Predicting Seizures using Graph Neural Networks

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Introduction

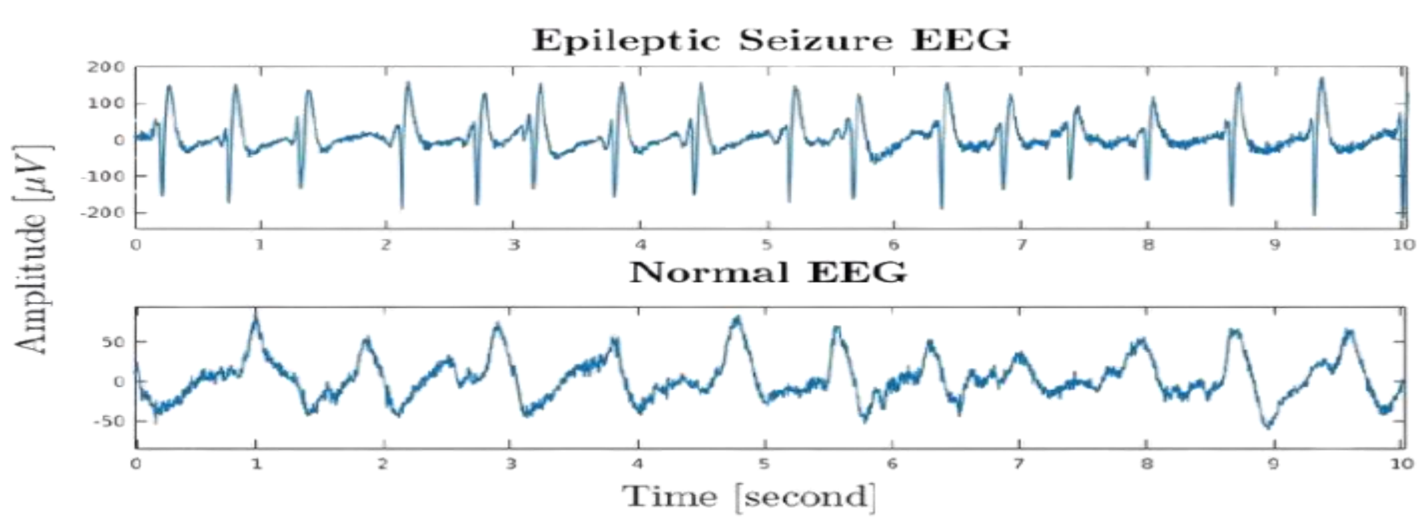
Background
•Seizures are unpredictable neurological events that can cause severe physical and cognitive effects.
•A major challenge in seizure management is the inability to accurately predict when a seizure will occur.
•Existing machine learning models lack the speed and accuracy necessary for real-time seizure prediction.

Objective
•Investigate whether **Graph Neural Networks (GNNs)** can enhance real-time seizure prediction.
•Explore if **combining different GNN models** can improve accuracy and reduce detection time.

Methods
•**Literature Review:** Analyzed existing GNN models to assess their strengths and limitations.
•**Mathematical Modeling:** Developed frameworks to determine effective GNN combinations.
•**Software Development:** Tested model combinations for improved seizure prediction.

Preliminary Findings
•Early results suggest that combining **two specific GNN models** enhances seizure prediction.
•This approach **reduces the time to detection**, making real-time intervention more feasible.
•Findings indicate that leveraging **complementary strengths of multiple GNNs** may improve prediction performance.

Significance
•Improved seizure prediction could lead to **better patient outcomes** by enabling faster medical interventions.
•This research highlights the potential of **GNN-based hybrid models** in neurological event forecasting.



Comparison of epileptic seizure EEG (top) and normal EEG (bottom), highlighting signal patterns in activity.

