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A Review on Deep Brain-Shapelet: A Framework for Capturing Non-Linear Instantaneous Abnormalities in ASD Diagnosis

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***Abstract*— Autism Spectrum Disorder (ASD) is a neurodevelopment disorder that is marked with abnormal brain connectivity and impaired temporal neural functionalities. Functional Magnetic Resonance Imaging (fMRI) has emerged as a powerful neuroimaging technology in the examination of such abnormalities because it is a high-resolution spatial and temporal neuroimaging technology that provides deep information about how the brain functions. Recently, the fMRI data have become more and more the target of deep learning methods to be used to automatically diagnose ASD, though non-linear and short-term interactions between space and time often make use of traditional machine learning methods and stationary models of connectivity inadequate to detect complex non-linear abnormalities in fMRI data. The current survey is a detailed survey of the currently available fMRI-based deep learning diagnosis of ASD with a special emphasis on spatial-temporal modeling frameworks. It is a systemic review of graph-based spatial learning techniques, temporal sequence modeling techniques and combined designs like Residual Graph Attention Network (ResGAT) and Bi-Directional Long Short-Term Memory (BiLSTM) design. Moreover, shapelet-based learning methods are examined in terms of their capability to detect discriminative and understandable temporal laws in neuroactivities. Among the critical issues, such as dynamic connectivity modeling, variability of datasets, and interpretability of models are discussed, and the future research perspectives are presented. It is hoped that this survey will contribute useful information to researchers and clinicians on the range of development of accurate, explainable, and clinically meaningful ASD diagnosis systems using fMRI information.**

***Keywords*— Autism Spectrum Disorder, Bi-Directional LSTM, fMRI, graph neural networks,spatial-temporal deep learning, shapelet learning**.

I. INTRODUCTION

Autism Spectrum Disorder is a neurodevelopmental disorder that complicated and influences the socialization, communication as well as the behavior. ASD is becoming more widespread in the world, and therefore, timely and correct diagnosis is a significant clinical and social issue. Neuroimaging results have indicated that ASD is closely related to dysfunctional functional connectivity and distorted temporal dynamics in the brain. The early identification of such abnormalities can facilitate early intervention and help a great deal to improve the long-term cognitive and behavioral outcomes.

fMRI is an important instrument in the research of brain functioning as it records the activity of specific areas of the brain as time progresses. In contrast to behavioral testing, fMRI allows analyzing functional interaction and dynamic correlation patterns in the brain. Nevertheless, abnormalities associated with ASD in fMRI data are usually delicate, non-linear, and transient, and thus they are difficult to observe with standard signal processing tools, as well as with the traditional machine learning methods.

Previous methods of fMRI-based ASD diagnosis were primarily based on handcrafted features, statistical measures of connectivity and conventional classifiers (including Support Vector Machines and Random Forests). In spite of the fact that these techniques gave decent results, they usually assumed brain connectivity as fixed and neglected the time dependence of neural activity. Consequently, relevant spatial-temporal interactions and instantaneous abnormalities related to ASD were frequently ignored. Current developments in deep learning have ensured a much better automated ASD diagnosis, allowing a complex spatial and temporal pattern to be learned from fMRI data. The spatial brain connection has been greatly modeled using graph-based neural networks by depicting the brain parts as nodes and the functional connections as edges. Likewise, recurrent neural networks and especially BiLSTM models have been used to model a time-dependence in fMRI time-series data. Regardless of these developments, a lot of current methods continue to use spatial and temporal modelling independently and provide a low level of interpretability, a factor that limits their clinical use.

II. RELATED WORK

A number of researches examined ASD diagnosis based on fMRI and deep-learning methods. Liu et al. [1] introduced an analysis of brain disease using a spatio-temporal weighted multi-hypergraph convolutional network through the integration of multi-template information. The method was effective to obtain the complex spatial-temporal relationships; however, the work was rather concentrated on the model design and evaluation of its performance, without offering a more general comparison of the available datasets and the current spatial-temporal frameworks applied to ASD studies.

