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REVIEW PAPER

Advancements in automated diagnosis of autism spectrum disorder through deep learning and resting-state functional mri biomarkers: a systematic review

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Abstract

Autism Spectrum Disorder(ASD) is a type of neurological disorder that is common among children. The diagnosis of this disorder at an early stage is the key to reducing its effects. The major symptoms include anxiety, lack of communication, and less social interaction. This paper presents a systematic review conducted based on PRISMA guidelines for automated diagnosis of ASD. With rapid development in the field of Data Science, numerous methods have been proposed that can diagnose the disease at an early stage which can minimize the effects of the disorder. Machine learning and deep learning have proven suitable techniques for the automated diagnosis of ASD. These models have been developed on various datasets such as ABIDE I and ABIDE II, a frequently used dataset based on rs-fMRI images. Approximately 26 articles have been reviewed after the screening process. The paper highlights a comparison between different algorithms used and their accuracy as well. It was observed that most researchers used DL algorithms to develop the ASD detection model. Different accuracies were recorded with a maximum accuracy close to 0.99. Recommendations for future work have also been discussed in a later section. This analysis derived a conclusion that AI-emerged DL and ML technologies can diagnose ASD through rs-fMRI images with maximum accuracy. The comparative analysis has been included to show the accuracy range.

Keywords ABIDE · Autism spectrum disorder (ASD) · Deep learning · Diagnosis · Machine learning · Rs-fMRI

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Introduction

Digital Psychiatry is a modern medical approach that is used to diagnose and treat different diseases. After COVID-19, there has been a huge emphasis on using technical methods to diagnose and treat diseases rather than conventional methods. Due to improved accuracy and timely service, digital psychiatry is being considered as a relevant method to diagnose various disorders.

A spectrum of developmental abnormalities known as autism spectrum disorders (ASD) have been linked to social communication difficulties because of compromised brain processes. Controlling the disorder's progression is one potential solution, but there is no surefire cure for ASD. The symptoms of ASD typically start early in life and tend to persist, securely into maturity and adolescence (Al-Hiyali et al 2021). According to the Centers for Disease Control and Prevention (CDC), one in fifty-four American children suffered from autism in 2020. ASD symptoms include being unresponsive, depressed, shy, hyperactive, and not making eye contact with others. Screening for ASD begins between the ages of 18 and 24 months, according to The American Academy of Paediatrics (Karuppasamy et al 2022). ASD tends to be a disorder where a person lacks social interaction and confidence but theoretically, this is a brain disorder. A brain disorder means that there are major differences in how brain regions are connected or structured.

One of the most important organs in the human body, the brain is the central component of the neurological system. Over time, numerous factors might cause partial or complete impairment of brain functions, including genetics and living situations (Khan et al 2022). Certain disorders like Multiple Sclerosis (MS), attention deficit hyperactivity disorder (ADHD), Parkinson's, Autism Spectrum Disorder (ASD), and depression arise because of these abnormalities in brain function (Sadiq et al 2022; Khan et al 2021b).

A brain disorder like Autism Spectrum Disorder (ASD) involves changes in brain connectivity that must be captured to identify the disorder and provide appropriate preventive measures. In this context, Magnetic Resonance Imaging (MRI), specifically Functional Magnetic Resonance Imaging (fMRI), has proven to be an effective technique. fMRI can reveal abnormalities in functional network connectivity and illustrate the brain's metabolism in various states. It detects dynamic physiological information, primarily reflecting changes in blood oxygenation levels (Xu et al 2021). Two notable examples of this imaging type are resting-state fMRI (rs-fMRI) and task-based fMRI. Research indicates that fMRI studies have demonstrated different neural connection patterns in children with and without autism (Feng and Xu 2023). Notably, rs-fMRI has been shown to yield more effective results in detecting ASD compared to other approaches (Bayram et al 2021).

Processing the complex and large data from rs-fMRI requires algorithms capable of identifying patterns within the data. Automated diagnosis using Artificial Intelligence (AI) algorithms, such as Deep Learning (DL) and Machine Learning (ML), can be particularly useful. Automated diagnosis involves using software-based technology to diagnose diseases by comparing new data with previously available records of similar patients. ML and DL algorithms excel at analyzing complex data and identifying trends within datasets related to ASD. The categorization of ASD benefits from highly consistent information patterns provided by ML algorithms. By integrating ML models with AI methods, classification accuracy can be enhanced while using the fewest feature subsets possible (Jain et al 2023a).

In neuroimaging research, DL approaches have been effectively employed alongside ML techniques to identify ASD-related issues (Ahammed et al 2021). Approaches such as Multi-Layer Perceptron (MLP) with unsupervised training of stacked autoencoders are utilized to achieve high classification accuracy (Jain et al 2023a). DL models can automatically learn multiple feature abstractions from input data, enhancing their ability to identify relevant patterns.

ASD automated diagnosis typically focuses on a few key technologies and procedures. Given that rs-fMRI has proven useful for detecting brain patterns associated with ASD, Deep Neural Networks (DNNs) have gained significant attention in fMRI studies due to their remarkable effectiveness in analyzing multimedia data, including images, videos, and speech. Recently, DNNs have also been used in the classification of brain networks (Liang et al 2021).

Convolutional Neural Networks (CNNs) have garnered significant interest in recent years for their capabilities in representation learning and classification. CNN models comprise components such as activation functions, convolutional layers, fully connected layers, normalization layers, and pooling layers (Khan et al 2021a). Using fMRI data, CNN methods can identify brain biomarkers in ASD patients and extract various properties from multi-sensor accelerometer signals (Sherkatghanad et al 2020). CNNs introduce weight sharing and receptive fields, making them a compelling choice for recent fMRI research focused on brain network classification (Liang et al 2021).

AI is increasingly being applied in healthcare to assist medical professionals in managing conditions like autism. Artificial Neural Networks (ANNs) have gained considerable attention for identifying characteristics in ASD patients that can be used to distinguish between individuals with and without ASD (Alsaade et al 2022). Research indicates that ANN techniques are more efficient than Support Vector Machines (SVM), another ML algorithm, for large datasets (Santana et al 2022). While ANNs are considered simpler than CNNs and DNNs, they remain useful in ASD detection.

For ML and DL models, feature extraction is a crucial part of developing any model. This process focuses on transforming raw data into meaningful stats. There can be different types of features used according to the scope of the study. Feature selection merely depends on the data. Such features should be used for analysis that can help one derive accurate results. For ASD, some relevant features include Functional Connectivity (FC), Region of Interest (ROI) analysis, and Time Series analysis.