Methodology

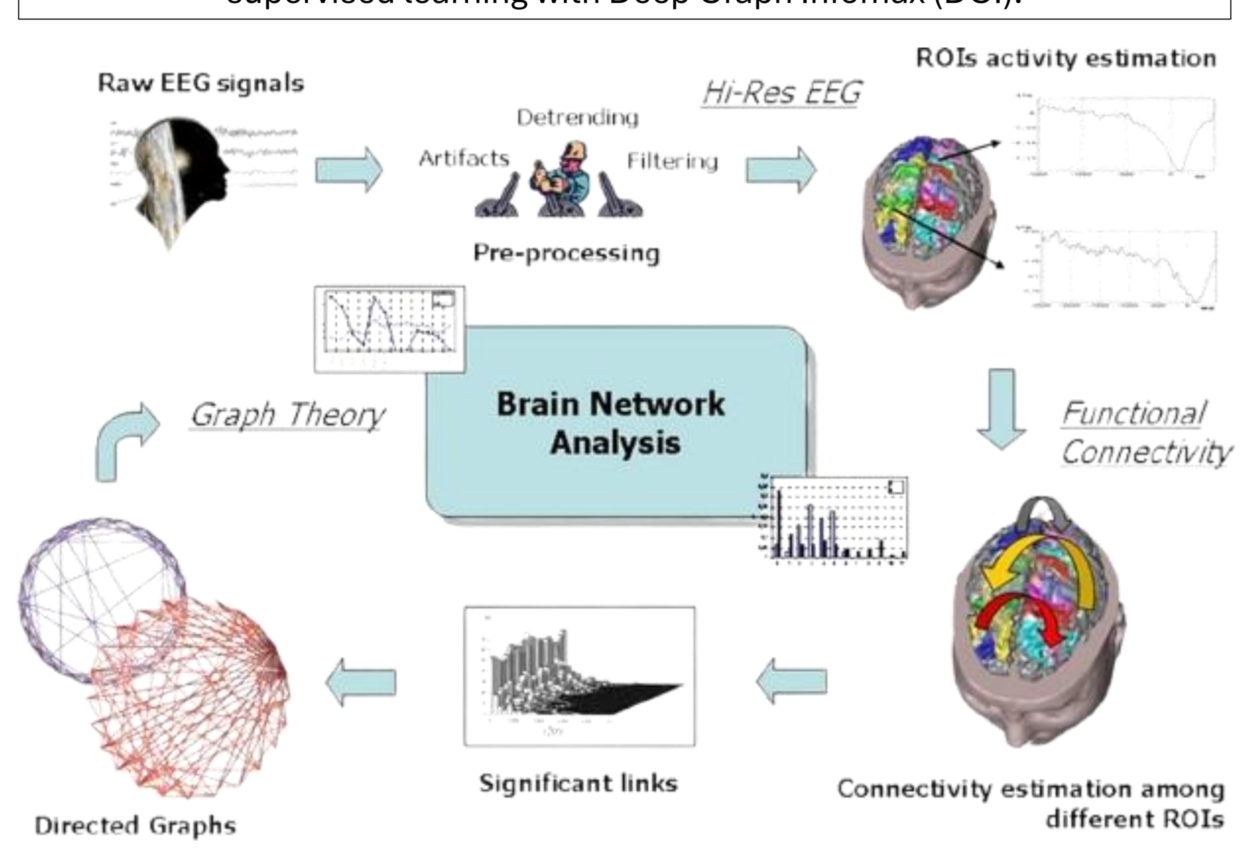
- *EEG data was obtained from a publicly available dataset, labeled for seizure and non-seizure recordings, and preprocessed to remove artifacts and noise.*
- *EEG signals were segmented into fixed time windows and transformed into functional brain networks, where nodes represent EEG channels and edges were based on Pearson correlation and mutual information.*
- *Multiple graph representations were generated over time to capture evolving brain activity.*
- *A novel neural network is being developed that integrates multiple GNN frameworks to improve seizure prediction.*
- *Deep Graph Infomax (DGI) is used for unsupervised learning of node embeddings, while another GNN-based temporal model enhances feature extraction.*
- *The goal is to fuse spatial and temporal features for improved prediction accuracy.*
- *The approach is refined through reviewing research papers, studying mathematical formulations, and testing different architectures.*

Preliminary Code

Preliminary Code.py > ...

```python
import torch
import torch.nn.functional as F
import networkx as nx
import numpy as np
from torch_geometric.nn import GCNConv, GATConv
from torch_geometric.data import Data

# 1. Construct EEG Graph (Nodes = EEG channels, Edges = functional connectivity)
def construct_graph(eeg_data):
    num_channels = eeg_data.shape[0]
    edges = []
    for i in range(num_channels):
        for j in range(i + 1, num_channels):
            correlation = np.corrcoef(eeg_data[i], eeg_data[j])[0, 1]
            if abs(correlation) > 0.5:  # Threshold for edge formation
                edges.append((i, j))

    edge_index = torch.tensor(edges, dtype=torch.long).t().contiguous()
    node_features = torch.tensor(eeg_data, dtype=torch.float)
    return Data(x=node_features, edge_index=edge_index)

# 2. Define Graph Neural Network for Seizure Prediction
class GNN(torch.nn.Module):
    def __init__(self, in_channels, hidden_channels, out_channels):
        super(GNN, self).__init__()
        self.conv1 = GCNConv(in_channels, hidden_channels)
        self.conv2 = GATConv(hidden_channels, out_channels)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = F.relu(self.conv1(x, edge_index))
        x = self.conv2(x, edge_index)
        return F.log_softmax(x, dim=1)

# 3. Train DGI (Self-Supervised Learning)
class DGI(torch.nn.Module):
    def __init__(self, encoder):
        super(DGI, self).__init__()
        self.encoder = encoder

    def forward(self, data):
        return self.encoder(data)

# Example usage
eeg_sample = np.random.rand(19, 100)  # Simulated EEG data (19 channels, 100 time points)
graph_data = construct_graph(eeg_sample)
model = GNN(in_channels=100, hidden_channels=32, out_channels=2)

output = model(graph_data)
print("Seizure Prediction Output:", output)
```

