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REVIEW ARTICLE

Diagnosis of autism spectrum disorder: a systematic review of clinical and artificial intelligence methods

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Abstract

Autism Spectrum Disorder (ASD) is a developmental disorder that affects one's interpersonal skills, communication, and the desire to engage in repetitive activities. Early detection is important for treatment and management to be beneficial. This implies that the search for strategies for diagnosing ASD as fast and as successfully as possible is quite urgent which leads us to ask What is the fastest and most accurate way to diagnose ASD at an early age? An electronic search of various databases was done up to the end of December 2023. This consisted of the Quality Assessment Tool for Diagnostic Accuracy Studies—2 which was applied to assess the quality of the chosen studies. In this review, 45 papers were used. Even simple diagnostic procedures such as ADOS and ADI-R showed moderate reliability but were time-consuming and dependent on clinicians' skills. Machine learning and deep learning techniques proved to have the potential to diagnose ASD with the help of many datasets, which can enhance the diagnostic precision and speed of the process. Conclusions: The application of AI techniques in identifying ASD has been stated as beneficial where there are few facilities for clinical examination. More investigations should be carried out to establish the real-life relevance of these approaches.

1 Introduction

This study aimed to address the following topics: artificial intelligence's influence on autism spectrum disorder, its subtypes, clinical diagnosis techniques, and how these techniques support diagnosis in both the traditional ways and the AI ways of diagnosing. This study intended to find evidence-based criteria and assessment methods for reliably diagnosing autism spectrum disorder by thoroughly evaluating the literature. The main question stays what can be the fastest and most accurate way to diagnose ASD at an early age? A neurodevelopmental disorder, autism spectrum disorder begins with the development of the human brain in the womb. According to a hypothesis, transcriptional programs or signaling pathways are disrupted by upstream, highly coupled regulatory ASD gene mutations, which leads to the deregulation of downstream processes like neurogenesis, synaptogenesis, proliferation, and brain activity. The intensity of social symptoms in ASD is connected with signaling pathway dysregulation (Courchesne et al. 2020). According to recent computational research, ASD is a multistage, multiprocess, progressive brain-wide illness of prenatal and early postnatal development that is highly heritable. Heterogeneity in clinical outcomes is caused by subtypes that occur during pregnancy (Courchesne et al. 2018). As a result, it affects a person's ability to engage and communicate with others effectively. Especially for kids with ASD, it can be challenging to learn language and to comprehend what other people are saying to them. Additionally, they frequently struggle with nonverbal cues including facial expressions, eye contact, and hand gestures [3]. Autism can make it difficult for individuals, especially children, to understand others' emotions. A study reveals that people with ASD perceive facial emotions based on specific features. They may form affect-related schemas based on certain facial traits, rather than the full face. They tend to focus on the lower face, like the mouth, rather than the upper face, like the eyes (Gross 2004). It can have an impact on their ability to express facial expressions; earlier studies have

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found deficiencies in standard facial emotion identification in people with ASD, indicating aberrant representations of emotional expressions. The unusual expressions of induvial with ASD can not be easily recognized by neurotypically developing individuals as well (Brewer et al. 2015). However, the majority of studies on social connections and emotion identification have focused on males, and little is known about how girls with autism maintain social relationships throughout their developmental years. Females with autism can adopt explicit tactics for managing social interactions, such as masking and mimicry. The use of such tactics had both advantages and disadvantages (Tierney et al. 2016). Another one of the primary symptoms of autism spectrum disorder (ASD) is restricted and repetitive patterns of behaviors and interests (RRB). They speculate that genetic factors may have a role in RRB, but research has also shown that in all investigated animal species, repeated motor and sensory activities are a consistent result of experience deprivation or restriction (Leekam et al. 2011). Several have drawn a connection between the person's repetitious behavior and potential anxiety. Anxiety severity is positively correlated with the degree of restricted and repetitive behavior in ASD (Baribeau et al. 2020). Additionally, repetitive activity can take many different forms. One study identified six distinct categories of repetitive behavior: restricted, self-injurious, compulsive, ritualistic, stereotyped, and sameness (Fatima et al. 2022). Restrictive interest is one of the well-known and prevalent subtypes of reactive behavior. Clinically affecting interests of extraordinary focus or intensity are known as restricted interests (RIs) in autism spectrum disorder (Carter et al. 2020). Many persons with ASD have strong preferences for particular things, and this is especially evident in younger people. Motor skills are another diagnosing criterion that is less frequently discussed. The term "motor skills" describes the body's muscles and coordination capacity to carry out physical actions and modify the surroundings. There is a strong correlation between ASD and substantial changes in motor skills (Craig et al. 2021). Despite being frequently disregarded in therapeutic settings, there are several reasons to take motor abnormalities in ASD into account. These issues typically appear early in infancy (Bhat et al. 2012), sometimes even before social and communicative impairments(Sacrey et al. 2018). In comparison to typically developing children and those with other developmental disorders, children with ASD showed greater impairments in FMS competencies, particularly in object control and locomotor skills. This was revealed by a symmetric review of 24 studies that measured the Fundamental movement skills in children with ASD. Impairments in FMS are highly prevalent across the ASD spectrum (Gandotra et al. 2020). Since autism is a disorder on the spectrum, there are numerous subtypes of the condition. The patient's doctor will diagnose if one of the diagnostic criteria is met. Today, there are many variations of diagnosis methods. The Diagnostic and Statistical Manual of Mental Disorders (DSM) is a popular diagnostic criterion that is frequently used. It is a set of uniform standards for identifying and categorizing various mental health conditions published by the American Psychiatric Association (APA). Asperger's disorder, autism disorder, childhood disintegrative disorder, and pervasive developmental disorder- not otherwise are the four subtypes of autism disorder that were previously recognized until (DSM-5) was released in 2013 and unified all of these terms under Autism spectrum disorder (Ousley and Cermak 2013). These diagnoses have been replaced with severity levels, ranging from 1 to 3, under the umbrella term autism spectrum disorder.

1.1 Asperger's syndrome

Individuals who have Asperger's syndrome may exhibit behavioral abnormalities, stereotypies, and narrow interests in addition to having trouble interacting with others and communicating verbally and nonverbally. They do not exhibit a language delay, and rather than having a general cognitive development delay, they have particular deficiencies in areas like executive skills (Mirkovic and Gérardin 2019). The most likely classification for a person who previously fulfilled the requirements for an AS diagnosis is Level 1 (McPartland et al. 2012). Some researchers hold the view that autism subtypes are necessary to assist them in identifying more comprehensive solutions for each case. AS frequently offered a label that supported a positive identity and enabled individuals to make sense of their own experiences. It was thought to aid in their understanding by others Chambers et al. (2019).

1.2 Childhood disintegrative disorder

Childhood disintegrative disorder is another subtype of autism. The validity of CDD as a distinct entity from autism spectrum disorder (ASD) has been called into question by various literature evaluations. It is known to be less common than autism. There are some major differences between CDD and ASD, both in terms of symptom profiles and regression patterns (Mehra et al. 2018). Some reviews have found that CDD has poorer overall function than ASD, with a higher rate of seizures, mutism, and more severe intellectual disability. Importantly, CDD has been linked to impairment in a broader set of domains than ASD, such as adaptive abilities and emotional and behavioral control (Volkmar et al. 2005). According to additional evaluations, this illness manifests itself after the first four years of life, at which point behavioral and developmental functions begin to decline. In that specific study, a case report was presented regarding an 11-year-old child who developed normally for up to 7 years before seeing a decline in previously acquired language, intellectual, and social skills (Di Vara et al. 2022).

1.3 Pervasive developmental disorder not otherwise specified

Those who did not fully fit the diagnostic criteria for autism, Asperger's syndrome, schizophrenia, schizotypal personality disorder, or avoidant personality disorder have historically been categorized as having pervasive developmental disorder not otherwise specified" (PDD-NOS). Autism-typical was included under "pervasive developmental disorder not otherwise specified" to denote a generalized disruption of the personality, with disharmonious relational and cognitive capacities that were intact in certain areas and severely affected in others Carbone and Dell'Aquila (2023). According to a study that analyzed the literature on pervasive developmental disorders not otherwise specified, children with PDD-NOS clearly show a tendency toward less impairment in socializing and communication. The findings regarding repetitive and restricted behaviors were more ambiguous. PDD-NOS had less of an impact on early development and family and child well-being (Coutelle et al. 2023). In summary, PDD-NOS is connected with a milder form of autism that has fewer symptoms and is not as closely linked to other disorders, such as mood disorders and schizophrenia.

1.4 Autism disorder

To be classified as having an autism disorder, a person must display six symptoms that fall into the three primary categories of sociability, communication, restricted behaviors, interests, and activities, according to the DSM 4 (Witwer and Lecavalier 2008). Nevertheless, DSM-5 would need you to have persistent deficiencies in social interaction and communication in a variety of settings and limited, recurring interests, activities, or behavioral tendencies to be classified under the term autism spectrum disorder. We can see that the two ideas center on comparable criteria, which relate autism disorder to the current core of autism spectrum disorder. After discussing the most frequent autistic symptoms and different subtypes of autism it's crucial to note that various environmental factors might influence these symptoms. Autism diagnoses vary significantly between countries and cultures. According to research from the United States, non-white children are less likely than white children to be diagnosed with autism (Mandell et al. 2009). That can be because families' opinions of autism are influenced by a lack of understanding of the disorder and its cultural, linguistic, and religious contexts, potentially leading to late diagnosis (Papoudi et al. 2020). Some civilizations, such as the Arab society, may be more accepting of children's actions that Western societies would deem abnormal (Taha et al. 2013), resulting in the impression of autistic behavior as normal. Other communities may regard some of the symptoms as normal behavior; for example, minimal eye contact is prevalent in Indigenous Australian and Asian cultures (Uono and Hietanen 2015; Shochet et al. 2020) and may not be recognized as an indication of autism. When studying autism, it's important to incorporate cultural norms (Freeth et al. 2014). Modifying the diagnostic procedure to accommodate people from other countries and cultures, as well as raising worldwide awareness of these challenges, is a step in the right direction. We will talk about the many approaches for diagnosing autism and examine how each one works. The main objective of this review is to find the most effective method of diagnosing ASD that can bypass the difficulties of typical medical methods and overlook cultural differences.

2 Methodology

2.1 Search strategy and selection criteria

The whole research process has complied with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards. To find relevant studies, a detailed search was performed on several databases, including PubMed, Scopus, and Web of Science. The search was oriented towards diagnosis methods for Autism Spectrum Disorder (ASD) and specifically towards studies incorporating Artificial Intelligence (AI) techniques. Such study-specific words as "ASD diagnosis," "AI diagnosis," "machine learning," "deep learning," "DSM-5," and Autism Diagnostic Observation Schedule were utilized to find relevant studies. The most relevant works were those that aimed at extending the abilities of the diagnosis using novel AI approaches. Otherwise, studies that only summarized what is already known without any new input in the discipline or those that did not have discernible diagnostics outcomes were omitted.

