International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

UNVEILING AUTISM EARLY: A HOLISTIC REVIEW OF DETECTION STRATEGIES

[1]Maha M. Hamzeh* ,[2] Salah Al- Obaidi, [3]Ali Y. Al-Sultan,
[1]Department of Computer Science, College of Science for Women, University of Babylon, Babylon, Iraq
scw410.maha.almamoori@student.ubabylon.edu.iq
[2]Department of Computer Science, College of Science for Women, University of Babylon, Babylon, Iraq
[3]Department of Computer Science, College of Science for Women, University of Babylon, Babylon, Iraq
*Corresponding author: Maha M. Hamzeh

Abstract
Autism spectrum disorder (ASD) is a neurodevelopmental disorder caused by environmental and genetic factors. ASD significantly impacts on social communication, interaction, and behavior. Therefore, early and accurate diagnosis is essential for timely intervention, which can improve outcomes by enabling tailored therapeutic strategies to deal with such disease. Traditional diagnostic approaches rely on behavioral assessments, which can be subjective, time-consuming, and resource-intensive. To address these limitations, researchers have explored automated diagnostic methods using artificial intelligence techniques, particularly machine learning and deep learning. This review presents a comprehensive analysis of ASD detection strategies that utilize various data modalities, including facial analysis, retinal imaging, electroencephalography (EEG), and eye-tracking, that are captured from ASD patients. Each modality offers unique insights into ASD characteristics, with AI-based models demonstrating promising results in distinguishing autistic from non-autistic individuals Given the improvement in diagnostic methods and algorithms for ASD, we examined research articles from the last decade (2015–2025) that highlight recent contributions in identifying ASD in children. In addition, this review outlines the key features of each approach, summarizes their results, and discusses the challenges they present.
Keywords: Autism Spectrum Disorder (ASD), Machine Learning, Deep Learning, Electroencephalography (EEG), Facial analysis, Retinal Imaging, Eye tracking,Early Diagnosis.

1. Introduction. Autism spectrum disorder (ASD) is a neurodevelopmental disorder caused by environmental and genetic factors [1]. ASD has become a widespread disease around world in recent years [2], and its rate has begun to increase, particularly in developed countries [3], [4]. The difficulties in communicating and interacting with society are the main symptoms of patients with autism [5], [6]. There is generally limited knowledge of the biological factors involved in the development of ASD. This lack of understanding leads to diagnosis ASD through clinical observation of an individual's behavior rather than through the use of established biological markers. This challenge has prompt experts to focus on identifying single measurements that can identify the autistic patient. However, due to the diverse nature of ASD,

Received: August 12 2025

these univariate methods are improbable to yield reliable diagnostic outcomes [7]. Therefore, multivariate analysis is necessary to reveal significant biological relationships for accurate ASD diagnosis. Autism can be identified at various stages of ages in individuals. In children, for example, autism typically detected in early stages based on the severity of symptoms [8], [4]. Early diagnosis of autism is considered crucial to enable on time intervention and improve skills [9]. In this context, the conventional methods of diagnosis ASD in toddlers are conducted through a series of screening, inquiries and evaluations of development and abilities of those youngsters using human expertise, e.g. psychologists and professionals [10]. For example, eye contact during social interactions is monitored because its pattern is often regarded as an indicator of autism [11]. These subjective methods require extensive examinations and assessments of diagnosis which are long term and time-consuming approaches [1]. These requirements make the diagnosis extremely challenging. Therefore, the development of an automated system for the diagnosis of autism is essential, particularly to facilitate screening and identifying this disease in the early stage of childhood. This automated early detection can significantly lead to decrease the symptoms and enhance the autistic person's quality of life [1]. Artificial intelligence-based approaches, such as machine learning and deep learning, make significant contributions to the diagnosis of ASD. These techniques are generally used to perform a binary autism classification using different autistic-based data modalities. Machine learning techniques, including Naive Bayes (NB), Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF), are extensively utilized in identifying youngsters with and without autism by analysing significant features extracted from collected data [12 - 15]. However, determining the However, determining the adequate sample sizes and selecting the most effective features are regarded as significant challenges for better diagnosis [16 - 17]. In the recent year, deep learning also contributes to ASD classification [18 - 23]. These AI-based autism detection approaches present several advantages, such as accuracy of diagnosis, privacy protection, efficiency, and cost. In addition, the automated techniques are considered safer for children compared to systems that require physical contact.

There are various automated models and approaches have been proposed to recognize ASD at an early-stage children. These methods can be categorized based on the source from which the ASD data are collected, including facial analysis [24 - 26], retina structure and disorder [27 - 31], electroencephalogram (EEG) [32 - 35], eye tracking [36 - 38], speech signals, and neuroimaging. This paper provides a detailed discussion of these various diagnostic approaches, outlining the benefits and limitations of each method. The main contributions of this review are:

- Introducing a thorough evaluation of machine learning and deep learning techniques based ASD. Several crucial data modalities methods for ASD diagnosis are demonstrated.

- We performed a literature review on the use of machine learning and deep learning to categorize ASD-based data for deciding the situation of the patient.

Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

- contrasting the current research on ASD from the viewpoints of non-invasiveness, privacy, and accuracy.

- Reviewing the widely used autistic datasets.

This paper is structured as follows. Firstly, explains the automated diagnosis methods to identify autistic disorders. Section 2 shows and discusses the most common datasets used for automated ASD diagnosis. The challenges and future research directions are presented in Section 3 followed by the conclusions in Section four.

2. automated autism diagnosis methods. The main authorities on the special needs of children with ASD are their parents. Diagnostic evaluations seek to inform children and caregivers about the disorder and connect them to the proper resources in addition to elucidating the diagnosis[39 - 40]. Understanding the diagnostic process is essential to maximizing therapy for kids with ASD and their families. Therefore, modern diagnostic methods need to consider the viewpoints and expertise of parents. As of right now, parents' experiences of parenting a kid with ASD in general have received more attention in diagnosis and evaluation than their responses to the child's diagnosis [41]. These are a few methods for identifying autism spectrum disorder. Here are a few techniques for diagnosing ASD.

2.1. face-based ASD. In the last few years, applications involving facial analysis has shown great promise in identifying early signs of autism. In this context, three categories have been found on face-based ASD: landmarks, features, and expression. In landmark-based detection, the scientists found a relation between the face pattern and the brain [42].