A FC metric is used to identify the pattern between different anatomical locations. A functional connectome is the word used to describe the brain's connection map. The nodes in a brain network are the ROIs, and the links that connect the nodes are called edges. With network-based methods, a brain cortex is divided into several ROIs to build a brain network from fMRI data. ROIs are nodes in a weighted functional brain network, and the edge weights of these nodes are typically determined by the Pearson correlation coefficient (PCC), other mathematical measures like tangent space, or a recently developed dynamic time warping between ROI pairs that were extracted from time series signals of blood oxygen levels [12]. ROI provides the structural medium by measuring the connectivity between each brain's active functional patterns (Ahammed et al 2021).

fMRI data-derived brain functional characteristics (FCFs) combined with DL can identify biomarkers that can differentiate ASD from normal development (TD) Jain et al (2023b). When diagnosing autism, facial recognition is more important than an individual's emotional condition. AI and ML have many practical uses that aim to address societal issues.

The scientific community produced the open-source dataset Autism Brain Imaging Data Exchange (ABIDE), which is widely used for grading ASD for brain scans (Jain et al 2023a). Research on identifying ASD on fMRI scans accelerated with the release of the ABIDE I data set. Bayram et al (2021).

Recent research suggests that there are still certain challenges to be solved in the use of DL information for ASD classification; one such challenge is the absence of data mining methodologies (Alsaade et al 2022). It is possible to expand this study and involve more people. To lessen variability, the datasets can be further divided based on additional demographic characteristics, which could improve the classifiers' ability to distinguish between TD and ASD (Jain et al 2023b).

Method

Literature review

The Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement (Sarkis-Onofre et al 2021) provided guidelines for the reporting of this systematic review. The terms "fMRI," "Autism Spectrum Disorder (ASD)," "Deep learning," "Machine Learning," "ABIDE," and "rs-fMRI" were used to search the publications. The selection procedure for these papers, which concentrate on the automated diagnosis of ASD, is depicted in Fig. 1.

Inclusion and exclusion criteria

The articles were included and excluded following the PRISMA guidelines. Table 1 shows three different filtering criteria that were used for the inclusion and exclusion of papers. Papers between the years 2019–2023 were used for the systematic review. As a result 83 papers collectively were eliminated. According to defined keywords, only those articles based on ABIDE datasets were considered. The filtering criteria were based on the initial screening of the title and abstract. The total papers after all the screening process were reduced to 26.

AI-based techniques used for ASD detection

AI has made it possible to diagnose neural disorders in a far better way than traditional clinical methods. AI helps in early detection i.e. it can analyze behavioral data such as eye movement, speech patterns, and brain connectivity (Khan et al 2023) which helps to identify early signs of ASD. Diagnostic support by AI uses ML algorithms that analyze various data including behavioral and medical history.

Machine learning (ML)

ML is a sub field of AI that focuses on using data and algorithms to increase accuracy and human learning. ML is an AI tool that can automatically identify patterns in a set of data (Bayram et al 2021). Supervised, unsupervised, semi-supervised, and reinforcement learning are the four categories of machine learning. Neural networks, on the other hand, are classified as supervised learning. Through the use of Virtual Reality (VR), which enables practice social interaction in a controlled setting, ML has enabled people with autism to receive social skill training.

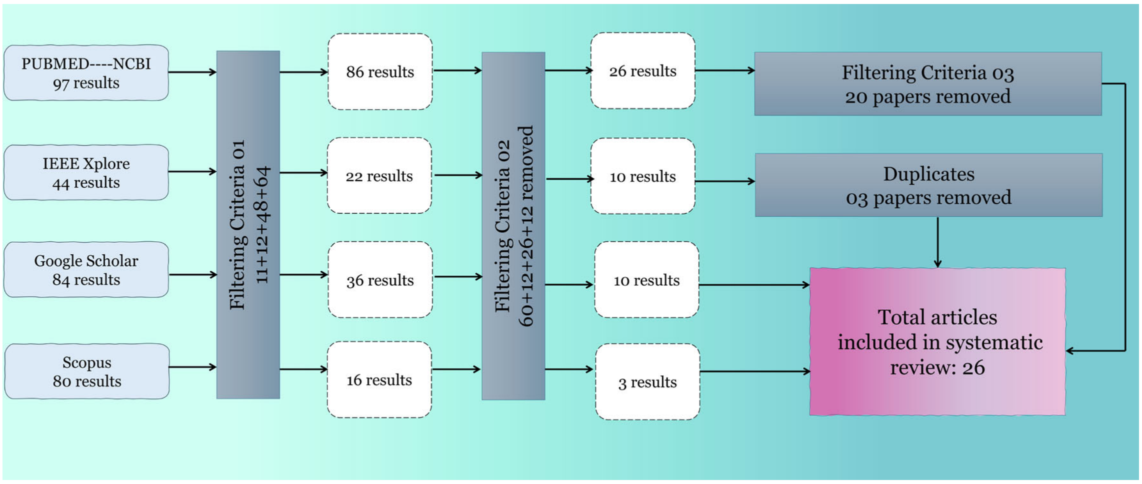

Fig. 1 Paper Selection Process under the guidelines of PRISMA

Table 1 Inclusion and exclusion criteria

Filtering Criteria	Inclusion	Exclusion
Number of years	Between 2019–2023	Before 2019
Initial Screening of title	Titles based on selected keywords: fMRI, ASD, DL, ML, rs-fMRI	Titles based on keywords: clinical methods, s MRI, brain disorder
Initial Screening of abstract	Abstract including ABIDE, DL and ML based techniques, high accuracy, higher subjects	Abstract using other technological methods then DL or ML, targeting other disorders then ASD

The ML method offers a highly consistent pattern of information for ASD categorization. By comparing several brain regions, a functionally related region of the brain was identified.ML Modes uses multiple voxels as a input to estimate the high level relationship between these features (Jain et al 2023a).

In earlier fMRI investigations, classifiers for the FC classification that are commonly utilized are traditional ML techniques including logistic regression (LR), random forest (RF), and support vector machine (SVM) Liang et al (2021). The diagnosis of ASD has also grown in popularity recently with the use of neural networks and DL techniques as CNN, autoencoders, DNN, and long short-term memory (LSTM) Eslami et al (2019).

Deep learning (DL)

To overcome the limitations of ML, DL-based models have been tested on large-scale datasets (Wang 2021). DL is a subset of ML that has been widely used for the detection of ASD. Recently, ML methods have been used to aid in the improvement of neurological disease diagnosis. When it comes to representation learning and classification problems, DL approaches are unquestionably one of the most effective machine learning algorithms (Aghdam et al 2019).

The system is trained to recognize complicated behavioural patterns, like eye gaze and facial expressions, in autistic patients using algorithms. To improve the precision of diagnosis, the algorithms are trained using clinical datasets. A wide range of medical specialties, including structural and functional neuroimaging, use DL algorithms (Khodatars et al 2021).

