Universal Brain Disease Classifier with Multi-head Attention for Capturing Spatio-Temporal Features in Dynamic Functional Connectivity on fMRI Images

Taehoon Kang[1], Minhyuk An[2], Jinmyung Kim[1]
[1]Department of Computer Science [2]Department of Artificial Intelligence
Yonsei University
{thkyang324, als7928, jmkim_}@yonsei.ac.kr

Abstract

Understanding the intricate neural network for diagnosing brain diseases across diverse spatial and temporal dimensions is paramount. While recent advancements in deep learning and functional connectivity (FC) graph-based methods show promise, they often overlook the transient and localized characteristics of brain diseases and struggle to capture dependencies among regional features adequately. To address these limitations, we introduce a novel deep learning approach that employs multi-head attention to model FC, capturing both transient and localized FC, and learning structural and temporal features in fMRI images. This method not only identifies correlations specific to regions but also emphasizes connections at particular, fleeting time points.

The extracted FC is transformed into a graph, with weighted labels assigned to edges reflecting the degree of correlation. This graph is then processed using a graph neural network capable of handling edge labels. Experiments carried out on four datasets pertaining to prominent brain disorders—specifically, autism and schizophrenia—demonstrate enhanced performance compared to state-of-the-art methods. The integration of features derived from multi-head attention in functional connectivity (FC) significantly improves the capability to differentiate between normal brains and those affected by these specific diseases. These results emphasize the effectiveness of our proposed method in elevating diagnostic accuracy and underscore its potential to advance neurological research, particularly in the context of diagnosing autism and schizophrenia.

1. Introduction

The human brain, overseeing vital functions such as thoughts, memory, emotions, motor skills, vision, and breathing [18, 26], stands as the pivotal organ in the body. Comprising 100 billion neurons and over 100 trillion synapses, the brain functions across diverse anatomical and functional scales, engaging in interactions across various spatial and temporal dimensions [34]. A profound comprehension of this intricate neural network proves crucial for the diagnosis and treatment of brain diseases, with early detection playing a pivotal role in enhancing the quality of life for patients and mitigating the progression of neurological conditions [28]. Consequently, the accurate capture of both the structural and functional characteristics of the brain emerges as a focal point in brain science and neurological research [8, 12].

In recent years, substantial research has focused on diagnosing brain diseases through neuroimaging techniques such as fMRI, employing deep learning to interpret and extract patterns from the intricate features of the brain [5, 10, 11, 21, 36]. A complementary approach, centered on functional connectivity (FC), has also gained prominence, seeking to enhance our understanding of the brain's functional relationships [1, 17, 27, 30, 38, 41]. Typically, FC-based methods leverage regional distinctions within the brain, designating each region as a biomarker and measuring correlations between regions based on their temporal attributes. The resultant graphs, which connect regions based on these measured correlations, explicitly depict the brain's spatial relationships and prove valuable in disease diagnoses, particularly when analyzed using tools like graph neural networks.

However, FC-based deep learning methods often overlook the transient and localized characteristics of brain diseases. Some conditions may manifest in concentrated forms within specific timeframes and localized regions. For example, seizure disorders or certain neurodegenerative conditions might exhibit changes in brain activity only at distinct, fleeting moments, triggered by external or internal stimuli [20, 32, 40]. In other words, these methods fall short in capturing the temporal and spatial specificity crucial for accurately representing and diagnosing manifestations of brain diseases. To overcome the challenges associated with

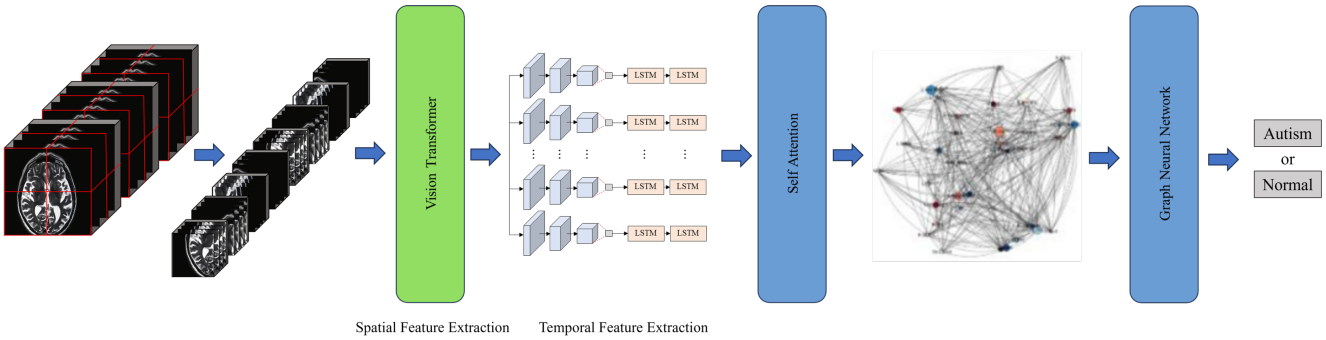


Figure 1. Overview of the proposed method

capturing the transient and localized characteristics of brain diseases, we present a novel deep learning method explicitly crafted to model functional connectivity (FC) using multi-head attention. This model is designed to extract both transient and localized FC patterns while concurrently learning structural and temporal features in fMRI images through an attention mechanism. Diverging from conventional approaches, our model not only identifies correlations specific to brain regions across the entire spectrum but also accentuates connections at specific, transient time points. Following this extraction process, the FC is transformed into a graph. In contrast to traditional FC-based methods for predicting brain diseases, which typically represent FC as a binary adjacency matrix, our method assigns weighted labels to the graph edges, reflecting the degree of correlation. To effectively process the graph enriched with edge information, our proposed method utilizes a graph neural network capable of handling edge labels, embedding the FC and facilitating disease diagnosis.

