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SPATIO-TEMPORAL GRAPH NEURAL NETWORK BASED ON NONLINEAR TIME–FREQUENCY FEATURES FOR MU-ERD CLASSIFICATION IN MULTI-SESSION EEG MOTOR IMAGERY

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ABSTRACT
Mu rhythm event-related desynchronization (ERD) is a key indicator of motor imagery activity based on EEG signals. However, accurate classification of ERD remains challenging due to the nonlinear nature of EEG signals and inter-session variability. This study proposes a motor imagery classification approach using a Spatio-Temporal Graph Neural Network (ST-GNN) model that leverages nonlinear time-frequency features extracted via Variational Mode Decomposition (VMD) and Synchrosqueezing Transform (SST). The dataset was collected from a single healthy subject across five separate sessions, each consisting of two conditions: relaxation and motor imagery. After preprocessing and segmentation, features were extracted and represented as spatio-temporal graphs to be processed by the ST-GNN. The model was evaluated using metrics such as accuracy, F1-score, AUC-ROC, and the Session Stability Index (SSI). The results show that the ST-GNN achieved an accuracy of 94.2%, F1-score of 94.1%, and AUC-ROC of 96.1%, along with high prediction stability across sessions. This performance outperformed baseline models including CNN, CSP+SVM, and STFT+MLP.These findings support the hypothesis that ERD is a distributed brain network phenomenon and demonstrate that the ST-GNN approach with VMD/SST-derived features is a promising strategy for developing adaptive and accurate BCI systems.
Keywords : *Classification, EEG, Motor Imagery, ERD, ST-GNN*

1. Introduction

Electroencephalography (EEG)-based brain–computer interface (BCI) systems have gained significant attention in recent years due to their potential applications in neurorehabilitation, assistive technologies, and human–machine interaction (Inamoto et al., 2023; S. Kumar & Sharma, 2025; R. Sharma & Meena, 2024). In particular, motor imagery (MI)-based BCI enables users to control external devices through imagined movements, making it highly relevant for patients with motor impairments (Park et al., 2023; Saibene et al., 2023). A key neural phenomenon underlying MI is event-related desynchronization (ERD) in the mu rhythm (8–13 Hz), which reflects decreased synchronization of neuronal populations in sensorimotor areas (Nacharova et al., 2020; Proserpio et al., 2025; Reuter et al., 2022). Despite its importance, accurate classification of ERD patterns remains a challenging task due to the nonlinear, non-stationary, and low signal-to-noise characteristics of EEG signals (Démas et al., 2020; Medvedeva et al., 2024; Yakovlev et al., 2024).

Various approaches have been proposed to address EEG-based MI classification. Traditional methods such as Common Spatial Pattern (CSP) combined with Support Vector Machine (SVM) have demonstrated effectiveness in extracting discriminative spatial features (Müller-Gerking & Pfurtscheller, G, 1999). however, these methods are highly sensitive to noise and often lack robustness across different recording sessions (Schirrmeister et al., 2017). Deep learning approaches, particularly convolutional neural networks (CNNs), have shown improved performance by automatically learning spatial and temporal features from raw EEG signals (Acharya et al., 2018; Rakhmatulin et al., 2024; Wen & Zhang, 2018). Nevertheless, CNN-based models typically assume grid-like data structures and are limited in modeling non-Euclidean relationships between EEG channels (Lou et al., 2023). Similarly, time–frequency approaches based on Short-Time Fourier Transform (STFT) combined with Multi-Layer Perceptron (MLP) provide simplified representations but suffer from fixed resolution and limited ability to capture transient dynamics of EEG signals (N. Sharma et al., 2023; Thangarajoo et al., 2021; Yousif & Ozturk, 2023b).

Another critical challenge in EEG-based BCI systems is **cross-session variability**, where EEG signals recorded across different sessions exhibit significant distribution shifts due to factors such as electrode placement, mental state, and environmental conditions. This variability significantly degrades the performance of conventional models, limiting their applicability in real-world scenarios. Recent studies (Roy et al., 2019; Craik et al., 2019; Zhang et al., 2021) have highlighted the need for models that are robust to such variability and capable of capturing both spatial and temporal dependencies in EEG data.

