

Attention-deficit/hyperactivity disorder (ADHD) Diagnosis Using Diffusion Convolutional Recurrent Neural Networks with Temporal Data

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Abstract

ADHD is one of the most common neuro-developmental disorders among children. Brain network provides a mathematical description of the complex connections and interactions among neurons in brain. In this research, we propose a graph deep learning method to classify ADHD using time series brain functional magnetic resonance imaging (fMRI) data. A graph diffusion convolutional recurrent network (GDCRN) architecture is presented for the time series graph-structured ADHD classification. The outcome of this research is expected to promote the implementation of deep learning for ADHD detection and brain network analysis in computer-aided diagnosis.

Methodology

- Based on diffusion convolution recurrent neural network (RNN)
- Trained by maximizing the likelihood of generating the target future time series using backpropagation through time.

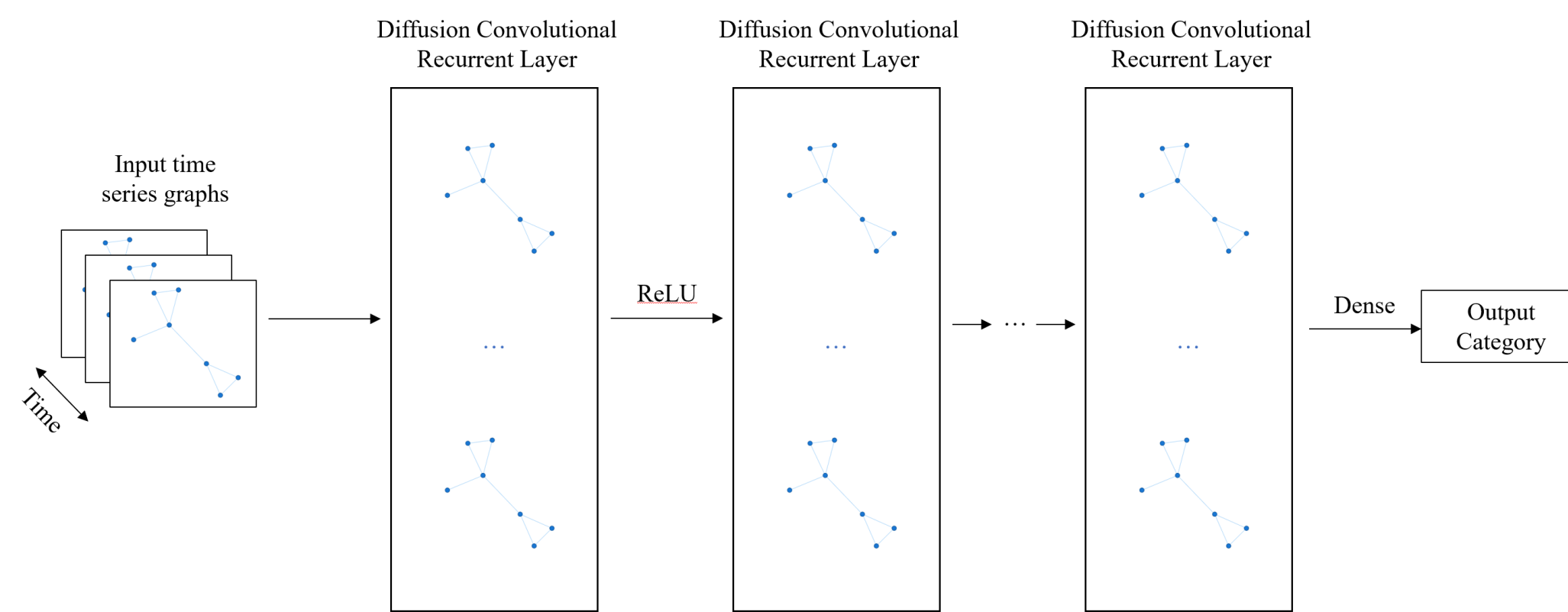


Figure 1: Proposed GDCRN model framework

- RNNs to model the temporal dependency
- Diffusion convolutional gated recurrent unit is used to modify the matrix multiplications in Gated Recurrent Units (GRU) with the diffusion as,

$$C^{(t)} = \tanh(\theta[X^{(t)}, (r^{(t)} \odot H^{(t-1)})] + b_c)$$

$$H^{(t)} = u^{(t)} \odot H^{(t-1)} + (1 - u^{(t)}) \odot C^{(t)}$$

Where $X^{(t)}$ and $H^{(t)}$ denote the input and output of at time t ; $r^{(t)}$ and $u^{(t)}$ are set gate and update gate, respectively. θ is parameter for the corresponding kernel filters. \odot refers to element-wise multiplication.