To assess the efficacy of the proposed method, we conducted experiments using four distinct datasets. The results of these tests showcase the method's superior performance compared to state-of-the-art (SOTA) techniques, with a performance increase of up to 3% points. A crucial factor contributing to this success is the incorporation of features derived from multi-head attention into functional connectivity (FC), which are subsequently analyzed using an edge label-based graph neural network. This innovative approach significantly augments the capacity to distinguish between healthy brains and those affected by diseases in FC analysis experiments, with a focus on disease prediction. These experimental outcomes not only validate the method's effectiveness in enhancing diagnostic precision but also underscore its potential to propel neurological research forward through the application of cutting-edge data processing and analysis methods.

2. Related Work

Ensemble convolutional neural networks (CNNs), incorporating architectures like ResNet and Inception V3, have proven effective in extracting spatial features from brain images—a crucial factor in understanding spatial conditions. These models not only achieve high accuracy but also facilitate the analysis of both structural and functional aspects of the brain [2, 3, 6, 9, 29, 33]. CNNs, however, excel at extracting only local features in the brain. Vision transformer (ViT), meanwhile, has strengths in considering global information across all regions of the brain. Through the self-attention mechanism, it can take into account interactions across all areas of the brain, enabling a comprehensive understanding of the overall context and extraction of features. Performing Spatial Feature Extraction with ViT allows for feature extraction from a different perspective compared to conventional methods. Combining spatial features from ViT and temporal features from recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, can capture intricate spatio-temporal characteristics, demonstrating superior performance in various disease diagnoses. This synergistic approach enables a comprehensive analysis of brain function and structure, leading to more accurate diagnoses and prognoses for various neurological conditions [13, 16, 24, 31, 40].

Functional connectivity (FC) analysis has become a fundamental tool in brain research, playing a critical role in identifying biomarkers for neurological and mental diseases [1, 30, 38]. Traditional FC-based methods are instrumental in mapping the brain's neural network, creating graphs where nodes represent regions of interest (ROIs)—specific areas relevant to the study or disease. Edges in these graphs symbolize functional connections between these regions, capturing communication pathways or networks within the brain.

Additionally, the application of graph-based methods in fMRI analysis has significantly advanced understanding of the brain's structure and functionality [14, 15]. These ap-

proaches provide a more comprehensive view of the interconnections of brain regions, surpassing traditional imaging techniques. By examining the intricate network of connections, researchers can uncover patterns and associations not immediately apparent through standard imaging analysis. This level of analysis is particularly valuable in studying complex brain disorders, where multiple regions of the brain may be affected simultaneously [19, 25, 37].

3. Proposed Method

Fig. 1 depicts the proposed model employing ViT and LSTM with a multi-head attention mechanism to extract spatial and temporal features. In the preprocessing phase, The 4D fMRI images in time, depth, width, and height are divided into 3D blocks along the t-axis. Each block has k consecutive slices, and these consecutive blocks pass through a vision transformer for spatial feature extraction. Extracted features then undergo processing in an LSTM to model overall temporal attributes. During this phase, the model employs multi-head attention to assign weights to temporal attributes, aiding the model in learning the significance of different temporal aspects in conjunction with $\mathcal{L}_{spatio-temporal}$.

The model explicitly maps dynamic (temporal) FC correlations of the input image sequence to brain regions using features extracted from the attention mechanism. This mapping constructs a graph, where FCs serve as the adjacency matrix, brain regions as nodes, and edges represent the degree of correlation. The constructed graph is utilized for disease diagnosis via a graph neural network. A graph neural network capable of processing edge labels is employed to utilize FC correlations more effectively.

3.1. Multi-head attention for temporal features

The spatial features of the brain, extracted using the residual network, are input into a Bi-LSTM-based multi-head attention mechanism to map time series attributes. The primary objective of our method is to extract and enhance transient brain features present in fMRI images, prompting the utilization of an attention-based mechanism to map these time series attributes. Multi-head attention is employed instead of single head attention due to the latter often being insufficient in fully capturing dependencies between temporal features within the complex spatial context of the brain. Multi-head attention allows for a more effective modeling of these dependencies.

When considering the features $x_1, x_2, ..., x_k$ extracted from the residual CNN blocks, their embedding through a Bi-LSTM and multi-head attention mechanism can be described by referencing the provided formula.

