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Prediction of autism spectrum disorder using Convolution Neural Network

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Abstract— **Autism Spectrum Disorder is a developing neurological disorder, and it starts in childhood, adolescence, and adulthood. The treatment of Autism Spectrum Disorder (ASD) necessitates an accurate diagnosis followed by appropriate rehabilitation. Physicians can use artificial intelligence (AI) technology to help them implement computerized diagnosis and rehabilitation processes. Neuroimaging-based approaches have been the focus of deep learning algorithms for ASD diagnosis. Neuroimaging techniques are benign disease indicators that could aid in identifying ASD. Neuroimaging procedures, both structural and functional, give doctors much information about the brain's anatomy and activity. Because of the brain's complex structure and function, developing optimal processes for ASD identification using neuroimaging data deprived of using Deep Learning is difficult. Our proposed work aims to identify Autism Spectrum Disorder(ASD) from a huge dataset based on brain patterns. Using a convolution neural network, the proposed work identifies ASD patients from ordinary people. It identifies the ROI using the feature extraction technique. The system performance is measured by accuracy, and it achieves 95% accuracy to identify ASD patients.**

Keywords*— *Autism Spectrum Disorder (ASD), Autism Brain Imaging Data Exchange(ABIDE), resting-state functional Magnetic Resonance Imaging (fMRI), CNN

I. INTRODUCTION

Autism Spectrum Disorder is a disability in development that influence communication with the world. The autism spectrum disorder differs for every person as mild or severe. They have restricted interests and repeatedly do some tasks and live in their world. The main reasons for autism spectrum disorder are genes and environmental situations. The signs of autism spectrum disorder appear in kids at the age of two. The Centers for Disease Control and Prevention (CDC) states that, in 2020, one in fifty-four children gets affected due to autism in the United States [1].

Paediatricians and psychiatrists diagnose Autism Spectrum Disorder(ASD) by absorbing the children's activities and caregivers' reports. The autism spectrum disorder signs include lack of eye contact, less interest in playing with other children, hyperactivity, depression, delay in talking, not responding to others' gestures [2]. The American Academy of Pediatrics suggests screening for ASD starts from 18 to 24 months of age. Early identification of ASD in children improves children's behavioural development, and there is no medicine available to cure it completely. The ASD children undergo occupational therapy, speech therapy and sensory therapy. They are used to minimize the symptoms and maximize the children's ability [3].

The awareness about ASD is to be given to people so that early prediction of ASD is possible. The treatments and therapies help the children overcome the difficulty early and quickly. The frequency of ASD diagnosis has risen intensely over the past few years [4]. In 1966, approximately 1 in 2000 people were affected by autism, and now it is increased to 1 in 59. The reason is improved diagnostic standards, services available and public awareness [5].

Structural neuroimaging is an important method for examining structural brain problems in ASD because it allows researchers to examine the architecture and structural relationships between brain areas. Magnetic resonance imaging (MRI) techniques are the primary instruments for structural brain imaging. Diffusion tensor imaging MRI is used to analyze anatomical connections, and structural MRI (sMRI) pictures are used to explore cerebral anatomy (DTI-MR) [6]. Functional neuroimaging can be used to investigate the functional connectivity of brain parts, which is beneficial in the research of ASD. Task-based (T-fMRI) and resting-state functional MRI (fMRI) are two of the utmost potential imaging techniques in functional brain disorders (rs-fMRI). Owing to the slow reaction of the brain's hemodynamic system and fMRI imaging time constraints, fMRI-based approaches have a better spatial resolution but a low temporal resolution, making them unsuitable for capturing fast dynamics of brain functions [7]. The methods are extremely sensitive to motion artefacts. DL techniques for exploring ASD or developing therapeutic aids have received less attention than traditional methodologies.

II. LITERATURE REVIEW

DL algorithms are being applied in a wide range of medical fields, particularly neuroimaging. Deep Learning in neural imaging extends from segmenting brain images to detecting brain trauma like cancers, diagnosing functional brain disorders like ASD, and creating artificial brain images [8]. Data acquisition, data preprocessing, feature extraction, and classification are all stages of a traditional artificial intelligence (AI)-based CADS. The effectiveness of existing standard ASD diagnostic algorithms has been examined. Unlike traditional approaches, feature extraction and classification are dynamically accomplished within the model in DL-based CADS. Because of the nature of DL networks, vast datasets are required to train them and identify layers in datasets [9].

There is no precise treatment available to cure autism. But if we can predict autism at early stages, we can treat children early and improve child activities. This section briefly explains the works carried out in predicting ASD at its early stages. Kazi [10] develops an application to predict autism at early stages using random forest techniques. The model is tested with the Autism Spectrum Quotient -10 dataset, and the performance measures are 97.10% accuracy. Pujari [11] surveys various classification algorithms and proposes an ensemble classification for ASD. Many analytical approaches are used for prediction to improve the classifier accuracy by up to 90%.

