Model for autism disorder detection using deep learning

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ABSTRACT

Autism spectrum disorder (ASD) is a neurodegenerative illness that impacts individuals' social abilities. The majority of available approaches rely on structural and resting-state functional magnetic resonance imaging (fMRI) to detect ASD with a small dataset, resulting in high accuracy but low generality. To detect ASD with a limited dataset, the bulk of known technologies involve Machine Learning, pattern recognition, and other techniques, leading to high accuracy but moderate generality. To address this constraint and improve the efficacy of the automated autism diagnosis model, an ASD detection model based on deep learning (DL) is provided in this work. The classification challenge is solved using a convolutional neural network classifier. The suggested model beats state-of-the-art methodologies in terms of accuracy, according to simulation findings. The proposed approach investigates how anatomical and functional connectivity indicators can be used to determine whether or not a person is autistic. The proposed method delivers state-of-the-art results, with the classification of Autistic patients achieving 93.41% accuracy and the localization of the classified data regressed to 0.29 mean absolute error (MAE).

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1. INTRODUCTION

Autism spectrum disorder (ASD) is a neurological aliment with different traits such as: difficulties with human engagement, cognitive impairments, and behaviors that are restricted and recurrent [1]. Autism has been linked to both morphological and functional engagement abnormalities in numerous previous studies. The most often utilized imaging modality for evaluating anatomical anomalies is structural MRI (sMRI) [2], whereas functional MRI (fMRI) is by far the most widely used technique for investigating neural activity [3].

As per the World Health Organization, one out of every 160 children have ASD, and these children frequently suffer from sadness and anxiousness. Timely detection after birth is essential since it can benefit individuals with ASD in developing their interpersonal abilities and communication issues, as well as improve their overall quality of life. Early detection is important for controlling and treating this disease. Designing a model based on physiological or structural region connections in the brain is one of the most crucial jobs for detecting brain diseases such as epilepsy, Alzheimer's, and autism.

It is attributed to a slew of behavioral problems, some of which can become out of hand if the diagnosis is delayed [4]. Despite the fact that symptoms appear in childhood, in most of the cases, a diagnosis is delayed [5]. This is due to the fact that the current ASD diagnosing technique is entirely subjective and based on pre-defined questionnaires, which necessitates the pediatricians going through a children's cognitive background and conduct despite the fact that these procedures are extremely clear-cut, they are unquestionably flawed, boundless, and may necessitate expertise that may not be accessible at the time at a large number of medical institutions.

With technological advancements, a great number of researchers are now analyzing an automatic computer assisted diagnosis of autism [6] as well as designing interactive technologies to assist in the treatment and rehabilitation of autistic people [7]. Subjectivity would be reduced, and diagnostic repeatability and availability would be improved. It would also go a long way toward assuring early detection [8]. Various neuropsychiatric and neurodegenerative conditions can be identified using magnetic resonance imaging (MRI).

In the past few years, machine learning (ML) techniques have shown significant promise in the analysis of pictures and videos. Particularly in a variety of fields, deep learning has achieved a lot of success. The success of deep learning has been aided by methodological developments as well as the widely accessible, massive datasets in the field of image processing [9]. Unfortunately, neuroimaging does not operate in this way. Large datasets are hard to come by, if they exist at all. However, a number of organizations have worked to create a useable dataset by fusing neuroimaging datasets of persons with autism spectrum disorder (ASD) and people who are Typically developed (TD) from diverse locations across the world [10]. About 2,150 participants, including ASD and TD, are included in the whole dataset, which comprises the first and second waves of data aggregation (ABIDE-I/ABIDE-II) [11]. Although such a database exists, the enormous density of the input data makes it difficult to employ without some sort of preprocessing or pattern discovery [12].

In the proposed work, 3D neurological images having height, depth and volume have been considered to classify whether a person is autistic or not based on multiple brain scans in the fMRI format. An attempt has been made to study and evaluate the abnormalities in specific part of brain to narrow down our experimentation to final classification. Certain regions of brain have been targeted in order to frame region of interest and carry out the entire experimentation. A custom convolutional neural network (CNN) model is built to manipulate the classification of brain scans and determine whether or not the person is autistic.