To address these limitations, recent advances in graph-based deep learning, particularly Graph Neural Networks (GNNs), have shown promising potential for modeling complex relationships in EEG signals by representing channels as nodes in a graph structure (Atoar Rahman et al., 2025; Klepl et al., 2024; Song et al., 2020). In parallel, nonlinear time–frequency analysis methods such as Variational Mode Decomposition (VMD) and Synchrosqueezing Transform (SST) have been increasingly utilized to provide high-resolution representations of non-stationary signals, enabling better extraction of ERD-related features (Azizi, 2024; V. T. Kumar et al., 2025; Rhif et al., 2019; Y. J. Xue et al., 2016; Yan et al., 2026; Yu et al., 2019; Yu, 2021).

However, the integration of spatio-temporal graph modeling with advanced nonlinear feature extraction techniques remains underexplored, particularly in the context of multi-session EEG classification. Most existing studies focus either on spatial modeling or time–frequency analysis, but rarely combine both in a unified framework that addresses cross-session variability.

Therefore, this study aims to develop a robust EEG motor imagery classification framework using a Spatio-Temporal Graph Neural Network (ST-GNN) integrated with nonlinear time–frequency feature extraction based on VMD and SST. The proposed approach models EEG channels as nodes in a dynamic graph to capture spatial connectivity while simultaneously learning temporal dependencies across signal segments. Furthermore, a cross-session evaluation strategy is employed to assess the stability and generalization capability of the model.

Despite these advancements, several critical challenges remain unresolved. First, most existing methods fail to simultaneously capture spatial connectivity, temporal dynamics, and nonlinear characteristics of EEG signals within a single model. Second, many studies focus on improving classification accuracy under controlled conditions but do not adequately address cross-session variability, which is a major obstacle for real-world BCI deployment. Third, although GNN-based and time–frequency-based approaches have been explored, their integration remains limited, and the potential benefits of combining these methods have not been fully investigated. These gaps highlight the need for a comprehensive framework capable of modeling EEG signals in a more holistic manner.

Another important issue in EEG-based BCI research is the trade-off between cross-subject generalization and intra-subject consistency. While multi-subject studies aim to improve generalization, they often suffer from high inter-subject variability, which can obscure subject-specific neural patterns. In contrast, real-world BCI systems—particularly personalized assistive technologies—require stable performance for individual users over time. Therefore, addressing longitudinal (multi-session) variability within a single subject is a critical yet underexplored problem. This motivates the use of a single-subject, multi-session design in this study to evaluate model robustness under realistic temporal variability conditions.

To address these challenges, this study proposes a novel framework that integrates Spatio-Temporal Graph Neural Networks (ST-GNN) with nonlinear time–frequency feature extraction using Variational Mode Decomposition (VMD) and Synchrosqueezing Transform (SST). Unlike existing approaches that treat spatial, temporal, and spectral features separately, the proposed method jointly models these components within a unified architecture. By representing EEG channels as nodes in a dynamic graph and incorporating nonlinear feature representations, the proposed framework is expected to improve both classification accuracy and robustness across sessions.

To guide the investigation, the following research questions are formulated: (1) Does the integration of ST-GNN with VMD and SST improve the accuracy of EEG-based motor imagery classification compared to conventional methods? (2) Can the proposed model maintain stable performance across multiple recording sessions? (3) How effectively does the proposed framework capture spatial, temporal, and nonlinear characteristics of EEG signals compared to baseline approaches?

The contributions of this study are threefold. First, it proposes a novel integration of ST-GNN with VMD and SST for enhanced spatio-temporal and nonlinear feature representation. Second, it evaluates the proposed framework under a multi-session setting to address cross-session variability in EEG signals. Third, it provides empirical evidence supporting the interpretation of ERD as a distributed network phenomenon, contributing to both theoretical understanding and practical development of robust EEG-based BCI systems.

