Dual-Path Parallel Graph Convolution Combining Brain Region Partitioning and Data-Driven Learning for EEG Emotion Recognition

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Abstract

Electroencephalogram (EEG) has become an important indicator reflecting emotions. Due to its natural graph structure characteristics, it has made significant progress in the emotional recognition using graph convolutional networks (GCN). However, existing methods face limitations: (1) insufficient integration of psychological prior knowledge, limiting the utilization of brain activity patterns, and (2) simplistic node relationship construction, neglecting the universality and functional connectivity of brain regions. Therefore, we propose a dual-path parallel graph convolutional network (DP-GCN). The first path leverages psychological prior knowledge to segment electrodes into brain regions and employs an attention mechanism to integrate features. The second approach employs a data-driven method, using a sparse stacked autoencoder to reconstruct brain region features, while a learnable, input-independent adjacency matrix captures EEG patterns associated with emotions. Finally, a cross-attention mechanism integrates features from both paths. DP-GCN has been evaluated on public dataset, achieving an accuracy of 82.69%±4.16%, demonstrating its competitive performance.

Keywords: EEG, Emotion Recognition, Graph Convolution Network, Brain Regions

Introduction

Emotions are integral to human behavior and mental states (Cowie et al., 2001), influences health, communication, and social interactions. Emotion recognition, mainly using EEG signals, has garnered significant attention due to its direct reflection of brain activity and wide applications in brain-computer interfaces, healthcare, and intelligent systems. EEG is a non-invasive technique that offers high temporal resolution and captures subtle neural activity associated with emotional states (Das, Singh, & Pachori, 2024). By analyzing EEG's domain and frequency-domain features, researchers can decode specific patterns associated with emotions, offering valuable insights into the neural mechanisms underlying affective processes.

Traditional EEG emotion recognition methods mainly rely on deep learning technology. Early methods mostly adopted Convolutional Neural Networks (CNNs) models to achieve emotion recognition by extracting local spatial features(D. Zhang et al., 2018). However, considering the time-series characteristics of EEG signals, subsequent research gradually introduced Recurrent Neural Networks (RNNs)(T. Zhang, Zheng, Cui, Zong, & Li, 2019) and Long Short-Term Memory (LSTM) networks (Xing et al., 2019)to enhance the modeling ability of temporal information. In addition to focusing on time-series information, Spatial-Spectral-Temporal Network (SST-EmotionNet) proposed a unified network framework that can simultaneously integrate spatial, spectral, and temporal features(Jia et al., 2020). These methods usually do not fully consider the spatial distribution and frequency information contained in EEG signals, resulting in an insufficiently comprehensive description of the overall characteristics of EEG signals.

EEG signals inherently exhibit a graph structure, where electrodes correspond to nodes, and functional connections or geometric adjacency relationships between electrodes represent edges. Leveraging this, researchers introduced Graph Convolutional Networks (GCNs) to extract spatially informed features. The Dynamical Graph Convolutional Neural Networks (DGCNN) method pioneered the application of graph convolution for emotion recognition, utilizing an adjacency matrix based on spatial distances between EEG electrodes to capture their inherent spatial relationships (Song, Zheng, Song, & Cui, 2020).

In the application of GCNs, the selection of node features is diverse. A standard method is to directly utilize EEG raw signals, extract their spatial features through graph convolution, and further mine temporal domain information using time series networks(Jia et al., 2021). In addition to the processing of the original signal, many studies have also attempted to use input forms based on Spectral features, such as differential entropy and power spectral density, which have been proven to have high effectiveness in emotion recognition tasks (Duan, Zhu, & Lu, 2013). The construction of the adjacency matrix is also important in GCN, and different methods have diverse explorations in the construction of edges. DGCNN constructs the adjacency ma-

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trix by using the spatial distance between electrodes, assuming that the relationship between nodes is negatively correlated with the electrode distance(Song et al., 2020). Learning from Local-Global-Graph Representations (LGGNet) introduces a symmetric trainable attention mask, which weights the basic global adjacency matrix, and generating a learnable global adjacency matrix(Ding, Robinson, Tong, Zeng, & Guan, 2024). Multi-View Spatial-Temporal Graph Convolutional Networks (MSTGCN) generates the adjacency matrix through the node distances in the feature space and utilizes the loss function to update the adjacency matrix (Jia et al., 2021). SparseDGCNN updates the adjacency matrix W according to the gradient of the loss function through an iterative optimization process, combining ℓ_1 regularization and activation function to achieve sparsity and non-negativity constraints, thereby adaptively learning the optimal graph structure(G. Zhang et al., 2023). The Pyramidal Graph Convolutional Network (PGCN) builds connections between EEG electrodes at three levels: local, mesoscale, and global. It uses the physical 3D layout of the electrodes, adds known functional relationships, and considers both electrode features and their positions to create a comprehensive model (Jin, Zhu, Du, He, & Li, 2023).

