Autism Spectrum Disorder Detection from Brain imaging innovative Data using Artificial Intelligence

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Abstract

Autism Spectrum Disorder (ASD) is a neurological condition that impacts an individual's cognitive, emotional, physical, and social well-being. This research focus on a multimodal method approach that utilizes both video and audio data. By integrating analyses of facial expressions and speech-related emotional indicators, this approach seeks to enhance the accuracy and reliability of autism diagnostics. Traditional methods, often limited to observational techniques and behavioral assessments, may not fully capture the subtle nuances of autism spectrum disorders (ASD). However, by analyzing synchronized video and audio data, it becomes possible to detect intricate patterns and variations in facial and vocal expressions that are characteristic of ASD. This multimodal system not only provides a richer dataset for analysis but also enables a more comprehensive understanding of the emotional and communicative cues associated with autism. Recognizing the gestures of autistic children is crucial for preventing meltdowns and self-harm. We introduced a method to identify gestures by detecting poses through a person pose estimation technique. The features extracted from the pose estimation are then used to develop a gesture classification model using supervised learning algorithms. Our proposed model achieved the highest accuracy with the Random Forest technique, exhibiting evaluation metrics of 83% precision and 71% recall.

Keywords: Autistic Children; Gesture Identification; Person Pose Estimation; Supervised learning; Random Forest Technique

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Introduction

In introduction we explore the application of deep learning techniques for detecting Autism Spectrum Disorder (ASD) using brain imaging data, specifically utilizing the Autism Brain Imaging Data Exchange (ABIDE) dataset. ASD is a complex neurodevelopmental condition characterized by varied symptoms and degrees of impairment, making its detection and diagnosis a challenging endeavor. Recent advancements in neuroimaging and data analysis have opened new avenues for understanding the neurological underpinnings of ASD. The ABIDE dataset, a comprehensive compilation of brain imaging data collected from numerous international sites, provides a rich resource for researchers aiming to identify biomarkers and structural differences in the brains of individuals with ASD compared to neurotypical controls. By applying sophisticated machine learning algorithms to analyze these complex datasets, researchers can uncover patterns and anomalies that may not be visible through traditional diagnostic methods. This chapter details the methodologies employed in preprocessing the data, the selection of appropriate machine learning models, the challenges encountered in such high-dimensional data analysis, and the implications of these findings for the clinical assessment and understanding of ASD.

Data Analysis

Autism spectrum disorder (ASD) is a highly heritable and heterogeneous neurodevelopmental disorder characterized by early-appearing social communication deficits and restricted, repetitive sensory-motor behaviors. Affecting about 1% of the global population, ASD is more prevalent in males, who are approximately four times more likely to be diagnosed than females. The social impairments associated with ASD often necessitate lifelong support, placing significant burdens on families and societies. Accurate and efficient diagnosis is crucial for enabling early interventions that can markedly enhance the daily living skills and social abilities of individuals with ASD. Currently, diagnosis primarily relies on clinical interviews and behavioral observations, which can sometimes lead to misdiagnoses and missed opportunities for optimal intervention.

Magnetic resonance imaging (MRI) has emerged as a promising non-invasive tool for obtaining objective measurements of the human brain, potentially aiding in ASD diagnosis. MRI techniques include structural MRI (sMRI), which provides detailed anatomical brain images, diffusion MRI (dMRI), which can detect subtle abnormalities in white matter tracts, and functional MRI (fMRI), which measures dynamic brain activity by monitoring changes in blood oxygenation levels. These techniques allow for the exploration of the neurological basis of ASD and the development of neuroimaging biomarkers. By analyzing brain connectivity patterns and comparing them between ASD subjects and healthy controls, researchers have identified dysfunctional networks associated with the disorder. Furthermore, differences in brain structures such as gray matter and white matter volumes have been documented. In recent years, the application of machine learning techniques to ASD classification has enabled the extraction of more informative features from imaging data, enhancing the potential for precise individual-level diagnoses. This approach represents a significant advancement over traditional methods, offering new insights into the complex imaging patterns characteristic of ASD.