The remaining portion of the paper has been presented using the following format: Section 2 presents a literature review of previous research articles on the topic of interest followed by problem formulation in section 3, and section 4 consist of detailed overview of the technology solution employed to achieve the intended goals. Section 5 delves into the technique employed, while section 6 outlines the review of the system's performance. The paper and recommended approach come to a close in section 7.

2. LITERATURE REVIEW

ABIDE, which is the result of a collaborative effort incorporating phenotypic data and neurobiological images acquired from 1,114 individuals, is the most widely used data-driven method for identifying biomarkers and diagnosing autism [13]. Recently, there have been numerous attempts to diagnose ASD using fMRI and deep learning. Koyamada *et al.* [14] investigated a deep neural network (DNN) model to build a subject-transfer decoder. The authors build a decoder to examine various characteristics of every individual in the dataset utilizing primary sensitivity analysis (PSA). Their recommended neural system contains two hidden layers, a softmax output layer, and two visible layers that classifies brain activity from 499 people into seven human categories using the two hidden layers in the center.

Based on the examination of brain activation in response to a speech experiment, Haweel *et al.* [15] suggested a novel computer-aided grading system for infants and toddlers (between 1 and 4 years). Using functional connectivity characteristics of resting-state fMRI data, Subah *et al.* [16] proposed an ASD detection model. Two widely used brain atlases, Craddock 200 (CC200) and automated anatomical labeling (AAL), as well as two uncommon atlases, bootstrap analysis of stable clusters (BASC) and Power, are employed in their suggested model.

Masood *et al.* [17] used the deep convolutional neural network (CNN) inception model to train the model on spatial features, and recurrent neural network (RNN) to train the model on temporal features that are present in video sequences to prepare a sign language recognition model. Eslami *et al.* [18] presented a model based on the deep learning and machine learning technique using CNN and SVN classifier respectively for identifying attention- deficit/hyperactivity disorder (ADHD) and autism spectrum disorder (ASD) the model is used to identify the traits of autism using functional and structural state MRI of the subject. As a result, it was proved that deep learning (DL) model works in a better way than the proposed ML model.

Choi [19] used a variational autoencoder to transform multidimensional and high-dimensional data into two-dimensional features and showed a functional connectivity pattern related to Autistic children. Rad *et al.* [20] worked on stereotyped motor movements (SMM) in autistic people, which have an effect on learning and social skills including body swaying and intricate hand gestures. The multi-sensor accelerometer readings from SMM are processed by the CNN to extract various attributes. Havaei *et al.* [21] proposed a completely automated brain tumor segmentation approach based on CNN.

Devika *et al.* [22] suggested ASD detection model based on structural MRI For this purposes authors used only healthy patients' s MRI data and trained it using generative adversarial network (GAN) to recognize spatio-temporal patterns in skeletal brain connections. The model was contrasted with two alternative baselines, a more complex self-attention GAN and a more basic UNet. Furthermore, compared to cross-sectional data, longitudinal data and achieved 17–28% greater accuracy (one scan per subject). Using structural MRI data, Khadem-Reza *et al.* [23] suggested a novel method for differentiating ASD patients from controls. The accuracy of this method is increased by simultaneously utilizing the structural photos' volume and surface attributes. The authors' investigation included a number of ML and DL techniques, which achieved diagnosis accuracy of 86.29%, 71.15%, 86.53%, and 88.46%, respectively. Artificial neural network (ANN) offered the most accurate diagnostic possible.

As the preceding section demonstrates, there is a compelling need to examine the viability of utilizing DL-based models to detect ASD in the human population. The majority of the work thus far has relied on classic machine learning techniques, which have performance restrictions. The performance of a DL model was investigated for this study.

3. PROBLEM FORMULATION

ASD is a neuro-disorder that has long-term consequences for a person's interactions and communication with others. Because symptoms typically start to show between the ages of two and four, autism is usually detected and referred to as a "behavioral syndrome" [24]. Experts believe that the ASD problem begins in childhood and continues through adolescence and adulthood.

The main goal of this study is to use convolutional neural networks of deep learning to categorize whether a patient is autistic or not. The brain scans have been classified and localized to the annotated areas to identify if the scan indicates autism or not. This study focuses on utilizing CNN with a neuroimaging dataset to automatically identify autism spectrum disorder (ASD) [25]. The most popular resting-state functional magnetic resonance imaging (R-MRI) data from the autism brain imaging exchange (ABIDE), a multi-site dataset based on structural connectivity patterns, were used to identify ASD patients. The proposed method was successful in classifying both ASD and control subjects [26].