However, the existing methods for emotion recognition based on EEG signals face key limitations in global feature extraction, utilization of psychological priors, and feature fusion. Most approaches use GCNs with fixed adjacency matrices, which overlook dynamic relationships in EEG pathways and limit global feature learning. Furthermore, they fail to leverage psychological priors, treating EEG nodes as independent entities and ignoring the structured role of brain areas in emotional processing. Feature fusion strategies are often simplistic, relying on direct concatenation or weighted summation, which inadequately model interactions between different information streams and hinder performance improvements.

To address these challenges, this paper proposes a dual-path parallel model that integrates brain electrical pathway learning with prior psychological knowledge of brain region segmentation, as illustrated in Figure 1. The first path leverages prior brain region segmentation to partition electrode nodes into corresponding brain areas. It employs attention mechanisms to aggregate intra-region features and constructs adjacency matrices to model inter-region correlations, thereby enhancing the psychological plausibility of spatial feature representation. The second path employs a data-driven approach, utilizing a sparse stacked autoencoder (SSAE) to reconstruct brain regions and extracting global features through a learnable adjacency matrix, which capturing latent patterns in EEG pathways and improving the global representation capacity for emotion classification. The two information streams are fused via cross-attention mechanisms, enabling collaborative optimization of global patterns and region-specific features. This approach effectively integrates generalizable features with psychologically informed priors, enhancing the comprehensiveness and accuracy of feature representation. The proposed framework provides a robust and holistic solution for emotion recognition tasks.

Methods

In this section, we provide a detailed introduction to the overall architecture of the proposed model and its core components. The model mainly includes the construction of two-path graph structures and the feature propagation mechanism of graph convolution.

Region-Prior Graph

Brain Regions Fusion Brain regions are divided based on medical prior knowledge to better simulate the signal transmission between brain regions, and adaptive feature fusion is achieved by combining attention mechanisms to construct a more reasonable prior medical graph structure.

The SJTU Emotion EEG Database (SEED) (Zheng & Lu, 2015), a widely used dataset for emotion recognition, was recorded using the ESI NeuroScan system with electrode positions aligned to the international 10-20 system (Homan & Homan, 1988). The dataset includes recordings from 62 channels, systematically classified into distinct brain regions according to the 10-20 system, as shown in Figure 2a.

In addition to the classification framework based on the 10-20 system, further refinements were introduced to enhance the discriminative capability of EEG features. Specifically, definitions of the frontal lobe and hemispheric mappings were proposed, as highlighted in (Ding et al., 2024). Extensive research has demonstrated that the prefrontal cortex plays a pivotal role in the emotional recognition (Wolf, Philippi, Motzkin, Başkaya, & Koenigs, 2014)(Fossati, 2012). Building upon the 10-20 system, we further subdivided the prefrontal region into more granular partitions, as depicted in Figure 2b. Hemispheric asymmetry is a significant feature in EEG analysis, with the left prefrontal lobe linked to positive emotion regulation and the right prefrontal lobe more engaged in negative emotion processing (Ahern & Schwartz, 1985). Consequently, we partitioned the symmetric regions into distinct brain areas, as shown in Figure 2c.

This refined classification approach provides a more nuanced understanding of the spatial and functional organization of brain activity, thereby facilitating more precise analysis of EEG signals in the context of emotional recognition and related cognitive processes.

Electrode nodes are assigned to brain areas for rational feature processing. To enhance fusion within each area, an attention mechanism calculates weights for electrode features, achieving more effective feature integration. Specifically, given a set of brain regions $R = \{r_1, r_2, ..., r_k\}$ and electrode channels $C = \{c_1, c_2, ..., c_n\}$, we define a region-channel mapping function $\phi : R \to \mathcal{P}(C)$ that maps each brain region to its corresponding set of electrodes:

$$\varphi(r) = \{c_i \in C \mid c_i \in \text{region}[r], \forall r \in R\}$$

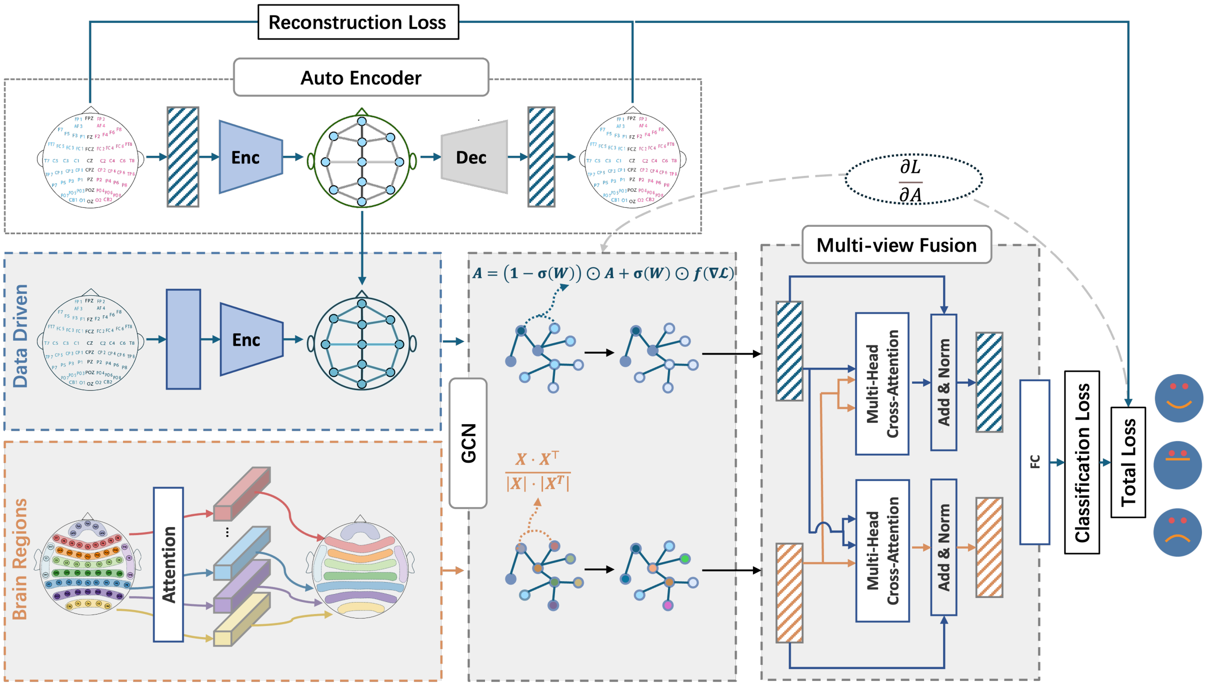


Figure 1: Dual-path parallel framework integrating brain region segmentation and data-driven learning for emotion recognition

where region$[r]$ denotes the anatomical boundary of the brain region $r$and $\mathcal{P}(C)$ represents the power set of C. For each brain region r, let $X_r \in \mathbb{R}^{n_r \times d}$ denote its channel feature matrix, where $n_r = |\varphi(r)|$ represents the number of channels in region r, and d is the feature dimension. The region-specific representation h_r is derived through an attention-weighted aggregation of the channel features $x_i \in X_r$:

$$h_r = \sum_{i=1}^{n_r} \alpha_i x_i, \quad \text{where } \alpha_i = \frac{\exp(w_{r,i})}{\sum_{j=1}^{n_r} \exp(w_{r,j})}$$

Here, x_i corresponds to the i-th row of X_r, and α_i represents the attention weight for the i-th channel, derived from learnable parameters $w_{r,i}$ (initialized to 1). These region-specific representations h_r serve as node features in subsequent graph convolutional operations, where each brain region is treated as a node in the graph. The attention weights are optimized during training through gradient descent:

$$\mathbf{w}_r^{(t+1)} = \mathbf{w}_r^{(t)} - \eta \nabla_{\mathbf{w}_r} \mathcal{L}$$

where η denotes the learning rate and $\mathcal{L}$ represents the task-specific loss function.

Integration of Brain Connectivity The construction of the adjacency matrix $\mathbf{A}$ aims to integrate local feature similarity and global prior structural information to effectively characterize the association between brain regions. Given the node feature tensor $\mathbf{X} \in \mathbb{R}^{B \times N \times F}$ (where B, N, and F denote batch size, number of brain regions, and feature dimension, respectively), we construct a hybrid adjacency matrix that combines both local feature correlations and global structural patterns. The adjacency matrix $\mathbf{A}^{(b)} \in \mathbb{R}^{N \times N}$ (with b denoting brain-region fusion) is formulated as:

$$\mathbf{A}^{(b)} = \alpha \mathbf{A}_{\text{local}}^{(b)} + (1 - \alpha)\mathbf{A}_{\text{global}},$$

where:

$$\mathbf{A}_{\text{local}}^{(b)} = \frac{\mathbf{X} \cdot \mathbf{X}^\top}{\|\mathbf{X}\| \cdot \|\mathbf{X}\|^\top},$$

