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GAT-LSTM Based Predictive Model for Developmental Dyslexia Diagnosis: A Graph-Attention and Time-Series Learning Approach

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Abstract: Developmental dyslexia is a common neurodevelopmental learning disorder that severely impacts children's reading abilities and social adaptation. In recent years, brain network analysis based on functional magnetic resonance imaging has provided new insights into its neural mechanisms, yet it struggles to capture the temporal characteristics of dynamic brain interactions. To address this, this paper proposes a GAT-LSTM framework for high-precision classification of DD. This method first constructs a dynamic functional connectivity network based on the AAL90 brain atlas. It then employs GAT to adaptively learn spatial dependencies between brain regions within each time window, followed by LSTM to model the temporal evolution patterns of node embedding sequences. To further enhance the model's temporal consistency and discriminative power, dynamic graph stability constraints are introduced during training. Experimental results demonstrate that the proposed method achieves an 85.36% classification accuracy, significantly outperforming baseline models. This study not only provides a novel computational paradigm for the objective diagnosis of DD but also offers robust support for the application of brain network modeling in neurodevelopmental disorder research.

Keywords: FMRI; Developmental Dyslexia; Graph Attention Network; LSTM; Feature Extraction.

1. Introduction

Developmental dyslexia (DD) is a neurodevelopmental learning disorder characterized by significant difficulties in word recognition, reading fluency, and spelling, despite normal intelligence, educational opportunities, and sensory abilities. These challenges severely impact academic achievement and social adaptation. Epidemiological studies indicate a prevalence of approximately 5%–20% among school-aged children [1], with marked familial clustering and a neurobiological basis. In recent years, advances in functional Magnetic Resonance Imaging (fMRI) technology have revealed abnormal brain connectivity patterns in DD patients during both resting-state and task-state conditions, particularly within networks involved in language processing, attentional control, and executive functions. Consequently, establishing a high-precision automated DD identification model holds significant importance for early screening and intervention.

Graph Attention Network (GAT), a significant advancement in graph neural networks, dynamically assigns weights to each neighboring node by introducing a self-attention mechanism, thereby adaptively learning the varying importance among nodes. Baek et al. [2] employed an MTAD-GAT to analyze functional time series variations, enabling dynamic analysis of fMRI data. Su et al. [3] utilized GAT to obtain rich graph representations for effective identification of major depressive disorder. This GAT mechanism not only enhances the model's perception of local structures but also effectively integrates global graph context information, demonstrating significant advantages when processing non-Euclidean data.

Despite this, traditional analysis methods based on static functional connectivity have limitations in capturing the temporal characteristics of dynamic brain interactions, which restricts our deep understanding of the neural mechanisms underlying DD. To better reveal the dynamic evolution of brain activity, recurrent neural networks (RNN) and their variants, particularly long short-term memory (LSTM) networks, have been widely applied in fMRI time series analysis. Weng et al. [4] proposed extracting features from time series at each voxel in fMRI data, advancing research and diagnosis of autism spectrum disorders. Sun et al. [5] introduced modeling dynamic sequences using LSTM and computing EC matrices, improving accuracy in identifying cognitive impairments. The LSTM effectively mitigates the vanishing gradient problem through its gating mechanism and can capture long-term dependencies, demonstrating strong performance in tasks such as brain state decoding and disease classification.

Given this, this paper proposes a developmental dyslexia classification model framework based on GAT-LSTM. The framework first utilizes the AAL brain atlas to partition fMRI data into multiple brain regions and constructs a dynamic functional connectivity network. Subsequently, the GAT module extracts structure-aware node embeddings at each time step, and these embedding sequences are then fed into an LSTM to model their temporal evolution patterns. Furthermore, we introduce Dynamic Stability Regularization (DSR) during training to enhance temporal consistency and feature discriminative power. The proposed method significantly improves classification accuracy for developmental dyslexia, offering a valuable methodological approach for intelligent diagnosis of reading disorders based on brain functional connectivity.

2. Method

2.1. Data Collection

This study recruited 524 fourth- and fifth-grade students from an elementary school in Beijing, China, and screened them as proficient readers or readers with reading difficulties [6]. Following screening, 17 participants with dyslexia and 16 control participants participated in the experiment. One dyslexic participant was excluded after an fMRI scan revealed a neurological disorder. The study was conducted at an MRI imaging center, employing a T2*-weighted gradient echo planar imaging sequence for fMRI scanning. Statistical information is presented in Table 1.

