PROCEEDINGS

IWAIN 2024

International Workshop on Artificial Intelligence for Neurosciencie

Program Committee

Alejandro Maté (Spain)
Il-Yeol Song (USA)
Ana Lavalle (Spain)
Alejandro Reina (Spain)
Alex MH Kuo (Canada)
Natalia Albaladejo (Spain)
Matteo Mantovani (Italy)
Mario Piattini (Spain)
Elena Navarro (Spain)
Pascual González (Spain)
Antonio Fernandez-Caballero (Spain)
Nicolás Ruiz (Spain)
Plinio Morita (Canadá)
Eliana Pastor (Italy)
Jaime Lloret (Spain)
Ángela Nicolás (Spain)

Conference Chairs

Juan C. Trujillo
Rosario Ferrer

Program Chair

Miguel A. Teruel

Preface

We are delighted to present the proceedings of the 1st International Workshop on Artificial Intelligence for Neuroscience (IWAIN 2024), held on November 26, 2024, at the University of Alicante, Spain. This inaugural workshop brought together researchers and practitioners from the fields of artificial intelligence (AI) and neuroscience to explore the latest advancements, challenges, and opportunities at the intersection of these rapidly evolving disciplines.

The primary objective of IWAIN 2024 was to foster interdisciplinary collaboration, encouraging innovative approaches that leverage AI to enhance our understanding of the brain and to develop novel neuro-technologies. These technologies aim to aid in tasks such as monitoring, diagnosis, and data generation, among others. To demonstrate the potential of this intersection, the workshop featured a special theme on Attention Deficit Hyperactivity Disorder (ADHD), while also welcoming submissions addressing other neurological and psychiatric conditions, as well as various joint applications of AI and neuroscience.

The workshop's program included a diverse range of topics, reflecting the breadth and depth of research in this interdisciplinary field. Key areas of focus encompassed AI models and algorithms for neuroscience applications, machine learning and deep learning in neural data analysis, brain-computer interfaces (BCIs) and neuroprosthetics, neural encoding and decoding, computational neuroscience, AI-driven neuroimaging techniques, cognitive neuroscience and AI, neuroinformatics and data integration, ethical considerations in AI and neuroscience, and applications of AI in clinical neuroscience.

We were honored to have esteemed invited speakers who shared their insights and expertise, contributing to the rich discourse of the workshop. Their presentations provided valuable perspectives on the current state and future directions of AI and neuroscience integration.

We extend our heartfelt gratitude to the authors for their high-quality submissions, the program committee for their diligent reviews, and the organizing committee for their unwavering commitment to making this workshop a success. We also thank our sponsors, including the Generalitat Valenciana, for their generous support.

We hope that the research presented in these proceedings will inspire further exploration and collaboration at the intersection of AI and neuroscience, ultimately advancing our understanding of the brain and improving human health and well-being.

June 2018

Miguel A. Teruel

Program Committee Chair, IWAIN 2024

Graph Neural Networks in Action: Uncovering Patterns in EEG Time Series Data

Alex Romanova[1,*,†]

[1]Independent Researcher, 7117 Warbler Ln, McLean, VA, USA

Abstract

Understanding brain connectivity is critical for uncovering the mechanisms behind cognitive and behavioral processes. In this study, we introduce a novel approach using Graph Neural Network (GNN) Link Prediction models to analyze connectivity patterns in Electroencephalography (EEG) data. By representing brain regions as nodes and their interactions as edges, we construct graph-based representations grounded in the spatial relationships between EEG electrodes. This allows us to capture the inherent structure of neural interactions across different experimental conditions.

Our analysis focuses on EEG data from Control and Alcohol groups, revealing subtle yet significant connectivity changes linked to altered brain function. The GNN Link Prediction models uncover neural dynamics and connectivity variations that are often overlooked by traditional methods. These findings provide new insights into how brain connectivity differs under varying conditions and suggest possible compensatory mechanisms in disrupted networks.

This framework is not limited to EEG data but is adaptable to other time series datasets, offering a versatile tool for analyzing connectivity patterns and physiological dynamics. By bridging AI-driven graph modeling with neuroscience, our work provides a new methodology for studying brain connectivity and enhances our ability to interpret neural behavior in both clinical and research contexts.

Keywords

Graph Neural Networks (GNNs), Link Prediction, Electroencephalogram (EEG), Neural Connectivity, Time Series Analysis, Neural Dynamics, AI in Neuroscience, Brain Function

1. Introduction

Electroencephalography (EEG) is a widely used non-invasive neuroimaging technique that captures electrical activity in the brain, providing valuable insights into cognitive processes, mental states, and neurological disorders. By recording voltage fluctuations across the scalp, EEG allows researchers to monitor the real-time dynamics of brain activity, providing critical insights into how different brain regions coordinate to support cognitive functions such as attention, memory, and motor control. This makes EEG a key tool for analyzing neural connectivity and understanding how these interactions shape brain function.

