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Microstate-Guided Dynamic Graph Neural Network with Prototypical Contrastive Learning for EEG Emotion Recognition

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Abstract: Emotion recognition from electroencephalogram (EEG) requires modeling how brain signals evolve over time and how different brain regions interact. Deep learning has substantially improved the extraction of spatiotemporal EEG features, yet models anchored to static connectivity templates struggle to follow the functional reorganization of brain networks as emotions unfold. We propose a microstate-guided fusion framework that embeds EEG microstate information at both feature and graph levels through a dedicated encoder and a multi-source dynamic graph generator, combined with prototypical contrastive domain adaptation for cross-subject alignment. On the SEED benchmark under the subject-independent protocol, the model achieves an average accuracy of 89.64%, consistently outperforming state-of-the-art baselines. Evaluation with leave-one-subject-out validation demonstrates robust generalization across subjects. These results suggest that microstate-guided dynamic graph modeling is an effective route to capturing task-relevant neural connectivity in EEG-based emotion recognition. Future work will extend the framework to cross-dataset validation on SEED-IV and explore adaptive microstate template selection.

Key words: EEG; Emotion Recognition; Graph Neural Networks; Microstate; Domain adaptation

Statements and Declarations

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Competing Interests The authors have no relevant financial or non-financial interests to disclose.

Ethics approval This study used a publicly available EEG dataset and did not involve new data collection from human participants or animal experiments.

Consent to participate Not applicable. All EEG data were obtained from the publicly available SEED dataset, whose original collection obtained informed consent from each participant (Zheng and Lu 2015).

Data availability The SEED dataset analyzed in this study is publicly available and can be applied for from the BCMI laboratory, Shanghai Jiao Tong University(<https://bcmi.sjtu.edu.cn/home/seed/>).

Code availability Not applicable.

Author contributions Zheng Liu: Conceptualization, Methodology, Writing – original draft. Lei Su: Supervision, Writing – review & editing, Methodology. Liping Wu: Supervision. Di Jiang: Supervision.

Introduction

Emotion recognition (ER) refers to the automatic inference of a person's affective state from physiological or behavioral cues, and it has become a central topic in affective computing. Its applications extend across human-computer interaction, intelligent healthcare, mental health monitoring (Du et al. 2021), and adaptive recommendation systems (Li and Han 2025). Electroencephalography (EEG) is one of the most informative signal sources for this task: it records neural activity directly, and unlike facial or vocal expressions it is difficult to disguise (Chen et al. 2025b). At the same time, EEG brings its own difficulties—high dimensionality, non-stationarity, and pronounced

variability across individuals (Chen et al. 2025a)—which make reliable recognition hard to achieve.

Earlier pipelines based on conventional machine learning improved performance only marginally (Alex et al. 2020), which has pushed recent research toward deep architectures that model the temporal (Huang and Li 2023), spatial (Feng et al. 2022), and functional (Shi et al. 2025) structure of EEG signals. These models do raise accuracy by exploiting long-range temporal dependencies (Li et al. 2024) and inter-channel correlations (Cheng et al. 2024; Wang 2019), yet the non-stationary and non-linear nature of neural recordings still limits both classification precision and the ability to generalize to unseen conditions. These problems are especially evident in graph neural networks (GNNs). The topology is

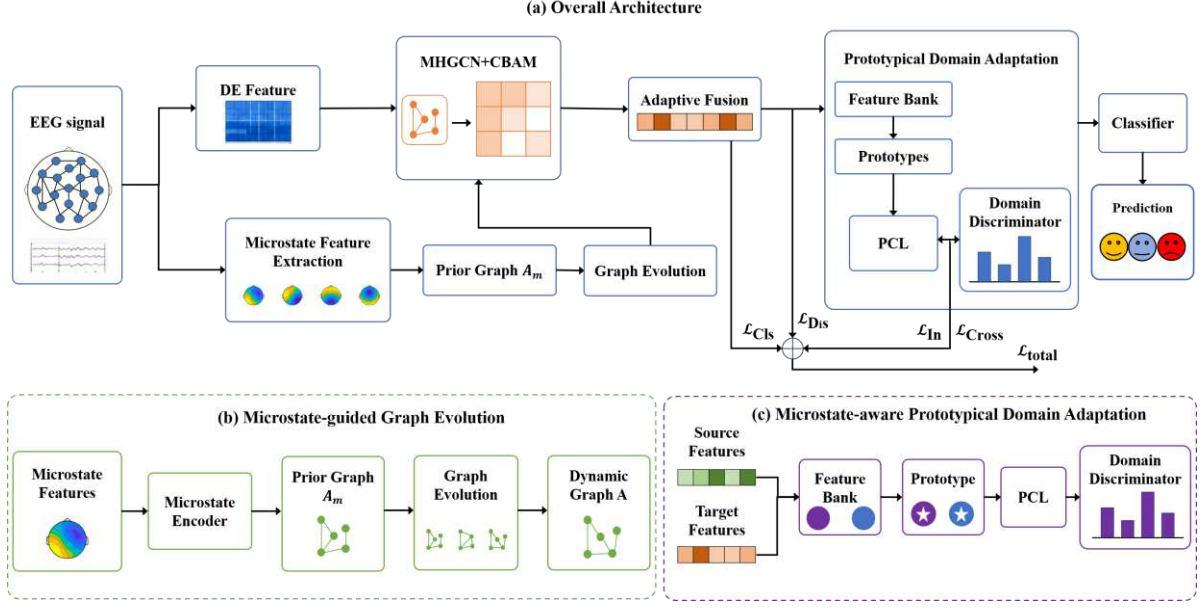


Fig. 1 Architecture of the proposed MG-PCL framework. (a) Overall architecture: EEG signals are encoded by parallel DE and microstate encoders; the resulting embeddings are fused by residual gating, followed by dynamic graph convolution and prototypical domain adaptation for classification. (b) Microstate-guided graph evolution: a dynamic graph generator constructs a sparse adjacency matrix from three parallel sources, followed by graph convolution and CBAM attention for spatiotemporal feature extraction. (c) Microstate-aware prototypical domain adaptation: intra-domain and inter-domain prototype alignment with an adversarial discriminator enables cross-subject semantic alignment for final emotion classification.

