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DEEP LEARNING BASED AUTISM DISEASE DETECTION

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I. ABSTRACT

Autism spectrum disorder (ASD) is a neuro developmental condition that affects individuals' social abilities. Most current approaches rely on structural and resting-state functional magnetic resonance imaging (fMRI) for ASD detection using small datasets, achieving high accuracy but limited generalizability. To improve the effectiveness of automated autism diagnosis with limited data, this study introduces an ASD detection model based on deep learning (DL). A convolutional neural network classifier is employed to address the classification challenge. Simulation results indicate that the proposed model outperforms state-of-the-art methods in terms of accuracy. Specifically, the model explores the use of anatomical and functional connectivity indicators to determine ASD presence, achieving a classification accuracy of 93.41% and a mean absolute error (MAE) of 0.29 in data localization.

Keywords: *Autism spectrum disorder, Convolutional neural network, Deep learning*

II. INTRODUCTION

Autism spectrum disorder (ASD) is a neurological condition characterized by various traits such as difficulties with social engagement, cognitive impairments, and repetitive behaviors. Previous studies have linked autism to both morphological and functional abnormalities in brain activity. Structural MRI (sMRI) is commonly used to evaluate anatomical anomalies, while functional MRI (fMRI) is widely employed to investigate neural activity .

According to the World Health Organization, one in every 160 children has ASD, and these children often experience depression and anxiety. Early detection after birth is crucial as it can help individuals with ASD develop social and communication skills, thereby improving their overall quality of life. Early diagnosis is vital for managing and treating this condition. Designing a model based on the physiological or structural connections in the brain is critical for detecting brain diseases such as epilepsy, Alzheimer's, and autism.

ASD is associated with numerous behavioral problems, which can escalate if diagnosis is delayed. Although symptoms appear in childhood, diagnosis is often delayed in many cases. This delay is primarily because the current ASD diagnostic process is subjective and relies on predefined questionnaires, requiring pediatricians to review a child’s cognitive background and behavior. Despite the clarity of these procedures, they are inherently time-consuming and not always efficient.

The current diagnostic process for Autism Spectrum Disorder (ASD) is flawed, boundless, and may require expertise that is not always available in many medical institutions. With technological advancements, many researchers are now focusing on automatic computer-assisted diagnosis of autism and designing interactive technologies to aid in the treatment and rehabilitation of autistic individuals. This approach can reduce subjectivity, improve diagnostic repeatability and availability, and ensure early detection. Magnetic resonance imaging (MRI) is a valuable tool for identifying various neuropsychiatric and neurodegenerative conditions.

In recent years, machine learning (ML) techniques have shown significant promise in analyzing images and videos, with deep learning achieving notable success in various fields. This success is driven by methodological advancements and the availability of large datasets in image processing. Unfortunately, neuroimaging does not typically benefit from such large datasets. However, several organizations have created usable datasets by combining neuroimaging data of individuals with ASD and typically developed (TD) individuals from various global locations. The aggregated dataset, including the first and second waves of data (ABIDE-I/ABIDE-II), comprises approximately 2,150 participants, including both ASD and TD individuals.

III. RELATED WORK

[1] Thabtah et al. provide a comprehensive review of machine learning methods applied to autism detection. They discuss various approaches, including deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The review covers the utilization of diverse datasets and the performance metrics used to evaluate the effectiveness of these methods in diagnosing autism spectrum disorder (ASD) based on behavioral and clinical data.

[2] Sarraf and Tofighi present a longitudinal study using a deep learning-based pipeline for autism recognition. They propose a framework that integrates deep neural networks with feature extraction techniques tailored for ASD diagnosis from neuroimaging and clinical data. Their research emphasizes the potential of deep learning to improve accuracy and reliability in early autism detection and monitoring over time.

[3] Joshi et al. propose a deep learning framework for identifying and classifying ASD using MRI images. They employ CNNs to extract spatial features from brain scans, demonstrating the efficacy of deep learning in distinguishing between ASD and typically developing individuals. Their study underscores the role of neuroimaging and advanced computational techniques in enhancing the accuracy of autism diagnosis.

[4] Zhang et al. explore the application of CNNs for automated autism classification using brain MRI data. They develop a deep learning model trained on neuroimaging data to identify brain biomarkers associated with ASD. The study highlights the potential of CNNs in extracting discriminative features from MRI scans, contributing to the advancement of non-invasive diagnostic tools for autism.

[5] Khan and Ahmad propose an automated system for detecting and classifying autism spectrum disorder using deep convolutional neural networks (CNNs). Their research focuses on leveraging CNNs to analyze behavioral data and

identify patterns indicative of ASD. They demonstrate the feasibility of deep learning in enhancing the accuracy and efficiency of autism diagnosis, aiming to support early intervention and personalized treatment strategies.