4. DATASET AND TECHNICAL APPROACH

ABIDE-I dataset is acquired from the sources to meet the research's purpose, and this dataset was then analyzed using numerous algorithms to determine its detection performance on 3D-image Data. Because the data contained a few non-contributing and subcategory attributes, it was preprocessed. Preprocessing is the process of transforming a data point before delivering it to the model. This is used to tidy up noisy or unreliable data so that it may be used for training and analysis. There is potential for enhancing the accuracy of existing approaches for identifying autism spectrum disorder using functional MRI to keep up with technological advances in the neuroimaging area.

The main goal of this research is to shorten the training period and improve the accuracy of mean time series signal-based ASD detection systems already in use. Table 1 presents the MRI data from 873 patients, including 405 individuals with ASD and 468 individuals without ASD, from the autism brain imaging data exchange (ABIDE) collection [12]. ABIDE, the largest repository of data has amassed and disseminated 1,114 R-fMRI data, together with related structural MRI and observable attributes statistics from 541 people with autism spectrum disorders (ASDs) and 574 age-matched classic controls (6-65 years).

Based on assessments of 362 male ASD subjects and 405 male age-matched TCs, this resource is described and its applicability for furthering knowledge of ASD neurobiology is demonstrated. Whole-brain intrinsic cognitive control, as well as a variety of voxel-level inherent functioning brain architecture measurements, have been taken into consideration. Whole-brain analyses in the ASD literature harmonized seemingly contradictory themes of hypo- and hyperconnectivity; both were identified, but hyperconnectivity predominated, particularly in corticocortical and interhemispheric functional connectivity.

4.1. Data transformation

Data preparation is the process of transforming raw data into a useable and understandable format. Real-world data is frequently fragmented and unreliable because it contains so many inaccuracies and null values. Good pre-processed data is always the source of a favorable outcome. Several data pre-processing procedures are used to deal with missing and irregular data, such as processing null values, anomaly analysis, data denoising, subsampling (size and numerosity reduction), and so on.

The images are of the Neuroimaging Informatics Technology Initiative (NIFTI) form, which is commonly utilized in neurological scanning as shown in Figure 1. The volume in the MRI scans is also accounted for in the NIFTI files, and this volume is normalized for every scanning so that the scans can be processed correctly. After normalizing the volume, the scans are shrunk by normalizing the width and height.

Table 1. Phenotypic information summary of the participants from the ABIDE dataset

Autism Brain Imaging Data Exchange (ABIDE) Dataset				
Site	Count			Age Range
	ASD	Control	Total	
Caltech	5	10	15	17–56
CMU	6	4	10	19–40
KKI	12	20	32	8–13
LEUVEN	26	30	56	12–32
MAX_MUN	19	27	46	7–58
NYU	74	98	172	6–39
OHSU	12	13	25	8–15
OLIN	14	14	28	10–24
PITT	24	26	50	9–35
SBL	12	14	26	20–64
SDSU	8	18	26	9–17
Stanford	12	13	25	8–13
Trinity	19	25	44	12–26
UCLA	48	37	85	8–18
UM	46	73	119	8–29
USM	43	24	67	9–50
YALE	22	18	40	8–18
TOTAL	402	464	866	6–64

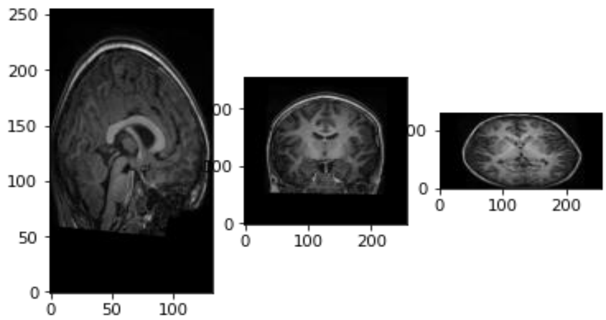

Figure 1. 3D images in ABIDE dataset

5. PROPOSED METHODOLOGY

Resting-state functional magnetic resonance image (RS-FMRI) is utilized in a task-negative situation to map the brain and examine regional relationships. The vast majority of studies rely on having access to raw fMRI image data; however, these data are difficult to analyze and necessitate a long time, which makes them vulnerable to overfitting. A deep learning approach to diagnosing autism spectrum disorder using functional connectivity patterns derived from preprocessed FMRI data is described, taking into account the aforementioned problems.

