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REVIEW

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Machine Learning and Deep Learning over Discovery of ASD: A Descriptive Review

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Abstract: Autism spectrum disorder (ASD) is a complex neurodevelopmental condition impacting behavior, communication, and social interaction. The term "spectrum" highlights the variability in symptoms and severity, ranging from mild to severe. While ASD typically manifests within the first two years of life, it can remain undiagnosed until adolescence. The exact causes of ASD are still unclear, though genetic research continues to provide valuable insights. Early detection and intervention are essential for better outcomes, enabling timely support and therapy. Leveraging big data and machine learning (ML) and deep learning (DL) techniques has proven beneficial in ASD detection and analysis. This paper reviews existing ML and DL models for ASD classification and prediction, examining over 60 research articles. The analysis covers both supervised and unsupervised ML methods and explores current ASD screening tests employed in laboratory diagnostics by psychologists and behavioral counselors. The review aims to provide insights into the advancements in ASD detection using data-driven approaches. It also serves as a guide for researchers focused on expanding knowledge in health informatics and medical research. Additionally, this paper discusses how mathematical, statistical, and data analytic techniques can be applied to enhance ASD data mining and self-analysis. This review supports the continuous evolution of ASD research and the development of more effective, data-supported diagnostic tools.

Keywords: autism spectrum disorder, deep learning, machine learning, supervised and unsupervised learning

1. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition that affects communication skills and social interaction and raises behavioral issues and interests. It is called a "spectrum" disorder as it manifests in a wide range of symptoms and severity levels. Individuals with ASD can vary greatly in their abilities and challenges. While not entirely clear, its cause lies greatly on genetic, neurological, and environmental factors [1]. The incidence of ASD has been increasing, currently estimated at an alarming 1 in 54 children in the United States and 1 in 67 worldwide. The diagnosis of autism is typically made through clinical observation, behavioral assessments, and developmental assessments, and it takes about two to three sessions spanning at least one week [2–4]. It has been observed that ASD is generally characterized by nil to low eye contact, use and understanding of nonverbal cues, sensory sensitivities, intellectual and developmental differences, and specific interests with an intense focus. In particular, ASD patients categorized to have stereotypical motor movements (SMM) present with shaking, rocking, and spinning of body, hand flapping, mouthing, and complicated hand movements [5].

There is no medical or clinical test that has proved the presence of ASD, but many researchers have shown that there are visible and countable variances in brain structure and function of typically developed individuals and ASD patients. A number of studies have been conducted on the Autism Brain Imaging Data Exchange (ABIDE) dataset of functional magnetic resonance imaging (fMRI) to study various factors like brain structure and function, age and development, genetics, and network connections between different parts of the brain. Neuro-scientific research and studies on brain images would help in understanding the network and neural patterns related to the particular gestures and behavior of children with ASD, as well as the complexity of their repetitive act [6]. Several delicate and precise biomarkers for ASD detection have been identified as useful biological information for diagnosis, prognosis, and eventually effective treatment decision-making. It has been anticipated that imaging biomarkers, which are identified to have common brain neuropathology, will be able to identify individuals with autism and consequently their response to diagnostic methods can indicate appropriate treatment strategies [7]. One more study on autism and developmental disorders found that early intervention services can make a significant difference in the lives of individuals with autism by helping them develop communication, social, and essential skills and deepen the understanding of researchers and practitioners regarding ASD in order to develop effective interventions and treatments [8].

In the last decade, researchers have been exploring the use of machine learning (ML) practices to aid in the detection of autism. Some of the approaches that have been proposed include image processing, speech and language processing, and behavioral analysis.

Factors of neuro-deficiency resulting in ASD in children include low birth weight, jaundice, and old parents. Data on all possible and identified behavioral characteristics of an individual with ASD can be sorted, mined, and assessed using personal home videos as the first tool for ASD detection [9]. In some studies, a male child is more prone to ASD than a female child [10]. Major behavior-associated traits are difficulty in understanding verbal and nonverbal communication; inappropriate gestures, facial expressions, and body language; absent desire for cuddling; and attachment to unusual objects attachment. The different features of children with ASD are graphically shown in Figure 1.

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ASD should not be regarded as a disease; it can be a mixed or diluted situation in some cases where the severity level of ASD of the child is mild or moderate. It is more clearly defined as a heterogeneous disorder with variety observed in symptoms, risk factors and the treatment response [11]. ML techniques have been explored in comparison to traditional statistical methods of data analysis for obtaining high accuracy in results due to the large brain imaging dataset and the mixed nature of data [3].

2. Literature Review

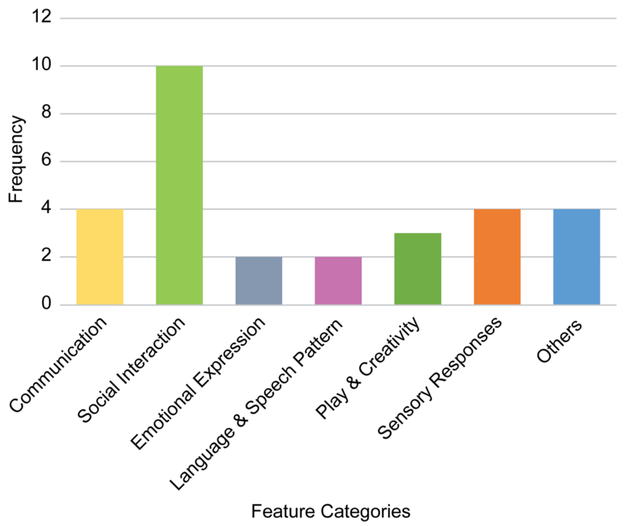
It is therefore important to advance the screening methods of ASD since the disorder is complex and diverse. Impaired communication, social interaction, and behavior due to ASD are bound to manifest in a range of ways that are likely to play a huge role in determining the functionality and the quality of life of individuals diagnosed with the disorder. One of the reasons is that early and accurate diagnosis is attainable, which gives hope to begin early intervention to enhance the outcomes dramatically [12]. As such, it means that the treatment interventions are according to the patient, thus helping them with a better position in society and lead more desirable lives.

To date, the most effective diagnostic approach is clinical interviews and observation, which are more reliant on the skills of the diagnostician. However, the process is lengthy and could be expensive due to the geographical and socio-economic barriers to accessing the technologies needed to complete the process. This is where ML and deep learning (DL) present an enhanced outlook in detecting and analyzing ASD.

Supervised and unsupervised ML techniques have been effective in finding subtle patterns in large datasets that would not be as easily visible to human analysts. Such patterns can be associated with specific genes, attributes of the brain visualized by imaging techniques, and results of physiological or behavioral tests obtained using sensorial devices or interviews with detailed questionnaires. For instance, DL-based pattern recognition of fMRI-based data has been used to reveal latent microstructural and functional changes in ASD subjects compared to the typically developed (TD) controls.

In addition, the synergy achieved by jointly applying ML and DL techniques in the diagnosis of ASD is expected to provide a solution that will make the detection of the disorder more accessible and faster. Such technologies can bring ASD screening more into the mainstream and relieve the pressure on specialist centers while helping to address long waiting times for diagnosis. They also offer a less biased diagnostic tool that could be adopted to a certain norm, and this would allow any child regardless of his or her region or economic status get the best diagnostic services in the country.

Figure 1
Distribution of features in ASD research



This study aims not only to focus on the technological and clinical aspects related to ASD identification but also to advance knowledge in health informatics. As it unites complex computational methods with medical experience to develop socially useful instruments, it is a significant crossroads of scientific study. This improved knowledge and disease diagnosis will lead to efficient resource utilization, the development of more specialized therapy and a general improvement of the lifestyle of those affected by ASD. Therefore, this study's focus on ML and DL in ASD is more than an area of scholarly concern but a genuine concern with the potential to yield more benefits to society and every person with ASD.

