



# The Use of Artificial Intelligence in Screening and Diagnosis of Autism Spectrum Disorder: A Literature Review

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**Objectives:** The detection of autism spectrum disorder (ASD) is based on behavioral observations. To build a more objective data-driven method for screening and diagnosing ASD, many studies have attempted to incorporate artificial intelligence (AI) technologies. Therefore, the purpose of this literature review is to summarize the studies that used AI in the assessment process and examine whether other behavioral data could potentially be used to distinguish ASD characteristics.

**Methods:** Based on our search and exclusion criteria, we reviewed 13 studies.

**Results:** To improve the accuracy of outcomes, AI algorithms have been used to identify items in assessment instruments that are most predictive of ASD. Creating a smaller subset and therefore reducing the lengthy evaluation process, studies have tested the efficiency of identifying individuals with ASD from those without. Other studies have examined the feasibility of using other behavioral observational features as potential supportive data.

**Conclusion:** While previous studies have shown high accuracy, sensitivity, and specificity in classifying ASD and non-ASD individuals, there remain many challenges regarding feasibility in the real-world that need to be resolved before AI methods can be fully integrated into the healthcare system as clinical decision support systems.

**Key Words:** Autism spectrum disorder; Artificial intelligence; Diagnosis; Screening.

Received: August 12, 2019 / Revision: September 2, 2019 / Accepted: September 16, 2019

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## INTRODUCTION

Autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by difficulties in social communication and interaction with restricted or repetitive patterns of behavior, interest, or activities [1]. In the absence of clear identifiable biomarkers [2], the current gold standard in diagnostic criteria relies on behavioral observations administered by healthcare professionals [3]. The reliability and validity of these results come into question when accounting for subjectivity [4], which can stem from differences in professional training and experiences [5], lack of resources [6], or cultural adaptability of the assessments [7]. Such limitations to the current diagnostic system call for the need to develop a novel method that can provide quick, accurate evaluations while affording a well-rounded understanding of the heterogeneous phenotype in

each individual with ASD.

Recently, artificial intelligence (AI) has risen as a promising alternative. Built based on the biological networks of the human brain [8], AI covers a wide range of technologies that are capable of performing cognitive functions by mimicking human intelligence [9]. While promising results in other fields (e.g., engineering, business, and everyday applications) have been shown, increasing efforts are being made to incorporate AI into healthcare settings [10,11]. Previous studies have applied AI in recognition of symptoms [12], classification [13], diagnosis [9,10], and prediction of outcome based on structured or unstructured data [9,10,14]. Equipped to improve accuracy through trials, AI can also reduce the likelihood of introducing inevitable human error [10]. For instance, AI is capable of capturing data that may not be visible to the human eye during behavioral observations, which can lead to precise datafication [15]. With an increasing interest in AI, there have been movements in making such programs accessible to the general public. For instance, by searching 'autism' and 'AI' in a search

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engine, one can easily find a phone application that advertises the use AI for detection of autistic traits. However, without enough evidence to support their validity and reliability, such programs may provide inaccurate information and cause unnecessary delays in provision of care.

One of the most commonly used subfields of AI in research is machine learning (ML). Machine learning can take a supervised approach by educating itself with a labeled dataset and constructing the best fitting algorithm to forecast an outcome of interest, or an unsupervised approach that analyzes the input features by deducing patterns without pre-existing knowledge [16]. By extracting useful information and building complex models that surpass human performance in analyzing large datasets [11,17], ML can enhance our understanding of ASD and may further help build a stronger foundation for better screening and diagnosis.

To develop a more objective method in detecting ASD through assessment of significant features linked to the disorder, previous studies have attempted using a range of data modalities with AI. For instance, as ASD is most likely associated with the combination of the interplay between variants of several genetic biomarkers [18], genetic research has been applied with several AI methods to explore and optimize ASD risk-associated gene candidates [19]. Limitations persist as the current combination of known ASD-associated genes is only capable of explaining a small portion of cases [20]. Additionally, neuroimaging techniques have been used in combination with several AI approaches to study different brain regions and network-wide connectivity that may be unique to individuals with ASD [21]. Unfortunately, based on the study populations and models used, predictive neuroanatomical findings have been inconsistent [22].