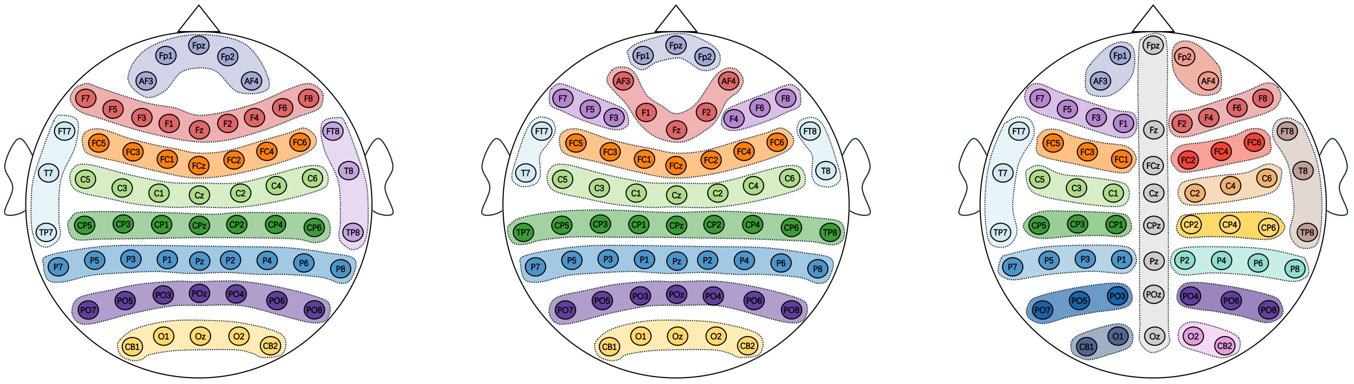
$$\mathbf{A}_{\text{global}}^{(b)} = \text{ReLU}(\mathbf{W} + \mathbf{W}^\top).$$

Here, $\mathbf{A}_{\text{local}}^{(b)}$ captures dynamic inter-regional correlations through cosine similarity (Perozzi, Al-Rfou, & Skiena, 2014), while $\mathbf{A}_{\text{global}}$ models learnable structural connectivity patterns with symmetry constraints. The hyperparameter $\alpha \in [0, 1]$ balances their relative contributions. The final adjacency matrix includes self-loops and is normalized using double random walk normalization, as described in (Ding et al., 2024). The final expression $\mathbf{A}^{(b)}$ is:

$$\mathbf{A}^{(b)} = \alpha \cdot \left(\frac{\mathbf{X} \cdot \mathbf{X}^\top}{\|\mathbf{X}\| \cdot \|\mathbf{X}\|^\top} \right) + (1 - \alpha) \cdot \text{ReLU}(\mathbf{W} + \mathbf{W}^\top).$$

Data-Driven Graph

In the emotional and cognitive domains, the propagation of EEG signals between brain regions presents task-related specific patterns, especially in emotional recognition tasks (Harmony et al., 2004). These patterns mainly manifest as the activation of specific brain regions and their propagation along fixed paths. Different emotional states activate brain regions with clear functional characteristics and propagate stably between regions. Therefore, a reasonable and input-independent fixed propagation pattern is crucial for emotion



(a) 10-20 System Brain Regions (b) Frontal Subdivision Brain Regions (c) hemispheric-Based Brain Regions

Figure 2: Brain Region Definitions Based on Physiological Priors

recognition. In addition, research has shown that the propagation of EEG signals between brain regions can be approximated as a linear process, which can be effectively modeled using a linear EEG mixing model. (Keil et al., 2002) (Xing et al., 2019).

We propose a data-driven framework for EEG feature extraction and dynamic graph modeling, focusing on brain region division and task-related signal propagation. The framework includes: (1) a linear Sparse Stacked Autoencoder (SSAE) that reconstructs multi-channel EEG signals, optimizing the mapping between channels and brain regions; and (2) a gradient-driven adjacency matrix optimization method, which dynamically models brain region connectivity and represents global emotional propagation patterns, fixed after training. The SSAE adopts an encoder-decoder structure where the encoder $E : \mathbb{R}^{d_{in}} \to \mathbb{R}^{d_L}$ compresses high-dimensional input data into a low-dimensional latent representation, and the decoder $D : \mathbb{R}^{d_L} \to \mathbb{R}^{d_{in}}$ reconstructs the original input from this latent space. The encoder consists of L stacked fully-connected layers with decreasing dimensions $d_{in} > d_1 > d_2 > ... > d_L$. For the i-th encoding layer, the transformation is defined as:

$$\mathbf{h}_i = f_i(\mathbf{W}_i \mathbf{h}_{i-1} + \mathbf{b}_i)$$

where $\mathbf{W}_i$ and $\mathbf{b}_i$ denote the weight matrix and bias vector, respectively, and $f_i(\cdot)$ represent a nonlinear activation function. The input to the first layer is $\mathbf{h}_0 = \mathbf{X}$. The decoder mirrors the encoder architecture with L layers of gradually increasing dimensions. The i-th decoding layer performs:

$$\mathbf{h}'_i = g_i(\mathbf{W}'_i \mathbf{h}'_{i+1} + \mathbf{b}'_i)$$

where $g_i(\cdot)$ is the activation function, with the final layer utilizing a linear transformation to generate the reconstruction $\hat{\mathbf{X}} = \mathbf{h}'_1$. The model is trained by minimizing a composite loss function that balances reconstruction fidelity with sparsity constraints:

$$\mathcal{L}_{SSAE} = \underbrace{\|\mathbf{X} - \hat{\mathbf{X}}\|_2^2}_{\text{reconstruction loss}} + \lambda \underbrace{\sum_{i=1}^{L} \|\mathbf{h}_i\|_1}_{\text{sparsity regularization}}$$

where: $\mathbf{X}$ and $\hat{\mathbf{X}}$ are the input and reconstructed data respectively. λ is the sparsity regularization weight, $\mathbf{h}_l$ is the output of the n-th encoder layer, and L is the number of encoder layers. During the training process, the total loss of SSAE and the final classification loss are jointly optimized. SSAE can extract meaningful feature representations for the classification task while maintaining sparsity and reconstruction ability:

$$\mathcal{L} = \mathcal{L}_{SSAE} + \alpha \mathcal{L}_{\text{classification}}$$

To model the connection relationships between functional brain areas and signal propagation paths, we introduce a data-driven adjacency matrix optimization method. The initial adjacency matrix $\mathbf{A}^{(d)} \in \mathbb{R}^{C' \times C'}$, where the superscript d denotes the data-driven path, is set as a learnable parameter and is dynamically updated through gradient-driven methods. The updated formula is as follows:

$$\mathbf{A}^{(d)} = (1 - \sigma(\mathbf{W})) \odot \mathbf{A} + \sigma(\mathbf{W}) \odot f(\nabla \mathcal{L}),$$

where the superscript d denotes data-driven. The learnable step matrix $\sigma(\mathbf{W})$, constrained by the Sigmoid function to $[0, 1]$, controls the update magnitude of $\mathbf{A}^{(d)}$. A non-linear mapping $f(\nabla \mathcal{L})$ enhances gradient expressiveness and avoids instability. To ensure stability and interpretability, $\mathbf{A}^{(d)}$ is normalized and symmetrized. During training, it is optimized via gradients, and after training, it becomes a fixed representation of emotion-related propagation pathways, balancing global priors with task-specific adaptability to improve expressiveness and generalization.

Feature Extraction and Integration

Graph Convolution Network This paper adopts a simplified graph convolution design based on spectral methods, leveraging the properties of the graph Laplacian operator(Bruna, Zaremba, Szlam, & LeCun, 2014). The graph convolution aggregates node features through the adjacency matrix to capture local and global relationships in the graph structure. Unlike traditional methods that rely on high-order polynomial expansions of the Laplacian, this approach directly uses the standard adjacency matrix as the propagation operator, reducing computational complexity. The core operation is defined as:

$$\mathbf{H} = \sigma\left(\tilde{\mathbf{A}}\mathbf{X}\mathbf{W}\right),$$

where $\mathbf{X} \in \mathbb{R}^{N\times F}$ is the input feature matrix, $\tilde{\mathbf{A}}$ is the symmetrically normalized adjacency matrix, $\mathbf{W} \in \mathbb{R}^{F\times F'}$ is a learnable weight matrix, and $\sigma(\cdot)$ is a nonlinear activation function. The adjacency matrix is preprocessed with symmetric normalization to ensure numerical stability and robust feature aggregation:

$$\tilde{\mathbf{A}} = \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}},$$

where $\mathbf{D}$ is the degree matrix (Defferrard, Bresson, & Vandergheynst, 2017). The weight matrix $\mathbf{W}$ is initialized using Xavier initialization to ensure stable gradient propagation during training.

Cross Attention To integrate data-driven global EEG features ($\mathbf{H}_{\text{data-driven}}$) and medical prior-based brain region features ($\mathbf{H}_{\text{brain-regions}}$), a cross-attention mechanism is employed (Huang et al., 2018). This mechanism computes weighted interactions between the two feature sets, enabling a balanced representation of global and local information. The output is refined through residual connections, dropout, and layer normalization, resulting in a fused representation $\mathbf{H}_{\text{fused}}$ that captures complex interactions and enhances the model's performance.

Results And Discussion

In this section, we introduce the SJTU Emotion EEG Database (SEED) (Zheng & Lu, 2015) and evaluate DP-GCN's emotion recognition performance in subject-dependent and subject-independent settings. SEED includes EEG and eye movement data from 15 participants (7 males, 8 females) who watched 15 emotion-eliciting movie clips (positive, neutral, negative). The experiment was repeated three times per participant. Data were recorded using a 62-channel ESI NeuroScan. Differential entropy (DE) features, extracted from 1-second non-overlapping EEG segments, were used as input signals. Moreover, the 62 channels were grouped into three brain regions, as shown in Figure 2, denoted as DP-GCN(10-20), DP-GCN(frontal), and DP-GCN(hemispheric), to evaluate their effectiveness.

Methods Comparison

In the subject-dependent experiment, we adopt the experimental paradigm described in (Li, Zheng, Cui, Zhang, & Zong, 2018) and (Li, Zheng, Wang, Zong, & Cui, 2022). For each subject, data from 15 trials are utilized, with the first 9 trials allocated for training and the remaining 6 trials reserved for testing. In the subject-independent experiment, we employed a leave-one-subject-out cross-validation (LOSO-CV) protocol to rigorously evaluate the model's generalizability across different individuals.