Initially, the features $x_1, x_2, ..., x_k$ from the CNN are input into the Bi-LSTM network, which processes these features to capture temporal dependencies, resulting in a series of hidden states $h_1, h_2, ..., h_N$. In the context of the multi-head attention mechanism, each pair of hidden states h_i, h_j is evaluated to compute attention weights a_{ij}. This computation is achieved through the following softmax function:

$$a_{ij} = softmax_j(h_{ij}) = \frac{exp(score(h_i, h_j \cdot W_v h_i))}{\sum_{n=1}^{N} exp(h_i, h_n \cdot W_v h_i)} \quad (1)$$

Here, $score(h_i, h_j)$ is a function that measures the compatibility of the hidden states h_i and h_j , which is calculated as:

$$score(h_i, h_j) = f(W_q h_i, W_k h_j) \quad (2)$$

where W_q and W_k are weight matrices for the query and key in the attention mechanism, respectively.

Finally, the output representation r_i for each hidden state h_i is computed as a weighted sum of all hidden states, with the weights being the attention scores:

$$r_i = \sum_{n=1}^{N} a_{in} \cdot h_n \quad (3)$$

This process is iteratively performed independently K times, and the outcomes are combined by concatenation to create a unified vector. The incorporation of spatial and temporal aspects in the proposed multi-head attention empowers it to concentrate on particular time frames and proficiently capture the transient characteristics of diseases. This mechanism facilitates the examination of disease attributes from various viewpoints, delivering a comprehensive and multi-faceted comprehension of the distinctive features associated with the disease.

3.2. Learning dynamic functional connectivity

Park et al. [22] demonstrated that the extraction of spatio-temporal features while preserving the integrity of dynamic connectivity significantly enhances accuracy. Nevertheless, a more direct method to learn the dynamic connectivity across 39 brain regions could offer further improvements. As depicted in Fig. 1, the method leverages the spatio-temporal model as a foundational, pre-trained model. We transform the output of the intermediate layer, which consists of time-series spatial feature maps, into a connectivity matrix that delineates the relationships between 39 distinct brain regions. Subsequently, this spatio-temporal feature map is merged with a connectivity adjacency matrix, incorporating attention weights between regions. The graph neural network is then employed to explicitly learn and articulate the connection information among these 39 brain regions.

Upon processing the fMRI data through the LSTM network, enhanced with an attention mechanism, the output consists of a series of feature representations, symbolized as $R = r_1, r_2, ..., r_\tau$. Each element r_t in this series represents the features for different brain regions at time t, which

Dataset (Setting)	Method	Accuracy [%]
ABIDE I (ASD)	ResNet-LSTM with self-attention	86.74±1.34
	Self-supervised ensemble	94.13±3.12
	Ours	**97.88±1.64**
COBRE (Schizophrenia)	SURF/FAST	88.49±3.48
	Capsuled Network	82.83±0.85
	Ours	**91.61±0.94**
ADHD-200 (ADHD)	**Triplet-Attention CNN**	**99.38±0.21**
	Distributed 3D-CNNs	99.22±0.23
	Ours	99.01±0.25
ADNI-Binary (Alzheimer)	**3D-CNN-LSTM**	**97.46±0.85**
	3D-CNN	93.52±0.96
	Ours	93.11±0.71

Table 1. Caption

are then fed into the '$ConnectivityMeasure$' module to compute the connectivity matrices.

The connectivity matrix, denoted as C, is derived from these feature representations. Specifically, for each pair of brain regions, denoted as i and j, over the entire time series T, the connectivity metric is computed, resulting in a matrix C of $N \times N$ dimensions, where N is the number of brain regions (we use 39 regions). This can be formally represented as:

$$C_{ij} = ConnectivityMeasure(r_i, r_j) \tag{4}$$

Here, C_{ij} represents the connectivity value between regions i and j. The '$ConnectivityMeasure$' method allows us to apply various metrics such as correlation, partial correlation, tangent, or covariance, depending on analysis needs. This results in different forms of the matrix C, each encapsulating unique aspects of inter-regional brain dynamics:

$$\begin{gathered} C_{metric} = metric(F), \\ where\ metric \in [Corr, P_{corr}, Tan, Cov] \end{gathered} \tag{5}$$

This method leads to the creation of a comprehensive connectivity matrix C, which captures the dynamic and complex inter-regional relationships within the brain. Such a matrix not only illustrates the direct interactions between different brain areas but also provides deeper insights into the overall functional network architecture.

4. Experimental Results

Experimental setup is conducted using a Nvidia DGX station equipped with 2560 Nvidia tensor cores, running on an Ubuntu desktop Linux OS. The hardware includes 4X Tesla V100 GPUs (64 GB each) and 256 GB of LRDIMM DDR4 memory.