usually built from static connectivity templates and therefore cannot track how functional brain networks reorganize while emotions unfold (Kong et al. 2023). In addition, the feature extractor often has a limited spatiotemporal receptive field (Liu et al. 2022), so local neural interactions and long-range functional dependencies are hard to capture at the same time. How to remove these two obstacles while improving both accuracy and generalization remains an open question.

To address this, we propose a microstate-guided fusion framework that embeds EEG microstate information at both feature and graph levels. EEG microstates are short-lived, quasi-stable configurations of the scalp potential field; each configuration lasts on the order of a hundred milliseconds before the field switches to another one, and this succession mirrors the rapid reorganization of large-scale brain networks. The literature distinguishes four archetypal classes, A-D, which have been related to auditory, visual, salience, and attention processing, respectively (Liu et al. 2023). Quantitative descriptors of these states—how long each state lasts (duration), how much time it occupies (coverage), how often it appears (occurrence), and how likely it is to succeed another state (transition probability) (Wang et al. 2024)—act as sensitive indicators of neural

dynamics and are increasingly reported in neuropsychiatric studies (Chen et al. 2025c).

In this work, we leverage microstate-derived features and topographical priors to enhance EEG emotion recognition, exploiting their rich spatiotemporal information that conventional spectral features cannot capture. The core leverages microstate temporal dynamics (coverage, duration, occurrence, transition probabilities) as semantic priors, encoded by a dedicated encoder and adaptively fused with DE features via residual gating. Additionally, the functional connectivity prior A_m , derived from microstate templates, captures local neural interactions and serves as a structural regularizer for the dynamic graph generator. The architecture comprises three modules: microstate-guided dual-prior learning, microstate-constrained dynamic graph evolution, and microstate-aware prototypical contrastive domain adaptation. The proposed method achieves $89.64\% \pm 6.74\%$ accuracy, consistently outperforming baselines and confirming the effectiveness of microstate-guided fusion.

Our main contributions are threefold:

- We propose a novel microstate-guided dual prior learning mechanism that encodes microstate temporal dynamics (coverage,

duration, occurrence, and transition probabilities) as a semantic prior and derives a functional connectivity prior from microstate templates, which are adaptively fused with DE features through residual gating, thereby complementing conventional spectral features with global brain dynamic information.

- We design a microstate-constrained dynamic graph evolution module that constructs the adjacency matrix from three parallel sources, with the microstate prior serving as a structural anchor. The graph is then refined via sparsification, multi-hop graph convolution, and attention, allowing the topology to track the dynamic reorganization of functional brain networks instead of relying on static connectivity templates.
- We introduce a microstate-aware prototypical contrastive domain adaptation strategy that aligns intra-domain samples toward class prototypes and minimizes cross-domain prototype entropy in parallel with adversarial domain discrimination, enabling fine-grained class-semantic alignment across subjects.

Extensive experiments on the SEED dataset under the subject-independent protocol demonstrate that our framework achieves an average accuracy of 89.64%, consistently outperforming representative baselines, and ablation studies confirm the contribution of each module.

Related work

EEG-based emotion recognition

Because EEG records neural activity directly and cannot be feigned as easily as facial or vocal expressions, it has become a preferred signal for emotion recognition. Classical machine-learning pipelines dominated early studies but plateaued on complex real-world data, and deep learning has since changed this picture. A representative example is the DNN trained on DE features (Zheng and Lu 2015), which highlighted the frequency bands and channels that carry discriminative information and has remained a widely used benchmark for EEG-based recognition. PeViT (Yunanto et al. 2027) applies Vision Transformer (ViT) combined with periodic shift patching to EEG-based emotion recognition, achieving

promising results. However, spectral features like DE and PSD merely capture instantaneous spectral characteristics, failing to account for the global dynamic organization of brain networks. Instead of optimizing spectral features, the proposed method introduces EEG microstates as complementary priors to capture the global dynamic organization of brain networks, which distinguishes it from existing feature-based recognition frameworks.

GNN-based emotion recognition

Since EEG signals are recorded from spatially distributed electrodes, graph neural networks (GNNs) have been increasingly applied to model the spatial dependencies among channels. Early studies typically construct the graph topology from fixed physical or data-driven functional connectivity. For instance, DGCNN (Song et al. 2020) derives its adjacency matrix from the physical distances between electrodes and lets deep graph convolution discover the channel relationships, providing early evidence that graph modeling suits emotion recognition. SparseDGCNN (Zhang et al. 2023) relaxes the fixed topology by allowing the adjacency matrix to evolve during training, while RGNN (Zhong et al. 2022) adds a regularization term that encourages biologically plausible connections so as to reflect the hemispheric asymmetry of emotional processing. PCL-TDGCN (Yang et al. 2026) combines a temporal dynamic graph convolutional network with prototypical contrastive learning and reports the strongest cross-subject results along this line. However, in these methods, the graph topology is either fixed or learned in a purely data-driven manner, so the learned connections lack physiological interpretability and fail to reflect how inter-regional coupling evolves across distinct brain states. Instead of constructing the topology in a purely data-driven manner, the proposed method constrains the dynamic graph evolution with EEG microstate priors, allowing the graph to switch among microstate-specific connectivity patterns, which differentiates it from existing GNN-based frameworks.