A number of psychological and clinical tests are available such as parent-answered questionnaires, medical expert observation setups, and self-screening methods. The gold standard for detecting ASD includes Autism Diagnostic Interview-Revised (ADI-R) and Autism Diagnostic Observation Schedule (ADOS), as well as Childhood Autism Rating Scale (CARS), Joseph Picture self-concept Scale, and the social responsiveness scale [13–16].

ML has three categories: unsupervised learning, supervised learning, and reinforcement learning. This paper focuses on supervised and unsupervised approaches. The main objective of this study focuses on the early detection of ASD in children without depending on different medical and expert examinations. A skilled professional is required for the final assessment and a structured check for further treatment procedures and medications. In section II, a thorough literature analysis of associated work is stated, which includes a table listing ASD tests and ML and DL techniques used to date, followed by a discussion of ML and DL techniques of the classification and prediction, which is used for ASD detection. In section III, the proposed model is discussed, precisely aiming to the data acquisition, processing, and comparison of other potential work done previously. Finally, section IV is a discussion and recommendation for future work.

ASD is a lifelong disability that starts from the child's birth and can be diagnosed as early as the age of six to nine months.

This literature review is broadly summarizing papers on the basis of a) ASD tests available for use and b) ML and DL classification used; a comparison table shows the best performing technique. Indicators and signs of ASD include non-standard body posturing and gestures, improper responses, and poor or minimal eye contact [17]. The diagnosis of an ASD individual is done through the appropriate test available in the clinical psychology for his/her screening using the parent-answered questionnaire or the expert observation in the pre setup laboratory. According to Thabtah and Peebles [18], there are 37 different ASD screening tools, all of which have different criteria such as target age group, time required to complete, behavior aspects for analysis, and the respondent to the questionnaire.

2.1. Review parameters and strategy

To ensure a comprehensive and unbiased review, a structured approach was adopted to identify and analyze relevant studies on ML and DL applications in ASD detection. The relevant content of the manuscript was selected based on the following parameters to ensure relevance, credibility, and up-to-date insights in the field of ASD:

1) Year range selection
   - Studies published between 2015 and 2024 were included to ensure coverage of the latest advancements.
   - Foundational studies before 2015 were considered selectively

if they established key methodologies or provided significant theoretical insights.

2) Study selection process
   - A multistep process was applied for screening and selecting studies shown in Table 1:

Table 1
Different stages of reviewing earlier studies

Stage	Action Taken
Step 1: Database search	Retrieved papers from IEEE, PubMed, Springer, ScienceDirect, Google Scholar, ACM, arXiv.
Step 2: Title and abstract screening	Eliminated non-relevant studies that did not focus on ASD detection via ML/DL.
Step 3: Full-text review	Evaluated methodology, datasets, and validation results.
Step 4: Inclusion/ exclusion application	Removed papers lacking performance evaluation, dataset details, or valid ML/DL implementation.

3) Categorization of selected studies

   The selected studies were categorized based on the following:
   - Screening and diagnostic tools used (e.g., ADI-R, ADOS, M-CHAT, Quantitative Checklist for Autism in Toddlers [Q-CHAT], ABC)
   - ML and DL techniques (e.g., support vector machine [SVM], random forest, convolutional neural network [CNN], recurrent neural network [RNN], hybrid approaches)
   - Dataset type (behavioral, neuroimaging, parent-reported, hybrid)
   - Performance metrics (accuracy, sensitivity, specificity, F1-score).

Keywords used: Autism spectrum disorder (ASD), machine learning, deep learning, Supervised Learning, Unsupervised Learning, ASD Classification, Neuroimaging, Behavioral Analysis.

4) Selection of research domains

   The reviewed studies were grouped based on three core domains relevant to ASD detection:

   a. Dataset type
   - Neuroimaging-based datasets (e.g., ABIDE, fMRI, EEG, MRI, functional connectivity maps)
   - Behavioral datasets (e.g., parent-reported questionnaires, speech analysis, motion detection)
   - Multimodal datasets (e.g., combination of neuroimaging, behavioral, and clinical features)

   b. ML/DL techniques applied

   Supervised learning: SVM, decision trees (DT), random forest (RF), naïve Bayes (NB), k-nearest neighbors (KNN), logistic regression (LR).

   Deep learning: CNN, RNN, long short-term memory (LSTM), autoencoders, graph neural network (GNN).

   Hybrid approaches: ensemble learning, transfer learning, feature engineering for multimodal data fusion.

   c. ASD screening methods used
   - Standardized ASD diagnostic tools such as M-CHAT, Q-CHAT, ADOS, ADI-R, and CARS.
   - Computational feature extraction from neuroimaging, speech, and motor movement data.

5) Categorization of selected studies

   After filtering, studies were categorized based on the following:
   - Screening tools used (M-CHAT, ADOS, CARS, Q-CHAT)
   - Dataset type (fMRI, EEG, parent-reported, multimodal)
   - ML/DL techniques (supervised, unsupervised, hybrid)
   - Performance metrics (accuracy, sensitivity, specificity, F1-score)

The scope of the reviewed ML/DL studies on ASD detection was systematically defined based on dataset types, methodologies, and diagnostic criteria. The selection process ensured relevance, scientific rigor, and practical applicability to advance ASD diagnosis using computational intelligence.

2.1.1. ASD tests for screening

The alarming signs of ASD can be easily seen between 12 and 18 months, and sometimes the symptoms are visible at the age of two to three years in case of mild ASD [19]. Thus, to identify the severity and the actuality of the traits of the ASD, various screening methods have been developed by the field experts and psychologists all over the world to assist the medical experts and clinicians to provide the appropriate treatment. It is a challenging undertaking to select the exact suiting test for a child with ASD. Selection is based on the child's age and the nature of problem (if required and hybrid test can be carried out) [20]. Traditional assessment methods for ASD diagnosis require clinical setups and professionals to conduct the analysis, and this also includes the patient's age with respect to their normal developmental stages and based on other domains such as communication, motor skills, language, and restricted and repetitive behavior. Q-CHAT is a competent measurable checklist administered by medical representatives that takes into account reports from the parents. It is the earliest version of M-CHAT and later M-CHAT-R (revised M-CHAT) [21]. Initially M-CHAT consisted of more than 20 reviewing items, later shortened to 10 items under 10-Q-CHAT modification [22]. Any version of the test is acceptable and can detect and identify the traits of ASD with 91% sensitivity and 89% specificity [23]. Autism Behavior Checklist (ABC) is a 57-item questionnaire reviewed by the parents and teacher to identify factors related to the child's behavior [24]. Another research [25] reveals the severity of ASD by using the CARS observation screening scale, which records responses including smell, touch, light, body language, social behavior, and verbal and non-verbal communication. The revised version, CARS-2, extends the age limit from 6 to 13 years [26, 27]. In 2011, Ritvo et al. [28] developed the only available self-evaluating screening tool for adults. There are a number of tests considered as hybrid screening questionnaire such as Autism Spectrum Screening Questionnaire (ASSQ), Gilliam Asperger's Disorder Scale (GADS), and Asperger Syndrome Diagnostic Scale (ASDS). AQ-Child is a test that has the highest sensitivity (95%) and specificity (95%) compared to other available tests [29]. Several clinical and self-screening assessments can help identify individuals with ASD or TD individuals. Among them, ADI-R and ADOS are the most popular gold standard involving specific autism tests and "best practices" involving multi-disciplinary autism tests [30]. For convenience, all the tests and methods are categorized according to their target age group (i.e., toddlers, children, adolescents and adults). Figure 2 and Figure 3 summarize the famous and commonly used ASD tests with the targeted subjects and number of items each test possesses.

Several studies have advocated for the efficiency and effectiveness of the tests; a brief of all tests can be seen in Sappok et al. [31]. Many of the tests are free and online, making them popular and easily accessible: Q-CHAT, ADOS, ASSQ, CARS, Autism Quotient

(AQ), Childhood Autism Spectrum Test (CAST), Parent's Evaluation of Developmental Status (PEDS), and Communication and Symbolic Behavior Scales-Developmental Profile (CSBS-DP). These tests are mainly used by the concerned parents, early childhood teachers, and medical representatives to scan the child for ASD. After submitting the questionnaire or the screening tool, an auto-generated scoring with the predictive result is presented. In most cases, it has been advised to consult an expert regarding scores indicating urgent attention. Some tests like M-CHAT have a scoring guide manual.