The performance metrics for all baseline methods are sourced from their respective references. DP-GCN is compared against several methods, including traditional machine learning approaches such as T-SVM (Collobert, Sinz, Weston, Bottou, & Joachims, 2006), RNN-based methods such as BiHDM (Li et al., 2021), and GCN-based methods such as DGCNN (Song et al., 2020), RGNN (Zhong, Wang, & Miao, 2020), and GCBNet (T. Zhang, Wang, Xu, & Chen, 2022), to further investigate its advantages. All methods utilize differential entropy (DE) features extracted from 1-second non-overlapping EEG segments. Since this comparison focuses on supervised learning without considering transfer learning, the domain adaptation modules in RGNN and BiHDM are removed, denoted as RGNN w/o DA and BiHDM w/o DA, respectively. As shown in Table 1, the subject-dependent experiment demonstrates competitive performance in terms of classification accuracy, highlighting the effectiveness of the proposed method.

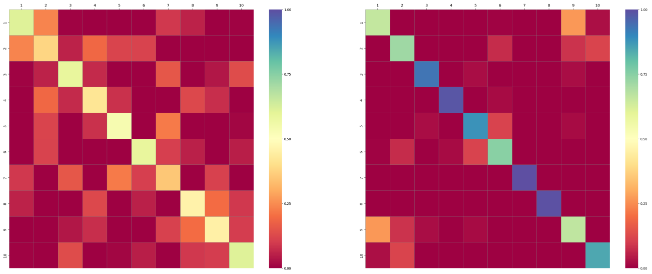
Table 1: Subject-Dependent Accuracy on the SEED.

Method	**Mean(%)**	**STD(%)**
SVM	83.99	9.72
DGCNN	90.40	8.49
BiHDM w/o DA	92.38	7.04
GCBNet	94.24	**6.70**
DP-GCN	**95.32**	6.83

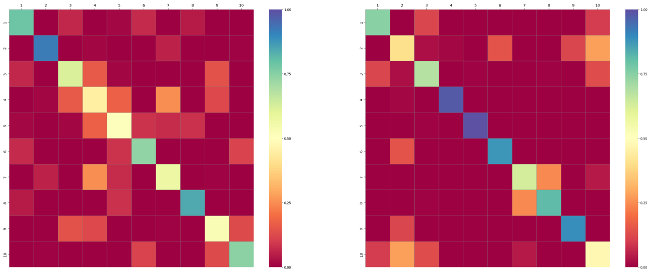
Table 2: Subject-Independent Accuracy on the SEED.

Method	**Mean(%)**	**STD(%)**
T-SVM	72.53	14.00
DGCNN	79.95	9.02
GCBNet	80.56	16.98
BiHDM w/o DA	81.55	9.74
RGNN w/o DA	81.92	9.35
DP-GCN (10-20)	81.73	4.82
DP-GCN (frontal)	**82.69**	**4.16**
DP-GCN(hemispheric)	80.89	4.88

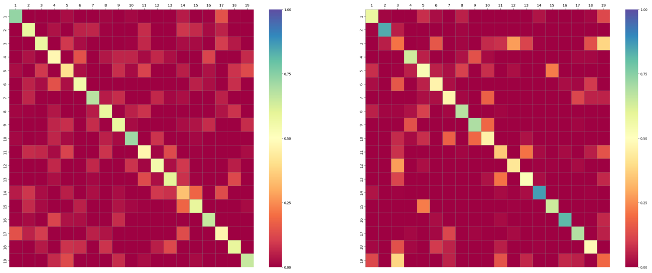
Table 2 presents the accuracy of the subject-independent experiments. The proposed model DP-GCN (frontal) demonstrates strong performance on the SEED dataset, achieving an accuracy of $82.69 \pm 4.16\%$. It is also noteworthy that DP-GCN exhibits a smaller standard deviation (4.16%), indicating greater stability in performance across different subjects and achieving relatively consistent classification results. This enhanced stability can likely be attributed to the integration



(a) Initial 10-20 system adj (b) Trained 10-20 system adj



(c) Initial frontal adj (d) Trained frontal adj



(e) Initial hemispheric adj (f) Trained hemispheric adj

Figure 3: Comparison of initial and trained adjacency matrix.

of brain region prior knowledge with data-driven dual-path learning, which combines a fixed adjacency matrix reflecting physiological connectivity priors and a learnable dynamic graph that captures data-specific structural patterns. This complementary design effectively overcomes the limitations of relying solely on a single graph structure. Furthermore, a cross-attention mechanism is introduced after graph convolution to facilitate deep and efficient feature fusion, enabling the model to achieve robust performance across diverse data.

