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# Eye Tracking Innovations and Artificial Intelligence in Autism Spectrum Disorder Diagnosis: A Systematic Review

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## Abstract

Eye-tracking, initially used in visual perception research, is now emerging as a tool for diagnosing autism spectrum disorder (ASD), with artificial intelligence (AI) enhancing its diagnostic potential. This systematic review, registered with PROSPERO, identified 53 studies using AI-assisted eye-tracking for ASD detection. Machine learning and deep learning models, including convolutional neural networks and long short-term memory networks, often achieved high diagnostic accuracy. Studies explored static and dynamic tasks, emotion recognition, and webcam-based methods, with lightweight models improving performance. However, methodological differences, small sample sizes, and inconsistent validation limit generalizability. AI-enhanced eye-tracking shows promise as a scalable, noninvasive diagnostic tool for ASD, but larger studies and standardized protocols are needed for clinical application.

**Keywords:** Eye-tracking technology; Artificial intelligence; Autism pectrum disorder; Deep learning; Machine learning; Neurodevelopmental disorders

## Introduction

Eye-tracking technology, initially developed in the early 1900s as a tool for investigating visual perception, has evolved into a sophisticated method with broad applications in both research and clinical settings [1]. Today, eye-tracking systems are primarily used to measure gaze patterns in response to visual stimuli, providing a noninvasive means to assess attention, engagement, and cognitive processing through precise tracking of eye movements and locations [2].

There are several methods of eye-tracking, each with distinct advantages. Infrared (IR) eye-tracking uses near-IR light to

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illuminate the eye and track its movements. In contrast, video-based eye-tracking analyzes eye movements through high-resolution cameras and image-processing algorithms. The latter method typically offers higher resolution and is particularly useful for applications requiring detailed gaze analysis, such as consumer research and scientific studies [1,3]. Electrooculography (EOG), though less common today, remains valuable in specific scenarios, such as tracking eye movements during sleep or when direct imaging is not feasible [1,4,5].

Eye-tracking technology uses several key variables to measure and examine eye movements. Fixation duration, for example, assesses how long the gaze remains steady at a specific point of interest. This can show how attention is distributed and how deeply visual information is processed. Saccadic movements—quick changes from one fixation point to another-can show how information is received and integrated across various visual fields. Pupil dilation is another measure frequently used to indicate cognitive exertion or emotional arousal in response to visual inputs. Additional factors such as sampling rate and gaze position accuracy enhance data precision and reliable tracking [3,6].

Recent advances in digital technology have notably improved the precision, accessibility, and range of eye-tracking devices [1,2]. These advancements have made eye-tracking a valuable tool for diagnosing, monitoring, and sometimes even treating various visual and neurological conditions [7]. For instance, eye-tracking studies have revealed insights into the visual exploration methods used by individuals with cerebral visual impairment, showing how changes in gaze patterns and image prominence can hinder object recognition [7]. Additionally, eye-tracking technology has been used to assess the efficacy of interventions for eye-related conditions. Research has demonstrated improvements in functional eyesight following medical treatment for wet age-related macular degeneration, with eye-tracking detecting subtle changes that traditional methods might overlook [8].

In addition to ocular conditions, eye-tracking technology has shown significant promise in diagnosing neurodevelopmental disorders, particularly autism spectrum disorder (ASD). By tracking early signs of ASD, eye-tracking offers a noninvasive way to observe deficits in social communication and theory of mind (TOM) abilities. It can identify measurable markers of these impairments, such as the duration of eye contact, the frequency and direction of gaze shifts, and the ability to respond to social cues such as facial expressions and gaze direction-core elements of TOM [9,10]. These social communication difficulties are key characteristics of ASD, as individuals with the disorder often struggle to interpret and engage in social interactions.

ASD imposes a significant burden on caregivers, with 33.8% reporting a high caregiver burden [11]. Globally, there were 283.25 million cases of ASD in 2019, contributing to 43.07 million disability-adjusted life years (DALYs) [12]. Early and accurate diagnosis is crucial, as timely interventions can improve developmental outcomes [13,14].

Recent advancements in artificial intelligence (AI), particularly deep learning (DL) and machine learning (ML) algorithms, have revolutionized eye-tracking systems. These AI techniques enable automated, high-accuracy analysis of eye movement data, facilitating earlier and more precise detection of ASD and offering more profound insights into the cognitive processes underlying social dysfunction [15].

Despite significant advancements, a critical gap remains in synthesizing and evaluating AI-enhanced eye-tracking for ASD detection. While existing literature provides valuable insights, it lacks a comprehensive assessment of the diagnostic accuracy, accessibility, and clinical integration of these tools. This systematic review seeks to fill this gap by critically evaluating the effectiveness and limitations of AI-assisted eye-tracking for ASD diagnosis while highlighting emerging innovations and future directions for clinical applications.

## Methods

This systematic review adhered to the guidelines set by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Supplementary File 1) and was registered with PROSPERO, the International Prospective Register of Systematic Reviews (ID: CRD42024514365).

### Search strategy

A comprehensive literature search was conducted across five digital databases, including PubMed, Cochrane, Web of Science, Scopus, and Embase, on April 15, 2025. The search strategy used both Medical Subject Headings (MeSH) and non-MeSH terms and was based on the study's Population, Intervention, Comparison, and Outcomes (PICO) framework. The complete search strategy is provided in Supplementary File 2. All search results were imported into EndNote 20 (Clarivate, Philadelphia, PA, USA) for reference management, and duplicates were eliminated. Publications in English, irrespective of their study design or publication date, were considered for assessment. The reference lists of the included studies were screened to identify additional eligible studies not captured by the primary search.

### Inclusion and exclusion criteria

Eligible articles were required to follow the PICO framework and be categorized as original research, systematic reviews, or meta-analyses.

The PICO framework was defined as follows:

1. Population (P): patients with ASD (e.g., autistic disorder, Asperger's, etc.), including all age groups (children, adolescents, and adults),

2. Intervention (I): Eye-tracking technologies integrated with AI models used to assist in the diagnosis of ASD,

3. Comparison (C): none,

4. Outcome (O): diagnostic accuracy, sensitivity, specificity, and any additional insights AI-enhanced eye-tracking provides.

Studies were excluded if they addressed unrelated topics, were non-English, appeared as abstracts, editorials, or letters, had inaccessible full texts, or were rated as poor quality based

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on the National Heart, Lung, and Blood Institute (NHLBI) quality assessment tool.

### Study selection

1. Screening of Titles and Abstracts: Two independent reviewers (FD and MM) initially assessed the relevance of all retrieved articles by screening their titles and abstracts. Studies that clearly did not meet the inclusion criteria were excluded at this stage.

2. Full-Text Review: The reviewers then reviewed the full text of the potentially eligible studies. Disagreements regarding study inclusion were resolved through discussion, and a third reviewer (SN) was consulted if necessary.

3. Quality Assessment: The quality of the included studies was evaluated using the NHLBI quality assessment tool for observational cohort and cross-sectional studies, as well as for systematic reviews (Supplementary File 3). The assessment focused on three key aspects: (A) the validity of the study results, (B) the results themselves, and (C) the applicability of the findings to local settings. Studies were rated as "good," "fair," or "poor," and only those rated as "good" or "fair" were included in the final review.

