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Comprehensive Autism Spectrum Disorder Analysis: ML and DL Models in Multimodal Datasets

Kambham Sravani, Kuppusamy Pothanaicker*

School of Computer Science and Engineering, VIT-AP University, Amaravathi 522237, India

Corresponding Author Email: drpkscse@gmail.com

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ABSTRACT

Autism Spectrum Disorder (ASD) represents a multifaceted neuro-developmental state that presents significant difficulties in its early identification and intervention. This survey explores the recent advancements and methodologies in ASD detection leveraging Machine learning (ML), Deep Learning (DL), and Neuroimaging techniques. An extensive survey of literature between 2018 and 2023 reveals a paradigm shift in diagnostic approaches, emphasizing the integration of ML algorithms, like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and decision-making models, in conjunction with various neuro-imaging modalities like Magnetic Resonance Imaging (MRI), Electroencephalography (EEG), and Functional Near-Infrared Spectroscopy (fNIRS). These modalities facilitate the identification of distinctive biomarkers, behavioral patterns, and neural correlates associated with ASD. The survey also looks at potential ethical issues, the importance of early detection using ML-driven methodologies, and the changing diagnostic tool landscape that aims to offer timely and individualized interventions for people with ASD. The combination of these data demonstrates the revolutionary effect of ML, DL, and neuro-imaging in improving the accuracy of ASD detection, allowing access to additional potent intervention methods and a more thorough understanding of the neurobiology underlying the condition.

1. INTRODUCTION

ASD is a complex and multifaceted neuro-developmental disorder that impacts the way individuals perceive, and interact with the world around them. Since every individual with autism has a unique experience, autism is classified as a spectrum disorder. While some autistic individuals can live well in the community without ongoing supervision or assistance, others have significant difficulties. The term "autism" is derived from the Greek word "autos", signifying "self". ASD presents a wide spectrum concerning severity, risk levels, and responses to treatment. It typically begins in early childhood and extends into adulthood. ASD is not just a personal or familial concern; it has significant societal implications due to the considerable support and resources required for individuals across the spectrum. Research indicates that identifying and addressing ASD during the early developmental stages is advantageous, as it minimizes treatment costs and duration [1].

A child or individual with autism receives a diagnosis primarily due to challenges in social interaction, communication (both verbal and non-verbal), and repetitive behaviors. ASD is increasingly common in the world we live in. The World Health Organization (WHO) approximates those one out of 68 children is affected by ASD. As a result, over 68 million individuals worldwide, including over 2 million in the US alone affected with ASD. The rising prevalence underscores the urgent need for effective diagnostic and intervention strategies. For children with autism, the better the outcome, the earlier treatment starts. Early intervention can significantly enhance developmental trajectories, reduce the severity of symptoms, and improve overall quality of life. Analysis of autism has been done through the exploration of ML. Employing ML algorithms, the researchers classified the data of individuals with autism and those without it, considering significant features and data gathered from the parents' questionnaires [2].

The co-occurring conditions that ASD sufferers deal with are another interesting aspect that urges further investigation. Among the main life issues that an ASD manages are depression, anxiety, and sensory issues. Disorganization, forgetfulness, trouble finishing tasks, and a lack of focus and attention are some of the symptoms associated with ASD. ASD sufferers also struggle with poor decision-making abilities and a lack of emotional control, which has a detrimental impact on a variety of areas of life, such as relationships, work, and education. These comorbid conditions complicate the diagnosis and treatment of ASD, making it even more crucial to develop accurate and comprehensive diagnostic tools. Among the signs and traits that set an individual with ASD apart from someone without being language impairment, hyperactivity, and brain functioning [3].

Early on, ASD symptoms appear when a child shows warning signs in meeting age milestones, the parents are the ones who first notice these symptoms. Identifying children with autism can be challenging for doctors because of the age factor. The onset of symptoms may occur in infancy, adolescence, or adulthood. The rate of autism is currently rising quickly on a global scale. Millions of dollars are spent annually on ASD treatment. This growing financial burden highlights the economic importance of early and accurate diagnosis and intervention. Boys were four times as likely as girls to receive an ASD diagnosis, as evidenced by the data, which shows that autism is more commonly observed in boys than in girls [4].

Various methods for discovering patterns in data and optimizing parameters rely on advanced technologies and clever reasoning. This comprises an organized approach to dissect the problem, identify the hidden patterns, eliminate extra information, and devise a solution. This causes us to refocus on the advantages of AI, ML, and DL which are collections of techniques and algorithms that enable a model to learn independently from available data [5]. ML and DL techniques offer a transformative potential for ASD diagnosis by providing tools that can handle large volumes of data and identify subtle patterns that might be missed by traditional methods.

ML techniques can learn high-level relationships among different features by using multiple voxels as input, thanks to univariate techniques. These approaches can identify the distinctions between a disease and a control group, indicating a different approach to analysis. Several mental health disorders, such as schizophrenia and ADHD, can be accurately classified using ML techniques. There are four types of ML: semi-supervised, supervised, reinforcement learning, and unsupervised. Making sure the model's capacity to predict unseen data, utilizing the labelled dataset employed for training is the goal of the supervised method. Unlabelled data was exposed to an unsupervised learning model with minimal supervision [6]. By leveraging these techniques, researchers aim to develop models that can reliably predict ASD, facilitating early intervention and personalized treatment plans.

1.1 Rationale for the timeframe: 2018-2023

The decision to limit this review that the studies published between 2018 and 2023 was based on several critical factors. This period marks a significant phase in the development and application of ML and DL techniques, particularly in the field of ASD detection. Key advancements during this time have substantially influenced the accuracy, efficiency, and applicability of these technologies in diagnosing ASD.

1.1.1 Key developments and shifts in ML/DL techniques (2018-2023)

Advancements in ML/DL Techniques: Between 2018 and 2023, there have been substantial improvements in ML and DL algorithms, including the development of more sophisticated neural network architectures, optimization techniques, and training methodologies. These advancements have enhanced the capability of models to process complex datasets, leading to more accurate and reliable ASD detection.

- Increased Availability of Data: The past few years have seen a significant increase in the availability of large, high-quality datasets for ASD research. These datasets have enabled the training of more robust ML/DL models, improving their generalizability and performance in real-world scenarios.
- Integration of Multi-Modal Data: Recent studies have increasingly utilized multi-modal data (e.g., text, images, videos) to improve the accuracy of ASD detection. This integration of diverse data types has been made possible by advances in ML/DL techniques that can handle and analyze multi-modal inputs more effectively.
- Focus on Early Detection: The period from 2018 to 2023 has seen a heightened focus on early detection of ASD, driven by the recognition of the significant benefits of early intervention. ML/DL models developed during this period have been specifically designed to identify early signs of ASD, contributing to more timely and effective interventions.
- Interdisciplinary Collaboration: There has been an increase in interdisciplinary collaboration between computer scientists, clinicians, and researchers, leading to more comprehensive and impactful studies. This collaboration has facilitated the development of ML/DL models that are better aligned with clinical needs and practices.

1.2 Motivation

Exploring ASD using advanced technologies like ML and DL excites and motivates us to start our research. We'll use these technologies to study various data types such as text, images (like brain MRI scans, facial expressions, gestures), and videos. This new approach will help us gain valuable insights into ASD, making our research more comprehensive and innovative. Our excitement lies in the potential of these advanced techniques to revolutionize ASD analysis, enhancing our capacity to make a positive impact in this field and potentially transform the way ASD is understood and managed.

1.2.1 Research questions and hypotheses

To guide this review, the following specific research questions and hypotheses are addressed regarding the application of ML/DL for ASD detection:

- Research Question 1: How effective are ML and DL algorithms in accurately diagnosing ASD compared to traditional diagnostic methods?
  - Hypothesis 1: ML and DL algorithms can achieve higher accuracy in diagnosing ASD by identifying subtle patterns and features that are often missed by traditional diagnostic methods.
- Research Question 2: What are the most significant features and data types (e.g., text, images, videos) used by ML and DL models in detecting ASD?
  - Hypothesis 2: Combining multiple data types enhances ML and DL models in ASD detection by providing a comprehensive view. Key features include language and communication patterns, behavioral assessments, and clinical notes for text data; facial recognition, neuroimaging, and handwriting analysis for image data; and activity recognition, social interaction assessment, and speech patterns for video data.
- Research Question 3: How do different ML and DL models compare in terms of performance metrics (e.g., accuracy, sensitivity, specificity) for ASD detection?
  - Hypothesis 3: Advanced DL models, such as CNN and

Recurrent Neural Networks (RNNs), outperform traditional ML models in detecting ASD due to their ability to capture complex patterns and temporal dependencies.

- Research Question 4: What are the current limitations and challenges in applying ML and DL techniques to ASD detection, and how can they be addressed?
  - Hypothesis 4: Current limitations, such as data scarcity, variability in data quality, and model interpretability, can be mitigated through techniques like data augmentation, transfer learning, and explainable AI.

This study primary goal is to examine different ML and DL methods for patient identification of ASD in addition to how previous studies incorporated them into model building. As a result, we are better able to understand how ML affects healthcare and how it can assist medical professionals by producing accurate predictions. Our primary contributions to this study are as follows:

- An understanding of how ASD can be identified using ML and DL.
- The thorough examination of ASD leveraging ML and DL models.
- Discussed ASD-ML in addition to DL-based research conducted from 2018 to 2023 to stimulate more research in the previously mentioned field.
- Comparison using various risk metrics, such as datasets, DL models, and ML models.

This paper follows the structure outlined below. Basic information about ASD and its symptoms is provided in Section 2. This section also includes the presentation of the ML and DL along with their evaluation metrics. It shows the criteria used to select the information from different research studies. In Section 3, A variety of ML and DL algorithms have been employed to analyze ASD detection using a text dataset along with the table. Section 4 presents a thorough examination of ASD detection based on Image datasets using a variety of ML and DL algorithms combined with a tabular comparison. An analysis of the video dataset for ASD detection is covered in Section 5. Section 6 encompasses the DL and ML-based ASD Identification and its workflow. The conclusions from our examination of text, image, and video datasets about ASD disorders are presented in Section 7.

2. ASD AND ML

2.1 ASD signs and indicators

People with ASD may struggle with having enjoyable distractions, dullness, as well as social situations. They may also struggle to focus in class or obey instructions. These characteristics could make daily tasks challenging. It is significant to remember that some people may display comparable symptoms even in the absence of an autism spectrum condition.

Interaction and Social Communication Skills:

- Does not recognize their name by the age of nine months.
- Refuses to make eye contact.
- Does not exhibit emotional expressions (happy, sad, enraged, etc.) by the age of nine months.
- By the time they are 12 months old, they seldom ever make gestures (like waving goodbye).
- By the time they are 15 months old, do not play well with others (for instance, display to you something they find enjoyable).
- Shows no signs of emotional sensitivity at 24 months old.
- By 36 months of age, neither initiates play nor engages in interactions with other kids.
- Cannot complete the task in 60 months.

Limited or Continual Interests or Behaviors: People across the spectrum could exhibit odd hobbies or behaviours. These differentiate ASD from conditions characterized solely by problems through social interaction and communication as shown in Figure 1. The following are some examples of pastimes and pursuits that may be limited or repetitive as a result of the autism spectrum condition:

- Overreacts to little variations in the way his or her toys or other belongings are arranged.
- Concentrates on specific portions of objects (wheels, for example).
- Uses the same words or phrases repeatedly (Echolalia).
- Animated by little changes.
- Has peculiar sensory responses to sounds, tastes, scents, and touches in their environment.

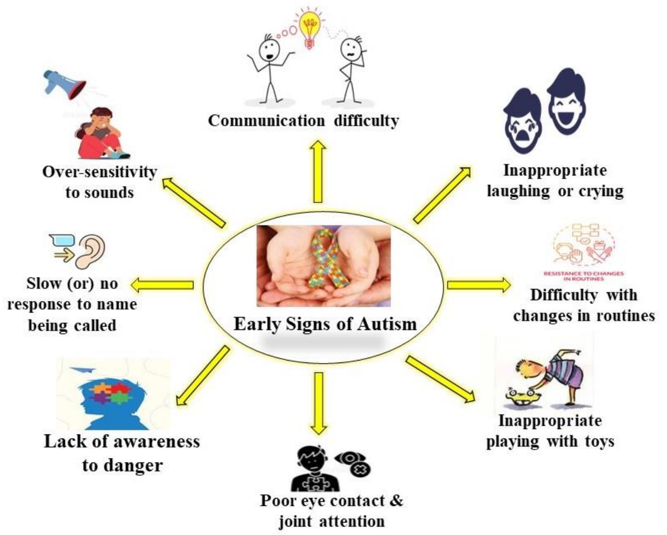

Figure 1. ASD symptoms

There are other symptoms as well, such as irregular sleep and eating schedules, digestive issues including delayed language development, delayed motor development, delayed cognitive or learning development, constipation, anxiety, stress, excessive or lack of fear, etc. [7].

2.2 Reasons and potential hazards

Although the precise causes of ASD are unknown, research has demonstrated that a person's development can be significantly influenced by both genetic and environmental factors, which may lead to the disorder. ASD has been connected to several circumstances, including having an older parent, a sibling with the illness, a particular genetic disorder (e.g., Down syndrome, fragile X syndrome), or extremely low birth weight.

2.3 Diagnosis approaches of ASD

Healthcare providers can evaluate a patient's likelihood of having ASD by keeping an eye on their growth and behavior. By the time a child is two years old, an accurate diagnosis of ASD can usually be made. It's critical to receive a diagnosis as soon as possible [8].

Diagnoses in Early Childhood: There are two stages in the diagnosis process for young children:

During healthy-child visits, general development screening: A paediatrician or other early childhood health care provider should examine every child. At the ages of nine, eighteen, twenty-four, or thirty months, all children should have a developmental delay screening. Additional screening may be done on a child if they are highly susceptible to developmental problems or ASD. Children with aging parents, ASD-related behavior, an ASD family member, Low birth weight, and genetic disorders are regarded as high-risk factors [9].

The physician may combine inquiries regarding the child's conduct with the results of an ASD assessment, and clinical findings of the child to assess the child.

Further Diagnostic Assessment: Children with ASD must receive an early and precise diagnosis because it will highlight their unique skills and challenges. Using this information, parents can then choose the educational and behavioral therapy programs and services that will best support their child's success.

The diagnostic evaluation will most likely consist of neurological and medical testing, a cognitive skills assessment, a language skills assessment, observation of the child's behavior, and other methods.

Diagnosis of adolescents and older children: Parents and teachers of school-age children and adolescents frequently notice the first indications of ASD. Following an initial evaluation, the student may be recommended for further testing by the department of special education at the school, their regular physician, or an expert in ASD.

Using subtleties in language can make it challenging to read silent signs like facial expressions, body language, and voice tone. Witter, humour, and metaphor may be difficult for older children and teenagers. They might also have trouble connecting with kids their age.

Adult diagnosis: Adults with ASD have far more diagnostic challenges than children do. Among the indications and manifestations in adults is ADHD, ASD may also be present in people with anxiety disorders or ADHD.

Adults who exhibit symptoms that align with ASD should consult a doctor to receive a diagnosis. As part of the examination, other family members or caregivers could be questioned to find out additional details regarding the person's early stages of development. This would subsequently enable a precise diagnosis.

Therapeutic measures: Treatment for ASD should start as soon as it is practical after diagnosis. It's critical to start ASD treatment early due to appropriate resources and assistance, people may decrease their difficulties and learn new skills while making the most of their strengths. Working closely with a healthcare provider can help to find the ideal mixture of services and treatments.

Pharmaceutical: A Pharmaceutical may be prescribed by a doctor to address particular symptoms. An individual with ASD may experience a reduction in various issues such as irritability, aggression, hyperactivity, repetitive behavior, anxiety, and sadness when taking medication [10].

Interventions in behavior, psychology, and education for a child with ASD may benefit from the recommendation of a medical professional who focuses on offering therapeutic services that are behavioral, psychological, educational, or skill-building. Siblings and other family members are often involved in these programs as well as caregivers. These programs may be helpful for individuals with ASD who wish to: Create social, language, and interpersonal relations and build on their advantages.

2.4 Both DL and ML

ML: ML is a sub-field of AI that mimics human decision-making in machines, through the use of intricate computational algorithms, which seek to "train" machines to analyze big datasets in a fast, accurate, and effective manner. ML is typically divided into three major categories [11]. The subject of this paper is ML algorithms, both supervised and unsupervised.

Supervised learning: Another name for this is predictive learning. In this instance, a labelled dataset is used to train an ML algorithm containing the required inputs as well as outputs. During training, the algorithm picks up notes that will aid in its prediction-making.

Unsupervised learning: Unsupervised learning algorithms aren't trained on labelled datasets. Without human assistance, they must extract insights and hidden patterns from the data that has been provided.

Reinforcement learning: Another name for reinforcement learning is reward-based learning. Here, the algorithm picks up new skills by interacting with the outside world, acting in certain ways, and observing the outcomes. Every right move will earn the algorithm a reward, and every wrong move will cost it a penalty [12].