Despite studies reporting on ways in which AI can be used with biomarkers to establish a data-driven approach in ASD classification, the current system relies heavily on behavioral observation data. However, in collecting information based upon actions or subtle responses to social situations and their interpretation by the administrator, behavioral observational data face numerous challenges. Unlike genetics and neuroimaging scans that have a well-established streamlined protocol for collection and analysis, there is no objectified system to capture the constant changes in the behavior of an individual. As ASD assessments rely on observational data and efforts are being made to use AI to independently perceive information from the environment [23], the combination of these two elements can help overcome limitations of data collection during the screening and diagnostic process.

While review studies such as Hyde et al. [24] and Thabtah [25] reported on ASD studies focusing on a single AI method, to our knowledge, no literature review has been conducted on

the broad use of AI technology to distinguish individuals with ASD through an emphasis on behavioral aspects. Therefore, the aim of this study is to summarize findings on how AI can be implemented into the current evaluation process and explore other potential behavioral aspects that can be used to enhance efficiency in the detection of ASD.

## METHODS

A literature review of studies using AI technology in relation to those with ASD was conducted on published peer-reviewed journal articles listed in PubMed from January 1, 2009, to July 31, 2019. Studies were included and excluded by following the practices of Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Fig. 1) [26].

### Search and exclusion criteria

For a comprehensive search, the keywords included Medical Subject Headings (MeSH) terms ‘autism spectrum disorder’ and ‘artificial intelligence.’ A total of 183 studies were identified through the initial search. Studies were excluded if they were: 1) methodological studies mainly focusing on AI technology; 2) animal studies; 3) studies that were not published (full text) in English; and 4) reviews, meta-analyses, narratives, or editorials. Based on the title and abstract screening, 70 articles were excluded as they met any of the exclusion criteria. The remaining 113 articles were selected for a full-text review and removed for further analysis if: 1) genetics or neuroimaging scans were used as the main source of data; 2) AI technology was not the major method employed in the study; and 3) they included fewer than 10 ASD participants. After full-text review exclusions, 13 studies were finally included in the analysis.

## RESULTS

We describe our findings by introducing how AI can be utilized to complement existing ASD assessment tools and introduce new behavioral components with the potential to be incorporated for screening or diagnosis.

### Use of AI with existing ASD assessments

To facilitate screening that is sensitive and specific, studies have used diverse AI methods on the existing battery of assessments to build models that can be used to classify individuals with ASD (Table 1).

### Increasing early predictive outcomes

While reliable diagnosis of ASD is usually made around 3 years of age [27], AI methods have been utilized to predict di-

