ASD diagnosis based on fMRI brain scans

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KEYWORDS

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1 INTRODUCTION

Identifying individuals with ASD specially in earlier stages of life is crucial for providing targeted interventions and support. Autistic people may struggle with communication, repeated behaviors, and sensory overload, which can affect their development and well-being. Early diagnosis means that autistic children and adolescents can receive essential therapies, support, and accommodations from an early developmental stage, improving their outcomes. Conversely, late diagnosis can result in missed opportunities for early interventions and can contribute to mental health problems. Therefore, differentiating individuals with ASD from neurotypical individuals is an important step in understanding the neural basis of ASD and developing effective interventions for this disorder.

Currently, ASD diagnosis is typically based on behavioral assessments and evaluations by clinicians, which can be time-consuming, subjective, and may lead to misdiagnosis or underdiagnosis. There is a need for more objective and reliable methods for diagnosing and characterizing ASD. In this study, we aim to explore the use of functional magnetic resonance imaging (fMRI) and machine learning algorithms for identifying individuals with ASD based on their brain connectivity patterns.

2 RELATED WORK

In recent years, there has been a focus on modeling the brain network and studying the effects of autism disorder (ASD) on brain connectivity. Previous studies have mainly relied on static functional connectivity [1], which assumes functional connectivity is constant during fMRI imaging. However, dynamic functional connectivity that considers temporal changes in connectivity can provide more reliable patterns to discriminate against healthy and autistic brains. This research proposes various methods, including clustering of connectivity matrices and feature extraction using different entropy methods, to evaluate the accuracy of autism diagnosis. The study concludes that the cmean algorithm is more accurate than other algorithms for classifying all laboratories at the same time, while the kmean algorithm performs best for the case where laboratories are classified independently. Furthermore, the study found that communication power is greater in healthy people than in people with autism.

3 METHODOLOGY

In this study, we use preprocessed fMRI data from the Autism Brain Imaging Data Exchange (ABIDE). The data consists of connectivity matrices that represent the functional connectivity between different regions of the brain. These matrices can be interpreted as graphs, where the nodes represent brain regions and the edges represent the functional connections between them. By analyzing these graphs, we aim to gain insights into the neural basis of Autism Spectrum Disorder (ASD) and develop novel approaches for diagnosing and characterizing ASD. Our approach to do so consists of three steps as follows.

3.1 Dimension reduction

in this project we first use the PCA algorithm to reduce the input connectivity matrices to a vector that well represents the original matrix. afterwards we use the ICA algorithm for effective feature extraction and further dimension reduction to produce spatial maps for every timestamp. In the field of fMRI data, both spatial and temporal ICA make sense for dimension reduction; the reason is that both can decrease the Enormous voxel[1] based BOLD(Blood Oxygen Level Dependent) signals into a few time series relevant to most effective brain regions.

3.2 Subject projection

in this step we project the sequences of the reduced data of test subject on the spatial maps of healthy and ASD data

[1] in fMRI, voxels represent a small volume of brain tissue, typically around 1-3 cubic millimeters in size

separately. afterwards we obtain two vector of weights.These vectors belong to four categories:

(1) The vectors obtained by projecting a healthy scan on the healthy spatial maps
(2) The vectors obtained by projecting a healthy scan on the ASD Spatial map
(3) The vectors obtained by Projecting a ASD scan on the healthy spatial maps
(4) The vectors obtained by projecting ASD scans on the ASD spatial maps

3.3 Clustering

Due to significant overlap between the four categories, classification algorithms cannot provide good performance. To address this, we divide each category vector into clusters and use the k-means algorithm to find the closest match.

4 EVALUATION

To evaluate the effectiveness of our proposed system, we will conduct a series of experiments on a dataset of size X. The dataset will be randomly split into training and testing sets with a ratio of n:m, and we will use stratified sampling to ensure an even distribution of samples across the classes. We will train and evaluate our model using standard evaluation metrics, such as accuracy, precision, recall, F1-score, and area under the curve (AUC)[2] of the receiver operating characteristic (ROC)[3] curve.
Our next goal would be to further evaluate our work for practical use in real-life scenarios, including scalability, robustness, and usability. We'll test scalability and real-time operation while maintaining accuracy and efficiency with large datasets. Additionally, we'll evaluate robustness to variations in input data and noise by testing on synthetic and real-world datasets. We'll also assess usability and interpretability to ensure user-friendliness and provide actionable insights. These evaluations demonstrate feasibility and potential for real-world use and promote adoption. we

5 CONCLUSION

In this study, we proposed a novel approach for identifying individuals with Autism Spectrum Disorder (ASD) based on their brain connectivity patterns, using functional magnetic resonance imaging (fMRI) data and machine learning algorithms. Our approach involves dimension reduction, subject projection, and clustering, and will be trained and evaluated on ABIDE dataset. Overall, our study highlights the potential of fMRI and machine learning for objective and reliable methods for diagnosing and characterizing ASD, and underscores the importance of early identification of individuals with ASD for providing targeted interventions and support. While our study focused on ASD, we believe that our approach can be extended to other neurodevelopmental disorders with similar neural basis, such as Attention Deficit Hyperactivity Disorder (ADHD).

[2]AUC is a scalar value that represents the area under the ROC curve. It provides a single number that summarizes the overall performance of the model

[3]ROC is a curve that shows the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR)

REFERENCES

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