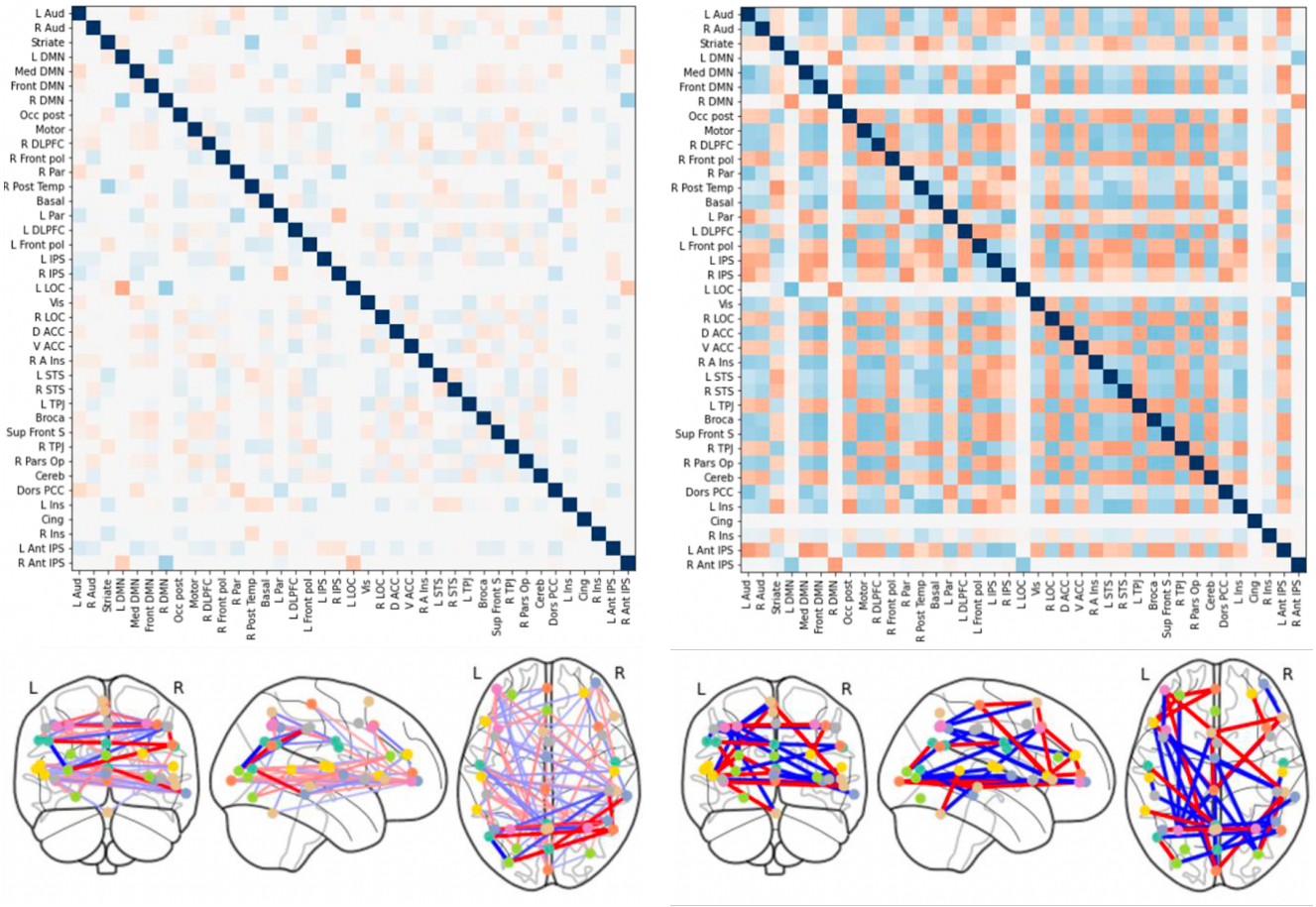
4.1. Data pre-processing and implementation

Autism: We employ the preprocessed ABIDE (Autism Brain Imaging Data Exchange) I dataset, accessible through a web-based platform. This dataset includes data from 800 individuals, each with their own set of 4D fMRI images. It encompasses 389 individuals diagnosed with ASD (Autism Spectrum Disorder) and 411 individuals in a control group. Given the variability in the size and length of each individual's fMRI images, we standardize all images to a uniform size of 24×24×24 and apply the sliding window technique to acquire serial images of fixed length. To ensure no overlap in patient information between training and test, the dataset is partitioned based on individual patients rather than the images themselves. Consequently, the dataset is split into a training set comprising 90% of the cohort (720 individuals) and a validation set consisting of the remaining 10% (80 individuals). The validation set is utilized for visualization and various analyses.

Alzheimer's disease: We utilize fMRI volumes from the ADNI online database for 120 subjects divided into four classes: AD, LMCI, EMCI, and CN, each with 30 subjects. Subjects are grouped by gender and age, with specific demographics for each class. The resting-state fMRI data were acquired using a 3T Philips MRI system, with each volume consisting of 48 axial slices and a total of 140 full brain volumes per subject. The fMRI data underwent a standard preprocessing pipeline in MATLAB 2019a and its SPM12 toolbox, including motion correction, intensity normalization, co-registration to the Montreal Neurological Institute (MNI) space, and removal of background noise and temporal signal drifts. In cases where motion exceeded one voxel, volumes are replaced from the ADNI database. A uniform binary mask in MNI space is applied to all volumes for consistency in further analysis [4, 23].