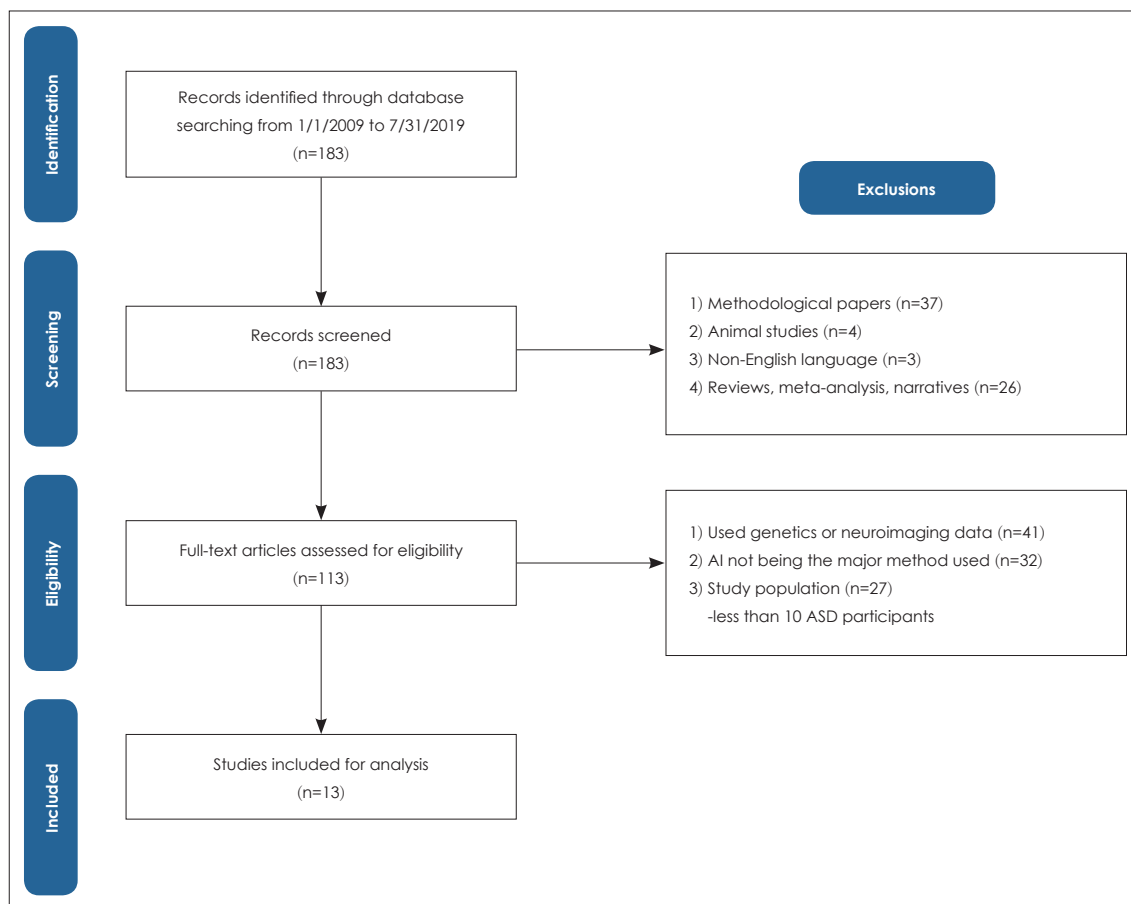


Fig. 1. Search strategy and article selection process. ASD: autism spectrum disorder.

agnostic outcome using developmental evaluations before the age of 3 years and enable more accurate predictions. For instance, Bussu et al. [28] used support vector machine (SVM), a type of supervised ML algorithm that is used to classify features by assigning binary labels [10], to predict ASD diagnosis at around 3 years of age, based on previous developmental evaluations such as the Mullen Scales of Early Learning (MSEL) and Vineland Adaptable Behavior Scale (VABS) during infancy [28]. The predictive diagnostic outcome at 3 years using SVM was compared to the clinical judgments made by researchers based upon review of the Autism Diagnostic Observation Schedule (ADOS) and Autism Diagnostic Interview Revised (ADI-R). Showing high predictive accuracy at 3 years based on the data obtained from 14 months of age, this study proved how combining information such as symptoms and adaptive functioning from multiple assessment measures could improve classification of atypical development.

#### Reducing the number of items in assessments

With the initial screening taking around 60 to 90 minutes and an average wait of 13 months before diagnosis [29], efforts are being made to use AI in reducing items to shorten the time

in administering lengthy evaluations. Researchers have used the gold-standard diagnostic tests, ADOS [30] and ADI-R [31], to identify a minimal set of items that are most distinguished by ASD characteristics and test whether the subset of features can uphold high sensitivity, specificity, and accuracy in diagnosis. After using classifier algorithms to identify optimal features that contribute to determining the diagnosis, models were trained using the reduced set of items and its performance was tested using a new dataset [32-34]. Of the 28 features in ADOS, studies by Levy et al. [32] and Kosmicki et al. [33] were able to uphold high accuracy while reducing the number of activities to five and nine items in module 2 and 10, and 12 items in module 3, respectively. The alternative decision tree (ADTree), a method combining features to build an accurate predictor, was used in a study by Wall et al. [34] and drastically lowered the number of questions in the ADI-R by 92%.