Apart from studies that aimed at the use of AI in the diagnosis of alto, we also looked at some papers that discussed the diagnosis of alto using traditional clinical methods (such as the DSM5 and ADOS) in order to find out how these traditional methods compare with the AI-enhanced methods. We also incorporated research that applied AI technology to the existing traditional methods of diagnosis.

Two independent researchers screened and reviewed each article and discussed and resolved any differences to come to a final decision on which studies to include in the review. In Fig. 1 you can view a more detailed representation of the initial research that was conducted.

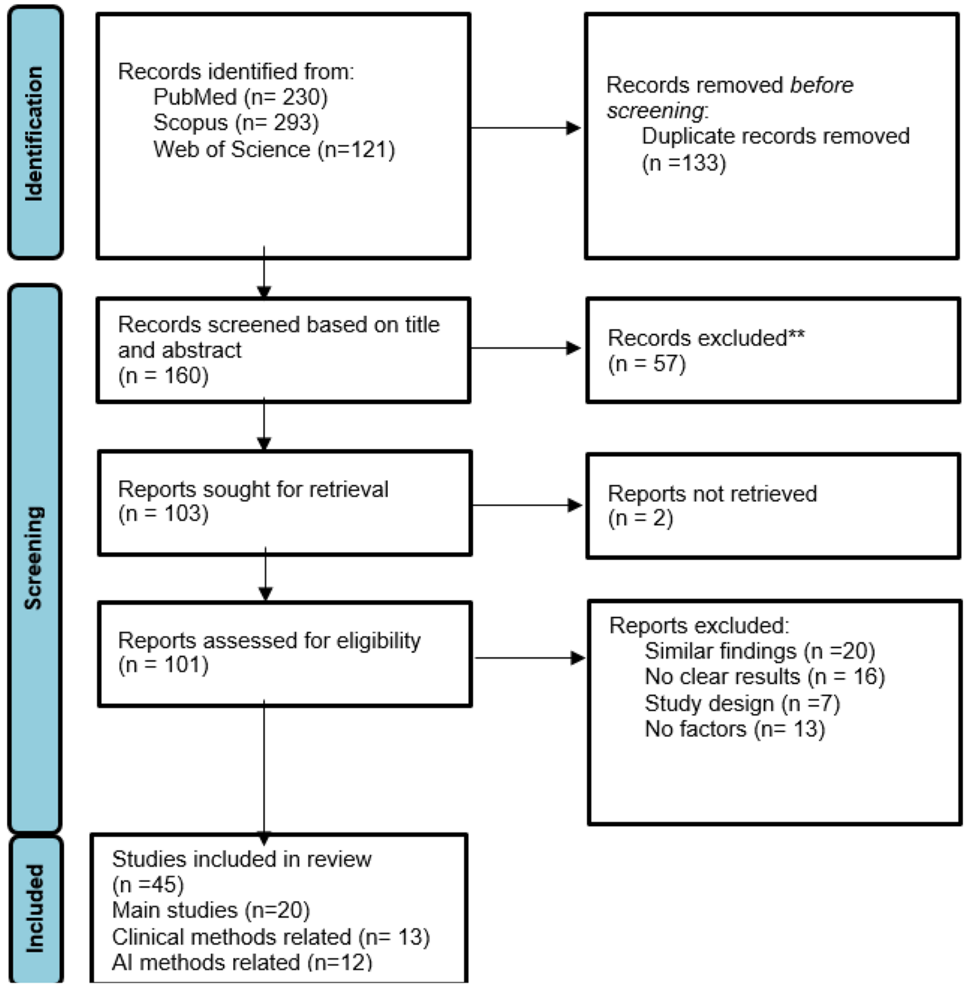

Fig. 1 PRISMA 2020 flow diagram for new systematic reviews

2.2 Data extraction and outcomes

From each study, we attempted to retrieve information on several primary outcome measures: diagnostic accuracy (including sensitivity and specificity), the time taken to render a diagnosis as well as the effectiveness of traditional and artificial intelligence-based techniques. For AI-based approaches, we additionally extracted the range of machine learning and deep learning architectures, types and sizes of datasets used, and the results of AI approaches versus conventional diagnostics.

Where measures of effect were reported in more than one (e.g. over different periods or test performance), we included only those of the strongest concern to the rapid and accurate diagnosis of Autism Spectrum Disorder (ASD). To enable a fair and equitable assessment of all traditional and AI diagnostic methods employed in different studies, we pursued all results about these outcomes across different studies.

Besides the key outcomes, we gathered information on more study attributes. This involved particulars of participants such as sample size, age range, and whether the study was conducted on children, adults, or both. We also accounted for the nature of the interventions employed, and whether the studies utilized classical diagnostic measures such as DSM-5 and ADOS or incorporated any AI enhancements. Where AI was involved, we obtained data on how the technology was used in the diagnostic procedure. In addition, the funding sources for each study were indicated, to establish any possible bias towards the outcomes.

To substantiate our claims in instances in which data was absent or ambiguous, we made informed judgments. In the case of missing key outcome data such as accuracy measures, quantitative synthesis of the study would not apply but perhaps the study was still useful in a qualitative analysis as it contained worthwhile information. Any such concerns regarding differences and/or missing information were settled via discussion and agreement between the two reviewers.

In this review, we examined the potential risk of bias within each study included through the utilization of the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool. The bias risk assessment by this tool is done in four domains: patient selection, index test, reference standard, and flow and timing. Studies, where assessments would be conducted, were greedily assigned to two independent reviewers, and any divergences were resolved by discussions and agreements. No automation tools were used in this process. The studies were rated in terms of the QUADAS-2 criteria as low, high, and unclear treatment recommendation bias, which aided in the overall evidence synthesis.

2.3 Methods review

These days, there are several ways to help identify autism. We now know the signs that patients with ASD typically exhibit, and we may use these symptoms to help these individuals receive a clinical diagnosis through an interview with a specialist. Early indicators of Autism Spectrum Disorder (ASD) include low eye contact, a lack of response to names, sharing and showing, no gestures by the age of one year, and a loss of language or social skills (Hodges et al. 2020). If any of these signs are shown it is best to refer to a specialist. Another method of diagnosing is test-like techniques which have been developed by various specialists as well to verify that all the criteria match the accurate diagnosis. Artificial intelligence has made significant advancements in the diagnosing process of ASD. It took some of the normally used methods and turned them into a more efficient and accurate process. These techniques would greatly increase the accuracy of the diagnosis procedure, improving the quality of life for those with ASD.

2.3.1 Clinical diagnosing methods

We'll examine the indications and symptoms that each approach emphasizes and how those influence their diagnosis. In a medical environment, these criteria are measured while the patient is being interviewed by a professional.

DSM-5

Clinical diagnosis methods refer to the conventional techniques employed in a medical setting when a professional evaluates the patient and makes a diagnosis based on the patient's symptoms. The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, is one of these techniques. DSM-5 was published, updating the diagnostic criteria for ASD from the previous 4th edition (DSM-IV). We have also stated the fact that the DSM-VI is the one that created subtypes for autism however, the DSM-5 came and introduced the term ASD. There have been some concerns regarding whether the other disorder still fits the new criteria for ASD (Yaylaci and Miral 2016). However, the goal of this revised definition is to improve accuracy and facilitate the early diagnosis of ASD in children (Halfon and Kuo 2013). The DSM-5's level system illustrates the severity of the issue; the higher the level, the more support the case requires. The primary symptoms typically observed in individuals classified as autistic patients form the basis of the DSM-5. Nonetheless, it outlines a few requirements to support the provided diagnosis. The following criteria are used by DSM-5 to diagnose ASD.

1. Persistent deficits in social communication and social interaction across contexts, not accounted for by general developmental delays.
2. Restricted, repetitive patterns of behavior, interests, or activities as manifested by at least 2 of 4 symptoms.
3. Symptoms must be present in early childhood (but may not become fully manifest until social demands exceed limited capacities).
4. Symptoms together limit and impair everyday functioning (American Psychiatric Association 2013).

Certain studies have sought to determine whether DSM-5 is still capable of diagnosing subtypes of autism that were first included in DSM-VI. According to that one study, most kids with DSM-IV PDD diagnoses would still be qualified for an ASD diagnosis provided the DSM-5 criteria were implemented. The DSM-5 ASD criteria have higher specificity than the DSM-IV criteria for PDD-NOS and Asperger's disorder, especially when anomalies are apparent from both parents and clinical observation (Huerta et al. 2012).

Autism Diagnostic Observation Schedule

Another approach commonly employed in medical settings to diagnose autism is the Autism Diagnostic Observation Schedule. The Autism Diagnostic Observation Schedule is an activity-based evaluation tool used by qualified clinicians to assess people suspected of having autism spectrum disorder (ASD) in terms of their social skills, inventive material use, and communication abilities. From young toddlers who have no expressive language to older people who are more verbally proficient, the four modules in the ADOS are designed for people with varying developmental and linguistic skills (Bastiaansen et al. 2010). There are multiple versions of ADOS, the ADOS-2 assesses individuals across their entire lives, starting at 12 months old and continuing into adulthood (Hurwitz and Yirmiya 2014). ADOS-2 was also revised to align with to better align with diagnostic criteria specified by the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (Dorlack et al. 2018).

In this method there are multiple models, the doctor selects the most appropriate of five overlapping modules for each individual, ranging from the most basic for young children with no spoken language to the most advanced for

Table 1 The modules of the ADOS-2 Module

Module	Age	Language level
Toddler	Young children, 12–30 months	Little or no phrase speech
1	31 months and older	Little or no phrase speech
2	Children	Phrase speech but not verbally fluent
3	Children and young adolescents	Verbally fluent
4	Adolescents and adults	Verbally fluent

teenagers and adults. In Table 1 you can see the 5 overlapping models.

Each module contains a variety of tasks, including playful elements (for example, "Free Play," "Bubble Play," and "Birthday Party" with a baby doll), activities (for example, "Telling a Story From a Book," "Demonstration Task"), and verbal tasks (for example, "Conversation and Reporting," questions about "Friends, Relationships, and Marriage") designed to provide the examiner with information on social, communicative, play, and stereotyped behavior (Kamp-Becker et al. 2018). The ADOS assigns codes to activities based on a 0-to-3-point system. A 0 indicates that the activity is normal, while a 3 indicates that it is aberrant and conflicts with the child's function (Akshoomoff et al. 2006).