### Data extraction

Data extraction was conducted independently by two reviewers using a standardized form aligned with the PICO framework. The extracted data encompassed several key study characteristics, including the study title, authors and year, country of origin, and the AI models/algorithms used. Participant demographics such as age and sex were also recorded. Furthermore, details about the study design and methods were documented, focusing on the AI models implemented in each study.

Outcome measures, such as the sensitivity and accuracy of AI models in diagnosing ASD, were systematically gathered, along with sample sizes for each study. In cases where discrepancies arose during data extraction, the reviewers resolved them through consensus discussions or, if necessary, by consulting a third-party reviewer.

The extracted data were subsequently synthesized qualitatively to identify patterns, trends, and gaps within the existing literature.

### Data synthesis

Data synthesis involved analyzing the key findings from the included studies on eye-tracking technology and its application in ASD diagnosis. The effectiveness of AI models, such as DL and ML, in enhancing diagnostic accuracy was also examined.

## Results

### Overview

Following PRISMA guidelines, 500 records were initially identified. After removing 199 duplicates, 301 titles and abstracts were screened, yielding 65 articles for full-text review. Finally, 53 studies that applied AI to eye-tracking data for ASD diagnosis were included (Figure 1).

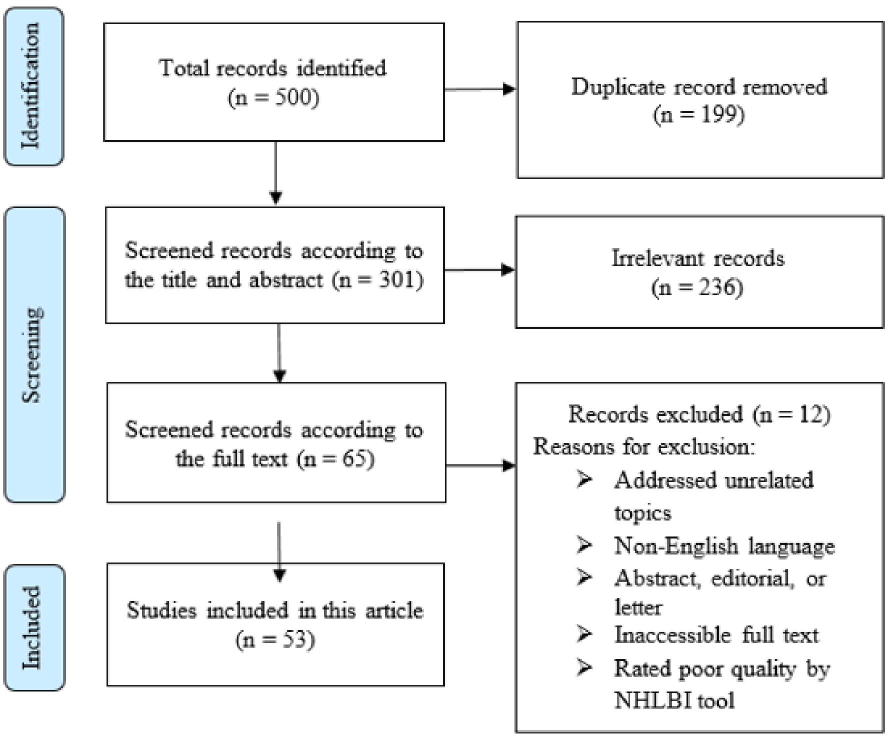


**Figure 1:** PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow chart.

**Table 1:** Summary of the included studies evaluating eye-tracking and AI for ASD diagnosis. Only the one with the best performance is reported when multiple models or algorithms were used. Abbreviations: AE: Autoencoder; ADHD: Attention Deficit Hyperactivity Disorder; ADI-R: Autism Diagnostic Interview-Revised; ADOS: Autism Diagnostic Observation Schedule; ANN: Artificial Neural Network; ASD: Autism Spectrum Disorder; AUC: Area Under the Curve; BiLSTM: Bidirectional Long Short-Term Memory; CBO: Chaotic Butterfly Optimization; CNN: Convolutional Neural Network; COVID-19: Coronavirus Disease 2019; DD: Developmental Delay; DNN: Deep Neural Network; DT: Decision Tree; ETASD-CBODL: Eye-Tracking-based Autism Spectrum Disorder diagnosis using Chaotic Butterfly Optimization with Deep Learning; FFNN: Feedforward Neural Network; GBAC: Gaze-Based Autism Classifier; GRU: Gated Recurrent Unit; INN: Involutional Neural Network; KELM: Kernel Extreme Learning Machine; KNN: K-Nearest Neighbors; LR: Logistic Regression; LSTM: Long Short-Term Memory; ML: Machine Learning; MLP: Multilayer Perceptron; NA: Not Available; NN: Neural Network; NR: Not Reported; NSN: Neuro Spectrum Net with Kalman Filtering; PART: Partial Decision Tree; PPV: Positive Predictive Value; RBF: Radial Basis Function; RED / RED-M: Eye-tracker models by SMI (e.g., RED250, RED-M); RF: Random Forest; RNN: Recurrent Neural Network; SD: Standard Deviation; SMI: SensoMotoric Instruments; STA: Scanpath Trend Analysis; SVM: Support Vector Machine; T-CNN-ASD: Tuned Convolutional Neural Network for ASD; TD: Typically Developing; TLD: Tracking-Learning-Detection; UASN: Uncertainty-inspired ASD Screening Network; UK: United Kingdom; USA: United States of America; VAM: Visual Attention Model; VGG: Visual Geometry Group; VR: Virtual Reality.

| Author | Study Title | Country | Study Design | Study Quality | Sample Size | | Age (Mean±SD year) | | Sex (M%) | | Eye-Tracking Device | AI Model/ Algorithm | Key Findings | Limitations | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (PPV%) | AUC (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Case | Control | Case | Control | Case | Control | | | | | | | | | |
| Liu et al., 2016[16] | Identifying Children with Autism Spectrum Disorder Based on Their Face Processing Abnormality: A Machine Learning Framework | China | Case-control | Good | 29 | 29 TD matched by age, 29 TD matched by IQ | 7.90±1.45 | TD-age: 7.86±1.38, TD-ability: 5.74±1.01 | 86.20 | 86.20 | Tobii T60 (60 Hz) | SVM with RBF kernel; K-means used for feature quantization | Eye-tracking with SVM reached 88.51% accuracy, distinguishing ASD from TD. | Sample bias, age/cultural differences, small size, no long-term validation, limited stimuli, lacking advanced models and combined measures | 88.51 | 93.10 | 86.21 | NR | 89.63 |
| Ozturk et al., 2018[17] | Statistical Analysis and Multimodal Classification on Noisy Eye Tracker and Application Log Data of Children with Autism and ADHD | Turkey | Case-control | Good | 12 | 10 | 10 ± 0.82 (F) 11 ± 1.89 (M) | 9.50 ± 1.12 (F) 9.25 ± 1.56 (M) | 75 | 60 | SMI Eye Tracking Glasses (30 Hz) | SVM, LR, RF | RF classifier with Tomek-link removal achieved 86.36% accuracy, distinguishing ASD from TD. | Small sample size, mobile eye trackers fit poorly; some ASD excluded. IQ, reading, and vision criteria also limited inclusion | 86.36 (RF) | 100 (RF) | 70.00 (RF) | NR | NR |