Traditional approaches to analyzing EEG data have relied on machine learning and signal processing techniques such as feature extraction, spectral analysis, and classification models like Support Vector Machines (SVM) or Convolutional Neural Networks (CNN). While these approaches have achieved moderate success, they often fail to fully model the complex, non-linear, and long-range spatial and temporal dependencies that characterize EEG signals. This limitation arises because conventional methods typically process each EEG channel in isolation or as part of predefined groups, missing the subtle yet crucial interactions across the broader neural network. As these conventional models typically treat each EEG channel independently or as part of predefined groups, they often overlook the intricate connectivity patterns between channels, resulting in a loss of crucial information about brain network dynamics.

The graph-like nature of EEG data, where electrode positions can be represented as nodes and their interactions as edges, has led to the adoption of Graph Neural Networks (GNNs) for more sophisticated

2024 International Workshop on Artificial Intelligence for Neuroscience, November 26, 2024, Alicante, Spain
sparkling.dataocean@gmail.com (A. Romanova)
http://sparklingdataocean.com (A. Romanova)
0000-0002-5927-2129 (A. Romanova)

EEG analysis. GNNs offer a powerful advantage by learning how each EEG channel (represented as a node) interacts with its neighboring channels (edges), capturing the intricate spatial relationships across the brain and uncovering temporal dependencies that evolve over time. This ability to model both local and global connectivity patterns makes GNNs particularly effective in EEG applications, such as cognitive state monitoring, emotion recognition, and neurological disorder diagnosis, where understanding the dynamics of brain connectivity is key. Recent studies have demonstrated that GNN-based models can effectively model these patterns, revealing connectivity variations and providing deeper insights into neural activity compared to traditional methods.

This study uses the publicly available 'EEG-Alcohol' dataset from Kaggle [1], featuring EEG recordings from subjects exposed to visual stimuli. Subjects experienced either a single picture stimulus or two picture stimuli. In the two-stimulus trials, the images were either matched (identical) or non-matched (different). This dataset helps investigate the impact of alcohol on brain connectivity and cognitive processing.

In our earlier work, we analyzed this dataset using different methodologies to study the neural patterns. In the first study [2], we employed a combination of time series analysis, Convolutional Neural Networks (CNN), and traditional graph mining techniques to identify connectivity patterns. In the second study [3], we advanced this by using GNN Graph Classification models to classify entire brain-trial graphs, providing a more comprehensive view of the brain's functional network. Building on these prior analyses, our current study focuses on applying GNN Link Prediction to uncover dynamic connectivity patterns at the node and edge level.

In our previous study [2], we converted EEG time series signals into images using Gramian Angular Field (GAF) transformations, which were subsequently classified using CNN-based image classification techniques to distinguish between Alcoholic and Control groups. By applying transfer learning techniques from the fastai library [4], we improved pattern recognition capabilities. Our results demonstrated that the CNN model trained on GAF-transformed data achieved higher accuracy metrics compared to a model trained on standard EEG plot images. However, despite the improved classification performance, the analysis revealed that the single stimulus condition did not result in significant differences between the two groups, as reflected in the CNN classification outputs.

In addition to CNN classification, we constructed graphs for multiple brain trials using the cosine similarity of EEG signals to analyze connectivity patterns through graph clustering. The single stimulus condition consistently showed minimal differences in connectivity patterns between the Alcoholic and Control groups, both in CNN-based and graph-based analyses.

Figure 1 from that study illustrates how connectivity patterns were analyzed using traditional graph mining techniques, revealing stronger and weaker similarities between EEG positions. This analysis confirmed that single-stimulus trials were not effective for distinguishing between the two groups. In this study, we build upon these findings by employing GNN Link Prediction models to comprehensively explore connectivity patterns across all trials and subjects, aiming for a more detailed understanding of neural dynamics.

In a subsequent study [3], we employed GNN Graph Classification models to represent each person-trial as a small graph, where electrode positions were defined as nodes and EEG signals as node features. We applied cosine similarity matrices to identify highly connected node pairs and introduced virtual nodes to ensure that all graphs formed single connected components. This approach facilitated a high-level comparison of connectivity patterns between the control and alcohol groups, allowing us to capture subtle variations in connectivity via graph embeddings.

While the GNN Graph Classification models achieved high accuracy in distinguishing between control and alcohol groups, they encountered prediction challenges, particularly with single stimulus trials, where detecting meaningful connectivity differences proved difficult. Additionally, several small graphs from a control group subject were misclassified as alcohol, revealing the model's sensitivity to nuanced variations in connectivity patterns.