EEG microstates

Beyond spectral and graph representations, EEG microstates offer a neurophysiologically grounded

description of whole-brain dynamics. A microstate is a topographical pattern of the scalp potential field that stays nearly unchanged for 80-120 ms and then switches abruptly to a different pattern; because this sequence repeats continuously, the successive patterns are often described as the building blocks of spontaneous brain activity (Khanna et al. 2015). The conventional analysis scans the global field power (GFP) curve for its peaks, collects the topographies at those peaks, and groups them, via a modified K-means procedure, into a small set of archetype maps usually labeled A-D; each class has been tied to a distinct large-scale network, namely auditory, visual, salience, and attention processing (Khanna et al. 2015). Once the maps are fixed, every time point can be assigned to one class, which yields the temporal statistics used in this work—coverage, duration, occurrence, and transition probabilities—that describe millisecond-scale switching among large-scale networks.

Encouragingly, recent studies have linked microstate dynamics to emotional processing. Liu (Liu et al. 2023) examined the EEG microstate representations of nine discrete emotions elicited by videos and reported that different emotions exhibited distinct microstate signatures, with the coverage and duration of class C and the occurrence of class B being the most discriminative. These findings suggest that microstate parameters carry emotion-relevant information beyond conventional spectral features. However, existing studies mostly treat microstate statistics as standalone descriptive features for group-level analysis or shallow decoding, and the topographical patterns embedded in microstate templates are largely discarded, leaving microstates disconnected from deep representation learning. Instead of using microstates merely as auxiliary statistics, the proposed method embeds them at both the feature level and the graph level, encoding temporal metrics as additional dynamic features and deriving connectivity priors from microstate templates to constrain graph evolution, which distinguishes it from existing microstate-based studies.

Cross-subject domain adaptation

Skull shape, cortical folding, and oscillatory dynamics differ from person to person, so EEG recordings from two individuals are rarely stationary with respect to each other, and a classifier fitted on labeled subjects typically loses accuracy on a subject it has never

seen. Domain adaptation was introduced precisely to learn representations whose behavior stays consistent across subjects. For instance, BiDANN (Li et al. 2021) attaches one global and two hemisphere-specific domain discriminators to the classifier and trains them adversarially, exploiting the hemispheric asymmetry of emotional responses to shrink the source-target distribution gap within each hemisphere. PR-PL (Zhou et al. 2024) organizes the feature space with prototypes and pairwise constraints instead, mapping individual EEG samples into a shared common space while making the model less sensitive to noisy labels. However, in these methods, the alignment is learned entirely in a data-driven feature space without physiological guidance, so the aligned representations may still entangle emotion-discriminative patterns with subject-specific information. Unlike these purely data-driven strategies, the proposed method anchors the prototypical contrastive alignment on microstate-aware representations. Since the same four archetypal microstates recur across individuals and explain most of the global topographic variance, they provide a subject-invariant physiological reference, guiding the alignment to preserve emotion discriminability while suppressing subject-specific discrepancies, which distinguishes it from existing cross-subject frameworks (Khanna et al. 2015).

Methods

This section details MG-PCL, a framework built on contrastive learning between microstate stimuli and EEG responses; its three main blocks are illustrated in Fig. 1.

Preprocessing and Feature Extraction

Most existing methods represent each EEG segment with spectral descriptors, which summarize the instantaneous power spectrum but say little about how the brain's global functional organization evolves over time. When the signal x is assumed to follow a Gaussian distribution (Zhao et al. 2023), the differential entropy (DE) of x takes the closed form:

$$\begin{aligned} h(x) &= - \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx \\ &= \frac{1}{2} \log(2\pi e \sigma^2) \end{aligned} \quad (1)$$

where μ and σ denote the mean and the standard deviation

of x .

To compensate for this deficiency, we introduce EEG microstates as complementary priors. To obtain the microstate information, we adopt the established procedure (Khanna et al. 2015). The global field power is first evaluated at every time point, and only the topographies located at GFP peaks are retained for clustering. A modified K-means algorithm then groups the retained maps into the four archetypal classes A-D; because the sign of a scalp map is physically arbitrary, centroids with negative polarity are flipped before comparison. One template matrix is produced for each subject and each session.

For each trial, we compute four classical microstate templates (A/B/C/D) (P. Pallav and K. Srivastava 2024) and extract three temporal metrics per microstate class: coverage, mean duration, and occurrence frequency (B. Gao et al. 2022), together with a 4×4 transition probability matrix. These statistics are concatenated into a 28-dimensional feature vector $x_m \in \mathbb{R}^{28}$, which is mapped by a lightweight Microstate Encoder $\Phi_m(\cdot)$ to a latent embedding $f_m \in \mathbb{R}^{64}$. Beyond trial-level features, we derive a functional connectivity prior $A_m \in \mathbb{R}^{62 \times 62}$ by computing the cosine similarity between columns of $T^\top$, where each column encodes the activation profile of an electrode across the four microstates. This matrix serves as a structural regularizer for subsequent dynamic graph learning.

To combine the DE feature f_e and the microstate feature f_m without allowing the weaker modality to dominate, we employ a residual gating mechanism:

$$f_{\text{fused}} = f_e + \lambda \cdot (g \odot f_e + (1-g) \odot f_m), \quad (2)$$

where σ is the sigmoid function, $\parallel$ denotes concatenation, $\odot$ is element-wise multiplication, and $\lambda = 0.3$ is a residual scaling factor. This design preserves the discriminative power of DE features while adaptively incorporating the complementary temporal semantics from microstates.

