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Autism Spectrum Disorder Detection Using Machine Learning

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Abstract
Convolutional Neural Networks (CNNs) have made significant strides in various domains such as image classifica- tion, speech recognition, automotive software engineering and neuroscience. In this study we leverage CNNs for the automated detection of Autism Spectrum Disorder using brain imaging data, specifically we utilize resting-state functional Magnetic Resonance Imaging (f-MRI) data from the Autism Brain Imaging Exchange (ABIDE) dataset. To identify ASD patients, our approach relies on analyzing patterns of functional connectivity to classify ASD and control subjects. Experimental results demonstrate that our proposed model achieves an accuracy of 96.40% on the ABIDE1 dataset using the CC400 functional parcellation atlas of the brain. Notably our CNN model exhibits computational efficiency by employing fewer parameters compared to state-of-the-art techniques. Our findings suggest that the developed model shows promise for prescreening asd patients and warrants further evaluation with additional datasets.
Keywords - *Autism Spectrum Disorder (ASD), Convolutionalneural network (CNN); Artificial Neural Network (ANN); K- Nearest Neighbors (KNN); Logistic Regression (LR); Support VectorMachine (SVM)*

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I. Introduction

Autism Spectrum Disorder (ASD) manifests as a multi-faceted neurodevelopmental condition marked by difficulties in social interaction and communication, as well as repetitive behaviors and narrow interests. Timely diagnosis is essential for tailored therapeutic interventions. Yet, traditional diagnos- tic methods often rely on subjective assessments, leading to prolonged and inconclusive outcomes. In contrast, functional magnetic resonance imaging (fMRI) has emerged as a valuable tool for objective and precise ASD diagnosis. Additionally, fMRI holds promise for personalized metabolic treatments, particularly through integrated PET-MRI systems, offering radiation-free imaging benefits. fMRI studies have revealed distinct neural connectivity patterns between individuals with and without ASD, with ASD subjects exhibiting increased lo- cal connectivity and decreased long-range connectivity. Lever-aging these insights, fMRI variables have been incorporated into deep learning algorithms, enhancing diagnostic capabili- ties. Despite significant advancements, much of the research focus has been on adult populations, leaving a notable gap in pediatric-focused studies.

Building on prior research, numerous studies have exploredthe utility of fMRI in ASD diagnosis, often integrating ma- chine learning techniques to improve accuracy. These investi- gations have examined fMRI's ability to detect abnormal neu- ral connectivity and automate diagnostic processes. However, there remains a lack of scholarly literature combining fMRI data with convolutional neural network (CNN) methodologies for early ASD diagnosis in pediatric populations.

This study aims to bridge these gaps by deploying a custom CNN framework for in-depth analysis of fMRI scans, with a specific focus on early ASD detection in pediatric subjects. The research endeavors to provide a rapid, accurate, and unbiased diagnostic approach, facilitating timely therapeutic interventions. Key contributions include the development ofa CNN tailored for fMRI data analysis, achieving notableaccuracy in distinguishing pediatric ASD from typical devel- opmental patterns. Additionally, thorough analysis and visu- alization of feature maps shed light on the model's ability to learn distinguishing features, highlighting its efficacy in ASD differentiation. The investigation utilizes CNNs to examine fMRI data for early ASD diagnosis in pediatric populations. Subsequent sections detail data acquisition, preprocessing, and segmentation procedures, the proposed CNN architecture and training methodology, empirical evaluations, and concluding remarks with potential avenues for future research.

II. Related Work

The viability of ASD classification in multisite neuroimag- ing repositories is facilitated by the substantial sample size they offer. Challenges arise from intersite variations due to diverse data acquisition parameters. (Madhura Ingalhalikar et al) proposed harmonization using the Combat approach, leveraging empirical Bayes formulation to eliminate intersite differences in data distribution and enhance classification accu- racy. (Yu Fu et al) addressed multisite issues through surface- based features generation, dictionary learning, and patch- based surface sparse coding, achieving over 80% classification accuracy by enhancing brain surface morphometry sensitivity. Diagnostic procedures for ASD are often time-consuming, prompting the need for easily accessible tools. (Camellia Ray et al) advocated for earlier diagnosis using a machine learning model and the WEKA tool. (Mishra et al) employed attribute selection methods like Greedy Step Wise Search, Chi-Square, Linear Forward Selection, Correlation Feature Selection, Best First Search, and Information Gain, achieving 86.8% accuracy with a 1.42s latency. Efficient ASD diagnosis requires spatial and temporal feature extraction. Haweel et al. used image markers and k-means clustering to minimize spatial dimensionality, achieving 80% correctness and 84% sensitivity with CNN-based architecture.