Alkahtani et al. [42] concentrated on facial landmark examination for early detection of autism in children. The method analyses the characteristics of the face parts, including eyes and nose, and their patterns, to diagnosis the autistic child from the normal ones. The transfer learning achieved the best accuracy rate at 92%. However, the performance accuracy of the proposed, cheeks system needs to be improved to make this method is reliable and efficient in health care system. Similarly, Madake [43] proposed the calculating of Euclidean distance between a specific face landmark to recognize between ASD and TD children. These distances are used as features to trained several ML based classifiers and the algorithm found that the maximum accuracy is achieved using XGBoost classifier by obtaining 83% of accuracy. Thamilselvan et al. [44] exploited the transfer learning models to diagnosis ASD in very young patients from the facial landmarks. These models gain 90% accuracy rate with EfficientNetB0. In the second category, the features that have been extracted from the facial images have been also explored in ASD recognition. Rahman and Subashini [45] exploited a pre-trained MobileNet to extract a discriminating features from face photos and then these features are forwarded to deep neural network to identify the autistic children from healthy controls. This method achieved an accuracy up to 88% based on the child face photo dataset of 2,936 found in the public domain. Li et al.[46] suggest diagnosis of ASD in children using four of facial attributes that are extracted from a video sequence. These attributes are facial expressions, AUs, arousal, and valence, which are driven using a deep learning technique. These features are concatenated and then fed into a binary classifier to identify the autistic children from TD children. This recognition algorithm yielded an improvement rate of 7%. This method enabled

Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

early intervention and outperformed the conventional diagnosing practices. Reddy and Andrew [47] proposed a deep feature extraction and binary classification model using facial images to recognize diagnose ASD in children. To obtain the deep features, three pre-trained deep learning models, e.g. VGG16, VGG19 and, EfficientnetB0, are employed based on their impressive performance. The extracted features are then fed into a binary classifier. These deep learning models achieved accuracies of 84.66%, 80.05%, and 87.9%, respectively. Ibadi and Lakizadeh [48] suggest a most recent work on using the facial features that are extracted from face images for early ASD detection. The models explore the use of artificial intelligence, specifically Vision Transformer (ViT) models enhanced with Squeeze-and-Excitation (SE) blocks, to improve ASD diagnosis. By analyzing static facial features, the study aims to establish a scalable biomarker for ASD detection. The results suggest that leveraging AI-driven facial analysis could significantly enhance early ASD diagnosis, potentially improving intervention strategies and patient outcomes.

Facial expressions and emotional traits are also regarded biomarkers for autism. These attributes are extensively explored in ASD classification. Golan et al. [49] aimed to explore the emotional attributes to recognize children with ASD. The study revealed that the children with ASD were much worse emotional reaction ability to surprise and anger. In addition, they found that there is a lowest score in face-to-face matching compared to voice-face and word-face. Khor et al. [50] performed image-based and video-based classification of stimming behaviors using both the extracted behavioral and emotional features. This done by predicting the basic emotion and continuous emotion prediction using convolutional neural network and deep regression model, respectively. Farhah [51] proposed a deep learning model to diagnose the autistic children using facial expression images. Although the accuracy was 95%, the efficiency requires extensive experiments to improve the accuracy of recognition. More recently, Muthukkumar [52] suggested a transfer learning methodology to recognize autistic children from facial images. This method combined two pre-trained models: densely connected networks and residual networks to detect ASD children from their facial images. Hosney et al. [53] presented a novel deep learning based on attention mechanism model to identify the autism in children in real-time mode. This model has the ability to define six facial emotions, including surprise, delight, sadness, fear, joy, and natural that can be exploited in diagnosing the autistic children. The obtained accuracy was 97.2%, presenting a potential diagnosing model for real-world applications.

Although research offers innovative solutions to improve the classification of facial expressions in children, there are some issues and challenges that may not be able to be fully solved, including:

- Lack of continuous data: Although some research uses transfer learning from adult data, the lack of documented data for facial expressions in children remains a challenge. The available data may not be sufficient to cover all expressions or different conditions.
- Developmental changes: Children undergo significant changes in their facial features and expressions as they age. Models may not be able to adapt to these changes effectively, which may affect classification accuracy as children age

International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

• Some researchers have adopted the video recording method, so the video recording quality from mobile applications may be inconsistent, which affects the accuracy of facial feature analysis. Any blurring or blurring in the image can lead to inaccurate results.

TABLE 1. Summarizing the main characteristics of face based existing methods

Source	Techniques	Dataset	Metrics
[42]	CNN, SVM	Fase based technique / land mark	Accuracy 92%
[43]	XGBoost classifier	Fase based technique / land mark	Accuracy 83%
[44]	CNN	Fase based technique / land mark	Accuracy 90%
[45]	CNN/ DNN	Fase based technique / land mark	AUC of 96.63%, a sensitivity of 88.46%, and an NPV of 88%.
[46]	CNN	Fase based technique / land mark	F1 score of 76%.
[47]	CNN models, VGG16, VGG19 and, Efficientne	Fase based technique / land mark	Accuracies of 84.66%, 80.05%, and 87.9%, respectively.
[48]	Vit-B	Fase based technique / land mark	Accuracy 97.77%
[49]	Cross-Modal FER Matching	Fase based technique / land mark	This model explained 47.9% of the variance in adaptive communication
[50]	KNN	Fase based technique / land mark	Accuracy 98%
[51]	DL/ VGG16	Fase based technique / land mark	Accuracy 95%
[52]	CNN/DenseResNet (DRN)	Fase based technique / land mark	Accuracy 97.07%

[53]	DCNN	Fase based technique / land mark	Accuracy 97.2%

2.2. Retina based ASD. One challenge in the detection of ASD is identifying a biological signature associated with it. It has been determined that the electroretinogram (ERG) waveform may serve as a potential indicator for classifying neurological disorders such as ASD. An indirect "window" into the central nervous system is provided by the ERG waveform, which is generated from the electrical activity of photoreceptors and retinal neurons in response to a brief flash of light [54].

To our knowledge, there are two classes that have been found on retina-based ASD: ERG and retina structure. In the first category, Manjur et al.[55] proposed a method to analyze the ERG in time -frequency domain to collect a statistical features that have a discriminating ability to recognize between ASD and control individuals. This method achieved a classification accuracy of 86%. Posada-Quintero et al. [54] investigated a method to analyze ERGs using variable frequency complex demodulation (VFCDM) in order to diagnose ASD. ERG waveforms are analyzed with DWT and VFCDM. Then, a set of time-domain and frequency-domain based features is extracted and used to train a ML model. This combination between frequency-based features and ML outperformed conventional methods with an AUC of 0.92, sensitivity of 0.85, and specificity of 77%. KULYABIN et al.[56] explored the potential of ERG waveforms as biomarkers for early diagnosis of ASD. They aim to improve classification accuracy using advanced machine learning techniques, specifically a gated multilayer perceptron (gMLP) model. They showed that the gMLP had a superior accuracy of classification with 89.7%. VIT transform was once utilized by KULYABIN et al. in [57] for ERG-based analyzing to improve the recognition of patients with autism. They introduced a Conditional Generative Adversarial Network (CGAN) framework to create synthetic ERG waveforms that mimic natural signals, enhancing dataset size and classification model performance. The findings demonstrated that incorporating synthetic ERG signals significantly improves the accuracy of classification models, offering a promising approach for early detection and diagnosis of ASD. Manjur et al.[58] explored the time-frequency analysis to capture the dynamic changes in the ERG-based signal. The extracted time-frequency features are used to train a set of machine learning models to recognize between ASD, Attention Deficit Hyperactivity Disorder (ADHD), and control groups, achieving an overall accuracy of 70%.