Microstate-Constrained Dynamic Graph Evolution

Recent advances have enabled dynamic graph convolution networks to generate adjacency matrices not only from node features but also from various data-driven sources. Departing from this purely feature-dependent paradigm, we propose an alternative approach that integrates a microstate prior, a learnable pattern memory, and a local context key

within a multi-source fusion graph generator. This design yields a robust and emotionally-relevant dynamic graph that is less susceptible to subject-specific noise and overfitting.

Given the transformed node feature matrix $H_f \in \mathbb{R}^{D \times N}$ (where D is the feature dimension after frequency-band transformation), we construct three parallel adjacency matrices. The feature-driven graph A_{feat} uses a trainable pattern memory $\Phi \in \mathbb{R}^{D \times N}$ as a key to compute the similarity with H_f (query), capturing global dynamic brain patterns analogous to the pattern-based adjacency matrix A_p in (Zhuo et al. 2025). The context-memory graph A_{mem} employs a historical key $K_h \in \mathbb{R}^{D \times N}$ to compute local temporal correlations within the current window, denoted as A_h . The microstate prior graph A_m , derived from the static functional connectivity matrix introduced above, serves as a structural anchor. These three matrices are concatenated along the channel dimension and passed through a learnable fusion layer $\text{FC}(\cdot)$ to produce the raw dynamic adjacency:

$$A_{\text{raw}} = \text{FC}([A_{\text{feat}} \parallel A_{\text{mem}} \parallel A_m]) \quad (3)$$

To eliminate noisy edges, we apply Top-k sparsification (retaining the top 80% strongest connections per row) followed by row-wise softmax normalization:

$$A_t = \text{Softmax}(\text{TopK}(A_{\text{raw}})) \quad (4)$$

This yields a sparse, microstate-constrained dynamic graph $A_t \in \mathbb{R}^{N \times N}$.

Subsequently, the graph convolution aggregates information over multiple hops (order $K = 2$) to capture long-range dependencies:

$$H_{\text{out}} = \sum_{k=0}^K (A_t^k) H_f W_k \quad (5)$$

where W_k are learnable weight matrices for each hop. The output features from all hops are concatenated. A Convolutional Block Attention Module (CBAM) is attached afterwards; it first re-weights the channels and then the spatial positions, so that emotionally discriminative regions—prefrontal and temporal areas in particular (Iidaka et al. 2001)—contribute more strongly than the rest. After a residual connection, the final spatiotemporal representation F_{de} is obtained.

In summary, the microstate-constrained dynamic graph A_t integrates data-driven flexibility with

neurophysiological priors through multi-source fusion and sparsification, while the subsequent multi-hop graph convolution and CBAM refinement jointly extract robust spatiotemporal features for downstream emotion recognition.

Microstate-Aware Prototypical Contrastive Domain Adaptation

Recent domain adversarial alignment methods have effectively reduced global distribution discrepancies in EEG-based cross-subject emotion recognition (Zhou et al. 2024; Liang et al. 2025), yet they primarily operate at the feature level and often overlook class-semantic structures. To complement these approaches, we introduce a prototypical contrastive learning strategy operating on the microstate-enhanced feature space. As the features already encode microstate information through the adaptive fusion and dynamic graph modules described in Sections *Preprocessing and Feature Extraction* and *Microstate-Constrained Dynamic Graph Evolution*, the learned prototypes become inherently microstate-aware, enabling fine-grained semantic alignment across domains.

For the labeled source domain, we maintain a feature memory bank $\mathcal{F}^s$ and a label memory bank $\mathcal{V}^s$. The prototype for class j is computed as the mean of features assigned to that class:

$$\mu_j^s = \frac{1}{|\mathcal{F}_j^s|} \sum_{f_i^s \in \mathcal{F}_j^s} f_i^s \quad (6)$$

where $\mathcal{F}_j^s$ contains source features whose predicted label (from $\mathcal{V}^s$) equals j . For the unlabeled target domain, we select the top 50% most confident predictions (based on softmax scores) and apply K-means clustering to obtain target clusters; the centroid of each cluster serves as the target prototype μ_j^t .

To enforce compactness within each domain, we define an intra-domain prototypical contrastive loss that pulls samples toward their corresponding class prototype:

$$\mathcal{L}_{\text{In}} = -\sum_{i=1}^{N_s} \log \frac{\exp(\mu_{y_i^s} \cdot f_i^s / \tau)}{\sum_{r=1}^K \exp(\mu_r^s \cdot f_i^s / \tau)} + \beta \sum_{i=1}^{N_t} \log \frac{\exp(\mu_{c_i^t} \cdot f_i^t / \tau)}{\sum_{r=1}^K \exp(\mu_r^t \cdot f_i^t / \tau)} \quad (7)$$

where τ is a temperature parameter, c_i^t is the cluster assignment of target sample i , and β is a dynamic balancing factor that increases with training progress (following a sigmoid schedule) to stabilize early training.

To align class-conditional distributions across domains, we minimize the conditional entropy of each sample with respect to the opposite domain's prototypes. For a source feature f_i^s , we compute its similarity distribution over target prototypes:

$$P_{i,j}^{s \rightarrow t} = \frac{\exp(\mu_j^t \cdot f_i^s / \tau)}{\sum_{r=1}^K \exp(\mu_r^t \cdot f_i^s / \tau)} \quad (8)$$

The inter-domain loss is then defined as the sum of entropies for both directions:

$$\mathcal{L}_{\text{Cross}} = \sum_{i=1}^{N_s} H(P_i^{s \rightarrow t}) + \sum_{i=1}^{N_t} H(P_i^{t \rightarrow s}) \quad (9)$$

where $H(\cdot)$ denotes Shannon entropy. This loss encourages confident assignment to the prototypes of the other domain, thereby reducing cross-domain semantic drift.