Data Preparation

- 120 patient samples including ADHD versus normal control.
- Time series fMRI signals are collected.
- Sliding window size of 60 seconds with 20% overlap has been applied to calculate correlation matrices.

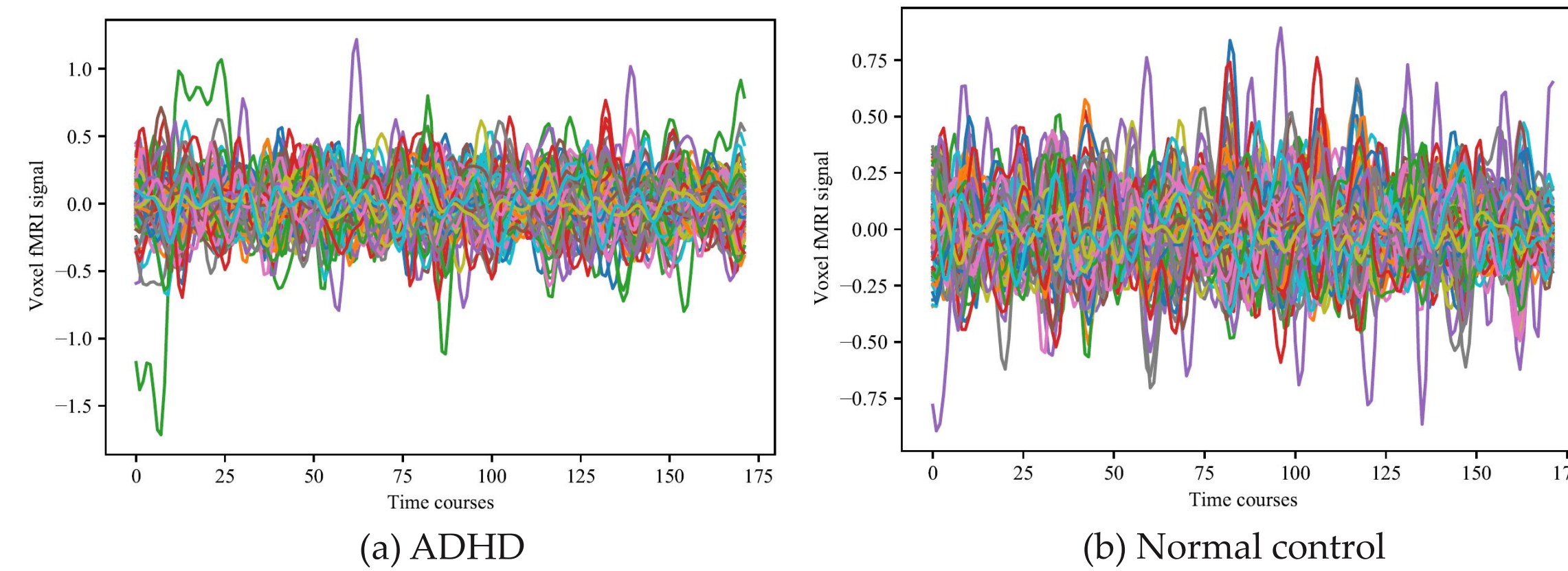