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The article by Zong et al. [2] proposed a paradigm of brain construction using diffusion-based graph contrastive learning in the process of brain disorder diagnosis. The experiment prioritized strong representation learning and enhanced generalization of subjects, but lacked a distinct study on short-term temporal abnormalities and also did not lack insight into interpretability. Ren et al. [3] introduced the Brain-Shapelet model to record instantaneous abnormalities of brain activities to diagnose ASD. Although, this piece of work emphasized the role of the extraction of non-linear time patterns, it was focused on one framework instead of systematically surveying other spatial-temporal models. Liu et al. [4] came up with spatio-temporal hybrid attentive graph network to diagnose mental disorders through fMRI time-series data. This shown that the dynamics of connectivity via attention mechanisms are effective in model-based modeling, but failed to give a comparison to other graph-based time-varying models or address problem-specific issues with the dataset.

Huang et al.[5] used a deep belief network to recognize ASD against resting-state fMRI images, and it demonstrated the ability of deep feature learning. However, the method considered fMRI data to be mostly as static as representations and failed to explicitly represent the changing functional connection. Zhao et al.[6] developed multi-view high-order functional connectivity networks in the diagnosis of ASD so that the complex interactions between the brain regions can be modeled. The presence of time-dependence of connectivity was not directly tackled, despite its effectiveness in the spatial representation of relations. The researchers suggested a multiview brain network transformer which combines the personalised information to diagnose ASD, as proposed by Dong et al. [7], with better performance but the understanding of the learned spatial-temporal representations was not so good. Ma et al. [8] came up with a multi-graph cross-attention-based region-based feature fusion network that utilizes multi-template information and is used to diagnose brain disorders. The model was successful in integrating several graph representations but emphasized more on the fusion of spatial features as opposed to the fine-grained detection of the abnormality in time.

Chen et al. [9] presented an adversarial learning-based node-edge graph attention network model to identify ASD, which includes the advantages of attention in graph learning, but the framework has not explicitly addressed instantaneous temporal irregularities. Ingalhalikar et al. [10] examined a predictive approach based on functional connectivity prediction of ASD with a site-harmonized ABIDE dataset.

Sravani and Kuppusamy [11] suggested an optimized deep convolutional neural network with DTPSO to identify ASD using structural MRI data which has better classification performance but the approach relies on the fixed anatomical features and does not use the functional connectivity and dynamism of the brain as the basis of the fMRI ASD analysis. Hajjej et al. [12] proposed a data mining and ensemble learning model to diagnose ASD and plan individual education, which showed effective results in classification, but it is based on tabular and behavioral variables instead of neuroimaging-based brain connectivity modeling.

The multimodal framework of ASD diagnosis in children introduced by Han et al. [13] is based on combining many data sources, which enhances the strength of the diagnosis; however, the framework fails to explicitly model the spatial-temporal brain connectivity patterns on the basis of the fMRI data. Bovery et al. [14] designed a scalable off-the-shelf attention pattern measurement system in small children and applied it to the analysis of ASD, which provides the information about attention behavioral mechanisms, yet the article does not work with fMRI data or brain network representations. According to Yaneva et al. [15], eye-tracking characteristics along with machine learning were used to diagnose the high-functioning autism among adults with promising results; nevertheless, the methodology relies on the analysis of visual behaviors and does not involve spatial-temporal brain modeling by means of neuroimaging.

Although the research touched upon the problem of data heterogeneity and cross-site variability, it was based on the traditional connectivity analysis and not covered the sophisticated spatial-temporal deep learning architectures. In general, the existing literature is largely based on specific deep learning model development to diagnose ASD by considering either spatial connectivity models or global temporal representations. Despite the promising performance of these methods, they tend to have a low level of comparative analysis of the spatial-temporal framework, they do not explicitly model short-duration non-linear abnormalities and have limited interpretability. The review of and categorization of the spatial-temporal deep learning designs, such as graph-based spatial learning, temporal model, and shapelet-based pattern extraction, is yet to be carried out in a systematic survey. The purpose of this survey is to fill these gaps and to thoroughly examine the deep learning techniques of ASD diagnosis based on fMRI with its strengths, weaknesses, and future directions of research.

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III. Autism Brain Imaging Data Exchange Datasets

The fMRI Data of ASD diagnosis Fig 1 illustrate Sample FMRI images of ABIDE Dataset with ASD and NC. FMRI datasets are important in development, evaluation, and benchmarking of automated ASD diagnostic systems. These data hold the empirical basis necessary to test machine learning and deep learning models through the spatial connection of the brain and time dynamics of the brain. Although they are very crucial, a significant proportion of the available survey papers only focus on the process of algorithmic improvements but provide minimal information about the nature, availability, and usability of fMRI data that may be of critical importance to researchers who are not yet into the field. Current fMRI data are facilitating diverse specialized research studies, such as ASD versus neurotypical control (NC) categorization, functional connectivity study, dynamic connection framework, brain network development and multimodal fusion. Yet, researchers tend to encounter difficulty in choosing suitable datasets in particular study goals because of the variation in acquisition protocol, scanning localities, demographics of subjects and preprocessing pipelines.