In parallel, we employ a domain discriminator D with a gradient reversal layer (Yang et al. 2026) to minimize the domain classification loss:

$$\mathcal{L}_{\text{Dis}} = -\frac{1}{N_s} \sum_{i=1}^{N_s} \log D(f_i^s) - \frac{1}{N_t} \sum_{i=1}^{N_t} \log(1 - D(f_i^t)) \quad (10)$$

The overall training objective integrates the source classification loss $\mathcal{L}_{\text{Cls}}$, the adversarial loss, and the two prototypical contrastive losses:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{Cls}} + \mathcal{L}_{\text{Dis}} + \gamma_1 \mathcal{L}_{\text{In}} + \gamma_2 \mathcal{L}_{\text{Cross}} \quad (11)$$

where γ_1 and γ_2 are trade-off hyperparameters. This unified objective ensures that the model learns discriminative, domain-invariant, and semantically coherent representations, leading to robust cross-subject emotion recognition.

Results

Experimental setup

Experiments were conducted using Python 3.10.16 with PyTorch 2.5.1 on a standard desktop computing environment. The model uses a 64-dim hidden space with two DGCN layers, CBAM, and prototypical contrastive domain adaptation. Models were trained for up to 1,000 epochs (early stopping, patience 20) using RMSprop (lr 10^{-3} , weight decay 10^{-3}). Classification loss is label-smoothing cross-entropy (0.0005), with $\tau = 1.0$ and intra-/inter-domain coefficients 0.5/0.1. Experiments use the SEED dataset (Zheng and Lu 2015)

under the subject-independent LOSO protocol. Accuracy is the primary metric, with standard deviation. All results are averaged over five independent runs, with statistical significance evaluated using paired t -tests ($p < 0.05$).

Comparison with baselines

For the traditional machine learning methods and the representative deep models, the numbers reported in Table 1 follow their original publications. Because those studies adopted different preprocessing pipelines and evaluation protocols, we additionally re-ran the deep baseline with its publicly available implementation under exactly the same settings as MG-PCL, so that the deep-learning comparison is not affected by protocol differences.

Among the traditional methods, SVM (Duan et al. 2013) obtains a considerably lower accuracy of 58.18%, while the transfer learning method TPT (Sanginetto et al. 2014) achieves 75.17%, indicating that simple domain adaptation strategies are insufficient for this challenging cross-subject task. For deep learning-based approaches, DGCNN (Song et al. 2020) yields 79.95%, and PGCN (Jin et al. 2024) improves upon it with 84.59%, demonstrating the benefit of graph-based feature extraction. The PCL-TDGCN (Yang et al. 2026) model attains a strong result of 88.08%, which is competitive, yet our MG-PCL further pushes the performance boundary by a margin of 1.56% in average accuracy and also achieves a lower standard deviation (6.74% versus 8.05%), indicating enhanced robustness across subjects.

These results validate the effectiveness of incorporating microstate-guided priors into the dynamic graph and prototypical contrastive learning framework, leading to superior generalization in cross-subject EEG-based emotion recognition.

Table 1

Comparison with published baselines. Metrics are reported in %.

Methods	ACC $\pm$ STD (%)
SVM (Duan et al. 2013)	58.18 $\pm$ 13.85
TPT (Sanginetto et al 2014)	75.17 $\pm$ 12.83
DGCNN (Song et al. 2020)	79.95 $\pm$ 09.02
PGCN (Jin et al. 2024)	84.59 $\pm$ 08.68
PCL-TDGCN (Yang et al. 2026)	88.08 $\pm$ 08.05
MG-PCL	89.64 $\pm$ 06.74

Table 2

Ablation study results for MG-PCL.

Methods	ACC (%)
<i>Ablation study</i>	
w/o Microstate Prior	88.08
w/o Microstate Graph Constraint	88.27
w/o Microstate-aware PCL	84.62
<i>Ablation study about hyperparameters in MG-PCL</i>	
w/ fixed β for the loss in Eq.7	87.94
w/o γ_1 and γ_2 for the loss in Eq.11	88.56
MG-PCL	89.64

Ablation study

We next isolate the effect of each core module—microstate-guided dual-prior learning, microstate-constrained dynamic graph evolution, and microstate-aware prototypical contrastive learning—by re-training MG-PCL with one component removed at a time, again under the subject-independent protocol on SEED. Table 2 lists the outcomes. Removing the microstate feature branch reduces accuracy from 89.64% to 88.08%, while discarding the microstate prior graph $\mathbf{A}_m$ from the dynamic graph generator leads to a marginal drop to 88.27%. In contrast, eliminating the microstate-aware intra-domain and inter-domain prototypical contrastive losses causes a substantial performance decline of 5.02% (from 89.64% to 84.62%), underscoring the critical role of prototype-based semantic alignment in cross-subject generalization.

We further investigate the sensitivity of key hyperparameters. Introducing a dynamic update for the balancing factor β in the intra-domain contrastive loss improves accuracy from 87.94% to 89.64%, while the trade-off coefficients γ_1 and γ_2 increase it from 88.56% to 89.64%. These results validate the effectiveness of each hyperparameter in refining model behavior and strengthening generalization.

Interpretability analysis

Fig. 2 (a) shows the confusion matrix of the run whose validation accuracy ranked in the middle of the five random seeds, which we treat as representative of typical behavior. Positive emotions are recognized best, at 94.20%, followed by neutral emotions at 90.80% and negative emotions at 86.80%.