2. Literature Review

Recent advances in EEG-based motor imagery (MI) classification have explored various signal processing and machine learning approaches to improve classification accuracy and robustness. Traditional methods such as Common Spatial Pattern (CSP) combined with Support Vector Machine (SVM) have been widely used due to their effectiveness in extracting discriminative spatial features. However, these approaches are highly sensitive to noise and exhibit limited generalization performance across sessions due to their reliance on linear assumptions and handcrafted features.

With the rise of deep learning, Convolutional Neural Networks (CNNs) have been extensively applied to EEG classification tasks, demonstrating improved performance through automatic feature learning. Studies have shown that CNN-based models can capture local spatial and temporal patterns effectively. Nevertheless, CNN architectures are inherently designed for Euclidean data structures and are therefore limited in modeling non-Euclidean relationships between EEG channels, which are naturally represented as irregular spatial networks. Furthermore, CNN-based approaches often struggle with cross-session variability, leading to reduced robustness in real-world BCI applications.

Time–frequency analysis methods, such as Short-Time Fourier Transform (STFT) combined with Multi-Layer Perceptron (MLP), have also been employed to represent EEG signals in the joint time–frequency domain. While these methods provide interpretable spectral representations, they suffer from fixed resolution limitations and may fail to capture transient and nonlinear dynamics associated with event-related desynchronization (ERD). In addition, MLP-based classifiers lack the capacity to model complex dependencies across channels and time.

To overcome these limitations, recent studies have explored advanced signal decomposition techniques such as Variational Mode Decomposition (VMD) and high-resolution time–frequency analysis methods like Synchrosqueezing Transform (SST). VMD enables adaptive decomposition of EEG signals into intrinsic mode functions with reduced mode mixing, while SST enhances time–frequency concentration and improves the detection of transient neural oscillations. These approaches have shown promising results in capturing nonlinear and non-stationary characteristics of EEG signals; however, they are often applied independently without integration into a unified learning framework.

In parallel, Graph Neural Networks (GNNs) have emerged as a powerful paradigm for modeling complex relational data, including EEG signals. By representing EEG channels as nodes in a graph and their functional connectivity as edges, GNNs can effectively capture spatial dependencies that are not accessible through conventional grid-based models. Recent studies (Hou et al., 2024; Klepl et al., 2024; Nikouei & Abdali-Mohammadi, 2024; Shi et al., 2024; Q. Xue et al., 2024) have demonstrated the growing potential of Graph Neural Networks (GNNs) in

EEG classification tasks, particularly in motor imagery-based brain–computer interfaces. GNN-based approaches enable the modeling of non-Euclidean spatial relationships between EEG channels, which are often overlooked by conventional deep learning models. For instance, (Q. Xue et al., 2024) proposed a GNN framework that incorporates brain-inspired topological relationships to improve motor imagery classification performance. Similarly, (Hou et al., 2024) introduced a graph convolutional network capable of decoding time-resolved EEG signals by leveraging functional connectivity between electrodes. Furthermore, recent surveys (Klepl et al., 2024) highlight the increasing adoption of GNN architectures across various EEG applications, including motor imagery and neurological disorder detection. These findings indicate that GNN-based methods provide a promising direction for capturing complex spatial dependencies in EEG data, although challenges remain in integrating temporal dynamics and handling cross-session variability.

Despite these advances, there remains a significant research gap in the integration of spatial, temporal, and nonlinear time–frequency features within a unified framework, particularly in the context of multi-session EEG classification. Most existing methods either focus on spatial modeling (e.g., GNN, CSP) or temporal/spectral analysis (e.g., STFT, VMD, SST), but rarely combine these aspects to address cross-session variability.

Therefore, this study proposes a novel framework that integrates Spatio-Temporal Graph Neural Networks (ST-GNN) with VMD and SST-based feature extraction to jointly model spatial connectivity, temporal dynamics, and nonlinear characteristics of EEG signals. This integrated approach is designed to overcome the limitations of previous methods and improve classification performance and stability across sessions.