A series of three-dimensional scans taken over time and evaluated by functional MRI scans are available and show a signal linked to brain activity (most often, the blood-oxygen-level-dependent signal, or BOLD signal). In this illustration, the individual is immobile inside the MRI scanner as a series of brain images showing the evolution of the BOLD signal strength are taken. A single preprocessed fMRI scan is therefore a four-dimensional time-series data collection with three spatial dimensions and time. Instead of analyzing the whole time series acquired from each brain voxel, certain brain regions of interest (as defined by the brain atlases) were evaluated. The photographs display the left brightly and temporal lobes, as well as the right frontal lobes. These specific regions have been chosen as the final test sites for our investigation.

5.1. Data preprocessing

Multiple augmentation approaches are applied to create synthetic data after preprocessing the scans and levelling their height, breadth, and volume. Below mentioned transforms are applied to the given dataset:
1. *Flipd* → For flipping when working with a dictionary.
2. *Rotated* → To apply rotations to a dictionary.

3. *Zoomd* → To apply a zoom.
4. *RandGaussianNoised* → To apply a gaussian noise to the dictionary.
5. Finally, there is *RandAffined* → Actually, this function can perform multiple transformations at the same time; it is used to perform *translations*, but it can also be used to perform *rotation* if the *Rotated* function is not supposed to be used.

5.2. Training and testing model

The complete dataset was divided into two halves with a 75:25 ratio, one for training and the other for testing. For cross-validation purposes, the training set has been separated into two halves. The training set is split in half, with one half used for training and the other for validation, with a 75:25 split. The final train, test, and validation sets that are utilized for classification are then separated and used for further processing.

5.3. Model training

The next step in the pipeline is to proceed to neural network building after augmenting the data. Three-dimensional CNN layers will be used in the neural network. The operations of 3D CNN layers are the same as 2D CNN layers, only the filter moves in three directions instead of two. Parametric rectified linear unit (PRelu) is used as the activation function, and 3D pooling layers are used in the network. The image is processed and passed through multiple layers before being classified into one of two classes as shown in Figure 2.

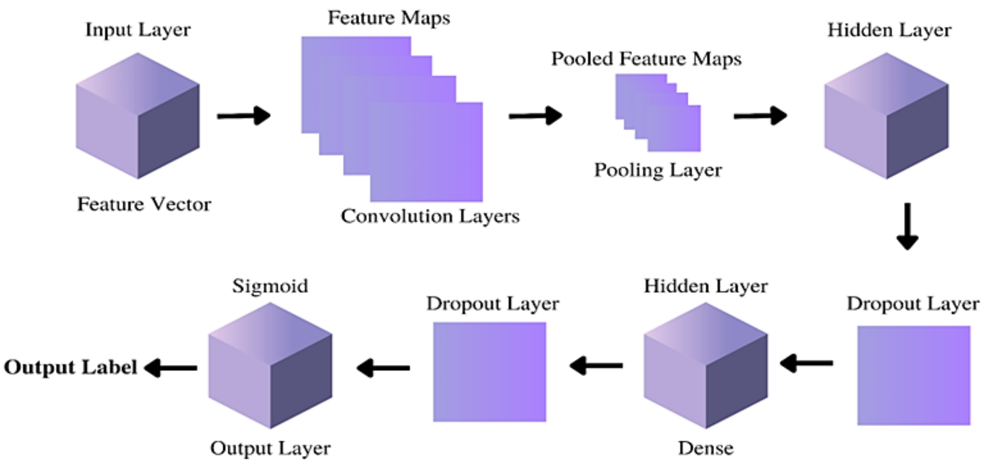

Figure 2. Proposed deep neural network architecture to predict ASD

The model uses pooling and convolutional neural network layers. Now that the features have been provided, the CNN layer filters the image in a 3×3 manner. Reducing the image's pixel size is the first step. This enables the image to be processed more quickly. The model's performance is improved by employing data augmentation techniques like picture rotation, image scaling, cropping, padding, translation, and so on to create fresh and varied cases for the model to train on. A sequential model is built utilizing 3D convolution layers, max pool layers, and the activation function "PRelu" after data augmentation is supplied to the training set. A PReLU, or parametric rectified linear unit, is a generalization of the classic restored unit with a gradient for negative values as shown in (3) and (4). Formally,

