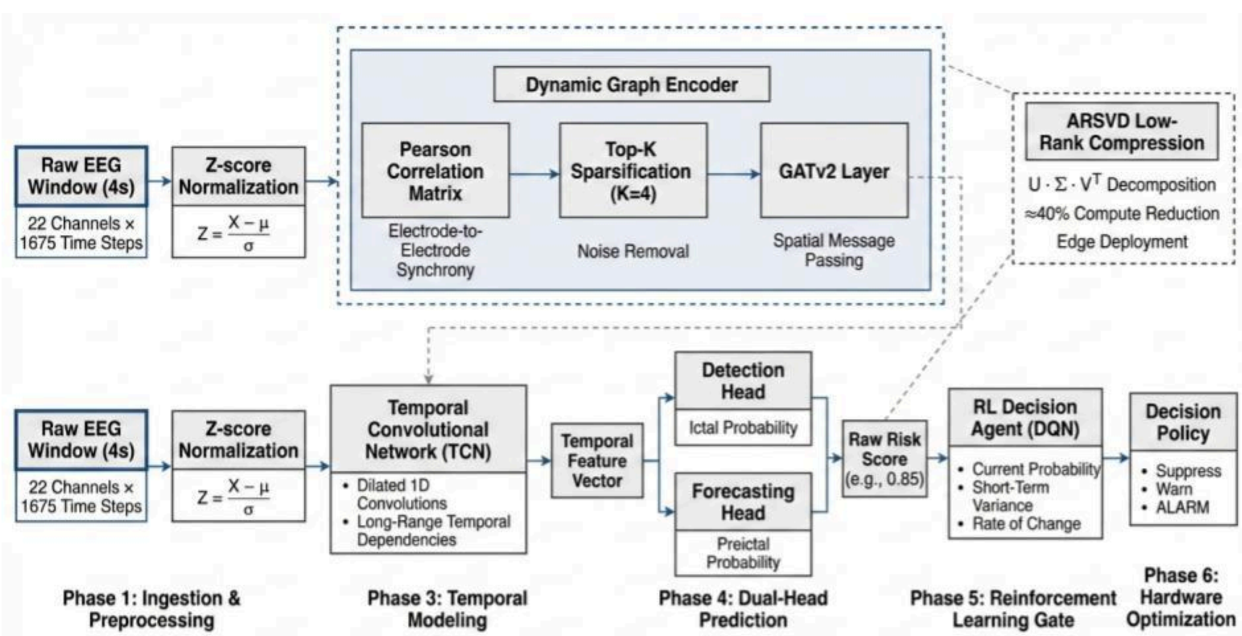

Figure 1: NeuralGraph end-to-end pipeline for dynamic EEG-based seizure detection and forecasting.

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Plan.

1. **Approach**: See Figure 1. The attention-based graph model was selected based on the results that were promising from STAN (Li et al. 2025). Temporal Convolutional Nets (TCN) are a natural choice as they use dilated convolutions to allow the model to have a larger 'history' window with a few layers, and is less prone to 'vanishing gradient' issues.
2. **Resources**: For the data, I utilized a subset of the MIT-CHB dataset, where the link can be found here. Regarding EEG signal processing and inference, I have a Raspberry Pi 4 board that I'll be using to run inference for the wearable processing. Along with institutional access to RTX 4060 and RTX 8000 compute to train the model.
3. **Goals**: To get a high-sensitivity result in predicting seizures at least 15 mins in advance, and achieve edge deployment with the EEG headset below. Then it would be to build an app to notify users live of imminent seizures, or if they're currently at risk of a seizure.
4. **Risks**: Electrode mismatches (the MIT-CHB dataset doesn't match), but the mitigation is to implement channel mapping, and noise with actual live data collection that can make it noisier than clinical settings, where we would need live filtering (i.e. Kalman Filters).

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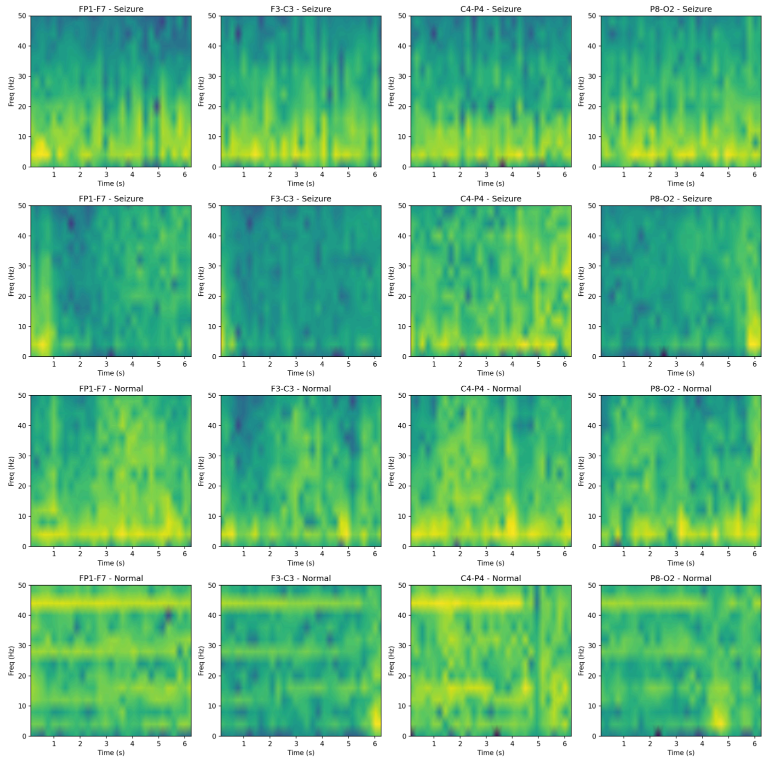

Figure 2. Time-frequency spectrogram visualizations of raw EEG signals from the MIT-CHB subset. Selected channels include FP1-F7, F3-C3, C4-P4, P8-O2. The top two rows depict Ictal states, with high-energy activity. The bottom two rows depict Interictal states, which have stable, lower-energy horizontal bands clearly visible, showcasing rhythms.