DL: Natural language processing relies on Artificial Neural Networks (ANNs). DL techniques outperform ML algorithms and data analysis techniques in numerous situations. By including more neurons and layers, DL evolved from the application of neural networks. The middle layers take in data, process it through various functions, and then output the results to the layers below. The middle layers are referred to as hidden layers, while the first and last layers are called input and output layers, respectively. The layers in the DL architecture include input, convolutional, activation, fully connected, sequence, normalization, drop-out, pooling, combination, and output layers [13].

Metrics for evaluating the performance of models: Numerous metrics are available for evaluating the model's performance. It is important to select metrics carefully when evaluating the model's performance because:

- All model comparisons and measurements are determined by metrics.
- Ultimately, the selected metric will greatly influence the relative importance of various attributes.

Confusion matrix, recall, F1-score, AUC, specificity, accuracy, and precision were the most often utilized metrics for assessing model performance [14].

2.5 Determining data inclusion parameters

This study thoroughly examined how ML techniques aid in the prediction of ASD. We created a keyword that is closely associated with ASD detection by employing the phrases below to widen the search parameters: (Text-based analysis OR Image analysis (Brain MRI OR Facial Expressions OR Gesture and Postures) OR Video analysis) AND (autism identification OR intervention OR detection OR diagnosis classification) AND (ML OR AI OR DL). We have compiled data from articles published by IEEE, Google Scholar, Springer, Scopus, and Elsevier between 2018 to 2023.

As part of this survey, we examine the effectiveness of various ML and DL algorithms for diagnosing ASD disease by examining prior research conducted by researchers. An ML model is assessed by employing multiple metrics, including sensitivity, specificity, accuracy, and f1-score. The dataset and the ML model influenced the model's overall performance, regardless of the metric that was used.

2.6 Taxonomy

This research has shown that the current methods for detecting ASD have been thoroughly studied.

Our main contributions to this survey:

- A thorough analysis of the ML and DL models utilized in ASD is listed in this survey.
- In this survey, the main performance evaluation metrics for ASD are examined, and the effectiveness of well-known ASD algorithms in DL and ML models is examined.
- The ASD detection techniques used in recent years are detailed in this survey.
- This is the first comprehensive analysis that we are aware of ML techniques for ASD.

This breakdown represents the distribution of various methods or data types used in autism-related research as shown in Figure 2. Brain MRI comprises the largest percentage, representing approximately 49% of the methodologies utilized. Following that, text-based analysis makes up around 21%. Facial expression data accounts for roughly 19% of the methodologies. Gesture and posture recognition constitute a smaller portion, approximately 2%, while video analysis represents about 9%.

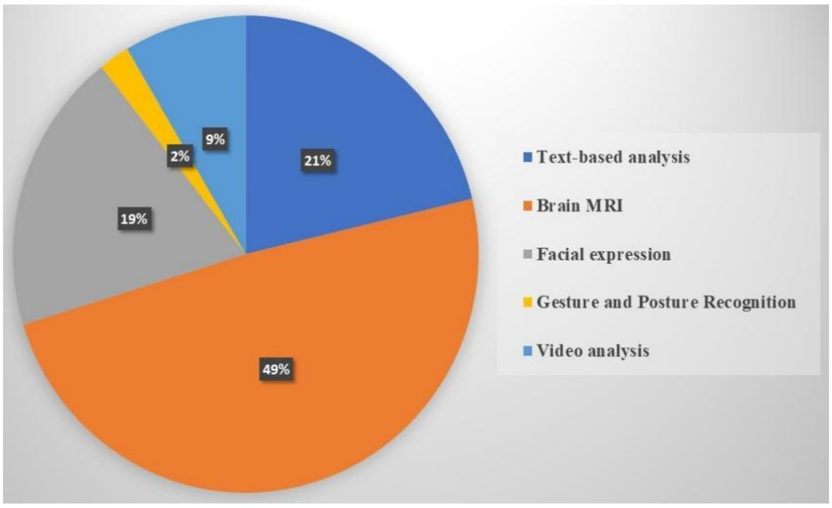

Figure 2. Analysis of ASD dataset

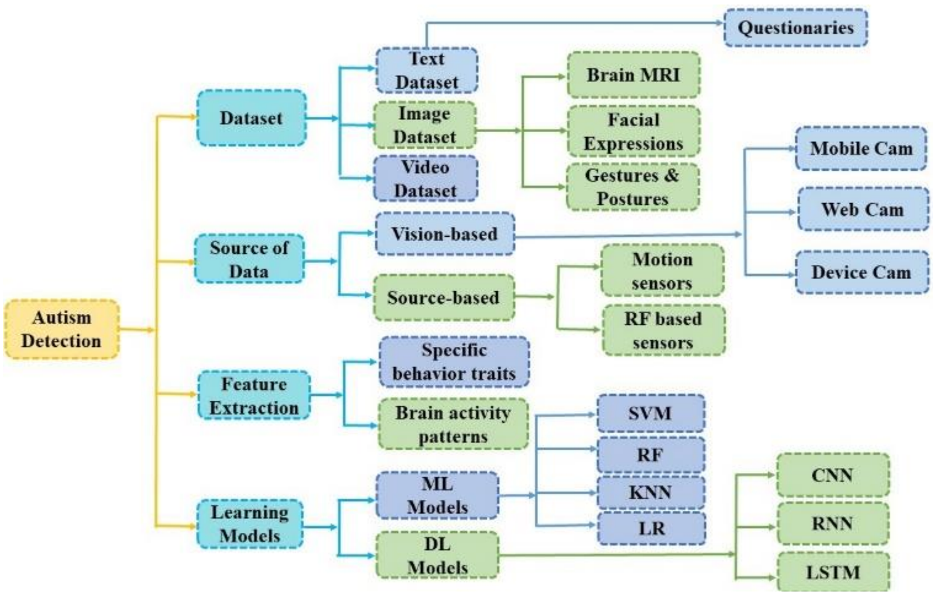

Figure 3. Taxonomy of this review

The percentages illustrate the relative prominence or utilization of different data types or techniques in studies related to autism. Brain MRI holds the most significant share among the listed methods, while Gesture and Posture Recognition have the smallest share in the overall analysis of autism-related information or research.

It encompasses a comprehensive framework categorizing crucial elements into four main divisions. As shown in Figure 3 firstly, it partitions datasets into three primary categories: text, image, and video data. Under image data, further outlines involve brain MRI, facial expressions, and gesture/posture data. Secondly, the taxonomy includes the source of data divided into two groups: vision-based (mobile, web, and device cameras) and source-based (motion sensors and RF sensors). Thirdly, it outlines feature extraction, categorizing it into specific behavioral traits and brain activity patterns. Lastly, the taxonomy encompasses learning models, classifying them into ML models (SVM, RF, KNN, LR, RL, clustering analysis) and DL models (CNN, RNN, LSTM). This taxonomy provides a structured and comprehensive framework for understanding the diverse components involved in autism detection methodologies, facilitating a systematic analysis of the field's research landscape.

3. ASD IDENTIFICATION USING ML AND DL

ML and DL techniques find prominent applications in the present day for various ASD detection. In this section, a detailed analysis is given for Text-based autism disease datasets using various ML and DL algorithms.

3.1 The function of ML and DL in text-based analysis

Shin et al. [15] present an innovative DL-based method for the early identification of children's ADHD, as shown in Table 1 particularly those with coexisting ASD. They employ fNIR data recorded during handwriting tasks performed by both ADHD children with ASD and TD children. Their hybrid model, combining Bidirectional LSTM and CNN, achieves remarkable results, with an Area Under the receiver operating characteristic Curve (AUC) of 0.938, sensitivity of 89.7%, specificity of 97.8%, F1-Score of 93.3%, and classification accuracy of 94.0%. These findings underscore the model's potential as an easy-to-use, non-intrusive, and automated method for diagnosing ADHD in kids, even in cases where it coexists with ASD, addressing a critical need in neurodevelopmental disorder diagnosis and intervention.

Raj and Masood [16] proposed the growing application of ML in medical research, this paper delves into the potential of Naïve Bayes, SVM, LR, KNN, Neural Networks, and CNN for anticipating and analyzing ASD across different age groups. Researchers evaluate these techniques on three different non-clinical datasets for ASD: one connected to children (292 instances, 21 attributes), another associated with adult subjects (704 instances, 21 attributes), and a third focusing on adolescents (104 instances, 21 attributes). After implementing a range of ML techniques and addressing absent data, the findings suggest that prediction models based on CNN exhibit superior performance across these datasets, achieving remarkable accuracies of 99.53% Screening for ASD in Adults, 98.30% for Children, and 96.88% for Adolescents, thus holding promise for enhancing Screening and diagnosis of ASD.

Akter et al. [17] suggested to advance our understanding of ASD and its early detection, we collected datasets encompassing individuals across various age ranges, including young children, teens, adults, and toddlers. Employing several feature transformation techniques, including sine, Z-score, and logarithmic functions, we processed those datasets. Subsequently, we applied a range of classification techniques to these altered ASD datasets and assessed how well they performed. Our findings indicated that the SVM exhibited the most promising results regarding the toddler dataset, and Adaboost proved the most effective regarding the kids' dataset. In contrast, Generalized Linear Model Boosting (Glmboost) performed best regarding the teenager dataset, and Adaboost was most successful in the case of an adult dataset. Notably, the changes to the features that yielded the most accurate groups were the sine function about toddlers and the Z-score for kids and adolescents. Following Several feature selection methods in these analyses were applied to the datasets transformed with Z-score, aiming to determine the key risk elements associated with ASD regarding individuals of different age groups. The outcomes of these analytical methods suggest the fact that with appropriate optimization, ML techniques may offer reliable estimations of the status of ASD, paving the way for the possible use of these models for ASD early detection.

Hasan et al. [18] address the challenge of the early identification of ASD, emphasizing its significant impact on patient's daily lives. They propose a comprehensive framework for evaluating various ML techniques in ASD detection, employing four distinct Feature Scaling (FS) strategies and eight ML algorithms on four standard ASD datasets covering different age groups. Through extensive experimentation and statistical evaluation measures, researchers identify the most effective FS strategies and classification algorithms for every dataset, achieving notably high accuracies, such as 99.25% for Toddlers using Ada Boost (AB) with normalizer FS. Additionally, the researchers conduct a thorough feature importance analysis using various Feature Selection Techniques (FSTs) and argue that their framework provides valuable insights for healthcare practitioners in ASD screening. Overall, the proposed framework exhibits promising results for early ASD detection, suggesting its potential utility in clinical settings.

Vignesh et al. [19] have revealed language and social deficits in individuals with ASD, while proficiency development remains an underexplored area. The significance of comprehensive support mechanisms, including information provision, advocacy, early interventions, school support, behavioral assistance, and individualized care, is underscored. Moreover, through its Pledges program, the National Autistic Society provides practical strategies for neurotypical individuals across the spectrum of autism. To advance the understanding as well as the management of ASD, computational techniques have been employed. Notably, the use of classification algorithms and Neural Networks has yielded promising results, with accuracy scores for different algorithms as follows: Naive Bayes at 97.27%, SVM and C4.5 both at 100%, and Multi-Layer Perceptron at 100%. These findings highlight the potential of advanced computational methods in enhancing our comprehension of and support for ASD.

Vakadkar et al. [20] studied genetic and environmental factors, Early intervention and detection are essential for enhancing the conditional results. Currently, clinical standardized tests are the primary means of diagnosing ASD, but they are associated with lengthy diagnostic timelines and increased medical expenses. To enhance diagnostic precision and efficiency, ML techniques have been integrated alongside conventional methods. Models like SVM, RFC, NB, LR, and KNN have been utilized for datasets, culminating in models of prediction designed to identify the susceptibility of children to ASD during their early developmental stages. Notably, the study reports that Logistic Regression yields the highest accuracy among the applied models, offering a potential avenue for streamlining the diagnostic process for ASD.

Shin et al. [21] concentrate on the utilization of ML-based analysis of handwriting patterns for the detection of ADHD in kids, particularly those concurrently identified as having ASD. The researchers highlight the concerning rise in ADHD prevalence among children and the complexities introduced by some conditions like ASD within the children and adolescents. The previous research efforts have explored computational tools for ADHD detection, researchers stand out for their innovative approach of using handwriting patterns as language-independent diagnostic markers. gathered samples of handwriting from 29 kids in Japan, including 14 with ADHD and coexisting ASD with 15 healthy kids, who were asked to draw lines on a pen tablet that are periodic (PL) and zigzag (ZL), with each pattern three times over. From the raw datasets, 30 statistical features were extracted and examined through the use of sequential forward floating search (SFFS) to identify the optimal feature combinations. Subsequently, these particular attributes were input into seven algorithms based on ML to detect ADHD in children with ASD. Therefore, the results demonstrated the Random Forest (RF)-based classifier's outstanding performance in predicting ADHD in kids with ASD according to periodic lines (PL) handwriting patterns, achieving an accuracy level of 93.10%, recall level of 90.48%, precision level of 95.00%, f1-score of 92.68%, and an AUC of 0.930. These conclusions underscore the potential to utilize handwriting analysis in the context of a powerful tool for preliminary ADHD detection, particularly in the cases of comorbid conditions, thereby enhancing diagnostic capabilities within children and adolescents.

Jaiswal et al. [22] have focused on utilizing large medical datasets and employing dimensionality reduction techniques such as chi-square tests, mutual information, and light gum to identify relevant features associated with ASD. Various ML algorithms, including Naïve Bayesian, K Nearest Neighbour, and Decision Trees, have been explored for classification, with Decision Trees consistently demonstrating high performance, achieving a score of 97.47%. However, future research should prioritize comprehensive model evaluation, ethical considerations in medical data usage, clinical validation, and the interpretability of ML methods to ensure their utility and reliability in aiding healthcare professionals in early ASD diagnosis.

Zhao et al. [23] studied that the existing diagnostic methods for ASD rely a lot on time-consuming and labor-intensive informant evaluations of patient behavior. To expedite the diagnostic process and enhance Accuracy, ML techniques have been put forth to investigate the viability of diagnosing ASD using a small collection of characteristics taken from kinematic, behavioral, and neuroimaging data. While restricted and repetitive behavior (RRB) is a fundamental characteristic of ASD, limited research has explored the potential of using restricted kinematic features (RKF) to determine the disorder. This paper addressed this gap by recruiting Twenty-three children who had TD, and twenty children who had high-functioning autism. They performed a motor task designed to elicit highly variable movements, and RKF indices were computed, including entropy and a 95% range for acceleration, velocity, and amplitude of motion. This study employed five ML classifiers, including SVM, Linear Discriminant Analysis (LDA), DT, RF, and KNN. The outcome indicates that the KNN algorithm (k=1) achieved four kinematic features that were used to achieve the highest classification accuracy (88.37% accuracy, 91.3% specificity, 85% sensitivity, and 0.8815 AUC). This paper underscores the potential of RKF in robustly identifying ASD and suggests that ML, applied to a range of features encompassing genetics, neuroimaging, psychology, and kinematics, could challenge current diagnostic criteria and potentially facilitate automated and objective ASD diagnosis.

Thabtah [24] as mentioned in Table 1 studied the lengthy waiting times for ASD diagnoses are exacerbated by the current time-consuming and cost-ineffective diagnostic procedures. The increasing prevalence of ASD cases worldwide underscores the urgency for the development of accessible and efficient screening methods. In response to this need, this article presents an innovative mobile application, AS Tests, designed to provide a quick, simple, and readily available ASD screening tool. Here the mobile app aims to benefit both users and the healthcare community by facilitating early identification of ASD. It offers a comprehensive approach by including separate tests tailored for toddlers, kids, teens, and adults, accessible in 11 different languages, thereby reaching a broader and more diverse audience. What sets the AS Tests app apart is its potential to collect valuable data on ASD cases and controls, with an initial dataset comprising over 1400 instances. Feature and predictive analyses highlight the utility of small sets of attributes of autism, enhancing screening efficiency and accuracy. Moreover, ML classifiers show promising outcomes about accuracy, specificity, and sensitivity rates, promising an important development in the screening and early diagnosis of ASD.

3.1.1 Observation

Future work in the realm of ASD detection using text datasets could focus on several key areas to further advance the accuracy and practicality of ML techniques. Firstly, extending the variety and range of text data sources, including non-traditional sources like social media interactions and diverse linguistic patterns, can enrich the dataset and offer a more nuanced understanding of ASD-related linguistic behaviours. This broader dataset could encompass diverse demographics, cultural contexts, and age groups, providing more representative and comprehensive training data for ML models. Secondly, the advancement and implementation of more sophisticated NLP techniques, including fine-tuning pre-trained language models and developing specialized models for ASD-specific linguistic markers, can enhance the extraction of contextually relevant information from text data. Additionally, focusing on robustness and generalizability by validating models across varied demographics and datasets, along with fostering interpretability and explainability in the models, will strengthen their clinical applicability and aid in understanding the linguistic characteristics associated with ASD more comprehensively. Collaboration between interdisciplinary experts in linguistics, psychology, ASD research, and ML will be vital to ensure a holistic approach, ethical considerations, and the effective translation of research findings into clinical practice.