ADHD: We use the ADHD-200 dataset, initially released for a global competition and shared under the 1000 functional connectomes project protocols. It includes data from five participating sites: Peking University, Kennedy Krieger Institute, NeuroIMAGE Sample, NYU Child Study Center, and Oregon Health & Science University. The dataset was balanced with both typically developing (TD) individuals and ADHD patients to prevent class imbalance. For data preprocessing, we utilize the preprocessed fMRI scans available from the Neuro Bureau, which follows "The Athena" pipeline. This preprocessing, integrating AFNI and FSL packages, is performed on the Athena computational cluster at Virginia Tech's ARC [7].

Schizophrenia: We utilize resting-state fMRI data from the COBRE project, consisting of 57 subjects with schizophrenia (SZ) and 64 healthy controls (HC). Diagnoses were based on DSM-IV criteria and assessed using the Positive and Negative Syndrome Scale (PANSS). Subjects with a history of significant neurological disorders, head trauma, or substance abuse were excluded. Imaging used single-shot EPI with specific parameters like TR/TE = 2000/30ms, and a total of 150 volumes were captured per



(a) Normal

(b) ASD

Figure 2. Correlation matrix and brain regional connectivity graph for normal and ASD.

subject. The initial 10 volumes were discarded for scanner stabilization. Data preprocessing is conducted using the DPABI toolbox. This includes slice timing correction, realignment, spatial normalization to an MNI template, and spatial smoothing. A band-pass filter (0.01∼0.08Hz) is applied, and the brain is parcellated into 120 ROIs using the AAL2 atlas. Finally, the mean time series are extracted from each ROI and normalized [35, 39].

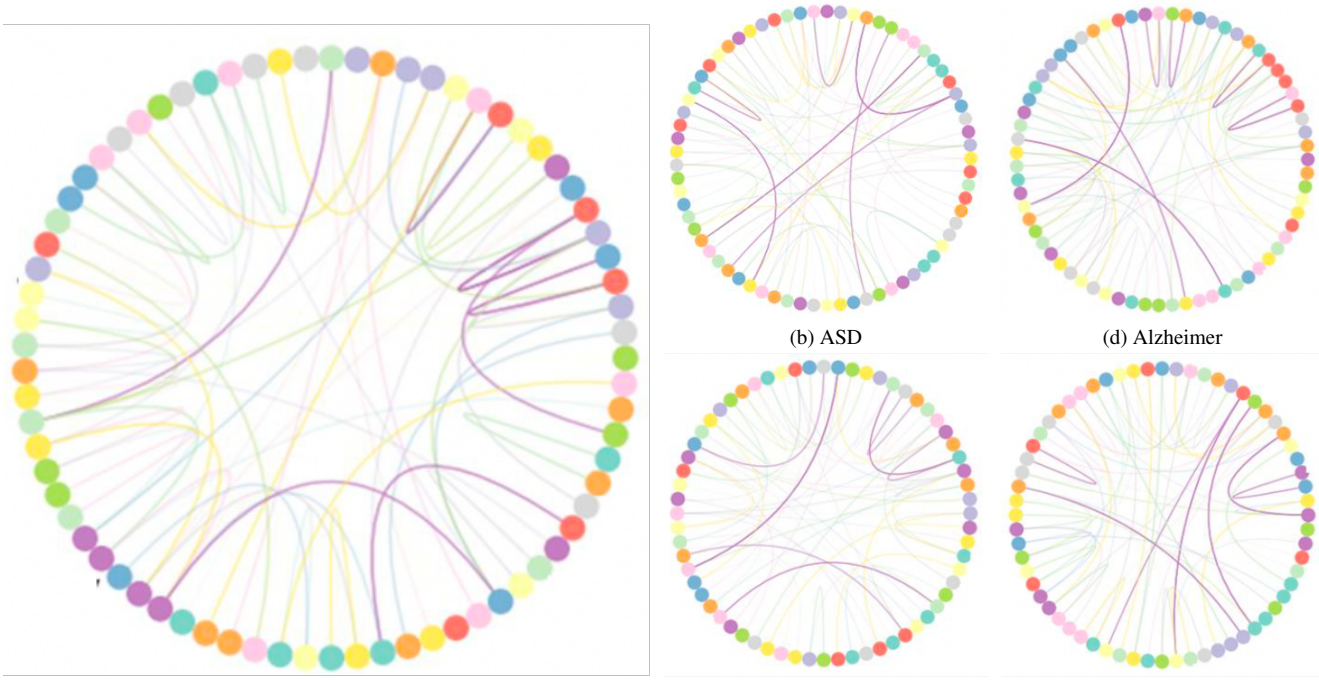
The spatio-temporal model receives a 4D image with a resolution of 10×24×24×24 as input, returns a softmax probability for two groups, and classifies the predicted group as the highest probability. The spatio-temporal model is composed of ViT and 2 Bi-LSTM with attention and 2 MLP layers. We simply employ graph convolutional networks (GCN). To reduce the training time caused by the two feature extraction processes, we adopt the Adam optimizer, which combines the advantages of AdaGrad and RMSprop, to optimize the loss function with less training time.