EEG-based seizure prediction using Graph Neural Networks (GNNs) and self-supervised learning with Deep Graph Infomax (DGI).



EEG processing pipeline for brain network analysis, transforming raw signals into functional connectivity graphs for seizure prediction.

Results

- *Preliminary experiments suggest that combining multiple Graph Neural Network (GNN) frameworks improves seizure prediction, with early tests on a publicly available EEG dataset showing that Deep Graph Infomax (DGI) with temporal modeling enhances spatial and temporal feature extraction.*
- *Initial evaluations indicate an accuracy in the mid-70% range, with F1-scores and AUC metrics showing improvements over single-GNN models.*
- *Several candidate algorithms blending these approaches have been developed, and ablation studies suggest improved seizure state classification.*
- *Results remain preliminary, with further testing on larger datasets and model refinement through hyperparameter optimization underway.*
- *Cross-validation and statistical analyses are planned to validate findings and determine the most effective approach for seizure prediction.*

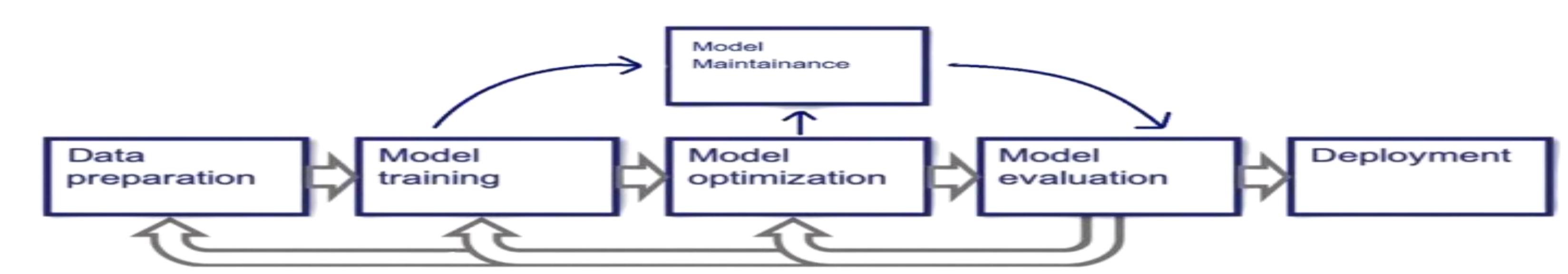


Illustration for the process of data preparation, model training, optimization, evaluation, and deployment

Conclusion

- Combining multiple Graph Neural Network (GNN) frameworks, particularly Deep Graph Infomax (DGI) with temporal modeling, enhances seizure prediction by capturing both spatial connectivity and temporal dynamics in EEG data.
- Early results show improved accuracy, F1-scores, and AUC metrics over single-framework models, demonstrating the potential for real-time seizure monitoring and clinical applications.
- Hybrid GNN models can better distinguish seizure from non-seizure states, aiding early intervention strategies and brain-computer interface technologies for epilepsy management.
- The next steps include refining model architecture, optimizing hyperparameters, and conducting cross-validation on larger datasets to ensure robustness.
- Expanding statistical analyses will help assess the real-world viability of this approach, aiming to develop a more accurate and reliable seizure prediction framework for improving patient outcomes.

Resources

Resources

- Tsy935. EEG-GNN-SSL: Graph Neural Networks for EEG-based Self-Supervised Learning. GitHub.
- Xu et al. (2021). Graph-based semi-supervised learning for seizure detection in EEG signals. arXiv.
- Xihaopark. Dynamic Graph EEG: A repository for dynamic graph-based EEG analysis using GNNs. GitHub.
- ScientificDirect. (2024). Neural Computation for EEG Analysis: Advances in Graph Neural Networks for Brain Dynamics

Special thanks to **Xihao Park from Osaka University** for providing valuable guidance on tackling complex material related to Graph Neural Networks and EEG analysis. Your insights have been instrumental in shaping our research approach and advancing our understanding of this challenging topic.