Anibal [12] collected data from ABIDE, which provides data in the scientific community. SVM and RF are used for evaluation which is based on 10-fold cross-validation. The system acquires 70% accuracy. Kristine [13] collects data of 5-14 years children from the clinic. The system predicts accuracy of about 94.6%. Jinseub [14] used a machine-learning algorithm to distinguish ASD from normal kids. The dataset is collected from the open database, and the system has 83% sensitivity and 84% specificity.

Maria [15] used retinal images of forty- six participants to identify ASD. ARIA methodology is a cloud-based algorithm used to attain the retina's information to classify ASD. The sensitivity of a system is 95.7%, and the system's specificity is 91.3%. Yangwang [16] used fMRI data from the ABIDE database, and a random SVM classifier is used to differentiate ASD, and the system's accuracy is 96.15%.

Yazhou [17] used a deep neural network to classify ASD. The brain network for each subject is constructed, and the features are extracted. The connectivity is ranked using F-Score, and the highly-rated features are selected. The system achieves an accuracy of 90.39%. Wasifa [18] used EEG of children, and discriminant analysis and SVM are used to predict ASD. The system gives an accuracy of 94.7%, sensitivity of 85.7% and specificity of 100%.

III. PROPOSED METHOD

The competence of CAD is dependent on the abundance of the input data, which is at the core of any CAD development. Numerous brain functional and structural datasets are accessible to diagnose ASD. The proposed system is a primary diagnostic tool that helps parents decide whether their child is affected by ASD. The data is collected from ABIDE [19], a public database that provides large samples of ASD data. Nowadays, more than 1% of children are affected by ASD. It contains data from 24 international brain imaging laboratories. Fig. 1 explains the architecture of the proposed work.

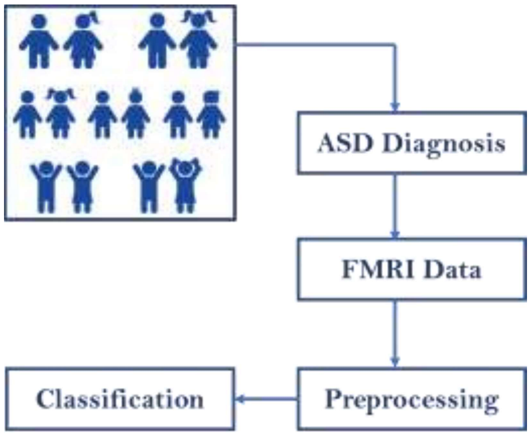

Fig. 1. Proposed System Architecture

A. Preprocessing

ABIDE is a collection of R-fMRI datasets of Autism Spectrum Disorder and age-matched typical controls of 1112 fMRI images of patients in which 539 patients with ASD and 573 age-matched typical controls. ASD neuroimaging can look for anomalies in brain connection and can also be used to look at intrinsic functional connectivity. The fMRI data are analyzed using the configurable pipeline to analyze connectomes(C-PAC) [20]. It is a robust set of existing software packages, and it helps to explore the data with a wide array of analytical tools. Slice timing and movement compensation, noise regression, and temporal filtering are all processes in the image preprocessing process [21]. The ROI is calculated by constructing a brain connectivity matrix for the partitioned regions' average time series.

B. System Architecture

In the proposed work, we attain the connectivity matrix for finding whether an individual is affected by ASD or not. Convolution Neural networks worked similar to classic neural networks inspired by the human visual system and used to process 2D images [22]. The architecture of ASD detection using CNN is shown in Fig. 2. CNN works on the features of the images, and it learns when the network train a certain number of images. It extracts features from input images. It applies filters to the pixel block of the input image using matrix multiplication. The depth of the filter and the input image is to be the same so that the filter multiplies the filter value with the original value. The final array we attain is called the activation map. Pooling reduces the image size and helps to detect objects in the image wherever it is located. It also reduces the number of parameters and the required computation, and hence it controls overfitting.

In the proposed work, a symmetric matrix is used to calculate the correlation between the mean value of the ROI. The Pearson correlation coefficient [23] is measured for every cell in the matrix, and the value ranges from -1 to 1. Each row contains an ROI value, and it represents the brain region. The proposed system consists of one hidden layer, and each layer is followed by a tanh activation function and ranges between -1 to 1.