Autism Diagnostic Interview

Along with other techniques like ADOS and DSM, the Autism Diagnostic Interview has been utilized to assess autism diagnosis. For those who may be suspected of having autism spectrum disorder, the ADI-R offers a comprehensive evaluation. The ADI-R, which consists of 93 items, is focused on three functional domains: Communication and Language, Mutual Social Contacts, Constrained, Repeated, and Stereotyped Behaviors, and Interest. However, as long as the subjects' mental ages are greater than two years and 0 months, this interview can be used. The findings can be utilized to bolster an autism diagnosis or assess the clinical requirements of different populations where a high prevalence of autism spectrum disorders may be anticipated (Rutter and LeCouteur 2003).

The ADI-R does not give scales or norms since it is an interview rather than a test, it tries to concentrate on behaviors that are not as common as other symptoms in autistic patients. Interview questions focus on the patient's background, behavior, early development, language acquisition, present functioning, social development, and other clinically important issues like violence, self-injury, and potential epileptic symptoms. The interview may include questions such as if the child "greeted" their parent upon returning home from work or shopping. The informant must understand what "greeting" implies, and the response is based on his or her overall impression of whether or not the youngster exhibits the set of activities specified by the concept. A well-planned interview schedule helps informants comprehend the specific behaviors to be addressed. However, the answer remains based on their overall perspective (Le Couteur et al. 1989).

Questionnaires

ASD Questionnaires have also become one of the tools that people can use independently to screen themselves. The inquiries are also designed to focus on the key symptoms of ASD, some of these questionnaires base their creation on known diagnosing measures such as DSM-5. They may be useful in facilitating psychiatrists' and psychologists' referrals to ASD services for diagnostic evaluation. However, the surveys should not be used in isolation, but rather in conjunction with clinical judgment and further ASD screening tools, if necessary (Brugha et al. 2020). Many different questionnaires have been devised to screen for autism and make diagnosis more accessible to everyone. We will discuss the methodologies that some of these questionnaires have used to reach a high level of accuracy in the diagnostic procedure.

Autism-spectrum quotient (AQ)

The adult autism-spectrum quotient (AQ) scale was established to examine the idea of autism as a trait with a continuous distribution in the general population (Baron-Cohen et al. 2001). Originally consisting of 50 items in five subscales (the AQ-50), abbreviated versions of 28 (AQ-Short) and 10 (AQ-10) have since been produced. Studies indicated that the AQ-50, AQ-S, and AQ-10 functioned well at discriminating between individuals with and without a clinical diagnosis of ASD, however, there was a little loss of discriminative power in AQ-10 (Booth et al. 2013). The AQ-50 was developed to assess the presence of autistic symptoms in adults with normal intelligence, as there were no self-administered tools available back then. The AQ-50 consists of 50 questions organized into five categories: social skills, attention switching, attention to detail, communication, and imagination. If the respondent describes abnormal or autistic-like behavior, each of the items listed above is worth one point. The AQ-50 was evaluated on adults with AS or

Table 2 Questions from AQ-50 (Baron-Cohen et al. 2001)

Question	The criteria it measures
1. I prefer to do things with others rather than on my own	Social skill
2. I prefer to do things the same way over and over again	Attention switching
5. I often notice small sounds when others do not	Attention to detail
7. Other people frequently tell me that what I've said is impolite, even though I think it is polite	Communication
3. If I try to imagine something, I find it very easy to create a picture in my mind	Imagination

high-functioning autism (HFA) as well as age-matched control groups. HFA or AS may impair comprehension of questionnaire items (Baron-Cohen et al. 2001). Some of the questions asked in the questionnaire are in the table in Table 2.

The AQ-short aimed to reduce the amount of items while maintaining high validity and a meaningful factor structure. The AQ-Short evaluates social behavior and a proclivity for numbers/patterns. It provides a reasonable alternative to the full 50-item version. They used a five-step process to minimize the number of items in the questionnaire. One of these methods involved lowering the number of questions by assessing the substance of all 50 items. Following these checks, certain goods were identified as potentially problematic. For example, goods with the same material and language may disrupt the factor structure of a greater number of things (Hoekstra et al. 2010). The AQ-10 was also developed in response to the demand for simple screening tools for autism spectrum disorders (ASD) that frontline healthcare providers may use to help determine whether an individual should be referred for a complete diagnostic assessment. To create AQ-10, they chose two items from each of the five subscales of the entire AQ with the highest discriminatory power. The 10 selected items in the validation sample were then tested for discriminative power using ROC analyses (Booth et al. 2013).

Ritvo autism-Asperger's diagnostic scale-revised

Another questionnaire used in the diagnosis procedure is the Ritvo autism-Asperger's diagnostic scale-revised. It is an 80-question scale intended to fill a significant gap in screening services for adults with autism spectrum disorders. This assessment is a good clinical tool that can help clinicians diagnose this rising demographic of higher-functioning adults (Ritvo et al. 2010).

The RAADS-R is a modified version of the Ritvo Autism Asperger's Diagnostic Scale (Ritvo et al. 2007). It was developed to meet the requirement for a clinical adjunct diagnostic tool. Unlike AQ, RAADS-R is intended to be delivered by a clinician in a clinical environment. Questions on the initial RAADS evaluate developmental dysfunction in three symptom areas: language, social relatedness, and sensory-motor. Following a critical assessment and factor analysis, a revised 80-item version (the RAADS-R) was created, which included a fourth symptom category (circumscribed interests), two new questions, and some word clarifications (Ritvo et al. 2010).

Modified checklist for autism in toddlers-Revised (M-CHAT-R) and The Social Communication Questionnaire (SCQ)

Two further questionnaires designed specifically for kid screening are the modified checklist for autism in toddlers-Revised (M-CHAT) and the social communication questionnaire (SCQ). They are parent-reported autism spectrum disorder (ASD) screening techniques that have been widely employed. The M-CHAT-R is used for screening toddlers aged 16–30 months, while the SCQ is for autistic individuals aged ≥ 4 years (Sangare et al. 2019).

An updated version of the M-CHAT questionnaire, M-CHAT-R (Robins et al. 2013), included examples, changed the item sequence, and streamlined the wording to discourage a set of positive responses. The Modified Checklist for Autism in Toddlers (M-CHAT) is a straightforward screening tool that may be administered to all toddlers during pediatric appointments. It consists of 23 yes/no items. It is based on parents' reports of their child's present abilities and behaviors rather than the doctor's observations of the youngster (Robins et al. 2001). The Checklist for Autism in Toddlers (CHAT) is expanded upon by the M-CHAT. Reporting actions like pointing, pretend play, and showing interest in other kids are among the items in CHAT. The first nine items of the M-CHAT and its format are directly lifted from the CHAT. The researchers also came up with a list of symptoms they believed to be common in very young autistic youngsters. The rest of the Items were developed based on clinical tools used to assess older children, literature-based assumptions, and their own clinical expertise (Baron-Cohen et al. 1992). With only 20 questions, the updated version, M-CHAT-R, is somewhat shorter in duration. Three items that showed poor performance were removed from the original version, and the item sequence was rearranged to lessen the bias toward affirmative responses (Khowaja et al. 2014). To identify as many cases of ASD as feasible, or maximize sensitivity, is the main objective of the M-CHAT-R. As a result, there is a large false positive rate, which indicates that not every child who receives a risk score will receive an ASD diagnosis. They created the Follow-Up questions (M-CHAT-R/F) in order to address this (Robins et al. 2014).

Based on the Autism Diagnostic Interview-Revised (ADI-R), the Social Communication Questionnaire (SCQ) is a parent-report screening tool for autism spectrum disorders (ASDs). It can be granted to caretakers of children older than four, but only about actions taken between the ages of four and five. The SCQ's components align with the Diagnostic and Statistical Manual of the American Psychiatric Association's (DSM-IV) criteria for diagnosing autism. Eight items cover language and communication, stereotyping, repeating patterns of conduct, and reciprocal social contact. A primary caregiver can typically complete the 40 yes/no answers on the SCQ in less than ten minutes (Eaves et al. 2006).

There are various other questions designed for screening purposes that have succeeded brilliantly. Therefore we attempted to cover the ones that are the most popular in the method of diagnosis.

2.3.2 Machine learning and deep learning diagnosing methods

With the development of numerous new approaches for diagnosing autism, artificial intelligence has played a role in applying new methods that can help achieve greater accuracy in the diagnosis process. Some of these strategies have taken clinical methods and adapted them using machine learning technologies to achieve a simpler process for everyone. Numerous models can be used to predict and classify autism and other neurological developmental problems based on different approaches. This section will go over some of the methods and strategies used in machine learning and deep learning to diagnose autism.

EGG

The EEG and MEG are two of the techniques they have used in conjunction with various machine learning techniques to diagnose autism. The dependable and non-invasive techniques of EEG and MEG enable the recording of neural activity in the brain (Singh 2014). In numerous electroencephalography (EEG) oscillatory tests, infants who are diagnosed with ASD later on and who are at high familial risk for the disorder exhibit abnormal activity (Huberty et al. 2021). Given that each autistic person's brain is unique and since research has shown that the brain may change dramatically even at very young ages (Bryson et al. 2008) (as early as 6 months), machine learning is the best approach for deciphering the neurobiological profiles of ASD utilizing EEG and MEG data. Accurately identifying ASD states of cognition, estimating the intensity of ASD symptoms, diagnosing high-risk infants with ASD as early as three months of age, and categorizing ASD symptoms are all possible with both machine learning and deep learning approaches (Das et al. 2023).

The anatomical and functional connections between different brain regions are impacted by neural abnormalities in ASD (Port et al. 2014). It is believed that microscopic neural alterations in ASD impair the brain's capacity to produce and maintain coherent oscillatory activity, which affects the way information is transmitted across different neuronal groups (Dickinson et al. 2021). From these kinds of patterns, we can implement an artificial intelligence model that can distinguish between them with enough training and testing. The first study participated in analyses for a larger ongoing study that looked at the development of infants with and without familial risk for ASD over the first three years of life in the first trial. While they finished an EEG recording session at three months for their research (Dickinson et al. 2021), these kids were still included in the primary study until they were three years old. The children were assessed at 18 months by a clinical professional using ADOS-T at 18 months and the results of both diagnoses were compared.