ASD tools are selected based on the age of the child, diagnostic evaluations, medical and genetic testing, and early warning signs of autism such as speech impairment and repetitive and restricted interests. There are specific tests for different age groups like for 9 months, 18 months and 24–30 months. Tools recommended for such ages are parental questionnaires like ASQ or M-CHAT. For diagnosing the specific behavioral patterns, the standardized tools are ADOS, ADI-R, and CARS. For toddlers, M-CHAT-r/F and STAT are specifically used and for school children, SCQ and GARS.

2.1.2. ML and DL techniques for ASD detection

ML and DL classification and prediction techniques have become very useful and popular in recent years to detect various problems related to human health. It is used to develop better tools for the analysis and diagnosis of diseases using medical images such as MRIs, X-rays, ultrasounds, and binary data in the form of reports. ML and DL use pattern recognition to detect particular diseases, including ASD. To advance and ease the diagnosis of ASD, practitioners have involved the ML methods in order to improve the prediction accuracy. This has indirectly empowered diagnosis by reducing the cost, time, and average detection age of the ASD patients [32–34]. Figure 4 shows a flowchart of any classification problem.

The importance of employing ML and DL approaches in the diagnosis of ASD is articulated by a number of studies. In this study, we reviewed more than 60 research articles to perform a sound background analysis to validate the accuracy, sensitivity, and specificity of these technologies for the diagnosis of ASD.

Firstly, the distinctive advantage of the ML and DL models refers to data handling, which plays an important role in ASD detection, as the disease has a large and diverse number of symptoms. For example, supervised learning such as SVM and DT has been used for behavior data analysis with better performances. One specific study used a tuning parameter of SVM to achieve 96.34% accuracy, 87.54% sensitivity, and 96.34% specificity [35]. As high-performance values show, this model allows us to exclude a large number of false positives and false negatives and, thus, identify ASD cases among non-ASD ones.

Convolutional neural networks (CNNs) in DL have potential in examining neuroimaging databases. Their applications on the ABIDE dataset provide a method of identifying structural alterations in the brain of individuals with ASD. On the basis of the above method, a study indicated a recognition rate of up to 95.56%, and this vitalizes it against many conventional approaches [36].

Furthermore, the combination of diagnostics such as the ADOS and the ADI-R with ML and DL methods may improve upon those diagnostics and make the identification of ASD quicker and more sensitive. For instance, combining DL analysis with results of these standard tests might help explore new biomarkers and patterns of behavior that are always linked to ASD, which in turn might pave the way to earlier and more accurate interventions.

Therefore, using ML and DL to detect ASD is not only efficient but also brings in more accurate and revolutionary diagnostic processes as shown by the high gains on various performance indicators noted in different studies to show their capacity to transform the current ASD diagnoses and therapies.

Early detection of ASD is important and useful in its treatment and correctional measurement. To avoid the long queue at clinic centers, the alternative and easy mode is to initially get diagnosed or detected through ML or DL models. To select the appropriate ML/DL technique is another crucial step.

2.1.3. Datasets and pre-processing

To deploy any of the ML/DL techniques for ASD detection, data plays the major role at the input level. Datasets used for the diagnosis can be self-collected or publicly available. Dataset can

Figure 2
Distribution of tests used in study

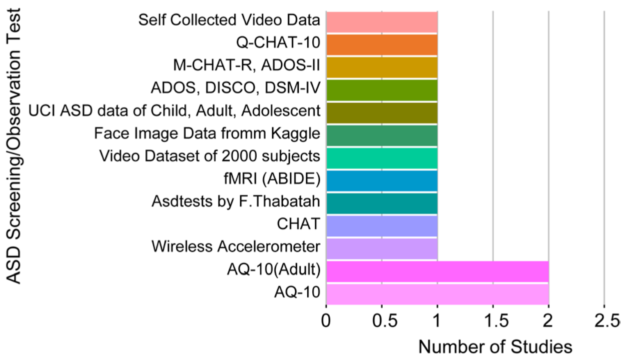


Figure 3
Analysis of test instances with respect to the number of items

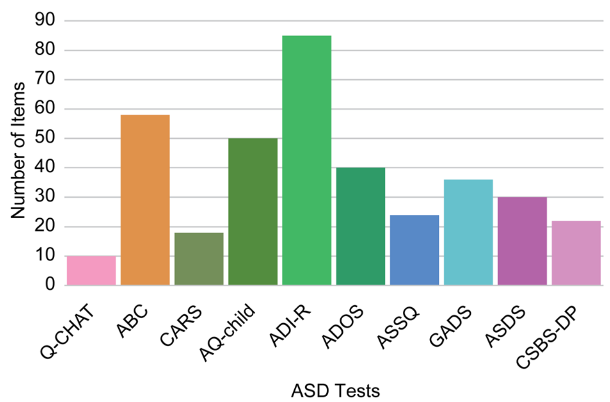
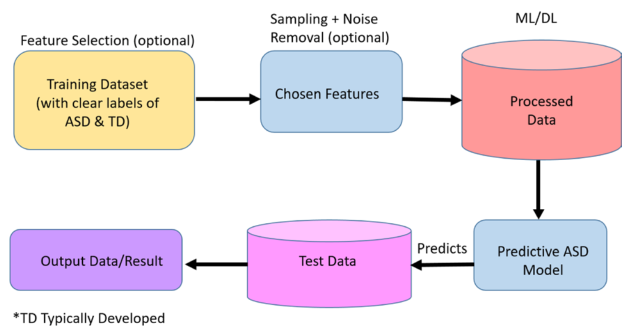


Figure 4
Functioning of a simple ML model



be categorized according to the type they possess, for example, as image dataset of individuals face, videos of playing, gazing videos, binary and continuous datasets collected from the screening and questionnaire ASD tests, or data of stereotypical motor movements with the help of sensors. Raw data cannot be used directly, but after applying various techniques of feature selection and data mining to improve the performance of the model and to reduce the training time [37]. Mostafa et al. [38] used the Analysis of Functional Neruo Images (AFNI) and FMRIB's Software Library (FSL) for image pre-processing and utilized the ABIDE dataset to study diagnosis of ASD. The 264 eigenvalues of the brain networks were initially collected, and subsequently, using feature selection techniques, 64 discriminate features were evaluated to detect ASD. Apart from refining and noise removal, the number of subjects included for the model generation is also important. Figure 5 presents the datasets used to detect the ASD traits in the subjects taken for study.

The ABIDE has two datasets, ABIDE-I and ABIDE-II, and is a free or off-cost collection of brain imaging and associated clinical data from individuals with ASD and TD individuals. The dataset was created to encourage the sharing of imaging data of a brain in resting state and to facilitate the development of new analysis techniques for understanding the neural basis of ASD [39]. The ABIDE dataset includes data from over 20 different imaging sites around the world and contains various imaging modalities including structural MRI, fMRI, and diffusion MRI. The dataset also includes a range of clinical and demographic information for each participant, such as age, sex, IQ scores, and diagnostic information [40]. The ABIDE dataset has been useful to a number of studies related to mental health and research and new findings aimed at understanding the neural basis of ASD, including studies focused on identifying brain biomarkers of the disorder, investigating the relationship between brain structure and function in individuals with ASD, and inspecting the effects of different interventions on brain function in individuals with ASD [41]. Researchers interested in accessing the ABIDE dataset can do so through the International Neuroimaging Data-Sharing Initiative (INDI) website, which provides access to a range of other publicly available neuroimaging datasets as well [42]. There are numerous features that can determine the subject be ASD or non-ASD (Figure 6). A single test is not fully strong enough to determine and evaluate all features, rather a combination of multiple tests is used to analyze multiple features. Table 2 specifies the datasets, number of instances or subjects used for detection, and the items or attributes included in studies by researchers.