The difficulty is particularly evident among beginner researchers that should be provided with the guidance when it comes to selecting the datasets that are best suited to the use of spatial-temporal models and deep learning. To reduce variability, enhance the reproducibility, and develop strong and generalizable models of ASD diagnosis, it is crucial to address this gap to facilitate the adoption of standardized assessment. This part will give a comprehensive description of common examples of fMRI data on ASD research, their availability, properties and penetration of ASD and NC classification tasks.

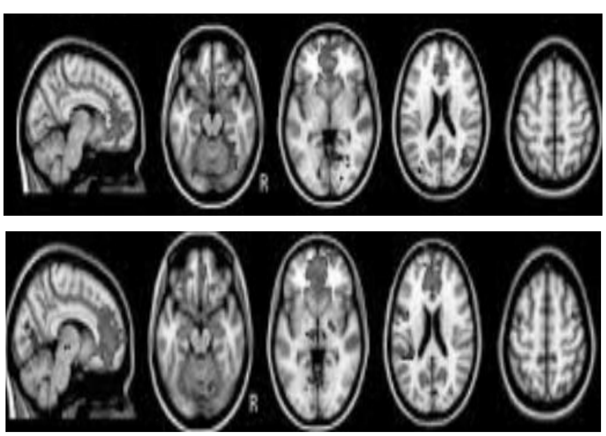

Fig 1:Sample FMRI images of ABIDE Dataset with ASD and NC

A. *Selection of Study*

The search in the Scopus database was conducted to select those publications dated between 2019 and 2025 associated with the diagnosis of ASD using fMRI and the analysis of the brain connectivity in Fig 2. Keywords were searched on such terms as autism spectrum disorder, fMRI, functional connectivity, brain network, graph neural networks, and deep learning. The search was narrowed down further to include only journal articles, computer science and biomedical engineering as the subject area and English as the language. After the screening of abstracts and methodological analysis, a collection of the most cited studies was chosen. These investigations relied on publicly available fMRI data mainly on classification of ASD vs. NC and brain network. In the literature review, the most popular benchmark dataset to apply in ASD research studies is the ABIDE that is as demonstrated by its wide usage in the literature, including [5], [6], [9], and [10].

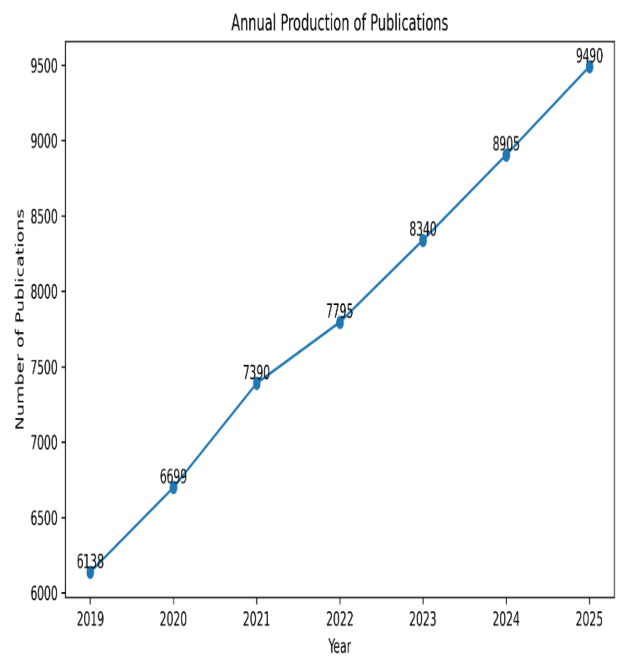

Fig 2:Annual Production of Publications from the year 2019 to 2025

B. *Overview of ABIDE Datasets*

The most outstanding and widely applied publicly available fMRI data on ASD diagnosis is ABIDE. ABIDE is a collection of resting-state fMRI data across several global imaging locations and it has ASD patients and normal controls.

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The harmonized version of the dataset has been also proposed to counter inter-site variability which enhances cross-site generalization and model robustness, as shown in [10].ABIDE offers resting-state fMRI time series, structural MRI, as well as phenotypic data, which allow a broad selection of analyses inclusive of the static functional connectivity, dynamic connectivity modeling and graph-based construction of brain networks.