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| Wan et al., 2019[18] | Applying Eye Tracking to Identify Autism Spectrum Disorder in Children | China | Case-control | Good | 37 | 37 | 4.6 ± 0.7 | 4.8 ± 0.4 | 89.19 | 72.97 | SMI RED250 (250 Hz) | SVM | Fixation times on mouth and body could distinguish ASD from TD with high accuracy. | Small sample size, no ADOS/ ADI-R confirmation, limited age group | 85.1 | 86.5 | 83.8 | NR | NR |
| Li et al., 2020[19] | Classifying ASD Children with LSTM Based on Raw Videos | China | Observational | Good | 136 | 136 | NR | NR | NR | NR | Tracking-Learning-Detection (TLD) algorithm using 360° web camera | LSTM | LSTM achieved high accuracy in differentiating ASD vs TD. | No public dataset, some misclassifications due to eye invisibility or hyperactivity | 92.65 | 91.91 | 93.38 | 93.28 | NR |
| Yaneva set al., 2020[20] | Detecting High-Functioning Autism in Adults Using Eye Tracking and Machine Learning | UK | Observational | Good | Study 1: 15, Study 2: 19 | Study 1: 15, Study 2: 19 | Study 1: 37±9.14, Study 2: 41±14 | Study 1: 33.6±8.6, Study 2: 32.2±9.9 | Study 1: 60, Study 2: 57.89 | Study 1: 53.33, Study 2: 31.57 | Gazepoint GP3 (60Hz) | LR classifier (tested alongside SVM, RF, Naive Bayes) | Eye-tracking + ML identified ASD with moderate-to-high accuracy. | Unsuitable for young children, small sample, unclear task effects, speculative explanations for unexpected results | Study 1: 71.40, Study 2: 75.30 | Study 1: 71.79, Study 2: 72.88 | Study 1: 71.06, Study 2: 78.43 | Study 1: 70.60, Study 2: 80.80 | NR |
| Cilia et al., 2021[21] | Computer-Aided Screening of Autism Spectrum Disorder: Eye-Tracking Study Using Data Visualization and Deep Learning | France | Observational | Good | 29 | 30 | 7.7±2.6 | 8±2.8 | 65.51 | 63.33 | SMI RED250 (250 Hz) | CNN | CNN model using scan-path images achieved high diagnostic accuracy for ASD. | Small sample size, short scenario durations, limited test score access | ≈90 | ≈83 | NR | ≈80 | ≈90 |
| He et al., 2021[22] | Automatic Classification of Children with Autism Spectrum Disorder by Using a Computerized Visual-Orienting Task | China | Observational | Good | 26 HFA, 24 LFA | 24 | HFA: 5.08 ± 0.83, LFA: 4.98 ± 1.09 | 5.24 ± 0.81 | HFA: 88.46, LFA: 79.17 | 75 | Tobii X120 eye tracker (120 Hz) | KNN | KNN classified ASD vs. TD with high accuracy. | Static images, ASD-ADHD differentiation, limited predictive ability, no gender-specific analysis | 93.24 | 96 | 87.5 | NR | 93.8 |

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| Kollias et al., 2021[23] | The Contribution of Machine Learning and Eye-Tracking Technology in Autism Spectrum Disorder Research: A Systematic Review | Greece | Systematic review | Good | 30 studies | Varied | Varied | Varied | Varied | Varied | Varied (commonly SMI, Tobii, Gazefinder, etc.) | Varied (SVM, RF, ANN, CNN, KNN, LSTM, etc.) | Eye-tracking + ML is promising for ASD diagnosis. | Search limited to PubMed, post-2015 studies only, varied methodologies across studies | many >80, some >90 | Reported as high in several studies (e.g., 91.9, 96) | Up to 93.4 | some studies note ~80–90 | many between 84–93 |
| Mazumdar et al., 2021[24] | Early Detection of Children with Autism Spectrum Disorder Based on Visual Exploration of Images | Italy | Observational | Fair | 14 | 14 | NR | NR | NR | NR | Dataset | TreeBagger (RF Ensemble) | AI and eye-tracking can modestly differentiate ASD from TD. | Small sample, age not controlled, moderate accuracy | 59 | 68 | 50 | 57 | NR |
| Oliveira et al., 2021[25] | Computer-Aided Autism Diagnosis Based on Visual Attention Models Using Eye Tracking | Brazil | Observational | Good | 76 | 30 | NR | NR | 64.47 | 66.67 | Tobii Pro TX300 | ANN with genetic algorithm | VAM-based ANN achieved strong performance in ASD vs TD classification. | Age heterogeneity, limited dataset size, same stimuli reused | NR | 69 | 93 | 90 | 82.2 |
| Zhao et al., 2021[26] | Classification of Children with Autism and Typical Development Using Eye-Tracking Data from Face-to-Face Conversations: Machine Learning Model Development and Performance Evaluation | China | Observational | Good | 19 | 20 | 8.3±2.1 | 9.1±2.3 | 89.47 | 85 | Tobii Pro Glasses 2 (50 Hz) | SVM, LDA, RF, DT | Eye-tracking during live conversations can classify ASD with 92.31% accuracy. | Small sample, limited ASD severity range, unbalanced sex ratio | 92.31 | 84.21 | 100 | 100 | 92.0 |

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| Ahmed et al., 2022[27] | Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques | Saudi Arabia | Observational | Good | 29 | 30 | NR | NR | 86.2 | 43.3 | a dataset | FFNN, ANN, GoogleNet, ResNet-18, SVM, hybrid CNN + SVM | FFNN and ANN outperformed CNNs in classifying ASD vs TD. | No device detail, only image data used, lacks age stratification. | 99.8 (FFNN and ANN) | 99.5 (FFNN), 100 (ANN) | 100 (FFNN), 99.7 (ANN) | 99.8 (FFNN), 100 (ANN) | 99.85 (FFNN), 99.77 (ANN) |
| Alcaniz et al., 2022[28] | Eye Gaze as a Biomarker in the Recognition of Autism Spectrum Disorder Using Virtual Reality and Machine Learning: A Proof of Concept for Diagnosis | Spain | Observational | Good | 35 | 20 | 5.26±0.51 | 4.75±0.77 | NR | NR | Tobii Pro Glasses 2 | the best performer was SVM | ML using eye-tracking in VR can differentiate ASD from TD with high accuracy. | Small sample, no external validation, default settings, high training cost, unmatched groups, broad AOIs, poor gaze detail, device intolerance, high cost, limited diagnosis | 86 | 91 | 82 | NR | 91 |
| Gaspar et al., 2022[29] | An Optimized Kernel Extreme Learning Machine for the Classification of the Autism Spectrum Disorder by Using Gaze Tracking Images | Mexico | Cross-sectional | Fair | 219 (images) | 328 (images) | NR | NR | NR | NR | SMI RED screen-based eye-tracker | KELM | GPC-KELM achieved 98.8% accuracy in ASD classification. | Small dataset, reliance on image-level rather than participant-level data | 98.81 | 98.43 | 99.06 | 98.59 | 98.18 |
| Kanhirakadavath & Chandran, 2022[30] | Investigation of Eye-Tracking Scan Path as a Biomarker for Autism Screening Using Machine Learning Algorithms | India | Observational | Good | 30 | 29 | 7.88 | | 64 | | SMI RED eye tracker | CNN+ DNN | The DNN model accurately distinguished ASD from TD by using eye-tracking images. | Limited diverse eye tracking data, data quality impacts accuracy, strict testing needed | NR | 93.28 | 91.38 | 94.46 | 97 |