Table 1. Demographic Data of Participants

Features	DD group (n = 16)	Healthy Control group (n = 16)	Statistical value
Average age	10 years and 6 months	10 years and 1 month	
Reading performance	35.63 ± 13.59	115.75 ± 13.57	$p < 0.001$
Gender (Male/Female)	12/4	9/6	
Nonverbal intelligence	75 ± 16.73	68.44 ± 15.78	$p = 0.26$

2.2. Data Preprocessing

The study employed solid-line correction and normalization, resampling each voxel to a 3 mm × 3 mm × 3 mm cubic voxel size, followed by spatial smoothing [7]. The first three images corresponded to data collected before the experiment began and were therefore discarded. The specific workflow is illustrated in Fig. 1.

Fig. 1 Data Preprocessing Flowchart

This paper employs a sliding time window method to segment the data. Using a 1TR overlapping time window length, the resulting 3,640-time windows are treated as independent samples.

2.3. Experimental Procedure

This paper proposes a study on dyslexia patient prediction based on the GAT-LSTM framework. Preprocessed data serve as input, with average BOLD time series extracted from each brain region using the AAL90 brain atlas. A sliding time window is employed to construct a dynamic functional connectivity network. GAT learns structure-aware embeddings for brain region nodes within each time window, and these embedding sequences are then fed into an LSTM to model their temporal evolution patterns. Finally, a fully connected layer combined with a Softmax function enables classification prediction for dyslexia. The detailed model architecture is illustrated in in Fig. 2.

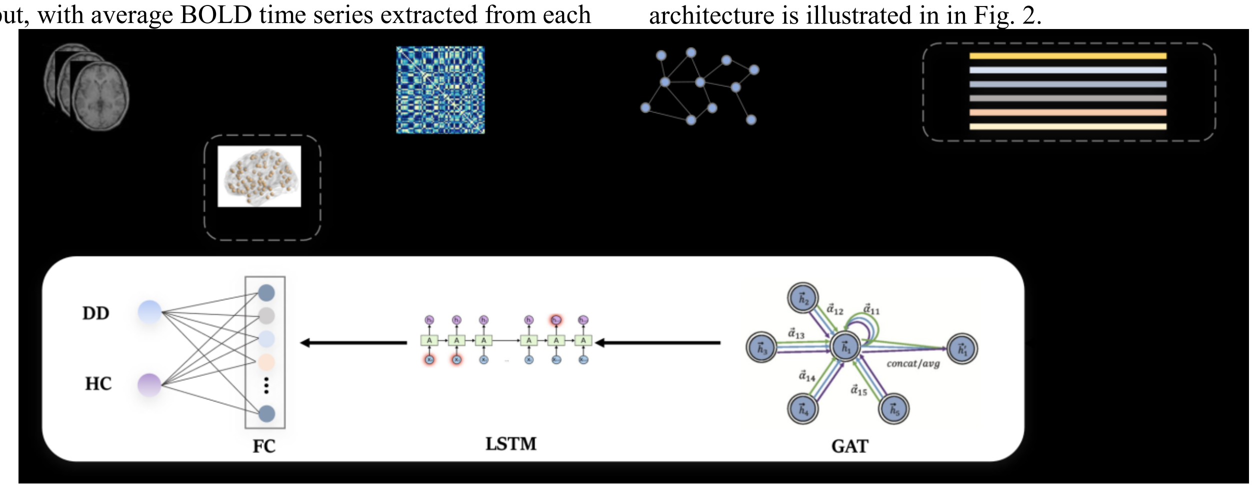

Fig. 2 Model Architecture Diagram

2.4. Brain Network

This study employed the automated anatomical labeling (AAL) 90 ROI brain atlas as nodes for brain networks, calculating the average fMRI time series for each brain region. For each subject, a $R^{90\times 90}$ adjacency matrix was obtained, resulting in a total of 3,640 functional brain network matrices. Edge weights were assigned based on Pearson correlation coefficients, calculated using the following formula:

$$\Upsilon_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

Among these, X and Y represent the BOLD time series from two distinct brain regions. The brain connectivity map is shown in Fig. 3. All functional brain networks underwent normalization processing.