The size and variety of ABIDE led to its being the most important dataset to test spatial-temporal deep learning systems, such as graph neural networks [6], attention-based systems [9], and transformer-based systems [7]. Besides the use of ABIDE, there has been a number of studies that have used proprietary or site-specific clinical fMRI datasets to supplement open data. Although the quality of images provided or the levels of control used in such datasets can be superior or the acquisition environment more controlled, they are limited in accessibility and hinder inter-study reproducibility and comparative analysis

C. Taxonomy of Dataset

ASD research on fMRI datasets is applicable in several tasks. These are binary ASD versus NC classification, functional connectivity estimation, high-order brain network construction, dynamic connectivity analysis, and individualized brain pattern learning. The vast majority of papers based on ABIDE are binary classification, in which deep learning models are trained on the basis of connectivity features or graph representations of ASD subjects versus neurotypical controls [5], [6], [10]. Other publications focus on brain network modeling, which builds the multi-view or high-order connectivity graphs to realize the intricate interaction between brain regions [1], [2], [6].

Recent research has also delved into the field of spatial-temporal modeling, combining temporal dynamics with spatial connectivity via attention mechanisms, transformers and recurrent architectures [4], [7], [9]. Temporal analysis of the resting-state fMRI time-series data can be performed at different resolutions, which allows more sophisticated approaches to the identification of short term abnormalities (e.g., shapelet-based learning to capture such abnormalities in a short time-period) [3] and cross-attention (to fuse region-sensitive features) [8]. These task capabilities render ABIDE specifically appropriate in the assessment of combined spatial-temporal deep learning systems.

D. Dataset Characteristics and Problem

Even though ABIDE is a good tool to provide a thorough benchmark of ASD research, it has a number of challenges.

The data set is highly inter-site variant owing to the variation of scanner hardware, scanner acquisition parameters and preprocessing pipelines. Such variability tends to cause shifts in distributions which affects the model generalization adversely as pointed out in [10]. Also, due to the lack of task-based or pixel-level annotations, direct use of supervised localization or segmentation methods cannot be used. The heterogeneity of the phenotypes of ASD is another issue thatcreates intra-class variability and makes classification activities more difficult. Besides, ethical issues and privacy limitations also limit the access to large-scale labeled clinical databases, which further underlines the relevance of publicly accessible benchmarks such as ABIDE.

E. Summary

Altogether, fMRI data, especially the ABIDE data, have a key role in the research on ASD diagnosis because they allow implementing spatial-temporal brain modeling and classification of ASD, compared to NC. Although ABIDE can facilitate a large variety of deep learning applications, there are still issues of data heterogeneity, inter-site variability, and limited annotations. The proper development of strong and clinically significant ASD diagnostic systems requires a clear understanding of the characteristics of datasets, their accessibility, and the appropriateness of the tasks.

IV. Challenges And Limitations

Good-quality annotated fMRI data is essential in the diagnosis of ASD, but publicly available datasets like ABIDE have different data quality variabilities caused by the hardware of scanners, acquisition parameters, and preprocessing pipelines, which restrict the robustness of a model. Moreover, inter-site variation and demographic divergence in distribution shift the results of classification models of ASD by fMRI, decreasing their generalization capabilities to a real-world setting. The heterogeneity of ASD is intrinsic, which additionally enhances the variation of the brain activity patterns within a single class and creates the risk of false positives and negative results. Besides, the lack of interpretability of most deep learning models decreases clinical trust, which is not always clear how well the prediction is related to the underlying neural processes. Access to large-scale fully annotated fMRI datasets limited cross-site validation and dataset expansion due to ethical and privacy limitations also found in large volumes of data.

V. Conclusion And Future Directions

Recent progress in both fMRI and deep learning have provided the capability of automated ASD diagnosis by performing useful spatial-temporal brain connectivity, but current models remain vulnerable to generalization through inter-site variation, subject heterogeneity and inconsistent preprocessing. These threats may be addressed with the help of better dataset standardization, domain-adaptive training approaches, and incorporation of explainable AI so as to achieve more clinical trust.

The future studies ought to be concerned with the creation of rigorous and understandable spatial-temporal models that can be generalized across datasets with high quality annotated fMRI data, to enhance the credibility and clinical utility of ASD diagnosis systems.

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