#### Classification between different neurodevelopmental disorders

Other studies have also expanded to using assessment tools with AI to differentiate between common neurodevelopmental disorders [35]. Duda et al. [36] used diverse ML algorithms

**Table 1.** Summary of studies using AI technology with existing ASD assessments

Author	Sample size	Mean age	Date type	Method	AUC (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Bone et al. [35]	1264 (ASD)	6.7–15.9 yrs	ADI-R	SVM	-	89.2	59	-
	462 (non-ASD)	6.6–17.2 yrs	SRS		86.7	53.4		
Bussu et al. [28]	32 (ASD)	8.1 m (visit1)	MSEL	SVM	69.2 (8 m)	68.8 (8 m)	64.4 (8 m)	66.4 (8 m)
	43 (atypical)	14.5 m (visit2)	VABS		70.8 (14 m)	60.7 (14 m)	67.5 (14 m)	64.4 (14 m)
	86 (typical)	25.4 m (visit3)	AOSI					
		38.4 m (visit4)						
Duda et al. [36]	2775 (ASD)	8.1 yrs (ASD)	SRS	SVC, LDA,	93.3–96.5	-	-	-
	150 (ADHD)	11.3 yrs (ADHD)		CL, LR, RF, DT				
Duda et al. [37]	248 (ASD)	8.2 yrs (ASD)	SRS	SVC, CL,	82–89	-	-	-
	174 (ADHD)	10.4 yrs (ADHD)		LR, LDA				
Kosmicki et al. [33]	1451 ASD (M2)	68 m ASD (M 2)	ADOS	SVM, ADTree,	-	96.7–99.7 (M2)	96.5–98.6 (M2)	-
	348 non-ASD (M2)	37 m non-ASD (M2)	(M2, M3)	FT, LR, NBT, RF				
	2434 ASD (M 3)	111 m ASD (M3)			96.1–100 (M3)	87.1–98.9 (M3)		
Levy et al. [32]	307 non-ASD (M 3)	108 m non-ASD (M 3)						
	1319 ASD (M 2)	83 m ASD (M 2)	ADOS	LR, LDA, SVM	93 (M2)	98 (M2)	58 (M2)	78 (M2)
Thabtah et al. [49]	707 (ASD)	6.3 yrs	AQ	CI	-	-	80	-
	393 (non-ASD)	14.1 yrs			80–87.3	80		
Wall et al. [34]	2867 (ASD)	8.06–8.75 yrs (ASD)	ADI-R	ADTree	-	-	93.8–99	99.9–100
	92 (non-ASD)	9.24–9.75 yrs (non-ASD)			80.95–82.54	90		

ADHD: attention-deficit/hyperactivity disorder, ADI-R: Autism Diagnostic Interview-Revised, ADOS: Autism Diagnostic Observational Schedule, ADTree: alternating decision tree, AI: artificial intelligence, AOSI: Autism Observational Scale for Infants, AQ: Autism Spectrum Quotient, ASD: autism spectrum disorder, AUC: area under the curve, CI: computational intelligence, CL: categorical lasso, DT: decision tree, FT: functional tree, LDA: linear discriminant analysis, LR: logistic regression, m: months, MSEL: Mullen Scales of Early Learning, M2: module 2, M3: module 3, NBT: naïve Bayes tree, RF: random forest, SRS: Social Responsiveness Scale, SVC: support vector classification, SVM: support vector machine, VABS: Vineland Adaptable Behavior Scale, yrs: years

to find the best classifying features using the Social Responsiveness Scale (SRS) to distinguish ASD and attention deficit hyperactivity disorder (ADHD). Of the 65 items on the SRS, they were able to identify five features while maintaining high accuracy (above 90%). Extending from their previous study, Duda et al. [37] applied 15 SRS-derived questions to a crowd-sourced dataset and created a novel classification algorithm to reflect real-world data as a source to validate its performance.

### Use of AI with novel observational data

To develop a more objective method in identifying ASD, researchers have investigated the feasibility of using AI to capture different types of behavioral features to use as valuable information in detecting characteristics that are unique to individuals with the disorder (Table 2).

#### Facial expressions

Many individuals with ASD report difficulty in recognition and expression of emotions [38]. Liu et al. [39] had attempted to use the difference in face scanning patterns between ASD and non-ASD participants as indicators of classification. First, participants were shown six faces to remember. Then, they were shown 18 faces and asked to choose the faces that they had been asked to remember. Eye-tracking was recorded to gain information on eye movement and fixation duration when viewing the faces. Support vector machine was then used to classify the boundary that differentiated between ASD and TD groups. With an overall accuracy of 88.51%, results showed the most distinguishable characteristic was that the TD group spent more time looking at the right eye while the ASD group spent more time on the left eye.