In recent years, the field of brain imaging in neurodevelopmental disorders has experienced a significant transformation, shifting from merely describing brain structures to a deeper understanding of neurodevelopmental changes and their implications. This shift has been largely driven by new methodologies that focus on identifying key biomarkers, enhancing the evaluation and interpretation of the links between neuroimaging changes and underlying pathology. Among the various neuroimaging techniques available, Magnetic Resonance Imaging (MRI) has been predominantly used in studies related to Autism Spectrum Disorder (ASD), forming the foundation for this review. MRI enables researchers to observe structural changes in the brains of individuals with ASD. These studies have explored the connections between neuroanatomical regions and ASD, which influence the development of the nervous system and can lead to atypical brain functions impacting emotions, learning abilities, self-control, and memory. The findings from these studies, which often include analyses of brain volume and thickness, indicate that brain volumes in individuals with ASD tend to be larger compared to typically developing controls.

In this study, we used the Autism Brain Imaging Data Exchange (ABIDE) dataset, which comprises both functional magnetic resonance imaging (fMRI) and magnetic resonance imaging (MRI) data. The dataset contains 1,112 scans, including 539 from individuals diagnosed with Autism Spectrum Disorder (ASD) and 573 from control subjects, collected from 17 different brain imaging centers. The preprocessing of fMRI signals was conducted. The data was processed with the Configurable Pipeline for the Analysis of Connectomes (CPAC), which includes several steps such as motion correction, slice timing adjustment, skull stripping, intensity normalization, and nuisance signal regression. Moreover, band-pass filtering and global signal regression were performed as part of the preprocessing routine. It's important to note the presence of feature imbalances within the dataset, particularly concerning gender distribution, which plays a crucial role in ASD prediction and impacts the predictive model's accuracy. Fig.1 shows the age distribution of the ASD and control groups across the various contributing research sites.

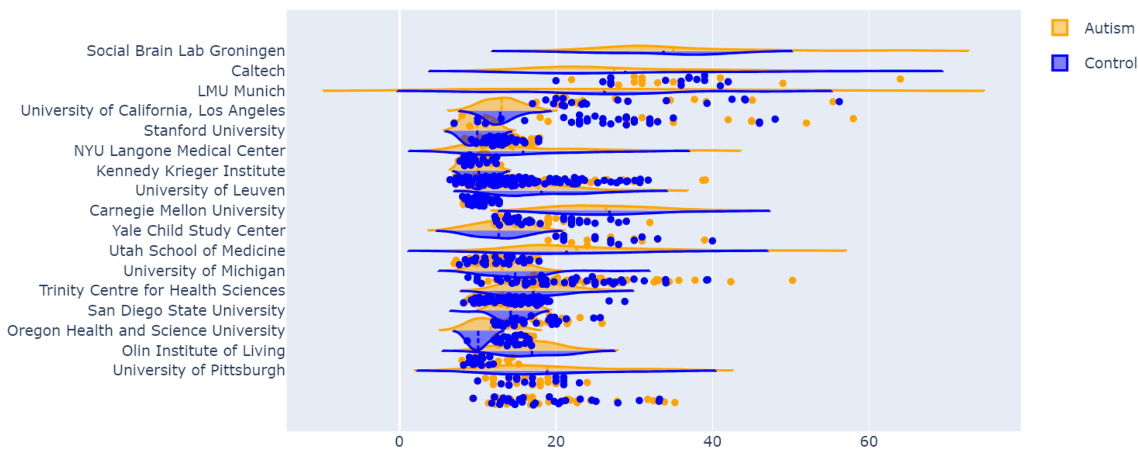

Fig.1- Data Analysis and Pre-processing

To reduce the dimensionality of the fMRI data, we segmented it into signals pertaining to specific regions of interest (ROIs). These ROIs represent time series data at the voxel level, covering 110 functional brain regions. This approach transforms the original four-dimensional brain imaging data into a two-dimensional format, consisting of the 110 regions and their corresponding time series data for each region. The process of feature processing is illustrated in Fig.2.