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| Kong et al., 2022[31] | Different Eye Tracking Patterns in Autism Spectrum Disorder in Toddler and Preschool Children | China | Observational | Good | Toddlers: 55, Preschoolers:37 | Toddlers: 40, Preschoolers:41 | Toddlers: 2.4±0.5, Preschoolers:4.6±0.5 | Toddlers: 2.2±0.6, Preschoolers:4.8±0.3 | Toddlers: 91, Preschoolers:89.2 | Toddlers: 82.5, Preschoolers:80.5 | SMI RED 250 (250 Hz) | SVM | SVM can distinguish ASD from TD with decent accuracy using fixation patterns. | Small sample, no developmental assessment, no ADOS/ ADI-R, no external validation, no developmental age data, early-stage technology, limited clinical readiness | Toddlers: 80 Preschoolers: 71 | Toddlers: 80 Preschoolers: 81 | Toddlers: 82 Preschoolers: 61 | NR | NR |
| Minissi et al., 2022[32] | Assessment of the Autism Spectrum Disorder Based on Machine Learning and Social Visual Attention: A Systematic Review | Spain and Italy | Systematic review | Good | 11 studies | | Varied | Varied | ~60–90 | | Varied | Varied (e.g., SVM, ANN, CNN-RNN, KNN, Naive Bayes, RF, LSTM) | ML with eye-tracking can effectively distinguish ASD from TD. | No registry protocol, limited databases, small samples, potential bias, lacks critical depth, poor reporting compliance | Up to 100 | Up to 93.10 | Up to 93.4 | NR | Up to 94.41 |
| N & R, 2022[33] | Classification of Autism Spectrum Disorder and Typically Developed Children for Eye Gaze Image Dataset Using Convolutional Neural Network | India | Observational | Fair | 14 | 14 | NR | NR | NR | NR | Tobii T120 Eye Tracker (120 Hz) | CNN | CNN model could classify ASD and TD using fixation maps with reasonable accuracy. | Small dataset, lack of demographic data such as sex, and no external validation | 75 | 75 | 75 | 73 | NR |
| Ozdemir et al., 2022[34] | Development of A Visual Attention Based Decision Support System for Autism Spectrum Disorder Screening | Turkey | Observational | Fair | 61 | 72 | 2.90 | 2.74 | 60.7 | 52.8 | SMI-Red250 remote eye tracker (250 Hz) | SVM and RF | ML-based DSS classified ASD vs. TD with up to 87.5% accuracy using eye-tracking features. | Class imbalance not fully modeled, small sample, no gender balance, too many false negatives | 87.5 | 80 | 95 | 94.1 | 88.8 |

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| Ahmed et al., 2023[35] | Applying Eye Tracking with Deep Learning Techniques for Early-Stage Detection of Autism Spectrum Disorders | India and Saudi Arabia | Observational | Fair | 29 | 30 | 7.88 | | 86.2 | 43.3 | RED mobile eye tracker (60 Hz) | LSTM, CNN-LSTM, GRU, BiLSTM | LSTM achieved 98.33% accuracy in distinguishing ASD from TD. | Small sample size, limited generalizability | 98.33 | 97.25 | 98.94 | NR | 98 |
| Al-Shaban et al., 2023[36] | Development and Validation of an Arabic Language Eye-Tracking Paradigm for the Early Screening and Diagnosis of Autism Spectrum Disorders in Qatar | Qatar | Observational | Fair | 144 | 84 (TD), 12 (DD) | 8.5±3.1 | 6.1±3.3 | 82.4 | 43.1 | SMI RED250 remote eye tracker (250 Hz) | SVM and RF | Arabic AI showed good diagnostic accuracy and reliability in distinguishing ASD from controls. | Small sample size and DD group, lack of IQ data, and possible bias from ASD sibling controls | NR | NR | NR | NR | 79.9 (SVM), 76.8 (RF) |
| Alarifi et al., 2023[37] | Machine Learning for Distinguishing Saudi Children with and without Autism via Eyetracking Data | Saudi Arabia | Observational | Fair | 63 | 41 | 8.00±3.89 | 8.21±4.12 | 81 | 56 | Tobii Pro Fusion (120 Hz) | LR, LSTM, SVM, RF | RF model could classify ASD using eye-tracking data with reasonable accuracy. | Unverified accuracy, small sample, limited test data, unclear TD matching, COVID-19-related effects | 76.8±8 | 84±7 | NR | 78±13 | NR |
| Aminoleslami et al., 2023[38] | Classification of Autistic and Normal Children Using Analysis of Eye-Tracking Data from Computer Games | Iran | Observational | Fair | 20 | 20 | 8.40±2.45 | 8.45±1.90 | 100 | 100 | Stationary eye-tracking device | MLP neural network | MLP network using all eye-tracking features achieved decent performance distinguishing ASD and TD children. | Small sample, only male participants, limited generalizability | 73.8 | 68.3 | 79.2 | 76.6 | NR |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Atyabi et al., 2023[39] | Stratification of Children with Autism Spectrum Disorder Through Fusion of Temporal Information in Eye-gaze Scan-Paths | USA | Observational | Fair | 54 | 32 | NR | NR | 81.48 | 46.88 | Eye-gaze scan-paths | CNN, DNN | Spatio-temporal scan-paths with velocity encoding enhance ASD vs TD classification. | Small sample, age not reported as mean±SD, possible overfitting, imbalanced dataset | 80.25 (CNN) | NR | NR | NR | 83.86 (CNN) |
| Elbattah et al., 2023[40] University of the West of England, Bristol, United KingdomEvolucare Technologies, Villers-Bretonneux, FranceCRP-CPO Lab, University of Picardie Jules Verne, Amiens, France</auth-address><titles><title>Applications of machine learning methods to assist the diagnosis of autism spectrum disorder</title><secondary-title>Neural Engineering Techniques for Autism Spectrum Disorder, Volume 2</secondary-title><alt-title>Neural Engineering Techniques for Autism Spectrum Disorder: Volume 2: Diagnosis and Clinical Analysis</alt-title></titles><pages>99-119</pages><volume>2</volume><keywords><keyword>ASD</keyword><keyword>autism spectrum disorder</keyword><keyword>eye-tracking</keyword><keyword>Machine learning</keyword></keywords><dates><year>2023</year></dates><publisher>El | Applications of Machine Learning Methods to Assist the Diagnosis of Autism Spectrum Disorder | France | Observational | Fair | 29 | 30 | 7.88 | | 64 | | SMI RED-M eye tracker (60 Hz) | CNN, Deep Autoencoder, K-Means Clustering | Eye-tracking scanpaths converted to images successfully discriminated ASD from TD using deep learning. | Small sample size, short video stimuli, no ADOS/ADI used | NR | NR | NR | NR | 90 |