Figure 2: Example of time series fMRI signals

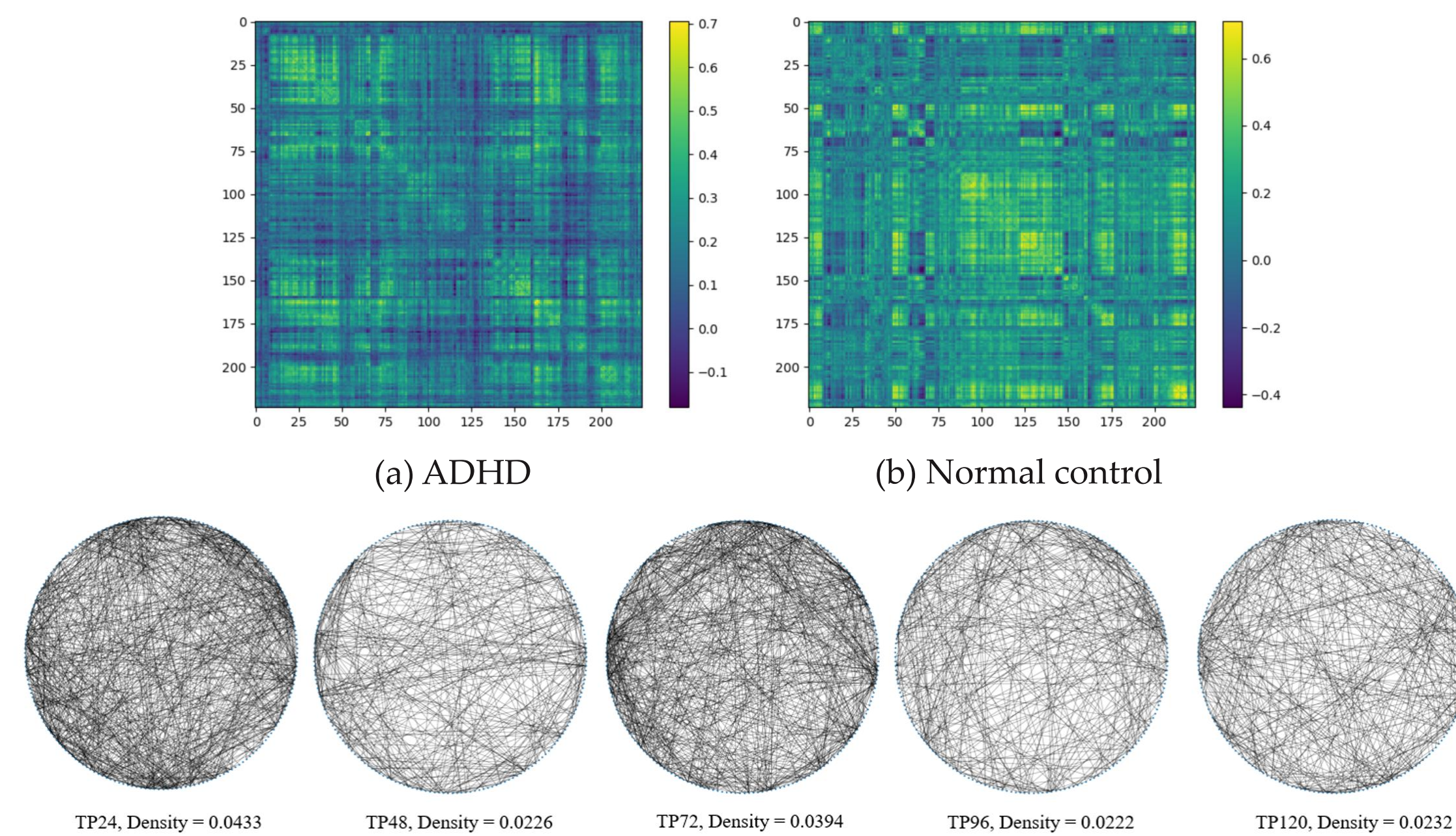


Figure 3: Example of adjacency matrices and time series graphs

- The strongest 3% edges are retained.
- 5 calculated time series matrices for each sample, and consequently, 5 time series graphs are constructed.