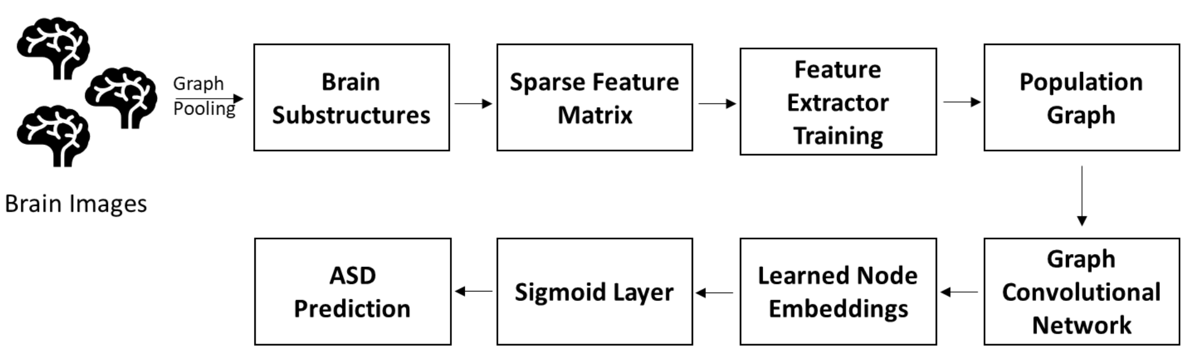

Fig.2 - Model Framework

Proposed Methodology

Sparse brain network representation is achieved by down sampling the brain's graphical representation using unsupervised graph pooling techniques. The extraction of higher-order features follows this step via a multilayer perceptron based on the pooling results. Subsequently, a two-layer graph convolutional network (GCN) generates embeddings by integrating population graph data with phenotypic information. During the graph pooling phase, key subgraphs within the brain network are identified using an unsupervised approach, which is essential for effectively down sampling in Graph Convolutional Networks, particularly for graph classification tasks. Before applying graph pooling, a framework is established, either using a Multi-Layered Perceptron or another method, to extract features from the functional connections. The combination of functional connectivity and regional brain activities through graph pooling has proven to be effective in enhancing the detection of Autism Spectrum Disorder (ASD). The details of these sparse features and the overall process are depicted in Fig.3.

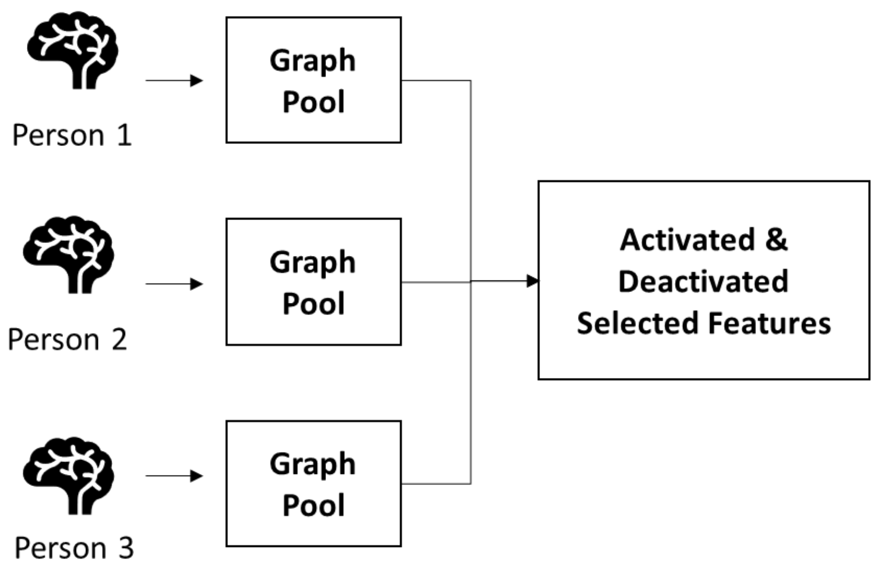

Fig.3 - Sparse Feature Details

A population graph is created where nodes symbolize individual participants, and the edges reflect the similarity in their phenotypic traits. Nodes with akin phenotypic traits are clustered together in the same group. This graph structure facilitates the application of a Graph Convolutional Network (GCN) to process the feature vectors derived from brain imaging, fostering the derivation of node embeddings and expanding the convolutional operations to the graph domain. The inclusion of phenotypic data aids in enhancing the model's classification performance through regularization.

In the preprocessing stage, the dataset is prepared using the Configurable Pipeline for the Analysis of Connectomes (CPAC), and the connections among nodes are established based on phenotypic similarities, such as age and gender. The GCN is structured in two layers: the initial layer follows the traditional GCN setup, while the subsequent layer implements the Cluster-GCN approach. Fig.4 and 5 provide visual depictions of the fMRI images with designated Regions of Interest (ROI) and the respective ROI images after the application of masking.