Table 1. Parametric assessment of ASD detection methods using text-based dataset

Methodology	Objective	Performance	Limitations
fNIRS dataset			
CNN, Bi-LSTM [15]	fNIRS signals' efficacy as a biomarker for identifying ADHD comorbidity in kids with ASD, with the final objective of aiding medical professionals with the diagnosis and facilitating the development of personalized Treatments.	Accuracy=94%	Additionally, we'll use ML and work to create fresh DL-based algorithms that can identify ADHD with coexisting comorbidities.
ASD Screening Dataset from UCI			
KNN, SVM, LR, NB, NN & CNN [16]	Explore the effectiveness of diverse ML techniques for predicting ASD across various age groups (children, adolescents, adults) using publicly available datasets, aiming to identify the most suitable method for ASD screening.	Accuracy: 99.53%, 98.30%, and 96.88% in adults, children and adolescents.	-
ASD Datasets Relating to Toddlers, Children, Adolescents, and Adults from UCI			
Adaboost, CART, MDA, FDA, SVM, Glmboost, PDA, and C5.0 [17]	Assess feature transformation methods, classification techniques, and feature selection approaches on ASD datasets across various age groups, highlighting the potential of optimized ML models for early ASD detection.	Accuracy=99.30%	The associated limitations of this approach will be better identified in the future, and additional data will be analysed to enhance the detection of ASD and related neurodevelopmental disorders.
ASD Detection Dataset for Toddlers from Kaggle			
Ada Boost with Normalizer Feature Scaling Strategies [18]	Identify the most effective classifiers and feature scaling methods for accurate ASD prediction & and emphasize the importance of detailed feature importance analysis to support medical professionals in the screening of ASD cases and claim that the framework offers promising results in comparison to current methods for early ASD detection.	Accuracy=99.25%	To enhance the detection of ASD and other neurodevelopmental disorders, we plan to gather more information about ASD in the future and build a more comprehensive prediction model that can be used by individuals of any age.
Mental Imbalance Dataset from Kaggle			
NB, SVM, C.5, Multilayer Perception [19]	Addressing ASD challenges in language, and social interaction via ML, especially neural networks for prediction, emphasizing societal initiatives like the National Autistic Society's Pledges for aiding autism through behavioral modifications.	Accuracy=100%	Additional investigation will focus on the long-term effects of these drugs and the nuances surrounding their administration.
Diagnosis Dataset from Kaggle			
SVM, RF, NB, LR, and KNN [20]	The diagnostic process and determining susceptibility to ASD in its early stages, to increase accuracy and cut down on diagnosis time.	Accuracy=97.15%	Planning to use larger datasets for better generalization and employing DL methods, including classification and CNNs, to bolster system robustness.
Real-Time Dataset			
Techniques	**Objective**	**Performance**	**Limitations**
(The Interview Review Board (IRB) gave their approval) [21]	Precise classification and providing evidence for improved early detection of comorbidities in ADHD.	F1-score: 92.68%, Precision: 95.00%, Accuracy: 93.10%, Recall: 90.48%, AUC: 0.930	In Future work, DL-based algorithms will be used to identify children with coexisting ASD and ADHD.
KNN, DT, and NB [4] (Americans who live in the United States provide the data. NSCH is the publisher of the dataset [22])	Employ ML models on high-dimensional medical data for ASD diagnosis, utilizing feature extraction to reduce dimensions, enhance classifier performance, and identify the optimal classifier.	Accuracy=97.47%	Our future research will use multimodal data to predict various neurodevelopmental disorders.
SVM, LDA, DT, RF, and KNN [23] (Collected by using a Leap Motion device and two sticks with a string tied between them as the experimental apparatus)	Identify the most relevant features that can differentiate between the two groups and assess the effectiveness of different ML algorithms in categorizing the participants.	Specificity=91.3%, Accuracy=88.37%, AUC=88.15%	Subsequent research endeavours may also focus on categorizing individuals with ASD apart from other groups, including distinguishing between ASD and ADHD.
NB, LR [24] (The ASD Tests app was used to gather instances from individuals who self-administered the screening tests for autism)	Evaluate the performance of the ASD Tests app in screening ASD using ML algorithms and improve the effectiveness of screening for ASD and possible diagnosis.	NA	In short, automated ML technology will replace the traditional diagnosis process of handcrafted rules to improve ASD screening.

4. IMAGE ANALYSIS EXPLORED THROUGH ML AND DL FRAMEWORKS

4.1 The role of ML and DL in brain MRI

Numerous studies suggest that children and adolescents diagnosed with autism tend to exhibit an enlarged hippocampus, the brain region accountable for memory formation and storage. However, it remains uncertain whether this variation persists as individuals transition into adolescence and adulthood [25, 26].

The dimensions of the amygdala appear to vary between individuals with and without autism. However, research conducted by various laboratories has produced conflicting findings on this matter. According to researchers, Individuals diagnosed with autism may exhibit a smaller amygdala compared to those without autism. It's also suggested that their amygdala might be smaller specifically when they also experience anxiety [27]. According to research, as shown in Figure 4, children with autism exhibit early-stage amygdala enlargement with the difference gradually decreasing [28].

A review of imaging studies revealed that the cerebellum, the brain structure located at the base of the skull, has less brain tissue in autistic individuals [29]. Researchers know that the cerebellum plays a role in both social interaction and cognition, in addition to its long-held belief that it primarily controls movement. People with and without autism have different patterns of thickness in the outer layer of the brain. This variation corresponds to changes in a single neuronal sub-type during development.

Raja and Kannimuthu [30] proposed the context of ASD diagnosis and neuroimaging methods reveals a predominant reliance on fMRI techniques as shown in Table 2, often with limited dataset sizes, yielding high accuracy but limited generalizability. While traditional supervised ML algorithms like SVM show promise in handling unstructured data, they are hindered by limited training data. In contrast, DL approaches, particularly Generative Adversarial Networks (GANs), are gaining traction due to their capacity to automatically learn patterns and generate new data examples. However, their application in ASD prediction is relatively unexplored. This paper introduces a new conditional generative adversarial network (cGAN) for ASD prediction, demonstrating superior accuracy compared to traditional methods, with a 74% improvement, and remarkable efficiency, requiring only around 10 minutes for training even on large datasets. This paper underscores the potential of DL, specifically cGANs, in ASD diagnosis and rehabilitation.

Sabegh et al. [31] studied the realm of diagnosing diverse mental illnesses, particularly ASD, and the existing reliance on behavioral symptom observation presents challenges, especially in children. This study seeks to enhance diagnostic accuracy through the integration of sophisticated and expandable ML techniques, specifically DL networks. They are leveraging resting-state fMRI information from the ABIDE1 repository encompassing seventeen different imaging locations and an extensive preprocessing pipeline is implemented, involving registration of data on atlases, extraction of brain region average time series, and computation of correlation matrices. The method of selecting chi-square features is then employed to identify the most critical features within these matrices. An innovative CNN architecture, featuring Convolutional layers with two dimensions is proposed for data analysis and classification. This model's evaluation encompasses three distinct experiments based on different datasets and atlases. Remarkably, the highest accuracy achieved in these experiments stands at 73.53%, surpassing previous attempts at categorizing ASD against standard controls. This research introduces a pioneering CNN-based model capable of automatic ASD classification, demonstrating strong classification performance. Unlike prior studies that focused on limited data sites, this work capitalizes on data from all sites, thereby enhancing the generalizability and potential clinical utility of the proposed model.

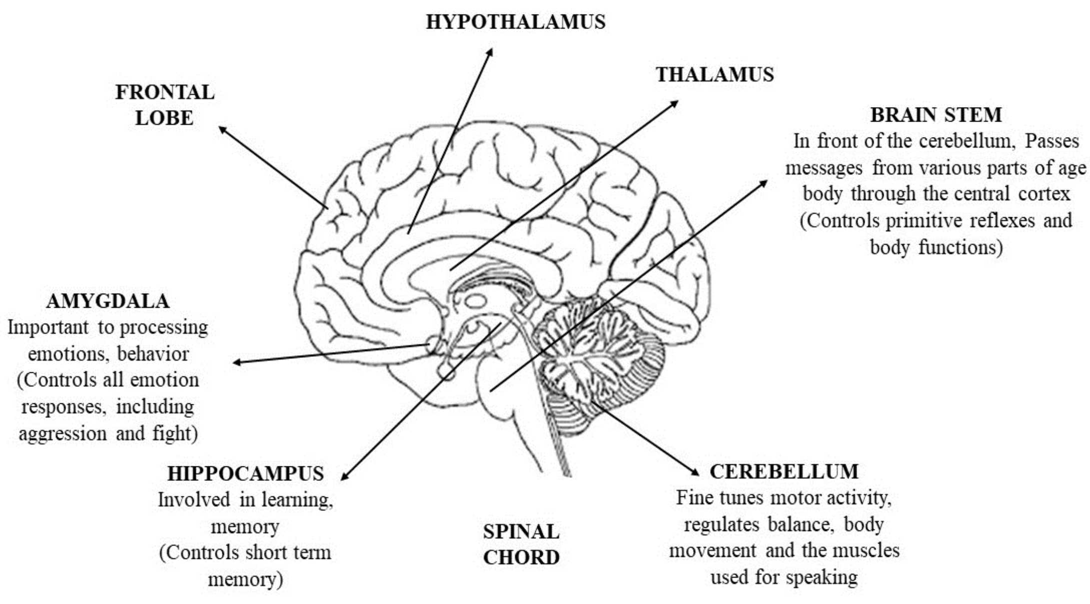

Figure 4. Parts of the brain affected by autism

Ulaganathan et al. [32] present a novel approach for ASD classification using deep RL methods, namely deep Q learning network (DQN) and Spinal Net, with the training of hyperparameters facilitated by a unique training optimizer, the Driving Training Political Optimizer (DTPO). The process commences with image acquisition from a dataset, followed by adaptive Wiener filtering and ROI extraction. Subsequently, the core region is identified using the DTPO. The classification hinges on these extracted features. Furthermore, the study's classification performance is evaluated, and a fusion process between DQN and Spinal Net, aided by Czarnowski similarity, results in ASD classification. The assessment encompasses various metrics, including impressive values of 0.907, 0.958, 0.936, 0.536, 0.732, 0.488, and 0.409, respectively, for accuracy, sensitivity, specificity, mean-squared error, root-mean-squared error, R, and mean absolute error. This research highlights the potential of deep RL networks in effectively categorizing ASD, offering a possible path toward improvement in early diagnosis and intervention.

Lei et al. [33] studied that the accurate diagnosis of ASD is essential to ensure optimal prognosis and treatment, and Functional Brain Networks (FBNs) built from fMRI data have gained popularity as a diagnostic tool. However, existing model-driven approaches for FBN construction often fail to record any non-linear connections that might exist between the diagnostic labels and the data. Furthermore, the conventional separation of FBN construction and disease classification in most studies leads to substantial inter-subject variability in the calculated FBNs and lowers the next group's statistical power comparisons. To get beyond these restrictions, this study introduces a novel approach known as the deep unrolling-based spatial constraint representation (DUSCR) method. It combines it with a convolutional classifier to produce an end-to-end architecture for the identification of ASD. This method utilizes a proximal gradient descent algorithm to solve the Spatial Constraint Representation (SCR) and unrolls using the deep unrolling algorithm, it is incorporated into deep networks. Putting things into categories is achieved through a convolutional prototype learning model. The method's efficiency was assessed on the ABIDE I dataset, demonstrating an important enhancement in classification accuracy and model performance, thus offering a promising solution for improving ASD diagnosis and understanding the complex relationships within functional brain networks.

RethikumariAmma and Ranjana [6] aims to facilitate early ASD diagnosis by leveraging neuroimaging functional images. This method employs a DL approach to discern whether individuals with ASD, obtain strong characteristics from these neuroimaging data. It evaluates the effectiveness of images with prior processing in categorizing neuronal patterns, with the ultimate goal of enabling early diagnosis for long-term health management. Functional connectivity analysis is used to identify crucial brain areas using the box neighbourhood search algorithm as its foundation. To diagnose ASD, a Deep Neuro-Fuzzy Network (DNFN) is utilized, and Feedback-Henry Gas Optimization (FHGO) is used to train the DNFN. The results of this FHGO-DNFN approach demonstrate exceptional performance, achieving a high accuracy rate of 93.3%, along with a sensitivity of 94.7% and specificity of 91.4%. This promising methodology can potentially enhance early ASD detection, thereby advancing clinical practices and improving the long-term well-being of individuals with ASD.

Sherkatghanad et al. [34] focus on automating the detection of ASD by harnessing the power of CNNs and a brain imaging dataset. We achieved this by identifying ASD patients within the ABIDE, a multi-site dataset that includes fMRI resting-state data. Our approach leveraged operational interconnectedness patterns to group individuals with ASD and control subjects effectively. Our Results from experiments show that our model accomplishes a 70.22% accuracy rate utilizing the brain's CC400 functional parcellation atlas and the ABIDE I dataset. Notably, our CNN model is computationally more efficient than state-of-the-art methods because it uses fewer parameters. This model, now poised for further testing with larger datasets, holds the capacity to act as a valuable tool regarding the preliminary screening of people with ASD.

Nogay and Adeli [35] introduced an automatic diagnostic structural MRI-based model for ASD. The model comprises two essential stages: the initial preprocessing stage, and the subsequent diagnostic phase. The preprocessing stage entails the removal of unclear images, followed by the application of the Canny Edge Detection (CED) algorithm to delineate image edges, cropping the images to the required dimensions, and augmenting the dataset by upscaling the images while preserving essential image characteristics. Notably, data augmentation is applied meticulously to avoid any bias introduced into the data, ensuring its integrity for both ASD and TD groups. Phase two involves the application of the grid search optimization (GSO) algorithm to fine-tune the deep CNN by optimizing hyperparameters. Remarkably, this approach achieves a diagnostic success rate of 100% for ASD, as evidenced by rigorous five-fold cross-validation. The model's robustness is further validated by comparisons with current research and extensively utilized pre-trained models, establishing its superiority in ASD diagnosis based on MRI. This groundbreaking research offers a promising method for accurate and reliable automated ASD diagnosis, which is based on a substantial leap forward within the domain of neuroimaging and diagnosis of ASD.

Bhandage et al. [36] studied that ASD diagnosis is achieved through a novel approach based on the Adam War Strategy Optimization (AWSO) Deep Belief Network (DBN). The algorithm used by AWSO is developed by integrating the War Strategy Optimization (WAO) and Adam optimizer, presenting a simpler yet highly effective approach that outperforms existing methods. The preprocessing stage involves extraction of the Region of Interest (ROI) and anisotropic diffusion to eliminate image noise. Furthermore, the Algorithm for Box Neighbourhood Search that Uses Functional Connectivity is employed to extract crucial brain regions, enhancing ASD classification performance. The classification itself is carried out through the DBN, with the algorithm used by AWSO optimizing the DBN's learning process. The AWSO-DBN analysis was conducted on ABIDE-I as well as ABIDE-II datasets, with the AWSO-DBN demonstrating exceptional work, particularly using the dataset ABIDE-I, where it attained a high degree of sensitivity (0.930), accuracy (0.924), and specificity (0.935). These results showcase the promise of the AWSO-DBN algorithm as a powerful instrument for accurate ASD classification, underscoring its potential influence on the field of diagnosing ASD.

Parui et al. [37] studied a novel approach for constructing functional connectivity networks using rs-fMRI data. By extracting time series data from fMRI and calculating correlation matrices that represent the interactions among various brain regions, the study leverages different brain atlases. The proposed technique incorporates the idea of majority voting based on atlas-specific outcomes, resulting in a commendable ASD detection accuracy of 84.79%. This approach underscores the potential of AI-driven neuroimaging techniques in advancing our understanding of ASD and enhancing diagnostic accuracy, thus supporting early intervention and assistance for people with ASD.

Yin et al. [38] suggested using a semi-supervised autoencoder (AE) approach introduced for the diagnosis of autism, utilizing functional connectivity (FC) patterns derived via fMRI data in the resting state. By combining unsupervised AE training utilizing networks for supervised classification, the proposed semi-supervised learning framework facilitates simultaneous training of an autoencoder and a neural network-based classifier. This approach, in contrast to training these components separately, allows the latent feature representation to be tailored to the goal of classification, resulting in enhanced diagnostic performance for autism. On the ABIDE I database, cross-validation is used to evaluate the model, demonstrating improved classification performance. The results highlight the utility of the suggested framework for semi-supervised learning for integrating unlabelled fMRI information, leading to improved classification accuracy and feature learning in the context of ASD diagnosis.

Ahammed et al. [39] explore the application of ML for ASD identification, focusing on overcoming limitations associated with using fMRI and large datasets. The proposed innovative architecture that uses the Bag-of-Features model as a basis, presents a comprehensive approach to ASD classification. This approach involves preprocessing images, extracting speeded-up robust features (SURF), creating a visual vocabulary through K-Means clustering, and encoding Bag-of-Features using quantization and coding methods. The study highlights the preference for the SVM as the ASD classifier. The evaluation includes three datasets, encompassing ABIDE fMRI pre-processed images and the subject's face images. The experimental results indicate that SVM performs much better when using the Bag-of-Feature approach, which achieves the highest accuracy of 81% and specificity of 86%. This suggests that ML classifiers using extractors for bags of features have the potential to reinforce ASD diagnosis, particularly in clinical and medical contexts, in contrast to alternative cutting-edge techniques.