In contrast to our previous studies, which generated separate person-trial graphs using cosine similarity thresholds between EEG signals, the current study introduces a unified landscape-based graph using physical distances between EEG channels as the foundational structure. This unified graph,

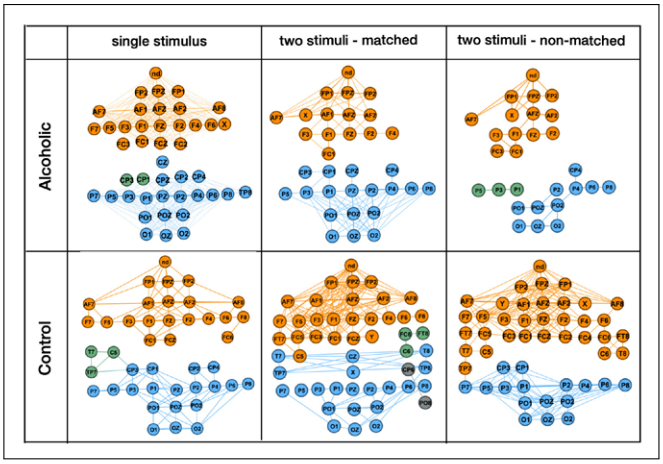

Figure 1: This figure from our previous study [2] shows how connectivity patterns were analyzed using traditional graph mining, revealing stronger and weaker similarities between EEG positions. We found that single-image trials were not effective for distinguishing Alcoholic and Control groups. In this study, we extend these findings by using GNN Link Prediction models.

where edges represent spatial relationships between electrodes, provides a consistent framework for analyzing brain-trial combinations, allowing for a more granular examination of connectivity at the channel position level.

In this approach, EEG signals from all trials are incorporated as node features within the unified graph, with each brain-trial configuration forming a subgraph of the larger structure. This setup captures both spatial and temporal dependencies in the EEG data, providing a robust foundation for analysis. The unified graph serves as input for the GNN link prediction model, which learns connectivity patterns at the node level. This comprehensive strategy allows us to detect subtle variations in connectivity and better understand how EEG signals differ across experimental conditions, offering insights that were previously not attainable with traditional methods.

By focusing on node-level analysis through the GNN link prediction models, this study provides a more detailed understanding of EEG connectivity patterns. The proposed method transforms EEG signals into high-dimensional embeddings, facilitating a deep exploration of spatial and signal-based relationships. Our new methodology uncovers complex interactions and connectivity variations, presenting a nuanced view of EEG dynamics that conventional techniques could not achieve.

The primary goals of this study are to:

- Develop a unified graph structure based on physical distances between EEG channels to ensure consistent analysis across all subjects and trials.
- Utilize GNN Link Prediction models to capture detailed connectivity patterns at the node level.
- Generate high-dimensional embeddings that reveal intricate spatial and signal-based relationships within the EEG data.
- Overcome the limitations of previous approaches by leveraging GNN Link Prediction models to uncover subtle connectivity variations, offering a more comprehensive understanding of EEG dynamics.

By concentrating on node-level analysis through GNN Link Prediction models, this study offers a more granular perspective on EEG connectivity patterns. Our approach transforms EEG signals into high-dimensional embeddings, enabling deeper exploration of spatial and signal-based relationships and revealing interactions that traditional methods could not fully capture.

2. Related Work

Graph Neural Networks (GNNs) have emerged as a transformative approach that bridges the gap between deep learning and graph-structured data, enabling sophisticated data analysis and relationship modeling. While traditional deep learning models like Convolutional Neural Networks (CNNs) demonstrated exceptional performance on grid-structured data, such as images [5], they are limited in capturing the intricate relational dependencies in non-Euclidean domains like graph data [6]. Similarly, graph-based methods excelled in processing structured relationships within knowledge graphs [7], but struggled to model temporal and spatial dependencies effectively. The evolution of GNNs has seamlessly integrated these strengths, facilitating the application of deep learning methods to complex graph-structured data and revolutionizing tasks such as node classification, link prediction, and graph classification [8]. This advancement has far-reaching implications, especially in fields requiring nuanced analysis of interconnected structures, including neuroimaging and social network analysis.

In recent years, GNNs have gained significant traction due to their ability to model both spatial and temporal dependencies, making them ideal for applications in chemistry, biology, and medicine. GNNs have been successfully employed in tasks like molecular graph analysis, protein structure prediction, and drug discovery, demonstrating their capacity to model complex relationships and interactions, thereby providing critical insights for therapeutic research and development [9, 10, 11]. These applications leverage GNNs' unique capability to learn from graph-structured data, where understanding the intricate relationships between nodes is as crucial as analyzing the properties of individual nodes. A recent survey [12] further highlights the effectiveness of GNN-based methods for graph classification and link prediction, particularly in modeling temporal dependencies for time series data. This survey discusses GNN applications for spatial-temporal analysis in areas like traffic flow and weather forecasting, showcasing how GNNs can integrate both spatial and temporal features for enhanced predictive performance. These strengths of GNNs have made them increasingly relevant for exploring spatial-temporal dynamics in neuroimaging studies, such as the analysis of EEG data.

Research on applying GNNs to EEG analysis has gained significant momentum in recent years, with numerous studies investigating GNN-based methods for tasks like emotion recognition, motor imagery, and neurological disorder detection. A recent survey [13] categorizes these studies, emphasizing the ability of GNNs to effectively capture complex spatial and temporal dependencies within EEG signals—dependencies that traditional deep learning models struggle to model accurately. Although these advancements have shown promising results, several challenges persist, including limited innovation in Graph Convolutional Network (GCN) layer design and difficulties in generalizing across diverse EEG datasets. These limitations suggest that while GNN-based approaches hold substantial potential, the field is still evolving and requires further refinement to fully realize their capabilities in EEG analysis. Addressing these challenges is crucial for advancing the applicability of GNNs to more nuanced EEG tasks and enhancing their performance on cross-subject and cross-condition data.