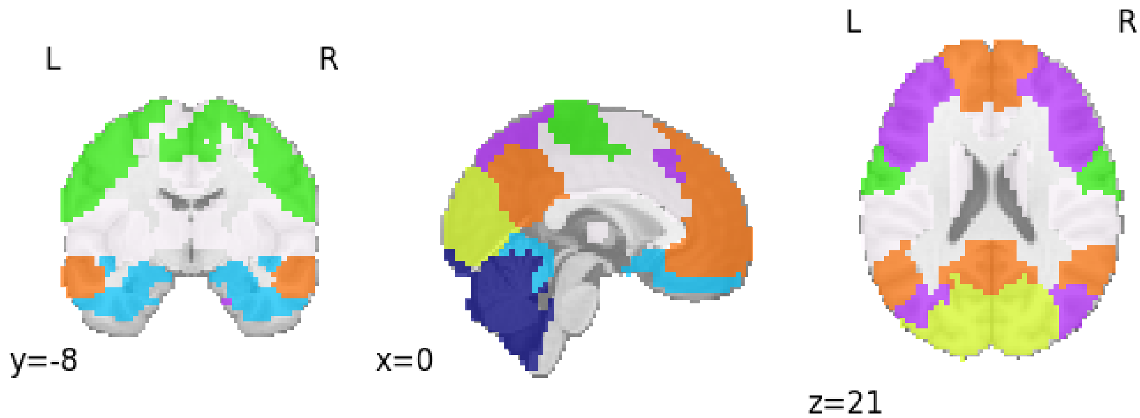

Fig.4- fMRI Images with Region of Interest (ROI)

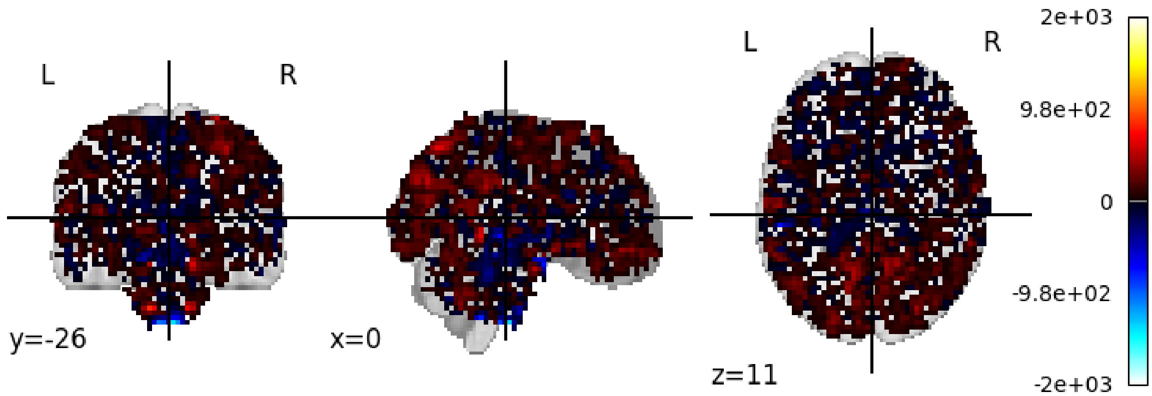

Fig.5 - fMRI Images with Region of Interest (ROI) after Masking

Conclusion

This chapter discusses into the advanced use of deep learning techniques for the detection of Autism Spectrum Disorder (ASD) through the analysis of brain imaging data, utilizing the Autism Brain Imaging Data Exchange (ABIDE) dataset. ASD's complex and varied symptoms make its detection and diagnosis notably difficult. However, recent breakthroughs in neuroimaging and data analysis technologies have provided new insights into the neurological basis of ASD. The ABIDE dataset, which aggregates brain imaging data from various global sources, serves as a vital tool for researchers. It allows them to identify potential biomarkers and understand structural differences in the brains of individuals with ASD compared to those without the condition. By employing sophisticated machine learning algorithms, researchers can detect subtle patterns and discrepancies that traditional diagnostic approaches might miss. The chapter discusses the techniques used for preprocessing this data, choosing the most effective machine learning models, and the challenges faced during analysis of such high-dimensional data. Moreover, it outlines the clinical implications of these neuroimaging findings, enhancing our understanding of ASD and potentially leading to more accurate diagnostic processes. This analytical approach not only broadens our comprehension of ASD but also enhances the methodologies for its diagnosis and understanding at a neurological level.

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