Artificial neural networks (ANN)

ANN is a computational model that comprises the structural and functional human brain's neural networks. The network consists of interconnected nodes known as neurons organized into layers. Nasser et al (2019), GeeksforGeeks (2023). Since it's built on human brain structure, it can identify the trends in brain connectivity and differences in brain connectivity for Autistic patients making it a suitable approach to detect ASD. The ANN consists of an input layer, hidden layers, and an output layer Memon (2022). The data is fed into the input layer and all the computational work is done in hidden layers and the final results appear at the output layer. The features of ANN such as pattern recognition and adaptability make it a favorable algorithm choice for ASD detection (Gill 2023). ANN architecture is simpler as compared to DNN and CNN but it can identify how brain regions are connected and can provide valuable outputs.

Convolutional neural networks (CNN) and deep learning neural networks (DNN)

CNN can identify patterns straight from pixel data and is used to analyze visual data, such as photos and movies. CNNs have been widely praised for their effectiveness in image recognition applications, including medical imaging (Sabir et al 2022; Aslam et al 2022; Feng and Xu 2023).

CNN use has garnered a lot of interest recently in the field of representation and classification learning (Sherkatghanad et al 2020). Based on the convolution filters, this research acquired multilevel abstract feature representations (Liang et al 2021). CNN models are more accurate in extracting features and have a large number of free parameters. CNN can use fMRI to interpret brain biomarkers in people with ASD (Sherkatghanad et al 2020). Using CNN for ASD is ongoing research in the field of medicine. CNN is used for MRI and fMRI data analysis, feature extraction, model training, validation, and testing.

DNN is another type of ANN that is composed of multiple layers. The DNN is used widely in the research of ASD detection, the authors mentioned the progress of DNNs and their results in their papers. The neural networks are designed to analyse the data representation and perform machine learning by extracting the high-level features from the input.

Many attempts have recently been made to use fMRI to detect ASD based on DL. A subject-transfer decoder was constructed by examining a DNN model. To build a decoder for showing the various attributes of every individual in the dataset, the authors employed principal sensitivity analysis (PSA). Their suggested neural network consists of a SoftMax output layer, two hidden layers in the middle that classify brain activity from 499 people into seven human types (Sherkatghanad et al 2020). The authors collected features from brain networks and utilized the F-score to determine which features were prominent in a DNN-based ASD detection technique. The features were then used as inputs to a deep learning-based classifier in the machine learning pipeline. Two stacked AEs and a SoftMax layer provided the classification output for the DL-based classifier (Yin et al 2021).

Conclusively, DNN cannot be utilized for specific data types. It can identify the classification, regression, and Language processing. It is used for structured datasets like tabular or unstructured data forms. However, CNN is more inclusively used in ASD detection because it can process and extract features from visual data like images and videos i.e. MRI and fMRI. CNNs are trained in the same way as DNN but they are specialized in learning hierarchical features from images and optimizing visual data.

Proposed approach

Due to its increased features, fMRI is being used widely for ASD detection rather than other MRI scans or modalities. It is can be used to extract the FC and ROI features from brain structure (Santana et al 2022). The papers included in this review used ML and DL algorithms to detect ASD with increased accuracy. Figure 2 briefly summarizes the process of ASD detection. The basic steps included dataset selection, preprocessing, feature extraction, model creation, computation, and validation. For preprocessing, maximum studies have used preprocessed data from Preprocessed Connectome Project (PCP), while few studies have performed minimal data processing steps for image enhancement and eliminating distortion (Jain et al 2023a).

The detailed information about each paper and its corresponding characteristics can be viewed in Table 2. It highlights the techniques, algorithms, and computation techniques used by different researchers. The prime goal of these studies was to develop a system or model that can be used to detect ASD with maximum efficiency. Furthermore, this review paper speaks briefly of ABIDE dataset and subjects, feature extraction, validation, and brain regions. Moreover, it also mentions different DL and ML approaches used for ASD detection, their network architecture and comparison of accuracy of each model (Subah et al 2021). DL has a variance type of architecture used to scout up Autism, which are CNN, ANN, and RNN architecture that are capable of detecting the disorder. ML algorithms frequently found in the research to detect ASD were KNN, RF, and SVM.

Classification of ABIDE dataset and subjects

The reviewed papers for this analysis have predominantly utilized the ABIDE dataset to develop their models. The ABIDE dataset comprises fMRI and demographic data on individuals with and without ASD. ABIDE-I includes data from 539 individuals with ASD and 573 control individuals from 17 different locations, while ABIDE-II comprises 521 ASD participants and 593 control subjects from 19 locations. Different studies have selected varying numbers of subjects for their analyses.

Although the ABIDE dataset has a total of 1,112 subjects, several studies have not utilized the entire dataset. Many studies have used a subset of 871 subjects, as shown in Table 2. This reduction is attributed to the quality inspection of the rs-fMRI data, which was visually

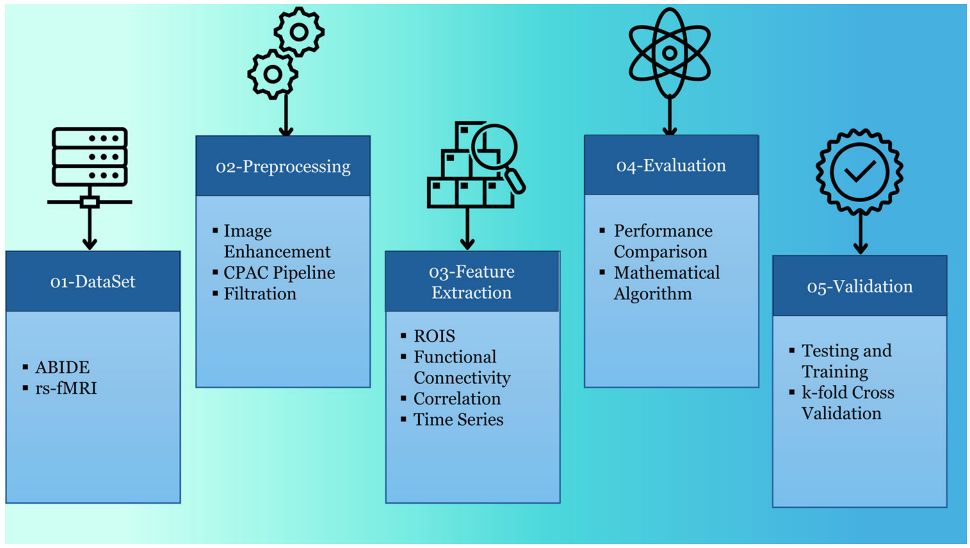

Fig. 2 Major steps in diagnosis of ASD

examined by three experts, leading to a refined dataset of 871 subjects (Shao et al 2021). This subset has been consistently used by various studies to maintain uniformity. However, some researchers have selected different numbers of subjects, such as 82 or 126, depending on the specific nature of their work.