$$f(yi) = yi \; if \; y > 0 \tag{1}$$

$$f(yi) = aiyi \; if \; y <= 0 \tag{2}$$

Now that the image has been loaded, the first Conv3D layer analyzes it using a 3×3 filter to search for distinctive features. After extracting both sharp and smooth features, the pooling layer modifies the weights based on the feature map's greatest value. The activation function PRelu only accepts positive values; all other inputs are 0. As a result, the model's effectiveness is increased because only chosen features are transferred to the following layer. PRelu enables the model to train more quickly and prevents the fading gradient issue. Before the model is saved and exported for use, Dense layers are used to correct the receiving vector's dimension as needed after all of the layers have been applied and the resultant picture vector has been flattened into an array. The model summary is shown in Table 2.

Table 2. Convolutional neural network model

S. No	Operation	Kernel Size	alpha_initializer	alpha_regularizer	alpha_constraint
	Input Image (300.300.3)				
1	Convolutional with PReLU	3*3@64	Zeros	None	None
2	Max-Pooling 3D	2*2	-	-	-
3	BatchNormalization				
4	Convolutional with PReLU	3*3@64	Zeros	None	None
5	Max-Pooling 3D	2*2	-	-	-
6	BatchNormalization				
7	Convolutional with PReLU	3*3@64	Zeros	None	None
8	Max-Pooling 3D	2*2	-	-	-
9	BatchNormalization				
10	Convolutional with PReLU	3*3@128	Zeros	None	None
11	Max-Pooling 3D	2*2	-	-	-
12	BatchNormalization				
13	Convolutional with PReLU	3*3@256	Zeros	None	None
14	Max-Pooling 3D	2*2	-	-	-
15	BatchNormalization				
16	Global-Average Pooling 3D	2*2	-	-	-
17	Dense Layer(512)+ ReLU				
18	Dropout(0.3)				
19	Dense Layer(1)+ Sigmoid				

6. RESULTS AND EVALUATION

In today's day and age, ASD is a fast-expanding disorder that affects people of all ages. Early detection of this neurological issue can aid in the subject's overall health and well-being. Early diagnosis based on a variety of medical and physiological factors now looks to be feasible, thanks to the rising use of deep learning-based models to forecast various diseases in humans.

CNN is frequently used today to categorize datasets. In this study, we developed a CNN model for automated ASD identification using the ABIDE I dataset. From the ABIDE I dataset, we used preprocessed neuroimaging data for our investigation. The 1,114 patients in the ABIDE I dataset-of which 541 had ASD and 574 were typical controls-were preprocessed down to 875.

A convolutional neural network-based model has been integrated into this work in order to diagnose persons with autism based on their facial expressions. Multiple convolutional layers are used to create a specific DL model. The collected findings support the model's sound performance. As a result, the method described in this study has, to the best of our knowledge, produced the highest accuracy when using the ABIDE I dataset.

6.1. Evaluation metric

Certain assessment criteria have been incorporated in order to evaluate the performance of the proposed model in classifying the patients as autistic or non-autistic. For classification purpose, the model is evaluated based on accuracy and F1-score. Accuracy (3) determines the ratio of successful assertions made to the total number of instances provided as input. The F1-score, which is defined as the harmonic mean of the recall and precision of the model, is a way of combining the model's performance is depicted in (4). The result is shown in Table 3.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \tag{3}$$

$$\boldsymbol{F-Score} = \frac{\boldsymbol{2*Precision*Recall}}{\boldsymbol{Precision+Recall}} \tag{4}$$

Table 3. Evaluation result of the CNN based classification model

Train/Test Split	Classification Accuracy Score	F1 Score
70/15/15	93.41%	0.9311
60/15/25	91.49%	0.9211

Another criterion taken for the is the mean squared error rate and mean absolute error rate, which received a score of 0.30 and 0.29 respectively. For all of the assessment indicators taken into account, the technique's results are substantial as shown in Table 4. The findings of the preceding investigation led to the following conclusions:

– The prediction model's accuracy is **93.41** percent after applying custom CNN architecture to the 3D brain dataset acquired from the source, while F1-Score is **0.93**.
– The score achieved for the Mean Squared Error is **0.29**.
– The score achieved for the Mean Squared Error is **0.30**.