One machine learning technique that has been used on EEG data is Support Vector Machines (SVM). It falls within the umbrella of machine learning techniques for supervised learning. It can be applied to regression analysis as well as categorization. To predict the risk of autism, the researchers used linear kernel support vector regression (SVR) models in this study. Before using SVM, the data is required to be preprocessed. To eliminate frequencies below 1 Hz and frequencies above 90 Hz, the data were low-pass and high-pass filtered. Then, high amplitude artifacts were eliminated in comparison to artifact-free reference data using artifact subspace reconstruction (ASR), a data cleaning technique that makes use of sliding window principal component analysis (Chang et al. 2018). For the feature selection, a subset of functional connections within each fold was chosen using an elastic net penalty regularized regression technique with LOOCV. The hybrid approach known as elastic net regularization combines the ℓ_1 penalty of lasso with the ℓ_2 penalty of ridge regression (De Mol et al. 2009). Going back into SVM, Support vector machines for regression (SVR) provide an opportunity to evaluate the value of functional connections for dimensionally predicting ASD behaviors, which is one of the reasons SVM was used in this study in addition to the benefits of binary classification provided by traditional SVM (Dickinson et al. 2021).

The second study used both linear and nonlinear Event-Related Potential (ERP) analysis of the Electroencephalogram (EEG) signals to categorize toddlers accompanying

Autism Spectrum Disorders (ASD) from normally developing (TD) toddlers. Three various classifications of first emotion stimuli-happy, scared, and neutral faces-were bestowed during the whole of the acquisition of the signals. For the features distillation, they first extract the Intrinsic Mode Functions (IMFs), which mention the latent activity of ERP parts, EEGs are first disintegrated utilizing the Multivariate Empirical Mode Decomposition (MEMD) approach. From each set of IMFs, the standard linear measures utilizing maximum (Max.), minimum (Min.), and standard deviation (Std.) are before brought back in addition to the nonlinear sample entropy (SampEn) traits. Following their judgment all mathematical reasoning tests, these features are employed in the production of the input vectors. After we have reached the input vector immediately we can engage the models. The Discriminant Analysis (DA), Support Vector Machine (SVM), and k-most forthcoming Neighbors (kNN) classifiers are the three types of models secondhand in this place study (Bakheet and Maharatna 2021).

In the last study, we looked at epilepsy and ASD were differentiated using a single system, we are attempting to locate them in single-channel and multi-channel EEG data using the independent components analysis ICA technique. The dataset artifacts are eliminated after that an elliptic band-pass filter is employed to segment and filter the EEG dataset to remove interference and noise after breaking down the filtered signal into its individual sub-bands gamma beta alpha and theta the discrete wavelet transform DWT is utilized to extract the features of the EEG signal. They have experimented with four distinct models: support vector machines (SVM), ANNs, k-nearest neighbor (KNN), and linear discriminant analysis (LDA) (Alturki et al. 2020).

Face Recognition

According to certain research, children who are developing normally do not have the facial characteristics of persons with ASD. The reason for this is that the brain and the growing facial tissues grow together and in unison, affecting one another's growth and sharing genetic signaling pathways. Within the same group of ASD patients, they were also able to find different subgroups. These subgroups were related to particular clinical and behavioral traits (Aldridge et al. 2011). Because of this, we can diagnose patients with autism using computer vision methodologies based on the facial image of the person. We'll examine a few research projects that have included this methodology.

In the first study, children with autism were identified through the use of facial images and several types of deep convolutional neural network (CNN) based transfer learning techniques (Alam et al. 2022). Their decision to adopt CNN stemmed mostly from its capacity to automatically extract characteristics from a huge number of photos, which will simplify the process (Jogin et al. 2018). They also alluded to the transfer learning technique, which involves using a pre-trained model that was created in the past with the aid of enormous datasets and supercomputers. It focuses on improving classification or prediction accuracy by adjusting the final output based on the application of the intended tasks utilizing the weights and parameters of these pre-trained models (Mishra and Passos 2021). The study tested five distinct pre-trained models: VGG19, Xception, ResNet50V2, MobileNetV2, and Efficient-NetB0, assuming no universal technique for model selection. Their performance was assessed by the use of many hyperparameters. To achieve high accuracy, they employed multiple optimizers and split ratios of the test-train data. A weighted drop-out layer was added to prevent overfitting after the features were max-pooled and supplied to the FC layer (Alam et al. 2022).

The CNN model has demonstrated its excellent ability in computer vision approaches (Chaudhuri 2020), Because of that it was also used in the upcoming study (Lu and Perkowski 2021). VGG16/VGG19 had the greatest levels of picture identification accuracy in a recent comparison analysis of well-known deep learning architectures for facial recognition, according to Gwyn (Gwyn et al. 2021). For this reason, they chose to concentrate their research on VGG16-based deep learning. Additionally, they used the transfer learning technique, which involves applying a pre-trained model to their dataset. Among these pre-trained models, VGG trained on the ImageNet dataset and earned one of the top 5 accuracies. Rectified linear unit (ReLU) has been employed as the activation function in the hidden layers, while Adam (stochastic gradient-based) has been used as the optimizer (Lu and Perkowski 2021).

They also sought to comprehend the role that racial characteristics have in the identification of ASD in their study. Their investigation concentrated on the incorrect categorization of youngsters who were Black and East Asian. They have divided their classification technique into four classes, each of which contains the diagnoses and the race label, in order to reduce the number of misdiagnoses based on race (Lu and Perkowski 2021).

In the last study (Awaji et al. 2023), we will examine hybrid methods that use facial image data for ASD diagnosis. Similar to earlier research, their first technique simply used pre-trained CNN models; however, their subsequent approaches integrated CNN models (VGG16, ResNet101, and MobileNet) with XGBoost and RF algorithms. Additionally, they employed a different technique that entailed employing XGBoost and an RF based on features of the VGG-16-ResNet101, ResNet101-MobileNet, and VGG16-MobileNet models to diagnose ASD. Deep learning models are prone to overfitting, particularly when the training data is sparse, which is one of the reasons they are using two coupled methodologies. Through the integration of RF and XGBoost techniques, this problem is reduced.

They have mentioned preparing their dataset; to eliminate noise, they first chopped the face from the picture, then they used a Gaussian filter and image normalization to ensure that the pixel values fell within a predictable range. By applying ReLU element-by-element to the convolved output, non-linearity is introduced into the model, enabling it to learn more intricate correlations between features. Following that, the pooling extracts the most crucial data from the feature maps' local regions. Every time they intend to employ CNN alone for feature extraction, the classification layer is eliminated. Rather, the machine learning algorithms are employed. The hybrid approach makes use of the advantages of both XGBoost and RF, perhaps leading to improved performance.

MRI/fMRI

In addition, magnetic resonance imaging and functional magnetic resonance imaging have been used in machine learning applications as well as clinics to diagnose ASD. Because ASD affects the structure and function of the brain, some imaging modalities can be used to identify the condition. When it comes to describing the changes in the brain that take place in ASD, functional magnetic resonance imaging (fMRI) has advanced significantly (Kaiser et al. 2010). Functional MRI demonstrated aberrant perfusion, neurovascular decoupling, and disruption of functional networks that are linked to the main symptoms of ASD. Structural magnetic resonance imaging (MRI) revealed abnormal developmental trajectories, changed network connectivity, and morphological changes in the brain at different ages (Wang et al. 2023). In addition to clinical diagnosis, some professionals also use imaging because they believe that diagnoses based solely on clinical symptoms may be incorrect. They believed that fMRI/MRI is one method that could assess early diagnoses at a very young age. In this review, we will examine three distinct studies that have utilized MRI/fMRI as a biomarker for autism diagnosis. They had previously relied on this approach in addition to more traditional techniques like clinical interviews, but thanks to newly emerging technologies, they have been able to combine these approaches with deep learning and machine learning models to create a diagnosing tool that will aid doctors in their day-to-day diagnosis processes. In the first study we reviewed(Li et al. 2018) they had aimed to develop the interpretation method for deciphering the regions in fMRI brain images that can distinguish ASD vs. control by the deep neural networks. Their primary driving force was the lack of model transparency in the previous models developed for fMRI-based ASD diagnosis. Even with encouraging outcomes, doctors usually want to know how to interpret the data and whether the model is reliable.

They have developed a novel two-stage pathway for biomarker interpretation. The primary contribution is an image corruption and generation process based on regions of interest (ROI). In their second step, they use statistical hypothesis testing and the distribution of DNN predictions to examine the feature relevance. The DNN (2CC3D) they used in the study consists of two fully connected, four max-pooling, six convolutional, and four output layers, which are followed by a sigmoid layer. To prevent overfitting, l2 regularization and dropout are used. The study in (Li et al. 2018) showed that since the 2CC3D framework integrates the spatial-temporal information of 4D fMRI, they may attain higher accuracy with it. After the picture has been corrupted, the next step is to interpret the output discrepancies. To obtain a fresh prediction, they tamper with the ROI of the original image and feed it into a trained DNN classifier (Li et al. 2018).

According to the second paper we looked at, conventional D-FCNs are low-order networks that ignore high-level interactions across several regions of interest (ROIs) because they are built on pairwise correlation across brain regions. To further investigate the higher level and more intricate interaction links across many ROIs, they first build novel high-order D-FCNs based on the idea of "correlation's correlation" to overcome the previous issues. Moreover, they suggest extracting temporal-invariance features from either low- or high-order D-FCNs using a central-moment technique. To diagnose ASD and normal control subjects, they combine the features taken from conventional FCNs, low-order D-FCNs, and high-order D-FCNs to create and train an ensemble classifier. To preprocess rs-fMRI data, Ventricle, and global signals were then regressed out as nuisance signals, and the Friston 24-parameter model was used to correct head motion. Subsequently, for every brain ROI, the average rs-fMRI time series was computed and displayed in a data matrix (Zhao et al. 2020).

For ASD classification, they employed SVM with a linear kernel after using the two-stage method to identify the most crucial features. Given that these features come from three FCNs with various levels, they trained an SVM classifier to handle each kind of feature. SVM looks for a hyper-plane with the greatest margin to divide samples into two groups. The hyperparameter can be used to balance the empirical risk of the training data and the model's complexity. To create the final result, we can finally merge these three SVM classifiers. To be more precise, every kind of feature is employed to train a particular classifier. Next, each Support Vector Machine (SVM) will produce an associated decision score for each test subject, which will represent the likelihood that the subject belongs to a class. To determine the classification outcome, we compute the weighted average of the three decision scores derived from these Support Vector Machine (SVM) models (Zhao et al. 2020).

In the third study (Shi et al. 2021), they suggested that the models usually would do poorly in the classification of fMRIs as a result of the absence of tagged ASD data. Due to this, people frequently blend photos from various resources, which causes the second issue they raised, which is that, in most situations, samples from various scanners or acquisition techniques do not follow the same distribution (Nielsen et al. 2013). Addressing these issues will lead to lessening the cost loss of target domain data prediction, a three-way decision model based on triangular fuzzy similarity is suggested. Additionally, they simultaneously use the structural information from the target. domain and the label information from the source domain, which lessens the variations in distribution between the domains and enhances the target domain data's recognition capacity. To put it simply, 3WD uses two upper and lower approximations to split the universe of discourse into three discrete segments: the positive region (Pos), the negative region (Neg), and the boundary region (Bnd). The Automatic Anatomical Labelling (AAL) (Tzourio-Mazoyer et al. 2002) atlas was then used to split the brain into 90 areas of interest (ROIs), from which the average time series was collected.