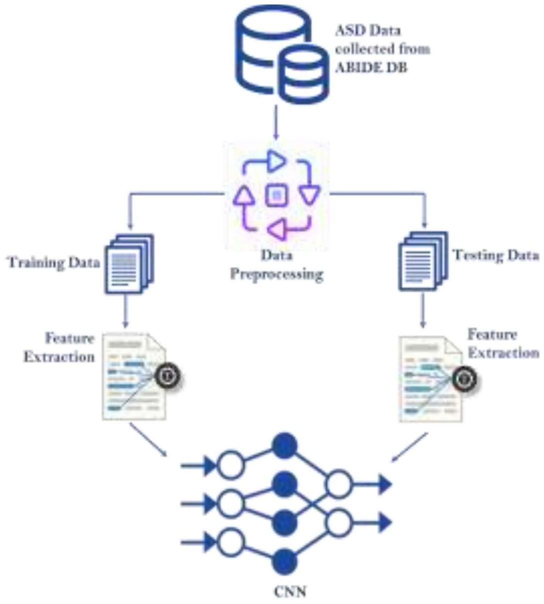

Fig. 2. The architecture of ASD detection using CNN

The tanh function [24] is used to classify between two classes. It is used in the neural network, and the mean for the hidden layer will be nearly zero. It helps in centring data by bringing the mean close to zero. The whole dataset is categorized into two parts: the training phase and the testing phase in a ratio of 80:20.

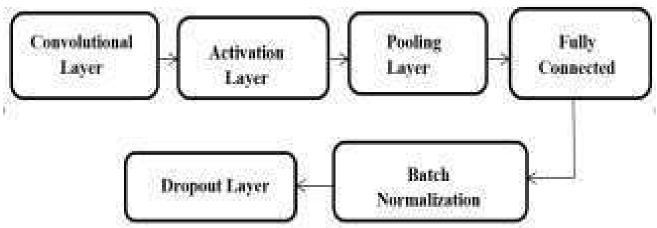

Fig. 3. CNN Architecture

The weight size is similar to the matrix representation of the convolution neural network. Max pooling [25] reduces the number of features and overfitting problems. Fully connected layers get connected to the activation layers, which is found in the last step of the network. The batch normalization layer normalizes input volume activation before passing it to the next layer of the network. It aids in the reduction of epochs CNN takes to train itself. Dropout is a regularization technique that helps to prevent overfitting by increasing the test accuracy and at the expense of training accuracy. The model is trained with 32 batch sizes and 300 epochs, and the learning rate is set to 0.005. It is developed using a ten-fold cross-validation strategy. The working of CNN is shown in Fig. 3.

IV. Results and Discussions

For dataset classification, CNN is generally utilized. We developed a CNN model for automatic ASD detection using the ABIDE dataset. The ABIDE dataset contains 1,112 patients, of which 539 with ASD and 573 are typical controls. There is also a phenotypic file that incorporates the computerized metrics for this dataset. The learning rate was set at 0.005 in training, with 32 and 300 epochs batch sizes. The width of the filter could be any size. The correlation between the corresponding region and the other regions of the brain is represented by each row of the connectivity matrix. As a result, we regarded the filter's breadth as the dimension of the associated region, which was equivalent to the size of every row of the connection matrix. The number of rows in the filter defines its length. The accuracy of the findings was not improved by using larger filters. Fig 4. Shows the working of the proposed CNN model.

Layer (type)	Output Shape	Param #
conv2d_26 (Conv2D)	(None, 300, 300, 64)	1792
conv2d_27 (Conv2D)	(None, 300, 300, 64)	36928
max_pooling2d_10 (MaxPooling	(None, 150, 150, 64)	0
conv2d_28 (Conv2D)	(None, 150, 150, 128)	73856
conv2d_29 (Conv2D)	(None, 150, 150, 128)	147584
max_pooling2d_11 (MaxPooling	(None, 75, 75, 128)	0
conv2d_30 (Conv2D)	(None, 75, 75, 256)	295168
conv2d_31 (Conv2D)	(None, 75, 75, 256)	590080
max_pooling2d_12 (MaxPooling	(None, 37, 37, 256)	0
conv2d_32 (Conv2D)	(None, 37, 37, 512)	1180160
conv2d_33 (Conv2D)	(None, 37, 37, 512)	2359808
max_pooling2d_13 (MaxPooling	(None, 18, 18, 512)	0
conv2d_34 (Conv2D)	(None, 18, 18, 512)	2359808
conv2d_35 (Conv2D)	(None, 18, 18, 512)	2359808
max_pooling2d_14 (MaxPooling	(None, 9, 9, 512)	0

Fig. 4. CNN Model

A Receiver Operator Characteristic (ROC) curve is a plot that depicts the diagnostic ability of a binary classifier. It is used in medicine, radiology, environmental catastrophes, and deep learning, among other domains. A ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) (FPR). The true positive rate (TP/(TP + FN)) is the fraction of all optimistic observations predicted to be optimized properly. The false-positive rate (FP/(TN + FP)) is the percentage of harmful observations incorrectly projected as optimistic. Fig.5 shows the ROC curve for the proposed model. The AUC is a separability measurement, while the ROC is a probabilistic curve. It shows how the model can identify among classes. The AUC measures how effectively the model predicts 0 and 1 classes. The greater the AUC, the higher the quality model calculates accurately. In the proposed model, the AUC value is 0.92. Hence the model predicts accurately.