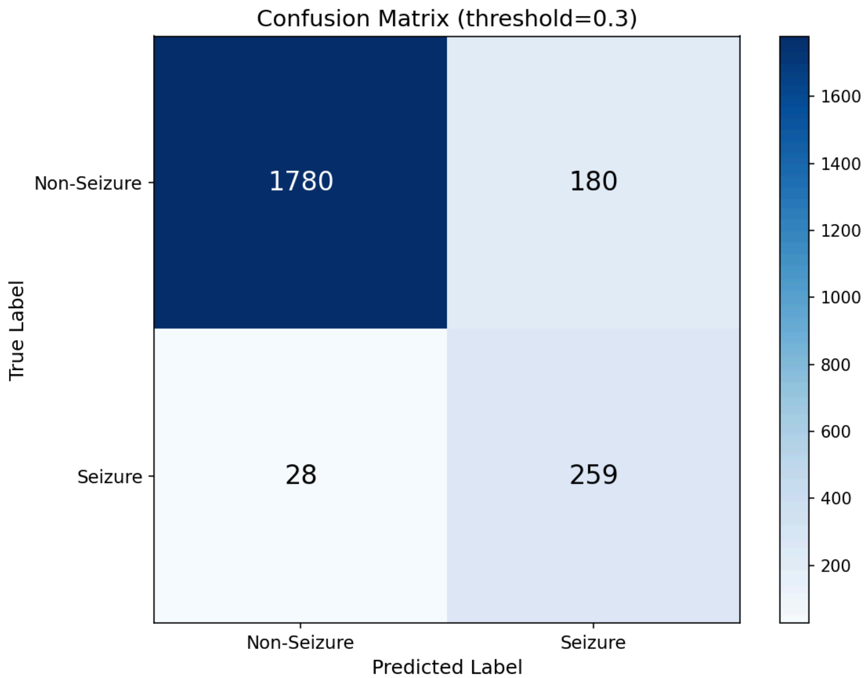

Figure 3. Confusion matrix. Out of 2247 test samples, the model achieved a sensitivity of 90.2%, correctly identifying 259 out of 287 seizure events. Crucially, there is a minimization of the dangerous cases (model predicts non-seizure, but there is a seizure) to only 28 cases.

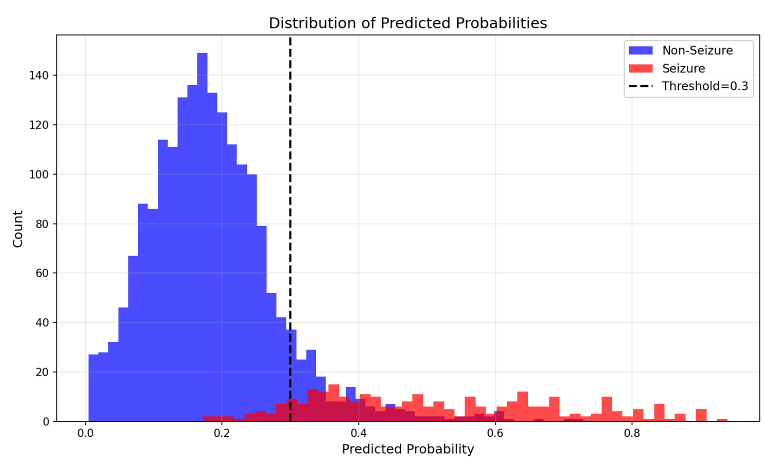

Figure 4. Histogram showing the distribution of the model's output probabilities for the test dataset. The blue distribution represents non-seizure samples, which are heavily concentrated

near 0.0, indicating the model is highly confident in identifying normal activity. The red shows the seizure samples that have a higher variance. The vertical dashed line is the RL decision threshold of 0.3.

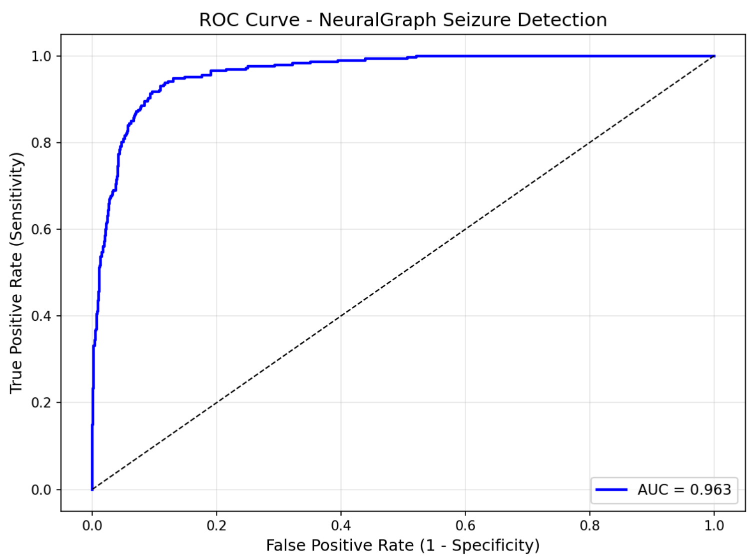

Figure 5. Receiver Operating Characteristic (ROC) curve, which illustrates a diagnostic performance of the NeuralGraph model on the held-out test set (80% train set, 20% test set). The Area Under the Curve (AUC) metric is 0.963, which indicates the model's exceptional performance in discriminating between the classes.

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