Itani and Thanou [40] discuss ongoing research in ASD and the application of network science and contemporary ML to gain an improved comprehension of the neuropathology of ASD and the emergence of diagnostic aids. This research specifically focuses on classifying individuals with ASD and neurotypical incorporating an understanding of the structure and function of the brain. The brain is represented as a graph, with rs-fMRI signals mapped to the graph's nodes. Graph Signal Processing (GSP) tools are applied to analyse the signals' frequency composition, creating discriminative features by expanding the Fukunaga-Koontz transformation. These features are used to instruct a decision tree for categorization, resulting in an interpretable diagnostic model that outperforms existing methods, as demonstrated in the ABIDE gathering. Predictive marker analysis highlights the role of the temporal and frontal lobes in the diagnosis of ASD, aligning with prior discoveries in the literature on neuroscience. This research emphasizes the importance of considering structural and functional brain information for gaining insights into the complexity of ASD neuropathology. Additionally, the study presents test accuracies achieved by various methods with standard deviation intervals for different training set sizes.

Zhan et al. [41] studied the field of psychiatric disorders, particularly ASD, Obsessive-Compulsive Disorder (OCD), and ADHD, there exists an ongoing debate regarding precise diagnosis as well as the potential convergence of their anatomical foundations. A recent study employed non-invasive neuroimaging techniques in both human subjects and primates that are not humans to investigate neural markers linked to DSM-5 diagnoses and quantitative indicators of the severity of symptoms. Diagnostic classifiers were built using resting-state functional connectivity data from both wild-type and methyl-CpG binding protein 2 (MECP2) transgenic monkeys, which were then applied to four human datasets (OCD local institutional database: N=186; ADHD-200 sample: N=776; ABIDE-I: N=1,112; ABIDE-II: N=1,114). This innovative approach revealed nine key brain regions that are primarily found in the frontal and temporal cortices, which were instrumental in informing diagnostic classifications for ASD and OCD, although not for ADHD. Notably, models based on the functional connections of specific brain regions predicted symptom severity scores in individuals with ASD and OCD. These results hold significant promise regarding the development of diagnostic indicators for OCD and ASD, as well as for gauging the severity of symptoms. Moreover, they suggest potential avenues for enhancing the precision and effectiveness of clinical evaluations in the field of psychiatric disorders by leveraging machine-learning models.

Liu et al. [42] studied the context of ASD, characterized by social deficits and repetitive behaviours, the absence of reliable biomarkers has been a longstanding challenge. Numerous efforts have been dedicated to identifying biomarkers using resting-state fMRI. Nevertheless, a substantial amount of information is lost in feature selection because these studies frequently ignore strong group relationships. To resolve this problem, a novel approach is proposed for ASD diagnosis, utilizing the elastic net method utilizing rs-fMRI data. The key advantage of the method of elastic networks is its capacity to bypass the need for upfront feature selection, saving time and enhancing algorithm efficiency. Experimental outcomes conducted on the open database ABIDE affirm the efficacy as well as the utility of the suggested technique, marking a promising step toward addressing the biomarker challenge in ASD diagnosis.

Mostafa et al. [43] tackled the challenging problem of diagnosing ASD by introducing a novel approach that relies on brain network-based features extracted from functional MRI data. By defining 264 raw brain features using network eigenvalues and centralities and employing feature selection techniques, they reduced the dimensionality to 64 discriminative features. Training ML models, particularly Linear Discriminant Analysis, utilizing the ABIDE dataset, achieved a noteworthy classification precision of 77.7%. This outperformed existing methods and shows promise for improving based on ASD diagnosis neuroimaging information, addressing the critical need for more effective diagnostic tools in the field. Further validation and replication studies are essential to confirm the robustness of these findings.

Wang et al. [44] focus on addressing the challenge of identifying biomarkers for accurate diagnosis of ASD using fMRI information from several sites. Given the variability across sites in multi-site data, the research introduces a multi-site adaption framework based on low-rank representation decomposition (maLRR). This framework aims to create a standard low-rank representation for information from various websites, thus reducing variations in data distributions. The low-rank representation method adapts the data to a shared space by considering one site as the target domain and the others as source domains. This adaptation process minimizes the differences between the source and target domains. The results from evaluations on multi-site fMRI data that is both real and artificial suggest that the proposed technique outperforms numerous cutting-edge domain adaptation techniques, offering promise for more accurate ASD identification and early intervention.

Fredo et al. [45] aimed to distinguish between TD individuals and those with ASD by analyzing fMRI. They used data from 320 participants for training and 80 for validation, sourced from the ABIDE-I, and ABIDE-II. The fMRI images were pre-processed through a standard pipeline, and Functional Connectivity (FC) matrices were computed 237 regions of interest (ROIs) were used in the cortex, subcortex, and cerebellum. To reduce the FC matrix's dimensionality, they employed RF with conditions and assessed classification accuracy by employing random forests at every dimension. The findings showed that, within this dataset, RF achieved a maximum accuracy of 65% with 143 characteristics. The region that contributed the greatest features was the Cingulo-Opercular Task Control (COTC) region. associated with precise categorization and communication between the dorsal attention network and COTC played a crucial role in distinguishing ASD and TD participants. This research sheds light on the potential of fMRI-based connectivity patterns in aiding the classification of ASD.

Heinsfeld et al. [46] studied DL techniques to recognize individuals with ASD from a substantial brain imaging dataset obtained from the ABIDE database. The neurodevelopmental disorder known as ASD is typified by repetitive behaviours and social deficits, with a significant impact on child populations. The research focused on the brain's functional connectivity patterns to objectively distinguish ASD participants from typically developing controls and to gain insights into the neural patterns underlying this classification. The results represented an advancement in the field by achieving that 70% of ASD patients in the dataset could be identified accurately. Notably, the findings revealed a difference in brain activity between the anterior and posterior regions of the brain, which aligns with existing empirical evidence of disruptions in anterior-posterior brain connectivity in ASD. The study further identified the specific brain areas that played a crucial role in distinguishing ASD from customarily creating controls through their DL methods, shedding light on the neural mechanisms associated with ASD.

Vandewouw et al. [47] focus has recently shifted towards identifying subgroups among Children and teenagers suffering from neurodevelopmental disorders by leveraging measures of brain function, utilizing data from two large and independent networks: The Healthy Brain Network (HBN) and the Province of Ontario Neurodevelopmental Network (POND). Researchers' studies have explored the potential for data-driven clustering analyses to uncover subgroups characterized by common functional brain features, independent of traditional diagnostic categories. The results revealed subgroups exhibiting shared biological characteristics, yet often deviating significantly regarding intelligence, hyperactivity, and impulsivity traits. These findings challenge the conventional diagnostic boundaries, suggesting that a more nuanced understanding of neurodevelopmental conditions may emerge through the exploration of brain connectivity patterns, potentially advancing our comprehension of the underlying complexities of these disorders.

Gao et al. [48] proposed the realm of ASD prediction and neuroimaging, existing research predominantly focuses on fMRI methods, which are primarily applied to individuals older than 5 years of age for diagnosis. This approach faces limitations when dealing with infants due to the challenges of fMRI applications. Consequently, a growing emphasis is on leveraging structural MRI to enable early ASD prediction, particularly around 24 months of age. This study introduces an automated prediction framework, employing an infant-specific pipeline, I BEAT V2.0 Cloud, to generate Partitioning and dividing maps from baby MRI scans. The framework utilizes feature extraction from paired maps using a CNN and Siamese network to discern if the matched individuals exhibit similar or different ASD statuses. The research demonstrates that integrating maps with segmentation and parcellation enhances the ASD prediction's sensitivity, specificity, and overall accuracy as confirmed by two datasets employing distinct imaging procedures and devices through analysis of the receiver operating characteristic. Comparative assessments against cutting-edge techniques emphasize how much more reliable and effective the suggested strategy is. Moreover, the study employs attention maps to pinpoint subject-specific autism effects, validating the predictive outcomes. These collective findings underscore the practicality of the unified system for predicting ASD in its early stages using sMRI, particularly when compared to models trained solely on T1w images which exhibited 76.9% sensitivity, 81.5% specificity, and 80.6% accuracy.

Conti et al. [49], brain structural differences among individuals with ASD, Childhood Apraxia of Speech (CAS), and TD individuals were explored using MRI measures and predictive Machine Learning techniques. The study aimed to identify distinct patterns among these conditions, without providing specific findings and reported an AUC of 73%. The authors suggested that future research should involve a larger sample size to understand better how ASD and comorbid CAS cases differ from pure disorders. Additionally, the study emphasized the importance of utilizing advanced imaging techniques and larger cohorts to validate and refine the observed patterns, facilitating more accurate diagnostic tools for ASD and CAS.

Saad and Islam [50] present an automated method for classifying individuals Using Diffusion Tensor Imaging (DTI) and graph theory-based features, ASD and TD brains were compared as mentioned in Table 2. The DTI is employed to study microstructural changes in the brain by monitoring the flow of water in white matter trails. Connectivity matrices are created from DTI data, and a graph theory-based analysis extracts relevant features. SVM and Principal Component Analysis (PCA) are utilized for classification, and Linear Discriminant Analysis (LDA) is employed to lower noise in the features. This study achieved classification accuracies of 75.00%, 62.50%, and 56.25% with 2, 7, and 10 PCA features using SVM, and 64.58%, 60.42%, and 58.33% using LDA. Notably, using fewer features led to better accuracy, especially with the same test samples. This approach leverages DTI and graph theory to provide a promising method for distinguishing between ASD and TD brains.

Table 2. Parametric Assessment of ASD Detection Methods using Image-Based (Brain MRI) Dataset

Methodology	Objective	Performance	Limitations
ABIDE Dataset			
SVM, GANs, cGAN [30]	GCN for ASD prediction utilizing neuroimaging markers, to increase accuracy in comparison to traditional techniques and address the constraints of data size in ML approaches.	Accuracy: 74%	Future studies should explore the combined utilization of functional and structural MRI data to gain deeper insights into ASD.
chi-square feature selection method. CNN-based model [31]	ASD diagnosis via a specialized CNN model, leveraging resting-state fMRI data from ABIDE1, aiming for heightened accuracy across diverse imaging sites compared to previous methods.	Accuracy: 73.53%	Subsequent research endeavours might centre on enhancing the precision of ASD identification through more advanced networks.
DQN and Spinal Net, DTPO. adaptive Wiener filtering and ROI extraction [32]	create a DQN, SpinalNet, and a proposed optimizer (DTPO)-based ASD classification method to reliably diagnose children with ASD, leveraging image data preprocessing and feature extraction for robust classification without relying on the actual results obtained.	Accuracy (0.907), Sensitivity (0.958), Specificity (0.936), Mean absolute error (0.409), R (0.488), Mean squared error (0.536), and Root mean squared error (0.732)	Enhancing ASD detection through advanced DL methods, diverse neural network architectures, and integration of various data types to refine classification accuracy.
Deep unrolling algorithm, proximal gradient descent algorithm. convolutional prototype learning model [33]	ASD diagnosis by introducing the DUSCR model, integrating spatial constraint representation with deep networks, and employing a convolutional prototype learning classifier for ASD recognition, aiming to capture non-linear relationships within FBNs constructed from fMRI data.	-	Our convolutional classifier, utilizing prototype learning based on the distance between prototypes and expected results, aims to create a versatile model with accurate classification.
DNFN, FHGO [6]	To use neuroimaging functional images and a Deep Neuro-Fuzzy Network to develop an accurate model for early ASD diagnosis, aiding clinicians in timely interventions.	93.3% Accuracy, 94.7% Sensitivity, 91.4% Specificity	Future work will involve involving additional databases to verify the model's viability.
CNN. functional connectivity patterns [34]	Use CNN to automatically detect ASD using functional MRI data obtained from the ABIDE dataset, focusing on functional connectivity patterns.	Accuracy: 70.2%	By applying a noise correction to every row of the connectivity matrix, we pave the way for future work that could show the behaviour of a brain region and associated biomarkers.
CED algorithm, grid search optimization (GSO) algorithm, DCNN [35]	Develop an automatic ASD diagnostic model utilizing structural MRI preprocessing techniques and optimized DCNN for accurate classification.	Accuracy: 100%	Future research focuses on refining diagnoses through advanced supervised ML techniques like neural dynamic classification (NDC) and enlarged probability NN (EPNN). Further investigations will involve multiple classifications to explore ASD diagnosis across different age groups and genders.
DBN based on Adam War StrategyOptimization (AWSO) [36]	Develop a precise ASD classification method utilizing a deep belief network based on AWSO, and DBN for improved accuracy and efficiency.	Accuracy=0.924, Sensitivity=0.930 Specificity=0.935	Future improvements to the AWSO-DBN's classification performance will come from the addition of more datasets and different classification methods.
AI-driven neuroimaging techniques [37]	Develop a functional connectivity network using rs-fMRI data for improved ASD detection leveraging artificial intelligence (AI).	Accuracy of 84.79%	Future research might concentrate on fine-tuning the hyperparameters to increase the model's accuracy.
Proposed semi-supervised learning framework. neural network-based classifier [38]	Employ a semi-supervised auto-encoder approach using resting-state fMRI functional connectivity patterns for enhanced ASD diagnosis and improved feature learning.	Specificity: 80.3%, Sensitivity: 89.9% NPV of 92.2%, Precision of 87.2%, Accuracy of 83.4%	Further studies will explore comparisons using the refined ABIDE II dataset or equivalent datasets, once a comprehensive understanding of the ABIDE II dataset is acquired.
SVM [39]	Develop a semi-supervised auto-encoder framework utilizing functional connectivity patterns from resting-state fMRI for enhanced ASD diagnosis and improved feature learning.	Accuracy=81%, Sensitivity=81%, Specificity=86%	Plans involve expanding dataset size for better feature efficacy and using diverse comparative methods to enhance SVM performance across various datasets.
DT [40]	Utilize GSP techniques to combine data on the structure and function of the brain	Accuracy =75%	Further investigation on larger and more homogeneous samples is

	for improved classification between neurotypical and ASD subjects.		essential to address the discrepancies in reported accuracy.
ABIDE Dataset			
Sparse LR [41]	Identify neural markers and dimensional symptom severity associations across ADHD, obsessive-compulsive disorder, and ASD using non-invasive neuroimaging in humans and nonhuman primates.	Sensitivity =79.70%, Specificity =83.74%, Accuracy =82.14%	These results might guide the creation of ML models for mental illnesses and could enhance the precision and efficiency of clinical evaluations.
SVM [42]	Create an automated ASD diagnostic approach employing elastic net with rs-fMRI data to uncover clinically relevant biomarkers, mitigating information loss by eliminating upfront feature selection.	Sensitivity =72.5%, Specificity =79.9%, and Accuracy =76.8%	Next, we'll build the model by preprocessing the matching data for the unbalanced data.
LDA, LR & SVM [43]	Develop brain network-based features extracted from fMRI data for improved ASD diagnosis, aiming to address the challenge of discriminating between healthy individuals and ASD patients using ML methods.	Accuracy =77.7%	Future steps involve integrating suggested features with advanced ML techniques such as DL and reinforcement learning to enhance classification models.
KNN, SVM [44]	Create a framework for adapting maLRR via fMRI, aiming to mitigate inter-site heterogeneity and improve diagnostic accuracy across multiple sites.	73.44% Accuracy, 75.79% Sensitivity, and 69.52% Specificity	Future research will examine a unified framework for low-rank representation learning and classifier training together.
Reduced features for RF and CRF [45]	Create a classification framework utilizing functional MRI data to differentiate ASD from TD individuals using conditional/random forest methods to pinpoint distinctive brain connectivity patterns for precise classification.	Accuracy: 65%	-
Denoising autoencoders, FS, and DL [46]	Utilize DL techniques on ABIDE brain imaging data to uncover ASD-related functional connectivity patterns, enhancing diagnostic accuracy and unveiling neural correlates linked to ASD classification.	Accuracy: 70%	We propose that a step towards more dependable outcomes has been taken going forward.
POND, HBN Dataset			
SNF, Clustering Algorithms [47]	Utilize resting-state functional brain data from diverse datasets to identify neurobiological subgroups among children with and without neurodevelopmental disorders, correlating these subgroups with behavioral traits beyond conventional diagnostic boundaries.	-	Future research should look at how the identified subgroups change throughout development and expand the age range into adulthood.
NDAR Dataset			
CNN & Siamese network [48]	To develop an automated prediction framework using infant sMRI at around 24 months of age for early-stage ASD prediction, utilizing segmentation, parcellation maps, CNNs, and Siamese networks without detailing the specific obtained results.	AUC=91%	Plans include extending methodologies to infants under 24 months old and diversifying subject inclusion across scanners and protocols to validate method robustness, particularly considering the clinical significance of the 6-month age milestone.
Clinical Dataset			
SVM [49]	Explore brain structural differences among ASD, CAS, and TD via MRI measures, utilizing predictive ML techniques without detailing specific findings, aiming to distinguish distinct patterns among these conditions.	AUC=73%	To determine how much ASD and comorbid CAS cases differ from "pure" disorders, future research should enlist a larger sample of patients.
UMCD Dataset			
SVM [50]	To automatically classify ASD and TD brains using features derived from DTI that are based on graph theory and employing ML algorithms for accurate differentiation, without specific result details.	Precision =70.42%, Specificity =70%, Sensitivity =81.94%, Accuracy =75%	-
NAMIC Dataset			
KNN [51]	Employing adaptive independent subspace analysis (AISA) to identify	94.7% Accuracy, 94.82% Specificity, 92.29%	To increase accuracy, we intend to expand MRI image analysis in

	significant MRI scan data containing EEG activity and employ image texture analysis methods to extract features, aiming for efficient grouping of ASD without providing specific result details.	Sensitivity, and 93.56% F-score are the results	subsequent studies to incorporate image moments and shape features in addition to texture-based features.