In the second category, the structure of retina has been explored to diagnosis children with autism.Lai et al [29] investigated a combination of transfer learning based features and advanced machine learning based features to recognize autistic and control children using retinal photographs. These features are fused and used to train SVM algorithm to achieve 95.7% sensitivity and 91.3% specificity. Kim et al. [59] used deep ensembles to prove that the retinal photographs can be serve as an objective screening tool for ASD. The fundus circle is firstly cropped and resized to eliminate the noninformative area. Then, convolutional neural networks

International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

with the ResNeXt-50 network are combined to construct the deep ensembles, achieving 100% of recognition accuracy. In the field of retina, there are some problems that researchers have not been able to solve.

• Data analysis: Although techniques such as discrete wave transform (DWT) have been used to analyze the electroencephalogram (ERG) waves, there is a need for more in-depth analysis to understand the neural pathways and neurotransmitters associated with the wave components.

• Overlap with Other Conditions: Symptoms may resemble ADHD, necessitating further evaluation to ensure accurate classification.

• Data processing challenges: One of the original goals was to input raw ERG data from a text file into the database, but due to the length of the file, this process was very difficult. It takes more time and effort to solve this problem.

• Signal analysis: Analysis of electrical signals such as ERG requires advanced techniques and there may be difficulties in interpreting the results correctly, especially when dealing with complex or noisy data.

Interaction with environmental factors: The influence of environmental factors such as age, gender, and iris color on electrical signals can be complex, making it difficult to isolate effects related to autism alone.

TABLE2. Summarizing the main characteristics of retina based existing methods

Source	Techniques	Dataset	Metrics
[55]	CNN	Retina based technique / ERG	Accurate 86%.
[54]	ML/ VFCDM	Retina based technique / ERG	AUC of 0.92, sensitivity of 0.85, and specificity of 77%.
[56]	ML/ gMLP		Accuracy 89.7%.
[57]	Conditional GAN (CGAN) framework		F1 0.759 AUC 0.836
[58]	ML		Accuracy 86%
[29]	CNN/ ResNet-50	Retina based technique / Structure	sensitivity 82% specificity 91%

International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[59]	CNN/ ResNet-50	Retina based technique / Structure	Accuracy 100%

2.3. EEG based ASD. EEG data has been increasingly used in recent years to diagnose several neurological illnesses, such as epilepsy [60][61], Alzheimer's disease [62][63], and autism [64][65]. Autism detection through the exploration of EEG data helps in identifying the neurological characteristics associated with autism [66]. The specificity of this approach lies in comparison of electrical patterns and differences in homoeostasis in neural networks which is useful for early detection in children to provide the right support that patients with autism require [67].

Therefore, several methods for exploring EEG signals have been proposed for early detection of autism. Grossi et al. [32] suggested a non-invasive diagnostic tool for early autism detection by exploring the potential of using EEG data processed by advanced computational algorithms for autism diagnosis. The method employs the Multi-Scale Ranked Organizing Map (MS-ROM) coupled with the Implicit Function as Squashing Time (I-FAST) algorithm, a machine learning-based method, to analyze EEG patterns in children with ASD. The research involved 15 ASD children and 10 typically developing controls, using EEG recordings to extract features for classification. Results demonstrated high predictive accuracy, with machine learning models achieving 100% accuracy in distinguishing ASD cases using a training-testing protocol and 84%-92.8% using a leave-one-out validation method. Kang et. al [33] tried to find a set of biomarkers of ASD found in EEG recordings of children. They extract bicoherence, entropy, coherence, and power spectrum-based features from EEG data, and then applied minimum redundancy maximum correlation (mRMR) algorithm for feature selection. They achieved a classification accuracy of 91.38%. Harun et al. [68] presented a new EEG recordings based fro autistic children detection. According to this model, the EEG signals undergo through signal processing preprocessing stages to remove noise and non-required signals from the recorded EEG data. Then, The Power Spectral Density mean values are extracted from filtered EEG to be used as input the two classifiers, SVM and ANN, achieving an accuracy between 83% and 86%. Kang et al.[69] combined features extracted from two data modalities; e.g. EEG and eye-tracking data to identify autistic patients in early stages. They utilized power spectrum analysis for EEG and selected specific facial features for eye-tracking to achieve a classification accuracy of 85.44%. %. Rogala et al.. [70] suggested a model to identify ASD in children by considering two different functional connectivity methods zero and non-zero phase differences and non-zero phase correlations. These two models are used to extract a set of statistical features to be used by machine learning algorithms to classify children with ASD. The achieved accuracy ranged between 83% and 86%. Ari et al. [71] proposed a novel method for detecting ASD using EEG signals by suggesting a different representing for EEG recording instead of spectrum representation. The EEG data of each channel undergoes in Douglas-Peucker algorithm, wavelet transform, and sparse coding to produce a histogram representation. Then, the histograms are concatenated to produce an image representation suitable for deep learning. This approach achieved an impressive accuracy of 98.88%, outperforming the existing work. Kabir et al. [72] suggested applying contrastive machine learning together with feature

International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

engineering to understand of autism spectrum disorders mechanism for accurate autism diagnosing. -. The model focused on analyzing the functional network built in the alpha band rather than other bands because this band shows important changes that can be used for accurate diagnosis of autism. The obtained features are filtered to identify the features that yielded to improve the performance and achieving accuracy around 95%. Xu et al.[73] presented a new hybrid deep learning model for diagnosing ASD in children through the integration of functional connectivity and a CNN–LSTM model. The functional connectivity maps of brain in time-domain are constructed. These maps are augmented using deep convolutional generative adversarial network and fed into a combination of CNN and LSTM to diagnose the autistic cases. This hybrid model achieved an accuracy between 74.55% and 81.08%. Falih et al. [74] diagnosed the ASD using brain hemisphere energy of EEG signals recorded during sleep mode and machine learning. The proposed approach used 19 channels to extract the differences of energy between the hemisphere of brain. Then, a sliding window technique was applied to compute three features: maximum, mean, and minimum energy features. Using these energy-based features with three types of SVM yielded to 91.7% of accuracy. A new deep learning model for identifying the level of autism in patients is presented by Noor et al. [75]. This model integrated per-trained CNN and ML to perform the classification. The features are modelled by the per-trained CNN and the classification is done by ML to get 87.8% of accuracy. However, this model used limited samples from only 30 autistic children. Karan Kakkar [76] suggested a diagnostic model using Chronological Sewing Training Optimization-Deep Residual Network (CSTO-DRN) and a set of statistical features and spectral-based features.