Notably, confusion between negative and neutral emotions persists, which may reflect the physiological

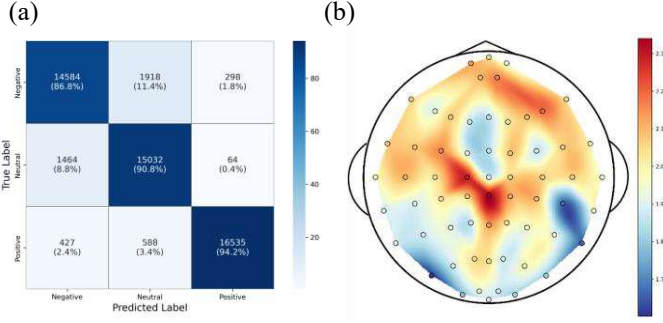


Fig. 2 (a) the confusion matrices of the proposed framework; (b) the degree centrality distribution of the MG-PCL.

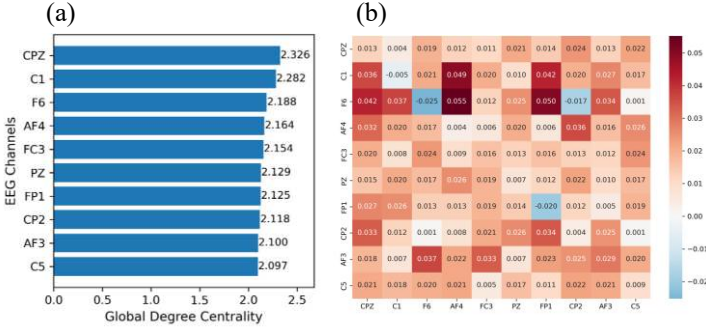


Fig. 3 (a) Top 10 degrees centrality ranking; (b) Learned functional connectivity among Top-10 channels.

similarity between these two affective states. To probe which electrodes dominate the learned topology, we further compute the degree centrality of every channel, that is, the total connection strength between a given electrode and all remaining electrodes in the learned adjacency matrix:

$$C_i = \sum_{j=1}^n (A_{i,j}^G + \sum_{k=1}^n (A_{i,k}^G - 2A_{i,i}^G)), (i = 1 \dots 62) \quad (12)$$

where n denotes the number of EEG channels (62 in this study). Fig. 2 (b) illustrates the degree centrality distribution of the global average adjacency matrix learned by the proposed MG-PCL model on the SEED dataset under the subject-independent protocol. The results reveal that the prefrontal and temporal regions exhibit the highest centrality values, which is consistent with the well-established roles of the prefrontal cortex in emotional regulation and the temporal lobe (including the amygdala) in affective evaluation (Iidaka et al. 2001).

To improve visualization clarity, the ten channels with the highest degree centrality were selected for detailed connectivity analysis. Fig. 3 (a) demonstrates that several centro-parietal electrodes (e.g., CPZ, C1, PZ, and CP2) emerge as highly connected hubs in the learned functional graph, suggesting their critical role in integrating

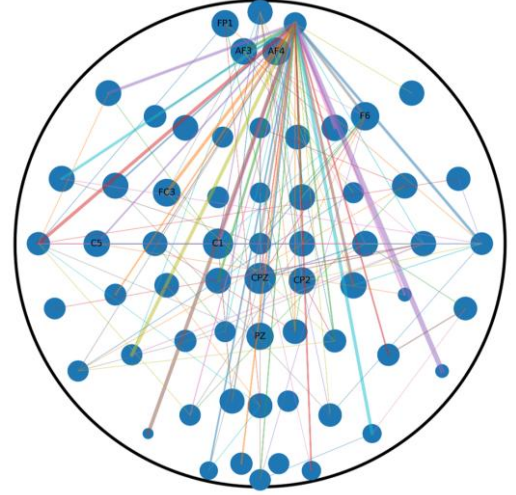


Fig. 4 Global Learned Functional Brain Network (Top 5% Connections)

distributed neural information during emotion recognition. In addition, frontal electrodes (FP1, AF3, AF4, and F6) exhibit high centrality, indicating that the proposed graph learning mechanism captures emotion-related frontal neural patterns. Fig. 3 (b) connectivity matrix among high-centrality channels reveals strong interactions between frontal and centro-parietal regions, further confirming the biological plausibility of the learned graph structure.

Fig. 4 visualizes the learned brain network, where each node corresponds to an EEG electrode and edges represent the functional connectivity strengths derived from the learned adjacency matrix. The observed connectivity distribution provides interpretable evidence that the learned graph topology reflects physiologically meaningful network organizations.

Discussion

This study proposed MG-PCL, a cross-subject EEG emotion recognition framework that embeds microstate priors into both the feature and graph levels of dynamic graph learning, and aligns subject distributions through microstate-aware prototypical contrastive learning. Under the subject-independent protocol on SEED, MG-PCL achieved an average accuracy of $89.64\% \pm 6.74\%$, outperforming the strongest baseline PCL-TDGCN by 1.56% with a lower standard deviation (6.74% vs. 8.05%). Beyond the aggregate gains, the following discussion examines why each module contributes, how the learned graph relates to known

emotional circuitry, and what remains open.

The ablation results suggest that the two microstate priors play complementary roles. Removing the microstate feature branch reduced accuracy from 89.64% to 88.08%, indicating that microstate statistics and transition probabilities capture temporal semantics that DE features leave implicit. This is consistent with the observation that a small set of canonical microstate classes recurs across subjects and cognitive states (Khanna 2015), which makes microstate-derived descriptors naturally comparable across individuals. In parallel, removing the structural prior $\mathbf{A}_m$ from the dynamic graph generator led to a drop to 88.27%, suggesting that constraining graph generation toward microstate-consistent topology regularizes the learned adjacency and discourages the graph encoder from fitting subject-specific spurious connections.

