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Research on Epilepsy Detection Based on Pyramid raph Convolution Network for Brain Electrical Activity Spatial Topological Features

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Abstract: To address the high cost of spatio-temporal modeling for epilepsy detection, this paper proposes a lightweight pyramid graph convolutional network model. This model abandons complex temporal mechanisms and focuses on mining the spatial topology of the EEG frequency domain: extracting multi-band power spectra and statistical moments as node features, and constructing a Gaussian adjacency matrix based on the 10-20 system to simulate functional connections; the core adopts multi-scale pyramid graph convolutional blocks to capture multi-receptive field spatial dependencies and fuse features. Additionally, EEG-specific augmentation, Borderline-SMOTE, and Focal Loss are combined to address class imbalance. On the CHB-MIT dataset, the model achieves a sensitivity of 97.53%, specificity of 96.50%, accuracy of 97.02%, F1 score of 97.04%, and AUC of 99.13%. Experiments confirm the sufficiency of spatial topological features in epilepsy discrimination, with performance superior to or comparable to mainstream methods, providing an efficient solution for portable clinical monitoring.

Keywords: EEG; Class Imbalance; Pyramid Graph Convolutional Network; Feature Extraction.

1. Introduction

Epilepsy is one of the most common neurological disorders, affecting over 50 million people worldwide. It may cause involuntary movements, loss of consciousness, and impairments in motor, sensory, emotional or mental functions, and even death [1][2][3].

Unique patterns observed in electroencephalogram (EEG) signals, such as triphasic waves, biphasic waves, generalized sharp and slow waves, and multiple spikes, can serve as indicators of various types of epilepsy and play a significant role in identifying epilepsy-related brain abnormalities, diagnosing specific epilepsy categories, and determining treatment goals[4][5]. In traditional epilepsy treatment, the identification of seizure segments is mainly carried out by epilepsy experts through observing long-term EEG records and subsequently marking them manually[6]. However, this manual approach is extremely disadvantageous when dealing with long-term continuous EEG and is prone to misjudgment. Therefore, the development of automated epilepsy detection algorithms needs to be explored.

In recent years, artificial intelligence technology has developed rapidly, and various machine learning and deep learning methods have been widely applied in the medical field[7]. The workflow of deep learning models includes initial feature extraction, followed by learning and classification using deep learning methods, which include convolutional neural networks (CNN), recurrent neural networks (RNN), autoencoders (AE), deep belief networks (DBN), etc.[8][9][10][11]. However, these efforts have failed to fully capture the spatial dependence of multi-channel EEG signals. Although these models have acceptable accuracy, they often face problems such as large parameter quantities, high computational costs, and long inference delays, making it difficult to deploy on resource-constrained wearable devices or edge computing nodes.

Furthermore, excessive focus on time series modeling sometimes leads to the model ignoring the rich spatial topological information contained in the EEG signals - that is, the functional connection patterns between different brain region electrodes, which are the key features of the synchronous changes in the whole brain or local networks during epileptic seizures.

In response to the aforementioned challenges, this paper proposes a lightweight pyramid graph convolutional neural network architecture. Our core assumption is that the spatial distribution "fingerprints" left by epileptic seizures in the frequency domain possess extremely strong discriminative power, enabling high-precision detection without relying on complex time encoders. The main contributions of this paper are as follows:

(1) Architectural innovation: Abandoned the traditional time recurrence or attention modules, and designed a purely space-topology feature-based pyramid graph convolutional network (Pyramid Graph Convolutional Network, PGCN).

(2) Multi-scale mechanism: Proposed a multi-scale graph convolution operator based on k-hop adjacency matrices, explicitly capturing the multi-level spatial dependencies from local neighbors to global brain regions.

(3) Efficient enhancement strategy: Addressing the extremely imbalanced problem of epilepsy data, combined the mixed enhancement strategy of physical signal perturbation and feature space SMOTE, and introduced Focal Loss to optimize the classification boundary.

(4) Empirical verification: Experiments show that this model maintains extremely low computational overhead while achieving comparable detection performance to complex spatiotemporal models, demonstrating the sufficiency and efficiency of spatial features in epilepsy detection.