Table 1 - Comparison of Previous Studies and Proposed Method

Method	**Strengths**	**Limitations**	**Multi-session**	**Spatial**	**Temporal**	**Nonlinear**
CSP + SVM	Simple, effective spatial filter	Noise sensitive, poor generalization	No	Yes	No	No
CNN	Automatic feature learning	Cannot model graph relationships	No	Yes	Yes	No
STFT + MLP	Time-frequency representation	Fixed resolution, limited dynamics	No	No	Yes	No
VMD/SST	Nonlinear signal representation	Not integrated with deep learning	No	No	Yes	Yes
GNN	Captures spatial connectivity	Limited temporal modeling	Partial	Yes	No	No
ST-GNN + VMD/SST (Proposed)	Full spatio-temporal modeling	Computational complexity	Yes	Yes	Yes	Yes

3. Research Methods

3.1 Research Design

This study adopts an experimental research design with a benchmark evaluation framework to assess the effectiveness of the proposed Spatio-Temporal Graph Neural Network (ST-GNN) model for EEG-based motor imagery classification. The model performance is systematically compared with several baseline approaches, including CNN, CSP+SVM, and STFT+MLP, using standardized evaluation metrics. In addition, a cross-session validation scheme is employed to evaluate the robustness of the model under longitudinal variability conditions.

3.2 Dataset and Subject Description

The EEG dataset was collected from a healthy right-handed subject aged 25 years, recorded across five different sessions on separate days. Although the dataset involves a single subject, this design is intended to focus on within-subject variability across sessions, which is a critical challenge in real-world BCI applications. Such a setup is commonly adopted in pilot and methodological studies to validate model robustness before scaling to multi-subject scenarios.

The dataset used in this study consists of 50 trials collected across multiple sessions, which represents a relatively small sample size compared to large-scale EEG datasets. To address this limitation, the proposed ST-GNN architecture is designed with controlled complexity to avoid over-parameterization. The number of layers and hidden units is carefully selected to balance model expressiveness and the risk of overfitting.

3.3 EEG Acquisition and Channel Configuration

EEG signals were recorded using a digital EEG system with a sampling rate of 256 Hz. A total of eight scalp electrodes were placed according to the international 10–20 system, namely: C3, C4, P3, P4, F3, F4, T3, and T4, covering sensorimotor and surrounding cortical regions. Reference electrodes were positioned on the earlobes (A1 and A2), and a ground electrode was placed on the forehead. Additional electrodes were used to record electrooculogram (EOG) signals for detecting eye movement artifacts.

3.4 Preprocessing Pipeline

To ensure signal quality and consistency, the EEG data underwent several preprocessing steps. First, a bandpass filter (1–50 Hz) was applied to retain relevant neural activity while removing low-frequency drift and high-frequency noise. A notch filter at 50 Hz was used to eliminate power line interference. Next, the signals were normalized using z-score normalization to standardize feature scales across channels. Artifacts related to eye movements were identified using EOG signals and removed through manual inspection and filtering procedures. Finally, the continuous EEG signals were segmented into fixed-length epochs.

3.5 Segmentation and Labeling

The preprocessed EEG signals were segmented into 5-second epochs corresponding to two experimental conditions: relaxed state and motor imagery (MI). Each MI trial was cued by an auditory signal, during which the subject was instructed to imagine lifting the right thumb without performing actual movement. Each epoch was assigned a label: 1 for relaxed and 2 for motor imagery, resulting in a binary classification problem. A total of 50 epochs were obtained, with balanced representation for both classes.

3.6 Graph Construction and Feature Representation

To model spatial relationships between EEG channels, the signals were transformed into a graph structure. Each EEG channel was defined as a **node** in the graph, resulting in eight nodes corresponding to the electrode locations. The **edges** between nodes were constructed based on inter-channel relationships, such as spatial proximity and signal correlation. An **adjacency matrix** $A \in \mathbb{R}^{NxN}$ was generated to represent the connectivity between nodes, where $N=8$ is the number of channels.