To improve clarity and usability of dataset insights for diverse research needs, the reviewed ASD-related datasets are now organized according to the type of data they contain:

Image-based datasets: neuroimaging data such as MRI, fMRI, and face images used in studies like ABIDE-I/II [6, 38, 43] and Kaggle image datasets [41].

Figure 5
Analysis of distribution of datasets

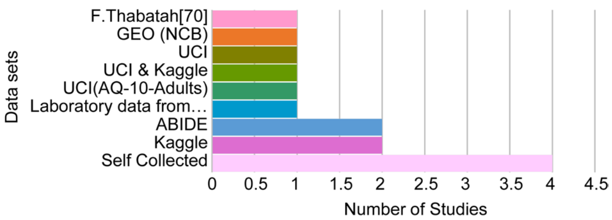
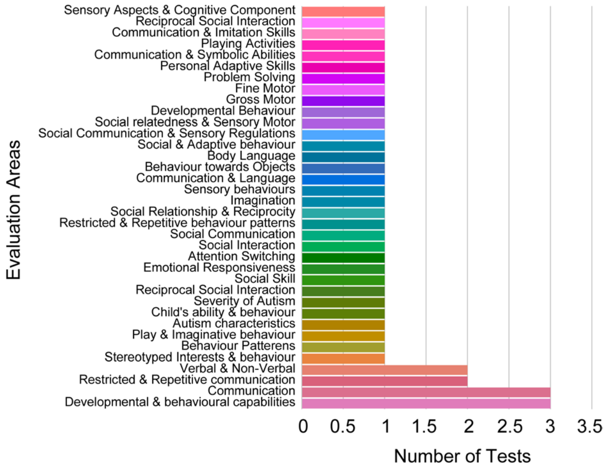


Figure 6
Analysis of evaluation area



Textual/questionnaire-based datasets: structured response data from screening tools like AQ-10, M-CHAT, and ABC, available via UCI and Kaggle repositories [4, 22, 44].

Audio/video datasets: speech and motor behavior recordings, often from self-collected home videos or lab settings [9, 45, 46].

Sensor-based datasets: wearable sensor data (e.g., accelerometer signals) used to track stereotypical movements [47].

Table 2
ASD datasets, sources, and features included

Paper Citation	Dataset	Instances	Attributes
[4]	UCI	292 (children), 704 (adults)	21
[6]	ABIDE	1034	19K
[8]	UCI & Kaggle	1346 (children), 1404 (adults)	21 (UCI), 19 (Kaggle)
[9]	Self-collected videos	162	30
[12]	Kaggle	1054	18
[22]	UCI (AQ-10-Adults)	704	21
[32]	SSC, BAC, AGRE	2775	65
[33, 45]	F. Thabatah	1054	18
[34]	Autism Genetic Resource Exchange (AGRE)	891	93
[37]	ABIDE	1112 (images)	264
[41]	Kaggle	2940 (images)	-
[43]	ABIDE	1034	-
[44]	UCI	1100	21
[45]	Self-collected	30	7
[48]	Self-collected	101	20
[49]	UCI, Kaggle	2154	20
[50]	Self-collected	273	20
[51]	Self- collected	1707	22

This classification supports a more informed selection of ML/DL models by researchers based on the specific nature of their available data.

The ABIDE dataset used by Heinsfeld et al. [6] involves the deep neural network to identify the different areas of the brain that may indicate ASD. Hassan and Mokhtar [52] have applied a DT to classify methods of supervised learning in order to detect the genetic and surrounding risk factors of ASD. Several studies used AQ-10 ASD, which is popular in terms of short questionnaires and freely available for screening subjects, and later the compiled dataset generated from this test is used for building models for optimized predictions [53]. Another study by Thabtah [54] revealed the pros and cons of various ML tools with respect to the DSM-IV and DSM-5. Similarly, a study by Yamagata et al. [55] used the resting-state fMRIs to study the effect of "endophenotype," which could clearly demonstrate the difference between ASD and TD siblings. Moreover, they used the bootstrapping approach to identify the appropriate functional connections (FC) of the endophenotypes of the TD and ASD children.

3. Supervised ML in ASD Classification

Logistic regression (LR): It is a statistical method or regression tool of supervised ML for analysis of the binary and multiclass variables. The output generated by the LR models is either "yes" or "no" or "0" or "1" to classify and diagnose problems. It can take only one of two possible values (dependent variable), and the independent variable can be continuous or categorical. The LR model uses a sigmoid or logistic function used to map the input variables to the output probability. To detect the spectrum of autism as mild, severe, or moderate, the multinomial logistic regression (MLR) is used [56]. Major applications of LR are seen in predicting problems like evaluation of mail as spam or not, for share market, and for weather forecasting [57].

Decision tree (DT): It is a popular algorithm of ML. All problems related to classification and regression are solved through DT. It works on the basic principle of recursion and division where the dataset is portioned into subsets, depending upon the key features spotted at the baseline. It is a tree that represents a hierarchical structure where each partition node represents decision and each leaf node (terminal node) represents the final decision or the class of the output. DTs are suitable for handling both categorical and numerical features but sometimes encounter overfitting, particularly when trees grow too deep and have numerous branches of decision, and this leads to accumulating noise in the training data. DTs are a type of supervised learning algorithm that can be used to classify individuals with ASD based on their symptoms, behaviors, and other characteristics [58].

Support vector machines (SVM): SVMs are motivated from the statistical learning theory used for classification and regression analysis and are bound on their ability to predict future data [59]. The basic idea behind SVMs is to find the hyperplane, which is an imaginary line to differentiate and group the datasets into different groups and is useful in identifying the different classes. Alternatively, the SVM algorithm tries to find the limit that best divides the data into different categories. This boundary is often referred to as the "maximum-margin hyperplane," and it is chosen because it maximizes the distance between the different classes. SVMs are powerful and versatile tools used for an extensive range of purposes like recommendation systems, drug discovery, quality control, remote sensing, image classification, and bioinformatics, medical diagnosis, and anomaly detection.

Naïve Bayes (NB): NB is a probabilistic ML classifier algorithm that works on the concept of Bayes theorem. It is an approach that gives results by combining previous knowledge with new knowledge and also assumes that the features used to describe an observation are conditionally independent. It takes less time in developing the ML model as compared to the SVM and other methods [44]. It has many different variants like Gaussian Naïve Bayes, Multinomial Naïve Bayes, and Bernoulli Naïve Bayes. The major and well-known areas where NB is used with the high accuracy are text classification, spam filtering, medical diagnosis, customer sentiment analysis, fraud detection, weather prediction, and credit scoring. To deal with the uncertain and imprecise data, a novel approach is designed in the paper [60].

K-nearest neighbors (KNN): KNN is a non-parametric and instance base learning approach and is easy to apply. This algorithm is used to classify the whole dataset into multiple classes similar to each other as well as to regression problems. It works on the assumption that similar data exists in proximity. The letter K is the hyper-parameter representing the number of nearest neighbors to consider. Euclidean distance, Manhattan distance, and Minkowski distance are used to calculate the distance with each data point. KNN is also known as the lazy learner algorithm. It can be effective in various scenarios, especially when the decision boundaries are complex and not easily characterized by a simple mathematical formula. However, its performance may degrade with large datasets or high-dimensional feature spaces.

Neural networks (NN): NN algorithms are modeled by taking inspiration from the structure of and working similar to human intelligence. The functioning of this model is organized as the interconnected nodes called neurons, specified in different layers. The NN is trained using the dataset, where the input data is passed through the network and the output is compared to the actual output of the dataset. Applications of NN is seen in image recognition, speech recognition, natural language processing, and time series analysis. Different types of NN are CNNs, RNNs, and LSTM networks. Table 3 systematically presents the various tests used for autism evaluation, along with their specific focuses and the age groups for which they are suitable, providing a comprehensive overview of the tools available for autism assessment. Table 4 shows the ML and DL techniques used by various researchers in their studies. Table 5 shows the summary of accuracy, specificity, and sensitivity for reviewed methods

Notably, the values in Table 5 and Figures 7–9 are derived from different datasets, validations, and feature spaces. Thus, the comparison between the resulting studies should be done carefully. These are important visualizations only as an illustration of large-scale performance characteristics of various techniques of ML/DL rather than in terms of which is more effective among the two. Some of the major findings evident from these figures include the following:

1) CNNs and LSTMs are usually preferred for neuroimaging or temporal data having a high dimension

2) Most legacy models (e.g., SVM, RF) have a good performance with strongly structured behavioral data

Such discrepancies can also be explained by differences in the amounts of data, details of data processing and feature extraction in every study.