The exact distribution of subjects used in each study, including those with ASD and typically developing controls (TC), can be viewed in Table 2. Some papers have also specified the gender distribution and age groups included in their analyses. The number of subjects is often limited due to factors such as data preprocessing steps, which may involve eliminating certain samples to ensure data quality and consistency. This highlights the critical importance of data preprocessing in neuroimaging research, as it directly impacts the reliability and comparability of study outcomes.

Brain regions

There are several, intricate connections between ASD and specific brain regions. Social impairments and repetitive behaviors are hallmarks of Autism Spectrum condition, a neurological condition (Liang et al 2021). People with and without autism have different brain structures. Different researchers found various regions in the brain studied using different MRI modalities but the most commonly used brain atlases are discussed below:

1. *AAL-Automated Anatomical Labelling* Anatomical features of a reference item are used to define 116 ROIs in this structural atlas. All three anatomical planes-the axial, sagittal, and coronal-have continuous color representations of ROIs Subah et al (2021). In the series of our reviewed papers, AAL atlas has been used in 7 papers that are Subah et al (2021), Santana et al (2022), Almuqhim and Saeed (2021), El Gazzar et al (2019), Lamani et al (2023), Karuppasamy et al (2022), and Benabdallah et al (2023).
2. *BASC-Bootstrap Analysis of Stable Clusters* A process known as bootstrap analysis of stable clusters was used to create this multi-scale functional brain parcellation atlas using rs-fMRI data. A variable number of ROIs-36, 64, 122, 197, 325, and 444-make up this composition. The papers that have utilized BASC atlas are Bayram et al (2021), and Yang et al (2022).
3. *CC200-Craddock 200* By using normalized cut spectral clustering to divide the whole brain into 200 spatially limited zones of homogenous functional activity, Craddock et al. produced the CC200 functional brain parcellation atlas. Papers that have worked with this atlas are Sherkatghanad et al (2020), Santana et al (2022), Almuqhim and Saeed (2021), Heinsfeld et al (2018), Yang et al (2022), and Lamani et al (2023).
4. *HO Atlas* Harvard-Oxford (HO) brain atlas is another probabilistic atlas that has many used by several researchers such as Almuqhim and Saeed (2021), El Gazzar et al (2019) and Benabdallah et al (2023). The probabilistic nature of this atlas determines the probability that each brain voxel belongs to a certain brain region.

It should be noted that several papers have utilized more than one brain atlas for the feature extraction process. This can be viewed from Table 2.

Feature selection

Features play a big role as inputs. They can impact how well the system classifies things, and they also help explain

Table 2 Main features of the included studies for review

	Dataset	Tech used	Subjects	Regions	Feature extraction	Model/ algorithm	Process evaluation	Splitting ratio	Validation	Performance
Subah et al (2021)	ABIDE	Colab notebook using python v3.6 (Keras, TensorFlow, Scitkit learn)	866 Subjects: 402 ASD 464 CS	1 Region: Brain Atlas	Time series extraction, ROI analysis, FC, 1D feature vector	DL: DNN	Binary cross-entropy loss function, L2 regularization	Training: 80% Testing: 20%	K-fold-CV K=5	Acc: 87.87%
Jain et al (2023a)	ABIDE	N/A	1112 Subjects: 539 ASD 573 TC	2 Regions: Cortical and sub cortical regions	GLM and RF, Entropy FC	DL: Deep CNN, 3D DNN	VGG-16 Network	Training: 80% Testing: 20%	K-fold-CV K=2,4,6,8,10	Acc: 99.83%
Liang et al (2021)	ABIDE	Python (Ubuntu) Intel Core i7 1050Ti GPU	1072 Subjects: 511 ASD 561 HCs	17 Regions	Time series analysis, FC, ROI analysis, correlation	DL: CNN (CNNPL) framework	D. Kendall Rank Correlation Estimation, Euclidean distance. Transfer learning strategy	10 subsets. Testing: 1 Training: 9	K-fold-CV K=10	Acc: 67.8%
Sherkatghanad et al (2020)	ABIDE	N/A	871 subjects: 505 ASD 530 TC	4 Regions: C115, C188, C247, C326	BCM, time series of the ROI, partitioned into 400 regions	DL: (CNN)	ML classifiers: SVM, KNN & RF (ROC) curve and CF	17 sites. Testing = 1 Training = 16	K-fold-CV K=10	Acc: 70.22%
Jain et al (2023b)	ABIDE I, ABIDE II	AFNI and FSL 5.0 for preprocessing; Deep learning (MobileNetV2 and DenseNet201)	N/A	236 Regions	Heat maps from FC matrices	DL: CNNs MobileNetV2 DenseNet201	Accuracy, sensitivity, precision, F1-Score for three age groups	N/A	N/A	Acc: 72.19%
Xu et al (2021)	Multiple MRI modalities	N/A	N/A	N/A	Gray matter & white matter volume, cortical thickness, surface area, fractional anisotropy, mean diffusivity, and FC	Both. CNN, and RNN. SVM, LR, decision trees	Performance metrics like accuracy, sensitivity, specificity, ROC curve area & statistical testing	N/A	CV	N/A
Yin et al (2021)	ABIDE I	AFNI and FSL for data preprocessing, DL techniques for feature extraction and classification	871 subjects: 403 with ASD 468 TC	264 regions	Spectrum of Laplacian matrices, assortativity, clustering coefficient, and average degree of brain networks	DNN for classification. Traditional ML algorithms like SVM & KNN for benchmarking	Performance metrics include classification accuracy and AUC. Models are compared for accuracy	N/A	N/A	Acc: 79.2% ML Acc: 74.6%

Table 2 (continued)