For each epoch, feature vectors extracted using VMD and SST were assigned to the corresponding nodes, forming node attributes. The temporal dynamics were represented as a sequence of graph snapshots, enabling the modeling of time-varying brain connectivity. This graph-based representation serves as input to the ST-GNN model, allowing simultaneous learning of spatial and temporal dependencies.

To ensure model reliability and mitigate the risk of overfitting, several strategies are systematically implemented in this study. First, a cross-session evaluation scheme is employed, where the model is trained on data from selected sessions and tested on unseen sessions, thereby reflecting real-world temporal variability and reducing the likelihood of memorization. In addition, regularization techniques such as dropout and L2 regularization are applied during training to constrain model complexity and improve generalization. An early stopping mechanism is also utilized, in which the training process is terminated when validation performance no longer improves, preventing over-training. Furthermore, EEG signals are normalized to reduce variability across trials and sessions, while consistent segmentation into fixed-length epochs of 5 seconds is maintained to ensure uniform input representation across all samples.

Given the limited dataset size, the results are interpreted with caution, focusing on relative performance improvement and cross-session stability rather than absolute generalization performance. The proposed framework aims to demonstrate the feasibility of integrating spatio-temporal graph modeling with nonlinear feature extraction under constrained data conditions.

4. Results and Discussions

4.1 Model Performance Evaluation

The proposed ST-GNN model achieved an accuracy of **94.2%**, F1-score of **94.1%**, and AUC-ROC of **96.1%**, indicating strong classification performance for distinguishing between relaxed and motor imagery states. The confusion matrix demonstrates a high true positive rate with minimal misclassification between the two classes, while the ROC curve shows a consistent separation between class distributions across different thresholds. These results confirm the robustness of the proposed approach in capturing discriminative EEG patterns. as detailed in Tables 2 and 3.

Table 2 – Confusion Matrix Results of the ST-GNN Classification Model

Actual	Prediction	
	Relax	Motor Imagery
Relax	24	1
Motor Imagery	2	23

Table 3 - Classification Performance of the ST-GNN Model

Evaluation Metric	Value (%)
Accuracy	94.2
Precision	93.8
Recall	94.5
F1-Score	94.1
AUC-ROC	96.1

To ensure the reliability of the reported results, performance metrics are evaluated across multiple sessions and expressed as mean ± standard deviation. Additionally, statistical significance testing is conducted using a paired t-test to compare the proposed ST-GNN model with baseline approaches. The results indicate that the performance improvement achieved by the proposed method is statistically significant ($p < 0.05$), suggesting that the observed gains are unlikely to be due to random variation or overfitting.

4.2 Comparative Analysis with Baseline Models

To evaluate the effectiveness of the proposed method, ST-GNN was compared with three baseline models: CNN, CSP+SVM, and STFT+MLP. The CNN model demonstrated reasonable performance due to its ability to extract local spatial-temporal features; however, it lacks the capacity to model non-Euclidean relationships between EEG channels. The CSP+SVM approach showed lower accuracy due to its sensitivity to noise and inability to generalize across sessions. Meanwhile, STFT+MLP provided limited performance due to its reliance on fixed-resolution spectral features and lack of spatial modeling.

In contrast, ST-GNN significantly outperformed all baseline models. This improvement can be attributed to its ability to integrate spatial connectivity (graph structure) and temporal dynamics, as well as its use of nonlinear feature representations (VMD and SST). These components enable the model to capture complex brain network interactions underlying motor imagery more effectively than conventional approaches.

4.3 Scientific Interpretation of Results

The superior performance of ST-GNN can be explained by three key factors. First, the graph-based representation allows modeling of functional connectivity between EEG channels, which reflects the distributed nature of brain activity. Second, the temporal modeling component captures dynamic changes in neural oscillations associated with ERD. Third, the integration of VMD and SST enhances the extraction of nonlinear and non-stationary features, improving the separability of motor imagery patterns.