4.2. Comparison of classification accuracy

When analyzing brain diseases through fMRI data, the way these diseases manifest over time can be complex and varies depending on the type and characteristics of the disease.

Tab. 1 shows a comparison of the accuracy between the proposed method and other comparative methods. Notably, the proposed method demonstrates a marked improvement in accuracy, underlining its ability to effectively harness attention mechanisms and achieves an accuracy of 97.88±1.64 in autism that exhibits characteristic information over the entire time axis and 91.61±0.94 in ADHD in which changes in brain activity can occur in response to specific tasks or stimuli. This superior performance is indicative of the method's enhanced capability in discerning nuanced changes in brain activity that are pivotal for accurate diagnosis.

The proposed method's ability to leverage the graphical representation of brain region correlations offers a distinct



(a) Normal (b) ASD (c) ADHD (d) Alzheimer (e) Schizophrenia

Figure 3. Visualization of functional connectivity in normal and diseased brains

advantage. It provides a more holistic view, enabling the model to make predictions with greater accuracy compared to other models that might focus on isolated aspects or specific time frames. Therefore, our results indicate that even without the primary reliance on attention mechanism, the graph-based approach significantly enhances the model's predictive capabilities, effectively addressing the challenges posed by the temporal dynamics of these neurological conditions.

4.3. Analysis of correlations of ROI

Fig. 2 illustrates the analysis of the correlation matrix extracted by the proposed method. As observed in this correlation matrix, the time-series features extracted from ASD patients and processed through attention mechanism closely connect various regions of the brain, reflecting their interdependencies and enabling effective prediction of ASD. In contrast, in a normal brain, the attention mechanism does not establish as strong connections between regions, indicating that the model fails to identify significant characteristics that could highlight connections across different brain areas. This distinction highlights the strength of the proposed method, which leverages attention-based feature extraction, graph transformation, and a graph neural network. These steps enhance the differentiation of disease-specific features, thereby improving the accuracy of disease diagnosis.

The method's effectiveness is rooted in its ability to accentuate the contrast between the neurobiological patterns of ASD and those of a typical brain, illustrating the nuanced complexities captured by the proposed method. The integration of attention mechanism with graph-based analyses provides a more comprehensive understanding of brain connectivity patterns, crucial for discerning the subtle yet significant differences in neurological conditions. This advanced methodology demonstrates a significant stride in enhancing diagnostic precision through sophisticated analysis of fMRI data.

Fig. 3 visualizes the functional connectivity (FC) for each disease. A total of 39 brain regions were examined, resulting in 78 views including directionalities. Each node in the figure represents a region, while the edges illustrate the degree of correlation present before the addition of labels. As can be seen in the figure, compared to a normal brain, distinct and specific correlations are captured in other diseases, demonstrating shared unique features among them. This observation indicates that our proposed method effectively utilizes attention to extract distinct disease characteristics and translates them into a graph.

5. Conclusions

In this paper, we present a significant advancement in understanding and diagnosing neurological conditions, using advanced neural network techniques applied to fMRI data.

The proposed method, which incorporates attention-based feature extraction, graph transformation, and graph neural networks, has demonstrated superior accuracy in identifying brain disease and differentiating it from normal (neurotypical) brain patterns. This approach has not only enhanced the accuracy of brain diseases diagnosis but also provided deeper insights into the underlying neurobiological mechanisms.

References

[1] Anees Abrol, Zening Fu, Yuhui Du, and Vince D Calhoun. Multimodal data fusion of deep learning and dynamic functional connectivity features to predict alzheimer's disease progression. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 4409–4413. IEEE, 2019. 1, 2

[2] Md Rishad Ahmed, Yuan Zhang, Yi Liu, and Hongen Liao. Single volume image generator and deep learning-based asd classification. *IEEE Journal of Biomedical and Health Informatics*, 24(11):3044–3054, 2020. 2

[3] Gangani Ariyarathne, Senuri De Silva, Sanuwani Dayarathna, Dulani Meedeniya, and Sampath Jayarathne. Adhd identification using convolutional neural network with seed-based approach for fmri data. In *Proceedings of the 2020 9th International Conference on Software and Computer Applications*, pages 31–35, 2020. 2

[4] John Ashburner, Gareth Barnes, Chun-Chuan Chen, Jean Daunizeau, Guillaume Flandin, Karl Friston, Stefan Kiebel, James Kilner, Vladimir Litvak, Rosalyn Moran, et al. Spm12 manual. *Wellcome Trust Centre for Neuroimaging, London, UK*, 2464(4), 2014. 4

[5] Zijiao Chen, Jiaxin Qing, Tiange Xiang, Wan Lin Yue, and Juan Helen Zhou. Seeing beyond the brain: Conditional diffusion model with sparse masked modeling for vision decoding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22710–22720, 2023. 1