Realigning head motion is one of the preprocessing processes that were carried out. After fitting the functional images into the echo planar imaging (EPI) template, spatial smoothing was done as the next step in the image standardization process. They designate the site's data as the source domain, utilize the original features to train an SVM model on it, and use the remaining site data as the target domain to evaluate the learned classifier. They used a linear kernel in the SVM classifier and the grid-search technique to look for the margin penalty.

Eye tracking

Children with ASD have abnormal attentional behavior in response to social stimuli, particularly in team gazing. Eye tracking technology allows for the measurement of social visual attention directly. When looking at faces, normal individuals have a particular gaze pattern that focuses mostly on the eyes but also on the nose and lips (Walker-Smith et al. 1977). On the other hand, autism sufferers focus less of their attention on the central aspects of their faces (Pelphrey et al. 2002). It may result in the development of a novel biomarker-eye movement-that we might employ to identify ASD. We can determine whether a person is autistic or not by observing how their eyes move in a certain situation. It also contributes to the early diagnosis of ASD because eye tracking is a simple technique that young children may use. This section will look at three distinct research that have added eye-tracking to their machine-learning or deep-learning models. Some of these studies have integrated eye-tracking with other techniques, including the ones we already discussed, like face recognition or EGG. They thought that merging approaches could result in a higher accuracy percentage.

They employed features from both the EGG and eye tracking for the diagnosis procedure in the first research (Kang et al. 2020). We'll pay closer attention to the characteristics they took out of the eye-tracking data. They used an eye-tracking device to record the necessary data while a collection of face pictures was shown to the kids in an arbitrary order. The young girls in the facial images were either of the same race or a different race. Every type of photo would show up six times, lasting ten seconds each. To catch kids' attention in between trials, a lively, sound-producing kitten was displayed. To analyze the data that they recorded Eight areas of interest (AOI)-the background, torso, face, eyes, mouth, nose, right eye, and left eye-were chosen. They used the minimum-redundancy-maximum-relevance (MRMR) method for feature selection (Peng et al. 2005). Support vector machines, or SVMs, were employed in this study to perform classification. Finding the separating hyperplane in feature space with the maximum margin distance across categories is the primary goal of data fitting for support vector machines (SVM). This allows instances of two classes to be split as widely as possible (Kang et al. 2020).

In the second study (Elbattah et al. 2022), we looked at, eye tracking and the transfer-learning method were both used to try and diagnose autism. To apply transfer learning to the features they recorded with eye-tracking, their goal was to convert them into visual data. They used the visual representation of eye-tracking output to learn the patterns linked to ASD through the use of a vision-based methodology. A series of images and video scenarios that were specifically created to excite the eye to glance across the screen were used in the eye-tracking research. The videos vary in duration and content to enable a multifaceted analysis of ocular activity. The degree of attention paid to other aspects and the participants' eye contact with the presenter were assessed. The main concept included condensing long-tailed eye-tracking records into a collection of pictures that might graphically represent the gaze activity. This way, the prediction problem may be treated like a process of classifying images. They experimented using VGG-16, ResNet, and DenseNet, three distinct CNN pre-trained models. They began by applying data augmentation, which was used to expand the dataset and improve the variety of photos. They retained the pre-trained model's base layers and based on the features that the convolutional base had extracted, the input image was classified using the classification lay (Elbattah et al. 2022).

In the last study (Ahmed et al. 2022), Three artificial intelligence methods for early autism detection using eye-tracking were created: machine learning, deep learning, and a hybrid method combining the two. Neural networks-both artificial neural networks (ANNs) and forward neural networks (FFNNs)-are the first method. The second method relied on deep feature map extraction and employed a pre-trained convolutional neural network (CNN) model, such as GoogleNet and ResNet-18. The third method, known as GoogleNet + SVM and ResNet-18 + SVM, combined machine learning (SVM) and deep learning (GoogleNet and ResNet-18) in a hybrid fashion. Important and precise features need to be obtained by treating this noise. A picture's initial phase is image optimization. In this work, Laplacian and average filters were used to enhance all photos as a part of preprocessing. They have also used the snake algorithm to segment their data. One of the newest techniques for properly segmenting, identifying, and isolating the area of interest (ROI) from the remainder of the image for additional analysis is the snake algorithm. Following that, they continued using the Morphological Method. Two algorithms, LBP and GLCM, were used to extract the most significant representative features from the ROI. Strong representative features were then created by combining the characteristics that had been retrieved from the two algorithms. After that, these features were fed into their 3 different methods and yielded the final results (Ahmed et al. 2022).

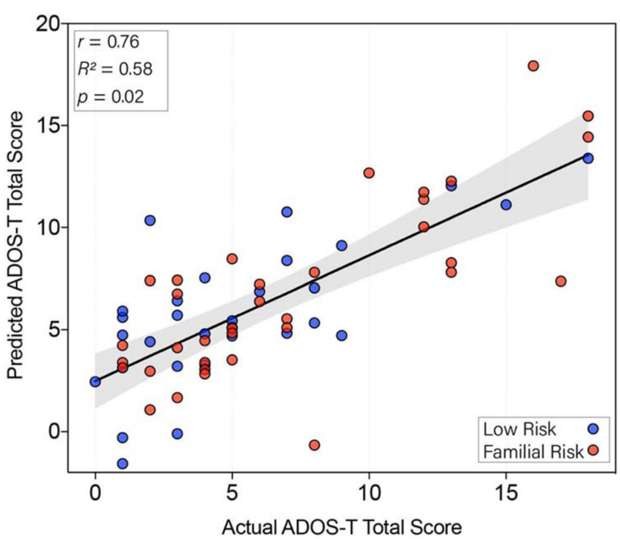

Fig. 2 Correlation between predicted and actual ADOS-T scores at 18 months based on EEG readings at 3 months (Dickinson et al. 2021)

3 Results

We will present the findings from each model utilized in the earlier research for every approach in this section. Each technique employed has produced impressive outcomes, contributing to the advancement of autism diagnosis tools.

3.1 EGG

The first study involved sixty-five community newborns recruited through the UCLA Center for Autism Research and Treatment (CART) to investigate multivariate brain connection patterns in early infancy using EEG. The Support Vector Regression (SVR) model was employed to estimate ADOS-T total scores, which significantly coincided with actual ADOS-T scores obtained at 18 months. The ultimate goal was to achieve a diagnosis at 3 months that matched the diagnosis obtained at 18 months using the ADOS-T screening test. The study achieved the following predictive performance between the actual ADOS-T results and the predicted results based on the EEG readings:

- Pearson's r: 0.76
- R^2: 0.58
- p-value: 0.02

Fig. 3 Classification performance of happy fear and neutral datasets using LDA QSVM and kNN classifiers (Bakheet and Maharatna 2021)

Classifier	Happy			Neutral			Fear		
	ACC	TPR	TNR	ACC	TPR	TNR	ACC	TPR	TNR
LDA	**100%**	**100%**	**100%**	33.3%	0%	66.7%	33.3%	33.3%	33.3%
QDA	66.7%	100%	33.3%	16.7%	0%	33.3%	50.0%	66.7%	33.3%
L-SVM	83.3%	66.7%	100%	16.7%	0%	33.3%	33.3%	33.3%	33.3%
Q-SVM	**100%**	**100%**	**100%**	16.7%	0%	33.3%	50.0%	100%	0%
C-SVM	83.3%	100%	66.7%	16.7%	0%	33.3%	33.3%	66.7%	0%
kNN	83.3%	100%	66.7%	33.3%	0%	66.7%	33.3%	33.3%	33.3%

These results are illustrated in Fig. 2, which depicts the correlation between the predicted and actual ADOS-T scores.

The second study used a dataset from previous EEG-based Event-Related Potential (ERP) research (Bakheet and Maharatna 2021). The dataset contains EEG signals from 24 patients (12 ASD and 12 TD). Ages range from 6 to 13 years. Signals were recorded at 250 Hz using a 128-channel HydroCel Geodesic Sensor net. The dataset was divided into 75% training and 25% testing data. Cross-validation was employed to ensure no overfitting occurred. The classification performance was evaluated using standard metrics such as accuracy (ACC) sensitivity (TPR) and specificity (TNR). Discriminant Analysis (DA), Support Vector Machine (SVM) and k-nearest Neighbors (kNN) classifiers were trained on various feature vector dimensions. These classifiers aimed to identify the most effective features for distinguishing between ASD and TD children. Combining features collected from the last three Intrinsic Mode Functions (IMFs) improved classification performance. Figure 3 shows that happy dataset produced the most accurate identification between ASD and TD children across all classifiers

- LDA and QSVM: 100% ACC, 100% TPR, 100% TNR.
- Fear dataset: Q-SVM: 50% ACC, 100% TPR, 0% TNR.
- QDA: 50% ACC, 66.7% TPR, 33.3% TNR.
- Neutral dataset: Best performance was with 33.3% ACC 0% TPR, 66.7% TNR using LDA and kNN

In the third study, three dataset types were used to both apply and verify the algorithms. The first two sets of data are applied to epilepsy diagnosis, whereas the third one serves for autism diagnosis. First Dataset: The data set used in this paper is provided by Bonn University in Germany and each set contains 100 single-channel EEG signals, including set A, set B, set C, set D, and set E. Sets A and B were obtained from invasive EEG recordings but from normal people's scalp EEGs, while sets C, D, and E were harvested from epileptic and intracranial EEGs. Second Dataset: Acquired from a research team at MIT, USA (Moody et al. 2000), this dataset has 23 epileptic patients with 906 h of collected EEG data. Third Dataset: This dataset was given by the King Abdulaziz University (KAU) Brain-Computer Interface (BCI) Group in Jeddah, Saudi Arabia that was recorded in relaxed condition and the data was divided into two groups. Neurotypical Group: Data collection was obtained ten healthy volunteer participants (all males, aged 9–16) with normal IQ and no history of mental illnesses. Autistic Group: Nine patients with ASD participated in the study (6 males, and 3 females); all of them were between the ages of 10 and 16. The EEG signals were obtained using EEG data acquisition equipment from the patients' scalps in a resting position. Now we'll look at the results from the first mode, which is the diagnosis of two classes: epilepsy versus Neurotypical and ASD versus Neurotypical, and the second mode, which is the most significant contribution to

Fig. 4 Classification accuracies of two-class classification methods (Alturki et al. 2020)