	Dataset	Tech used	Subjects	Regions	Feature extraction	Model/ algorithm	Process evaluation	Splitting ratio	Validation	Performance
Al-Hiyali et al (2021)	ABIDE	N/A	82 subjects: 41 ASD 41 NC	DMN area	CWT-generated scalogram images capture temporal dynamics	Pre-trained CNNs (ResNet-18, GoogLeNet, ResNet-101, DenseNet-201) SVM, and KNN	Models assessed with accuracy, sensitivity, specificity	N/A	N/A	DenseNet-Acc: 86.6% DenseNet-201 + KNN Acc: 86.6%
Feng and Xu (2023)	ABIDE	N/A	126 subjects: 56 ASD 70 TC	whole-brain rs-fMRI data without regional isolation	Conv2D layers, Batch Normalization, MaxPooling2D for dimension reduction	DL: CNN architecture	17,740 samples across 50 epochs and demonstrated diagnostic metrics	N/A	N/A	Acc: 99.39%, Recall: 98.80%, Prec: 99.85%, F1: 99.32%
Ahammed et al (2021)	ABIDE-I	N/A	N/A	N/A	DarkASDNet architecture	DarkASDNet	Precision, recall, F1-score, ROC curve, and AUC score	N/A	Validated through comparison with recent literature	Acc: 94.70%
Alsaade et al (2022)	Kaggle Platform, ImageNet Dataset	Processor core I7, 8GB RAM, TensorFlow, Keras, Panda Seaborn, Matplotlib, Numpy	2940 facial images: 65 samples collected	Facial Features Images	Matrix, Fine Tuning, Pooling Layer	DL: CNN	Xception, VGG19, NASNetMobile	Training: 86.39% Testing: 11.81%	N/A	Three Models Acc: 91%, NASNetMobile model: 78%
Bayram et al (2021)	ABIDE I	N/A	871 Subjects: 403 ASD 468 TC	Brain parcels, BASC	Correlation matrices, ROI parcellation schemes	DL: CNN, RNNs, LSTM, CNN-RNN	An edge between a pair of ROIs is usually weighted with the PCC. For this process, time-series of the brain network obtained	Use each data for both training and testing	K-fold-CV K=10	Acc: 81.4%
Santana et al (2022)	ABIDE I, ABIDE II	N/A	ABIDE I: 100 samples ABIDE II: 9 samples	2 Regions: AAL116 CC200	FC, PCC(MV/MT, RF, LR; LDA)	ML: SVM ANN	N/A	N/A	Split-sample validation, Temporal or geographic validation	L-SVM shows more sensitivity to the ANN
	Dataset	Tech used	Subjects	Regions	Feature Extraction	Model/ Algorithm	Process Evaluation	Splitting ratio	Validation	Performance
Sabegh et al (2023)	ABIDE I	N/A	1035 subjects: 505 ASD 530 TC	Anterior and posterior areas	FCof ROI's using rs-fMRI data	DNN	Performance comparison using SVM and RF	Training: 80% Testing: 20%	K-fold-CV K=10	Acc: 66%-71%

Table 2 (continued)

	Dataset	Tech used	Subjects	Regions	Feature extraction	Model/ algorithm	Process evaluation	Splitting ratio	Validation	Performance
Almuqhim and Saeed (2021)	ABIDE I	N/A	1112 subjects: 539 ASD 573 TC	(AAL), (HO) atlas, Craddock 2oo atlas	Correlation Matrix, Time series chi-square feature selection method	DL: (CNN)	Confusion matrix, Three statistical criteria: accuracy, sensitivity & specificity	N/A	K-fold-CV K=10	Acc: 73.53%
Heinsfeld et al (2018)	ABIDE I	N/A	1035 Subjects, 505 ASD 530 HC	200 s (ROIs) using (CC200) functional parcellation	Time series extraction, PCC	DNN	Pearson's correlations of 200 regions of the brain	Evaluation: 1035 testing separately	K-fold-CV K=10	Acc: 70.8%
Yang et al (2022)	ABIDE I	N/A	871 Subjects: 403 ASD 468 TD	CC400 and BASC444 atlases	Covariance matrix of each subject's time-series signal, ROIs time series, FC matrix	DNN	Comparison of four ML classifiers: LR, lSVM, kernel SVM kSVM, and DNN	Data: 5 parts. Testing: 1 part, Training: 4 parts	(FFCV)	Acc: 69.43%
El Gazzar et al (2019)	ABIDE	NVIDIA Pascal GPU	61% autistic, 25% Asperger, 14% PDD-NOS	3 Regions: AAL atlas, Schaefer Atlas, HO atlas	Mean time series within each ROI	DL: 1-D CNN	Motion correction, slice time correction, spatial smoothing, high pass filtering	Training: 70% Validation: 10% Testing: 20%	K-fold-CV K=10	Harvard Oxford provides the highest average test accuracy across sites and lowest variance
Lamani et al (2023)	ABIDE	Python Windows 10 OS, Intel i5 processor, 6GB RAM	ABIDE I: 539 ASD & 573 other ABIDE II: 521 ASD & 593 CS	3 Regions: CC200, CC400, AAL116.	FC, matrices of FC between pairs of ROI	DL: CNN GoogLenet, DenseNet201, ResNet18, ResNet101	Slice timing, motion, voxel intensity	Training loss 0.3014 Validation loss 0.3074	N/A	Acc: 92.22%
Wang (2021)	ABIDE	N/A	1112 Subjects: 539 ASD 573 TC	N/A	Connectivity matrices, Brain region correlations, PCC	DL:CNN	Accuracy analysis, Confusion matrix evaluation for binary classification	N/A	N//A	Acc: 95%.

Table 2 (continued)

	Dataset	Tech used	Subjects	Regions	Feature extraction	Model/ algorithm	Process evaluation	Splitting ratio	Validation	Performance
Karuppasamy et al (2022)	ABIDE	TensorFlow - 1.12.0 to implement an enhanced (CNN) for (ASD) identification from functional MRI data	857 Subjects: 416 ASD 441 TC	116 ROIs	PCC, flattening lower triangles into 1D vectors & applying PCA whitening for dimensionality reduction	DL: CNN	CNN architecture utilized changes in the convolutional kernel, activation functions (PReLU), pooling methods (mean and max), and classifiers (softmax and SVM)	N/A	K-fold-CV K=10	Acc: 84.44% Sensitivity: 85.39% Specificity: 80.57%
Yang et al (2019)	ABIDE	N/A	1035 Subjects: 505 ASD 530 TD	400 ROIs	FC of ROIs, Connectivity matrix, Python package nilearn	ML, LR, Ridge, LSVM	grid-search method was used. Comparison of four differed classifiers	N/A	K-fold-CV K= 5	Acc: 71.98%
Aghdam et al (2019)	ABIDE I, ABIDE II	Keras, TensorFlow Intel Core i7 CPU (2.2 GHz) and 16 GB DDR3 memory	ABIDE I:116 ABIDE II:343	N/A	Fourier Transform, Transfer learning	DL:CNN	Adam Adamax Optimization technique	N/A	K-fold-CV K=10	Acc: ABIDE I: 72.73% ABIDE II 70%
Thomas et al (2020)	ABIDE I, ABIDE II	N/A	1162 Subjects: 620 ASD, 542 Other	HO atlas	Regional homodenity, Amplitude of low frequency fluctuations, Degree centrality, Local FC density, Entropy, Auto-correlation	DL: CNN ML: SVM	N/A	Training: 90% Testing: 10%	K-fold-CV K= 5	Acc: CNN = 64% SVM = 60%
Benabdallah et al (2023)	ABIDE I	TensorFlow and Keras	N/A	AAL atlas	3D Connectivity Matrix, Correlation	DL:CNN	N/A	N/A	N/A	Acc: 90%

which parts of the brain are involved to some degree. The feature selection process helps in identifying the most suitable features for the used data. The correct selection results in improved the identification accuracy and a quick diagnosis. It also simplifies the data such that data trends can be easily extracted Guyon and Elisseeff (2003). Feature engineering involves optimizing the use of distinctive attributes within imaging data.