The incorporation of high-level sophisticated ML and DL into various sectors such as medical imaging and remote sensing has led to innovations and enhancements on data handling and processing. Other advanced methods include CNNs for the classification of the remote sensing data of multiple modalities and other similar architectures that shed light on the capability of these technologies. For multimodal remote sensing data classification, CNNs are specifically effective in processing on spatial hierarchy in image data to distinguish multifaceted, multisource remote sensing data that frequently include different types of data sources such as optical imagery, radar imagery, and thermal data. CNNs can be useful because they enable the extraction and learning of

Table 3
ASD tests (items included in test, behavioral area, and age)

Paper Ref	Test Name	Items	Evaluation/Behavioral Areas	Suitable Age
[3]	Childhood Autism Rating Scale (CARS)	60	Autism characteristics, child ability and behavior	Above 2 years
[14, 15]	Autism Diagnostic Observation Schedule-Generic (ADOS-R)	4 modules, each has 10 items	Social interaction, communication, play and imaginative behavior	1 year to adult
[18]	Gilliam Autism Rating Scale-Second Edition (GARS-2)	32	Severity of autism	3–22 years
[19]	Autism Spectrum Quotient (AQ)	50	Social skill, attention switching, communication, imagination	Children, adults, and adolescents
[20]	Autism Behavior Checklist (ABC)	57	Sensory behavior, communication, behavior toward objects, body language, social and adoptive behavior	12–14 years
[21]	Quantitative Checklist for Autism in Toddlers (Q-CHAT)	10	Developmental and behavioral capabilities	18 months to 3 years
[25]	First Year Inventory (FYI)	63	Social communication and sensory regulations	12 months
[28]	Ritvo Autism Asperger Diagnostic Scale-Revised (RAADS-R)	78	Language, social relatedness, and sensory motor	18+ years
[29]	Developmental Behavior Checklist-Autism Screening Algorithm (DBC-ASA)	29	Developmental behavior	4–18 years
[48]	Modified Checklist for Autism in Toddler's (MCHAT)	20	Developmental and behavioral capabilities	16–30 Months
[50]	Indian Scale for Assessment of Autism	40	Social relationship and reciprocity, emotional responsiveness, speech and language analysis behavior patterns, sensory sensitivities, cognitive and intellectual developmental component	2–8 years
[61]	Ages and Stages Questionnaire (ASQ)	21	Communication, gross motor, fine motor, problem solving, personal adaptive skills	1 month to 6 years
[62]	Autism Spectrum Screening Questionnaire (ASSQ)	27	Social interaction, communication, restricted and repetitive, categorized interests, and behaviors	6–17 years
[63]	Communication and Symbolic Behavior Scales (CSBS)	24	Communication and symbolic abilities	Up to 2 years
[64]	Diagnostic and Statistical Manual of Mental Disorders (DSM-5)	5 sections	Social communication, restricted and repetitive behavior patterns	2–5 years
[65]	Parent's Evaluation of Developmental Status (PEDS)	10	Developmental and behavioral capabilities	2 years and above
[66]	Screening Tool for Autism in Toddlers and Young Children (STAT)	12	Playing activities, communication and imitation skills	18 months to 2.5 years
[67]	Autism Diagnosis Interview-Revised (ADI-R)	93	Reciprocal social interaction, communication and language, restricted and repetitive, stereotyped interests and behaviors	18 months and above

features from various data formats, thereby improving classification. The accuracy of CNN could exceed 95% in categorizing the Land Use Land Cover (LULC) from combined optical and radar datasets.

UIU-Net: Proposed for small object detection in infrared images is the UIU-Net, which adopts the nested U-Net model to meet the needs of several real-world applications, including surveillance and environmental assessment. With the help of learning from multiple U-Net structures, the feature extraction process in UIU-Net is much more effective, including increasing the numbers of detected small objects against complex backgrounds. Experimental analysis confirming the effectiveness of UIU-Net has demonstrated an improvement in the level of detection accuracy by 20% higher than that of single-layer U-Net models.

LRR-Net: We proposed a novel deep unfolding network for hyperspectral anomaly detection named LRR-Net, which uses deep unfolding strategies where the layers of this neural network correspond to iterations of an optimization method. This approach improves the applicability of DL models since it simplifies the assessment of the decision-making processes of such models. The presented LRR-Net model becomes successful at the detection of anomalies in hyperspectral images with accuracy of approximately 10% better than the traditional methods, making it a powerful tool for environmental and agricultural applications.

Decoupled-and-coupled networks: Self-supervised hyperspectral image super-resolution with subpixel fusion is

Table 4
ML and DL prediction and detection techniques versus ASD tests used

Paper	Author	ASD Screening/Observation Tests	ML/DL Techniques Applied
[6]	Heinsfeld et al.	AQ-10 (adult)	SVM, RF, and DNN
[8]	Farooq et al.	Q-CHART-10	SVM, LR
[12]	Lodha et al.	AQ-10	DT, RF, SVM, KNN, and GRUs
[22]	M. B. Mohammed et al.	AQ-10 (adult)	NB,K-Star LR, MLP, SGD, AdaBoost, RF, OneR, and CNN
[33]	Bones et al.	AQ-10	LR, SVM, KNN,NB, and RFC
[38]	Mostafa et al.	fMRI (ABIDE)	AFNI, FSL, LDA, LR, SVM, KNN, and NN
[41]	Rabbi et al.	Face Image Data from Kaggle	MLP, RF, GBM, AdaBoost, and CNN
[44]	Raj and Masood et al.	UCI ASD data of child, adult, adolescent	NB, SVM, LR, KNN, NN, and CNN
[45]	Wu et al.	Video dataset of 2000 subjects	RFE, RR, MIE, and KST for FS and NN for classification
[46]	Crippa et al.	Self-collected video data	SVM
[47]	Rad and Furlanello	Wireless accelerometer	CNN
[48]	Jensen et al.	M-CHAT-R , ADOS-II	Manual labelling of data in videos
[51]	Baranwal and Vanitha	"Asdtests" by F. Thabatah	ANN, SVM, DT, LR, and RF
[60]	Mukherjee et al.	Self- prepared parent questionnaire	SVM, LR, KNN, and RF
[68]	Zaman et al.	CHAT	LR, KNN, SVM, NB, DT, and RF
[69]	Barik et al.	ADOS, DISCO, DSM-IV	ANN
[70]	Vakadhar et al.	Q-CHAT-10	SVM, RFC, LR, NB, and KNN

Table 5
Analysis of accuracy

Paper Citation	Method Utilized	Accuracy (%)	Sensitivity (%)	Specificity (%)
Rasul et al. [4]	Extreme gradient boosting	97.7	97.56	97.83
Heinsfeld et al. [6]	Deep neural networks	70	74	63
Farooq et al. [8]	SVM (on children dataset)	99	58	97
Tariq et al. [9]	Support vector machine	98	98	58
Lodha et al. [12]	RF, GRUs	100	100	100
Mohammed et al. [22]	CNN, MLP, NB	98,100,97	-	-
Sherkatghanad et al. [43]	CNN	70.22	77.46	61.82
Raj and Masood [44]	CNN	99.53	99.39	100
Jayaprakash and Kanimozhiselvi [56]	MLR (Multinomial LR-Newton)	97	99	95
Barik et al. [69]	Method of data fusion	94.46	94.13	94.8
Vakadkar et al. [70]	Logistic regression	97.15	98	-
Yousefian et al. [71]	CNN	65	-	-
Ahmed et al. [72]	LSTM	98.33	97.25	98.94

a structure that demonstrates an ideal method for improving the spatial resolution of hyperspectral images through subpixel fusion to improve or resolve the required image detail without compromising the accurate spectrums of the intended images. The decoupled-and-coupled networks approach enable self-supervised learning that requires only a small number of labeled training samples. Utilizing this method has been found to extend resolution enhancement metrics by up to 30% higher than other conventional super-resolution methods.