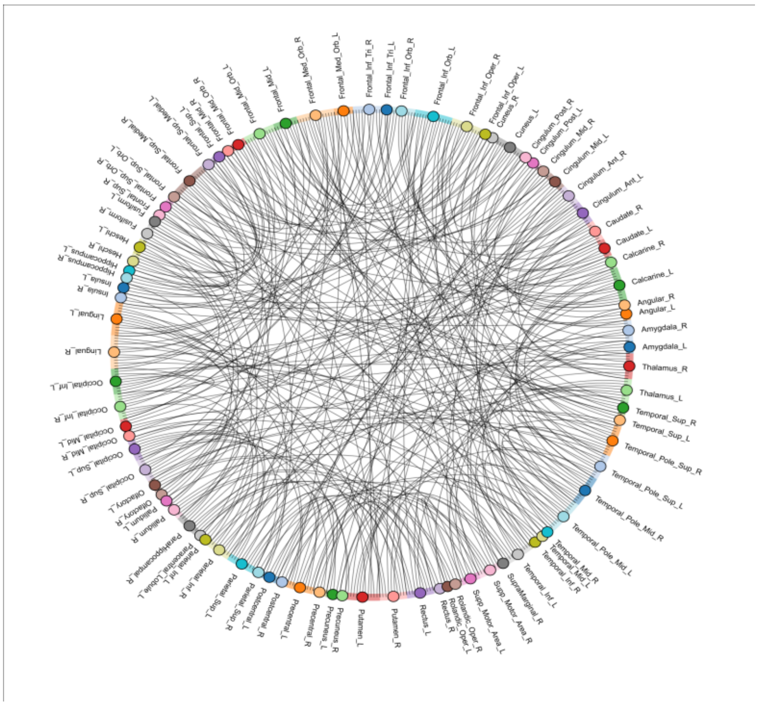

Fig. 3 Brain functional connectivity map constructed based on the AAL90 ROI atlas

2.5. Graph Feature Extraction

In this study, spatial topological analysis was performed on the constructed brain functional network using the GRETNA toolkit. The network sparsity threshold range was set from 0.05 to 0.45, with increments of 0.05. Graph features were calculated for all threshold points within this range for both groups of subjects.

This study incorporates four types of spatial topological features to comprehensively characterize the organizational properties of brain networks [8]: Degree Centrality (DC) identifies key brain regions serving as information transmission hubs within the network; Betweenness Centrality (BC) reflects a node's intermediary role in global information flow, aiding in the identification of critical communication pathways within the network; Clustering Coefficient (C) characterizes the tightness of connections within local neighborhoods, with higher values indicating stronger local functional integration capabilities; Shortest Path Length (SPL) describes the minimum number of steps required for information transmission between any two brain regions. A shorter SPL typically indicates more efficient information integration.

2.6. GAT-LSTM Model

2.6.1. GAT Spatial Modeling

In this study, the functional connectivity network for each time window is processed using GAT. GAT employs a multi-head self-attention mechanism to compute the embedded features for each node, thereby effectively capturing the spatial relationships between nodes within the brain network.

The feature matrix $X_w \in \mathrm{R}^{90\times 4}$ for each node and the adjacency matrix $A_w \in \mathrm{R}^{90\times 90}$ serve as inputs to the GAT model. The node feature matrix X_w incorporates four graph-theoretic features, with each node corresponding to the feature vector of a brain region. The adjacency matrix A_w represents the functional connectivity relationships among brain regions within time window w. Using these inputs, the GAT model computes weighted feature representations for nodes at each layer, progressively extracting complex spatial relationships between nodes.

At the first layer of GAT, each node's feature X_i must first be mapped to a new space via a shared linear transformation matrix W, namely:

$$h_i^{'} = WX_i \tag{2}$$

Here, h_i' denotes the transformed feature vector of node i, $W \in \mathrm{R}^{4\times d}$ is a learnable weight matrix, and d represents the dimension of the embedding space. Following this transformation, the resulting node features h_i' will be utilized to compute attention coefficients.