Most current GNN-based EEG studies focus on node classification or graph classification tasks, often for emotion recognition or motor imagery. These methods, while effective for certain tasks, overlook the potential of GNN link prediction models to uncover subtle and nuanced connectivity patterns at a more granular level. Our study addresses this gap by applying GNN link prediction to a unified graph structure, designed to capture dynamic connectivity changes across multiple subjects and trials. This approach moves beyond traditional graph classification by providing node- and edge-level analysis, allowing for a more detailed exploration of brain activity and connectivity variations. Ultimately, our framework for cross-subject and cross-condition connectivity analysis offers deeper insights into EEG dynamics, pushing the boundaries of current methods in neural data analysis.

3. Methods

3.1. EEG Channel Position Mapping and Graph Construction

In this section, we describe the process of extracting EEG channel positions in 3D space and constructing an initial graph to capture the spatial relationships between the electrodes. The goal is to build a graph where nodes represent EEG channels and edges reflect spatial proximity between these channels.

EEG Channel Position Extraction:

- We load the standard EEG montage (*'standard_1005'*) using the *mne* library.
- Channel positions are retrieved as (x, y, z) coordinates, representing each EEG channel in 3D space.
- Pairwise Euclidean distances between channels are calculated using *scipy.spatial.distance*, capturing their spatial proximity.

Distance Matrix Construction:

- The computed distances are used to generate a distance matrix that encapsulates the spatial relationships between the EEG channels.
- This matrix is formatted into a structured dataset, making it suitable for graph-based modeling.

Minimum Distance Filtering and Graph Creation:

- To ensure that no channel is isolated in the graph, we identify the shortest distance for each channel.
- We apply a distance threshold, defined as the maximum of these minimum distances, to retain only the closest pairs of channels.
- The final graph is constructed with nodes representing EEG channels and edges indicating spatial proximity, ensuring that the graph is fully connected for subsequent analysis.

Initial EEG Graph Construction:

- We build an initial graph that represents the spatial configuration of the EEG channels.
- In this graph, nodes correspond to EEG channels, while edges represent their spatial proximity on the scalp.
- Time-series EEG signals for each channel are then incorporated as node features, capturing both spatial and temporal dependencies within the EEG data.

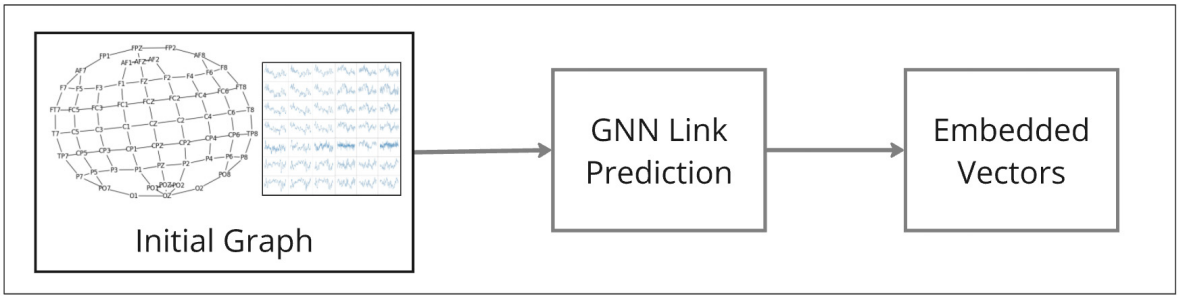

Figure 2: An overview of the EEG graph analysis pipeline. The initial graph (left) is built using spatial and temporal EEG data. The GNN Link Prediction model (center) processes the graph to learn node connections, generating embedded vectors (right) that capture complex relationships within the EEG signals for subsequent analysis.

3.2. GNN Link Prediction

In this section, we outline the process of refining the initial EEG graph using a Graph Neural Network (GNN) Link Prediction model to capture both spatial and temporal relationships within the EEG data. This process is illustrated in Figure 2. Once the initial graph structure is defined, we employ the GNN Link Prediction model to analyze the graph's topology and node attributes. By doing so, the model identifies previously hidden connections and refines the graph's structure, enhancing its ability to capture meaningful interactions between EEG channels.

We implement the GraphSAGE link prediction model [14] using the Deep Graph Library (DGL) [15]. This model is particularly suited for our data as it employs two GraphSAGE layers to generate node embeddings. These embeddings are formed by aggregating information from neighboring nodes, allowing the model to capture latent connections and interactions within the EEG signals. The model effectively discovers potential links and complex relationships between EEG channels by leveraging both the spatial properties of the EEG electrodes and signal-based similarities.