There are some problems in this field:

- Analysis of electroencephalogram (EEG) signals requires advanced techniques, and there may be difficulties in applying these techniques uniformly across all studies.
- Some research has suggested that results may be affected by medications some participants are taking, which could affect the accuracy of the results.

The EEG data processing process requires multiple steps such as noise removal, feature extraction, and normalization, but in some research, it has not been shown how to effectively optimize these processes to ensure classification accuracy.

TABLE3. Summarizing the main characteristics of EEG based existing methods

Source	Techniques	Dataset	Metrics
[32]	ANN	EEG based technique	Achieved accurcy 84% - 92.8%
[33]	SVM-linear	EEG based technique	Accuracy 91.38%
[68]	ANN	EEG based technique	Accuracy 83-86%
[69]	ML	EEG based technique	Accuracy 85.44%

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[70]	ML	EEG based technique	Accuracy 86%
[71]	CNN	EEG based technique	Accuracy 98.88%,.
[72]	ML	EEG based technique	Accuracy 94.95%
[73]	CNN–LSTM model	EEG based technique	Accuracy 81%
[74]	ML/SVM	EEG based technique	Accuracy 91.7%
[75]	CNN	EEG based technique	Accuracy 87.8%
[76]	DL	EEG based technique	Accuracy 86.6%

2.4. Eye tracking based ASD. Eye-gaze analyses is one of the biomarkers and a non-invasive system for detecting the autistic children, allowing for timely intervention [77]. Eye-gaze measurement and visual attention are used to diagnose ASD through eye-tracking technology. Studies have shown that individuals with ASD exhibit distinct gaze patterns, including decreased focus on faces and eye contact. [78]. Carette et al. [79] developed an automatic system for ASD detection based on eye-tracking. Eye movement patterns were analyzed to be considered as a key feature to recognize between autistic and non-autistic cases. using. E The method achieved a classification accuracy of 83% using Long Short-Term Memory (LSTM) neural networks. Yaneva et al. [80] suggested eye gaze data for autism detection by analyzing visual attention patterns during web browsing and searching tasks. -The data is collected from participants with autism and a control group, exploring various factors affecting classification performance. –The findings show that variations in visual attention can be useful for classification ASD with reasonable accuracy reaching up to 75%. Virtual reality (VR) environment is also explored in early detection of ASD by Alcañiz et al. [81]. The eye gaze behavior was examined to extract a set of features that are test by traditional machine learning to recognize between autistic and normal children. The proposed model attained classification accuracy of 86%. The study also showed that with use of the VE, mainly, there were more accurate evaluations on social interaction skills. Ahmed et al.[82] proposed a novel method for diagnosing ASD using an eye-tracking based visual attention. They developed three proposed systems: a feedforward neural network (FFNN), an artificial neural network (ANN), Deep learning, and a hybrid model combining deep learning (GoogleNet and ResNet-18) with SVM based ASD diagnosis. The traditional machine learning technique with feature extraction achieved the highest diagnosis accuracy of 99.8%. Bidwe et al.[83] proposed analysis of autistic traits that focused on attention- directed eye gaze and the use of the transfer learning.They analyzed a few types like VGG 16, ResNet152V2, and ConvNextBase. From the dataset it was observed that the ConvNextBase model has the highest prediction accuracy

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

of 80.71%.Vargas-Cuentas1 et al. [84] investigated an eye-tracking algorithm designed to facilitate the early diagnosis of ASD in children. The proposed algorithm introduces eye attention as a feature for the first time, which can be exploited to identify the autism. In addition, eye position is also considered by the algorithm and concatenating with the autistic features that are extracted from attentiveness to predict the autism in children accurately. This model achieved an accuracy of 80.71%. However, the experimental dataset includes few samples which can be augmented and balanced to improve the accuracy pf prediction. Wei et al. [85] established an early identification ASD system based on ML using both social and non-social cognitive eye-tracking models. This model achieved 76.9% of accuracy using Random Forest and Shapley feature selection.

The difficulties in eye section:

- Some research has developed algorithms that rely solely on pupil position, meaning they may register a child's gaze to the left or right, but they cannot always determine the exact object the child is looking at. This can lead to misinterpretations if the child tilts his or her head off-center.
- Optimize the network structure: There is a need to optimize the structure of the neural network, including the type of nodes used, the size and number of layers.
- Identifying different levels of autism spectrum disorder: Research only provides a general idea of autism status (presence or absence) and does not identify different levels of the disorder. This means that there is a need to develop similar systems that can give early guidance about the severity of the disorder.
- Data accuracy Machine learning and deep learning techniques may struggle to achieve high accuracy in diagnosing ASD due to the quality of the data used for training, such as images or videos.
- Diversity of conditions: Autism spectrum disorder manifests in different ways in individuals, which can make it difficult for models to learn effectively from a limited dataset.
- Complexity in data analysis: Techniques such as deep learning algorithms require significant computational resources, which can be challenging in some environments.

3. Compring diagnostic methods. Each data modality-based method of identifying ASD in children has its pros and cons. EEG and ERG signals-based decisions, for example, encounter uncertainty due to the non-stationary nature of these signals. However, these data modalities ensure privacy without revealing any personal information. Table 5 presents a comparison of various methods used to identify ASD, evaluating them based on various factors and discussing their respective strengths and weaknesses in the context of ASD recognition. In general, diagnostic models depend on machine learning and deep learning algorithms, which facilitate the identification of ASD. While deep learning algorithms take a long time to train due to their large number of parameters, traditional machine learning algorithms can be trained much more quickly. During testing, the scenario is reversed. Testing time for deep learning algorithms is substantially reduced, while a traditional machine learning approach will result in a longer test. However, a number of machine learning algorithms also have short evaluation periods [86]..

