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EEG Anomaly Detection Using Temporal Graph Attention for Clinical Applications

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Abstract: This paper proposes a temporal-graph attention-based method for EEG anomaly detection, aiming to effectively model the spatiotemporal dependencies in multi-channel EEG data. The raw EEG signals are first transformed into a sequence of dynamic graphs, where the neural channel structure at each time point is naturally represented as a graph. A temporal-graph attention module is then introduced, combining graph structural attention across nodes and self-attention along the temporal dimension. These components are used to extract spatial interaction patterns and dynamic temporal features, respectively. The model constructs joint node-time representations to focus precisely on local abnormal signals and to capture cross-channel abnormal propagation patterns. During feature fusion, a global aggregation strategy is applied to enhance the model's ability to discriminate whole-brain states. Experiments are conducted on the TUH Abnormal EEG dataset, with systematic evaluations under different window lengths, channel numbers, and labeling proportions. Results demonstrate the stability and effectiveness of the proposed method in various complex modeling settings. The model consistently outperforms existing methods in terms of accuracy, sensitivity, and specificity, showing advantages in modeling sparse anomalies and non-Euclidean dependencies. In addition to general neurological disorders, this framework holds promise for aiding tumor-related brain activity monitoring, as certain brain neoplasms can induce electrophysiological disruptions detectable by EEG. The proposed method is well-suited for automated and structure-aware EEG anomaly detection in clinical monitoring scenarios.

Keywords: EEG modeling; graph attention mechanism; spatiotemporal feature extraction; anomaly detection

1. Introduction

In modern medicine and intelligent health monitoring, electroencephalography (EEG) has become a widely used tool due to its high temporal resolution and non-invasive nature. It is applied in key tasks such as epilepsy detection, sleep analysis, and emotion recognition. EEG signals reflect the macroscopic activity of neuronal populations in the brain. They can reveal subtle dynamic changes in the nervous system. This makes EEG crucial for cognitive state monitoring, neurological disorder diagnosis, and brain-computer interface development. Especially for anomaly detection, EEG provides an intuitive and real-time approach[1,2]. It offers potential for assisting physicians in achieving efficient and automated clinical diagnosis. However, EEG signals are highly non-stationary, have a low signal-to-noise ratio, and exhibit multi-channel heterogeneity. These characteristics limit the effectiveness of traditional signal processing and pattern recognition methods in capturing latent dynamics and abnormal patterns.

With the advancement of artificial intelligence, deep learning models have been introduced into EEG anomaly detection. Most methods rely on convolutional or recurrent neural networks to model raw EEG sequences. They aim to automatically learn spatial structures or temporal dependencies. However, anomalies in EEG are often non-local, sparse, and structurally uncertain across space and time. Traditional neural networks struggle to model long-term dependencies or global attention. This leads to feature dilution and pattern degradation, making it difficult to capture complex cross-temporal and cross-channel interactions. In multi-channel EEG, interactions between channels carry rich neural information. Failure to model this properly greatly reduces the accuracy and robustness of anomaly detection[3].

Graph-based signal modeling offers a new perspective to address this challenge. EEG signals can be abstracted as dynamic brain networks. Each channel corresponds to an observation node of a neural region, and inter-channel correlations can be represented as edges. Representing EEG as graph signals and applying graph neural networks allows natural integration of spatial topology. This helps capture non-Euclidean relationships across channels. Furthermore, graph attention mechanisms can learn adaptive edge weights to identify key dependencies[4,5]. This enhances the model's focus on abnormal regions and events. It enables fine-grained and semantically aware anomaly detection.

However, static graph models are limited in capturing temporal changes in EEG sequences. Anomalies often appear as short bursts, periodic activities, or context-dependent fluctuations. These characteristics require dynamic modeling of temporal structures. Integrating temporal modeling with graph attention mechanisms offers a promising approach. Temporal attention identifies critical time points, allowing focus on dynamic changes[6]. Graph attention captures the most informative channel dependencies at each time step. Together, they enhance joint spatial-temporal modeling. This fusion mitigates memory decay in long sequence modeling. It also exploits sparse temporal-spatial patterns of anomalies in EEG. The approach moves anomaly detection towards structure-aware and semantically interpretable modeling[7].