Facial expression-based behavioral analysis for autistic in- dividuals was reviewed by (Camellia Ray et al) while (Jia- Wei Sun et al) utilized Image-based Meta-Analysis for spatial pattern extraction, achieving an AUC value of 0.788 with SVM classification. ASD diagnosis performance relies on accurate MRI brain image classification. (Zhongyi Hu et al) introduced an ASD classification model based on TSK Fuzzy Infer- ence Systems, multi-center ASD classification, and Feature correlation Multi-task group sparse TSK, demonstrating high accuracy and interpretability. (Hrudaya Kumar Tripathy et al) presented an interactive query-based virtual session for ASD categorization, highlighting the RF classifier model's superior accuracy of 77.5%.

Addressing generalization issues in existing research, the proposed work by (Zhongyi Hu et al) resolved poor gener- alization using structural information from brain MRI. The deep learning approach ResNet, combined with hyperparam- eter optimization, demonstrated improved generalization and classification accuracy.

Color	Red	Blue	Green	Yellow
ROI number	C115	C188	C247	C326
Center of mass	(61.9; −36.3; 34.4)	(−27.6; −40.2; −17.6)	(−2.1; −43.0; −40.7)	(−22.5; −85.5; 31.0)

Table I
Human Brain Areas For Asd Classification

Visualization Of Human Brain

Presently we are analyzing the brain regions crucial for dif- ferentiating ASD from control subjects in the ABIDE I datasetadvances in computer vision have greatly facilitated the visual- ization of CNN models in neuroimaging. This approach offersdeeper insights into biomarkers, critical for early diagnosisand treatment through visualization. Techniques applied for image classification models trained using deep convolutional networks or content can uncover the significant regions of interest ROIs essential for classification. We acquired crucial regions of interest ROIs for detecting ASD using our model with the saliency technique.

This method involves computing the gradient of the class score concerning the input image and generating the classsaliency map in simpler terms. We assessed the gradient of the output category relative to the input image, where output refersto the output category and input pertains to the input image.A positive ratio indicates that a slight alteration in the input image pixel results in an increase in the output. Consequently, we can identify salient images of brain areas pivotal in ASD detection, we noted that four particular brain regions are pivotal in diagnosing ASD subjects, these regions are identifiedbased on the brain atlas for functional parcellation known as CC400. C188, C247, and C326 with their centers of mass located at (61.9; 36.3; 34.4), (27.6; 40.2; 17.6), (2.1; 43.0; 40.7), and (22.5; 85.5; 31.0), respectively.

Our findings highlight the importance of certain brain regions in autism diagnosis, specifically our results indicate the significance of the right supramarginal gyrus known for its role in preserving self-other distinction during empathy in ASD patients. The fusiform gyrus which is typically hypoactivein individuals with autism, is also identified as influential in ASD prediction. Furthermore, the cerebellar vermis emergesas a key area for ASD classification consistent with previous findings of its reduced size in autism cases.

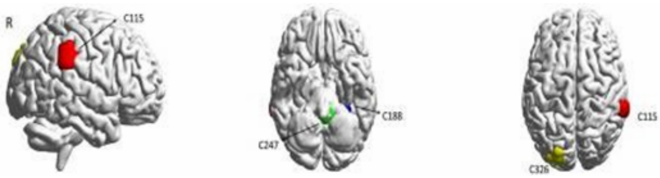

Fig. 1. Human Brain ROIs for ASD classification

III. Methodology

Materials

In this study, we utilized data from the beginning phase of resting-state f-MRI gained from the multi-site ABIDE I initiative. ABIDE I comprises resting-state fMRI collected from 17 international imaging sites along with corresponding controls intended for scientific research purposes. Each site within the ABIDE I dataset employs distinct parameters and protocols for data collection with the f-MRI protocol being consistent across all sites. Brain volume was represented using small cubic elements known as voxels. The inclusion criteria for sites required a minimum of 20 subjects meeting addi- tional criteria like successful pre-processing and manual visual inspection of normalization to MNI space of MPRAGE. The majority of sites utilized the Autism diagnostic observation tool and interview-revised for ASD diagnosis or confirmation of typical controls resting-state f-mri relies on neural assess- ments of the functional connections among different regions of the brain calculated through correlation of average time series from regions of interest ROI. Fluctuations in blood oxygenation result in low-frequency fluctuation correlationsin resting-state f-mri generating the connectivity matrix. Our study analyzed datasets comprising 535 ASD patients and 560 typical controls containing T1 structural brain images f-MRI images and phenotypic information about different patients. Phenotypic information was categorized based on sex, age, and Autism diagnostic observation schedule (ADOS) score for ASD subjects along with mean framewise displacement (FD) quality a measure of the motion of the subject's head.