TABLE4. Summarizing the main characteristics of eye tracking based existing methods

International Journal of Applied Mathematics
Volume 38 No. 1s , 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Source	Techniques	Dataset	Metrics
[79]	LSTM - neural networks	Eye-tracking based technique	accuracy 83%
[80]	ML	Eye-tracking based technique	accuracy 75%
[81]	ML	Eye-tracking based technique	accuracy 86%
[82]	FFNN	Eye-tracking based technique	accuracy 99%
[83]	ConvNext Base	Eye-tracking based technique	accuracy 80.7%
[84]	an eye-tracking algorithm	Eye-tracking based technique	Accuracy 98.48%
[85]	ML/ Random Forest	Eye-tracking based technique	Accuracy 76.9%

4. COMPARING DIAGNOSTIC METHODS. Each data modality-based method of identifying ASD in children has its pros and cons. EEG and ERG signals-based decisions, for example, encounter uncertainty due to the non-stationary nature of these signals. However, these data modalities ensure privacy without revealing any personal information. Table 5 presents a comparison of various methods used to identify ASD, evaluating them based on various factors and discussing their respective strengths and weaknesses in the context of ASD recognition. In general, diagnostic models depend on machine learning and deep learning algorithms, which facilitate the identification of ASD. While deep learning algorithms take a long time to train due to their large number of parameters, traditional machine learning algorithms can be trained much more quickly. During testing, the scenario is reversed. Testing time for deep learning algorithms is substantially reduced, while a traditional machine learning approach will result in a longer test. However, a number of machine learning algorithms also have short evaluation periods [86].

TABLE5. Comparison between various ASD diagnosing approaches by considering several factors.

Diagnostic Method	Usage	Efficiency	Generalizability	Uncertainty	Cost	Complexity	Privacy Protection
Facial Features	Low	High	High	Medium	Medium	Medium	Low

EEG signals Medium	Medium	Medium to high	Medium	Low	Low	High	High
ERG signals Medium	Low	High	Medium	Low	Low	High	High
Eye Tracking	Medium	Medium	Medium	Medium	Medium	Medium	Medium

5. Conclusion. This review has presented a comprehensive analysis of various diagnosis 5 methods used for the early detection of ASD, emphasizing the potential of automatic techniques to improve accuracy and efficiency. The examined studies have demonstrated that machine learning and deep learning models, applied to different biometric and behavioral data modalities, provide effective solutions for ASD diagnosis. Techniques such as facial analysis, retinal imaging, EEG recordings, and eye-tracking have shown promise, each with unique strengths and challenges.

Despite the notable progress in such approaches, several challenges remain, including dataset limitations, generalizability, and ethical concerns. Future research must address these challenges through providing refine models, optimize deep learning architectures, and integrate multiple data modalities for enhanced accuracy. Collaboration between researchers, medical professionals, and technology developers is essential to translate these findings into practical, clinically viable ASD screening tools.

While traditional diagnostic methods remain vital, AI-driven approaches offer transformative potential for early ASD detection, ultimately improving intervention and quality of life for individuals with ASD and their families.

Acknowledgment. The authors would like to thank the University of Babylon for supporting this work

References

[1] Vakadkar K, Purkayastha D, Krishnan D. Detection of autism spectrum disorder in children using machine learning techniques. SN computer science. 2021 Sep;2:1-9.

[2] Khare SK, March S, Barua PD, Gadre VM, Acharya UR. 1 for automated detection of children with developmental and mental disorders: A systematic review of the last decade. Information Fusion. 2023 Jun 25:101898.

[3] Reddy P. Diagnosis of Autism in Children Using Deep Learning Techniques by Analyzing Facial Features. Engineering Proceedings. 2024 Jan 22;59(1):198.

[4] Shi, Chunlei, and Jun Gao. "A novel deep domain adaptation method based on three-way decisions for identifying autistic patients." Biomedical Signal Processing and Control 100 (2025): 106934.

[5] “F. Mainas, B. Golosio, A. Retico, and P. Oliva, "Title of the Paper," presented at the

[Conference/Workshop Name, if applicable], 2022, [City, Country, if applicable]. [Online]. Available: [Link, if applicable]."

[6] Alkahtani H, Aldhyani TH, Alzahrani MY. Deep learning algorithms to identify autism spectrum disorder in children-based facial landmarks. Applied Sciences. 2023 Apr 12;13(8):4855.

[7] J. C. McPartland, "Considerations in biomarker development for neurodevelopmental disorders," Curr. Opin. Neurol., vol. 29, no. 2, pp. 118–122, Apr. 2016, doi: 10.1097/WCO.0000000000000300.

[8] Akter T, Satu MS, Khan MI, Ali MH, Uddin S, Lio P, Quinn JM, Moni MA. Machine learning-based models for early stage detection of autism spectrum disorders. IEEE Access. 2019 Nov 11;7:166509-27.

[9] Xu L, Geng X, He X, Li J, Yu J. Prediction in autism by deep learning short-time spontaneous hemodynamic fluctuations. Frontiers in neuroscience. 2019 Nov 8;13:1120.

[10] N. I. Vargas-Cuentas, D. Hidalgo, A. Roman-Gonzalez, M. Power, R. H. Gilman, and M. Zimic, "Diagnosis of autism using an eye tracking system," in 2016 IEEE Global Humanitarian Technology Conference (GHTC), Seattle, WA: IEEE, Oct. 2016, pp. 624–627. doi: 10.1109/GHTC.2016.7857343.

[11] Talukdar J, Gogoi DK, Singh TP. A comparative assessment of most widely used machine learning classifiers for analysing and classifying autism spectrum disorder in toddlers and adolescents. Healthcare Analytics. 2023 Nov 1;3:100178 .

[12] N. I. Vargas-Cuentas et al., "Developing an eye-tracking algorithm as a potential tool for early diagnosis of autism spectrum disorder in children," PLOS ONE, vol. 12, no. 11, p. e0188826, Nov. 2017, doi: 10.1371/journal.pone.0188826

[13] Bala M, Ali MH, Satu MS, Hasan KF, Moni MA. Efficient machine learning models for early stage detection of autism spectrum disorder. Algorithms. 2022 May 16;15(5):166.

[14] Shayea GG, Zabil MH, Albahri AS, Joudar SS, Hamid RA, Albahri OS, Alamoodi AH, Zahid IA, Sharaf IM. Fuzzy Evaluation and Benchmarking Framework for Robust Machine Learning Model in Real-Time Autism Triage Applications. International Journal of Computational Intelligence Systems. 2024 Jun 17;17(1):151.

[15] George B, Chandra Blessie E. Effective Classification of Autism Spectrum Disorder Using Adaptive Support Vector Machine. InICCCE 2021: Proceedings of the 4th International Conference on Communications and Cyber Physical Engineering 2022 May 16 (pp. 427-440). Singapore: Springer Nature Singapore.

[16] Tseng YL, Lee CH, Chiu YN, Tsai WC, Wang JS, Wu WC, Chien YL. Characterizing Autism Spectrum Disorder through Fusion of Local Cortical Activation and Global Functional Connectivity using Game-Based Stimuli and a Mobile EEG System. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2024 Aug 20.