Implementation and Model Details:

- The constructed graph, combined with the time-series EEG signals, serves as input to the GraphSAGE-based link prediction model.
- The GNN model learns connectivity patterns by generating node embeddings, which incorporate both node attributes (EEG signals) and spatial relationships between the EEG channels.
- The model outputs high-dimensional vectors (embeddings) that capture the interaction and connectivity patterns between nodes (EEG channels) within the EEG data.

The node embeddings produced by the GNN model provide a detailed representation of the spatial and temporal relationships in the EEG data. These embeddings are further analyzed to identify key connectivity patterns across different experimental conditions, such as variations between the control and alcoholic groups. These embeddings serve as a foundation for subsequent classification, pattern discovery, and analysis of connectivity differences, which are discussed in detail in the 'Experiments' section.

3.3. Analysis and Visualization of EEG Node Embeddings

This subsection presents the analysis and visualization of EEG node embeddings generated by the GNN Link Prediction model. These embeddings offer a high-dimensional representation of the EEG graph, encapsulating both spatial and temporal aspects of neural activity.

Output and Embedding Extraction:

- The GNN Link Prediction model generates a set of embedded vectors, each representing the learned connectivity and interaction patterns between EEG channels.
- These embeddings capture both the spatial relationships among electrode positions and the temporal dependencies within the EEG signals, providing a holistic view of neural connectivity dynamics.

Graph-Based Analysis:

- The node embeddings produced by the GNN Link Prediction model are utilized for various graph-based analyses, including classification, pattern discovery, and exploration of connectivity differences between control and alcohol groups.
- Through these analyses, we can pinpoint nodes with high and low connectivity, compare connectivity patterns across experimental conditions, and gain deeper insights into how neural activity shifts in response to different stimuli.

Visualization and Interpretation:

- The aggregation of node embeddings is visualized to summarize and compare connectivity patterns in the EEG data.
- These visual representations highlight key differences in neural activity between experimental groups and identify important nodes and regions within the EEG graph.

By summarizing the embeddings, these visuals help to illustrate how brain connectivity changes under different experimental conditions, providing a clearer understanding of the underlying neural dynamics.

4. Experiments

4.1. EEG Data Source and Preprocessing

We utilized the publicly available 'EEG-Alcohol' dataset from Kaggle [1], which contains EEG recordings collected to investigate the neural correlates of genetic predisposition to alcoholism. Each subject was exposed to visual stimuli, either as a single picture or two consecutive pictures. In the two-picture trials, the stimuli were presented in matched (identical) or non-matched (different) conditions. The pictures used were objects selected from the 1980 Snodgrass and Vanderwart picture set. The dataset comprises EEG data from 8 subjects in each group (Alcohol and Control), with brain activity recorded using 64 electrodes at a sampling rate of 256 Hz over 1-second trials. Due to data quality issues in certain channels, we restricted our analysis to 61 out of the 64 EEG channels. In total, 61 person-trial pairs were included in the analysis.

Our data preparation process was partly inspired by Ruslan Klymentiev's Kaggle notebook on EEG Data Analysis [16], which provided a foundation for transforming raw data into a usable format. We extended this approach by implementing additional transformations to convert the EEG recordings into a structured time series format for each channel, enabling graph-based modeling.

The raw sensor data was organized by sensor position and trial number, then pivoted into a structured dataset where each row represents a time point, and each column represents the sensor value for that moment. For further details on this transformation process, refer to our related blog posts [17, 18]. This step produced a complete time series dataset for each EEG channel, providing the basis for the graph-based analysis and modeling that followed.

4.2. Prepare Input Data for GNN Link Prediction Model

The initial graph structure was created by calculating pairwise Euclidean distances between EEG channels, as outlined in the EEG Channel Position Mapping and Graph Construction subsection of the Methods section. These distances capture the spatial relationships between electrodes based on their physical positions on the scalp. The maximum of the minimum distances between EEG channels was calculated to be 0.038, and to prevent isolated nodes, a slightly higher threshold of 0.04 was used to filter and retain the closest channel pairs. This process resulted in a consistent graph structure with 61 nodes and 108 edges, representing the spatial layout of EEG channels across all subjects and trials. This shared graph provides a uniform topology for all subsequent subject-trial graphs, facilitating comparative analysis.

After establishing the graph structure, we defined graph nodes and their features for each subject-trial combination. Each node corresponds to one of the 61 EEG channels, while node features are derived from the time series signals recorded at these positions during the trials. The data was grouped by type (Alcohol and Control), subject, trial, and channel position, forming structured datasets that capture both spatial and temporal characteristics of the EEG signals. While the spatial configuration of the graph remains constant, node features vary based on each subject and trial, enabling the GNN Link Prediction model to detect connectivity patterns specific to different experimental conditions. For further details on the data preparation process, refer to our related blog post [19].

Table 1
Cosine Similarity for Different Conditions. The table shows that the 'Single stimulus' condition does not effectively distinguish between Alcohol and Control groups, while greater differences are observed in the 'Two stimuli' conditions.