[6] Ahmed El-Gazzar, Mirjam Quaak, Leonardo Cerliani, Peter Bloem, Guido van Wingen, and Rajat Mani Thomas. A hybrid 3dcnn and 3dc-lstm based model for 4d spatio-temporal fmri data: an abide autism classification study. In *International Workshop on OR 2.0 Context-Aware Operating Theaters*, pages 95–102. Springer, 2019. 2

[7] Centers for Disease Control (US). *Morbidity and mortality weekly report: MMWR*. US Department of Health, Education, and Welfare, Public Health Service . . . , 2011. 4

[8] Alex Fornito, Andrew Zalesky, and Michael Breakspear. The connectomics of brain disorders. *Nature Reviews Neuroscience*, 16(3):159–172, 2015. 1

[9] Manu Gaur, Kunal Chaturvedi, Dinesh Kumar Vishwakarma, Savitha Ramasamy, and Mukesh Prasad. Self-supervised ensembled learning for autism spectrum classification. *Research in Autism Spectrum Disorders*, 107:102223, 2023. 2

[10] Jinlong Hu, Lijie Cao, Tenghui Li, Shoubin Dong, and Ping Li. Gat-li: a graph attention network based learning and interpreting method for functional brain network classification. *BMC bioinformatics*, 22(1):1–20, 2021. 1

[11] Jinlong Hu, Yuezhen Kuang, Bin Liao, Lijie Cao, Shoubin Dong, Ping Li, et al. A multichannel 2d convolutional neural network model for task-evoked fmri data classification. *Computational intelligence and neuroscience*, 2019, 2019. 1

[12] Thomas R Insel and Bruce N Cuthbert. Brain disorders? precisely. *Science*, 348(6234):499–500, 2015. 1

[13] Wei Li, Xuefeng Lin, and Xi Chen. Detecting alzheimer's disease based on 4d fmri: An exploration under deep learning framework. *Neurocomputing*, 388:280–287, 2020. 2

[14] Xiaoxiao Li, Nicha C Dvornek, Yuan Zhou, Juntang Zhuang, Pamela Ventola, and James S Duncan. Graph neural network for interpreting task-fmri biomarkers. In *Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part V 22*, pages 485–493. Springer, 2019. 2

[15] Xiaoxiao Li, Yuan Zhou, Nicha Dvornek, Muhan Zhang, Siyuan Gao, Juntang Zhuang, Dustin Scheinost, Lawrence H Staib, Pamela Ventola, and James S Duncan. Braingnn: Interpretable brain graph neural network for fmri analysis. *Medical Image Analysis*, 74:102233, 2021. 2

[16] Kai Lin, Biao Jie, Peng Dong, Xintao Ding, Weixin Bian, and Mingxia Liu. Convolutional recurrent neural network for dynamic functional mri analysis and brain disease identification. *Frontiers in Neuroscience*, 16:933660, 2022. 2

[17] Regina J Meszlényi, Krisztian Buza, and Zoltán Vidnyánszky. Resting state fmri functional connectivity-based classification using a convolutional neural network architecture. *Frontiers in neuroinformatics*, 11:61, 2017. 1

[18] Heba Mohsen, El-Sayed A El-Dahshan, El-Sayed M El-Horbaty, and Abdel-Badeeh M Salem. Classification using deep learning neural networks for brain tumors. *Future Computing and Informatics Journal*, 3(1):68–71, 2018. 1

[19] Josh Neudorf, Shaylyn Kress, and Ron Borowsky. Structure can predict function in the human brain: a graph neural network deep learning model of functional connectivity and centrality based on structural connectivity. *Brain Structure and Function*, pages 1–13, 2022. 3

[20] Cong Pan, Haifei Yu, Xuan Fei, Xingjuan Zheng, and Renping Yu. Temporal-spatial dynamic functional connectivity analysis in schizophrenia classification. *Frontiers in Neuroscience*, 16:965937, 2022. 1

[21] Junren Pan, Baiying Lei, Yanyan Shen, Yong Liu, Zhiguang Feng, and Shuqiang Wang. Characterization multimodal connectivity of brain network by hypergraph gan for alzheimer's disease analysis. In *Pattern Recognition and Computer Vision: 4th Chinese Conference, PRCV 2021, Beijing, China, October 29–November 1, 2021, Proceedings, Part III 4*, pages 467–478. Springer, 2021. 1

[22] Kyoung-Won Park, Seok-Jun Bu, and Sung-Bae Cho. Learning dynamic connectivity with residual-attention network for autism classification in 4d fmri brain images. In *Intelligent Data Engineering and Automated Learning–IDEAL 2021: 22nd International Conference, IDEAL 2021, Manchester, UK, November 25–27, 2021, Proceedings 22*, pages 387–396. Springer, 2021. 3

[23] Harshit S Parmar, Brian Nutter, Rodney Long, Sameer Antani, and Sunanda Mitra. Automated signal drift and global fluctuation removal from 4d fmri data based on principal component analysis as a major preprocessing step for fmri data analysis. In *Medical Imaging 2019: Biomedical Applications in Molecular, Structural, and Functional Imaging*, volume 10953, pages 300–308. SPIE, 2019. 4