Next, the graph attention network computes the attention coefficient α_{ij} between each pair of nodes. This coefficient reflects the extent to which node j influences the features of node i. Specifically, the calculation is performed as follows:

$$\alpha_{ij} = \frac{\exp\left(Leaky\,\mathrm{Re}LU\left(a^T\left[h_i^{'}||h_j^{'}\right]\right)\right)}{\sum_{k\epsilon N(i)}\exp\left(Leaky\,\mathrm{Re}LU\left(a^T\left[h_i^{'}||h_k^{i}\right]\right)\right)} \tag{3}$$

Where a is a learnable weight vector representing the parameters of the attention mechanism. The resulting attention coefficients α_{ij} are used to weight the features of neighboring nodes to compute the new feature representation of node i. Specifically, the new representation $h_i^{(1)}$ of node i is given by the following formula:

$$h_i^{(1)} = \sum_{j\epsilon N(i)} \alpha_{ij} h_j^{'} \tag{4}$$

Among these, $\mathcal{N}(i)$ denotes the set of neighbors for node i, and h_j' represents the transformed feature vector of neighbor node j. Through this weighted averaging approach, GAT can incorporate information from neighboring nodes to update the representation of node i.

To further extract deep dependencies between nodes, GAT models typically stack multiple layers. The second layer of GAT processes the first layer's output $h_i^{(1)}$ again, computes new attention coefficients, and performs another aggregation of nodes. Specifically, the second layer's output $h_i^{(2)}$ is defined as:

$$h_i^{(2)} = \sum_{j\epsilon N(i)} \alpha_{ij}^{(2)} h_j^{(1)} \tag{5}$$

Here, $\alpha_{ij}^{(2)}$ represents the attention coefficients for the second layer, and $h_j^{(1)}$ denotes the node features output from the first layer.

By stacking multiple layers of GAT, the node representations progressively incorporate increasing amounts of local and global information, enabling GAT to capture deeper structural features. Finally, to obtain a graph-level representation g_w, we perform global average pooling on the node embedding matrix $H_w \in R^{90\times 64}$ for each time window. Specifically, we average the features of all nodes to obtain a fixed-dimensional graph-level representation:

$$g_w = \frac{1}{N}\sum_{i=1}^{N} h_i^{(2)} \tag{6}$$

where $N = 90$ denotes the number of nodes in the graph, and $h_i^{(2)}$ represents the feature vector of node i in the second-layer GAT. The pooled graph-level representation $g_w \in R^{64}$ will serve as input to the downstream LSTM network, which further learns dynamic changes within the time series.

2.6.2. LSTM Time Series Modeling

The graph-level embedding g_w from each time window is fed into the LSTM, enabling it to capture the temporal dynamics of brain network activity. The hidden state h_W from the final time step is passed as the temporal feature to the classification layer.

The input to the LSTM network is a sequence composed of graph-level embeddings $\{g_1, g_2, \ldots, g_W\}$ from multiple time windows, where W is the total number of time windows. Each graph-level embedding g_w is a 64-dimensional vector representing the brain network features of the w time window. The LSTM network takes these embedding sequences as input, progressively updates its internal state, and learns long-term dependencies through gating mechanisms. The input sequence has length W, with each time step's input being $g_w \in R^{64}$.

At each time step in an LSTM, the network updates the current state h_w by combining the input g_w of the current time step with the state h_{w-1} from the previous time step, through its built-in memory cell and hidden state. In this way, the LSTM progressively captures the temporal evolution patterns of neural networks.

2.7. Dynamic Stability Regularization

To enhance the stability of temporal dynamic features, we introduce DSR. This regularization term preserves the smoothness of time series by constraining the variation in graph-level embeddings between adjacent time windows. The specific calculation is as follows:

$$L_{stability} = \frac{1}{W-1}\sum_{w-1}^{W-1} ||g_{w+1} - g_w||_2^2 \tag{7}$$

During training, the objective is to update the network parameters by minimizing the total loss L, where:

$$L = L_{cls} + \lambda L_{stability} \tag{8}$$

Here, L_{cls} denotes the cross-entropy classification loss, and λ controls the weight of stability regularization.