2. Methodology

The framework proposed in this study mainly consists of four parts: frequency domain feature extraction, graph construction, pyramid graph convolutional network, and optimization strategies.

(1) Frequency Domain Spatial Feature Extraction

Then, time-domain and frequency-domain features were extracted for each segment. In the frequency-domain analysis, the Welch method was used to estimate the power spectral density (PSD) [29], and the spectrum was divided into five commonly used clinical frequency bands: δ (1-4 Hz), θ (4-8 Hz), α (8-13 Hz), β (13-30 Hz), and γ (30-50 Hz) [30]. Within each frequency band, two key statistics were calculated: one was the root mean square (RMS) value of the PSD in that frequency band, which reflects the energy intensity of the band, and was defined as:

$$\mathrm{RMS}=\sqrt{\frac{1}{N_b}\sum_{f\in b}\mathrm{PSD(f)}} \tag{1}$$

The second is the standard deviation of PSD, which characterizes the unevenness of the spectral distribution and is defined as:

$$\mathrm{RMS}=\sqrt{\frac{1}{N_b\text{-}1}\sum_{f\in b}(\mathrm{PSD(f)}\text{-}\overline{\mathrm{PSD}_b})^2} \tag{2}$$

Combining five time-domain statistical quantities including mean, standard deviation, peak-to-peak value, average rate of change, and energy, a time-frequency domain feature set for each channel is formed. Finally, the RMS and PSD standard deviations of all frequency bands are concatenated with the above time-domain features along the channel dimension to form a complete sample feature vector. To reduce the distribution differences of EEG data among different patients, the z-score normalization method is used to normalize the features, and the method formula is as follows:

$$X_{\mathrm{norm}}=\frac{X\text{-}\overline{X}}{\mathrm{std}(X)} \tag{3}$$

(2) Graph Construction

To simulate the functional connectivity of the cerebral cortex, we constructed an undirected weighted graph G = (V, E, A) based on the physical coordinates of electrodes in the international 10-20 system. Here, the node set V represents 18 EEG channels, and the edge set represents the spatial relationships between electrodes. The adjacency matrix A was not obtained through data-driven learning but was pre-generated based on the Gaussian kernel function: using the Euclidean distance between electrodes as the weight basis, the closer the electrodes are, the higher the connection weight is, thereby embedding the prior knowledge of the physical topology of the brain into the model. This static graph construction method not only reduces the computational complexity but also ensures the interpretability of the model for spatial dependencies. Additionally, to enhance the models perception of spatial positions, we directly superimposed the normalized coordinates of the electrodes as positional encoding (Positional Encoding) onto the node features.

(3) Pyramid Graph Convolutional Network, PGCN

The core of the model is a deep multi-scale pyramid graph convolution block. Traditional graph convolutions usually only aggregate information from direct neighbors (1-hop), which is insufficient to capture long-range spatial dependencies. To address this, we designed a parallel multi-branch structure that utilizes pre-computed k-hop adjacency matrices (k=1,2,4) to capture spatial context information at local, intermediate, and global scales respectively. After each branch independently performs the graph convolution operation, multi-scale features are fused through concatenation. To further enhance the robustness of the features, we introduced a "pyramid pooling-upsampling" mechanism after each convolution block: by adaptively averaging pooling, the number of nodes is successively downsampled to different scales (e.g., 18 -> 9 -> 4 -> 1), extracting multi-granularity global semantics, and then through linear interpolation upsampling, it is restored to the original number of nodes and fused with the original features. This structure, combined with residual connections and GELU activation functions, constitutes the stacked encoder core, which can extract deep spatial features with very low parameter quantities. Finally, after global average pooling (Global Average Pooling), the graph-level features are compressed into vectors, and input into a classification head composed of multiple layers of perceptrons (MLPs) to output the probability of epileptic seizures.