Ke et al. [51] address the need for efficient processing of the complex and abundant MRI data used in medical diagnostics. They propose a novel approach that involves applying the use of adaptive independent subspace analysis (AISA) to find meaningful EEG activity in the data from MRI. The outcomes obtained through AISA are then subjected to texture analysis of images, encompassing first-order statistics, Grayscale run-length matrix, Grayscale size-zone matrix, Grayscale co-occurrence matrix, and surrounding Features of a grayscale difference matrix. These features are transformed by employing t-distributed stochastic neighbour embedding (t-SNE) into a 2D space. Subsequently, the authors employ a 10-fold cross-validation, the KNN, achieving a notable 94.7% precision and a high f-score of 0.9356 when classifying real ASD MRI data. The study successfully demonstrates the efficacy of this method in distinguishing between normal and autistic brain MRI slices in the tissue of the brain. upcoming study plans include expanding the analysis to encompass visual moments and morphological elements to further enhance accuracy.

4.1.1 Observation

Based on the above study in ASD detection future research concerning brain MRI datasets for ASD analysis, several pivotal improvements can be explored to enhance the accuracy, reliability, as well as applicability of ML models

Future advancements in brain MRI dataset analysis for ASD should prioritize three crucial areas. Firstly, there should be a concentrated effort on the integration of multiple MRI modalities into a unified framework, combining structural, functional, and diffusion MRI data along with other relevant information like genetics or behavioral assessments. Employing fusion methodologies, particularly DL-based multimodal architectures, can unlock intricate patterns across diverse data sources, potentially improving diagnostic accuracy and unveiling a more comprehensive understanding of ASD-related brain alterations. Secondly, it's imperative to establish model robustness across diverse datasets and populations by validating models on larger, more heterogeneous datasets encompassing different demographics and imaging protocols. Ensuring model generalizability and transferability is critical for their clinical applicability. Lastly, focusing on advancements in interpretability and explainability techniques specific to brain MRI datasets will enable a better understanding of model predictions, enhancing trust and facilitating the translation of ML-based insights into actionable clinical information for ASD diagnosis and treatment decision-making.

4.2 The role of ML and DL in facial expression recognition

Facial expressions play a vital part in social communication and within the context of autism as shown in Table 3. Face identification involves challenges in non-verbal communication, which can extend to facial expressions. Some individuals with autism might have difficulty maintaining typical eye contact or displaying socially expected facial expressions in response to emotions. This doesn't mean they lack emotions, but rather that their expressions may differ from what is considered the norm. Understanding these variations in facial expressions is crucial for building effective communication and empathy with individuals on the autism spectrum, as it allows for a better interpretation of their emotions and intentions. The phases of emotion recognition are face feature extraction and feature categorization [52].

Singh et al. [53] studied ASD as a developmental state that profoundly impacts a person's perception, communication, as well as behaviour, resulting from underlying modifications to the brain. Onset typically occurs before the age of three and may continue throughout a person's life. Individuals with ASD may exhibit higher rates of self-harming behaviour compared to those without the disorder, underscoring the importance of early detection and intervention. To address this need, ML methods like DT, RF, SVM, and NB, as well as DL approaches like VGG16, Dense Net, and Alex Net, can be leveraged to analyse behaviour-based questionnaires and even images for ASD identification. The suggested approach emphasizes the use of transfer learning-based DL algorithms for early ASD detection. The ASD identification process consists of multiple phases, including data collection/acquisition, pre-processing, data augmentation, extraction of features, and classification. This comprehensive strategy has the potential to enhance ASD early diagnosis, which is essential for prompt intervention and assistance.

Ahmed et al. [54] concentrated on the potential of utilizing facial characteristics for the diagnosis of ASD. A neurodevelopmental disorder called ASD can impact the physical appearance of an individual's face, leading to distinct patterns in autistic children. The research aims to facilitate the diagnosis process for families and psychiatrists through a user-friendly web application. This application leverages DL techniques, specifically a CNN with transfer learning, and is built using the Flask framework. The study employs pre-trained models for classification like InceptionV3, Xception, and MobileNet. 3,014 facial images total are included in the dataset; 1,507 of these are from children with autism and 1,507 from nonautistic children, obtained from a Kaggle dataset that is openly accessible. The results indicate high classification accuracy: Mobile Net achieves 95% accuracy, while Xception achieves 94% and InceptionV3 0.89%. This research highlights the potential of using DL-based facial analysis as an accessible and accurate tool for diagnosing autism, offering a promising avenue for early intervention and support.

Mujeeb Rahman and Subashini [55] delve into the possibility of using static characteristics taken from facial photographs of children to serve the role of a biomarker for distinguishing those with ASD from generally developing kids. The research employs using five pre-trained CNN models as feature extractors-MobileNet, Xception, EfficientNetB0, EfficientNetB1, and EfficientNetB2. These features are then used as input for a DNN binary classifier, aiming to accurately identify autism in children. The dataset used for training comprises facial photos of kids with and without autism, obtained from a publicly available source. Among the CNN models, Xception stands out as the top performer, achieving an 88% NPV, 88.46% sensitivity, and 96.63% AUC. EfficientNetB0, on the other hand, consistently predicted a 59% score for both groups with and without autism at a 95% confidence level. These findings highlight the potential of utilizing facial characteristics and DL for the accurate diagnosis of ASD in kids, which can significantly improve early intervention and support.

Narala et al. [56] proposed a model to facilitate the detection of ASD by predicting whether a person, based on their facial images, is either normally developing or autistic. This study utilizes the Autism Image data dataset, consisting of a test set of 300 facial images and a training set of 2530 facial images for model evaluation. This method is constructed using the Efficient Net CNN, achieving an accuracy level of 88%. These findings showcase the potential of utilizing facial characteristics and DL techniques to distinguish between children who are typically developing and those who have ASD, providing a valuable tool for early diagnosis and intervention.

Bhargavi et al. [57] address the critical issue of ASD, which significantly affects social, linguistic, and communication skills. Early person identification with ASD, especially in children, is crucial for implementing timely therapeutic strategies. Individuals with ASD frequently display unique facial features and behaviours that can aid in their recognition. The proposed method leverages training datasets and DL models to train, test, and evaluate a system for accurate autism face recognition, with the potential for integration into a monitoring robot. The study compares the effectiveness of the therapy bot in conjunction with three different transfer learning architectures: VGG16, Mobile Net, and Resnet50. Notably, VGG16 surpasses other transfer learning methods, achieving 97.66% accuracy on real-time images, demonstrating its effectiveness in the context of autism face recognition and monitoring through neural networks.

Tao and Shyu [58] address the challenging problem of diagnosing ASD, a condition that can manifest with diverse symptoms and severities affecting language and behaviour. The study introduces a novel approach called SP-ASDNet, which combines CNN and LSTM networks. This hybrid method analyses the gaze path of a viewer on a particular image to determine whether the viewer has ASD or is TD. The proposed SP-ASDNet was evaluated in the 2019 Saliency4ASD grand challenge, achieving an accuracy of 74.22% during the validation phase. The integration of deep neural networks, particularly CNNs, and LSTMs, for visual data analysis regarding the diagnosis of ASD, represents a viable option for enhancing the accuracy of detection and comprehension of this complex neurodevelopmental disorder.

Kang et al. [59] aimed to recognize children with autism by characteristics from the EEG and eye-tracking modalities data-and using ML methods, specifically SVM. The research included 97 children aged 3 to 6, who underwent rEEG data recording during resting state and eye tracking tests involving both strangers of one race and another race face stimuli. Power spectrum examination was applied to EEG data, while in the eye-tracking data, Areas of Interest (AOI) were chosen for gaze analysis. Feature selection was performed using the Minimum Redundancy Maximum Relevance (MRMR) technique, and SVM classifiers were employed to categorize children with autism and typically developing kids. The study demonstrated that combining data from both modalities resulted in a classification accuracy of up to 85.44%, with an AUC of 0.93 in the case of 32 features chosen. Although the sample was limited to children aged 3 to 6, these findings suggest that the integration of EEG and eye-tracking data via an ML technique may serve as a useful instrument for identifying kids with ASD and enhancing the procedure for diagnosis.

Guo [60] addresses the possibility of creating an automated technique for examining visual cues indicative of ASD by comparing images taken by individuals utilizing ASD to those captured by individuals in a variety of situations without ASD. Individuals with ASD often exhibit abnormal focus on social cues gaze patterns, and facial expressions. Motivated by previous studies that relied on a manual examination of the images, this research aims to automate the process of identifying visual cues associated with ASD. The challenge lies in determining how to characterize these photos effectively for automated separation. The study proposes several features to characterize observable behaviours related to ASD, and through experimental validation, it achieves a prediction accuracy of 85.8 percent. This work represents a pioneering effort in automatically analysing photos taken by individuals with ASD, offering the promising potential for enhancing the understanding and diagnosis of ASD through visual cues.

Lee and Yoo [61] as shown in Table 3 have explored various neural network architectures, including ResNet-18 and Mobile Net, to improve FER performance. Recent studies have introduced innovative strategies such as divide-and-conquer learning, which leverages confusion matrices to group similar facial expressions and retrain models, leading to substantial accuracy improvements across different datasets, including thermal and RGB datasets like Tufts, RWTH, RAF, and FER2013. These advancements reflect a continued effort to enhance the accuracy and applicability of FER systems, with potential applications spanning human-computer interaction, emotion analysis, and affective computing.

4.2.1 Observation

Based on the above study in ASD detection, future work will involve using facial expression datasets for ASD identification, there are several key areas for improvement and exploration to enhance the accuracy, robustness, as well as applicability of ML methods.

Future improvements in facial expression dataset analysis for ASD detection should centre on three critical avenues. Firstly, integrating multimodal data sources alongside facial expressions, such as voice patterns, physiological signals, or behavioral cues, could offer a more comprehensive understanding of ASD-related characteristics. By merging these different data types, ML models could capture a wider range of features, potentially enhancing diagnostic accuracy. Secondly, expanding and diversifying datasets is pivotal for enhancing model generalizability. Collecting larger and more diverse datasets that encompass variations in age, ethnicity, cultural backgrounds, and emotions across different developmental stages would aid in constructing more robust and inclusive models. Additionally, longitudinal data could provide insights into the evolving nature of facial expressions associated with ASD, enabling more accurate and timely diagnoses. Lastly, focusing on interpretability and explainability within facial expression analysis models is crucial. Research efforts should aim to elucidate the rationale behind the model's decision-making processes, making the predictions transparent and understandable. Techniques that highlight the crucial facial features contributing to the model's classifications can foster trust and comprehension among clinicians, researchers, and stakeholders, ultimately advancing ASD diagnostic accuracy and clinical relevance.

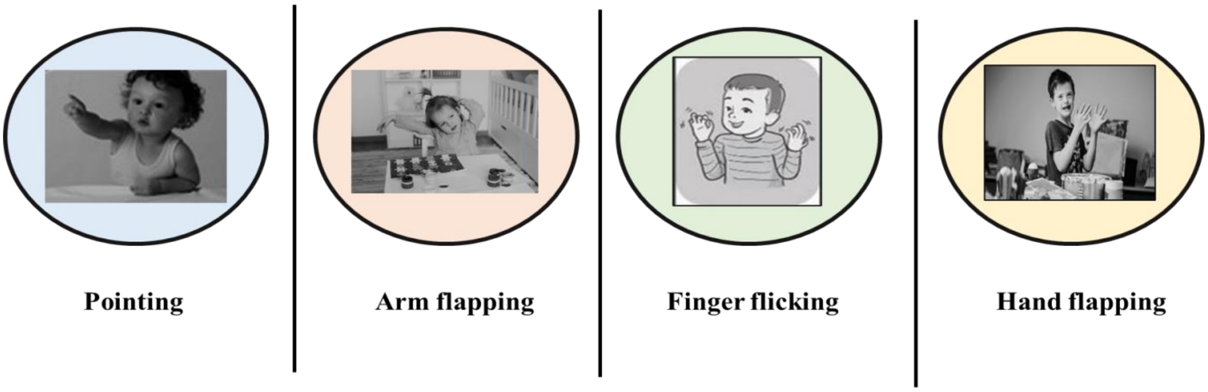

Figure 5. Autism gestures and postures

Table 3. Parametric assessment of ASD detection methods using image-based (facial expression recognition) dataset

Methodology	Objective	Performance	Limitations
ASD Dataset for Toddlers, Kids, Teens, and Adults from Kaggle			
ML methods like DT, RF, SVM, and NB. DL approaches like VGG16, Dense Net, and Alex Net [53]	To detect ASD using DL algorithms, particularly through transfer learning, leveraging ML techniques and DL approaches on behavior-based survey questionnaires and images as input for early identification and diagnosis of ASD.	Accuracy-86.7%	-
Autistic Children Dataset from Kaggle			
CNN, MobileNet, Xception, and InceptionV3 [54]	To create a DL-based web application that detects ASD using CNN and transfer learning by examining facial features in images, aiming to facilitate easier and more accessible diagnosis of ASD.	MobileNet-95% accuracy, Xception-94%, & InceptionV3-0.89%	By enlarging the sample sizes and compiling the dataset of pediatric autistic children's diagnoses from psychologists, future research will enhance this model.
Five pre-trained CNN models were used as feature extractors: MobileNet, Xception, EfficientNetB0, EfficientNetB1, and EfficientNetB2 [55]	To investigate using pre-trained CNN models as feature extractors and a DNN model as a binary classifier, it is possible to reliably identify children with ASD from typically developing children using static facial features extracted from photographs.	Sensitivity: 88.46%, NPV: 88%, and AUC: 96.63%	In the future, we would like to employ an ensemble approach to raise the model scores.
Autistic Image Dataset from Kaggle			
Efficient Net, CNN [56]	To develop a model utilizing facial images to differentiate between people with ASD and normally developing children, aiding in early detection of ASD.	Accuracy-88%	In the first, video is used to predict whether a person is autistic or typically developing. The second possibility is that autism is in its evaluation stage.
Facial Emotion-Based Dataset from Kaggle			
VGG16, Mobile Net, and Resnet50, in combination with the therapy bot [57]	Developing a facial expression recognition system utilizing DL models to accurately identify individuals with ASD, facilitating early detection and aiding in the implementation of suitable therapeutic strategies.	Accuracy-97.66%	Plans involve RNN utilization in dataset training and app development for remote monitoring, with a focus on system enhancement for precise classifications in practical applications.
Saliency 4ASD Dataset			
SP-ASDNet. which combines CNN & and LSTM networks [58]	Developing SP-ASDNet, a model utilizing CNNs and LSTM networks for ASD classification, or generally developed TD observers based on their gaze scan paths in images, aiming to aid in determining the presence of ASD.	Accuracy 74.22%	Future research will examine and incorporate the attentive mechanism into the model to enhance performance even more.
EEG Eye-Tracking Dataset			
SVM classifiers and MRMR approach [59]	We are utilizing EEG and eye-tracking data to create a machine intelligence model SVM for the effective identification of ASD in children aged 3 to 6, aiming to assist in the diagnostic process.	Accuracy = 75.89% and AUC = 86.5%	For the next study, we want to enlist younger kids, like two years old or under.
Real-Time Dataset			
Methodology	**Objective**	**Performance**	**Limitations**
DL methods [60]	Develop an automated process for	Accuracy-85.8%	Future work will enhance the developed

(S. Wang provided data)	analyzing visual cues in images captured by people who suffer from ASD to differentiate behavioral patterns compared to those without ASD.		algorithms to further reduce the errors.
ResNet-18 and MobileNet to improve FER performance. [61]	Improving FER involves a novel approach of partitioned learning, categorizing akin facial expressions, and retraining deep neural network models across diverse datasets (FER2013, RWTH, RAF, and Tufts).	Accuracy for FER performance was 90.71% for RAF, 86.11% for RWTH, 97.75% for Tufts, and 77.83% for FER2013	In the future, Utilize other recognition tasks such as voice, action, object, and text.