[24] Harshit S Parmar, Brian Nutter, Rodney Long, Sameer Antani, and Sunanda Mitra. Deep learning of volumetric 3d cnn for fmri in alzheimer's disease classification. In *Medical Imaging 2020: Biomedical Applications in Molecular, Structural, and Functional Imaging*, volume 11317, pages 66–71. SPIE, 2020. 2

[25] Elena N Pitsik, Vladimir A Maximenko, Semen A Kurkin, Alexander P Sergeev, Drozdstoy Stoyanov, Rositsa Paunova, Sevdalina Kandilarova, Denitsa Simeonova, and Alexander E Hramov. The topology of fmri-based networks defines the performance of a graph neural network for the classification of patients with major depressive disorder. *Chaos, Solitons & Fractals*, 167:113041, 2023. 3

[26] Cyrus A Raji, April J Ho, Neelroop N Parikshak, James T Becker, Oscar L Lopez, Lewis H Kuller, Xue Hua, Alex D Leow, Arthur W Toga, and Paul M Thompson. Brain structure and obesity. *Human brain mapping*, 31(3):353–364, 2010. 1

[27] Lizhen Shao, Cong Fu, Yang You, and Dongmei Fu. Classification of asd based on fmri data with deep learning. *Cognitive Neurodynamics*, 15(6):961–974, 2021. 1

[28] Afshin Shoeibi, Marjane Khodatars, Mahboobeh Jafari, Navid Ghassemi, Parisa Moridian, Roohallah Alizadesani, Sai Ho Ling, Abbas Khosravi, Hamid Alinejad-Rokny, HK Lam, et al. Diagnosis of brain diseases in fusion of neuroimaging modalities using deep learning: A review. *Information Fusion*, 2022. 1

[29] Christopher Sims. Highly accurate fmri adhd classification using time distributed multi modal 3d cnns. *arXiv preprint arXiv:2205.11993*, 2022. 2

[30] Heung-Il Suk, Chong-Yaw Wee, Seong-Whan Lee, and Dinggang Shen. State-space model with deep learning for functional dynamics estimation in resting-state fmri. *NeuroImage*, 129:292–307, 2016. 1, 2

[31] Haijing Sun, Anna Wang, and Shanshan He. Temporal and spatial analysis of alzheimer's disease based on an improved convolutional neural network and a resting-state fmri brain functional network. *International Journal of Environmental Research and Public Health*, 19(8):4508, 2022. 2

[32] Yu Takagi and Shinji Nishimoto. High-resolution image reconstruction with latent diffusion models from human brain activity. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14453–14463, 2023. 1

[33] Yibin Tang, Ying Chen, Yuan Gao, Aimin Jiang, and Lin Zhou. Adhd classification with biomarker identification using a triplet loss attention auto-encoding network. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023. 2

[34] Paul M Thompson, Tyrone D Cannon, Katherine L Narr, Theo Van Erp, Veli-Pekka Poutanen, Matti Huttunen, Jouko Lönnqvist, Carl-Gustaf Standertskjöld-Nordenstam, Jaakko Kaprio, Mohammad Khaledy, et al. Genetic influences on brain structure. *Nature neuroscience*, 4(12):1253–1258, 2001. 1

[35] Nathalie Tzourio-Mazoyer, Brigitte Landeau, Dimitri Papathanassiou, Fabrice Crivello, Octave Etard, Nicolas Delcroix, Bernard Mazoyer, and Marc Joliot. Automated anatomical labeling of activations in spm using a macroscopic anatomical parcellation of the mni mri single-subject brain. *Neuroimage*, 15(1):273–289, 2002. 5

[36] Md Zasim Uddin, Md Arif Shahriar, Md Nadim Mahamood, Fady Alnajjar, Md Ileas Pramanik, and Md Atiqur Rahman Ahad. Deep learning with image-based autism spectrum disorder analysis: A systematic review. *Engineering Applications of Artificial Intelligence*, 127:107185, 2024. 1

[37] Lebo Wang, Kaiming Li, and Xiaoping P Hu. Graph convolutional network for fmri analysis based on connectivity neighborhood. *Network Neuroscience*, 5(1):83–95, 2021. 3

[38] Dong Wen, Zhenhao Wei, Yanhong Zhou, Guolin Li, Xu Zhang, and Wei Han. Deep learning methods to process fmri data and their application in the diagnosis of cognitive impairment: a brief overview and our opinion. *Frontiers in neuroinformatics*, 12:23, 2018. 1, 2

[39] Chao-Gan Yan, Xin-Di Wang, Xi-Nian Zuo, and Yu-Feng Zang. Dpabi: data processing & analysis for (resting-state) brain imaging. *Neuroinformatics*, 14:339–351, 2016. 5

[40] Wutao Yin, Longhai Li, and Fang-Xiang Wu. Deep learning for brain disorder diagnosis based on fmri images. *Neurocomputing*, 469:332–345, 2022. 1, 2

[41] Jin Zhang, Fan Feng, Tianyi Han, Xiaoli Gong, and Feng Duan. Detection of autism spectrum disorder using fmri functional connectivity with feature selection and deep learning. *Cognitive Computation*, 15(4):1106–1117, 2023. 1