Fig. 2. Block Diagram for ASD classification

Data Preprocessing

The dataset utilized in our research is sourced from the ABIDE I comprising 1,112 fMRI images among these 539 fMRI images belong to a group of individuals with autism disorder while the remaining 573 fMRI images are from non- autistic individuals. ABIDE is a publicly available datasetspecifically designed to provide functional magnetic resonance imaging (fMRI) data from both ASD and typically developing control subjects to pre-process the fMRI data. We utilized the configurable pipeline for the analysis of connectomes (CPAC).CPAC executes a series of pre-processing steps including motion correction spatial normalization and estimation of functional connectivity ensuring the integrity and consistency of the dataset. Furthermore, we extended the dataset using files with a .1D extension. This file format is commonly used in neuroimaging research, particularly in the context of fMRI data analysis, .1D files contain time series data representing brain activity recorded from various regions of interest (ROIs).Each row in a .1D file corresponds to the time series data ofa single ROI while columns represent time points or samples the values in the file indicate the level of activity in each ROI at specific time points. This data is typically stored in a plain text format facilitating readability and processing with software tools in the subsequent sections. We will provide a detailed description of our proposed CNN architecture.

Network Architecture

In this study, we acquired connectomes or functional con- nectivity representations. These representations illustrate the correlation between the mean values of time series obtained from regions of interest (ROI). Each cell in the representation

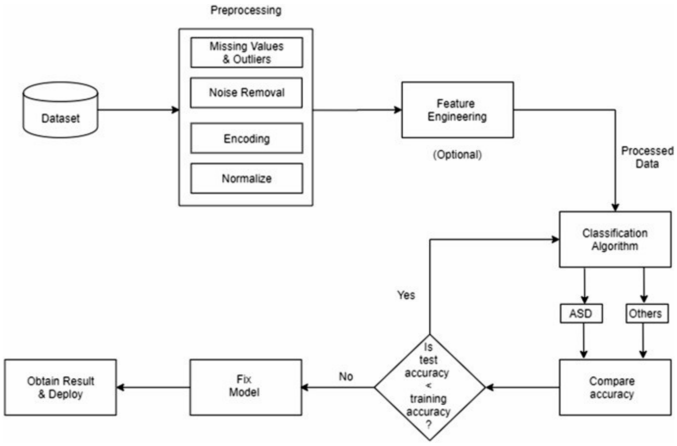

Fig. 3. Architecture of ASD classification

Contains a Pearson Correlation Coefficient (PCC) representing the correlation between two brain regions ranging from (-1 to 1), the representation typically 392x392 in size reflects the co- activation correlations of 392 brain areas based on the CC400 functional parcellation atlas. We proposed a CNN architecture for connectomic data, comprising one convolutional layer followed by max-pooling and densely connected layers. The functional connectivity representations between pairs of ROI serve as input to the convolutional layers. Our final CNNmodel consists of a fully connected hidden layer and linear layers with a tanh activation function. Various parallel filters ranging from 1x392 to 7x392 operate on rows representing brain regions. This setup accounts for 400 filters of length 1 and width 392 and 400 filters of length 7 and width 392. The hidden layer followed by max-pooling reduces feature num- bers and mitigates overfitting. Dropout regularization retains 25 of the nodes during training the output node connects to a dense layer for classification. The model trained for 300 epochs with a batch size of 32 and a learning rate of 0.005 employs 10-fold cross-validation. Our CNN model concate- nates convolution layers and utilizes ensemble learning to complete classification. Each convolution layer has a specific role, smaller filter sizes focus on inter-area connections while larger filters examine neighboring areas. The next section delves into visualizing features contributing most to ASD classification using our CNN model.