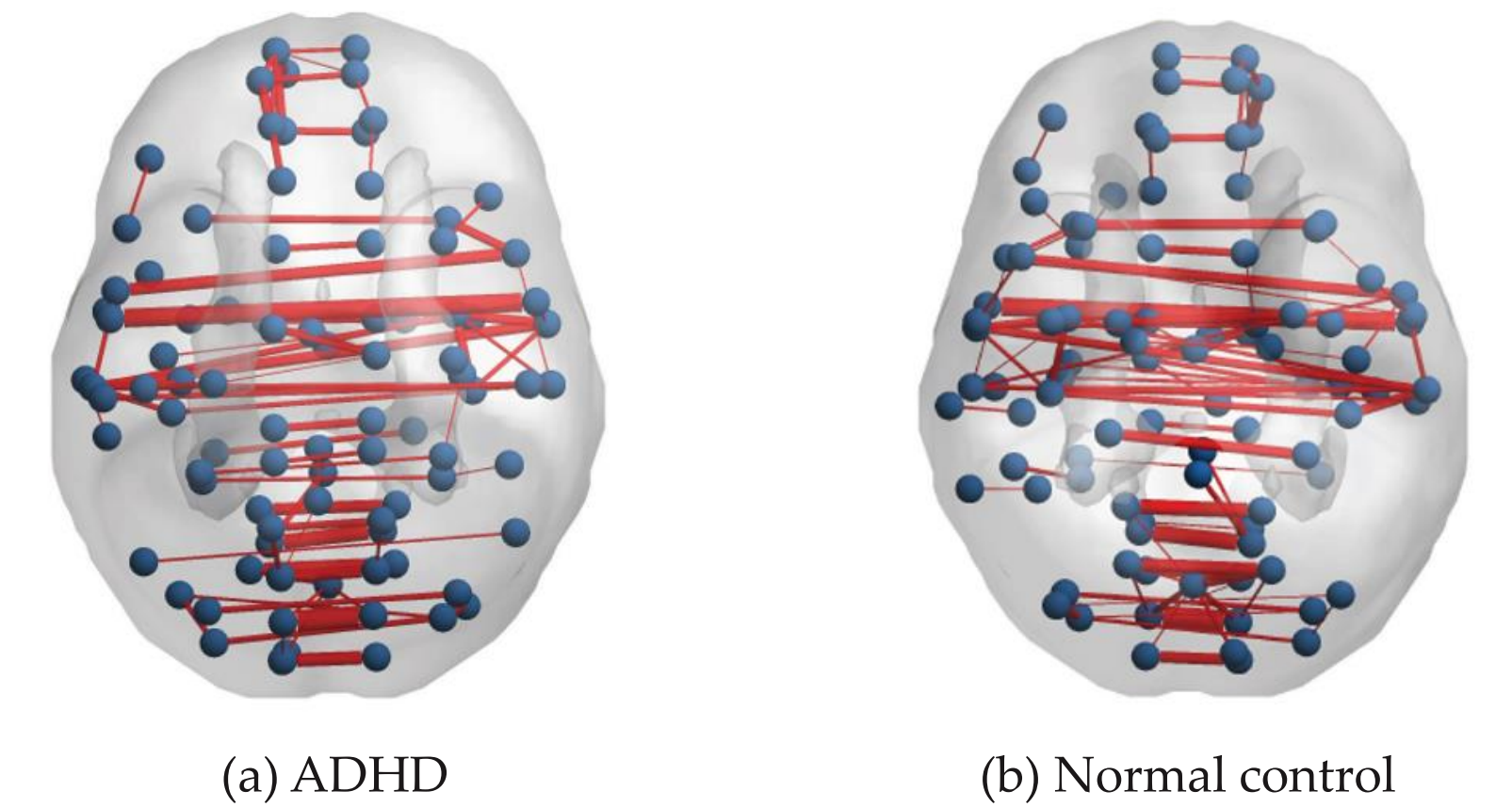


Figure 4: Constructed ADHD and normal control brain networks

Experimental Results

Model	Performance Measurement			
	Accuracy	Precision	Recall	F1-score
DCNN	0.656	0.507	0.791	0.618
DEMO-Net	0.689	0.532	0.772	0.630
GDCRN	0.575	0.592	0.764	0.667

Table 1: Test results for different graph deep learning methods

- GDCRN is compared with DCNN model and DEMO-Net.
- It is expected to find a more effective way to embed more dynamic node features.

Conclusions and Future Work

- Studied ADHD classification using the proposed GDCRN model with graph-structured temporal MRI data.
- Demonstrated that GDCRN is applicable to classify ADHD and non-ADHD patients, whereas GDCRN can also handle time series graphs considering both spatial and temporal information.

- Long-range spatial dependencies between individual nodes or non-local graph behavior are interesting to explore.

References

- Wang, Y., Marufuzzaman, M., & Wang, H. (2021). Graph Deep Learning-Based Attention-Deficit/Hyperactivity Disorder Diagnosis for Brain Network. In IIE Annual Conference. Proceedings (pp. 513-517). Institute of Industrial and Systems Engineers (IISE).
- Pirimy, H., Fan, M., & Wang, H. (2020, December). Brain Functional Connectivity Pattern Recognition for Attention-deficit/hyperactivity Disorder Diagnosis. In 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 2806-2811). IEEE.
- Pirimy, H., Fan, M., & Wang, H. Dynamic Network Connectivity Analysis for Understanding Attention Deficit Hyperactivity Disorder. In 2022 IEEE International Conference on Healthcare Informatics (ICHI). Accepted.