Comparison of Brain Region Partitioning

The evaluation includes three brain region configurations: a 10-region classification based on the 10-20 system (2a), a 10-region frontal-focused configuration Figure (2b), and a 19-region asymmetric configuration Figure (2c). The specific numerical results, as shown in Table 2, indicate that the model based on the frontal partition achieved the best performance. This superior performance may be attributed to the strong association between emotional tasks and the frontal brain region. In contrast, the model based on hemispheric partitioning demonstrated slightly inferior results. This discrepancy could potentially be explained by the increased number of brain regions, which leads to a larger model parameter space and a higher risk of overfitting. To further analyze intrinsic functional connectivity in emotional EEG, we visualize the initial adjacency matrices and the trained matrices learned from three distinct brain region partitioning models, as shown in Figure 3. It can be observed that, after training, the connections between brain regions become sparser, with significant connections being more prominently highlighted. Additionally, self-loop connections play a crucial role in the construction of the adjacency matrices.

Conclusion

In this work, we propose the DP-GCN model for EEG-based emotion recognition, which integrates a physiology-driven path and a data-driven path to jointly learn EEG representations for the emotion recognition task. The physiology-driven path leverages prior knowledge of brain region parcellation, where node features are fused using an attention mechanism, and node relationships are constructed based on inter-node correlations. In contrast, the data-driven path employs SSAE to induce a functional brain parcellation by dimensionality reduction, with both the node embeddings and the adjacency matrix optimized via gradient descent. By complementing physiological priors with data-driven information, the model achieves an accuracy of 82.69% on the SEED dataset. Additionally, we evaluate the effectiveness of three proposed brain parcellation schemes in the context of emotion recognition. Future work will focus on enhancing the model's generalization in other tasks, such as motor imagery and fatigue detection, and further investigating the importance of different brain regions across various tasks. It is encouraging that DP-GCN achieves better performance than all compared models.

Acknowledgments

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References

Ahern, G., & Schwartz, G. (1985). Differential lateralization for positive and negative emotion in the human brain: Eeg spectral analysis. *Neuropsychologia*, *23*, 745-755. doi: 10.1016/0028-3932(85)90081-8 (document)

Bruna, J., Zaremba, W., Szlam, A., & LeCun, Y. (2014, May). *Spectral networks and locally connected networks on graphs* (No. arXiv:1312.6203). arXiv. doi: 10.48550/arXiv.1312.6203 (document)

Collobert, R., Sinz, F., Weston, J., Bottou, L., & Joachims, T. (2006). Large scale transductive svms. *Journal of Machine Learning Research*, *7*(8). (document)

Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., & Taylor, J. (2001, January). Emotion recognition in human-computer interaction. *IEEE Signal Processing Magazine*, *18*(1), 32–80. doi: 10.1109/79.911197 (document)

Das, K., Singh, V. K., & Pachori, R. B. (2024). Introduction to EEG signal recording and processing. In *Artificial Intelligence Enabled Signal Processing based Models for Neural Information Processing.* CRC Press. (document)

Defferrard, M., Bresson, X., & Vandergheynst, P. (2017, February). *Convolutional neural networks on graphs with fast localized spectral filtering* (No. arXiv:1606.09375). arXiv. doi: 10.48550/arXiv.1606.09375 (document)

Ding, Y., Robinson, N., Tong, C., Zeng, Q., & Guan, C. (2024, July). LGGNet: Learning From Local-Global-Graph Representations for Brain–Computer Interface. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(7), 9773–9786. doi: 10.1109/TNNLS.2023.3236635 (document)

Duan, R.-N., Zhu, J.-Y., & Lu, B.-L. (2013, November). Differential entropy feature for EEG-based emotion classification. In *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)* (pp. 81–84). doi: 10.1109/NER.2013.6695876 (document)

Fossati, P. (2012). Neural correlates of emotion processing: From emotional to social brain. *European Neuropsychopharmacology*, *22*, S487-S491. doi: 10.1016/j.euroneuro.2012.07.008 (document)

Harmony, T., Fernández, T., Gersenowies, J., Galán, L., Fernández-Bouzas, A., Aubert, E., & Díaz-Comas, L. (2004, August). Specific EEG frequencies signal general common cognitive processes as well as specific task processes in man. *International Journal of Psychophysiology*, *53*(3), 207–216. doi: 10.1016/j.ijpsycho.2004.04.006 (document)

Homan, R., & Homan, R. (1988). The 10-20 electrode system and cerebral location. *American Journal of Electroneurodiagnostic Technology*, *28*, 269-279. doi: 10.1080/00029238.1988.11080272 (document)

Huang, Z., Wang, X., Wei, Y., Huang, L., Shi, H., Liu, W., & Huang, T. S. (2018). Ccnet: Criss-cross attention for semantic segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*, 6896-6908. doi: 10.1109/TPAMI.2020.3007032 (document)