Type	Condition	Cosine Similarity
Alcohol	Single stimulus	0.5920
Alcohol	Two stimuli - matched	0.5673
Alcohol	Two stimuli - non-matched	0.5276
Control	Single stimulus	0.5809
Control	Two stimuli - matched	0.6465
Control	Two stimuli - non-matched	0.6437

4.3. Train the Model

We utilized the GraphSAGE link prediction model [14], implemented with the Deep Graph Library (DGL) [15], to train our model on the EEG graph data. GraphSAGE uses two layers to aggregate information from neighboring nodes, enabling the model to capture complex connectivity patterns and interactions between EEG channels.

- Total Nodes: 3,721
- Total Edges: 13,176
- Node Feature Size: 256

The model's performance was evaluated using the Area Under the Curve (AUC) metric, achieving an accuracy of 81.45%. This high AUC score demonstrates the model's effectiveness in predicting connectivity patterns and capturing the underlying signal dependencies within the EEG data.

4.4. Interpreting Model Results

4.4.1. Condition-wise Analysis of Cosine Similarities

To compare connectivity patterns between the Alcohol and Control groups, we computed the average cosine similarities from the embedded vectors generated by the model. These similarities represent the strength of connectivity between brain regions, with higher values indicating stronger connections. The computed values were aggregated by condition type and match status to assess differences across the experimental groups.

As shown in Table 1, the 'Single stimulus' condition revealed minimal differences between the Alcohol and Control groups, which aligns with our previous studies [2, 3]. Since the 'Single stimulus' condition did not show significant variation in connectivity patterns, it was excluded from further analysis.

We instead focused on the 'Two stimuli - matched' and 'Two stimuli - non-matched' conditions, where clearer distinctions between the groups were observed.

- Alcohol group: Average cosine similarity of 0.546.
- Control group: Average cosine similarity of 0.645.

The higher average cosine similarity in the Control group suggests stronger overall connectivity compared to the Alcohol group. In the following sections, we will explore these patterns further at the node level, highlighting regions of the brain with both high and low signal correlations between the groups.

Table 2
Top connected node pairs based on cosine similarity for Alcohol and Control groups. The Alcohol group shows strong connectivity in the parietal and occipital regions, while the Control group exhibits even stronger connections in the occipital area, reflecting more stable brain network organization for visual and sensory integration in the Control group.

Group	Left Position	Right Position	Cosine Similarity
Alcohol	P5	P7	0.8367
Alcohol	PO8	P8	0.8014
Alcohol	PO1	POZ	0.7665
Alcohol	OZ	PO1	0.7487
Control	PO1	POZ	0.8838
Control	PO2	POZ	0.8783
Control	PO1	PO2	0.8771
Control	P5	P7	0.8676

Table 3
Top nodes with the highest cosine similarity values for Alcohol and Control groups. Strong connectivity in the parietal region is observed for the Alcohol group, while the Control group shows dominance in the occipital region, reflecting differences in how each group processes sensory and visual information.

Group	Position	Cosine Similarity
Alcohol	P7	0.7450
Alcohol	P5	0.7358
Alcohol	PO7	0.7013
Alcohol	P3	0.6862
Control	PO2	0.8358
Control	POZ	0.8224
Control	PO1	0.8154
Control	P7	0.8053

4.4.2. Strongly Connected Positions

In our analysis, we applied a GNN Link Prediction model to examine the EEG connectivity patterns of both the Alcohol and Control groups. This model was designed to capture the complex spatial relationships and temporal dependencies present in the EEG data. By focusing on connectivity patterns at a high granularity level, the GNN Link Prediction model enabled us to investigate how different regions of the brain communicate under varying experimental conditions.

The GNN Link Prediction model produced embedded vectors, from which edge weights were calculated based on the initial graph structure. Node-level cosine similarities were determined by combining left and right node positions, grouping them by type and position, and averaging the values to assess overall connectivity strength.

Tables 2 and 3 show the top highly connected node pairs and nodes, respectively. In the Control group, the strongest connections are found in the occipital and parietal regions, which are essential for visual processing and sensory integration. These areas display stable and efficient brain network organization, indicating robust connectivity that supports the processing of sensory and visual information. The occipital region dominance in the Control group suggests a healthy neural pattern, with no major disruptions. This allows for consistent and efficient neural communication in areas critical for interpreting visual input.

In contrast, the Alcohol group shows more disruptions, with overall lower connectivity values. While connections in the parietal and occipital regions are also observed, they are weaker than those seen in the Control group. This suggests a less organized and consistent brain network in the Alcohol group, likely reflecting the impact of alcohol on neural connectivity. The parietal region dominance in the

Alcohol group could be indicative of a compensatory mechanism, where the brain attempts to increase connectivity in areas responsible for sensory processing and spatial awareness, potentially as a response to alcohol-induced disruptions.

4.4.3. Weakly Connected Positions

As shown in Tables 4 and 5, the nodes and node pairs with the lowest cosine similarity values for both the Alcohol and Control groups are concentrated in the central brain regions, such as CZ, C1, and C2, which are associated with motor function. Since the trials focused on reactions to visual stimuli, it is expected that these motor-related regions would not show high connectivity.