The largest degradation was observed when the microstate-aware prototypical contrastive losses were removed, where accuracy fell by 5.02% to 84.62%. This indicates that prototype-based semantic alignment, rather than feature re-encoding or graph regularization, carries the main burden of cross-subject generalization: by pulling intra-domain samples toward class prototypes and pushing inter-domain prototypes apart, the model matches class-level distributions across subjects instead of relying on subject-specific feature geometry. Unlike adversarial alignment, which matches global distributions and may discard class-discriminative information, prototype alignment preserves class boundaries, consistent with recent prototype-based domain adaptation studies (Zhou et al. 2024). The hyperparameter analysis further supports this design: the dynamic update of β improved accuracy by 1.70%, and the trade-off coefficients γ_1 and γ_2 contributed another 1.08%.

The learned functional graph also shows physiologically meaningful organization. Its degree centrality concentrated in prefrontal and temporal regions, consistent with the established roles of the prefrontal cortex in emotional regulation and the temporal lobe, including the amygdala, in affective evaluation (Silberstein et al. 2012). High-centrality hubs were mainly located at centro-parietal sites (CPZ, C1, PZ, CP2) and frontal sites (FP1, AF3, AF4, F6), with strong frontal-centro-parietal interactions, suggesting that the learned topology reflects emotion-related network organization rather than dataset-specific noise. The confusion pattern provides a further check: misclassifications were concentrated between negative and neutral states, whose physiological signatures are known to overlap, whereas

positive emotions were recognized with 94.20% accuracy. The remaining errors therefore appear task-intrinsic rather than model-specific.

Our study has three limitations that point to future work. All experiments were run on SEED under a subject-independent protocol; this setting is stricter than within-subject evaluation, yet claims about generalization would be stronger once the framework is validated across datasets such as SEED-IV. The microstate templates and the four-class setting follow convention; learning the microstate-constrained topology adaptively may better reflect individual EEG dynamics. Finally, we did not analyze how individual frequency bands contribute to recognition; decomposing the microstate priors by band is a natural extension and could show which oscillatory channels benefit most from microstate guidance.

Conclusion

In this work, we first design a microstate-based feature extraction pipeline and subsequently employ the derived microstate statistics and transition probabilities as a novel representation for EEG signals. Then, we propose MG-PCL, an EEG emotion recognition model that integrates microstate mechanisms with graph neural networks. Compared with the baseline methods, the proposed approach achieves superior performance on the SEED dataset, attaining an average accuracy of 89.64%. The experimental results demonstrate that the MG-PCL model with microstate features consistently outperforms all competing baselines. The ablation studies further confirm that MG-PCL plays a beneficial role in EEG feature reconstruction and enhances feature expressiveness, confirming the contribution of each module of the proposed model. Future work will further investigate the frequency-band specific contributions to emotion recognition performance.

References

- Alex M et al (2020) Discrimination of genuine and acted emotional expressions using EEG signal and machine learning. IEEE Access 8:191080-191089. <https://doi.org/10.1109/ACCESS.2020.3032380>
- Chen CLP et al (2025a) AdamGraph: adaptive attention-modulated graph network for EEG emotion recognition. IEEE Trans Cybern 55:2038-2051. <https://doi.org/10.1109/TCYB.2025.3550191>
- Chen R et al (2025b) A progressive multi-domain adaptation network with reinforced self-constructed graphs for cross-subject EEG-based emotion and consciousness recognition. IEEE Trans Neural Syst Rehabil Eng 33:3498-3510.