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| sevier</publisher><isbn>9780128244210</isbn><label> Scopus</label><urls><related-urls><url>https://www.scopus.com/inward/record.ri?eid=2-s2.0-85156204502&doi=10.1016%2fB978-0-12-824421-0.00013-8&partnerID=40&md5=a1f1a79a16ae9656a058b92dceccc9a4</url></related-urls></urls><electronic-resource-num>10.1016/b978-0-12-824421-0.00013-8</electronic-resource-num><remote-database-name>Scopus</remote-database-name><language>English</language></record></Cite></EndNote> | | | | | | | | | | | | | | | | |
| Fernandez-Lanvin et al., 2023[41] | Towards an Automatic Early Screening System for Autism Spectrum Disorder in Toddlers Based on Eye-Tracking | Spain | Observational | Good | 61 | 61 | 1.18±0.37 | | NR | NR | Tobii Pro Spectrum (up to 1200 Hz) | RF, SVM, Naïve Bayes, AdaBoost, ANN, KNN, J48 (C4.5), PART,LR | RF classified ASD vs. TD toddlers with 94.07% accuracy using gaze data. | Small, single-country sample; high equipment cost; cultural generalizability not assessed | 94.07 (RF) | 94.39 (RF) | 93.76 (RF) | 93.79 (RF) | 98.54 (RF) |
| Franco et al., 2023[42] | Computer-Aided Autism Diagnosis Using Visual Attention Models and Eye-Tracking: Replication and Improvement Proposal | Brazil | Observational | Fair | 33 | 44 | 6.8±3.7 | 6.7±3.0 | 87.9 | 90.9 | Tobii Pro Fusion (250 Hz) | NN, SVM, RF | RF model outperformed NN and SVM in classifying ASD vs. TD using saliency maps from eye-tracking data | Stimulus dependency, small sample, no comorbidity control | 67 (RF) | 67 (RF) | 67 (RF) | 61 (RF) | 74 (RF) |