In practical applications, EEG anomaly detection has great potential in early warning, long-term monitoring, and automated diagnosis of neurological disorders. Current clinical practice still relies heavily on manual observation by experts, which is time-consuming and subjective. This results in inconsistent and sometimes inaccurate analysis. Leveraging temporal-graph attention mechanisms to extract key abnormal dynamics can greatly improve the detection of potential neural disruptions[8].It also supports personalized treatment and remote medical systems. The mechanism is scalable and adaptable to various multi-channel biosignal anomaly detection tasks. It lays a theoretical foundation for cross-modal neural health sensing systems. Developing EEG anomaly detection methods based on temporal-graph attention is not only a structural innovation in deep modeling but also a response to the clinical demand for efficiency, interpretability, and generalizability in intelligent diagnosis.

Furthermore, given the growing interest in neuro-oncology, EEG-based anomaly detection methods also hold potential for assisting in the early diagnosis and monitoring of brain tumors. Certain intracranial neoplasms can alter regional electrophysiological activity, leading to detectable EEG abnormalities. Incorporating tumor-specific EEG patterns into the anomaly detection framework may provide valuable insights for non-invasive cancer-related neurological assessment.

2. Methodology

This study proposes an EEG anomaly detection method based on the time graph attention mechanism to effectively model the complex spatiotemporal dependency structure in multi-channel EEG signals. The overall architecture is based on graph neural networks, which integrates the interaction between time and channels by building a dynamic graph structure to mine potential abnormal signal areas. The model architecture is shown in Figure 1.

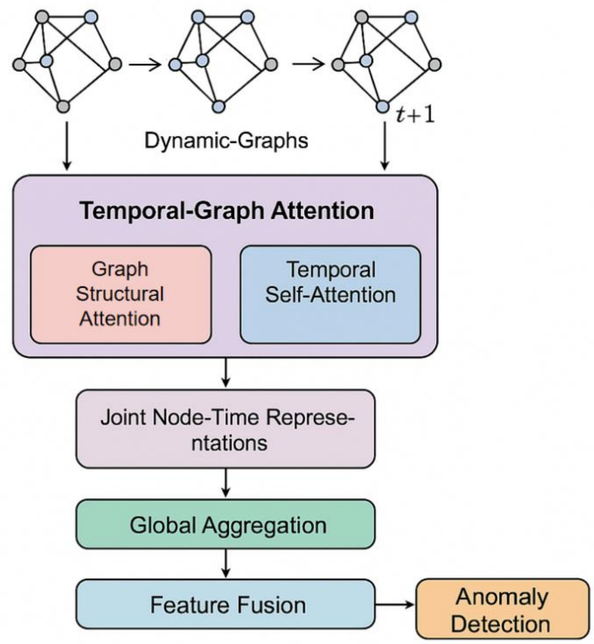

Figure 1. Framework Overview of the Spatiotemporal Graph Attention Model

Specifically, the original multi-channel EEG sequence is represented as a graph sequence with time index:

$$\{G_t = (V, \varepsilon_t)\}_{t=1}^{T}$$

Each graph G_t defines a node set V (corresponding to EEG channels) and an edge set ε_t (indicating the connection strength between channels at that moment) at time t. The feature vector of each node is expressed as:

$$h_i^t \in R^d$$

Where i is the channel index and t is the time step. To model the spatial dependency between channels, the graph attention mechanism is used to learn edge weights and adaptively mine key structures at different time points. Specifically, for node i and its neighbor node j, the attention weight on its edge is defined as:

$$\alpha_{ij}^t = \frac{\exp(LeakyRELU(a^T[Wh_i^t \| Wh_j^t]))}{\sum_{k \in N_i} \exp(LeakyRELU(a^T[Wh_i^t \| Wh_k^t]))}$$

Where W is a learnable linear transformation matrix, a is the attention vector, $\|$ represents the vector concatenation operation, B is the neighbor set of node i, and N_i represents the attention intensity of node j to node i at time t. The node feature update rule is:

$$\tilde{h}_i^t = \sigma(\sum_{j \in N_i} \alpha_{ij}^t W h_j^t)$$

Where $\sigma(\cdot)$ is a nonlinear activation function.