[17] Rogala J, Żygierewicz J, Malinowska U, Cygan H, Stawicka E, Kobus A, Vanrumste B. Enhancing autism spectrum disorder classification in children through the integration of traditional statistics and classical machine learning techniques in EEG analysis. Scientific Reports. 2023 Dec 8;13(1):21748.

[18] Rahman MM, Usman OL, Muniyandi RC, Sahran S, Mohamed S, Razak RA. A review

of machine learning methods of feature selection and classification for autism spectrum disorder. Brain sciences. 2020 Dec 7;10(12):949.

[19] Niu K, Guo J, Pan Y, Gao X, Peng X, Li N, Li H. Multichannel deep attention neural networks for the classification of autism spectrum disorder using neuroimaging and personal characteristic data. Complexity. 2020;2020(1):1357853 .

[20] Heinsfeld AS, Franco AR, Craddock RC, Buchweitz A, Meneguzzi F. Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical. 2018 Jan 1;17:16-23.

[21] Ahmed IA, Senan EM, Rassem TH, Ali MA, Shatnawi HS, Alwazer SM, Alshahrani M. Eye tracking-based diagnosis and early detection of autism spectrum disorder using machine learning and deep learning techniques. Electronics. 2022 Feb 10;11(4):530 .

[22] Ke F, Yang R. Classification and biomarker exploration of autism spectrum disorders based on recurrent attention model. IEEE Access. 2020 Nov 17;8:216298-307.

[23] Jain S, Tripathy HK, Mallik S, Qin H, Shaalan Y, Shaalan K. Autism Detection of MRI Brain Images Using Hybrid Deep CNN With DM-Resnet Classifier. IEEE Access. 2023 Oct 18.

[24] M. A. Witherow, M. D. Samad, N. Diawara, and K. M. Iftekharuddin, "Facial landmark feature fusion in transfer learning of child facial expressions," in Applications of Machine Learning 2022, M. E. Zelinski, T. M. Taha, and J. Howe, Eds., San Diego, United States: SPIE, Oct. 2022, p. 34. doi: 10.1117/12.2641898.

[25] H. Alkahtani, T. H. H. Aldhyani, and M. Y. Alzahrani, "Deep Learning Algorithms to Identify Autism Spectrum Disorder in Children-Based Facial Landmarks," Appl. Sci., vol. 13, no. 8, p. 4855, Apr. 2023, doi: 10.3390/app13084855.

[26] S. Poudel et al., "Autism Spectrum Disorder Detection using Facial Landmark Detection and Artificial Neural Network".

[27] Kim JH, Hong J, Choi H, Kang HG, Yoon S, Hwang JY, Park YR, Cheon KA. Development of deep ensembles to screen for autism and symptom severity using retinal photographs. JAMA Network Open. 2023 Dec 1;6(12):e2347692 .

[28] Li M, Wang Y, Gao H, Xia Z, Zeng C, Huang K, Zhu Z, Lu J, Chen Q, Ke X, Zhang W. Exploring autism via the retina: Comparative insights in children with autism spectrum disorder and typical development. Autism Research. 2024 Aug;17(8):1520-33.

[29] M. Lai et al., "A machine learning approach for retinal images analysis as an objective screening method for children with autism spectrum disorder," EClinicalMedicine, vol. 28, p. 100588, Nov. 2020, doi: 10.1016/j.eclinm.2020.100588.

[30] M. Kulyabin, P. A. Constable, A. Zhdanov, I. O. Lee, D. A. Thompson, and A. Maier, "Attention to the Electroretinogram: Gated Multilayer Perceptron for ASD Classification," IEEE Access, vol. 12, pp. 52352–52362, 2024, doi: 10.1109/ACCESS.2024.3386638.

[31] Q. Huang et al., "Retinal GABAergic Alterations in Adults with Autism Spectrum Disorder," J. Neurosci., vol. 44, no. 14, p. e1218232024, Apr. 2024, doi: 10.1523/JNEUROSCI.1218-23.2024.

[32] E. Grossi, C. Olivieri, and M. Buscema, "Diagnosis of autism through EEG processed by

advanced computational algorithms: A pilot study,” Comput. Methods Programs Biomed., vol. 142, pp. 73–79, Apr. 2017, doi: 10.1016/j.cmpb.2017.02.002.

[33] J. Kang, T. Zhou, J. Han, and X. Li, “EEG-based multi-feature fusion assessment for autism,” J. Clin. Neurosci., vol. 56, pp. 101–107, Oct. 2018, doi: 10.1016/j.jocn.2018.06.049.

[34] J. Kang, X. Han, J. Song, Z. Niu, and X. Li, “The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data,” Comput. Biol. Med., vol. 120, p. 103722, May 2020, doi: 10.1016/j.compbiomed.2020.103722.

[35] A.-M. DePape and S. Lindsay, “Parents’ Experiences of Caring for a Child With Autism Spectrum Disorder,” Qual. Health Res., vol. 25, no. 4, pp. 569–583, Apr. 2015, doi: 10.1177/1049732314552455.

[36] R. Carette, F. Cilia, G. Dequen, J. Bosche, J.-L. Guerin, and L. Vandromme, “Automatic Autism Spectrum Disorder Detection Thanks to Eye-Tracking and Neural Network-Based Approach,” in Internet of Things (IoT) Technologies for HealthCare, vol. 225, M. U. Ahmed, S. Begum, and J.-B. Fasquel, Eds., in Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol. 225. , Cham: Springer International Publishing, 2018, pp. 75–81. doi: 10.1007/978-3-319-76213-5_11.

[37] V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, and R. Mitkov, “Detecting Autism Based on Eye-Tracking Data from Web Searching Tasks,” in Proceedings of the 15th International Web for All Conference, Lyon France: ACM, Apr. 2018, pp. 1–10. doi: 10.1145/3192714.3192819.

[38] Z. A. Taha Ahmed and M. E. Jadhav, “A Review of Early Detection of Autism Based on Eye-Tracking and Sensing Technology,” in 2020 International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India: IEEE, Feb. 2020, pp. 160–166. doi: 10.1109/ICICT48043.2020.9112493.

[39] L. Myers, S. M. Karp, M. S. Dietrich, W. S. Looman, and M. Lutenbacher, “Family-Centered Care: How Close Do We Get When Talking to Parents of Children Undergoing Diagnosis for Autism Spectrum Disorders?,” J. Autism Dev. Disord., vol. 51, no. 9, pp. 3073–3084, Sep. 2021, doi: 10.1007/s10803-020-04765-0.

[40] I. Caven, C. Nguyen, J. Wiegelmann, E. Laframboise, and M. Penner, “Understanding how behaviour therapists use autism spectrum disorder diagnostic information for intervention planning,” Front. Psychiatry, vol. 14, p. 1242748, Sep. 2023, doi: 10.3389/fpsyt.2023.1242748.