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| Iwauchi et al., 2023[43] | Eye-Movement Analysis on Facial Expression for Identifying Children and Adults with Neurodevelopmental Disorders | Japan | Observational | Fair | Adults: 15, Children: 15 | Adults: 16, Children: 15 | Adults: 32.1±9.13, Children: 10.9±1.39 | Adults: 29.3±3.72, Children: 10.0±1.55 | Adults: 60, Children: 86.7 | Adults: 50, Children: 46.7 | Tobii Pro Fusion (120 Hz) | CNN, RF | Weighted CNN improved the classification of ASD vs. TD by modeling emotion-specific gaze differences. | Small dataset, no IQ control, poor detection in participants using peripheral vision | Adults: 71.0, Children: 66.7 (Weighted CNN) | Adults: 73.3, Children: 60.0 (Weighted CNN) | Adults: 68.8, Children: 73.3 (Weighted CNN) | NR | NR |
| Meng et al., 2023[44] | Machine learning-based early diagnosis of autism according to eye movements of real and artificial faces scanning | China | Observational | Fair | 117 | 44 | 3.23±1.1 | 3.83±0.99 | 77.8 | 52.3 | Senso-Motoric Instruments RED500 (500 Hz) | RF | Gaze behavior to real vs. cartoon faces can distinguish ASD from TD children. | Undersampling, no age control in model, not ecologically validated | 73 | 75 | NR | 73 | 81 |
| Potluri et al., 2023[45] | Detecting Autism of Examinee in Automated Online Proctoring Using Eye-Tracking | India | Observational | Fair | NR | NR | NR | NR | NR | NR | Appearance-based tracking using Hourglass module | ML, LR | Eye-tracking during web tasks enables autism detection within an online proctoring system. | Accuracy is modest (73), no demographic data, not validated on a large or diverse sample | 73 (standalone module); 78 (using all tasks combined) | NR | NR | NR | NR |
| Thanarajan et al., 2023[46] | Eye-Tracking Based Autism Spectrum Disorder Diagnosis Using Chaotic Butterfly Optimization with Deep Learning Model | India and Saudi Arabia | Observational | Fair | 219 (images) | 328 (images) | NR | NR | NR | NR | Figshare dataset (Eye-tracking scanpaths in ASD dataset | DL+Inception v3 + LSTM optimized with CBO | ETASD-CBODL classified ASD vs TD with very high accuracy. | Small dataset, lacks demographic details, limited generalizability, technical dependency, user acceptance concerns, ethical and interpretability issues | 99.29 | 99.29 | 99.29 | 98.78 | NR |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wei et al., 2023[47] | Machine Learning Based on Eye-Tracking Data to Identify Autism Spectrum Disorder: A Systematic Review and Meta-Analysis | China | Systematic review and meta-analysis | Good | 1396 individuals (24 studies) | | 4–43 | | NR | NR | Varied | ML | ML with eye-tracking achieves high accuracy in identifying ASD, especially in preschoolers. | Possible overlooked studies, small samples, high heterogeneity, no test-set evaluation, few toddler studies limiting early ASD identification | 81 | 84 | 79 | NR | 88 |
| Zhao et al., 2023[48] | Use of Oculomotor Behavior to Classify Children with Autism and Typical Development: A Novel Implementation of the Machine Learning Approach | China | Case-control | Good | 19 | 21 | 8.3±2.09 | 9.07±2.25 | 89.5 | 85.0 | Tobii Pro Glasses 2 (50 Hz) | SVM | Oculomotor patterns during conversation can distinguish ASD from TD. | Limited generalizability due to narrow age range, exclusion of severe cases, gender imbalance, lack of early-age applicability | 87.18 | 89.47 | 85.00 | NR | NR |
| Alsaidi et al., 2024[49] | A Convolutional Deep Neural Network Approach to Predict Autism Spectrum Disorder Based on Eye-Tracking Scan Paths | Jordan | Observational | Fair | 29 | 30 | 7.88 | | 64.41 | | SMI RED-m (250Hz) | T-CNN-ASD | T-CNN-ASD model effectively distinguishes ASD from TD with high accuracy. | Lack of external validation, small sample, limited generalizability | 95.59 | 77.6 | 79.91 | NR | NR |
| Alsharif et al., 2024[50] | Utilizing Deep Learning Models in an Intelligent Eye-Tracking System for Autism Spectrum Disorder Diagnosis | Saudi Arabia | Observational | Fair | 328 (images) | 219 (images) | NR | NR | NR | NR | Public eye-tracking image dataset | MobileNet, VGG19, DenseNet169, Hybrid | MobileNet achieved 100% accuracy in classifying ASD from TD using eye-tracking data. | Lacks demographic data; small test set | 100 | 100 | 100 | 100 | 100 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Amirbay et al., 2024[51] | Development of an Algorithm for Identifying the Autism Spectrum Based on Features Using Deep Learning Methods | Kazakhstan | Observational | Fair | NR | NR | NR | NR | NR | NR | Custom software tracked pupils via webcam | LSTM+CNN<br>LSTM+Autoencoder | LSTM+AE model outperformed LSTM+CNN in diagnosing ASD from gaze patterns. | Limited age range and gender imbalance, exclusion of severe cases, and limited generalizability | 93 (LTSM+AE) | 92 (LTSM+AE) | NR | NR | 98 (LTSM+AE) |
| Benabderrahmane et al., 2024[52] | A Novel Multi-Modal Model to Assist the Diagnosis of Autism Spectrum Disorder Using Eye-Tracking Data | Algeria | Observational | Fair | 29 | 30 | 7.88 | | NR | NR | RED mobile eye tracker (60 Hz) | CNN-GRU-ANN | Temporal features from eye-tracking improve ASD classification accuracy. | Small sample size, limited generalizability | 86.71 | 85.52 | 88.8 | 93.10 | 87.16 |
| Cheekaty & Muneeswari, 2024[53] | Exploring Sparse Gaussian Processes for Bayesian Optimization in Convolutional Neural Networks for Autism Classification | India | Observational | Fair | 219 (images) | 328 (images) | NR | NR | NR | NR | SMI RED eye-tracking device | Bayesian-optimized CNN | CNN with Bayesian optimization achieved high classification performance for ASD using eye-tracking images. | Complex ASD traits, small biased datasets, data imbalance, overfitting, lack of interpretability, high computational demands limiting clinical use | 97.8 | NR | NR | NR | 99.66 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cheekaty & Muneeswari, 2024[54] | Advancing Autism Prediction Through Visual-Based AI Approaches: Integrating Advanced Eye Movement Analysis and Shape Recognition with Kalman Filtering | India | Observational | Fair | 59 | | NR | NR | NR | NR | dataset | NSN, Kalman Filtering | NSN outperforms RNN in classification performance for ASD detection using eye-tracking. | Small heterogeneous sample, unclear participant demographics, no numerical confusion matrix, limited generalizability, lacks standardized eye-tracking protocols | NR | 85.4 | NR | 98.2 | NR |
| Colonnese et al., 2024[55] | Enhancing Autism Detection Through Gaze Analysis Using Eye Tracking Sensors and Data Attribution with Distillation in Deep Neural Networks | Italy | Observational | Fair | 14 | 14 | NR | NR | NR | NR | Tobii T120 Eye Tracker | GBAC (CNN + LSTM + TracIn) | Using self-influence scoring improved model performance and efficiency. | Small dataset, no external validation | 94.35 | 93.1 | NR | 93.2 | NR |
| de Belen et al., 2024[56] | Using Visual Attention Estimation on Videos for Automated Prediction of Autism Spectrum Disorder and Symptom Severity in Preschool Children | Australia | Observational | Fair | 57 | 17 | 4.63±0.80 | 4.61±0.47 | 84.2 | 47.1 | Tobii X2-60 eye tracker (60 Hz) | DNN, SVM | CNN-LSTM-based eye-tracking model achieves 94.59% accuracy in ASD diagnosis and predicts symptom severity with high precision. | Small TD sample, gender imbalance, limited generalizability beyond preschool age | 94.59 | 100 | 76.47 | NR | 96 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jaradat et al., 2024[57] | Using Machine Learning to Diagnose Autism Based on Eye Tracking Technology | Jordan | Observational | Fair | ETSDS dataset: 215, Eye Gaze Fixation Map dataset: 300 | ETSDS dataset: 319, Eye Gaze Fixation Map dataset: 300 | NR | NR | 80 | | Public datasets | MobileNet + Stacking Ensemble Learning (SVM + KNN) | Hybrid model achieved up to 98.1% accuracy in ASD diagnosis from eye-tracking data. | Used public datasets with no real-time collection, lacks detailed demographic reporting | Eye Gaze Fixes Map: 96.1 ETSDS: 98.0 | Eye Gaze Fixes Map: 96.5 ETSDS: 98.2 | Eye Gaze Fixes Map: 95.8 ETSDS: 97.8 | Eye Gaze Fixes Map: 96.9 ETSDS: 98.4 | NR |
| Kanchana & Khilar, 2024[58] | A Survey on Genetic Disease – Autism Spectrum Disorder Prediction and Classification in Machine Learning | India | Systematic review | Fair | NA | NA | NA | NA | NA | NA | Varied | Varied | ANN, CNN, and SVM models show high accuracy for ASD prediction | No registered protocol, poor reporting compliance, lacks search strategy, terms, criteria, databases, more narrative than a systematic review, limited analysis, potential bias | Up to 100 | Up to 100 | Up to 91 | Up to 98.3 | Up to 96 |
| Mumenin et al., 2024[59] | ASDNet: A Robust Involution-Based Architecture for Diagnosis of Autism Spectrum Disorder Utilising Eye-Tracking Technology | Bangladesh, Saudi Arabia | Observational | Fair | Dataset 1: 30, dataset 2: 14 | Dataset 1: 29, dataset 2: 14 | Dataset 2: ~8 | | Dataset 1: 64.4 | | Dataset 1: SMI RED mobile Dataset 2: Tobii T120 | INN | INN outperforms state-of-the-art models in ASD detection from eye-tracking images. | Limited dataset size, no external validation | Dataset 1: 98.12, Dataset 2: 96.83, 97.61 | Dataset 1: 99.03, Dataset 2: 96.13, 98.33 | NR | Dataset 1: 97.89, Dataset 2: 95.43, 95.17 | Dataset 1: 99.72, Dataset 2: 99.10, 95.17 |
| Sa et al., 2024[60] | Enhancing Ensemble Classifiers Utilizing Gaze Tracking Data for Autism Spectrum Disorder Diagnosis | Brazil | Observational | Good | 56 | 30 | 10 | 10 | 67.9 | 66.7 | Tobii Pro TX300 | RF, SVM, KNN, Naive Bayes, and NN | Heterogeneous stacking ensemble achieved superior classification performance. | Small and imbalanced dataset, low specificity, limited generalizability | 90.7 | 95.4 | 68.5 | 94.1 | NR |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wei et al., 2024[61] | Early Identification of Autism Spectrum Disorder Based on Machine Learning with Eye-Tracking Data | China | Observational | Good | 290 | 239 | NR | NR | 79.3 | 51.0 | Tobii 4C (90 Hz) | RF, SVM, LR, ANN XGBoost | Eye-tracking with machine learning can help detect ASD early. | Single-center data, relatively small sample vs features | Dataset 1: 76.9, Dataset 2: 76.5 | Dataset 1: 83.1, Dataset 2: 82.2 | Dataset 1: 69.4, Dataset 2: 69.4 | NR | Dataset 1: 85.0, Dataset 2: 84.9 |
| Zhang et al., 2024[62] | Uncertainty Inspired Early Autism Spectrum Disorder Screening via Contrastive Image-viewing Paradigm | China | Observational | Good | 33 | 26 | 3.89±1.22 | 4.56±0.62 | NR | NR | SMI iView X RED (120 Hz) | UASN | Contrastive eye-tracking with UASN improves early ASD screening. | Small sample size and pre-school-only participants | 93.2 | 97.0 | 88.5 | 97.8 | 97.8 |
| Zhou et al., 2024[63] | Gaze Patterns in Children with Autism Spectrum Disorder to Emotional Faces: Scanpath and Similarity | China | Observational | Good | 54 | 41 | 5.5±2.29 | 8.78±3.43 | 87.04 | 43.90 | Tobii Eye Tracker 4C (90 Hz) | LSTM | Scanpaths reveal atypical gaze dynamics in ASD; LSTM achieves high accuracy. | Small sample size, calibration and noise issues in eye-tracking | 97 | NR | NR | NR | NR |
| Bouchouras & Kotis, 2025[64] | Integrating Artificial Intelligence, Internet of Things, and Sensor-Based Technologies: A Systematic Review of Methodologies in Autism Spectrum Disorder Detection | Greece | Systematic review | Good | 30 studies | | NA | NA | NA | NA | Varied | Varied | AI, IoT, and sensor-based tools can enhance ASD diagnosis with high accuracy and accessibility. | Limited dataset diversity and generalizability, real-world integration and ethical concerns | up to 99.29 | up to 98.4 | up to 91 | up to 89.5 | up to 92 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eraslan et al., 2025[65] | A Systematic Evaluation of Autism Spectrum Disorder Identification with Scanpath Trend Analysis (STA) | Turkey | Observational | Good | Dataset-1: 15, Dataset-2: 19, Dataset-3: 10 | ASD: Dataset-1: 15, Dataset-2: 19, Dataset-3: 10 | Dataset-1 & 2: Adults, Dataset-3: Children | | NR | NR | Dataset-1 & 2: GazePoint GP3 (60 Hz), Dataset-3: Tobii T120 (20 Hz) | STA | STA provides consistent accuracy across pages and tasks. | Requires fixation data and page-specific training | ~60 | ~58-60 | NR | ~56-62 | NR |
| Islam et al., 2025[66] | Involution Fused Convolution for Classifying Eye-Tracking Patterns of Children with Autism Spectrum Disorder | Bangladesh | Observational | Good | 519 | 628 | NR | NR | NR | NR | Public dataset | Involution and Convolution layers | Hybrid model with three involution and three convolution layers outperforms pure models. | No raw eye-tracking hardware data, uses processed fixation/ saliency maps | Up to 96.32 | Up to 97.63 | NR | Up to 97.42 | NR |
| Kesavan et al., 2025[67] | Adaptive Deep Convolution Neural Network for Early Diagnosis of Autism through Combining Personal Characteristic with Eye Tracking Path Imaging | India and Malaysia | Observational | Fair | 219 (images) | 328 (images) | NR | NR | NR | NR | scan path imaging dataset | CNN with Grey Wolf Optimization | Combining personal traits and eye tracking improves ASD detection. | Lack of demographic details and limited dataset variety | 86.45 | 92.38 | 91.09 | NR | 94.51 |
| Rezaee, 2025[68] | Machine Learning in Automated Diagnosis of Autism Spectrum Disorder: A Comprehensive Review | Iran | Systematic review | Fair | 97 studies | | Varied | Varied | Varied | Varied | Varied | ML | ML can accurately diagnose ASD using various inputs (EEG, MRI, speech, etc.). | Data variability, computational complexity, unclear search terms, limited clinical translation, lack of standardization, no protocol registration. | Up to 100 | NR | NR | NR | NR |