Table 4. Evaluation result of the localisation of the brain data

	Localisation	
Train/Test Split	MAE	MSE
70/15/15	0.29	0.30
60/15/25	0.34	0.49

The results have a high level of significance as a result of everything. The results of the trials indicate that the proposed model is capable of accurately predicting and classifying ASD. Taking into account all of the data and model findings, the proposed technique is determined to be far more efficient than alternative frameworks now in use. As a result, the proposed methodology can be described as a suitable model for distinguishing between autistic and non-autistic people.

7. CONCLUSION

In this study, ASD was predicted using a deep learning technique based on multisite resting-state fMRI. ASD identification is a challenging task due to the lack of a standard modeling solution and the wide variety of current practice. The results show that our model outperformed the previous best accuracy on this dataset, with an average accuracy of 92.45 percent using the test data. For novel models, it has been found that a CNN model with lower dimensionality is more effective and has lower operational expenses. Because of this, it is possible that our model will be able to train with fewer features and still be as accurate as the best models. Predicated to the results obtained by the experimentation on this problem, the CNN classifier showed significantly reliable performance when all of the feature's characteristics were included after missing values were handled. In comparison to previous investigations, the current study showed a considerable improvement in performance. Despite this, there are several restrictions that must be addressed.

REFERENCES

[1] B. Banire, D. Al Thani, M. Qaraqe, and B. Mansoor, "Face-based attention recognition model for children with autism spectrum disorder," *Journal of Healthcare Informatics Research*, vol. 5, no. 4, pp. 420–445, 2021, doi: 10.1007/s41666-021-00101-y.

[2] D. Bone, S. L. Bishop, M. P. Black, M. S. Goodwin, C. Lord, and S. S. Narayanan, "Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion," *Journal of Child Psychology and Psychiatry and Allied Disciplines*, vol. 57, no. 8, pp. 927–937, 2016, doi: 10.1111/jcpp.12559.

[3] C. Tang *et al.*, "Automatic identification of high-risk autism spectrum disorder: A feasibility study using video and audio data under the still-face paradigm," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 11, pp. 2401–2410, 2020, doi: 10.1109/TNSRE.2020.3027756.

[4] A. Sharma and P. Tanwar, "Identification of autism spectrum disorder (ASD) from facial expressions using deep learning," *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing, COM-IT-CON 2022*, pp. 478–484, 2022, doi: 10.1109/COM-IT-CON54601.2022.9850892.

[5] O. Rudovic *et al.*, "Culturenet: A deep learning approach for engagement intensity estimation from face images of children with autism," *IEEE International Conference on Intelligent Robots and Systems*, pp. 339–346, 2018, doi: 10.1109/IROS.2018.8594177.

[6] P. Washington *et al.*, "Activity recognition with moving cameras and few training examples: Applications for detection of autism-related headbanging," *Conference on Human Factors in Computing Systems - Proceedings*, 2021, doi: 10.1145/3411763.3451701.

[7] M. Leo *et al.*, "Computational analysis of deep visual data for quantifying facial expression production," *Applied Sciences (Switzerland)*, vol. 9, no. 21, 2019, doi: 10.3390/app9214542.

[8] J. Han *et al.*, "Global synchronization of multichannel EEG based on Rényi entropy in children with autism spectrum disorder," *Applied Sciences (Switzerland)*, vol. 7, no. 3, 2017, doi: 10.3390/app7030257.

[9] X. Liu, Q. Wu, W. Zhao, and X. Luo, "Technology-facilitated diagnosis and treatment of individuals with autism spectrum disorder: An engineering perspective," *Applied Sciences (Switzerland)*, vol. 7, no. 10, 2017, doi: 10.3390/app7101051.

[10] D. Johnston, H. Egermann, and G. Kearney, "SoundFields: A virtual reality game designed to address auditory hypersensitivity in individuals with autism spectrum disorder," *Applied Sciences (Switzerland)*, vol. 10, no. 9, 2020, doi: 10.3390/app10092996.

[11] D. Johnston, H. Egermann, and G. Kearney, "Measuring the behavioral response to spatial audio within a multi-modal virtual reality environment in children with autism spectrum disorder," *Applied Sciences (Switzerland)*, vol. 9, no. 15, 2019, doi: 10.3390/app9153152.