[41] A.-M. DePape and S. Lindsay, “Parents’ Experiences of Caring for a Child With Autism Spectrum Disorder,” Qual. Health Res., vol. 25, no. 4, pp. 569–583, Apr. 2015, doi: 10.1177/1049732314552455.

[42]H. Alkahtani, T. H. H. Aldhyani, and M. Y. Alzahrani, “Deep Learning Algorithms to Identify Autism Spectrum Disorder in Children-Based Facial Landmarks,” Appl. Sci., vol. 13, no. 8, p. 4855, Apr. 2023, doi: 10.3390/app13084855

[43] Madake, Jyoti, Isha Venikar, Jaai Joshi, and Shripad Bhatlawande. "Autism Spectrum Disorder detection in children by calculating the distances between facial landmarks." In

2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-6. IEEE, 2023.

[44] Thamilselvan, R., T. Kalpana, P. Natesan, S. Surendiran, and Sayeem Showket. "Autism Spectrum Disorder Diagnosis using Deep Learning Techniques." In 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC-ROBINS), pp. 402-407. IEEE, 2024.

[45] K. K. Mujeeb Rahman and M. M. Subashini, "Identification of Autism in Children Using Static Facial Features and Deep Neural Networks," Brain Sci., vol. 12, no. 1, p. 94, Jan. 2022, doi: 10.3390/brainsci12010094

[46] Li, Beibin, Sachin Mehta, Deepali Aneja, Claire Foster, Pamela Ventola, Frederick Shic, and Linda Shapiro. "A facial affect analysis system for autism spectrum disorder." In 2019 IEEE international conference on image processing (ICIP), pp. 4549-4553. IEEE, 2019.

[47] P. Reddy and A. J, "Diagnosis of Autism in Children Using Deep Learning Techniques by Analyzing Facial Features," in RAiSE-2023, MDPI, Jan. 2024, p. 198. doi: 10.3390/engproc2023059198.

[48] Ibadi, Hayder, and Amir Lakizadeh. "ASDvit: Enhancing Autism Spectrum Disorder Classification Using Vision Transformer Models Based on Static Facial Features Images." Intelligence-Based Medicine (2025): 100226.

[49] O. Golan, I. Gordon, K. Fichman, and G. Keinan, "Specific Patterns of Emotion Recognition from Faces in Children with ASD: Results of a Cross-Modal Matching Paradigm," J. Autism Dev. Disord., vol. 48, no. 3, pp. 844–852, Mar. 2018, doi: 10.1007/s10803-017-3389-5.

[50] Khor, Stephen Wen Hwooi, Aznul Qalid Md Sabri, and Alice Othmani. "Autism classification and monitoring from predicted categorical and dimensional emotions of video features." Signal, Image and Video Processing 18, no. 1 (2024): 191-198.

[51] N. Farhah, "Utilizing Deep Learning Models in an Intelligent Facial Expression Classification System for Autism Disorder Diagnosis".

[52] Muthukkumar, R., 2025. Enhancing the identification of autism spectrum disorder in facial expressions using DenseResNet-Based transfer learning approach. Biomedical Signal Processing and Control, 103, p.107433.

[53] Hosney, Reham, Fatma M. Talaat, Eman M. El-Gendy, and Mahmoud M. Saafan. "AutYOLO-ATT: an attention-based YOLOv8 algorithm for early autism diagnosis through facial expression recognition." Neural Computing and Applications 36, no. 27 (2024): 17199-17219.

[54] H. F. Posada-Quintero, "Autism spectrum disorder detection using variable frequency complex demodulation of the electroretinogram," Res. Autism Spectr. Disord., 2023.

[55] Manjur, Sultan Mohammad, Md-Billal Hossain, Paul A. Constable, Dorothy A. Thompson, Fernando Marmolejo-Ramos, Irene O. Lee, David H. Skuse, and Hugo F. Posada-Quintero. "Detecting autism spectrum disorder using spectral analysis of electroretinogram and machine learning: Preliminary results." In 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society

(EMBC), pp. 3435-3438. IEEE, 2022

[56] M. Kulyabin, P. A. Constable, A. Zhdanov, I. O. Lee, D. A. Thompson, and A. Maier, “Attention to the Electroretinogram: Gated Multilayer Perceptron for ASD Classification,” IEEE Access, vol. 12, pp. 52352–52362, 2024, doi: 10.1109/ACCESS.2024.3386638.

[57] M. Kulyabin et al., “Synthetic Electroretinogram Signal Generation Using Conditional Generative Adversarial Network for Enhancing Classification of Autism Spectrum Disorder,” Jul. 11, 2024, arXiv: arXiv:2407.08166. Accessed: Oct. 23, 2024. [Online]. Available: http://arxiv.org/abs/2407.08166

[58] S. M. Manjur et al., “Detecting Autism Spectrum Disorder and Attention Deficit Hyperactivity Disorder Using Multimodal Time-Frequency Analysis with Machine Learning Using the Electroretinogram from Two Flash Strengths,” J. Autism Dev. Disord., Feb. 2024, doi: 10.1007/s10803-024-06290-w.

[59] Kim, Jae Han, JaeSeong Hong, Hangnyoung Choi, Hyun Goo Kang, Sangchul Yoon, Jung Yeon Hwang, Yu Rang Park, and Keun-Ah Cheon. "Development of deep ensembles to screen for autism and symptom severity using retinal photographs." JAMA Network Open 6, no. 12 (2023): e2347692-e2347692

[60] R. F. Alwash, A. K. Idrees, and S. Al-Obaidi. "EEG Data reduction with Epileptic Seizure Detection based machine learning in IoMT Networks." In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-7. IEEE, 2023.

[61] Y. Du, Y. Ren, N. Wong, and E. C. H. Ngai. "Hyperdimensional Computing with Multi-Scale Local Binary Patterns for Scalp EEG-Based Epileptic Seizure Detection." IEEE Internet of Things Journal (2024).

[62] R. Sharma, and H. K. Meena. "Graph based novel features for detection of Alzheimer’s disease using EEG signals." Biomedical Signal Processing and Control 103 (2025): 107380.

[63] D. V. Puri, J. P. Gawande, P. H. Kachare, and I. Al-Shourbaji. "Optimal time-frequency localized wavelet filters for identification of Alzheimer’s disease from EEG signals." Cognitive Neurodynamics 19, no. 1 (2025): 12.

[64] N. P. Tigga, S. Garg, N. Goyal, J. Raj, and B. Das. "Brain-region specific autism prediction from electroencephalogram signals using graph convolution neural network." Technology and Health Care Preprint (2024): 1-25.

[65] R. S. Lalawat, and V. Bajaj. "An Automatic Framework For Detecting Autism Spectrum Disorder From EEG Signals Using TFD." IEEE Sensors Journal (2024).