In the Control group, these regions show low connectivity, aligning with the task focus on visual processing. In the Alcohol group, the connectivity is even weaker, suggesting that alcohol exposure may cause broader disruption across brain networks, even in regions not directly involved in the task.

Table 4
Node pairs with the lowest cosine similarity values, highlighting weakly connected regions in both Alcohol and Control groups. Connectivity is particularly reduced in central regions, with the Alcohol group showing more pronounced disruptions.

Group	Left Position	Right Position	Cosine Similarity
Alcohol	CZ	FCZ	0.2371
Alcohol	CZ	C2	0.2349
Alcohol	C1	CZ	0.2046
Alcohol	CZ	CPZ	0.1982
Control	C2	CP2	0.2457
Control	C2	FC2	0.2036
Control	CZ	C2	0.2021
Control	CZ	FCZ	0.1761

Table 5
Nodes with the lowest cosine similarity values in both groups, primarily in central regions. The Alcohol group shows more pronounced disruptions, while the Control group maintains slightly higher connectivity.

Group	Position	Cosine Similarity
Alcohol	C2	0.3361
Alcohol	CPZ	0.3121
Alcohol	C1	0.2853
Alcohol	CZ	0.2187
Control	C1	0.3339
Control	FCZ	0.3239
Control	C2	0.2564
Control	CZ	0.2536

4.4.4. Graphical Representation of High and Low Connectivity Nodes

Figure 3 displays a topographical map of EEG channels, highlighting nodes based on their overall cosine similarity values for the Alcohol and Control groups. Nodes with the highest connectivity are shown in turquoise for the Alcohol group and in blue for the Control group, while those with the lowest connectivity are represented in yellow for the Alcohol group and orange for the Control group. This visualization offers a clear comparison of connectivity patterns, identifying regions of stronger and weaker signal correlations.

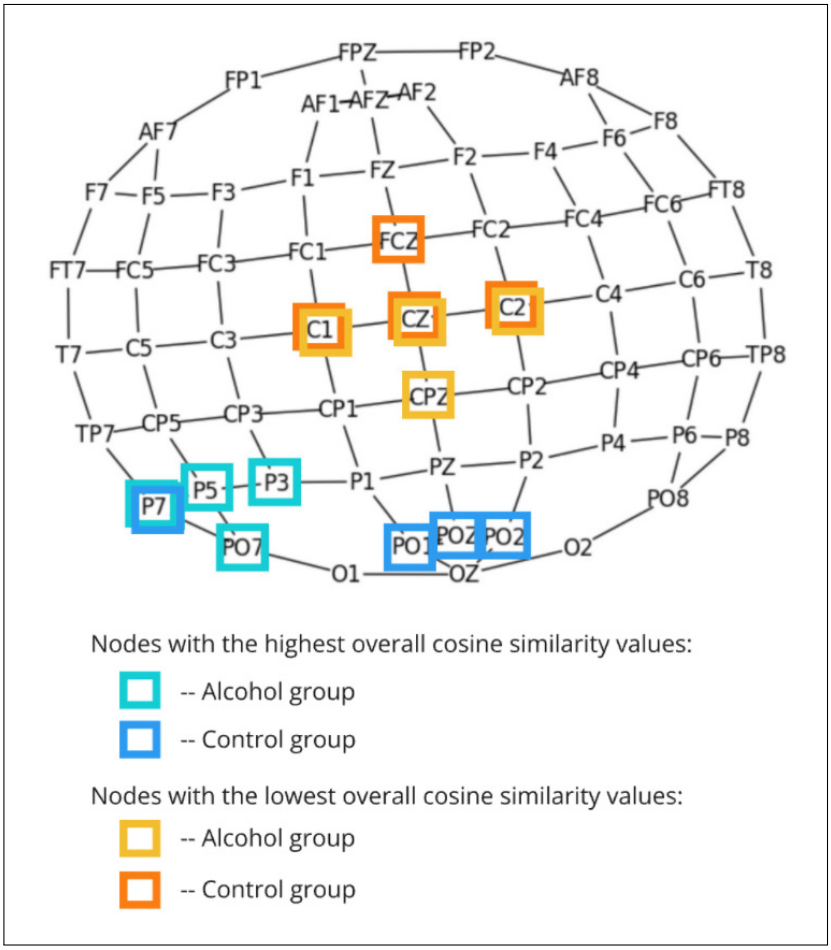

Figure 3: Nodes with the highest and lowest overall cosine similarity values for Alcohol and Control groups. The diagram compares connectivity patterns across different EEG channels, showing stronger connectivity in the parietal and occipital regions and weaker connectivity in the central and frontal regions.

In the Control group, the high-connectivity nodes are primarily located in the occipital region, which is responsible for visual processing. This stable neural interaction is expected during visual trials, indicating efficient brain network organization in response to visual stimuli. In contrast, the Alcohol group exhibits stronger connections in the parietal region, with fewer occipital nodes involved. This shift in connectivity may indicate how alcohol alters brain activity, possibly disrupting normal visual processing and causing compensatory activity in other regions.