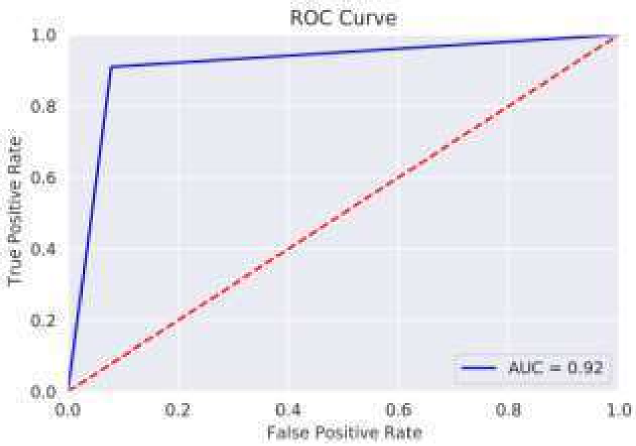

Fig. 5. ROC Curve

For binary classification problems, a confusion matrix is a table that summarises the number of correct and wrong predictions made by a classifier. A user could evaluate the accuracy by monitoring the diagonal values to measure the number of accurate classifications by visualizing the confusion matrix. Fig. 6. Shows the confusion matrix of the proposed model. The TP, TN, FP, FN can be calculated using a confusion matrix, and the proposed model's accuracy can be calculated.

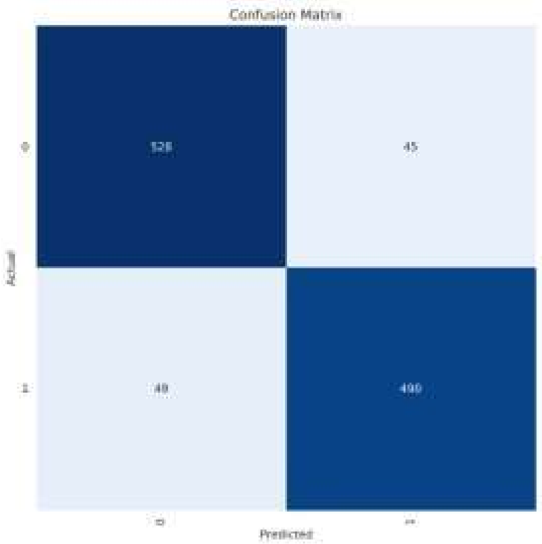

Fig. 6. Confusion Matrix

- True Positives (TP): The measure of positive instances accurately categorized as such by the model.
- True Negatives (TN): The measure of the negative class is accurately recognized as such by the model.
- False Positives (FP): The measure of negative cases wrongly categorized as positive by the model.
- False Negatives (FN): The model's measure of positive cases are wrongly categorized as negative.

The accuracy of the system is calculated using the formula:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Number\ of\ Samples}$$

Accuracy of other methods and the proposed method is compared in Table 1.

TABLE 1 RESULT COMPARISION

Author	Dataset	Methodology	Accuracy
Alexandre Rosa Franco[9]	ABIDE	Deep Neural Network	70%
Lingyu Xu[10]	fNIRS	CNN-GRU	92.2%
Kazi Shahrukh Omar [11]	AQ-10 dataset and 250 real dataset	Random Forest-CART	93.78%
Maria Lai[16]	46 ASD participants & 24 normal control	ARIA	95.7%
Xia-an B[17]	ABIDE	Multiple SVM	94.15%
Yazhou Kong[18]	ABIDE	DNN	90.39%
Proposed Method	**ABIDE**	**CNN**	**95%**

V. Conclusion

We presented a CNN architecture to recognize and categorize ASD patients and control people in this research. Social difficulties, communication deficits, and stereotyped behaviours are common features of ASD. To help people with autistic problems, various computer-aided methods and restoration aids have been established. The preprocessed ABIDE dataset's performance was evaluated. According to the outcomes, our model's average accuracy utilizing the test data is 95%. The CNN architecture can achieve superior classification performance with limited training data, decreasing training time in half. As a result, our proposed model is less difficult and speedier compared to other existing models.

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