[12] M. Magrini, O. Curzio, A. Carboni, D. Moroni, O. Salvetti, and A. Melani, "Augmented interaction systems for supporting autistic children. Evolution of a multichannel expressive tool: The semi project feasibility study," *Applied Sciences (Switzerland)*, vol. 9, no. 15, 2019, doi: 10.3390/app9153081.

[13] S. Minaee, M. Minaei, and A. Abdolrashidi, "Deep-emotion: Facial expression recognition using attentional convolutional network," *Sensors*, vol. 21, no. 9, 2021, doi: 10.3390/s21093046.

[14] S. Koyamada, Y. Shikauchi, K. Nakae, M. Koyama, and S. Ishii, "Deep learning of fMRI big data: a novel approach to subject-transfer decoding," 2015, [Online]. Available: http://arxiv.org/abs/1502.00093.

[15] R. Haweel *et al.*, "A Novel Grading System for Autism Severity Level Using Task-Based Functional MRI: A Response to Speech Study," *IEEE Access*, vol. 9, pp. 100570–100582, 2021, doi: 10.1109/ACCESS.2021.3097606.
[16] F. Z. Subah, K. Deb, P. K. Dhar, and T. Koshiba, "A deep learning approach to predict autism spectrum disorder using multisite resting-state fmri," *Applied Sciences (Switzerland)*, vol. 11, no. 8, 2021, doi: 10.3390/app11083636.
[17] S. Masood, A. Srivastava, H. C. Thuwal, and M. Ahmad, "Real-time sign language gesture (word) recognition from video sequences using CNN and RNN," *Advances in Intelligent Systems and Computing*, vol. 695, pp. 623–632, 2018, doi: 10.1007/978-981-10-7566-7_63.
[18] T. Eslami, F. Almuqhim, J. S. Raiker, and F. Saeed, "Machine learning methods for diagnosing autism spectrum disorder and attention- deficit/hyperactivity disorder using functional and structural MRI: A survey," *Frontiers in Neuroinformatics*, vol. 14, 2021, doi: 10.3389/fninf.2020.575999.
[19] H. Choi, "Functional connectivity patterns of autism spectrum disorder identified by deep feature learning," 2017, [Online]. Available: http://arxiv.org/abs/1707.07932.
[20] N. M. Rad, S. M. Kia, C. Zarbo, G. Jurman, P. Venuti, and C. Furlanello, "Stereotypical motor movement detection in dynamic feature space," *IEEE International Conference on Data Mining Workshops, ICDMW*, vol. 0, pp. 487–494, 2016, doi: 10.1109/ICDMW.2016.0076.
[21] M. Havaei *et al.*, "Brain tumor segmentation with Deep Neural Networks," *Medical Image Analysis*, vol. 35, pp. 18–31, 2017, doi: 10.1016/j.media.2016.05.004.
[22] K. Devika, D. Mahapatra, R. Subramanian, and V. R. M. Oruganti, "Outlier-based autism detection using longitudinal structural MRI," *IEEE Access*, vol. 10, pp. 27794–27808, 2022, doi: 10.1109/ACCESS.2022.3157613.
[23] Z. K. Khadem-Reza and H. Zare, "Automatic detection of autism spectrum disorder (ASD) in children using structural magnetic resonance imaging with machine vision system," *Middle East Current Psychiatry*, vol. 29, no. 1, 2022, doi: 10.1186/s43045-022-00220-1.
[24] P. Tanwar and A. Sharma, "Machine learning techniques for autism spectrum disorder (ASD) detection," *International Journal of Forensic Engineering*, vol. 5, no. 2, p. 111, 2021, doi: 10.1504/ijfe.2021.10042591.
[25] X. Xing, J. Ji, and Y. Yao, "Convolutional neural network with element-wise filters to extract hierarchical topological features for brain networks," *Proceedings - 2018 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2018*, pp. 780–783, 2019, doi: 10.1109/BIBM.2018.8621472.
[26] L. L. Zeng *et al.*, "Multi-site diagnostic classification of schizophrenia using discriminant deep learning with functional connectivity MRI," *EBioMedicine*, vol. 30, pp. 74–85, 2018, doi: 10.1016/j.ebiom.2018.03.017.

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