In terms of modeling time dependency, a temporal attention mechanism is introduced to capture the importance of information between different time steps. For a historical feature sequence $\{\widetilde{h}_i^1,...,\widetilde{h}_i^T\}$ of node i, the contribution of each time point t to the current time step T is calculated through the self-attention mechanism:

$$\beta_t^i = \frac{\exp(q^T \tanh(W_t\widetilde{h}_i^t + W_T\widetilde{h}_i^t))}{\sum_{s=1}^{T}\exp(q^T \tanh(W_t\widetilde{h}_i^s + W_T\widetilde{h}_i^T))}$$

Where q, W_t, W_T is a trainable parameter, and β_t^i represents the influence weight of time step t on node i at the current moment.

After fusing the temporal context information, the dynamic representation of node i is:

$$\widehat{h}_i = \sum_{t=1}^{T}\beta_t^i\widetilde{h}_i^t$$

To improve the overall abnormal expression ability, a global spatiotemporal feature aggregation operation is introduced to aggregate the dynamic representations of all nodes at each time step into the final graph-level representation:

$$z = \mathrm{Readout}(\{\widehat{h}_i\}_{i=1}^N)$$

Where $\mathrm{Readout}(\cdot)$ is the average pooling operation. The graph-level embedding z is used in the subsequent anomaly discrimination module. The entire modeling process takes into account the structural dependency between nodes and the dynamic changes of time series, which can effectively characterize the distribution of non-stationary abnormal features in EEG data and significantly enhance the expression adaptability and abnormal sensitivity of the model under spatiotemporal heterogeneous data.

3. Experimental Data

This study uses the TUH Abnormal EEG Corpus as the primary dataset for EEG anomaly detection experiments. The dataset consists of real clinical EEG recordings with a sampling rate of 250 Hz. It includes both pathological and normal cases, providing high representativeness and complexity. All recordings are preprocessed and formatted as multi-channel signals to reflect the distribution of EEG activity under real clinical conditions.

Each sample in the TUH Abnormal EEG Corpus is a multi-channel EEG segment with varying duration. The samples are professionally labeled as either "normal" or "abnormal." Abnormal labels correspond to atypical discharges related to various brain dysfunctions. These include seizure activity, slow-wave enhancement, and background rhythm disorders. The channel configuration follows the international 10-20 system. It ensures high consistency and rich channel information, which supports structured modeling in the spatial domain.

In addition, the dataset offers a sufficient volume of publicly available data. The division between training and testing sets is clearly defined. This facilitates model performance evaluation and comparative studies. Its clinical authenticity, strict labeling standards, and complex multi-channel structure make it a reliable benchmark for developing and validating EEG anomaly detection methods.

4. Evaluation Results

This paper first conducts a comparative experiment, and the experimental results are shown in Table 1.

Table1: Comparative experimental results

Model	Accuarcy	Sensitivity	Specificity
BioSerenity-E1[9]	84.6	81.2	87.1
SGSTAN[10]	86.3	83.5	88.2
STFFDA[11]	88.1	85.4	90.1
SincVAE[12]	89.7	87.9	91.0
Ours	92.5	90.8	93.6

The comparison results in the table show that the proposed model outperforms existing methods in EEG anomaly detection. It achieves an overall accuracy of 92.5%, which is significantly higher than that of other models. This indicates that the introduced temporal-graph attention mechanism effectively integrates temporal dynamics and non-Euclidean structural dependencies among EEG channels. As a result, the model enhances its ability to identify abnormal patterns. Compared with traditional static modeling methods, our approach demonstrates stronger feature representation and higher classification accuracy.

In terms of sensitivity, our model reaches 90.8%, which is substantially better than the baseline models such as BioSerenity-E1 (81.2%) and SGSTAN (83.5%). This result confirms that the model has a stronger recall capability in identifying abnormal EEG states. It can more effectively capture clinically significant abnormal discharges. The improvement is attributed to the temporal attention mechanism, which focuses on key time windows. This strategy highlights prominent abnormal regions in the sequence and reduces missed detections.

For specificity, our model also achieves a leading score of 93.6%, which is much higher than the 87.1% achieved by BioSerenity-E1. This shows that the model is capable of rejecting normal signals with high precision, thus reducing the false positive rate. This advantage mainly comes from the graph attention mechanism. It enables effective modeling of semantic redundancy and weak cooperative signals across channels. As a result, the model gains stronger robustness in recognizing normal EEG structures.