Both groups demonstrate low connectivity in the central region, which is typically linked to motor and sensorimotor processing. The lower activity in these areas during visual trials suggests they are not heavily engaged, aligning with their expected limited role in visual perception and processing tasks.

5. Conclusion

In this study, we introduced a novel framework that integrates Graph Neural Network (GNN) Link Prediction models with unified graph structures based on spatial distances between EEG electrodes. This approach successfully captured intricate spatial and temporal connectivity patterns, providing a detailed view of brain dynamics that traditional methods often fail to uncover.

Our analysis revealed that GNN Link Prediction models effectively identify subtle variations in neural connectivity. In the Control group, high-connectivity nodes were predominantly located in the occipital region, reflecting stable and efficient neural responses to visual stimuli. In contrast, the Alcohol group exhibited stronger connectivity in the parietal region, suggesting compensatory mechanisms in response

to alcohol-induced disruptions. These findings provide insights into how neural connectivity adapts under altered conditions, particularly in regions associated with sensory and cognitive processing.

This framework extends beyond EEG data, offering adaptability to other time series datasets and making it a versatile tool for analyzing connectivity patterns across diverse physiological and experimental contexts. By combining AI-driven graph modeling with neuroscience, this study advances our understanding of neural dynamics and provides new methodologies for research.

Looking ahead, integrating GNN-based frameworks with multimodal data and real-time monitoring could further enhance our ability to decode brain connectivity and predict neural behavior. These advancements hold great potential for addressing complex neuroscience challenges, such as understanding the impact of neurological disorders and exploring brain function in greater detail. By leveraging the power of graph-based approaches, this work paves the way for new discoveries and deeper insights into neural systems.

References

[1] Kaggle.com, EEG-Alcohol Data Set, 2017.

[2] A. Romanova, Time series pattern discovery by deep learning and graph mining, in: Database and Expert Systems Applications, DEXA, 2021.

[3] A. Romanova, Enhancing time series analysis with gnn graph classification models, in: Complex Networks & Their Applications XII, 2024. doi:10.1007/978-3-031-53468-3-3.

[4] J. Howard, S. Gugger, Deep Learning for Coders with Fastai and PyTorch, O'Reilly Media, 2020.

[5] A. Krizhevsky, I. Sutskever, G. Hinton, Imagenet classification with deep convolutional neural networks, Advances in Neural Information Processing Systems (2012).

[6] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444. doi:10.1038/nature14539.

[7] N. Noy, Y. Gao, A. Jain, A. Narayanan, A. Patterson, J. Taylor, Industry-scale knowledge graphs: Lessons and challenges, acmqueue (2019).

[8] M. Bronstein, J. Bruna, T. Cohen, P. Veličković, Geometric deep learning: Grids, groups, graphs, geodesics, and gauges, arXiv (2021). doi:10.48550/arXiv.2104.13478.

[9] J. Adamczyk, Application of graph neural networks and graph descriptors for graph classification (2022).

[10] H. He, O. Queen, T. Koker, C. Cuevas, T. Tsiligkaridis, M. Zitnik, Domain adaptation for time series under feature and label shifts (2023).

[11] W. Hu, B. Liu, J. Gomes, M. Zitnik, P. Liang, V. Pande, J. Leskovec, Strategies for pre-training graph neural networks (2020).

[12] X. Liu, J. Chen, Q. Wen, A survey on graph classification and link prediction based on gnn, arXiv (2023). ArXiv:2307.00865 [cs.LG].

[13] D. Klepl, M. Wu, F. He, Graph neural network-based eeg classification: A survey, arXiv (2023). ArXiv:2307.00865 [cs.LG].

[14] W. Hamilton, Z. Ying, J. Leskovec, Inductive representation learning on large graphs, arXiv (2017). URL: https://arxiv.org/abs/1706.02216.

[15] Deep Graph Library (DGL), Link prediction using graph neural networks, 2018. URL: https://www.dgl.ai, available online.

[16] R. Klymentiev, EEG Data Analysis, 2019.

[17] EEG Patterns by Deep Learning and Graph Mining: how to find patterns of time-series in two-dimensional space, http://sparklingdataocean.com/2020/08/19/brainGraphEeg/, 2020.

[18] GNN Graph Classification for EEG Pattern Analysis: Graph Neural Network for time-series analysis, http://sparklingdataocean.com/2023/05/08/classGraphEeg/, 2023.

[19] Graph Neural Networks for EEG Connectivity Analysis: Using GNN Link Prediction to Uncover Hidden Patterns in EEG Time Series Data, http://sparklingdataocean.com/2024/11/09/GNN_timeSeries_EEG/, 2024.


GENERALITAT
VALENCIANA
Programa Prometeo 2021
PROMETEO/2021/088


CEUR
Workshop
Proceedings
ceur-ws.org
ISSN 1613-0073


Universitat d'Alacant
Universidad de Alicante


Balladeer


PSYBHE

PROCEEDINGS
IWAIN 2024 - International Workshop on Artificial Intelligence for Neurosciencie