IV. Autism Diagnostic And Therapeutic Interface

This research paper introduces an innovative interactive webapp designed for autism therapy and detection recom- mendation, aiming to address the current hurdles encoun- tered by people seeking timely analysis and personalized recommendations for autism. Emphasizing user experience, the platform ensures a seamless and user-friendly journey for patients throughout the diagnosis and therapy recommendation process. Initially, the platform offers a simple registration and login interface, allowing patients to easily create accounts and securely access the platform. Upon logging in, patients are guided through the process of uploading their MRI images directly onto the platform, with detailed instructions provided to ensure accurate image uploads while maintaining data confidentiality and integrity.

Behind the scenes, the platform employs state-of-the-art algorithms and methodologies to analyze the uploaded fMRI images for potential indicators of autism disorder, deliver- ing swift and accurate diagnosis results to patients. Further- more, the platform formulates individualized therapy plans in addition to diagnosis, comprising a range of therapeutic This commitment to user engagement ensures continuous improvement and adaptation of the platform to meet the evolving needs of people with autism and their guardians. Overall, the interactive platform for autism detection and remedy recommendation represents a significant advancement in autism therapy guidance. By integrating advanced technol- ogy with user-centric design principles, the platform has the potential to enhance accessibility and effectiveness in autism diagnosis and therapy recommendations, ultimately improving the well-being of individuals affected by autism.

	SVM		KNN		RF		CNN
	BO	**AO**	**BO**	**AO**	**BO**	**AO**	
Mean of accuracy	0.8532	0.8591	0.8257	0.8324	0.8115	0.8167	0.9452
Variance of accuracy	0.0022	0.0011	0.0011	0.0006	0.00062	0.00052	0.0020
Mean of sensitivity	0.8683	0.8542	0.8326	0.8251	0.8193	0.8265	0.9467
Variance of sensitivity	0.0028	0.0026	0.0045	0.004	0.0045	0.005	0.0078

Mean of specificity	0.8376	0.8523	0.8114	0.8261	0.8023	0.8085	0.9443
Variance of specificity	0.0057	0.0049	0.012	0.008	0.0065	0.003	0.0098
Mean of AUC	0.8511	0.8531	0.8239	0.8294	0.8093	0.8182	0.9462
Variance of AUC	0.0018	0.0017	0.0021	0.0013	0.0005	0.0012	0.0006
Mean of F-score	0.8374	0.8421	0.8156	0.8235	0.8103	0.8116	0.9435

Table II
Results Of Roc For Cnn, Svm, Knn, And Rf Classifiers Before Optimization (Bo) And After Optimization (Ao)

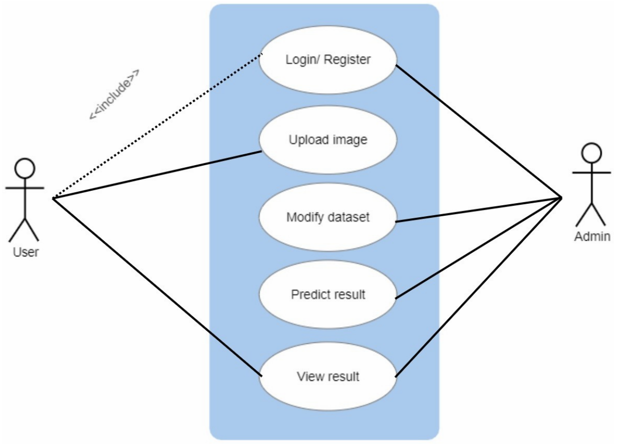

Fig. 4. Use Case of ASD classification

Fold	Accuracy	Sensitivity	Specificity	F-score
1	0.9534	0.9612	0.9443	0.9521
2	0.9657	0.9478	0.9721	0.9645
3	0.9712	0.9583	0.9834	0.9702
4	0.9476	0.9735	0.9398	0.9603
5	0.9634	0.9521	0.9712	0.9665
6	0.9723	0.9656	0.9812	0.9734
7	0.9589	0.9732	0.9523	0.9598
8	0.9782	0.9721	0.9887	0.9812
9	0.9731	0.9598	0.9803	0.9753
10	0.9512	0.9802	0.9345	0.9576
Mean	**0.9640**	**0.9640**	**0.9600**	**0.9650**

Table III
Cnn With 10-Fold Cross-Validation Performance Metrics

V. Results And Analysis

In contemporary research, Convolutional Neural Networks (CNN) are extensively utilized for categorizing datasets. In interventions meticulously customized to meet the unique requirements of each patient. These interventions encompass behavioral therapy, speech therapy, and occupational therapy, among others.