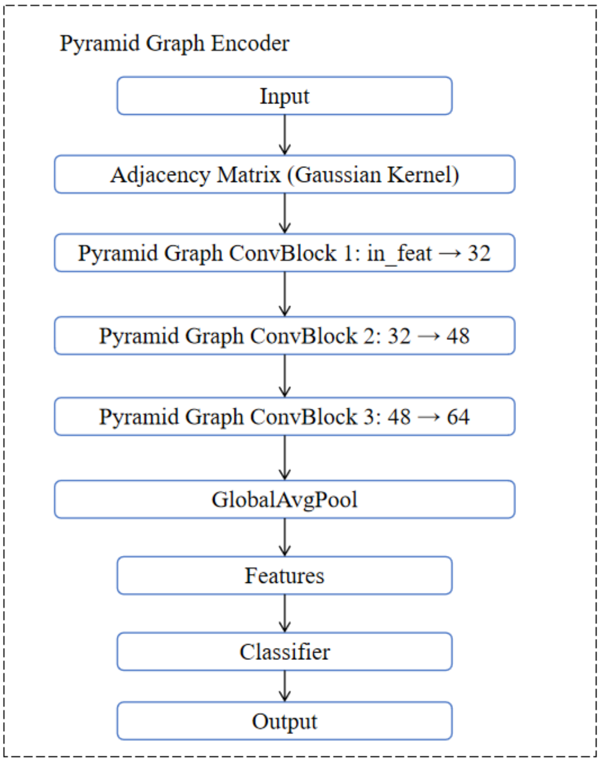

Figure 1. Pyramid Graph Convolution Network

(4) Unbalanced Learning and Training Strategies

During the training phase, to address the remaining classification difficulty differences and boundary ambiguity issues, we employed Focal Loss as the optimization objective. Focal Loss incorporates a modulation factor to automatically reduce the weight of easily classified samples, compelling the model to focus on the learning of difficult samples (Hard Examples), thereby sharpening the classification boundaries. The model uses the AdamW optimizer for parameter updates and is accompanied by the Cosine Annealing learning rate scheduling strategy to prevent getting stuck in local optima and improve generalization performance. The entire training process monitors the F1 score on the validation set, dynamically adjusting the classification threshold to balance sensitivity and specificity, ensuring the reliability of the model in clinical applications.

3. Experiments and Results

(1) Experimental Setup

To verify the generalization ability of the model in a cross-patient scenario, this study conducted experiments on the publicly available CHB-MIT EEG dataset, and the evaluation metrics included accuracy (Acc), sensitivity (Sens), specificity (Spec), F1-score, recall, precision, and AUC.

(2) Experimental Results and Analysis

The experimental results show that the proposed Pyramid Graph Convolutional Network performs exceptionally well in all metrics (as shown in Table 1).

Table 1. CHB-MIT Experimental Data

Patient	Acc (%)	Precision (%)	Recall (%)	F1(%)	AUC (%)	Sensitivity (%)	Specificity (%)
chb01	98.16	96.75	99.67	98.19	99.8	99.67	96.67
chb02	98.29	100.00	96.58	98.26	099.46	96.58	100.00
chb03	98.35	97.48	99.27	98.37	99.77	99.27	.97.44
chb04	96.08	93.68	98.82	96.18	99.52	98.82	93.33
chb05	99.07	98.68	99.47	99.07	99.98	99.47	98.67
chb06	91.28	93.27	88.99	91.08	96.31	88.99	93.58
chb07	97.95	98.61	97.26	97.93	99.82	97.26	98.63
chb08	96.51	96.43	9659	96.51	99.44	96.59	96.43
chb09	99.73	100.00	99.47	99.73	99.99	99.47	100.00
chb10	99.17	98.69	99.67	99.18	99.79	99.67	98.68
chb11	98.98	098.89	99.07	98.98	99.61	99.07	98.89
chb12	91.39	87.79	96.14	91.78	97.38	96.14	86.63
chb13	95.07	92.95	97.53	95.19	98.8	97.53	92.60
chb14	94.49	94.12	94.92	94.51	98.12	94.92	94.07
chb15	97.73	98.27	97.17	97.71	99.52	97.17	98.28
chb16	96.83	98.36	95.24	96.77	97.63	95.24	98.41
chb17	97.97	97.03	98.99	98.00.	99.00	98.99	96.95
chb18	96.06	95.85	96.30	96.07	99.05	96.30	95.81
chb19	97.81	98.11	97.50	97.81	99.89	97.50	98.11
chb20	95.78	94.26	97.52	95.86	98.59	97.52	94.03
chb21	98.15	97.79	98.52	98.15	9891	98.52	97.79
chb22	96.74	95.10	98.55	96.80	099.57	98.55	94.93
chb23	99.83	99.65	100.00	099.83	100.00	100.00	99.65
average	97.02	96.60	97.53	97.04	99.13	97.53	96.50