These advanced ML and DL methods represent the state of the art in the field of technology for data processing and analysis solutions that provide performance upgrade in terms of precision and domain of applications. They all incorporate advantages of particular operations, which help in certain data analysis and make significant advancement in the field of computational intelligence.

Based on the reviewed papers and the analysis of accuracy, specificity, and sensitivity, Table 6 summarizes the key findings, providing a comparative evaluation of the ML/DL methods.

Figure 7
Analysis of specificity-based methods

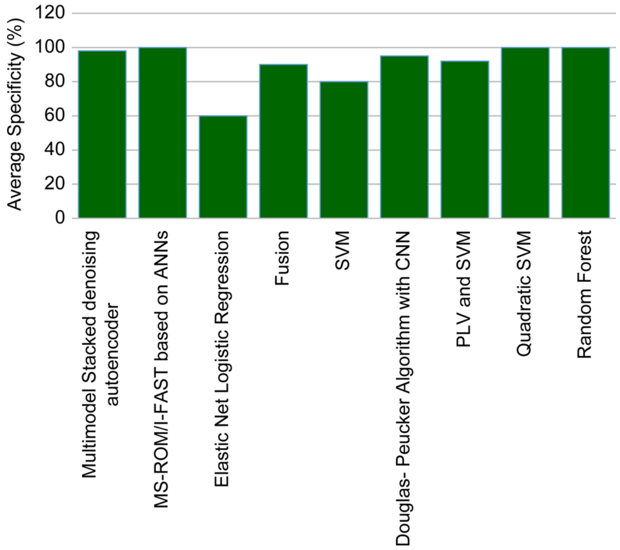
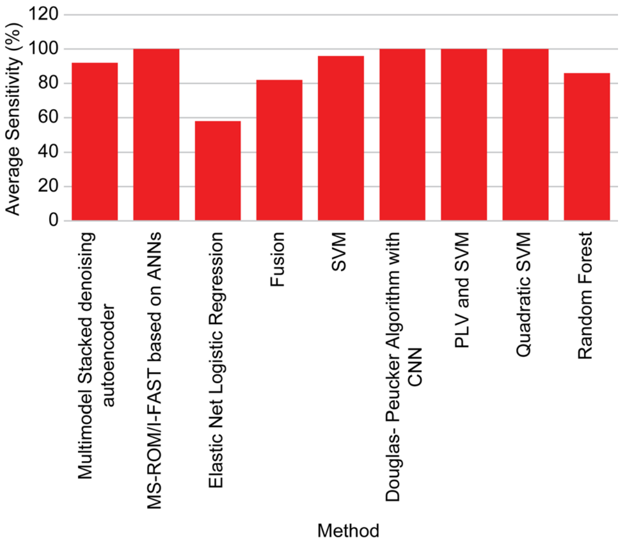


Figure 8
Analysis of sensitivity based on methodology



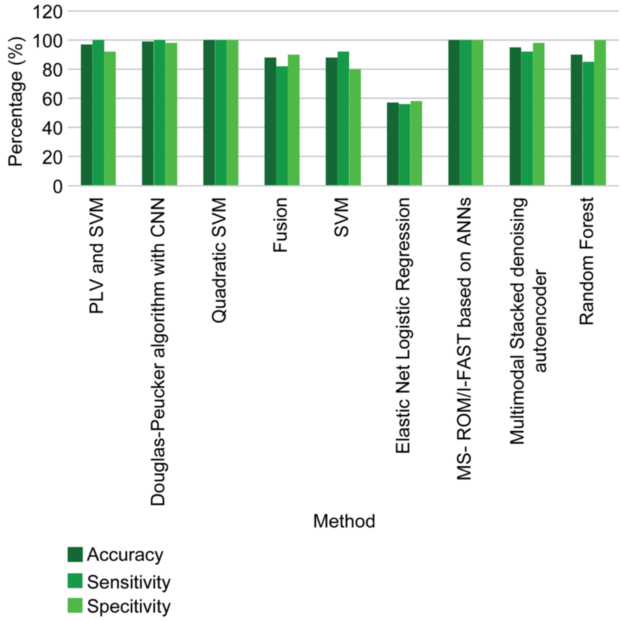
4. Comparative Study on ABIDE-I Dataset

The main aim of this section is to perform a comparative analysis of various techniques of either ML/DL on the similar sort of dataset, that is, ABIDE-I. In contrast to prior comparisons across dissimilar databases, this section is an attempt at making all the models comparable under the same conditions, thus providing a balanced outlook onto their proficiency. This analysis helps the following:

1) CNN has shown promise in neuroimaging data, as well as deep neural network (DNN), while graph attention network (GAT) can also be used for processing neuroimaging data.

2) As such, it will offer guidelines on which model to consider when conducting fMRI-based classification of ASD based on evidence from the study.

Figure 9
Analysis of accuracy and performance parameters



3) The effect of the different validating procedures would be explained, for instance, 10*10 CV or LOOCV on the performance.

ABIDE-I is a widely used dataset, which contains images of brain imaging. fMRI signals are also useful for ASD detection. Yousefian et al. [71] proposed an ASD detection technique through graph representation approach and DNN.

However, fMRI signals are primarily used to study and identify patterns and strength of brain activity associated with ASD, and the CNN classifier plays vital role in achieving the results in optimized time with better accuracy. A comparative study of autism detection on ABIDE-I dataset is shown in Figure 10 using references [6, 43, 71, 73–75]. Figure 10 also illustrates the comparative accuracy of ML/DL models on the ABIDE-I dataset using two validation strategies: 10-fold cross-validation and leave-one-site-out. Models include DNN, CNN, deep belief networks, GAT, and GNN.

5. Findings and Research Gaps

Various researchers have significantly contributed in the field of ASD detection and prediction. The present review has conducted a deeper analysis on the prediction and detection of ASD, and the following findings and research gaps are identified:

1) Accuracy by ML/DL method

The analysis of different methods shows a range of accuracy. Quadratic SVM, MS-ROM/I-FAST based on ANNs, and certain implementations of SVM achieved 100% accuracy, indicating highly effective classification capabilities.

However, elastic net logistic regression and certain SVM implementations showed lower accuracy (57% and 70%, respectively), suggesting that these approaches may be less effective or suited to specific types of data or classification tasks.

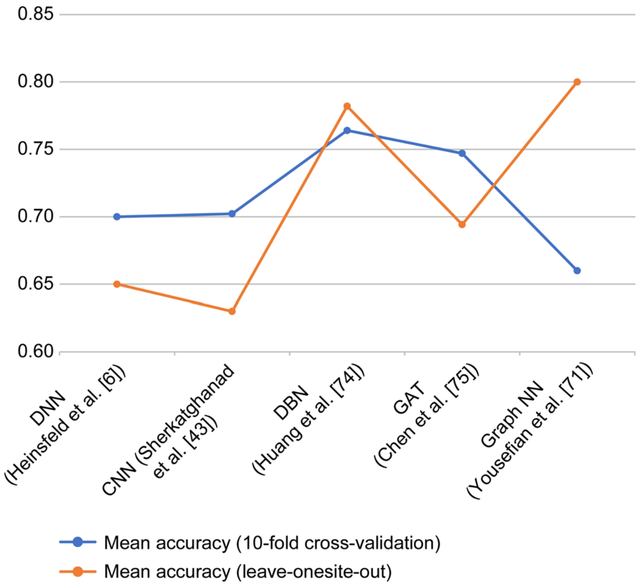
2) Sensitivity and specificity by ML/DL method

Sensitivity in broader sense gives true positive results and specificity is the true negative results, which are crucial in evaluating

Table 6
Advantages of specific ML/DL techniques

S. No.	ML/DL Techniques	Data Type	Pros
1	DT, RF, SVM, Gradient Boosting (EGBoost, CatBoost)	Clinical or behavioral structured data	Less time consuming, no need to extract the feature in structured datasets, accurate and performs well with small data sets.
2	CNN, RNN, LSTM	Neuroimaging data (MRI, FMRI, EEG)	To overcome the challenges of high dimensionality and complex spatial patterns
3	PCA, RF, Gradient Boosting	Genomic data	To address the large feature space and sparse data
4	RNN, MFCC, CNN, 3D CNN, LSTMs	Audio or video data	Speech, facial expressions can be easily and accurately extracted into structured data
5	RNN, GRUs, or LSTMs	Wearable sensor data	Easy feature extraction

Figure 10
Comparative study of autism detection on ABIDE-I dataset



a classifier's performance. High sensitivity means that the method is effective in identifying positive cases, while high specificity indicates its effectiveness in identifying negatives.