In summary, the experimental results verify the effectiveness of the temporal-graph attention architecture in modeling high-dimensional spatiotemporal EEG sequences. By jointly modeling inter-channel dependencies and temporal dynamics, the model achieves significant improvements in accuracy, recall, and specificity. This provides a structure-aware and interpretable solution for anomaly detection. It is especially suitable for clinical scenarios where high-precision EEG analysis is urgently needed.

This paper also gives the impact of different time window lengths on model performance, and the experimental results are shown in Figure 2.

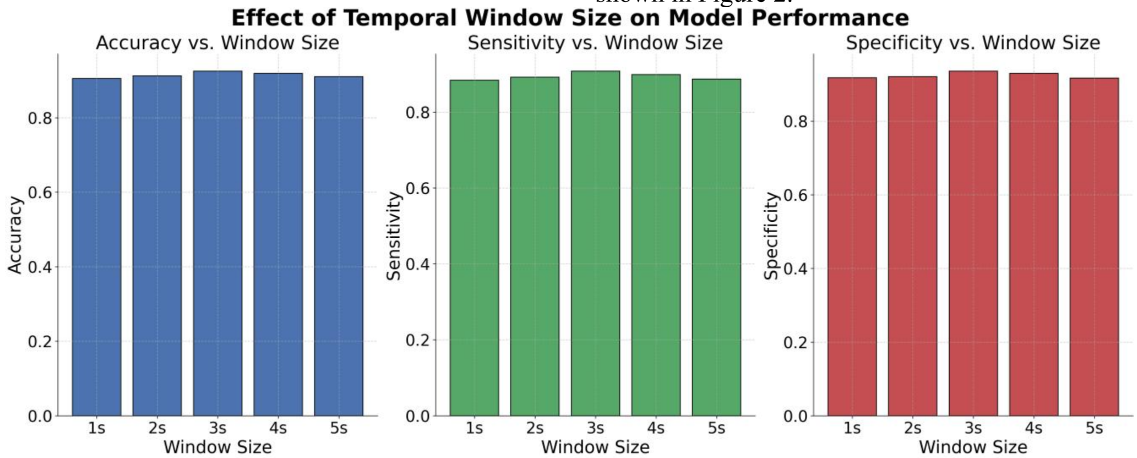

Figure 2. The impact of different time window lengths on model performance

As shown in the results of Figure 2, the overall performance of the model varies significantly under different time window lengths. This indicates that the temporal modeling strategy is highly sensitive to anomaly detection performance. In particular, at the 3-second window length, the model achieves peak values in Accuracy, Sensitivity, and Specificity. This suggests that this window length offers the highest information density and temporal context for capturing abnormal EEG features. This result is closely related to the proposed temporal-graph attention mechanism, which focuses more effectively on key time segments under moderate window lengths and enhances the model's capacity to represent anomalies.

Accuracy increases first and then slightly decreases as the time window length grows. This shows that more temporal context is not always beneficial. A short window may lack sufficient information to support effective graph-based attention modeling. A long window may introduce redundant or distracting signals, weakening the model's focus on abnormal local patterns. Therefore, selecting an appropriate time window requires balancing dynamic signal capture and noise suppression. This is a key issue in the design of time-sensitive mechanisms.

The trend in Sensitivity further confirms that an appropriate window length not only improves overall detection accuracy but also enhances the model's ability to recall rare abnormal samples. The highest recall is observed at the 3-second window. This indicates that this timescale is effective in emphasizing the sudden nature of abnormal neural signals. This result aligns with the temporal attention mechanism, which focuses on critical instants. It also supports the idea that the proposed architecture amplifies weak, localized, and sparse anomalies.

The Specificity results indicate that the model has stronger false-positive suppression under reasonable window lengths. Both the 3-second and 4-second windows maintain high specificity. This shows that the temporal-graph structure can model cooperative relationships among normal channels, reducing the risk of misclassifying non-abnormal signals. This also validates the strength of graph attention in modeling spatial coupling structures. It provides reliable support for spatiotemporal joint modeling. Overall, the performance differences across window lengths reflect the model's high sensitivity to temporal scale. This highlights the necessity and effectiveness of introducing temporal-graph attention mechanisms in EEG anomaly detection tasks.