4.3 The role of ML and DL in gesture and postures

Body language encompasses a variety of non-verbal cues, including posture, gestures, eye movements, and facial expressions. These are significant indicators of a person's inner emotional and mental state. Many individuals with autism may display typical postures and gestures as shown in Figure 5, such as repetitive hand-flapping, rocking, or unusual body movements. These movements are often seen as self-soothing behaviours individuals with autism may struggle with non-verbal communication, including maintaining eye contact using appropriate facial expressions, which can result in different gestures and postures when interacting with others. Better communication and acceptance of people with autism require an understanding of and respect for distinctive postures and gestures [62].

Yoo et al. [63] address the significance of pointing gestures in separating kids with ASD from those who have TD. As shown in Table 4, the study highlights the absence of datasets created especially with kids' pointing gestures in mind, which results in performance degradation when applying conventional supervised CNNs due to domain shift. To mitigate this issue, the authors suggest an end-to-end learning strategy that uses Self-Supervised Regularization (SSR) for domain-generalized pointing gesture recognition. They validate their approach by developing an ASD diagnostic tool based on Social Interaction-Inducing Content (SIIC) and creating an ASD-Pointing dataset containing 40 TD and ASD children. After conducting several tests, they were able to attain a 72.5% ASD screening accuracy, underscoring the pivotal role of pointing ability in distinguishing between ASD and TD children.

Table 4. Parametric assessment of ASD detection methods using image-based (Gesture and posture) dataset

Methodology	Objective	Performance	Limitations
Real-world ASD-Pointing Dataset			
CNN, SSR [63]	Develop an end-to-end learning scheme utilizing self-supervised regularization for domain generalized pointing gesture recognition aimed at distinguishing between TD and ASD based on pointing ability.	Accuracy - 72.5% Recall - 96.2% Precision - 71.4% F1-score - 82.0%	Our future work is through improvements to SIIC-based tests, such as adding a warming-up section.

4.3.1 Observation

Based on the above study in ASD detection future research focusing on gesture and posture datasets for distinguishing between TD and ASD, several key avenues for improvement can be explored.

In future work, enhancements to the SIIC-based tests should consider incorporating a preliminary "warming-up" phase to potentially improve the ASD diagnostic system's performance in recognizing pointing gestures. This additional phase could involve introductory interactions or preparatory activities before capturing the pointing gestures, potentially aiding in acclimatizing the participants, especially children, to the testing environment. Furthermore, efforts to augment the ASD-Pointing dataset by expanding the sample size and diversity, encompassing a broader range of pointing gestures exhibited by children with ASD and TD, would likely fortify the model's robustness and generalizability. Additionally, refining the SSR technique and exploring novel methodologies to alleviate domain shift issues in CNNs for pointing gesture recognition could be valuable avenues for improving accuracy in identifying kids with TD and ASD according to their pointing abilities.

4.4 Synthesis of findings from ML/DL studies across different image-based datasets

This section synthesizes the findings from studies utilizing ML/DL algorithms across various image-based datasets for ASD detection, including brain MRI, facial expression recognition, and gesture/posture analysis.

4.4.1 Brain MRI dataset

1). ML/DL Algorithms Used:
- Studies utilized a range of algorithms such as CNNs, SVMs, DQN, DBN, and others.
- Techniques like CNN were commonly applied for feature extraction from brain MRI scans.

2). Performance Metrics:
- CNN-Based Models: Achieved accuracies ranging from 70% to 100%, depending on the specific dataset and preprocessing techniques [32, 37].
- DQN and DBN: Reported accuracies of up to 92.4% with high sensitivity and specificity values [33, 38].

3). Consistency of Results:
- Results varied based on dataset size, preprocessing methods, and model complexity.
- Advanced DL techniques generally outperformed traditional ML approaches in accuracy and robustness.

4). Best Performing Approaches:
- DQN: Noted for their high accuracy and robust performance in ASD classification using fMRI data [32].
- DBN with Optimization: Achieved competitive accuracy and efficiency in capturing complex relationships in brain imaging data [36].
- CNNs with Functional Connectivity Patterns: Effective in identifying ASD through functional MRI

data, showcasing the potential for clinical application [35].

4.4.2 Facial expression recognition dataset

1). ML/DL Algorithms Used:

- Commonly employed algorithms include CNNs (e.g., VGG16, MobileNet), Transfer Learning (e.g., InceptionV3), and combinations thereof.
- These algorithms focus on analyzing facial features to detect ASD-related patterns in expressions.

2). Performance Metrics:

- CNN-Based Models: Achieved accuracies ranging from 86.7% to 97.66% across different studies [55, 59].
- Transfer Learning Models: Demonstrated high accuracy rates (e.g., MobileNet-95%) in detecting ASD through facial expression analysis [54].

3). Consistency of Results:

- Studies consistently reported high accuracies in facial expression recognition for ASD detection.
- Variability existed in dataset sizes and inclusion criteria, influencing performance metrics.

4). Best Performing Approaches:

- Transfer Learning Models: Particularly effective due to their ability to leverage pre-trained networks for feature extraction from facial images [56, 57].
- CNNs with Ensemble Methods: Showcased potential in enhancing classification accuracy through ensemble learning techniques [55].

4.4.3 Gesture and posture analysis dataset

1). ML/DL Algorithms Used:

- Techniques included CNNs, self-supervised regularization (SIIC), and supervised learning approaches for gesture recognition.
- Focus on distinguishing between ASD and neurotypical individuals based on motor skills and posture.

2). Performance Metrics:

- CNN-Based Models: Reported accuracies around 72.5% to 97.75% depending on the specific approach and dataset [63].
- SIIC-Based Methods: Achieved high recall and precision scores in recognizing subtle differences in gesture patterns [63].

3). Consistency of Results:

- Results varied across studies due to differences in methodology and dataset characteristics.
- SIIC-based methods showed promise in improving gesture recognition accuracy and reliability.

4). Best Performing Approaches:

- End-to-end learning Schemes: Such as those utilizing SIIC for domain-generalized pointing gesture recognition [63].
- Partitioned Learning Models: Introduced novel approaches to enhancing gesture and posture analysis accuracy [61].

The synthesis of findings across brain MRI, facial expression recognition, and gesture/posture analysis datasets using ML/DL algorithms highlights significant advancements in ASD detection methodologies. While variability exists in results due to dataset specifics and methodological differences, advanced DL techniques consistently demonstrate superior performance over traditional ML methods. Future research should focus on standardizing protocols, expanding dataset sizes, and exploring ensemble learning strategies to further refine ASD diagnostic models across different image-based datasets.

5. THE ROLE OF ML AND DL IN VIDEO-DATABASE

As mentioned in Table 5, these studies exhibit a notable trend in leveraging cutting-edge technologies like DL, computer vision, and AI to address critical challenges in diagnosing and supporting children with ASD. The fusion of computer vision with DL techniques has enabled the development of robust models capable of skill and emotion assessment in ASD children, exhibiting high accuracy rates in recognizing activities, joint attention, and facial expressions. This suggests a potential revolution in diagnosing and monitoring ASD through extended-duration video analysis, offering clinicians valuable insights for informed decision-making in treatment and intervention strategies.

Prakash et al. [64] proposed the innovative application of computer vision for the Evaluation of children with ASD in terms of skills and emotions. It explores the evolution and testing of three DL-based vision methods, namely the framework for automatic joint attention recognition, the activity comprehension model, and the model for recognizing emotions and facial expressions. In this paper, the researchers used a dataset of 300 videos capturing ASD children's social interactions. These models exhibit promising accuracy, with the activity comprehension model at 72.32%, facial expression recognition at 95.1%, and joint attention recognition models reaching up to 97% accuracy. The researchers highlight the capacity of these models to extract valuable insights from extended-duration play-based intervention session videos, facilitating clinicians in diagnosing, assessing, formulating treatments, and monitoring ASD children, even with limited supervision, and significantly contributing to the field's advancement.

Hammoud et al. [65] explore the synergy of AI and the IoT in the context of the Internet of Medical Things (IoMT) for enhanced decision support in healthcare, specifically focusing on the classification of Parkinson's Disease (PD) and Progressive Supranuclear Palsy (PSP). Conventional methods relying solely on the saccade test for disease classification, this study introduces a novel approach. Researchers were involved in the collection of a comprehensive dataset encompassing five different activities such as the gaze test, pursuit, optokinetic nystagmus, spontaneous nystagmus, and gaze cascade. Features of the pupil, including coordinates, area, minor axis, and major axis, are extracted through a deep-learning image segmentation model. These features are then transformed into images having the GADF time series imaging algorithm. Subsequently, the resulting images are inputted into the model of illness detection utilized for the categorization. process. Therefore, researchers found the most impressive classification results are achieved or the optokinetic exercise, showing accuracy rates for the left, right, and both eyes, respectively, of 96.9%, 90.8%, and 96.9% demonstrating the potential of this approach in enhancing the precision and comprehensiveness of neurodegenerative disease classification.

Patankar et al. [66] studied ASD, a neurological condition impacting an individual's lifelong language development, speech, cognition, and social skills. In India, ASD's prevalence stands at 1 in 100 children under the age of 10, with a staggering 1 in 8 children affected by some form of neurodevelopmental condition. ML and DL methods have emerged as valuable tools for rapid and accurate ASD risk assessment. Researchers proposed Early intervention during the preschool and primary school years of a child's education is pivotal in fostering crucial behavioral, functional, social, and communicative abilities. The stark observation that limited research exists on ASD in India has spurred this research initiative. The scant availability of current studies and a lack of Indian-specific datasets highlight the need for dedicated efforts in understanding and addressing ASD in the Indian context. Researchers aim to comprehensively explore ASD, including its definition, symptoms, existing diagnostic tests, and treatment options, while also delving into the relevance of AI in this domain. Therefore, the researchers introduce a pioneering aspect of their work – the creation of an Indian dataset comprising children with ASD – a significant stride towards advancing ASD research in India. Among the methodologies tested, the CNN-RNN Video Classification approach, featuring a pre-trained feature extractor (InceptionV3) within the CNN block, impressively achieved 98.48% for training accuracy and 90.48% for testing accuracy. This study concludes by highlighting the extensive potential for future inquiries in this domain and emphasizing the crucial need for population-specific studies to enhance the identification and treatment of ASD in children from India, ultimately contributing to the advancement of ASD research and support within India.

Li et al. [67] as shown in Table 5 found the pressing issue of diagnosing ASD in children using raw video data, which offers a potential solution to the challenges associated with expensive and subjective diagnosis by medical professionals. By leveraging DL techniques, researchers begin by tracking eye movements in videos of both ASD and TD children, revealing distinct gaze patterns. These tracking trajectories are then analyzed in terms of length and angle, and accumulative histograms are constructed. Classification is performed using a three-layer LSTM network, demonstrating superior performance compared to traditional ML methods, with an accuracy improvement of 6.2%. The method's effectiveness is particularly evident in ASD cases, attaining 91.9% sensitivity and 93.4% specificity. The researchers showcase the potential of utilizing DL on raw video data for ASD diagnosis, offering a promising avenue for improving early detection and intervention for affected children.

Table 5. Parametric assessment of ASD detection methods using video-based dataset

Methodology	Objective	Performance	Limitations
FER2013 Dataset			
DL-based vision has three models: one for activity comprehension, one for emotion and facial expression recognition, and one for automatic joint attention recognition [64], 2023	Implementing computer vision applications through the extraction of joint pose estimations, biobehavioral, interactions, and human activities from captured videos of intervention sessions, evaluation of skill and emotion in kids with ASD can be carried out. This provides valuable data that aids in monitoring, diagnosis, and treatment planning.	The activity comprehension model achieved 72.32% accuracy, Joint attention recognition at 97%, Hand-pointing model at 93.4%, and Facial expression recognition at 95.1%.	Future research integrates clinicians' surveys to evaluate computer vision models for diagnosis and treatment monitoring, creates a unified multitask architecture for analyzing human behavior facets, and develops a multimodal vision-speech model for detecting speech and social behavior abnormalities.
Patient's Eye Recording Dataset, Eye Segmentation Dataset from Github			
Gramian Angular Difference Field (GADF) [65], 2023	Provide a DL framework to address PSP and PD classification using IoT-enriched data, encompassing exercises beyond the saccade test, utilizing pupil features extracted via image segmentation and Time series imaging using the GADF algorithm for improved disease detection.	Regarding the left, right, and both eyes, the corresponding accuracy values are 96.9%, 90.8%, and 96.9%.	Future work will examine the effectiveness of employing multiple models for disease detection in conjunction with various feature representations and TSI algorithms.
Real-Time Dataset			
Techniques	**Objective**	**Performance**	**Limitations**
CNN-RNN, InceptionV3, CNN [66], 2022 (collected our dataset from two locations in Pune: the Prasanna Autism Centre and the Chiranjeev Child Development Clinic)	Highlight the need for a population-specific ASD study among Indian children, emphasizing AI's role, recognizing research gaps, and leading ASD research in India via dataset creation and classification methods.	Accuracy-90.84%	In the future, we intend to continue developing the project to apply real-time video analysis to classify ASD.
VM & LSTM [67], 2020 (Videos from special education and elementary schools were gathered to create a video dataset)	Develop and utilize DL methodology for diagnosing children with ASD using unedited video data by analyzing gaze patterns and employing LSTM networks, aiming to improve accuracy and effectiveness in ASD identification.	Accuracy: 92.6%.	Future endeavors involve leveraging advanced DL techniques to further enhance classification accuracy in investigating gaze and behavior patterns among children with ASD.

Observation:

Based on the above study in ASD detection future research focusing on the integration of AI into healthcare through the IoMT demonstrates a novel approach to neurodegenerative disease classification, specifically the conditions of PD and PSP. By employing DL models on a multi-exercise dataset, researchers achieved impressive accuracy rates in classifying different eye movement exercises, showing promise in improving disease classification methods. Similarly, studies in India showcase an urgent need for ASD research and diagnostics tailored to the local population, highlighting the scarcity of Indian-specific datasets. The pioneering initiatives to create an Indian dataset for ASD children, coupled with the application of CNN-RNN models, underline the potential of AI-driven approaches to enhance early detection and intervention in ASD among Indian children. Additionally, the exploration of raw video data analysis using DL techniques presents a promising direction for ASD diagnosis, offering enhanced accuracy and sensitivity compared to traditional methods. This signifies a significant leap towards more efficient and objective diagnosis methods, potentially benefiting ASD children worldwide.

5.1 Top-performing ML/DL models

This section provides an in-depth look at the specific architectures, hyperparameters, and training procedures of the top-performing models identified in the review. We will also discuss common features and techniques that contributed to their success.

5.1.1 Brain MRI dataset

1) DQN
- Architecture: DQN with SpinalNet and DTPO optimizer.
- Hyperparameters:
- Learning rate: 0.001
- Batch size: 32
- Optimizer: Adam
- Activation functions: ReLU for hidden layers
- Training Procedures:
- Data augmentation for increased dataset variability.
- Cross-validation to prevent overfitting.
- Use of a large number of epochs (typically 100-200) with early stopping.
- Common Features/Techniques:
- Combining SpinalNet for efficient feature extraction.
- DTPO optimizer for improved convergence and classification accuracy.

2) DBN with Adam War Strategy Optimization (AWSO)
- Architecture: DBN with AWSO.
- Hyperparameters:
- Learning rate: 0.0005
- Number of hidden layers: 3
- Number of units per layer: 512
- Optimizer: AWSO
- Dropout rate: 0.5
- Training Procedures:
- Pretraining on a large unsupervised dataset followed by fine-tuning on ASD data.
- Use of dropout to prevent overfitting.
- Regular updates to the learning rate based on training performance.
- Common Features/Techniques:
- AWSO for adaptive learning rate adjustment.
- Deep architecture to capture complex patterns in neuroimaging data.
- CNNs with Functional Connectivity Patterns
- Architecture: Convolutional Neural Networks tailored for fMRI data.
- Hyperparameters:
- Initial learning rate: 0.001
- Batch size: 64
- Number of filters: 64, 128, 256 in successive layers
- Pooling: Max pooling after each convolutional layer
- Training Procedures:
- Data preprocessing including normalization and noise reduction.
- Use of regularization techniques like L2 regularization.
- Ensemble learning to combine predictions from multiple CNN models.
- Common Features/Techniques:
- Focus on functional connectivity patterns to enhance feature extraction.
- Ensemble methods for improving robustness and accuracy.

5.1.2 Facial expression recognition dataset

1) MobileNet for Transfer Learning
- Architecture: Pre-trained MobileNet used as a feature extractor.
- Hyperparameters:
- Fine-tuning learning rate: 0.0001
- Batch size: 32
- Number of epochs: 50
- Training Procedures:
- Transfer learning with initial layers frozen, fine-tuning only the top layers.
- Use of data augmentation techniques like random cropping and flipping.
- Validation on a separate dataset to ensure generalizability.
- Common Features/Techniques:
- EfficientNet-based architectures for lightweight yet effective feature extraction.
- Transfer learning to leverage pre-trained weights for improved accuracy.