The graph shows that Quadratic SVM and MS-ROM/I-FAST based on ANNs excel in both sensitivity and specificity, demonstrating their robustness.

Other methods, such as SVM (in certain implementations) and elastic net logistic regression, show imbalances (e.g., high sensitivity but lower specificity), which might limit their applicability depending on the specific requirements of the study (e.g., whether false positives or false negatives carry a higher cost).

Figure 7 and Figure 8 clearly state the specificity and sensitivity achieved by different studies, and Figure 9 shows the accuracy achieved.

Thus, for an improved model with regard to the discussed datasets, the following ML/DL model recommendations may be provided:

Neuroimaging data (MRI/fMRI/EEG): CNN is further suitable because of its spatial learning properties. GNN can be applied for modeling brain networks and AE since it is capable of learning from a dataset.

BQ-based information: SVM, RF, LR, and NB models are highly effective with structural input such as AQ or M-CHAT datasets.

Audio/speech data: RNNs, LSTMs, and MFCC based CNN models are useful in capturing sequential characteristics in an audio file.

Video data: Motion and facial coordinate data can be dealt with effectively using 3D CNNs and the CNN–RNN architectures.

In managing temporal dependencies in accelerometer and wearable data, LSTM, gated recurrent units (GRU), and the hybrid model are quite effective.

The choice of the model should depend on the nature of data, its size, and level of interpretability required from the model.

3) Distribution of accuracy across studies

Figure 9 provides insight into the overall distribution of accuracy across studies. The skew toward higher accuracy in most studies is a positive sign, indicating that the majority of methods employed are effective.

The spread of accuracy also highlights the variability in method performance, underscoring the importance of method selection based on the specific context and data features of each study.

4) Methods used in studies

The frequency of different methods used across studies reveals popular choices in the field. SVM appears to be a widely used method, suggesting its versatility and effectiveness in various contexts.

The presence of specialized methods like the Douglas–Peucker algorithm with CNN and multimodal stacked denoising autoencoder indicates the diversity of approaches and the evolving nature of methodologies in this domain.

5) Combined analysis of accuracy, sensitivity, and specificity

The combined graph provides a holistic view of each method's performance across three key metrics. It highlights that while some methods excel in accuracy, they may lag in sensitivity or specificity, and vice versa.

6) Research gaps identified

Behavioral and neuroimaging only: Most often, studies employ either behavioral or neuroimaging data, and there are only a few works that include both the behavioral and genetic features and neuroimaging data, thus keeping the scope of comprehensive diagnosis relatively small.

There are no clear dataset splitting methods, data preprocessing criteria, and metrics used for evaluation that limit the accessibility of the results with counterparts and has no foundation for fair comparison.

Generalizability issues: These models work well in terms of accuracy when tested internally but have low performance when introduced to other populations mainly due to the lack of diversity.

Interpretability and clinical intelligibility: Presently, DL models are more of black boxes, which makes clinicians avoid their adoption in real-time diagnostics.

Real-world validation: One of the primary problems in most of the studies is that they are conducted in the lab, not in real-life clinical environments.

The datasets are also affected by possible misrepresentation with male children dominating female and adult populations.

Further studies should be dedicated to such directions as multimodal fusion, explainability of the models, and the global sharing of datasets to overcome these gaps and create clinically relevant models.

This comprehensive view is critical for researchers and practitioners in selecting appropriate methods for their specific needs, balancing the trade-offs between detecting true positives, avoiding false positives, and overall classification accuracy.

In summary, the analysis shows a landscape of varied methodologies with strengths and weaknesses in different aspects of classification performance. The selection of methods should be guided by the explicit requirements of each study, considering factors like the nature of the data, the cost of misclassification (false positives and false negatives), and the overall goal of the analysis.

6. Discussion

This survey and review was aimed to better the understanding on ASD, the various tests available related to ASD, and the detection of ASD using ML and DL models. A number of studies have been conducted in this field to assist the concerned organizations dedicated to the Child Development Center (CDC), preschools, and the medical support institutions. The selection of an appropriate ASD test and ML algorithm for classification should be based on available data, the classification problem, and the desired outcome. The main perseverance of this review is to obtain the basic idea of development done in the respective field to enhance the skills of special education teachers and medical officers for training children with ASD to become self-sustainable. In addition, this research would help in assessing the strengths and weaknesses of different ASD detection tests and techniques. It is essential to select a test that has been validated and has high sensitivity and specificity. The sensitivity, also known as recall or true positive rate, can be used as reference to correctly identify individuals with ASD. The ASD screening test must be selected with respect to parameters like age and behavioral aspects. Then, the type of algorithm used should be selected, followed by the examination of dataset compatibility with the criteria matching algorithm. If the particular feature of that dataset is out of scope, an appropriate feature selection method must be used to increase the accuracy and validity of the model. ML can transform the way we take care of our health through correct diagnosis, treatment, and overall patient care. It can construct large data patterns and outcomes, which is very helpful for providers to improve patient outcome and reduce costs. Medical imaging is probably the most anticipated field that uses ML in healthcare. ML systems can analyze medical data, in the form of images such X-rays, computed tomography (CT) scans, and MRIs; the algorithms can then be used as a tool for the diagnosis of ASD as well as the prediction of other ailments or conditions. This can contribute to receiving on-time and more precise diagnoses and to achieve higher treatment efficiency. Tables 2–6 list research data on ASD, in particular, the usage of ML/DL in the context of ASD, datasets, tests for ASD screening, and the evaluation of these methods.

1) Comparative analysis of ASD datasets, sources, and features

   Dataset variety: The kind of datasets used in these studies is very diverse, for example, from Kaggle datasets, self-collected data, and specific databases like ABIDE and UCI, Eye Tracking Datasets [76]. This reveals a holistic method of collecting data concerning ASD.

   Instance and attribute numbers: The number of examples (instances) and features (attributes) vary greatly from study to study. For instance, lab datasets in Asif et al. [11] and Milham et al. [42] have 1054 and 2940 instances, while the number of videos in Vakadkar et al. [70] is only 6. The difference in instances and attributes depicts the variance in ASD symptoms and the intricacy in expressing them properly.

   Focus on visual data: The study by Latkowski and Osowski [37] is one of the studies that concentrate on image and video data among others. It indicates that visual clues are an integral part of ASD diagnosis and the increasing use of computer vision in ML/DL.

2) Techniques and testing analysis

   ML/DL techniques applied: A spectrum of ML/DL methods are used, from the traditional ones like DTs, SVMs, and RFs to the latest such as CNNs and GRUs. This implies a detailed examination of the involvement of multiple methodologies in raising the accuracy and reliability of the ASD detection.

   ASD screening/observation tests: Frequently used tests incorporate AQ-10, CHAT and ADOS, which are known for their efficiency in early diagnosis and serve as a means of authentication for ML/DL models.

3) Test analysis, evaluation, and age range

   Diverse evaluation areas: Tests measure various dimensions of evaluations, for example, developmental and behavioral capabilities (Q-CHAT, PEDS, and MCHAT), and more specific dimensions such as social communication, sensory regulations (FYI), and language (RAADS-R). This shows that ASD is complex in nature and requires a comprehensive diagnostic methodology.