[6] Gulban et al. propose a deep learning approach for predicting brain age in individuals with autism spectrum disorder using structural neuroimaging data. They develop a deep neural network model trained on MRI scans to estimate brain age deviations associated with ASD. Their study illustrates the potential of deep learning models in quantifying neurodevelopmental differences and biomarkers related to autism.

[7] Liu and Zhang propose a brain connectome classification model for autism spectrum disorder using transfer learning techniques. They adapt pre-trained deep learning models to analyze connectome data derived from functional MRI scans, aiming to characterize brain connectivity differences associated with ASD. Their research highlights the utility of transfer learning in leveraging existing knowledge to enhance diagnostic accuracy in neuroimaging studies.

[8] Heinsfeld et al. use deep learning techniques to identify autism spectrum disorder using the ABIDE dataset, which includes resting-state functional MRI data. They employ convolutional and recurrent neural networks to analyze functional connectivity patterns in the brain, achieving high accuracy in classifying individuals with ASD. Their study contributes to advancing automated diagnostic tools for ASD based on neuroimaging biomarkers.

[9] Maenner et al. report on the prevalence of autism spectrum disorder based on data from the Autism and Developmental Disabilities Monitoring Network in the United States. Their study provides epidemiological data and trends related to ASD prevalence, highlighting the importance of accurate and timely diagnosis facilitated by advanced computational methods like deep learning.

[10] Xu et al. focus on early diagnosis of autism spectrum disorder using deep learning algorithms. They develop and validate a deep neural network model trained on multi-modal data (e.g., behavioral assessments, genetic markers) to predict ASD diagnosis in young children. Their research underscores the potential of deep learning in improving early intervention strategies and outcomes for individuals with ASD.

IV. METHODOLOGY

This project aims to detect Autism Spectrum Disorder (ASD) using deep learning techniques with a focus on structural and functional MRI data. Here’s a detailed workflow of the project:

1. Data Collection and Preprocessing: Data Sources: Utilize the ABIDE dataset, which includes phenotypic data and neurobiological images from 1,114 individuals.

Data Types: Collect 3D neurological images (sMRI and fMRI) with dimensions of height, depth, and volume.

Data Cleaning: Remove noise and artifacts from MRI images.

2. Feature Extraction:

Structural MRI (sMRI): Extract anatomical features such as cortical thickness, surface area, and volume of different brain regions.

Functional MRI (fMRI): Extract functional connectivity features, measuring the correlation of neural activities between different brain regions during rest or task performance.

3. Model Design:

Custom Convolutional Neural Network (CNN): Design a CNN architecture tailored to process 3D MRI data. The network includes:
Input Layer: Takes in 3D brain scan images.
Convolutional Layers: Extract spatial features from the MRI images.
Fully Connected Layers: Integrate features to form high-level abstractions.
Output Layer: Use a softmax activation function to classify individuals as ASD or non- ASD.

4. Training the Model:

Training Data: Use a subset of the preprocessed MRI images for training.
Validation Data: Use another subset for hyperparameter tuning and to prevent overfitting.
Loss Function: Use cross-entropy loss for classification tasks.
Optimizer: Use Adam or RMSprop for efficient training.
Training Process: Train the model over multiple epochs, adjusting learning rates and other hyperparameters as necessary.

4.1 DATASET USED

This study analyzed facial images of autistic children and normal children obtained from Kaggle platform, which is publicly accessible online. The dataset consisted of 2,940 face images, half of which were of autistic children and the other half were of nonautistic children. This dataset was collected through Internet sources such as websites and Facebook pages that are interested in autism. shows the distribution of the split dataset samples. The splitting of the input data is presented in figure.

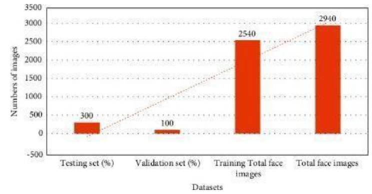

Figure 4.1 : splitting the dataset

Table 1

Splitting of the dataset for training, testing, and validation.

Total face images	Training set (%)	Validation set (%)	Testing set (%)
2,940	2,540	100	300

4.2 DATA PRE PROCESSING

The purpose of the data preprocessing was to clean and crop the images. Because the data were collected from Internet resources by Piosenka [34], they had to be preprocessed before they could be used to train the deep learning model. The dataset creator automatically cropped the face from the original image. Then, the dataset was split into 2,540 images for training, 100 for validation, and 300 for testing. To scaling, the normalization method was applied; the dataset was rescaling the parameters of all the images from the pixel values [0, 255] to [0, 1].