A range of ML and DL models were employed, including support vector machines (SVM), convolutional neural networks (CNN), long short-term memory (LSTM) networks, random forests (RF), and hybrid ensemble approaches. Studies varied widely in sample size, demographics, tasks, and settings (Table 1).

## Diagnostic performance of AI models

Across studies, AI models achieved high diagnostic performance Ahmed, et al. [15]. reported 99.8% accuracy using feedforward neural networks (FFNN), and Thanarajan, et al. [46]. reached 99.29% with a CNN-LSTM hybrid. CNNs trained on gaze heatmaps and fixation maps (Cilia, et al. [21]. Colonnese et al. [55], and Alsaidi et al [49]) consistently achieved over 90% accuracy, validated further by Elbattah, et al. [40] and Ozdemir, et al. [34].

Temporal modeling was effective, with LSTM models by Li, et al. [19], Zhou et al. [63], and Bouchouras, et al. [64] exceeding 90% accuracy, the latter improved by attention mechanisms. Ensemble methods such as RF and kernel extreme learning machine (KELM) also demonstrated high accuracies (Fernandez-Lanvin et al. [41] and Gaspar et al. [29]), while hybrid models by Amirbay, et al. [51] and Benabderrahmane, et al. [52] surpassed 90%. Traditional models, such as decision trees [24], showed limited accuracy (~60%).

Advanced sequential models, including bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and CNN-LSTM [35], further demonstrated high classification rates (~96-98%). Lightweight architectures (MobileNet, VGG19) [50] and optimization strategies such as Bayesian-tuned CNNs [53] and Kalman-filter-based models [54] enhanced performance. The involution-based ASDNet [59] achieved up to 98.12% accuracy, and stacking ensemble methods [60] reached an F1 score of 95.5%.

## Sample characteristics and participant profiles

Sample sizes ranged from fewer than 20 participants [20,24] to large datasets [66]. Most studies focused on preschool children [31, 56], though adolescents and adults [20,43] were also included. Cultural diversity was limited; however, studies such as Alarifi, et al. [37] addressed underrepresented populations. Al-Shaban, et al. [36] validated an Arabic-language eye-tracking paradigm in Qatar, improving cross-cultural applicability. Demographic reporting remained incomplete in many studies (e.g., Potluri, et al. [45]and Islam, et al. [66]).

## Eye-tracking tasks and stimulus designs

### Static visual paradigms

Static images were widely used to study social attention differences. He, et al. [22] achieved 93.24% accuracy using K-nearest neighbors (KNN), while Mazumdar [24] reported lower performance (59%) with decision trees. Static paradigms efficiently captured key anomalies, such as reduced eye fixation, but lacked temporal depth.

Wan, et al. [18] demonstrated that a short 10-second video of a speaking female could distinguish ASD from TD children with 85.1% accuracy, suggesting that brief, simple stimuli are highly effective for early ASD screening.

### Dynamic social interaction tasks

Dynamic paradigms provided richer temporal data. Zhao, et al. [26] and Zhou et al. [63] achieved 86–90% accuracy using real-time interactions and video-based tasks with SVM and LSTM models. Kanhirakadavath, et al. [30] and Zhao, et al. [48] further highlighted gaze transitions as strong ASD indicators. Although dynamic tasks increased ecological validity, they also introduced interpretative variability.