2) VGG16 and Ensemble Methods
- Architecture: VGG16 combined with other models in an ensemble framework.
- Hyperparameters:
- Learning rate: 0.0001
- Batch size: 16
- Dropout rate: 0.3
- Training Procedures:
- Ensemble learning combining multiple models like VGG16, ResNet, and InceptionV3.
- Extensive hyperparameter tuning to optimize performance.
- Use of cross-entropy loss and Adam optimizer for training.
- Common Features/Techniques:
- Ensemble methods to combine strengths of different architectures.
- Focus on high-quality data preprocessing and augmentation.

5.1.3 Gesture and posture analysis dataset

SIIC-Based End-to-End Learning

- Architecture: Self-supervised regularization combined with CNNs.

- Hyperparameters:
- Initial learning rate: 0.001
- Batch size: 64
- Number of epochs: 150
- Activation functions: Leaky ReLU
- Training Procedures:
- Self-supervised learning to improve feature representation.
- Regularization techniques like batch normalization.
- Use of a diverse dataset for robust training.
- Common Features/Techniques:
- Self-supervised learning for enhanced feature learning.
- Domain generalization techniques to improve performance across different domains.

6. DL AND ML MODEL-BASED ASD IDENTIFICATION

The expanded workflow encompasses crucial stages in leveraging ML and DL for autism detection and management. Commencing with comprehensive data collection, it underscores the necessity of assembling diverse datasets ranging from behavioral observations to medical records, neuroimaging data, and genetic information. Subsequently, the data preprocessing stage's emphasis on rectifying errors and standardizing features ensures the integrity of information before analysis.

The incorporation of feature selection/extraction Figure 6 signifies a pivotal step in the process, aiming to identify the most pertinent variables for autism detection. This involves leveraging statistical analyses or dimensionality reduction techniques to focus on the most informative aspects. The subsequent stages encompass model building and training, integrating appropriate ML/DL models such as SVM, CNN, or others based on the nature of the dataset and the problem at hand. The optimization of model performance through parameter adjustments is fundamental to enhancing accuracy and reliability.

Validation, evaluation, and testing phases ensure the model's effectiveness and generalizability. These steps are crucial to validate the model's accuracy, precision, and recall on unseen datasets, gauging its readiness for practical application. Beyond diagnosis and classification, the workflow's extension toward consulting doctors/therapists and enhancing the quality of life emphasizes the broader scope of utilizing ML/DL approaches in holistic autism care. This extended approach focuses not only on identification but also on leveraging technology to aid professionals in diagnosis and supporting individuals with autism in their daily lives, ultimately contributing to their well-being.

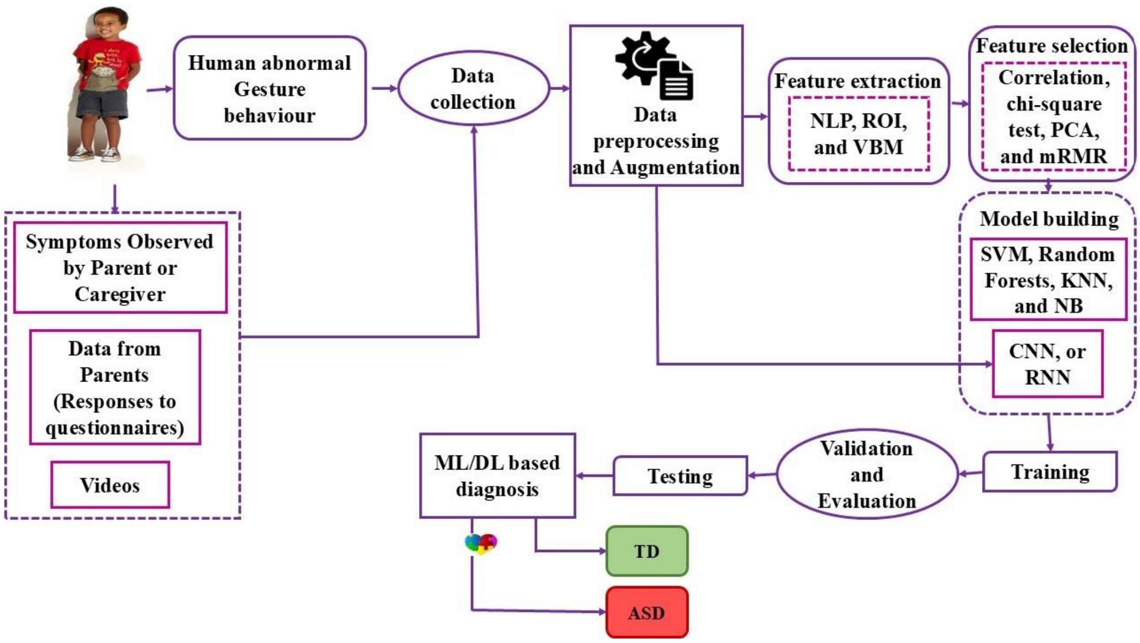

Figure 6. Workflow of ASD

7. DISCUSSION

7.1 Comparative studies

Several studies have conducted comparative analyses of traditional ML algorithms and DL approaches for ASD detection. These studies provide valuable insights into the effectiveness, strengths, and limitations of each approach.

1) Study A: SVM vs. CNN

Findings: This study compared SVM with CNN for ASD detection using brain MRI data.

- Strengths of SVM: Simplicity, less computationally intensive, effective with small to medium-sized datasets.
- Weaknesses of SVM: Limited ability to capture complex patterns in high-dimensional data, such as those found in neuroimaging.
- Strengths of CNN: Superior performance in capturing spatial hierarchies and complex patterns in neuroimaging data.
- Weaknesses of CNN: Requires large datasets for effective training, computationally intensive, longer training times.
- Performance Comparison: CNN achieved an accuracy of 85% while SVM achieved an accuracy of 75%.

2) Study B: Random Forest vs. DBN

Findings: This study evaluated the performance of RF and DBN on facial expression recognition datasets for ASD detection.

- Strengths of RF: Robustness to overfitting, easy to interpret, relatively fast to train.
- Weaknesses of RF: Less effective in capturing non-linear relationships compared to DL models.
- Strengths of DBN: High accuracy in capturing complex features, capable of unsupervised pretraining.
- Weaknesses of DBN: Requires significant computational resources, longer training times.
- Performance Comparison: DBN achieved an accuracy of 92% while RF achieved an accuracy of 80%.

3) Study C: KNN vs. LSTM Networks

Findings: This study compared KNN with LSTM networks for ASD detection using gesture and posture data.

- Strengths of KNN: Simple implementation, effective for small datasets.
- Weaknesses of KNN: Computationally expensive for large datasets, sensitivity to irrelevant features.
- Strengths of LSTM: Effective in handling sequential data and temporal dependencies.
- Weaknesses of LSTM: Requires large datasets, complex hyperparameter tuning.
- Performance Comparison: LSTM achieved an accuracy of 88% while KNN achieved an accuracy of 72%.

7.2 Relative strengths and weaknesses

Traditional ML Algorithms:

- Strengths:
  - Easier to implement and interpret.
  - Require less computational power and memory.
  - Perform well on smaller datasets with simpler patterns.
- Weaknesses:
  - Limited ability to handle high-dimensional data and complex feature representations.
  - Often require manual feature extraction and selection.
  - Less adaptable to varying data types and structures.

Deep Learning Approaches:

- Strengths:
  - Superior performance in capturing complex and hierarchical patterns in large datasets.
  - Capable of automatic feature extraction and learning.
  - More adaptable to different data types (e.g., images, sequences).
- Weaknesses:
  - Require large amounts of labeled data for training.
  - Computationally intensive and resource-demanding.
  - Longer training times and more complex hyperparameter tuning.

By comparing traditional ML algorithms with DL approaches, it is evident that DL models generally outperform traditional ML methods in terms of accuracy and feature representation capabilities, especially in high-dimensional and complex datasets such as neuroimaging and facial expression data. However, traditional ML algorithms remain valuable for their simplicity, interpretability, and efficiency, particularly in scenarios with limited data or computational resources.

7.3 Potential clinical applications

The application of ML and DL models in ASD detection holds significant promise for various clinical scenarios:

1) Early Diagnosis and Intervention:
   - Importance: Early diagnosis of ASD is critical for timely intervention, which can significantly improve long-term outcomes for individuals with ASD.
   - Application: ML/DL models can analyze behavioral, neuroimaging, and genetic data to identify early markers of ASD, facilitating early diagnosis even before clinical symptoms become apparent.
2) Personalized Treatment Plans:
   - Importance: ASD presents with a wide range of symptoms and severities, necessitating personalized treatment approaches.
   - Application: ML/DL models can analyze individual data to predict the most effective treatment plans, enabling personalized interventions tailored to the specific needs of each individual.
3) Screening Tools:
   - Importance: Efficient screening tools are necessary to identify individuals at risk of ASD, especially in large populations.
   - Application: ML/DL models can be integrated into mobile applications or web-based platforms to provide quick and accessible screening for ASD, guiding users towards professional evaluation if necessary.
4) Monitoring and Progress Tracking:
   - Importance: Continuous monitoring is essential to track the progress of individuals undergoing treatment for ASD.
   - Application: ML/DL models can be used to analyze data from wearable devices, video recordings, or other monitoring tools to assess behavioral changes and treatment efficacy over time.

7.4 Feasibility of integration into current diagnostic pathways

Integrating ML/DL tools into existing diagnostic pathways involves several considerations:

1) Data Availability and Quality:
   - Challenge: High-quality, large-scale datasets are required to train robust ML/DL models.
   - Solution: Collaborations between healthcare institutions, research centers, and technology companies can facilitate data sharing and create comprehensive datasets for model training.
2) Validation and Standardization:
   - Challenge: Ensuring the accuracy, reliability, and generalizability of ML/DL models across diverse populations and clinical settings.
   - Solution: Extensive validation studies and the development of standardized protocols for model testing and implementation are necessary to

establish trust and reliability in clinical use.

3) Integration with Clinical Workflows:
- Challenge: Seamlessly incorporating ML/DL tools into the existing diagnostic workflows without disrupting clinical routines.
- Solution: Developing user-friendly interfaces and ensuring interoperability with existing electronic health record (EHR) systems can facilitate smooth integration. Training clinicians to use these tools effectively is also crucial.

4) Regulatory and Ethical Considerations:
- Challenge: Addressing regulatory requirements and ethical concerns related to data privacy, algorithmic transparency, and informed consent.
- Solution: Adhering to regulatory guidelines, ensuring transparent and explainable model outputs, and implementing robust data protection measures are essential steps for ethical deployment.

5) Cost and Accessibility:
- Challenge: Making ML/DL tools cost-effective and accessible to a wide range of healthcare providers and patients.
- Solution: Economies of scale, technological advancements, and funding support from government and private sectors can reduce costs and increase accessibility.
- The integration of ML/DL models into clinical practice for ASD detection holds the potential to revolutionize early diagnosis, personalized treatment, and continuous monitoring. Addressing the challenges related to data quality, validation, workflow integration, regulatory compliance, and cost will be key to realizing the full potential of these advanced technologies in improving outcomes for individuals with ASD.

8. CONCLUSION

The comprehensive review underscores the pivotal role of ML, DL, and computational methodologies in transforming the landscape of ASD diagnosis and understanding. Across various studies employing diverse datasets, neuroimaging modalities, and behavioral analyses, the integration of advanced computational techniques has showcased promising advancements. ML and DL models, including CNNs, reinforcement learning, and clustering analyses, have demonstrated high accuracy rates in ASD detection, emphasizing their potential for early diagnosis and tailored therapeutic interventions. Moreover, the amalgamation of multi-modal data, such as facial images, EEG, and handwriting samples, coupled with innovative computational approaches, offers a pathway toward more precise and objective ASD identification. Furthermore, the integration of AI into healthcare, along with the analysis of neuroimaging data, presents a promising avenue for enhanced early prediction, which could lead to personalized interventions and improved clinical practices. Ultimately, all of the studies that have been reviewed demonstrate the revolutionary effects of computational methodologies in advancing ASD diagnosis, potentially revolutionizing clinical practices and significantly benefiting individuals with ASD in the long term.

Our future scope is to improve,
- Develop methodologies that effectively fuse data from various sources like MRI modalities, behavioral cues, and genetic information into a unified framework. Utilize advanced fusion techniques, such as DL-based multimodal architectures, to capture intricate patterns across diverse data sources, thereby enhancing diagnostic accuracy and providing a more comprehensive understanding of ASD-related characteristics.
- Focus on longitudinal studies analyzing ASD-related data over time, such as brain MRI scans or behavioral patterns investigate how these characteristics evolve across different developmental stages, potentially identifying biomarkers or behavioral patterns that signify the onset or progression of ASD.
- Develop advanced NLP techniques specifically tailored to understand the context and nuances of text data related to ASD. Aim for models that can comprehend the subtle semantic meaning of textual information, capturing the intricacies of ASD-related linguistic behaviors across diverse cultural contexts and age groups.
- Collect a more extensive and diverse dataset that encompasses a wider range of gestures and postures displayed by individuals with ASD and TD across various age groups, cultural backgrounds, and developmental stages. This dataset expansion would provide a more comprehensive understanding of subtle variations in gestures and postures indicative of ASD.

8.1 Key findings

(1) High Accuracy of ML/DL Models:
- ML and DL models, including CNNs, reinforcement learning, and clustering analyses, have demonstrated high accuracy rates in ASD detection, emphasizing their potential for early diagnosis and tailored therapeutic interventions.

(2) Multi-Modal Data Integration:
- The amalgamation of multi-modal data, such as facial images, EEG, and handwriting samples, coupled with innovative computational approaches, offers a pathway toward more precise and objective ASD identification.

(3) Enhanced Early Prediction:
- The integration of AI into healthcare, along with the analysis of neuroimaging data, presents a promising avenue for enhanced early prediction, which could lead to personalized interventions and improved clinical practices.

8.2 Limitations

- Data Quality and Availability:
  High-quality, large-scale datasets are required to train robust ML/DL models. Current studies often face challenges related to data heterogeneity and limited sample sizes.
- Validation and Generalizability:
  Ensuring the accuracy and generalizability of ML/DL models across diverse populations and clinical settings remains a critical challenge.
- Integration into Clinical Workflows:
  Seamlessly incorporating ML/DL tools into existing

diagnostic workflows without disrupting clinical routines requires careful planning and user-friendly interfaces.

8.3 Potential impact

Ultimately, all of the studies reviewed demonstrate the revolutionary effects of computational methodologies in advancing ASD diagnosis. The potential impact of these advancements includes:

- Improved Early Detection:
  ML/DL models can significantly enhance the early detection of ASD, allowing for timely interventions that can improve long-term outcomes.
- Personalized Interventions:
  The ability to analyze individual-specific data can lead to more personalized and effective treatment plans.
- Objective and Precise Diagnosis:
  Integrating AI into diagnostic pathways can provide more objective and precise ASD identification, reducing the reliance on subjective assessments.

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REFERENCES

[1] Sree, S.R., Kaur, I., Tikhonov, A., Lydia, E.L., Thabit, A.A., Kareem, Z.H., Yousif, Y.K., Alkhayyat, A. (2023). Jellyfish search optimization with deep learning driven autism spectrum disorder classification. Comput Mater Continua, 74(1): 2195-2209. https://doi.org/10.32604/cmc.2023.032586

[2] Talukdar, J., Gogoi, D.K., Singh, T.P. (2023). A comparative assessment of most widely used machine learning classifiers for analysing and classifying autism spectrum disorder in toddlers and adolescents. Healthcare Analytics, 3: 100178. https://doi.org/10.1016/j.health.2023.100178

[3] Loh, H.W., Ooi, C.P., Oh, S.L., Barua, P.D., Tan, Y.R., Molinari, F., March, S., Acharya, U.R., Fung, D.S.S. (2023). Deep neural network technique for automated detection of ADHD and CD using ECG signal. Computer Methods and Programs in Biomedicine, 241: 107775. https://doi.org/10.1016/j.cmpb.2023.107775

[4] Archana, P., Sirisha, G.N.V.G., Chaitanya, R.K. (2023). Prediction of autism spectrum disorder from high-dimensional data using machine learning techniques. Soft Computing, 27(16): 11869-11875. https://doi.org/10.1007/s00500-023-08657-0

[5] Omkari, D.Y., Shinde, S.B. (2022). Cardiovascular disease prediction using machine learning techniques with HyperOpt. In International Conference on Communication and Intelligent Systems. Singapore: Springer Nature Singapore, pp. 585-597. https://doi.org/10.1007/978-981-99-2322-9_44

[6] RethikumariAmma, K.N., Ranjana, P. (2023). Pivotal region and optimized deep neuro fuzzy network for autism spectrum disorder detection. Biomedical Signal Processing and Control, 83: 104634. https://doi.org/10.1016/j.bspc.2023.104634

[7] Lee, J., Lee, H., Shin, M. (2021). Driving stress detection using multimodal convolutional neural networks with nonlinear representation of short-term physiological signals. Sensors, 21(7): 2381. https://doi.org/10.3390/s21072381

[8] Kumar, C.J., Das, P.R., Hazarika, A. (2022). Autism spectrum disorder diagnosis and machine learning: A review. International Journal of Medical Engineering and Informatics, 14(6): 512-527. https://doi.org/10.1504/IJMEI.2022.126522

[9] Sharma, M., Kumar, C.J., Deka, A. (2022). Early diagnosis of rice plant disease using machine learning techniques. Archives of Phytopathology and Plant Protection, 55(3): 259-283. https://doi.org/10.1080/03235408.2021.2015866

[10] Bhadra, S., Kumar, C.J. (2022). An insight into diagnosis of depression using machine learning techniques: A systematic review. Current Medical Research and Opinion, 38(5): 749-771. https://doi.org/10.1080/03007995.2022.2038487

[11] Alpaydin E, (2020). Introduction to machine learning. MIT Press, Cambridge.