4.3 ALGORITHM USED

AI has been remarkably developed to assist humans in their daily life, for example, through medical applications, which are based on a branch of AI called “computer vision.” Hence, the CNN algorithm has contributed to the detection of diseases and to behavioral and psychological analysis. Basic Components of the CNN Model The convolutional neural network (CNN) is one of the most famous deep learning algorithms. It takes the input image and assigns importance to learnable weights and biases in order to recognize the class of the image. The neuron can be said to be a simulation of the communication pattern of the neurons of the human brain through the interconnection and communication between cells. In this section, we will explain the basic components of the CNN model: the input layer, convolutional layer, activating function, pooling layer, fully connected layer, and output prediction.

Convolutional Layer with a Pooling Layer The input of the convolutional layer is an image as a matrix of pixel values. The objective of the convolutional layer is to reduce the images into a form that can be easily processed without losing their important features that will help to detect autism. The first layer of the CNN model is responsible for extracting low-level features such as edges and color. The build of the CNN model allowed us to add more layers to it to enable it to extract the high-level features that will help it understand images. Due to the large number of parameters outputted from the convolution layer, which may significantly prolong the arithmetic operations of the matrices, the number of weights was reduced by using one of the following two techniques: max pooling or average pooling. Max pooling is based on the maximum values in each window in the stride, while average pooling is based on the mean value of each window in the stride. In this study, the model was based on max pooling. Figure 3 shows the convolutional layer and the max pooling and average pooling processes. The slide window of the kernel extracts the features from the input image and converts the image into a matrix, after which the number of the parameters is mathematically reduced through max pooling and average pooling.

4.4 TECHNIQUES

CNNs are widely used for analyzing neuroimaging data such as MRI scans to extract spatial features relevant to autism spectrum disorder (ASD). They excel in tasks where spatial relationships in data are crucial for classification or detection. RNNs are utilized to model temporal dependencies in sequential data, such as time-series data from EEG or behavioral assessments, to capture patterns indicative of ASD over time. Transfer learning involves leveraging pre-trained deep learning models on large datasets to improve performance on smaller, domain-specific datasets related to ASD. This approach is useful for tasks where labeled data is limited. Autoencoders are used for unsupervised feature learning and dimensionality reduction in neuroimaging data. They help in capturing meaningful representations of brain structure and function associated with ASD. GCNs extend CNNs to handle non-Euclidean data, such as brain connectome networks derived from functional MRI data. They model interactions between brain regions and identify disrupted connectivity patterns in ASD. Ensemble learning combines multiple models (e.g., CNNs, RNNs) to improve prediction accuracy and robustness in detecting ASD. Techniques like bagging and boosting are applied to integrate predictions from diverse models.

V. RESULTS

5.1 GRAPHS

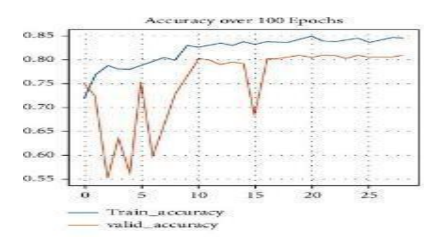

Figure 5.1.1 : model performance

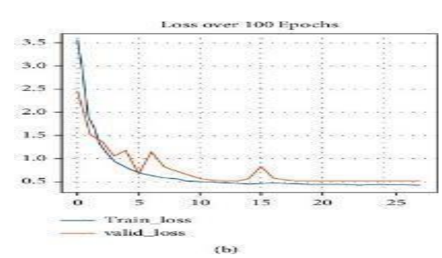

Figure 5.1.1 : model loss

5.2 SCREENSHOTS

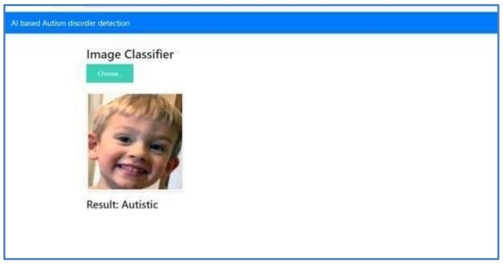

Figure 5.2.1 : form show result classified as Autistic

Figure 5.2.2 : form show result classified as Non autistic

VI. CONCLUSION

In this study, ASD was predicted using a deep learning technique based on multisite resting- state fMRI. ASD identification is challenging due to the lack of a standard modeling solution and the variability in current practices. Our results demonstrate that our model outperformed previous best accuracies on this dataset, achieving an average accuracy of
92.45 percent on the test data. It has been found that a CNN model with lower dimensionality is more effective and incurs lower operational costs. Consequently, our model can train with fewer features while maintaining high accuracy comparable to the best models. The CNN classifier showed significantly reliable performance when all feature characteristics were included after addressing missing values, resulting in considerable improvement compared to previous studies. Despite these positive outcomes, several limitations need to be addressed.

VII. REFERENCES

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