### Emotion recognition-based eye tracking

Ozturk, et al. [17] demonstrated that emotion-based gaze features could effectively distinguish ASD-related differences, achieving an accuracy of 86.36%. Building on this, Iwauchi, et al. [43], Cilia, et al. [21], Li et al. [19], and Colonnese, et al. [55] reported consistently higher accuracies exceeding 90%, further establishing emotional gaze processing as a robust diagnostic marker.

### Virtual reality (VR) and serious games approaches

VR environments and serious games enhanced engagement and ecological validity. Alcaniz, et al. [28] achieved 86% accuracy through VR social interaction scenarios, while Aminoleslami, et al. [38] demonstrated robust gaze data collection via gamified tasks. However, scalability remained challenged by technical demands.

### Webcam-based eye tracking

Webcam-based methods emerged as scalable alternatives. Jaradat, et al. [57] and Li, et al. [19] achieved comparable accuracies to hardware-based trackers (>90%). Zhang, et al. [62] introduced uncertainty-inspired paradigms to improve screening efficiency. Despite challenges such as lower precision, webcam-based approaches showed strong potential for broader ASD screening.

# Discussion

## Overview

Integrating AI, including ML and DL, with eye-tracking technologies has revolutionized diagnostic capabilities, particularly for early ASD detection [15, 69]. Eye-tracking paired with AI has demonstrated high diagnostic accuracy and is especially effective at identifying visual attention anomalies and abnormal gaze patterns in ASD [10,70,71]. Children with ASD frequently exhibit reduced fixation on social stimuli, a divergence that AI models efficiently detect, providing a reliable early biomarker.

Various AI architectures, such as SVM, CNN, and LSTM models, have been deployed to classify ASD based on eye-tracking data. These approaches offer cost-effective, reliable, and unbiased neural and ocular function assessments, facilitating individualized interventions [1,72].

## Atypical gaze patterns in ASD

Studies combining fixation metrics and application logs strengthened diagnostic precision during emotion recognition tasks [17,18]. These findings align with a broader pattern observed across almost all included studies, where individuals with ASD consistently exhibited gaze abnormalities, most notably a reduced fixation on faces and eyes [21,44,63,73]. Static paradigms [22, 24] and dynamic video tasks [26] confirmed this pattern. Furthermore, live social interaction studies [26, 30] revealed impaired gaze-following and joint attention.

Emerging paradigms, including virtual reality [28] and serious games [38], further validated that gaze avoidance persists in more ecologically valid environments. Emotion recognition tasks heightened sensitivity for detecting these differences, with ASD individuals showing diminished fixations on key facial regions during emotional expression identification [21,41,43].

Additionally, simplifying visual materials in children's books and employing multiple deictic signals improved visual attention and comprehension in children with ASD, as evidenced by greater fusiform gyrus activation [74,75].

### Diagnostic performance across AI models

AI models demonstrated robust classification capabilities. CNNs trained on gaze heatmaps consistently achieved 85-90% accuracy [21, 40, 49, 55], while SVMs also performed strongly [16,76,77]. Hybrid models, such as CNN-LSTM architectures enhanced by chaotic butterfly optimization, reached accuracies as high as 99.29% [46], and FFNNs achieved 99.8% [15].

Temporal models (LSTM) effectively captured scanpath dynamics [19,63,64], and ensemble methods, such as stacking approaches [29,60], further improved performance. Novel techniques, including graph convolutional networks [78] and scanpath trend analysis [79], diversified methodological approaches. Overall, categorized ML-based eye-tracking accuracies averaged 81%, with subgroup analyses showing the highest performance in preschool children [69].

Lightweight CNNs, such as MobileNet [50] and involutional networks [59], demonstrated that compact architectures can match or surpass traditional models. Bayesian-optimized CNNs [53] and multimodal gaze behavior analyses [80, 81] also contributed to improved understanding and diagnosis of ASD.

### Influence of task design and stimulus type

Task design critically shaped diagnostic success. Static tasks [22,24,76] reliably measured fixations but lacked ecological validity compared to dynamic paradigms [26,63]. Emotion recognition tasks were particularly sensitive [21,41,43], and even brief 10-second video clips enabled effective ASD screening [18]. Studies emphasized that targeted emotional and social stimuli are crucial for maximizing gaze-related diagnostic signals [17].

### Impact of eye-tracking device types

Device precision influenced outcomes. High-end Tobii systems generated robust data [15,55], but cost-effective webcam-based solutions [57] [19] proved viable for ASD detection with proper feature correction. Studies in resource-limited settings [13,37] confirmed that reliable screening is possible without premium hardware. Innovations such as contrastive image viewing with uncertainty modeling [62] further improved diagnostic accuracy despite lower hardware precision.

### Novel paradigms: virtual reality, webcams, serious games

VR created immersive environments eliciting naturalistic gaze behaviors [28], while serious games boosted participant engagement [38]. Webcam-based and online eye-tracking approaches [57,66] increasingly support remote ASD assessment. Combining gaze features with interaction metrics enhanced diagnostic potential [61,64], and incorporating spatiotemporal scanpaths with pupil velocity [39] enabled more individualized stratification.

## Methodological Challenges

Several challenges persist. Considerable heterogeneity in gaze tasks (static, dynamic, VR), device types, and calibration standards complicates comparability. Small, often nonrepresentative sample sizes and inconsistent validation practices increase overfitting risk [45,68]. Region of interest variability in dynamic stimuli [25] and inconsistent feature extraction methods [58] further undermine model robustness. The absence of standardized reporting and data division procedures also hampers reproducibility across studies [15, 69, 82]. Larger, better-designed datasets and transparent model training pipelines are urgently needed to enhance generalizability [32,67].

## Limitations

This systematic review has limitations. The included studies exhibited methodological variability, particularly in eye-tracking paradigms and ML model implementation, which precluded meta-analysis. While care was taken to maintain reference accuracy, heterogeneity in study design and reporting standards limited direct comparison. Potential publication bias and the predominance of research from high-income countries may also affect generalizability.

## Future directions

Future research should prioritize multicenter collaborations to expand sample diversity and improve external validation. Establishing standardized eye-tracking and AI evaluation protocols will enhance reproducibility. Combining gaze data with neuroimaging modalities such as magnetic resonance imaging (MRI) and (electroencephalography) EEG [73,81] may offer more profound insights. Developing lightweight, privacy-preserving mobile solutions and conducting longitudinal studies could enable scalable, early interventions for ASD in community settings.

## Conclusion

AI-enhanced eye-tracking presents a noninvasive, promising avenue for early ASD diagnosis. Consistent markers, such as reduced social gaze and preference for nonsocial stimuli, were reliably identified across diverse tasks and populations. Despite encouraging diagnostic performances with CNNs, LSTMs, and hybrid models, methodological heterogeneity and limited external validation challenges must be addressed. Future standardization and multimodal integration efforts will be key to translating these technologies into accessible, personalized diagnostic solutions.

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## Declarations

### Ethics approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Availability of data and materials

Contact the corresponding author to receive the data at sananiazi@sbmu.ac.ir

### 11.4. Competing interests

No competing interests exist for any author.


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## Conflict of Interest

None.

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