Geometric features like convexity and curvature, anatomical features like gray matter volume (GM) and white matter volume (WM), and cortical morphological features like cortical thickness and surface area are frequently used for structural imaging-based diagnosis to identify potential subtle structural changes of ASD (Xu et al 2021). Three types of feature building techniques exist: network-based, region-based, and voxel-based techniques. The feature is calculated at the voxel level in voxel-based techniques, and on multiple preset ROIs in region-based approaches. Multi-voxel or area interaction profiles are extracted as features using network-based techniques (Xu et al 2021).

1. *Time Series Extraction* As rs-fMRI measures BOLD signal activity at different time instances time series extraction is a suitable technique to study the data pattern. fMRI signal is a 4D signal with one dimension defining a number of time points and another specifying the number of ROI. This fMRI scan is reduced to a 2D-time series using the Python neuroimaging library Nilearn. Instead of extracting time series for the whole brain, certain ROIs are defined using brain atlases. The resulting 2D-time series defines two quantities, time points, and number of regions (Subah et al 2021).
2. FC is labeled to be the most suitable feature for functional data employed in ML experiments because they can highlight special relevance of ASD (Liu et al 2021).The temporal correlation of a neuro-physiological variable recorded in several brain regions within the framework of functional neuro-imaging is referred to as FC. Correlation between the mean values of the time series obtained from a ROI is shown by various matrices such as functional connectivity, brain connectivity, covariance matrix, and co-relation matrix. A connectivity matrix is used to show correlation between different brains regions or ROIs as defined by the corresponding brain atlas (Subah et al 2021). This matrix contains time series points as fMRI scan is based on time series data (data at several instants). The matrix is based on correlation of mean values of time series. The row represents ROI whereas column shows PCC (Sherkatghanad et al 2020).
3. *Covariance Matrix* Covariance Matrix is another method to define FC like PCC. The sample covariance matrix is extracted from the time points of the fMRI signal. By using Covariance and Inverse Covariance Matrices, the coefficients of Partial Correlation are calculated easily. A tangent space matrix is also created using this covariance matrix. Firstly a group covariance matrix is constructed by mean influence on the covariance matrix. Then the transpose and negative fractional powers of the group covariance matrix are calculated and multiplied with each to obtain a product. The covariance matrix is diagonalized by this product and then the matrix logarithm is calculated after this (Yang et al 2022).
4. *CWT (Continuous Wavelet Transform)* Another common method is CWT (Continuous Wavelet Transform). CWT has gained popularity as a method in bio-sign analysis (Al-Hiyali et al 2021). CWT is an approach based on Convolution technique. The convolution of bold signal with mother wavelet lies under CWT where mother wavelet used is simplified by scaling and translation. This convolution captures how the BOLD signal varies across different scales and time translations.
5. *VGG-16* According to Jain et al (2023a), VGG-16 was used for the feature extraction process as it is a suitable method for a dataset based on image features. The defined architecture of VGG-16 features an input layer, convolution layers, pooling layers, fully connected layers, and output layers. To apply a transition to the input layer, the Convolution layer is used to introduce linearity, and the ReLU activation function is used to introduce non-linearity. This combination positively influences the performance of the network. VGG-16 architecture is based on tiny kernels with more layers as adding more layers can extract complex and minute features. With every additional layer, the depth of the network increases resulting in an improved feature extraction process. With the depth increase, higher accuracy can be achieved Jain et al (2023a). This augmentation of layers with numerous weight layers contributes to improved performance. Furthermore, VGG offers multiple options for creating various architectures with the same underlying concept. The feature extraction in this context involves extracting ROI based FC features using the VGG16 architecture. VGG16, being a DNN, effectively captures the dataset characteristics for image feature extraction. Its architecture, comprising convolutional, fully connected, flat, and pooling layers, proves advantageous for extracting features, especially in scenarios involving complex backgrounds and large- scale datasets.
6. *Fast Fourier Transform* Fast Fourier is used for the dimension reduction of an MRI scan from 4D to 2D. Firstly the 4D sMRI signal is reduced to 3D by

extracting a 2D spatial slice of each sMRI around a specific time point. Then Fast Fourier transform is applied to the time dimension of each 3D image and the highest frequency component of each voxel to transform the image from 3D to 2D (Aghdam et al 2019).

Feature reduction

Due to the curse of dimensionality, which occurs frequently in medical imaging analysis when the dimensionality of the features greatly exceeds the number of samples, feature reduction is an essential and crucial step for neuroimaging studies Xu et al (2021).Effective feature reduction not only minimizes redundancy and noise but also aids in comprehending the neural underpinnings of a disease. There are two types of feature reduction techniques: supervised and unsupervised. Supervised methods, which can be further divided into filter, wrapper, and embedding approaches, require training labels to select informative and discriminative features. Principal component analysis (PCA), recursive feature elimination (RFE), T-test, autoencoder (AE), conditional random forest (CRF), Chi-squared, and least absolute shrinkage and selection operator (LASSO) are a few techniques that have been used in research papers in the past. The Chi-Square method quantifies the degree of association between two variables, allowing the selection of features that show connections with the target variable. The method computes the Chi-Square statistic that is defined as the difference between observed and expected frequencies. It uses those categories that are present in the contingency table. Chi-Square is appropriate when dealing with categorical features and a categorical target variable, often seen in classification tasks.

Discussion

This section presents the comparison of different characteristics and features used to review the papers. The first subsection focuses on the number of papers published in different years. Second subsection presents a comparison between accuracy of models and number of subjects used. The third subsection highlights how many papers worked with DL models and how many focused on ML algorithms. The next subsection shows different distributions of ASD and TC subjects used. The last section shows different types of DL and ML algorithms that have been mentioned in the papers.

Number of papers published yearly

This section gives a detailed report on the ASD research established in different years. With the rapid development in technology and AI, different studies have started working on automated diagnosis of ASD (Subah et al 2021). Since 2017, different approaches for ASD detection using fMRI and DL are being studied Moridian et al (2022). To make sure that the most recent information is utilized for improved accuracy, this paper focuses on papers published between 2018–2023. Figure demonstrates that there has been maximum development in 2021 and later years in this field. This shows that in recent years, the development of automated ASD diagnosis has increased (Fig. 3).

Accuracy and number of subjects

The accuracy of any model depicts how efficiently it can distinguish between ASD and TC patients. A comparison has been shown between the accuracy obtained and several subjects. The number of samples that are being used to train the model does affect the accuracy of the model. The Fig. 4 shows different number of subjects and their corresponding accuracy.It can be observed that papers that utilized lower number of subjects attained accuracy above 0.9. The average accuracy is around 0.82. This shows that for future work maximum number of subjects should be utilized while aiming for higher accuracy.