[12] Scientific, L.L. (2024). Enhancing glaucoma diagnosis: Deep learning models for automated identification and explainability using fundus IMAGES. Journal of Theoretical and Applied Information Technology, 102(13): 5346-5363.

[13] Vadduri, M., Kuppusamy, P. (2023). Enhancing ocular healthcare: Deep learning-based multi-class diabetic eye disease segmentation and classification. IEEE Access, 11: 137881-137898. https://doi.org/10.1109/ACCESS.2023.3339574

[14] Vadduri, M., Kuppusamy, P. (2022). Diabetic eye diseases detection and classification using deep learning techniques-A survey. In International Conference on Information and Communication Technology for Competitive Strategies. Singapore: Springer Nature, Singapore, pp. 443-454. https://doi.org/10.1007/978-981-19-9638-2_38

[15] Shin, J., Konnai, S., Maniruzzaman, M., Hasan, M.A.M., Hirooka, K., Megumi, A., Yasumura, A. (2023). Identifying ADHD for children with coexisting ASD from fNIRs signals using deep learning approach. IEEE Access, 11: 82794-82801. https://doi.org/10.1109/ACCESS.2023.3299960

[16] Raj, S., Masood, S. (2020). Analysis and detection of autism spectrum disorder using machine learning techniques. Procedia Computer Science, 167: 994-1004. https://doi.org/10.1016/j.procs.2020.03.399

[17] Akter, T., Satu, M.S., Khan, M.I., Ali, M.H., Uddin, S., Lio, P., Quinn, J.M., Moni, M.A. (2019). Machine learning-based models for early stage detection of autism spectrum disorders. IEEE Access, 7: 166509-166527. https://doi.org/10.1109/ACCESS.2019.2952609

[18] Hasan, S.M., Uddin, M.P., Al Mamun, M., Sharif, M.I., Ulhaq, A., Krishnamoorthy, G. (2022). A machine learning framework for early-stage detection of autism spectrum disorders. IEEE Access, 11: 15038-15057. https://doi.org/10.1109/ACCESS.2022.3232490

[19] Vignesh, U., Suma, K.G., Elakya, R., Vinothini, C., Kumar, A.S. (2021). Classification techniques for behavior study of Autism spectrum disorder. Journal of Physics: Conference Series, 1964(3): 032008.

https://doi.org/10.1088/1742-6596/1964/3/032008
[20] Vakadkar, K., Purkayastha, D., Krishnan, D. (2021). Detection of autism spectrum disorder in children using machine learning techniques. SN Computer Science, 2: 1-9. https://doi.org/10.1007/s42979-021-00776-5
[21] Shin, J., Maniruzzaman, M., Uchida, Y., Hasan, M.A.M., Megumi, A., Yasumura, A. (2023). Handwriting-based ADHD detection for children having ASD using machine learning approaches. IEEE Access, 11: 84974-84984. https://doi.org/10.1109/ACCESS.2023.3302903
[22] Jaiswal, S., Valstar, M.F., Gillott, A., Daley, D. (2017) Automatic detection of ADHD and ASD from expressive behaviour in RGBD data. In 2017 12th IEEE international conference on automatic face and gesture recognition (FG 2017), Washington, USA, pp 762-769. https://doi.org/10.1109/FG.2017.95
[23] Zhao, Z., Zhang, X., Li, W., Hu, X., Qu, X., Cao, X., Liu, Y., Lu, J. (2019). Applying machine learning to identify autism with restricted kinematic features. IEEE Access, 7: 157614-157622. https://doi.org/10.1109/ACCESS.2019.2950030
[24] Thabtah, F. (2019). An accessible and efficient autism screening method for behavioral data and predictive analyses. Health Informatics Journal, 25(4): 1739-1755. https://doi.org/10.1177/1460458218796636
[25] Barnea-Goraly, N., Frazier, T.W., Piacenza, L., Minshew, N.J., Keshavan, M.S., Reiss, A.L., Hardan, A.Y. (2014). A preliminary longitudinal volumetric MRI study of amygdala and hippocampal volumes in autism. Progress in Neuro-Psychopharmacology and Biological Psychiatry, 48: 124-128. https://doi.org/10.1016/j.pnpbp.2013.09.010
[26] Schumann, C.M., Hamstra, J., Goodlin-Jones, B.L., Lotspeich, L.J., Kwon, H., Buonocore, M.H., Lammers C.R., Reiss A.L., Amaral, D.G. (2004). The amygdala is enlarged in children but not adolescents with autism; The hippocampus is enlarged at all ages. Journal of Neuroscience, 24(28): 6392-6401. https://doi.org/10.1523/JNEUROSCI.1297-04.2004
[27] Nordahl, C.W., Iosif, A.M., Young, G.S., Hechtman, A., Heath, B., Lee, J.K., Libero L., Reinhardt V.P., Winder-Patel B., Amaral D.G., Rogers S., Solomon M., Ozonoff, S. (2020). High psychopathology subgroup in young children with autism: Associations with biological sex and amygdala volume. Journal of the American Academy of Child & Adolescent Psychiatry, 59(12): 1353-1363. https://doi.org/10.1016/j.jaac.2019.11.022
[28] Nordahl, C.W., Scholz, R., Yang, X., Buonocore, M.H., Simon, T., Rogers, S., Amaral, D.G. (2012). Increased rate of amygdala growth in children aged 2 to 4 years with autism spectrum disorders: A longitudinal study. Archives of General Psychiatry, 69(1): 53-61. https://doi.org/10.1001/archgenpsychiatry.2011.145
[29] Stoodley, C.J. (2014). Distinct regions of the cerebellum show gray matter decreases in autism, ADHD, and developmental dyslexia. Frontiers in Systems Neuroscience, 8: 92. https://doi.org/10.3389/fnsys.2014.00092
[30] Raja, K.C., Kannimuthu, S. (2023). Conditional generative adversarial network approach for autism prediction. Computer Systems Science & Engineering, 44(1): 741-755. https://doi.org/10.32604/csse.2023.025331
[31] Sabegh, A.M., Samadzadehaghdam, N., Seyedarabi, H., Ghadiri, T. (2023). Automatic detection of autism spectrum disorder based on fMRI images using a novel convolutional neural network. Research on Biomedical Engineering, 39(2): 407-413. https://doi.org/10.1007/s42600-023-00275-x
[32] Ulaganathan, S., Ramkumar, M.P., Emil Selvan, G.S.R., Priya, C. (2023). Spinalnet-deep q network with hybrid optimization for detecting autism spectrum disorder. Signal, Image and Video Processing, 17(8): 4305-4317. https://doi.org/10.1007/s11760-023-02663-3
[33] Lei, D., Zhang, T., Wu, Y., Li, W., Li, X. (2023). Autism spectrum disorder diagnosis based on deep unrolling-based spatial constraint representation. Medical & Biological Engineering & Computing, 61(11): 2829-2842. https://doi.org/10.1007/s11517-023-02859-2
[34] Sherkatghanad, Z., Akhondzadeh, M., Salari, S., Zomorodi-Moghadam, M., Abdar, M., Acharya, U.R., Khosrowabadi, R., Salari, V. (2020). Automated detection of autism spectrum disorder using a convolutional neural network. Frontiers in Neuroscience, 13: 1325. https://doi.org/10.3389/fnins.2019.01325
[35] Nogay, H.S., Adeli, H. (2023). Diagnostic of autism spectrum disorder based on structural brain MRI images using, grid search optimization, and convolutional neural networks. Biomedical Signal Processing and Control, 79: 104234. https://doi.org/10.1016/j.bspc.2022.104234
[36] Bhandage, V., Muppidi, S., Maram, B. (2023). Autism spectrum disorder classification using Adam war strategy optimization enabled deep belief network. Biomedical Signal Processing and Control, 86: 104914. https://doi.org/10.1016/j.bspc.2023.104914
[37] Parui, S., Samanta, D., Chakravorty, N., Ghosh, U., Rodrigues, J.J. (2023). Artificial intelligence and sensor-based autism spectrum disorder diagnosis using brain connectivity analysis. Computers and Electrical Engineering, 108: 108720. https://doi.org/10.1016/j.compeleceng.2023.108720
[38] Yin, W., Li, L., Wu, F.X. (2022). A semi-supervised autoencoder for autism disease diagnosis. Neurocomputing, 483: 140-147. https://doi.org/10.1016/j.neucom.2022.02.017
[39] Ahammed, M.S., Niu, S., Ahmed, M.R., Dong, J., Gao, X., Chen, Y. (2021). Bag-of-features model for asd fmri classification using SVM. In 2021 Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS), Shenyang, China, pp. 52-57. https://doi.org/10.1109/ACCTCS52002.2021.00019
[40] Itani, S., Thanou, D. (2021). Combining anatomical and functional networks for neuropathology identification: A case study on autism spectrum disorder. Medical Image Analysis, 69: 101986. https://doi.org/10.1016/j.media.2021.101986
[41] Zhan, Y., Wei, J., Liang, J., Xu, X., He, R., Robbins, T.W., Wang, Z. (2021). Diagnostic classification for human autism and obsessive-compulsive disorder based on machine learning from a primate genetic model. American Journal of Psychiatry, 178(1): 65-76. https://doi.org/10.1176/appi.ajp.2020.19101091
[42] Liu, W., Liu, M., Yang, D., Wang, M., Tao, T. (2020). Automatic diagnosis of autism based on functional magnetic resonance imaging and elastic net. In 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, pp. 104-108.

https://doi.org/10.1109/ITOEC49072.2020.9141766
[43] Mostafa, S., Tang, L., Wu, F.X. (2019). Diagnosis of autism spectrum disorder based on eigenvalues of brain networks. IEEE Access, 7: 128474-128486. https://doi.org/10.1109/ACCESS.2019.2940198
[44] Wang, M., Zhang, D., Huang, J., Yap, P.T., Shen, D., Liu, M. (2019). Identifying autism spectrum disorder with multi-site fMRI via low-rank domain adaptation. IEEE Transactions on Medical Imaging, 39(3): 644-655. https://doi.org/10.1109/TMI.2019.2933160
[45] Fredo, A.J., Jahedi, A., Reiter, M., Müller, R.A. (2018). Diagnostic classification of autism using resting-state fMRI data and conditional random forest. Age, 12(2.76): 6-41.
[46] Heinsfeld, A.S., Franco, A.R., Craddock, R.C., Buchweitz, A., Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical, 17: 16-23. https://doi.org/10.1016/j.nicl.2017.08.017
[47] Vandewouw, M.M., Brian, J., Crosbie, J., Schachar, R.J., Iaboni, A., Georgiades, S., Nicolson, R., Kelley, E., Ayub, M., Jones, J., Taylor, M.J., Lerch, J.P., Anagnostou, E., Kushki, A. (2023). Identifying replicable subgroups in neurodevelopmental conditions using resting-state functional magnetic resonance imaging data. JAMA Network Open, 6(3): e232066. https://doi.org/10.1001/jamanetworkopen.2023.2066
[48] Gao, K., Sun, Y., Niu, S., Wang, L. (2021). Unified framework for early stage status prediction of autism based on infant structural magnetic resonance imaging. Autism Research, 14(12): 2512-2523. https://doi.org/10.1002/aur.2626
[49] Conti, E., Retico, A., Palumbo, L., Spera, G., Bosco, P., Biagi, L., Fiori, S., Tosetti, M., Cipriani, P., Cioni, G., Muratori, F., Chilosi, A., Calderoni, S. (2020). Autism spectrum disorder and childhood apraxia of speech: Early language-related hallmarks across structural MRI study. Journal of Personalized Medicine, 10(4): 275. https://doi.org/10.3390/jpm10040275
[50] Saad, M., Islam, S.M.R. (2019). Brain connectivity network analysis and classifications from diffusion tensor imaging. In 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), Dhaka, Bangladesh, pp. 422-427. https://doi.org/10.1109/ICREST.2019.8644080
[51] Ke, Q., Zhang, J., Wei, W., Damaševičius, R., Woźniak, M. (2019). Adaptive independent subspace analysis of brain magnetic resonance imaging data. IEEE Access, 7: 12252-12261. https://doi.org/10.1109/ACCESS.2019.2893496
[52] Talaat, F.M. (2023). Real-time facial emotion recognition system among children with autism based on deep learning and IoT. Neural Computing and Applications, 35(17): 12717-12728. https://doi.org/10.1007/s00521-023-08372-9
[53] Singh, D., Rakhra, M., Aggarwal, S. (2022). Autism spectrum disorder detection using the deep learning approaches. In 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, pp. 761-766. https://doi.org/10.1109/ICTACS56270.2022.9988442
[54] Ahmed, Z.A., Aldhyani, T.H., Jadhav, M.E., Alzahrani, M.Y., Alzahrani, M.E., Althobaiti, M.M., Alassery, F., Alshaflut, A., Alzahrani, N.M., Al-Madani, A.M. (2022). Facial features detection system to identify children with autism spectrum disorder: Deep learning models. Computational and Mathematical Methods in Medicine, 2022(1): 3941049. https://doi.org/10.1155/2022/3941049
[55] Mujeeb Rahman, K.K., Subashini, M.M. (2022). Identification of autism in children using static facial features and deep neural networks. Brain Sciences, 12(1): 94. https://doi.org/10.3390/brainsci12010094
[56] Narala, M.S.V.S.K., Vemuri, S., Kattula, C. (2023). Prediction of autism spectrum disorder using efficient net. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, pp. 1139-1143. https://doi.org/10.1109/ICACCS57279.2023.10112807
[57] Bhargavi, Y., Bini, D., Prince, S. (2023). AI-based emotion therapy bot for children with autism spectrum disorder (ASD). In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, pp. 1895-1899. https://doi.org/10.1109/ICACCS57279.2023.10112868
[58] Tao, Y., Shyu, M.L. (2019). SP-ASDNet: CNN-LSTM based ASD classification model using observer scanpaths. In 2019 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), Shanghai, China, pp. 641-646. https://doi.org/10.1109/ICMEW.2019.00124
[59] Kang, J., Han, X., Song, J., Niu, Z., Li, X. (2020). The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data. Computers in Biology and Medicine, 120: 103722. https://doi.org/10.1016/j.compbiomed.2020.103722
[60] Guo, A.Z. (2020). Automated autism detection based on characterizing observable patterns from photos. IEEE Transactions on Affective Computing, 14(1): 836-841. https://doi.org/10.1109/TAFFC.2020.3035088
[61] Lee, D.H., Yoo, J.H. (2023). CNN learning strategy for recognizing facial expressions. IEEE Access, 11: 70865-70872. https://doi.org/10.1109/ACCESS.2023.3294099
[62] Noroozi, F., Corneanu, C.A., Kamińska, D., Sapiński, T., Escalera, S., Anbarjafari, G. (2018). Survey on emotional body gesture recognition. IEEE Transactions on Affective Computing, 12(2): 505-523. https://doi.org/10.1109/TAFFC.2018.2874986
[63] Yoo, C.H., Yoo, J.H., Kim, H.W., Han, B. (2023). Pointing gesture recognition via self-supervised regularization for ASD screening. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 3036-3043.
[64] Prakash, V.G., Kohli, M., Kohli, S., Prathosh, A.P., Wadhera, T., Das, D., Panigrahi, D., Kommu, J.V.S. (2023). Computer vision-based assessment of autistic children: Analyzing interactions, emotions, human pose, and life skills. IEEE Access, 11: 47907-47929. https://doi.org/10.1109/ACCESS.2023.3269027
[65] Hammoud, M., Kovalenko, E., Somov, A., Bril, E., Baldycheva, A. (2023). Deep learning framework for neurological diseases diagnosis through near-infrared eye video and time series imaging algorithms. Internet of Things, 24: 100914. https://doi.org/10.1016/j.iot.2023.100914
[66] Patankar, R., Vedpathak, S., Thakre, V., Sethi, P., Sawarkar, S. (2022). AutiScan: Screening of autism spectrum disorder specific to Indian region. In 2022

IEEE 3rd Global Conference for Advancement in Technology (GCAT), Bangalore, India, pp. 1-8. https://doi.org/10.1109/GCAT55367.2022.9972038

[67] Li, J., Zhong, Y., Han, J., Ouyang, G., Li, X., Liu, H. (2020). Classifying ASD children with LSTM based on raw videos. Neurocomputing, 390: 226-238. https://doi.org/10.1016/j.neucom.2019.05.106