Feature Extraction	Classification Accuracy (%)			
	LDA	SVM	KNN	ANN
DWT + LBP	84 ± 0.5	85.2 ± 0.4	90.4 ± 0.3	91.2 ± 0.3
DWT + SD	74.4 ± 0.5	82.7 ± 0.2	88 ± 0.5	89 ± 1
DWT + Variance	49 ± 1	75.5 ± 0.5	85.3 ± 0.5	72 ± 4
DWT + Kurtosis	63.8 ± 0.5	58.4 ± 0.4	79.2 ± 0.4	78 ± 1
DWT + Entropy	86.2 ± 0.2	86 ± 0.2	90.5 ± 0.3	90.8 ± 0.2

Fig. 5 Classification accuracies of multi-channel classification methods (Alturki et al. 2020)

Feature Extraction	Classification Accuracy (%)			
	LDA	SVM	KNN	ANN
DWT + LBP	95.3 ± 0.5	96.5 ± 0.5	95.2 ± 0.5	97.1 ± 0.5
DWT + SD	89 ± 1	92 ± 1	91 ± 1	94 ± 1
DWT + Variance	83 ± 1	83 ± 1	90 ± 1	67 ± 3
DWT + Kurtosis	73 ± 1	78 ± 2	82 ± 1	78 ± 2
DWT + Entropy	97.5 ± 0.5	97.6 ± 0.5	97.9 ± 0.5	98.2 ± 1

Fig. 6 Classification accuracies of three-class classification methods (Alturki et al. 2020)

Feature Extraction	Classification Accuracy (%)			
	LDA	SVM	KNN	ANN
DWT + LBP	96.6 ± 0.3	96.7 ± 0.5	95.8 ± 0.5	97 ± 1
DWT + SD	91.5 ± 0.2	92.1 ± 0.1	93.6 ± 0.3	73.7 ± 1
DWT + Variance	73.8 ± 2.5	67.5 ± 0.6	88.3 ± 0.6	61.6 ± 0.6
DWT + Kurtosis	63.8 ± 0.2	65.2 ± 0.7	65.9 ± 0.5	65.5 ± 2.5
DWT + Entropy	95.2 ± 0.2	95.5 ± 0.2	93.9 ± 0.5	96.2 ± 1

Model	Adagrade		Adam		Adamax	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
VGG19	0.8169	0.8927	0.7857	0.8621	0.7991	**0.8922**
Xception	0.8571	**0.9174**	0.8080	**0.8894**	**0.8303**	0.8887
ResNet50V2	**0.8661**	0.8966	**0.8169**	0.8858	0.7991	0.8682
MobileNetV2	0.7991	0.8842	0.6875	0.7321	0.8258	0.8727
EfficientNetB0	0.7053	0.8143	0.6607	0.7465	0.4821	0.5075

Fig. 7 The accuracy of different models with different optimizers (Alam et al. 2022)

Model	Learning Rate					
	0.01		0.001		0.0001	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
VGG19	0.6875	0.7234	0.8169	0.8927	**0.8438**	**0.8910**
Xception	0.7901	0.8724	0.8571	**0.9174**	0.7991	0.8747
ResNet50V2	0.7857	0.8674	**0.8661**	0.8966	0.8259	0.8859
MobileNetV2	**0.8571**	**0.8844**	0.7991	0.8842	0.7813	0.8552
EfficientNetB0	0.6250	0.6712	0.7053	0.8143	0.7009	0.7824

Fig. 8 The accuracy of different models with different learning rates (Alam et al. 2022)

this research, which is the diagnosis of three classes: epilepsy versus ASD versus Neurotypical. The accuracy values for neurotypical vs. epilepsy for an ingle channel were 99.5 ± 0.5 using DWT + LBP and entropy with all classifiers, whereas DWT + entropy with KNN classifier yielded an accuracy of 98.5 ± 0.5%. For a single channel, the ANN classifier attained the maximum accuracy (91.2 ± 0.3) when comparing neurotypical and autistic groups, you can refer to figure (4) to see the results for the rest of the classifiers (Alturki et al. 2020) (Fig. 4).

The combination of DWT with LBP and entropy outperforms other combinations for multi-channel EEG data for Neurotypical vs. Epilepsy, and the SVM classifier is an excellent choice for achieving the best classification accuracies. Figure 5 shows that a combination of DWT, LBP, and entropy outperforms other combinations for multi-channel EEG data for Neurotypical vs. Autistic and that the ANN and KNN classifiers attain the highest classification accuracy.

For three-class classification with a single channel, the combination of DWT, LBP, and entropy performs better than other combinations for single-channel EEG data. The best

Model	Accuracy	AUC	Precision	Recall
VGG19	0.8645	0.9214	0.8645	0.8645
Xception	0.9201	0.9625	0.9097	0.9097
ResNet50V2	0.9097	0.9571	0.9097	0.9097
MobileNetV2	0.868	0.9483	0.868	0.868
EfficientNetB0	0.8576	0.9214	0.8576	0.8576

Fig. 9 The results of different models with different epochs (Alam et al. 2022)

results for the multi-channel situation were attained using the same approach; see Fig. 6 for detailed details (Alturki et al. 2020).

3.2 Face recognition

For the first study, the dataset includes photos of children between the ages of 2–14 years, most of them being within 2–8 years. The male-to-female ratio is approximately 3:1, while that of the autistic class versus the normal control class is approximately 1:1. Images were divided into three: the training set, test set, and validation set. This dataset was downloaded online from Kaggle.

Experiments were tested with multiple optimizers whose results were documented. The results are depicted in Fig. 7 below (Alam et al. 2022).

Experiments were run with the three models using a learning rate of 0.01, 0.001, and 0.0001 which returned different performances as observed in Fig. 8 below Alam et al. (2022).

They tried different ratios of testing vs. training data, the best results for this were 90–10. Tried different batch sizes; 32 seemed like the optimum number where larger batches require more system resources.

Different numbers of epochs were tried. It was found that the models were overfitting at less than 50 epochs and underfitting at more than 100 epochs. The best setting of each component is as shown in Fig. 9 (Alam et al. 2022).

Two different datasets were used in the second study:

1. **East Asia ASD Children Facial Image Dataset (East Asian Dataset):**
   - **Total Images:** 1122 facial images, equally divided between typically developing (TD) and ASD children.
   - **Source:** 600 face images were collected from the Elim Autism Rehabilitation Center in Shandong, China, and 561 images of TD students were obtained from various kindergartens and elementary schools in China.
   - **Age Range:** 2 to 12 years old.
   - **Race:** All subjects in this dataset are East Asian children.
2. **Kaggle Autism Face Dataset:**
   - **Total Images:** 2936 facial images, equally divided between TD and ASD children.
   - **Source:** The images were sourced online, though the contributor noted the difficulty in obtaining ASD images from organizations or credible sources.

The two datasets were combined to examine the effect of racial diversity on classification accuracy. The combined dataset consisted of facial images from both East Asian and Caucasian children.

		Predicted				
		CNormal	*ENormal*	*EAutism*	*CAutism*	Σ
Actual	*CNormal*	231	3	0	55	289
	ENormal	3	80	9	11	103
	EAutism	1	6	105	8	120
	CAutism	63	11	6	219	299
	Σ	298	100	120	293	811

Fig. 10 The results of the classification displayed by a Confusion matrix (Lu and Perkowski 2021)

A confusion matrix, as given in Fig. 10, was prepared to display the results of the classification. Analysis of Confusion Matrix Groups:

Caucasian (C): The largest racial group in the dataset. East Asian (E): The second largest racial group in the dataset.

East Asian Test Set (ENormal): Total Images: 103 Correctly Classified as Normal: 80 FP Rate: 22.3% (23 out of 103 images misclassified). Interpretation The model worked better with increasing racial diversity in the training dataset. A multiracial balanced dataset is required to improve the accuracy of the classification of ASD using facial images.

The authors of the third work have used the **Autism_Image_Data** dataset obtained from Kaggle. This dataset includes facial images of children who have autism and neurotypical children. As such, it is the only online dataset relating to the diagnosis of ASD that has been adopted for this work.

- **Composition:** 2940 images of faces, with an equal number of children who have autism and neurotypical children.
- **Age Range:** 2 to 12 years old.
- **Format:** Images in JPG format of different resolutions, ranging from 168x207 to 799x947 pixels.
- **Purpose:** This dataset allows examination of distinguishing facial traits associated with autism in children.

Division of Data

- **Training and Validation:** 80% of the images were used for model training and validation. This includes generat-

Fig. 11 The outcome that was obtained in each scenario (Awaji et al. 2023)

Classifiers	CNN for Features	Classes	AUC %	Accuracy %	Precision %	Sensitivity %	Specificity %
XGBoost	VGG16	Autistic	97.2	95.6	95.9	96.2	95.8
		Non_Autistic	97.5	95.9	95.6	96.4	96.1
		Average ratio	**97.35**	**95.7**	**95.75**	**96.3**	**95.95**
	ResNet101	Autistic	96.5	94.2	94.9	94.3	94.8
		Non_Autistic	96.8	94.9	94.3	95.1	93.8
		Average ratio	**96.65**	**94.6**	**94.6**	**94.7**	**94.3**
	MobileNet	Autistic	96.9	94.9	95.5	94.7	96.1
		Non_Autistic	97.3	95.6	94.9	96.4	94.9
		Average ratio	**97.1**	**95.2**	**95.2**	**95.55**	**95.5**
RF	VGG16	Autistic	95.2	94.9	94.9	95.4	94.7
		Non_Autistic	96.1	94.9	94.9	94.9	95.3
		Average ratio	**95.65**	**94.9**	**94.9**	**95.15**	**95**
	ResNet101	Autistic	96.8	95.9	94.9	95.7	95.4
		Non_Autistic	97	94.9	95.9	95.3	95.9
		Average ratio	**96.9**	**95.4**	**95.4**	**95.5**	**95.65**
	MobileNet	Autistic	97.1	95.6	96.2	95.8	96.2
		Non_Autistic	97.3	96.3	95.6	95.6	96.4
		Average ratio	**97.2**	**95.9**	**95.9**	**95.7**	**96.3**

Fig. 12 The outcome that was obtained in feature extraction scenario (Awaji et al. 2023)

Classifiers	Models for Fusion Features	Classes	AUC %	Accuracy %	Precision %	Sensitivity %	Specificity %
XGBoost	VGG16-ResNet101	Autistic	98.1	97.3	97.3	96.7	96.9
		Non_Autistic	98.6	97.3	97.3	97.1	97
		Average ratio	**98.35**	**97.3**	**97.3**	**96.9**	**96.95**
	ResNet101-MobileNet	Autistic	97.3	98.3	95.4	98.1	95.2
		Non_Autistic	97.5	95.2	98.2	94.9	97.7
		Average ratio	**97.4**	**96.8**	**96.8**	**96.5**	**96.45**
	VGG16-MobileNet	Autistic	98.4	98.6	97	98.8	97.2
		Non_Autistic	98.8	96.9	98.6	96.9	98.6
		Average ratio	**98.6**	**97.8**	**97.8**	**97.85**	**97.9**
RF	VGG16-ResNet101	Autistic	97.6	96.3	97.9	96.4	98.3
		Non_Autistic	98	98	96.3	98.2	96.2
		Average ratio	**97.8**	**97.1**	**97.1**	**97.3**	**97.25**
	ResNet101-MobileNet	Autistic	98.2	97.6	97.3	98.2	96.9
		Non_Autistic	98.3	97.3	97.6	96.8	98.2
		Average ratio	**98.25**	**97.4**	**97.45**	**97.5**	**97.55**
	VGG16-MobileNet	Autistic	99.1	98.6	99	98.7	98.9
		Non_Autistic	99.4	99	98.8	99.3	99.3
		Average ratio	**99.25**	**98.8**	**98.9**	**99**	**99.1**

ing training templates, conducting validation, and optimizing weights and parameters.