Comparison between DL and ML technique

However, according to the papers reviewed for this analysis, most of the cases were based on DL techniques. Figure 5 depicts a similar fact. The reason for more focus on DL is that it offers accurate detection as compared to ML algorithms. Many DL models were able to outperform the previously built models in terms of accuracy and efficiency. The detailed discussion about different models and algorithms has been covered in section 3. Few papers have covered both DL and ML algorithms in different ways. The compared accuracy of these models is mentioned in Table 2.

Number of ASD and TC samples

To show how different researchers have divided or used their data into ASD and TC, a short comparison has been shown for each reference used in Fig. 6. Few models have used samples from both ABIDE-I and ABIDE-II. In all the cases, approximately equal number of ASD and TC patients are considered. A slight difference has been observed in all the cases which is shown in Fig. 6.

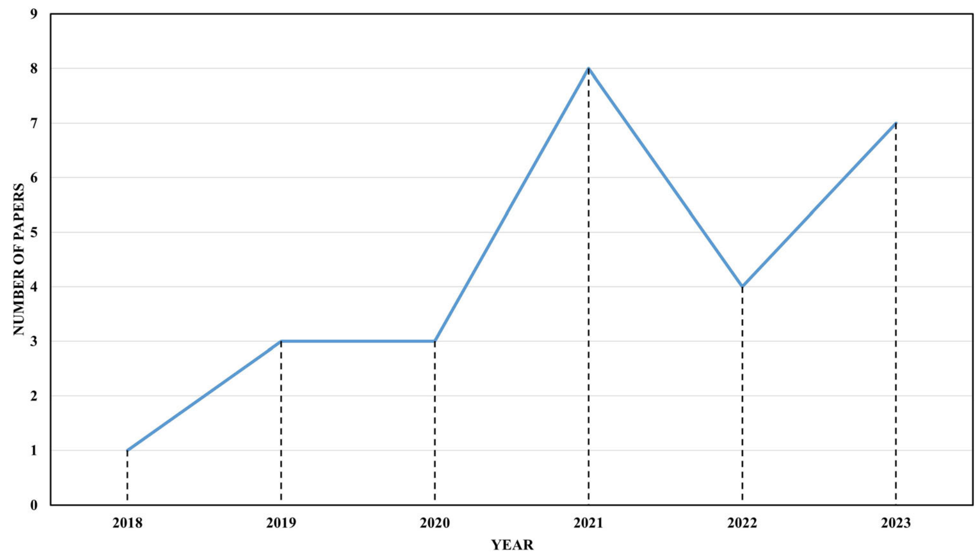

Fig. 3 Comparison of number of papers published between 2018 and 2023

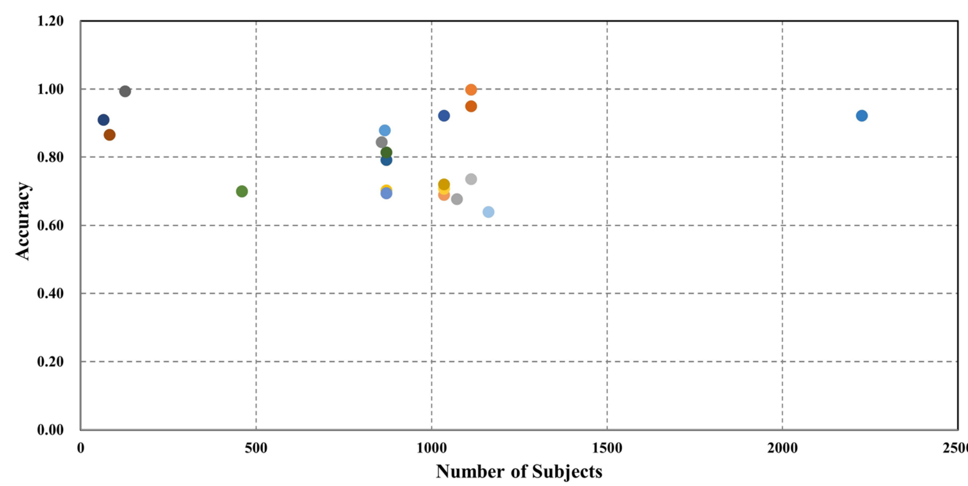

Fig. 4 Comparison of Accuracy and Subjects

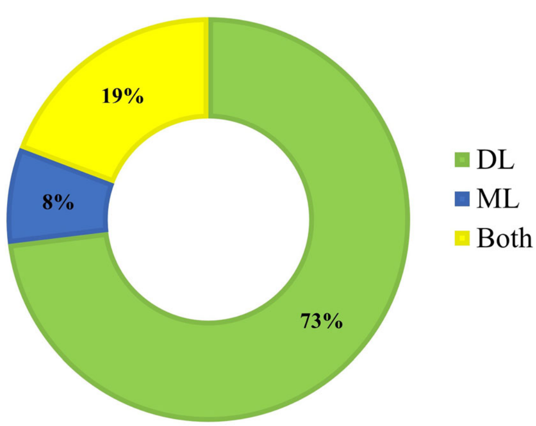

Fig. 5 Comparison of DL and ML Models

Comparison of models

The most commonly used ML and DL techniques for automated diagnosis of ASD are SVM, DNN, and CNN. All these models are built on different network architectures, hence they have different evaluation processes and corresponding efficiencies. DL and ML techniques that have been utilized by various researchers for ASD detection are covered in Fig. 7. It can be observed that in many cases where DL algorithms are used, the accuracy is little less than other models. Hence, the upcoming work needs to target accuracy of DL models in detecting ASD.

Comparative analysis

This section provides a summarized Analysis of the trends and patterns that have been observed in this systematic review.

1. *Publication trends*

    (a) It can be seen that there has been significant improvement in the work on ASD detection using DL and ML since 2017.

(b) The maximum number of papers have been published in 2021.
(c) This increasing trend in the studies ensures that in the near future early diagnosis of ASD will be implemented frequently.

2. *Accuracy versus number of subjects*

(a) It has been observed that papers that utilized less number of subjects were able to give models with higher accuracy such as Feng and Xu (2023) utilized 126 subjects and got an accuracy of 0.99. This shows smaller datasets corresponds to over fitting.
(b) The maximum average accuracy in these studies is around 0.82. Hence the future work may target ways to improve this accuracy even more.

3. *DL versus ML*

(a) It was observed that most of the papers utilized DL algorithms because DL algorithms are more suited for large datasets as compared to ML algorithms.
(b) But even in DL algorithms, there is still room for improvement in accuracy and other metrics.

4. *Algorithm performance*

(a) The most commonly used algorithms are SVM, DNN and CNN.