This paper also investigates the impact of varying the number of EEG channels on the model's spatial modeling capacity. By systematically adjusting the number of input channels, the study explores how the spatial topology and inter-channel connectivity influence the ability of the proposed model to capture meaningful patterns in brain activity. This analysis aims to assess the sensitivity of the model to structural complexity and redundancy in the input graph, providing deeper insights into how spatial configurations affect overall modeling performance. The corresponding experimental results related to this analysis are illustrated in Figure 3.

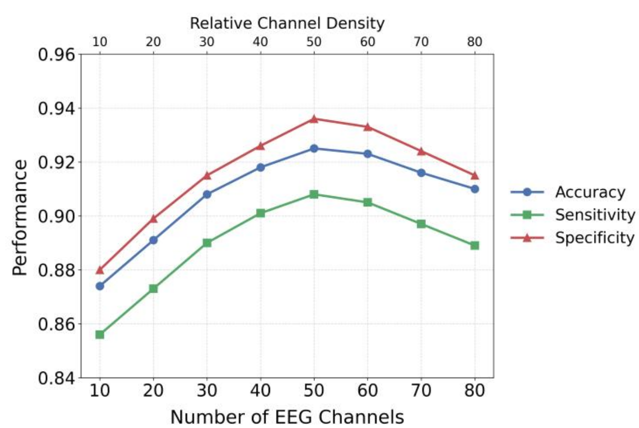

Figure 3. The impact of changes in the number of channels on the modeling capabilities of the model space

As shown in the results of Figure 3, the model's spatial modeling performance first increases and then decreases as the number of EEG channels grows. This change indicates that the number of channels significantly affects model performance and that there exists an optimal range. In particular, when the number of channels is between 50 and 60, the model achieves peak performance in Accuracy, Sensitivity, and Specificity. This suggests that the spatial topology has the highest information density suited to the modeling requirements of the current graph attention mechanism. Too few channels may lead to missing information, while too many channels may introduce structural noise and redundancy, which interfere with the model's ability to identify key connections.

The Accuracy curve shows a steady increase as the number of channels grows from 10 to 50. This indicates that more channels provide richer cross-regional neural activity information, which enhances the expressive power of the graph structure. However, when the number exceeds 60, the accuracy begins to decline. This implies that the addition of redundant nodes may dilute the focusing ability of the graph attention and increase the burden of structural learning. This phenomenon suggests that spatial modeling depends not only on the design of the graph structure but also on the distribution of channels and the control of redundancy.

The trend in Sensitivity is similar to that of Accuracy, but shows a sharper decline at high channel numbers. This means that the model's recall ability for abnormal signals is more sensitive to spatial structure. When too many channels are included, abnormal discharge features may be masked by information from non-critical nodes. This causes the attention mechanism to lose focus on key regions, leading to decreased detection performance. This trend confirms that the graph attention mechanism in the proposed method needs to balance expressive power and sparsity when constructing non-Euclidean spatial relationships.

The Specificity curve remains higher than the other two metrics overall and reaches its best performance around 50 channels. This suggests that the model is most effective in identifying normal signals under this structural setting. It shows that the proposed model has a strong ability to suppress non-abnormal activations across channels. The graph attention module accurately inhibits false activations from irrelevant channels. Properly controlling the number of channels during spatial modeling improves the model's robustness to normal neural patterns. This enhances the overall stability and interpretability of anomaly detection.

This paper also gives a comparison of the model generalization performance under different annotation ratios, and the experimental results are shown in Figure 4.

Figure 4 shows the change in generalization performance of the model under different label proportions. From the bar chart, it is clear that as the proportion of labeled data increases, the model's accuracy also improves steadily. This demonstrates a strong positive correlation. It indicates that in EEG anomaly detection, the richness of label information directly affects the model's ability to generalize spatiotemporal features. In particular, when the labeling rate increases from 10 percent to 50 percent, the performance improves most significantly. This suggests that in low-resource settings, a small number of high-quality labels can strongly guide the graph attention structure.