- **Testing:** The remaining 20% of images were used for testing the efficiency and adaptability of the models.

To categorize the ASD dataset, the three pre-trained models' performances-VGG16, ResNet101, and MobileNet-were assessed. With an AUC of 86.65%, accuracy of 84.4%, precision of 84.75%, sensitivity of 84.05%, and specificity of 84.15%, the VGG16 model outperformed the others. The next way they employ is to categorize using machine learning techniques in conjunction with CNN models. Figure 11 shows the outcome that was obtained in each scenario (Awaji et al. 2023).

In the last approach, we examine the outcomes obtained by utilizing CNN models solely for feature extraction, leaving the classifications to be handled by the machine learning algorithm. Figure 12 shows the outcome that was obtained in each scenario (Awaji et al. 2023).

3.3 MRI/fMRI

In the first paper we reviewed, They tested their methods on 48 healthy controls who were matched for age and IQ and a group of 82 ASD children for their dataset. Every participant had a task fMRI scan. They divided the subjects into three groups: 85% for training, 7% for early stopping validation, and 8% for testing. The model's accuracy for the Task-fMRI Experiment was 87.1% for each 3D pair input in the testing set. Additionally, they have experimented with the Resting-State fMRI dataset from ABIDE I. 85.3% accuracy was attained using the dataset and the same classifier that was previously employed. Figure 12 displays the biomarker detection results. Blue-hued emotion-related areas are highlighted for both groups; red-hued seeing and movement-related regions are linked to the identification of ASD; and green-hued executive and lingual regions are linked to the identification of control (Li et al. 2018).

Visual patterns were identified in their first experiment since the participants were performing a visual activity. In contrast, no visual areas were identified in their second experiment since the participants were at rest.

The second paper's (Zhao et al. 2020) rs-fMRI dataset was also obtained from the Autism Brain Imaging Data Exchange (ABIDE) database, which is accessible to the general public. They exclusively took into account the rs-fMRI data obtained from 45 ASD patients and 47 normal controls (NCs), who were scanned at New York University Langone Medical Center between the ages of 7 and 15. This reduces data heterogeneity.

The average classification performance of nine models, each with a unique feature combination, is displayed in Figs. 13, 14.

We can conclude from Fig. 13 that the ensemble classifier consistently produces better classification results than a single feature type. This finding validates the hypothesis that combining multi-order connectional features will improve classification outcomes. The best classification performance was obtained by fusing C-, Lo-, and Ho-level FCNs. This suggests that different-level FCNs can offer supplementary, pertinent information for the diagnosis and classification of ASD and that fusing this information can further enhance the classification performance. In the third study, the ABIDE dataset, which is available to the general public, provides the experimental data. ABIDE is a multisite platform that has compiled structural and functional brain imaging data from 17 different laboratories worldwide, comprising 573 neurotypical controls and 539 patients with ASD. Corresponding resting-state fMRI scans and phenotypic data, including age and gender, were available for each patient. They employed

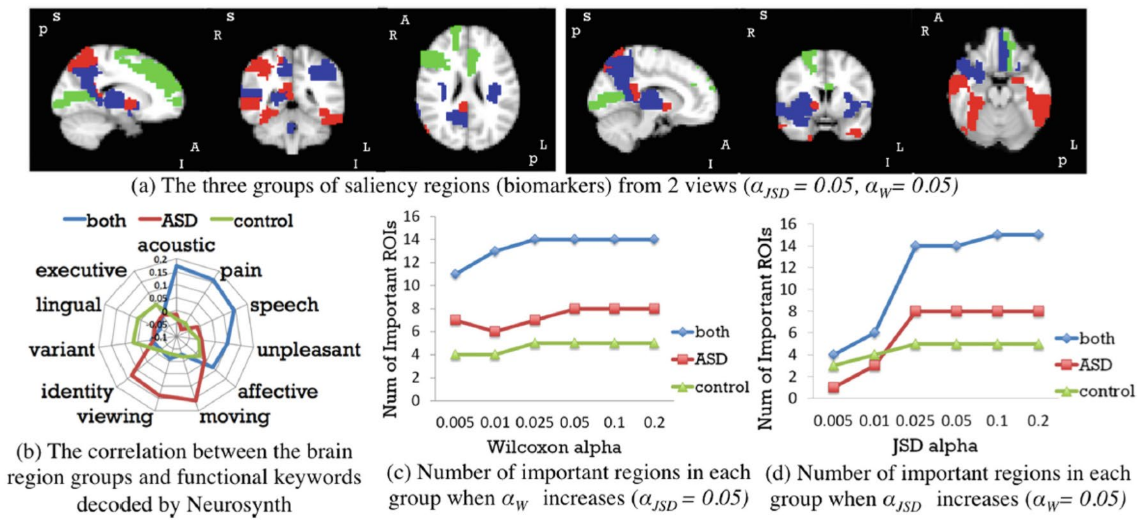

Fig. 13 Biomarker detection results (Li et al. 2018)

Fig. 14 Average classification performance of nine models (Zhao et al. 2020)

Model	ACC (%)	TPR (%)	TNR (%)	PPV (%)	NPV (%)	F1 (%)
C_C	74 ± 0.04	72 ± 0.23	76 ± 0.01	74 ± 0.05	74 ± 0.08	73 ± 0.07
$C_{Lo-D}(1)$	75 ± 0.12	73 ± 0.14	76 ± 0.29	74 ± 0.23	75 ± 0.08	74 ± 0.12
$C_{Lo-D}(4)$	79 ± 0.15	79 ± 0.10	79 ± 0.53	79 ± 0.38	79 ± 0.07	79 ± 0.12
$C_{Ho-D}(2)$	78 ± 0.06	79 ± 0.49	77 ± 0.24	76 ± 0.09	80 ± 0.25	77 ± 0.11
HiO	72 ± 0.16	71 ± 0.21	73 ± 0.32	72 ± 0.18	73 ± 0.28	72 ± 0.16
$C_C + C_{Lo-D}(4)$	80 ± 0.20	78 ± 0.25	82 ± 0.39	80 ± 0.38	79 ± 0.17	79 ± 0.20
$C_C + C_{Ho-D}(2)$	78 ± 0.11	79 ± 0.20	77 ± 0.26	77 ± 0.17	79 ± 0.12	77 ± 0.11
$C_{Lo-D}(4) + C_{Ho-D}(2)$	81 ± 0.06	82 ± 0.31	80 ± 0.11	80 ± 0.06	83 ± 0.17	81 ± 0.08
$C_C + C_{Lo-D}(4) + C_{Ho-D}(2)$	**83 ± 0.16**	**82 ± 0.10**	**84 ± 0.46**	**83 ± 0.34**	**83 ± 0.08**	**82 ± 0.13**

Values highlighted in bold show best results.

data from three separate locations (NYU, UM, and USM) with over 50 patients utilizing varied fMRI techniques since different sites have different amounts of limited samples. An unsupervised adaptive experimental setup is used for the three domain adaptation methods-TCA, JDA, and DALSC (computational methods) and compared with the study's own noval method. Figure 15 displays the categorization performance outcomes of several techniques.

Using the SVM classifier directly to forecast the target domain is less accurate than using the domain adaptive technique based on feature representation. The experimental findings indicate that the suggested approach performs well in SEN, SPE, BAC, and other indicators and that its classification accuracy outperforms that of the domain adaptive methods already in use (such as TCA, JDA, and DALSC) in six tasks.

3.4 Eye-tracking

The first study included 97 youngsters in total. Children between the ages of 3 and 6 who had an official diagnosis of ASD (N = 49; 10 females and 39 males; M = 4.29, SD = 1.07) and TD children (N = 48; 12 females and 36 males; M = 4.26, SD = 1.00) made up the participants. Significant differences in the percentage of fixation length for the backdrop, face, mouth, and nose were found between ASD and TD using independent t-tests. ASD looked less at the face, nose, and mouth of own-race strangers and more at their backgrounds. In the meantime, the ASD group focused less on the mouth and nose and more on the background of strangers of different races' faces. Figure 16 shows the categorization accuracy based on the own-race and other-race face stimuli's AOI gaze durations and their combinations (Kang et al. 2020).

For the second study (Elbattah et al. 2022) the dataset under review was gathered as part of previous research on the use of eye tracking in the study of autism (Carette et al. 2018). Fifty-nine school-age youngsters were selected from French schools in the Hauts-de-France region. Participants ranged in age from three to twelve years old on average. It was very important that the individuals be in their early developmental stages. Three-fold cross-validation was used to divide the dataset into train and test sets. Three cross-validation cycles were used to assess each model's performance.

Fig. 15 The categorization performance outcomes of several techniques (Shi et al. 2021)

Task	Method	ACC (%)	SEN (%)	SPE (%)	BAC (%)	PPV (%)	NPV (%)
NYU →UM	Baseline	54.87	49.23	62.5	55.87	64	47.62
	TCA	62.83	58.46	68.75	63.61	71.69	55.00
	JDA	64.50	66.67	61.64	64.16	69.57	58.44
	DALSC	64.60	56.92	**75.00**	65.96	75.51	56.25
	Ours	**70.80**	**72.31**	68.75	**70.53**	**75.81**	**64.71**
NYU →USM	Baseline	67.21	78.26	60.53	69.39	54.55	82.14
	TCA	68.85	82.61	60.53	71.57	55.88	85.19
	JDA	70.49	86.96	60.53	73.74	57.14	88.46
	DALSC	72.13	73.91	**71.05**	72.48	60.71	81.81
	Ours	**75.41**	**91.30**	65.79	**78.55**	**61.76**	**92.59**
USM →UM	Baseline	57.52	35.38	**87.50**	61.44	**79.31**	50.00
	TCA	58.41	38.46	85.42	61.94	78.13	50.62
	JDA	61.06	61.54	60.42	60.98	67.80	53.70
	DALSC	64.60	73.85	52.08	62.96	67.61	59.52
	Ours	**69.91**	**76.92**	60.42	**68.67**	72.46	**65.91**
	Baseline	53.25	35.42	76.71	56.06	66.67	47.46
	TCA	57.39	40.63	**79.45**	60.04	**72.22**	50.43

The VGG-16 model has the potential to perform at its peak with ROC-AUC ≈ 0.78. Refer to Fig. 17 for a thorough explanation of each model's accuracy (Elbattah et al. 2022).