[66] Bosl, W. J., Tager-Flusberg, H., & Nelson, C. A. (2023). "EEG biomarkers for early detection of autism spectrum disorder: A machine learning approach." Journal of Neurodevelopmental Disorders, 15(1), 12.

[67] Dickinson, Abigail, Manjari Daniel, Andrew Marin, Bilwaj Gaonkar, Mirella Dapretto, Nicole M. McDonald, and Shafali Jeste. "Multivariate neural connectivity patterns in early infancy predict later autism symptoms." Biological Psychiatry: Cognitive Neuroscience and Neuroimaging 6, no. 1 (2021): 59-69.

[68] N. F. Harun, N. Hamzah, N. Zaini, M. M. Sani, H. Norhazman, and I. M. Yassin, "EEG Classification Analysis for Diagnosing Autism Spectrum Disorder based on Emotions",2018.

[69] J. Kang, X. Han, J. Song, Z. Niu, and X. Li, "The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data," Comput. Biol. Med., vol. 120, p. 103722, May 2020, doi: 10.1016/j.compbiomed.2020.103722.

[70] Rogala, Jacek, Jarosław Żygierewicz, Urszula Malinowska, Hanna Cygan, Elżbieta Stawicka, Adam Kobus, and Bart Vanrumste. "Enhancing autism spectrum disorder classification in children through the integration of traditional statistics and classical machine learning techniques in EEG analysis." Scientific Reports 13, no. 1 (2023): 21748.

[71] B. Ari, N. Sobahi, Ö. F. Alçin, A. Sengur, and U. R. Acharya, "Accurate detection of autism using Douglas-Peucker algorithm, sparse coding based feature mapping and convolutional neural network techniques with EEG signals," Comput. Biol. Med., vol. 143, p. 105311, Apr. 2022, doi: 10.1016/j.compbiomed.2022.105311

[72] M. S. Kabir, S. Kurkin, G. Portnova, O. Martynova, Z. Wang, and A. Hramov, "Contrastive machine learning reveals in EEG resting-state network salient features specific to autism spectrum disorder," Chaos Solitons Fractals, vol. 185, p. 115123, Aug. 2024, doi: 10.1016/j.chaos.2024.115123.

[73] Y. Xu, Z. Yu, Y. Li, Y. Liu, Y. Li, and Y. Wang, "Autism spectrum disorder diagnosis with EEG signals using time series maps of brain functional connectivity and a combined CNN–LSTM model," Comput. Methods Programs Biomed., vol. 250, p. 108196, Jun. 2024, doi: 10.1016/j.cmpb.2024.108196.

[74] Falih, Bashar S., Mohannad K. Sabir, and Ahmet Aydın. "Impact of Sliding Window Overlap Ratio on EEG-Based ASD Diagnosis Using Brain Hemisphere Energy and Machine Learning." Applied Sciences 14, no. 24 (2024): 11702.

[75] Al-Qazzaz, Noor Kamal, Alaa A. Aldoori, A. Buniya, Sawal Hamid Bin Mohd Ali, and Siti Anom Ahmad. "Transfer Learning and Hybrid Deep Convolutional Neural Networks Models for Autism Spectrum Disorder Classification from EEG Signals." IEEE Access (2024).

[76] Singh, Joy Karan, and Deepti Kakkar. "Chronological sewing training optimization enabled deep learning for autism spectrum disorder using EEG signal." Multimedia Tools and Applications (2024): 1-28.

[77] Thorup, Emilia, Pär Nyström, Gustaf Gredebäck, Sven Bölte, Terje Falck-Ytter, and EASE Team. "Altered gaze following during live interaction in infants at risk for autism: an eye tracking study." Molecular autism 7 (2016): 1-10.

[78] Stuart, N., Whitehouse, A., Palermo, R. et al. Eye Gaze in Autism Spectrum Disorder: A Review of Neural Evidence for the Eye Avoidance Hypothesis. J Autism Dev Disord 53, 1884–1905 (2023). https://doi.org/10.1007/s10803-022-05443-z .

[79] R. Carette, F. Cilia, G. Dequen, J. Bosche, J.-L. Guerin, and L. Vandromme, "Automatic Autism Spectrum Disorder Detection Thanks to Eye-Tracking and Neural Network-Based Approach," in Internet of Things (IoT) Technologies for HealthCare, vol. 225, M. U. Ahmed, S. Begum, and J.-B. Fasquel, Eds., in Lecture Notes of the Institute for

Computer Sciences, Social Informatics and Telecommunications Engineering, vol. 225. , Cham: Springer International Publishing, 2018, pp. 75–81. doi: 10.1007/978-3-319-76213-5_11

[80] V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, and R. Mitkov, "Detecting Autism Based on Eye-Tracking Data from Web Searching Tasks," in Proceedings of the 15th International Web for All Conference, Lyon France: ACM, Apr. 2018, pp. 1–10. doi: 10.1145/3192714.3192819.

[81] M. Alcañiz et al., "Eye gaze as a biomarker in the recognition of autism spectrum disorder using virtual reality and machine learning: A proof of concept for diagnosis," Autism Res., vol. 15, no. 1, pp. 131–145, Jan. 2022, doi: 10.1002/aur.2636.

[82] I. A. Ahmed et al., "Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques," Electronics, vol. 11, no. 4, p. 530, Feb. 2022, doi: 10.3390/electronics11040530

[83] R. Vasant Bidwe, S. Mishra, S. Kamini Bajaj, and K. Kotecha, "Attention-Focused Eye Gaze Analysis to Predict Autistic Traits Using Transfer Learning," Int. J. Comput. Intell. Syst., vol. 17, no. 1, p. 120, May 2024, doi: 10.1007/s44196-024-00491-y.

[84] R. Vasant Bidwe, S. Mishra, S. Kamini Bajaj, and K. Kotecha, "Attention-Focused Eye Gaze Analysis to Predict Autistic Traits Using Transfer Learning," Int. J. Comput. Intell. Syst., vol. 17, no. 1, p. 120, May 2024, doi: 10.1007/s44196-024-00491-y.

[85] Wei, Q., Dong, W., Yu, D., Wang, K., Yang, T., Xiao, Y., Long, D., Xiong, H., Chen, J., Xu, X. and Li, T., 2024. Early identification of autism spectrum disorder based on machine learning with eye-tracking data. Journal of Affective Disorders, 358, pp.326-334.

[86] K. Rezaee, G. Jeon, M. R. Khosravi, H. H. Attar, and A. Sabzevari, "Deep learning-based microarray cancer classification and ensemble gene selection approach," IET Syst. Biol., vol. 16, no. 3–4, pp. 120–131, May 2022, doi: 10.1049/syb2.12044.