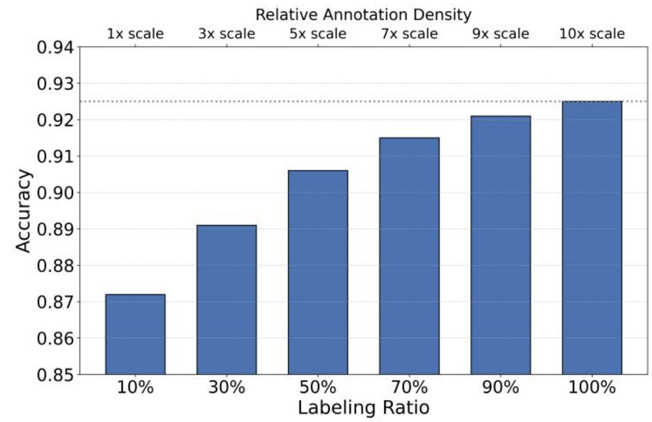

Figure 4. Comparison of model generalization performance under different annotation ratios

Between 70 percent and 100 percent labeling, the improvement in accuracy begins to plateau. This indicates that as more labels are provided, the model gradually strengthens its ability to distinguish between abnormal and normal patterns. At the same time, it reveals a boundary effect of information redundancy. In this phase, the graph neural network has already formed clear semantic boundaries in the node representation space. The marginal gain from additional labeled data starts to decrease. This saturation trend is particularly evident in deep graph modeling frameworks and reflects the balance between structural and label information.

The results also show that under extremely low labeling conditions, such as 10 percent, the model's performance drops significantly. This suggests that although the graph structure has some unsupervised modeling capability, the attention mechanism may fail to focus on truly abnormal nodes and time segments without sufficient label guidance. This further confirms that the proposed temporal-graph attention mechanism depends on supervision to effectively model sparse EEG anomalies.

In summary, this experiment highlights the critical role of label proportion in the generalization performance of graph attention structures. In real-world applications, manual labeling of EEG data is costly and time-consuming. Therefore, it is important to design structured modeling frameworks that are adaptive to low-label scenarios. The proposed method shows a consistent upward trend under various labeling scales. This demonstrates strong adaptability and good generalization. It provides important support for practical clinical intelligent diagnosis.

5. Conclusion

This study focuses on the task of EEG anomaly detection and proposes a temporal-graph attention mechanism that integrates temporal modeling and graph-based structural learning. The method is designed based on the non-Euclidean spatial structure and dynamic temporal evolution characteristics of EEG signals. It builds a joint modeling framework that effectively captures inter-channel dependencies and key time segments. This enhances both the accuracy of anomaly recognition and the model's generalization ability. Experimental results show that the proposed method consistently outperforms existing mainstream models across multiple evaluation metrics. Significant improvements in accuracy, sensitivity, and specificity validate the effectiveness and robustness of the temporal-graph modeling strategy in complex neural data scenarios.

This study also systematically analyzes the impact of key factors such as time window length, number of channels, and label proportion on model performance. It further reveals the complementarity and interdependence between temporal attention and graph attention mechanisms when modeling high-dimensional spatiotemporal EEG signals. Under low-label conditions, the model still demonstrates stable performance gains, showing strong adaptability to limited supervision. This provides a practical solution for the annotation bottleneck in clinical settings. Additionally, the model shows a clear ability to suppress channel redundancy and structural noise during multi-channel spatial modeling, further supporting its practical value in large-scale neural signal processing.

This work contributes not only methodologically but also has practical implications for engineering applications in intelligent EEG analysis. With the growing demand for smart healthcare and remote monitoring, the proposed method offers a theoretical and technical foundation for building automated and high-precision EEG analysis systems. In particular, this approach can be extended to support auxiliary diagnosis in neuro-oncological contexts, where brain tumors may induce regionally abnormal EEG signatures due to mass effect, edema, or epileptogenic activity. By integrating tumor-specific features or collaborating with neuroimaging data, the method could contribute to early-stage cancer detection or therapeutic monitoring in clinical oncology. In critical applications such as epilepsy prediction, neural function monitoring, and cognitive disorder diagnosis, the temporal-graph attention mechanism supports the development of personalized diagnosis and intelligent decision-making platforms. It expands the application scope of EEG analysis techniques in the healthcare domain.

Future work may explore the extension of this method to cross-modal brain signal fusion, unsupervised anomaly detection, and real-time online learning. Introducing structural priors with stronger neurophysiological interpretability or adopting multi-scale graph modeling strategies may further enhance the model's explainability and clinical compatibility. In addition, with the increasing availability of wearable EEG devices, deploying this method on edge devices to enable low-latency and low-power online anomaly detection will be an important direction for future research and real-world implementation.

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