In the last study, Carette et al. (2019) acquired and prepared the photos that made up the dataset from the Figshare data source. 547 photos of kids in two classes-ASD, which has 219 photos, and TD, which has 328 photos-are included in the collection. Furthermore, photographs were gathered from 59 kids: 30 kids with TD (13 boys and 17 girls) and 29 kids with ASD (25 boys and 4 girls) (Visualization of eye-tracking scanpaths in autism spectrum disorder 2024). The dataset was split up as follows: 20% was put aside for testing (109 photos), while the remaining 80% was used for training and validation (350:88 images). The FFNN algorithm's performance on Epoch 15, with an entropy of 0.002613. In contrast, by epoch 37, the ANN algorithm reached an entropy of 7.2545x10-7. As a result, the FFNN outperformed the ANN. Figure 18 provides more metrics that were measured for both FFNN and ANN (Ahmed et al. 2022).

The results produced by GoogleNet and ResNet-18 are summarized in Fig. 19. It was discovered that the ResNet-18 model outperformed the GoogleNet model. The two models produced better outcomes for ASD early diagnosis, which makes them crucial for supporting physicians' diagnostic judgments and aiding in diagnosis.

The two hybrid approaches that have been developed are ResNet-18 + SVM and GoogleNet + SVM. Figure 20 provides an overview of these hybrid approaches' outcomes. In comparison to the ResNet-18 + SVM system, the GoogleNet + SVM system produced superior results.

Fig. 16 Categorization accuracy (Kang et al. 2020)

	ACC	AUC
Own-race stranger's faces	72.33%	0.8269
Other-race stranger's faces	66.67%	0.7460
Both types of stranger's faces	75.89%	0.8652

Model	Recall (~)	Precision (~)
VGG-16	**0.56**	**0.67**
ResNet	0.54	0.65
DenseNet	0.55	0.65

Fig. 17 Explanation of each model's accuracy (Elbattah et al. 2022)

4 Discussion

4.1 Advantages and challenges of current diagnostic methods

4.1.1 Clinical diagnosing methods

The traditional methods of diagnosing autism spectrum disorders through therapy are well known to be used regularly to measure ASD levels. DSM criteria and diagnostic interviews for example are among them. They are mainly used to assess patients on the basis of their observable behaviors and communication patterns. Nevertheless, this kind of diagnosis heavily depends on how subjective it can be from one clinician to another hence not able to capture all symptoms related to autism spectrum disorder (ASD).

4.1.2 Artificial intelligence (AI) tools

Autistic Spectrum Disorder (ASD) diagnostics can be strongly promoted by new Artificial Intelligence advancements. For instance, big data like those from Electromyography (EEG) and MRE as well as genes if coupled with machine learning could reveal patterns underpinning these disorders. In addition to enhancing the diagnostic precision of doctors, these programs simplify their diagnostic processes thus saving time but identifying factors involved may become impossible without such mechanisms a set of which involves everything from neural activation measures to imaging rate of development abnormalities associated with this diagnosis. Some of these methodologies have the drawback of requiring computational resources to develop in the first place. Additionally, some of these procedures, like MRIs, might be costly for the patient. According to one study, EEG is especially well-suited for clinical screening since it is more portable, less expensive, and requires fewer tests than MRI (Debener et al. 2012). Face recognition is another approach that has numerous issues. A very large variation of data is required to train a deep neural network. But it is somewhat annoying when the researcher has to obtain consent from every individual he wants to use his face as data due to rights and permissions. Additionally, obtaining this type of data is challenging since many people view their face images as private belonging, unlike MRI images, which are often easier to acquire permission to take.

Dataset	Measure	FFNN	ANN
ASD	Accuracy %	99.8	99.8
	Precision %	99.8	100
	Sensitivity %	99.5	100
	Specificity %	100	99.7
	AUC %	99.85	99.77

Fig. 18 Measured for both FFNN and ANN (Ahmed et al. 2022)

Dataset	Measure	GoogleNet	ResNet-18
ASD	Accuracy %	93.6	97.6
	Precision %	93	97.5
	Sensitivity %	94.5	97
	Specificity %	94.5	97
	AUC %	99.48	97.56

Fig. 19 The results produced by GoogleNet and ResNet-18 (Ahmed et al. 2022)

4.2 Integration of cultural factors

4.2.1 Cultural awareness

One cannot overemphasize cultural norms and beliefs as significant factors that involve their friends or family members while seeking diagnosis of autism spectrum disorder (ASD). The main reason why there is such wide variation between countries regarding whether or not this condition is diagnosed lies with what is considered normal behavior within different societies: so people living in some areas will think nothing of a child who is very "hyper". Additionally, the majority of diagnosis techniques were created using Western standards without taking into account the needs of individuals in other regions of the world. This highlights how crucial it is to raise awareness of ASD globally in order to unify the accurate perception of individuals with autism.

4.2.2 AI and cultural competence

In order to ensure their accuracy and reliability AI-based diagnostic tools must be created and validated across diverse cultural contexts. To guarantee equitable access to ASD diagnosis for people with various cultural backgrounds there is a need for culturally sensitive models and algorithms. AI-based diagnostic tools, like MRIs, can be used to reconcile cultural differences, removing the possibility that a child won't receive a diagnosis because of someone else's perspective.

Dataset	Measure	GoogleNet + SVM	ResNet-18 + SVM
ASD	Accuracy %	95.5	94.5
	Precision %	95	95
	Sensitivity %	96	93.5
	Specificity %	96	93.5
	AUC %	99.69	94.51

Fig. 20 Overview of these hybrid approaches' outcomes (Ahmed et al. 2022)

4.3 Future directions and implications

4.3.1 Personalized interventions

Clinicians can combine insights from conventional clinical methods and AI technologies to create personalized interventions for people with ASD. This can involve the use of AI algorithms to identify different forms of ASD as well as estimate how individuals might respond to treatment.

4.3.2 Ethical considerations

Due to its use in diagnosing ASD, the idea of using AI has dire ethical implications concerning data privacy, informed consent and algorithmic bias. For this reason, clinicians together with researchers ought to look at prioritizing ethical principles by upholding strict standards that govern data collection processing as well as interpretation.

4.4 Collaboration and interdisciplinary research

4.4.1 Collaborative partnerships

Clinicians, researchers, AI experts, and community stakeholders need to work together to improve the diagnosis and treatment of ASD. Collaborations between researchers, clinicians, artificial intelligence experts, as well as community members, have been argued to be fundamental for progress in the diagnosis and treatment of Autism Spectrum Disorders.

4.4.2 Knowledge translation

It is very essential to connect research to clinical practice so as to make sure people quickly adopt novel diagnostic techniques. Translation work should be about spreading scientifically proven methods, training healthcare workers, and informing people with ASD and their relatives in a correct way.

By offering a thorough comparison between current AI-based techniques and conventional diagnostic techniques (such as the DSM-5 and ADOS), this work advances the expanding field of ASD diagnosis. In contrast to earlier evaluations, this study focuses on cutting-edge deep learning and machine learning methods that have demonstrated promise in improving diagnostic speed and accuracy, such as eye tracking, facial recognition, and EEG-based diagnosis. The study clarifies the potential for AI to speed up the diagnostic process without sacrificing reliability by directly comparing these AI-driven techniques with well-established clinical instruments. Furthermore, this review is distinctive in that it examines hybrid approaches that combine AI and conventional techniques, providing useful advice for medical professionals who might want to enhance existing tools with AI. In addition to offering academics and healthcare professionals practical suggestions, the findings point out significant shortcomings in the state-of-the-art diagnostic techniques and offer ideas for future research lines that can expand on these developments.

5 Conclusion

The diagnosis of autism spectrum disorder (ASD) is still a complex procedure that is influenced by a person's genetic makeup, environmental factors, and culture. ASD is a condition that affects people all over the world. Even though there are some cutting-edge approaches to more traditional clinical explanations, such as the DSM criteria about different areas in which this can manifest itself in the general population, it is still not distinct enough to explain, which puts us in a position where we are unable to identify it when we see it occurring in our environment.

Artificial intelligence (AI) technologies promise enormous changes in diagnostic ways which offer solutions to age-old challenges faced in dealing with modern disease diagnosis. Tools enabled by AI as they are driven by machine learning algorithms alongside big data kind of analytics can be seen to have capabilities of increasing efficiency and accuracy in addition to the availability of diagnostic services.

The development, as well as implementation of AI-based diagnostic tools, require the integration of cultural factors and ethical considerations. It is necessary to use culturally sensitive methods and maintain strict productive solutions so that ASD testing is possible for everyone on an equal basis and algorithmic prejudices are minimized.

To advance ASD diagnosis and get positive outcomes for autistic individuals and their families, coming together from different academic disciplines and translating knowledge traditions into action is fundamental. It is also possible to update old assessment methods by combining the strong sides of customary clinical techniques with artificial intelligence tools that allow clinicians to create more customized treatments based on particular patient's needs.

The study's conclusions have important ramifications for future research on diagnosing ASD as well as clinical practice. This review illustrates how AI tools have the potential to improve the speed and accuracy of diagnosing ASD by contrasting conventional diagnostic techniques with AI-based methodologies. In early detection, where traditional approaches may be time-consuming or have limited sensitivity, using AI techniques like eye tracking, facial recognition, or EEG-based analysis could help clinicians make more accurate diagnoses. The study also indicates that hybrid approaches, which combine AI with conventional diagnostic instruments like ADOS and DSM-5, may provide a more balanced strategy by fusing the advantages of both approaches to produce a more thorough diagnostic framework In light of these results, we advise medical professionals to take into account implementing AI-enhanced instruments as supplemental assistance in the evaluation of ASD, especially in cases when early diagnosis is crucial. Future studies should also concentrate on improving accessibility and minimizing any lingering biases in AI algorithms to make sure they work for a variety of demographics. To guarantee reliable, broadly applicable outcomes, it is also recommended to continue investigating hybrid diagnostic models and cross-validate AI technologies in various clinical contexts. These initiatives may open the door to more precise and easily available ASD diagnostic tools, which would eventually improve patient outcomes and encourage a wider integration of technology into clinical practice.

Data availability Not applicable.

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