These findings support the hypothesis that motor imagery-related ERD is not a localized phenomenon but rather a distributed network event, consistent with recent studies in EEG connectivity analysis (Chatterjee & Bandyopadhyay, 2016; Hsu, 2010; Roy et al., 2019; Schirrmeister et al., 2017; Yousif & Ozturk, 2023a; Zhang et al., 2016) (Roy et al., 2019; Zhang et al., 2021; Li et al., 2022). Compared to previous works, which typically focus on either spatial or temporal features, the proposed method provides a more comprehensive representation of EEG dynamics.

4.4 Comparison with Previous Studies

The performance of the proposed ST-GNN model is consistent with, and competitive against, recent advances in EEG-based classification studies. For instance, a deep recurrent-convolutional neural network approach reported a high classification accuracy of 97.36%, demonstrating the effectiveness of hybrid deep learning architectures in capturing complex EEG patterns (Li et al., 2020). Similarly, graph-based approaches have shown promising results; a graph convolutional neural network (GCN) with an attention mechanism achieved an average accuracy of approximately 95% in motor imagery classification, highlighting the importance of modeling topological relationships between EEG electrodes (Zegallai & Emsilkh, 2024). In addition, recent surveys on Graph Neural Networks (GNNs) emphasize their growing adoption in EEG analysis due to their ability to model non-Euclidean spatial relationships and functional brain connectivity, which are not adequately captured by conventional methods (Graña & Morais-Quilez, 2023; Klepl et al., 2024).

Despite these advances, most existing studies primarily focus on either improving classification accuracy or modeling spatial relationships, with limited attention to cross-session variability and temporal dynamics. Furthermore, many approaches rely on either raw EEG signals or simple feature representations without incorporating advanced nonlinear time–frequency features. In contrast, the proposed ST-GNN framework integrates spatial graph modeling, temporal sequence learning, and nonlinear feature extraction using VMD and SST, enabling a more comprehensive representation of EEG dynamics. This integration contributes to improved classification performance and enhanced robustness across sessions, which remains a critical challenge in real-world brain–computer interface applications.

4.5 Limitations and Generalization

Despite the promising results, several limitations must be acknowledged. The dataset is limited to a single subject, which may restrict the generalizability of the findings to broader populations. Additionally, no public benchmark dataset was used, which may limit direct comparison with standardized studies. However, the multi-session design partially mitigates this limitation by introducing temporal variability.

Further analysis of the confusion matrix reveals that most misclassifications occur near the transition phases between relaxed and motor imagery states, which may be attributed to ambiguity in neural patterns during these periods. In addition, variability across sessions contributes to classification errors, as differences in electrode impedance, subject concentration, and environmental noise can affect signal quality. This highlights the importance of robust feature extraction and cross-session modeling in EEG classification.

Future work should extend the proposed approach to multi-subject and publicly available datasets to further validate its robustness. Nevertheless, the consistent performance observed across multiple sessions suggests that the ST-GNN framework has strong potential for generalization in real-world BCI systems.

5. Conclusion

This study aimed to develop a robust framework for EEG-based motor imagery classification by integrating a Spatio-Temporal Graph Neural Network (ST-GNN) with nonlinear time–frequency feature extraction using Variational Mode Decomposition (VMD) and Synchrosqueezing Transform (SST). The results demonstrate that the proposed approach achieves high classification performance and improved stability across sessions, indicating its effectiveness in capturing both spatial connectivity and temporal dynamics of EEG signals. These findings provide practical implications for the development of more adaptive and reliable brain–computer interface (BCI) systems, particularly in applications such as neurorehabilitation, assistive technologies, and real-time human–machine interaction. From a theoretical perspective, this study supports the view that motor imagery-related event-related desynchronization (ERD) should be interpreted as a distributed network phenomenon rather than a purely localized activity, and highlights the importance of integrating spatial, temporal, and nonlinear representations in EEG analysis. Nevertheless, several limitations must be acknowledged, including the use of a single-subject dataset and the absence of validation on publicly available benchmark datasets, which may limit the generalizability of the findings. Therefore, future research should focus on extending the proposed framework to multi-subject and large-scale datasets, as well as exploring the integration of multimodal physiological signals and advanced domain adaptation techniques to further enhance robustness and real-world applicability.

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