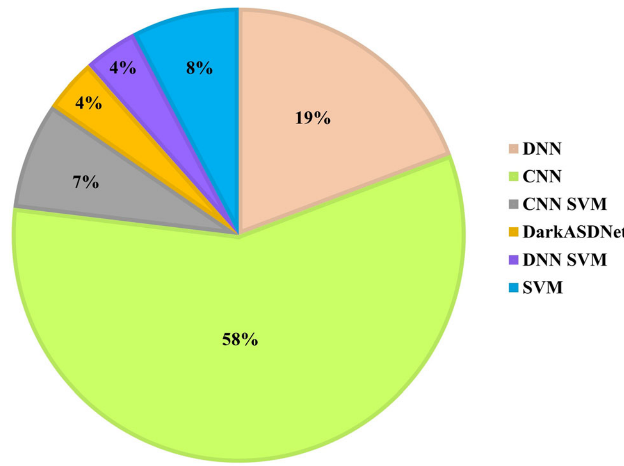

Fig. 7 Comparison of Models/Algorithms Used

(b) The future work should address the limitations of these algorithms and develop such architecture that can detect ASD with higher accuracy.

Recommendations

There has been significant progress in ASD detection through the use of advanced AI algorithms, including deep learning and machine learning. However, future research should focus on several key areas to enhance and expand upon existing methodologies.

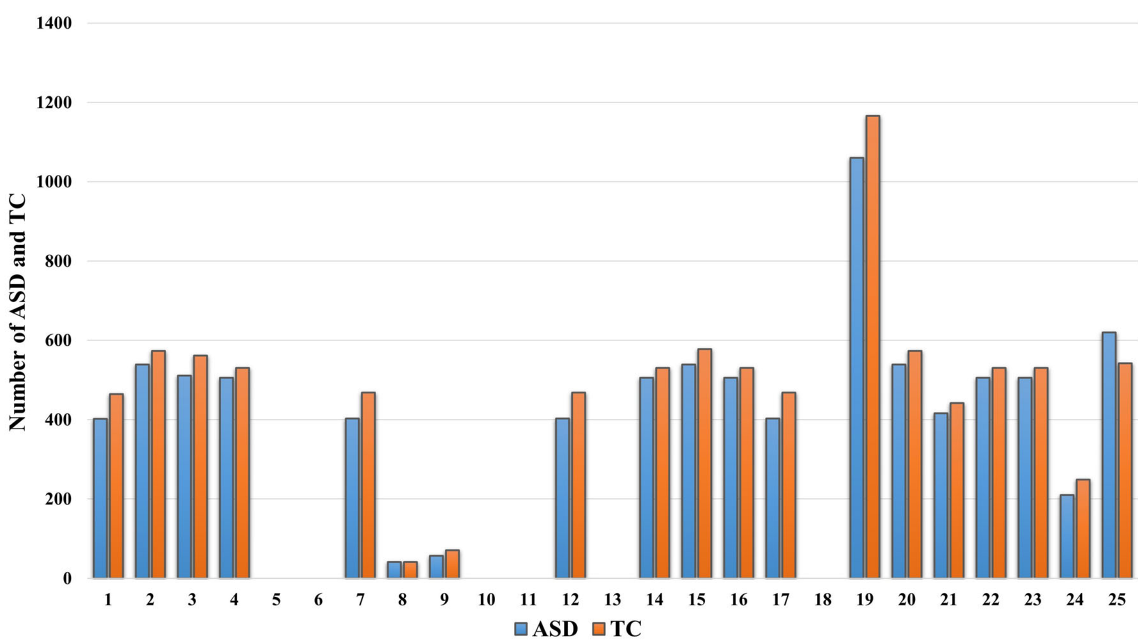

Fig. 6 Distribution of ASD and TC subjects

Firstly, integrating IoT cloud platforms for data storage, visualization, and remote medical consultation represents a promising direction for future work. Implementing a system where fMRI data from patients can be uploaded and securely stored on a compatible cloud platform would enable comprehensive processing and remote sharing of diagnostic results. This setup would facilitate timely and efficient communication of diagnostic reports to patients and enable collaborative consultations with other medical professionals, thereby enhancing the treatment planning process. It is also imperative to implement robust security measures to protect patient data on cloud platforms.

Secondly, the review highlights the prevalent use of the ABIDE I dataset across many studies. While ABIDE I offers a diverse dataset collected from 17 different universities, its complexity due to varying parameters and time points used by each institution poses challenges for data processing. To mitigate these challenges and improve ASD diagnosis methods, future research should explore alternative datasets beyond ABIDE I. Diversifying the datasets used in ASD detection studies will likely contribute to more robust and generalizable diagnostic models.

Furthermore, advancing ASD diagnosis methods for real-time detection is crucial. Deploying the developed models onto suitable hardware devices can transform them into portable detection tools, facilitating real-time assessment. Additionally, alongside the algorithm development, creating a user-friendly interface is essential. Such an interface would enhance usability for both doctors and patients, ensuring that the technology is accessible and practical in clinical settings.

Conclusion

This review paper provides a comprehensive examination of the ongoing advancements in the automated diagnosis of Autism Spectrum Disorder, a neurological condition commonly diagnosed in children aged between 6 and 17 years. ASD affects brain connectivity, leading to symptoms such as social anxiety and lack of confidence. Early diagnosis and intervention can significantly mitigate the impact of ASD.

The study primarily utilized the publicly available ABIDE I dataset, which has been extensively used by researchers to enhance ASD diagnostic methodologies. ABIDE I, featuring resting-state functional MRI data, serves as a critical biomarker for brain connectivity, capturing brain activity across different time points. The advent of artificial intelligence, particularly machine learning and deep learning, has significantly advanced the field of automated ASD diagnosis.

Following a systematic review approach guided by PRISMA guidelines, this paper offers a thorough overview of ASD, DL, and MRI in its introductory section, setting the foundation for a detailed exploration of the subject. Covering the period of last five years, this review not only consolidates recent advancements in ASD research but also provides direction for future investigations, promoting innovative approaches for automated ASD diagnosis.

Key findings from this review highlight notable progress in automated ASD diagnosis studies. Numerous papers published since 2017 showcase various architectural frameworks aimed at ASD identification. The ABIDE dataset emerges as a prevalent choice among researchers, maintaining consistent distribution between autistic and control classes. Notably, DL models, particularly Convolutional Neural Networks and Deep Neural Networks, are more frequently recommended over traditional ML algorithms for ASD detection. The average accuracy reported across these studies is approximately 0.82, indicating the need for future research to focus on enhancing diagnostic accuracy for more reliable outcomes.

Future research on ASD diagnosis using DL and ML techniques should prioritize the exploration of additional datasets beyond ABIDE to improve efficiency and accuracy. Furthermore, models developed for ASD prediction should be designed for real-time detection. This can be achieved by integrating the models into portable devices or user-friendly interfaces, facilitating practical use for healthcare professionals and enhancing diagnostic capabilities.

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Data availibility Not applicable.

Declarations

Conflict of interest The authors have declared that no Conflict of interest exist.

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