The hidden state h_W from the last time step is passed to the fully connected layer for classification. Parameter updates are performed using Adam with a learning rate of 0.01. The classification layer maps the input features through a softmax function, outputting the probability distribution for each class. In this study, the output classes represent developmental dyslexia patients and healthy controls. The classification layer aims to accurately distinguish between categories based on the temporal features learned by the LSTM. Specifically, the output class labels are computed using the following formula:

$$y = soft\max(W_{out}h_W + b_{out}) \tag{9}$$

Among these, W_{out} is the weight matrix for the classification layer, b_{out} is the bias term, and the softmax function transforms the output into a probability distribution, ultimately predicting the probability of belonging to a specific category.

3. Result

3.1. Model Experiment Results

The GAT-LSTM-based brain network classification method proposed in this study combines graph neural networks with LSTM models to simultaneously capture both the spatial topological features and temporal dynamic characteristics of brain networks. Additionally, the introduction of DSR enhances the stability of temporal features. This approach enables more accurate identification of brain network differences between individuals with developmental reading disorders and healthy controls.

This study employs five-fold cross-validation and runs on NVIDIA 4060 GPU hardware. To validate the accuracy and performance of our method in classification tasks, we utilize accuracy, precision, recall, and F1 score as evaluation metrics, with the formulas as follows.

$$Accurary = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$\text{Re}call = \frac{TP}{TP + FN} \tag{12}$$

$$F1\ Score = 2\cdot \frac{Precision\cdot \text{Re}call}{Precision + \text{Re}call} \tag{13}$$

By comparing the results of different models in Table 2, it is evident that the proposed GAT-LSTM-based model outperforms other traditional methods. The GAT-LSTM model achieved an accuracy rate of 83.31%. This result indicates that the GAT-LSTM model, based on the graph attention mechanism, can better capture complex features within brain networks, thereby enhancing the diagnostic accuracy of DD.

Table 2. Model Comparison

Methods	Accuracy	Precision	Recall	F1 Score
Random Forest	0.6627	0.7024	0.6874	0.6948
SVM	0.6910	0.6855	0.7246	0.7045
CNN-4	0.7843	0.7771	0.7691	0.7731
GCN	0.8145	**0.8592**	0.8263	0.8425
Ours	**0.8536**	0.8419	**0.8522**	**0.8470**

3.2. Melting Experiment

This study extracts topological spatial features using GAT, analyzes their temporal characteristics through LSTM, and normalizes the sequence features via DSR. To further validate the advantages of the proposed GAT-LSTM model, the impact of different components on model performance was evaluated by removing certain feature modules. The results are shown in Table 3. The findings indicate that removing any single component leads to varying degrees of accuracy decline, with optimal classification performance achieved only when all three components are combined.

Table 3. Ablation Experiment Results

Methods	Accuracy	Precision	Recall	F1 Score
GAT	0.8244	0.8127	0.8240	0.8183
LSTM+DSR	0.8185	0.7858	0.8072	0.7964
GAT+LSTM	0.8463	0.8406	0.8496	0.8451
Ours	**0.8536**	**0.8419**	**0.8522**	**0.8470**

4. Discussion

The GAT-LSTM model proposed in this study demonstrates outstanding performance in identifying brain network differences between DD patients and healthy controls. As a powerful model for processing temporal data, LSTM effectively learns time dependencies, making it particularly suitable for capturing the dynamically evolving time-series characteristics inherent in brain functional data. The graph attention mechanism introduced via the GAT module enables the model to focus more precisely on key nodes across different regions within the brain network, thereby enhancing classification accuracy. Compared to traditional SVM- or CNN-based approaches, GAT-LSTM better handles structured brain network data and reveals underlying neural mechanisms associated with dyslexia.

Although the GAT-LSTM model proposed in this study achieved relatively superior results in the developmental dyslexia classification task, several limitations remain. First, the dataset sample size is relatively small; future work could further validate the model's generalization ability by increasing the number of samples. Second, while the model demonstrated good performance in the classification task, its practical effectiveness in clinical applications requires further validation and optimization.

GAT-LSTM effectively extracts spatiotemporal features from brain networks and significantly improves classification accuracy. The introduction of DSR further enhances the stability of temporal features and the robustness of the model. Future research can further optimize the model, expand the dataset size, and explore additional brain network modeling approaches to advance the early diagnosis and personalized treatment of developmental reading disorders.

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