- <https://doi.org/10.1109/TNSRE.2025.3603190>
- Chen X et al (2025c) Abnormal EEG microstates in poststroke patients: a pilot study. *IEEE Sens J* 25:19863-19873. <https://doi.org/10.1109/JSEN.2025.3559489>
- Cheng C et al (2024) Hybrid network using dynamic graph convolution and temporal self-attention for EEG-based emotion recognition. *IEEE Trans Neural Netw Learn Syst* 35:18565-18575. <https://doi.org/10.1109/TNNLS.2023.3319315>
- Duan R-N et al (2013) Differential entropy feature for EEG-based emotion classification. In: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER), San Diego, CA, USA, pp 81-84. <https://doi.org/10.1109/NER.2013.6695876>
- Du C et al (2021) Deep learning-based mental health monitoring scheme for college students using convolutional neural network. *Int J Artif Intell Tools* 30. <https://doi.org/10.1142/S0218213021400145>
- Feng L et al (2022) EEG-based emotion recognition using spatial-temporal graph convolutional LSTM with attention mechanism. *IEEE J Biomed Health Inform* 26:5406-5417. <https://doi.org/10.1109/JBHI.2022.3198688>
- Gao B et al (2022) EEG microstate analysis of transcranial alternating current stimulation in healthy people. In: 2022 16th ICME International Conference on Complex Medical Engineering (CME), Zhongshan, China, pp 165-168. <https://doi.org/10.1109/CME55444.2022.10063327>
- Huang X, Li X (2023) Modulation identification method based on time-frequency analysis and support vector machine. In: 2023 IEEE 2nd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA), Changchun, China, pp 551-554. <https://doi.org/10.1109/EEBDA56825.2023.10090561>
- Iidaka T et al (2001) Neural interaction of the amygdala with the prefrontal and temporal cortices in the processing of facial expressions as revealed by fMRI. *J Cogn Neurosci* 13:1035-1047. <https://doi.org/10.1162/089892901753294338>
- Jin M et al (2024) PGCN: pyramidal graph convolutional network for EEG emotion recognition. *IEEE Trans Multimed* 26:9070-9082. <https://doi.org/10.1109/TMM.2024.3385676>
- Khanna A, Pascual-Leone A, Michel CM, Farzan F (2015) Microstates in resting-state EEG: current status and future directions. *Neurosci Biobehav Rev* 49:105-113. <https://doi.org/10.1016/j.neubiorev.2014.12.010>
- Kong W et al (2023) Causal graph convolutional neural network for emotion recognition. *IEEE Trans Cogn Dev Syst* 15:1686-1693. <https://doi.org/10.1109/TCDS.2022.3175538>
- Li C et al (2024) Attention-based temporal graph representation learning for EEG-based emotion recognition. *IEEE J Biomed Health Inform* 28:5755-5767. <https://doi.org/10.1109/JBHI.2024.3395622>
- Li S, Han T (2025) Personalized learning resource recommendation text emotion recognition method based on deep transfer learning. *Int J High Speed Electron Syst* 34:2540333. <https://doi.org/10.1142/S0218001424570143>
- Li Y, Zheng W, Zong Y, Cui Z, Zhang T, Zhou X (2021) A bi-hemisphere domain adversarial neural network model for EEG emotion recognition. *IEEE Trans Affect Comput* 12:494-504. <https://doi.org/10.1109/TAFFC.2018.2885474>
- Liang L et al (2025) DRDG-Net: generalizable driver distraction detection with decoupled representation and gradient reversal layer. In: 2025 IEEE 2nd International Conference on Deep Learning and Computer Vision (DLCV), Jinan, China, pp 1-5. <https://doi.org/10.1109/DLCV65218.2025.11088862>
- Liu J et al (2023) The EEG microstate representation of discrete emotions. *Int J Psychophysiol* 186:33-41. <https://doi.org/10.1016/j.ijpsycho.2023.02.002>
- Liu S et al (2022) 3DCANN: a spatio-temporal convolution attention neural network for EEG emotion recognition. *IEEE J Biomed Health Inform* 26:5321-5331. <https://doi.org/10.1109/JBHI.2021.3083525>
- Pallav P, Srivastava K (2024) Stress analysis of EEG signal using K-means clustering and hybrid classifier. In: 2024 2nd International Conference on Advancements and Key Challenges in Green Energy and Computing (AKGEC), Ghaziabad, India, pp 1-5. <https://doi.org/10.1109/AKGEC62572.2024.10869062>
- Sangineto E, Zen G, Ricci E, Sebe N (2014) We are not all equal: personalizing models for facial expression analysis with transductive parameter transfer. In: Proceedings of the 22nd ACM International Conference on Multimedia, pp 357-366. <https://doi.org/10.1145/2647868.2654916>
- Shi C et al (2025) Functional connectivity patterns learning for EEG-based emotion recognition. *IEEE Trans Cogn Dev Syst* 17:480-494. <https://doi.org/10.1109/TCDS.2024.3470248>
- Silberstein RB, Nield GE (2012) Measuring emotion in advertising research: prefrontal brain activity. *IEEE Pulse* 3:24-27. <https://doi.org/10.1109/MPUL.2012.2189172>
- Song T et al (2020) EEG emotion recognition using dynamical graph convolutional neural networks. *IEEE Trans Affect Comput* 11:532-541. <https://doi.org/10.1109/TAFFC.2018.2817622>
- Wang Y et al (2024) Objective neurophysiological indices for the assessment of chronic tinnitus based on EEG microstate parameters. *IEEE Trans Neural Syst Rehabil Eng* 32:983-993. <https://doi.org/10.1109/TNSRE.2024.3367982>
- Wang Z-M et al (2019) Channel selection method for EEG emotion recognition using normalized mutual information. *IEEE Access* 7:143303-143311. <https://doi.org/10.1109/ACCESS.2019.2944273>
- Yang Y et al (2026) Prototypical contrastive learning with temporal dynamic graph convolutional network for EEG-based emotion recognition. *IEEE Trans Affect Comput* 17:1999-2011. <https://doi.org/10.1109/TAFFC.2026.3671020>
- Yunanto W, Pao H-K, Wibawa AD, Huang Y, Iqbal M (2027) Periodic shifted patching on vision transformer for electroencephalogram signal-based emotion recognition. *Biomed Signal Process Control* 129:111220. <https://doi.org/10.1016/j.bspc.2026.111220>
- Zhang G, Yu M, Liu Y-J, Zhao G, Zhang D, Zheng W (2023) SparseDGCNN: recognizing emotion from multichannel EEG signals. *IEEE Trans Affect Comput* 14:537-548. <https://doi.org/10.1109/TAFFC.2021.3051332>
- Zhao Q et al (2023) Emotion recognition based on EEG and DE-CNN-RNN. In: 2023 China Automation Congress (CAC), Chongqing, China, pp 3376-3380. <https://doi.org/10.1109/CAC59555.2023.10450238>
- Zheng W-L, Lu B-L (2015) Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. *IEEE Trans Auton Ment Dev* 7:162-175. <https://doi.org/10.1109/TAMD.2015.2431497>
- Zhong P, Wang D, Miao C (2022) EEG-based emotion recognition using regularized graph neural networks. *IEEE Trans Affect Comput* 13:1290-1301. <https://doi.org/10.1109/TAFFC.2020.2994159>
- Zhou R et al (2024) PR-PL: a novel prototypical representation based pairwise learning framework for emotion recognition using EEG signals. *IEEE Trans Affect Comput* 15:657-670. <https://doi.org/10.1109/TAFFC.2023.3288118>
- Zhou Y et al (2025) EEG emotion recognition based on dynamic temporal causal graph convolutional network. *Knowl Based Syst* 323:113752. <https://doi.org/10.1016/j.knosys.2025.113752>