#### Motor movements

In a study by Hilton et al. [40], it was reported that 83% of individuals with ASD had lower motor composite scores than non-ASD individuals. Therefore, researchers have attempted to capture differences in movement patterns to use as a distinctive characteristic of ASD [41,42]. Studies by Li et al. [43] and Anzulewicz et al. [44], each used imitation based on observation and gesture patterns using smart tablet devices to detect kinematic parameters to use for classifying between ASD and non-ASD.

Crippa et al. [45] investigated whether SVM could be used with the reach, grasp, and drop movement in the upper-limb to identify children with ASD. Trials were designed to observe those motor movements because they are important milestones in the developmental trajectory. Each action was divided into sub-movements and analyzed. Using SVM, a total of 17 kinematic measurements were chosen as classifiers to distinguish preschool children with ASD and their typically

**Table 2.** Summary of studies using AI technology with novel observational data

Author	Sample size	Mean age	Date type	Method	AUC (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Tariq et al. [48]	116 (ASD)	4.10 yrs (ASD)	Behavioral features	ADTree, SVM, LR, RK, LISVM	89–92	90–100	1.13–100	94–100
	46 (TD)	2.11 yrs (TD)		Sparse 5 feature LR classifier				
Liu et al. [39]	29 (ASD)	7.9 yrs (ASD)	Eye-tracking	SVM	89.63	93.1	86.21	88.51
	29 (TD)	7.86 yrs (TD)						
Li et al. [43]	14 (ASD)	32 yrs (ASD)	Hand movement	NB, SVM, RF, DT	-	57.1–85.7	68.8–87.5	66.7–86.7
	16 (TD)	29.31 yrs (TD)						
Anzulewicz et al. [44]	37 (ASD)	4.5 yrs (ASD)	Hand movement	RF, RGF	88.1–93.2	76–83	67–88	-
	45 (TD)	4.7 yrs (TD)						
Crippa et al. [45]	15 (ASD)	3.5 yrs (ASD)	Upper-limb movement	SVM	-	82.2–100	89.1–93.8	84.9–96.7
	15 (TD)	2.6 yrs (TD)						

ADTree: alternating decision tree, AI: artificial intelligence, ASD: autism spectrum disorder, AUC: area under the curve, DT: decision tree, LISVM: linear support vector machine, LR: logistic regression, NB: naïve Bayes, RF: random forest, RGF: regularized greedy forest, RK: radial kernel, SVM: support vector machine, TD: typically developing, yrs: years



developing peers. Tasks that were related to transporting an object to the target was where the two groups showed substantial differences, suggesting that differences in goal-oriented movements may be a strong identifier of ASD.

## DISCUSSION

The purpose of this study was to review literature that has applied AI technologies to the current assessment instruments for ASD and to assess whether other behavioral characteristics could potentially be used as identification of observable markers for diagnosis. A total of 13 articles were reviewed with a majority of the studies using supervised ML methods such as SVM to distinguish between individuals with and without ASD. Findings demonstrate that algorithms were used to identify features that were most representative of ASD characteristics and were able to exclude duplicate items to reduce the amount of time and effort required in the assessment process. Other studies have also tried to use other behavioral aspects with AI to analyze whether it could be used to distinguish individuals.

With constant development in the field of AI, its use has rapidly spread to the healthcare arena [10,11]. Being relatively easy to input data, the most advanced areas with AI technology are diagnostic imaging, followed by genetics [10]. Due to the exponential growth in medical image analyses and pipelines that extract features to be used as valuable decision supporting data, a new practice termed radiomics has emerged [46]. Unfortunately, this trend has been focused on the fields of cancer or diseases related to the cardiovascular or nervous system [10]. According to Jiang et al. [10], based on the literature in PubMed, the leading disease areas using AI technology are: neoplasms, nervous, cardiovascular, urogenital, pregnancy, digestive, respiratory, skin, endocrine, and nutritional. These 10 areas have approximately 9000 papers published since 2013. Yet, despite ASD having evolved into a public health issue with one in 59 children diagnosed [47], only 119 studies were published during the same time.