Jia, Z., Lin, Y., Cai, X., Chen, H., Gou, H., & Wang, J. (2020, October). SST-EmotionNet: Spatial-spectral-temporal based attention 3D dense network for EEG emotion recognition. In *Proceedings of the 28th ACM International Conference on Multimedia* (pp. 2909–2917). New York, NY, USA: Association for Computing Machinery. doi: 10.1145/3394171.3413724 (document)

Jia, Z., Lin, Y., Wang, J., Ning, X., He, Y., Zhou, R., ... Lehman, L.-w. H. (2021). Multi-View Spatial-Temporal Graph Convolutional Networks With Domain Generalization for Sleep Stage Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *29*, 1977–1986. doi: 10.1109/TNSRE.2021.3110665 (document)

Jin, M., Zhu, E., Du, C., He, H., & Li, J. (2023, February). *PGCN: Pyramidal Graph Convolutional Network for EEG Emotion Recognition* (No. arXiv:2302.02520). arXiv. doi: 10.48550/arXiv.2302.02520 (document)

Keil, A., Bradley, M. M., Hauk, O., Rockstroh, B., Elbert, T., & Lang, P. J. (2002, September). Large-scale neural correlates of affective picture processing. *Psychophysiology*, *39*(5), 641–649. doi: 10.1017/S0048577202394162 (document)

Li, Y., Wang, L., Zheng, W., Zong, Y., Qi, L., Cui, Z., ... Song, T. (2021, June). A Novel Bi-Hemispheric Discrepancy Model for EEG Emotion Recognition. *IEEE Transactions on Cognitive and Developmental Systems*, *13*(2), 354–367. doi: 10.1109/TCDS.2020.2999337 (document)

Li, Y., Zheng, W., Cui, Z., Zhang, T., & Zong, Y. (2018). A novel neural network model based on cerebral hemispheric asymmetry for eeg emotion recognition. In *Ijcai* (pp. 1561–1567). (document)

Li, Y., Zheng, W., Wang, L., Zong, Y., & Cui, Z. (2022, April). From regional to global brain: A novel hierarchical spatial-temporal neural network model for EEG emotion recognition. *IEEE Transactions on Affective Computing*, *13*(2), 568–578. doi: 10.1109/TAFFC.2019.2922912 (document)

Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). Deepwalk: Online learning of social representations. In *Proceedings of the 20th acm sigkdd international conference on knowledge discovery and data mining* (pp. 701–710). (document)

Song, T., Zheng, W., Song, P., & Cui, Z. (2020, July). EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. *IEEE Transactions on Affective Computing*, *11*(3), 532–541. doi: 10.1109/TAFFC.2018.2817622 (document)

Wolf, R. C., Philippi, C., Motzkin, J. C., Başkaya, M., & Koenigs, M. (2014). Ventromedial prefrontal cortex mediates visual attention during facial emotion recognition. *Brain : a journal of neurology*, *137 Pt 6*, 1772-80. doi: 10.1093/brain/awu063 (document)

Xing, X., Li, Z., Xu, T., Shu, L., Hu, B., & Xu, X. (2019). SAE+ LSTM: A new framework for emotion recognition from multi-channel EEG. *Frontiers in neurorobotics*, *13*, 37. (document)

Zhang, D., Yao, L., Zhang, X., Wang, S., Chen, W., Boots, R., & Benatallah, B. (2018, April). Cascade and parallel convolutional recurrent neural networks on EEG-based intention recognition for brain computer interface. *Proceedings of the AAAI Conference on Artificial Intelligence*, *32*(1). doi: 10.1609/aaai.v32i1.11496 (document)

Zhang, G., Yu, M., Liu, Y.-J., Zhao, G., Zhang, D., & Zheng, W. (2023, January). SparseDGCNN: Recognizing Emotion From Multichannel EEG Signals. *IEEE Transactions on Affective Computing*, *14*(1), 537–548. doi: 10.1109/TAFFC.2021.3051332 (document)

Zhang, T., Wang, X., Xu, X., & Chen, C. L. P. (2022, January). GCB-Net: Graph Convolutional Broad Network and Its Application in Emotion Recognition. *IEEE Transactions on Affective Computing*, *13*(1), 379–388. doi: 10.1109/TAFFC.2019.2937768 (document)

Zhang, T., Zheng, W., Cui, Z., Zong, Y., & Li, Y. (2019, March). Spatial–temporal recurrent neural network for emotion recognition. *IEEE Transactions on Cybernetics*, *49*(3), 839–847. doi: 10.1109/TCYB.2017.2788081 (document)

Zheng, W.-L., & Lu, B.-L. (2015). Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks. *IEEE Transactions on Autonomous Mental Development*, *7*(3), 162-175. doi: 10.1109/TAMD.2015.2431497 (document)

Zhong, P., Wang, D., & Miao, C. (2020, May). *EEG-Based Emotion Recognition Using Regularized Graph Neural Networks* (No. arXiv:1907.07835). arXiv. (document)