The platform's user interface is meticulously designed to be intuitive and user-friendly, enabling patients to navigate seamlessly through its features, from uploading images to accessing diagnosis results and therapy recommendations. Moreover, the platform prioritizes user feedback and support, providing channels for patients to share their experiences and seek assistance as needed.

Our study, we devised a CNN model aimed at automating the detection of Autism Spectrum Disorder (ASD) using the ABIDE dataset. This dataset comprises preprocessed neu- roimaging data, originally consisting of 1,112 subjects, with 539 diagnosed with ASD and 573 classified as typical controls. Post-preprocessing, the dataset was reduced to 871 subjects. Additionally, a phenotype file accompanies this dataset, in- cluding automated metrics. Among these metrics, we evaluated the functional metric known as mean framewise displacement,removing outliers where this parameter exceeded 0.2 during training. For our training process, we set the learning rate to 0.003 with batch sizes of 32 and 800 epochs. The input to our CNN model is a 392x392 matrix, where each row represents aregion of interest. In our architecture, we employed filter sizes ranging from 1x382 to 200x382. Despite experimenting with larger filter sizes, we observed no significant improvement in accuracy. Our proposed architecture involves concatenat- ing multiple convolutional layers, followed by feeding theresulting features into a Multilayer Perceptron (MLP) for categorization.

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Fig. 5. Building Models using different algorithms

For instance, a filter size of 1x382 in the convolutional layerexamines the connection of each area with others, while a sizeof 4x382 explores the connection of four adjacent areas with others. Finally, we aggregate the outputs to obtain the final result. The execution time for our study totaled approximately 4 hours and 30 minutes, employing 10-fold cross-validation with the NVIDIA Tesla K80 GPU. We achieved an accuracy rate of 91.22%, the highest reported accuracy to date with the ABIDE I dataset. It compares the automatic identification of ASD and control classes achieved by different studies using the same database. Our results outperform other cutting- edge techniques. We also assessed the performance of Support Vector Machine (SVM), k-nearest Neighbors (KNN), and Random Forest (RF) classifiers on the preprocessed ABIDE I dataset. Following optimization and hyperparameter tuning, SVM achieved a mean accuracy of 69%, KNN 62%, and RF 60%. Our CNN-based architecture surpassed these machine learning classifiers in accuracy, specificity, and sensitivity.

We evaluated the performance of SVM, KNN, and RF classifiers before and after optimization using the Receiver Operating Characteristic (ROC) curve and confusion matrix. Before optimization, we employed a leave-site-out strategy, utilizing each site as a separate fold for testing while applying cross-validation on the remaining sites. Our proposed CNN model demonstrated significant accuracies exceeding 70% for several sites.

VI. Conclusion

In this study, we introduced a CNN architecture aimed at distinguishing ASD patients from control subjects and classi- fying them accordingly. Furthermore, we assessed the perfor- mance of three supervised learning techniques SVM, KNN, and RF classifiers on the preprocessed ABIDE I dataset. The findings reveal that our model achieved an average accuracyof 91.22% on the test data surpassing the previously recorded highest accuracy of 70.22% for this dataset. Notably, it was observed that a CNN model with fewer parameters exhibits greater efficiency and reduced overhead for new models. Bear-ing this in mind our model demonstrated the ability to train effectively with fewer parameters while achieving superioraccuracy compared to existing models. For instance, whilethe previously top-performing method utilized a significant number of parameters 19,961,200. Our model utilized only 4,398,802 parameters, hence our proposed CNN architecture attains better classification performance while utilizing fewer parameters resulting in reduced training time. Consequently, our model is simpler and faster compared to similar models. Additionally, we analyzed utilizing each row of the connec- tivity matrix to illustrate the correlation between distinct brainregions, allowing for the investigation of the behavior of individual brain regions and their related biomarkers.

In future studies, we aim to: 1. Refine this analysis by apply-ing noise correction techniques to each row of the connectivity matrix. 2. We've employed a limited number of images within each class, indicating a necessity for increased data volume to enhance the robustness of our model. 3. Decreasing the time complexity of the model is imperative when handling the entiredataset comprising all subjects. 4. The study should account for the influence of two variables, namely sex and average age,on the outcomes. 5. Enhanced performance may be achieved through the utilization of balanced data.

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