This may largely be due to the challenges that need to be resolved before AI methods can be applied in research and clinical settings. As ML requires big data, the majority of the studies in this analysis used collected data from data repositories [32-37]. Therefore, there was a large imbalance between individuals with and without ASD. To adjust for such limitations, different approaches were undertaken by researchers in deciding who to include and exclude. Whether this has any effect on results would need to be further investigated through replication studies. Second, we may need to consider if we are oversimplifying the assessments by only choosing a few items. A majority of the studies in this analysis reduced features by

more than 50% [25,32-34,36,37]. However, a wide range of autistic symptoms with different levels of severity may not have been captured with the reduced number of items. There could also be individuals who do not meet the cut-off threshold but still have some sort of developmental delay. Therefore, simple dichotomous results may not be the most appropriate method to interpret the output data. Additionally, there has yet to be a study that examines how the accuracy, sensitivity, or specificity would be affected if one or more of the items were left unanswered. Third, there remains a lack of clear understanding of the technique that is being used. A number of studies used multiple algorithm approaches and report on the highest predictive value [32,33,36,37,43,44,48,49]. Before arguing on the best algorithm to use, it would be important to understand why there are such differences in the results and the reason as to which approach would be most appropriate depending on the characteristics of the dataset and what sort of an output one is trying to achieve. To enable this, advancement with a theoretical background rather than being strictly data-driven would be needed.

In addition to the limitations from previous studies, implementing AI in the general healthcare system still faces numerous obstacles. While machine learning algorithms heavily depend on the training dataset, there has not yet been any extensive research assessing how the quality of the input data affects the accuracy or targeting to establish a protocol on data collection and cleaning. Requiring vast amounts of data, the ethical challenge around data privacy is also another topic that is under debate [9]. Additionally, while complex disorders like ASD influence both the brain and behavior, there is a lack of reports on current AI technology integrating multiple modalities for a more comprehensive understanding of an individual [11]. Lastly, the majority of current advancements in AI technology have been based on retrospective data. Validation and feasibility studies of such techniques in the real-world are still needed [10,11]. Being able to overcome these challenges to incorporate AI in clinical settings will not only enhance our understanding of ASD, but also enable healthcare professionals to use this technique as a clinical decision support system that can objectively intervene throughout the screening, diagnosis, and treatment process.

## CONCLUSION

Without a definite biomarker, ASD screening and diagnosis depend on behavioral observations. To overcome administrator bias during assessments, many have attempted to use AI technology to improve the frequency of accurate detection. In this literature review, we found that studies have attempted to classify items from assessment instruments that

are most predicative of the diagnosis to make the process less time-consuming. Other studies have experimented with other behavioral characteristics that may be unique to individuals with ASD to use as markers for classification. However, as research in ASD and AI are both still relatively new, there are numerous obstacles that need to be resolved before applying these methods in research or clinical settings.

### Acknowledgments

This work was supported by an Institute for Information & Communications Technology Promotion (ITTP) grant funded by the Korean government (MSIT) (No.2019-0-00330, Development of AI Technology for Early Screening of Infant/Child Autism Spectrum Disorders based on Cognition of the Psychological Behavior and Response).

### Conflicts of Interest

The authors have no potential conflicts of interest to disclose.

### Author Contributions

Conceptualization: Hee Jeong Yoo. Data curation: Da-Yea Song, So Yoon Kim. Formal analysis: Da-Yea Song, So Yoon Kim. Funding acquisition: Hee Jeong Yoo. Investigation: Da-Yea Song, So Yoon Kim. Methodology: Da-Yea Song, So Yoon Kim. Project administration: Da-Yea Song, So Yoon Kim, Guiyoung Bong, Jong Myeong Kim. Supervision: Hee Jeong Yoo. Validation: Guiyoung Bong, Jong Myeong Kim, Hee Jeong Yoo. Writing—original draft: Da-Yea Song, So Yoon Kim. Writing—review & editing: Guiyoung Bong, Jong Myeong Kim, Hee Jeong Yoo.

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