Overall, the model achieved an accuracy of 97.02%, a sensitivity (Recall) of 97.53%, a precision of 96.60%, and a specificity of 96.50%. The F1-score reached 97.04% and the AUC value was as high as 99.13%. This result confirms that the model not only can accurately identify epileptic seizure events (with high sensitivity), but also can effectively suppress false alarms during non-seizure periods (with high specificity), achieving an excellent balance between the sensitivity and specificity required for clinical monitoring.

(3) Comparison With the State-of-the-Art Methods

In order to comprehensively verify the superiority of the Pyramid-GCN (PGCN) model, this study conducted a horizontal comparison between it and various mainstream and advanced algorithms on the CHB-MIT dataset. The results are shown in Table 2. The results indicate that PGCN achieved the best comprehensive performance in the three core indicators of sensitivity, specificity, and accuracy. Specifically, PGCN significantly outperformed traditional machine learning methods based on nonlinear dynamic features (such as Zabihiet al.s Nullcline+ANN/LDA, with a sensitivity of only 91.15%) and ensemble learning strategies (such as Guo et al.s Isolation Forest+EasyEnsemble, with an accuracy of 92.62%), demonstrating the advantage of end-to-end deep feature extraction over manual feature engineering. In the comparison with deep learning models, PGCN also performed well, with a sensitivity 3.64 percentage points higher than the classic LSTM+CNN hybrid architecture (Yang et al., 93.89%), indicating that focusing on the mining of frequency domain spatial topology is more capable of capturing the essential laws of epileptic seizures than simply stacking time series modules; moreover, although Tao et al.s Graph Isomorphism Network (GIN) had a slightly higher specificity (97.00%), PGCN achieved a lower false negative rate with a sensitivity of 97.53% and a higher overall accuracy (97.02%) than GIN (96.20%), which fully confirmed the strategy of the multi-scale pyramid structure combined with static physical topology prior proposed in this paper, which can maintain the models lightweight while achieving more robust and accurate epilepsy seizure detection results than general graph neural networks.

Table 2. Comparisons with various methods using the chb-mit eeg database

Authors	Methods	Sen(%)	Spe (%)	Acc (%)
Zabihi et al.[12]	Nullcline features+ANN,LDA	91.15	95.16	95.11
Guo et al.[13]	Isolation forest and EasyEnsemble	95.55	92.57	92.62
Yang et al.[14]	LSTM+CNN	93.89	96.48	95.47
Tao et al.[15]	GIN	95.40	97.00	96.20
Ours	PGCN	97.53	96.50	97.02

4. Conclusion

This paper proposes a spatial-only encoder model based on pyramid graph convolution network for efficient epilepsy detection. By deeply exploring the frequency-domain spatial topological features of EEG signals and utilizing multi-scale graph convolution to capture the interactions between brain regions under different receptive fields, this model achieves comparable detection performance to the current state-of-the-art spatio-temporal models without the need for complex time modeling. Experimental results show that spatial structure information is the key basis for epilepsy discrimination, and the simplified architecture brings significant computational efficiency improvement, making it highly potential for deployment in portable medical devices and real-time monitoring systems. Future work will explore dynamic graph construction mechanisms to adaptively capture changes in functional connections and further validate the models generalization ability on multi-center datasets. This research provides a new paradigm for lightweight and high-precision EEG analysis.

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