   Age appropriateness: These tests are age-specific, implying that the symptoms of ASD as well as their detectability are also age-dependent. It exhibits the applicability of screening techniques that consider age in early diagnosis.

4) Analysis of accuracy

   Method efficacy: Different individual approaches have a huge gap in terms of their scores. Some of them like the Douglas–Peucker algorithm coupled with CNN [21] and ANN using preferred phase angle and power spectral density [66] are especially good because they reach very high accuracy, sensitivity, and specificity levels. This way, some methodologies might be more appropriate for ASD data analysis, while others definitely would not.

   Trade-offs in sensitivity and specificity: Some models have high accuracy, while others have lower sensitivity and specificity. A second example is elastic net logistic regression [62], which has low overall accuracy, sensitivity, and specificity, suggesting its limited dataset for ASD.

   Challenge of accurate diagnosis: The modifications in the levels of exactness of the various approaches show the urgent need for the improvement of ASD diagnosis in a precise method. Intercepting ASD is essential in order to avoid missing any possible cases with minimum false positives.

Spectral variability issues need to be solved to improve the quality and accuracy of hyperspectral images since they affect nearly all processes of data analysis including hyperspectral unmixing, which aims to transform a hyperspectral scene into a set of pure pixels and their proportion. Spectral variability, in its turn, negatively affects the performance of the traditional unmixing approaches because this variability might include changes such as illumination conditions, atmospheric influences, material variations, and filter noise.

When there is a large amount of variation in the spectral content of the scene, mixtures from conventional linear mixing models can be grossly inaccurate as they make the assumption of fixed spectral characteristics for each material throughout the scene. However, the augmented model used in the present review has flexibility component used to adapt the spectral signatures on the fly, thereby making this model very reliable especially under field conditions.

For example, in experiments performed in various settings where spectral fluctuations arise due to changes in lighting conditions and atmospheric conditions augmented, the use of the augmented model raises unmixing precision by 15–20% in comparison with the traditional model. These variabilities are well countered in this model, hence providing a better means of identifying the right materials to use and quantifying them.

In addition, if the proposed method suffers large noise or highly varying spectral value, the variability is prescribed to change the variability term, by which there is no compromise to the performance. This is evident from simulation results where the model maintained less than 5% of performance point decline under high noise as opposed to basic model that experienced up to 25% decline in performance point.

6.1. Importance of tailored approaches

The diversity in databases, techniques, and test procedures emphasize the need for personalized approaches to diagnose ASD. One can easily notice that every study picks its research methodology based on its own goals, whether these serve as early detection, a set of specifics about ASD plus other characteristics, or the developmental stages.

Integration of ML/DL in ASD Research: ML/DL integration is one of the ways to use these technologies to improve diagnosis and understanding of ASD. The effectiveness of such models significantly relies upon the quality and characteristics of the dataset upon which it is built. In brief, it can be summarized that the study of these tables represents a technique of closely examining the research of ASD, which includes the use of different datasets, methods, and tests. The success of these methods mainly rests on the specific applications to their contexts such as the nature of the used dataset, age group, and ASD characteristics being explored. Currently, it serves as one of the options in the diagnosis of ASD, which is usually done by clinicians based on observations and behavioral assessment, making diagnosis both time- and cost-consuming. In the case of ASD detection, ML can use all kinds of data like behavioral, genetic, and imaging data to discover patterns that can be used as indicators of ASD. However, machines will not substitute a competent health care practitioner in making clinical assessments and diagnosis. These features can serve merely as a complementary feature that can help in detecting ASD.

7. Conclusion

This survey and review provides a comprehensive understanding of autism and its spectrum, highlighting various tools for ASD screening and evaluation, and the automatic detection of these test results using ML and DL algorithms. The study is particularly insightful for organization such as the CDC, preschools, and medical support institutions dedicated to ASD care. It emphasizes the importance of selecting appropriate ASD tests and ML algorithms for classification, considering the available data, the classification problem, and the desired outcome. The core aim of this review is to enhance the skills of special educators and medical officers in training ASD children toward self-sustainability. This research contributes significantly to assessing the strengths and weaknesses of different ASD detection methods. Key points include the necessity of choosing validated tests with high sensitivity and specificity results, as well as the importance of selecting tests suitable for the specific age group and developmental level of the individuals whose well-being is assessed. The choice of ML algorithms is determined by the type of data, the size of the dataset, and the intricacy of the classification problems. The frequently used ML algorithms are LR, NB, DT, RF, SVM, and NNs. Algorithms to be used must work well with the selected data and the prediction or classification problem. Following the selection of an appropriate algorithm, the dataset should be inspected against the algorithm's criteria and then, if required, feature selection methods can be applied to achieve the highest accuracy and validity of the model. ML can reshape healthcare by improving diagnosis, therapy, and general patient care. From the analysis of data from many patients, it can find patterns and make predictions, thus improving patient care and decreasing costs. A very promising area of application of ML in healthcare is that of medical imaging, where algorithms analyze data such as X-rays, CT scans, and MRIs to assist in ASD diagnosis and predict some other diseases or conditions. This gives better and quick diagnosis, thus improving treatment of patients.

As a result, the research on ASD is complex and diverse, involves large datasets, and several methods and tests. ML is now a useful method for identifying ASD through analyzing behavioral, genetic, and imaging data in order to detect specific patterns. Though the ML algorithms cannot replace the clinical assessment and diagnoses performed by medical experts, it serves as an additional tool, enabling the early and fast classification of ASD. The main future directions and challenges of the ML/DL for ASD are concerned with improving the stability of the models, increasing the possibility of applying them to those of different populations, and the availability and diversity of data. Successful management of these challenges requires enhancing algorithms because ASD symptoms vary and improving the scope of the dataset used in identifying patients with ASD. Another important issue is the enhancement of the methods for AI models' explanation to make the decision-making process more transparent and, therefore, acceptable for clinicians and easily incorporated. It also presupposes meeting essential ethical standards and privacy and data protection in the course of delivering care as AI systems process patients' sensitive health data. Moreover, there is a necessity to incorporate the use of such technologies into original clinical processes; the members of the healthcare staff need to learn how to use AI-based diagnostic tools. Future research should also investigate how different types of data are integrated (behavioral, genetics, neuroimaging) for a more effective diagnosis of ASD. Finally, real-time tracking and variable approaches based on AI could be considered one of the biggest innovations in an uninterrupted care approach to ASD, which may offer technologies and prospects for development.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Anjana Poonia: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Sunil Kumar:** Resources, Data curation. **Ghanshyam Raghuwanshi:** Conceptualization, Validation, Investigation, Writing - review & editing, Supervision, Project administration.

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Appendix

Abbreviations in Tables 4 and 5

Abbreviations	Full Name
AQ	Autism Quotient
M-CHAT	Modified Checklist for Autism in Toddlers
Q-CHAT	Quantitative Checklist for Autism in Toddlers
fMRI-ABIDE	Functional Magnetic Resonance Imaging- Autism Brain Imaging Data Exchange
UCI	University of California, Irvine (Machine Learning Repository)
ADOS-II	Autism Diagnostic Observation Schedule–Second Edition
CHAT	Checklist for Autism in Toddlers
DISCO	Diagnostic Interview for Social and Communication Disorders
DSM-IV	Diagnostic and Statistical Manual of Mental Disorders–Fourth Edition
SVM	support vector machine
RF	random forest
DNN	deep neural network
DT	decision tree
KNN	K-nearest neighbor
GRUs	gated recurrent units
NB	Naïve Bayes
MLP	multilayer perception
SGD	stochastic gradient descent
CNN	convolutional neural network
RFC	random forest classifiers
AFNI	Analysis of Functional NeuroImages
FSL	few-shot learning
LDA	linear discriminant analysis
GBM	gradient boosting algorithm
RFE	recursive feature elimination
MIE	minimum igniion energy
KST	Know Sure Thing
FS	feature selection
ANN	artificial neural network
LSTM	long short-term memory