The Scientific Temper (2024) Vol. 15 (2): 2404-2409
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2024.15.2.59
https://scientifictemper.com/

RESEARCH ARTICLE

# Role of artificial intelligence in evaluating autism spectrum disorder

**Archana Verma**

## Abstract

Autism spectrum disorder (ASD) is a neurological illness characterized by challenges with repetitive tasks, social interaction, and communication. Even if genetics is the primary cause, early detection is vital, and using ML presents a promising way to diagnose the condition more quickly and affordably. In an effort to improve and automate the diagnostic process, this research uses a variety of machine-learning techniques to pinpoint important ASD features. With the rapid growth of artificial intelligence techniques, it has become possible to use intelligent methods to carry out early large-scale senseless screening and diagnosis of autism. In the future, research should focus on building an intelligent medical screening and diagnosis system for autism patients, developing screening tools and constructing an intelligent identification model for patients that integrates multimode data.

**Keywords:** Artificial intelligence, Autism spectrum disorder.

## Introduction

The WHO estimates that ASD may impact 67 million individuals globally. The impact on men is four times greater than that on women (Rafiee, F., Rezvani Habibabadi, R., Motaghi, M., Yousem, D. M., & Yousem, I. J. 2022). ASD's precise etiology is yet unknown. There are several hypothesized heterogeneous and multifactorial reasons involving genetic background (Duda, M., Zhang, H., Li, H. D., Wall, D. P., Burmeister, M., & Guan, Y. 2018).

A significant amount of study was done to create an efficient and successful way to accurately identify ASD patients with impressive ASD detection efficiency and precision using AI and ML techniques. The goal was to minimize all the drawbacks, such as the lengthier diagnosis times, higher costs, and the need for more personnel. Nevertheless, a dearth of considerable research exists that comprehensively examines the advantages and disadvantages of utilizing various components of ML algorithms for the accurate and dependable identification of characteristics associated with ASD.

A neurodevelopmental illness that affects communication and is linked to compulsive and restrictive behaviors, ASD is a lifelong condition. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5), fifth edition, states that the establishment of repetitive and restricted behavioral patterns or hobbies and trouble with social communication are the main markers of ASD (Ap Association. 2000). Due to the increasing occurrence of ASD, it is imperative to obtain an early diagnosis at a reasonable cost in order to facilitate effective and suitable treatment (Chauhan, A., Sahu, J. K., Jaiswal, N., Kumar, K., Agarwal, A., Kaur, J., ... & Singh, M. 2019). Additionally, prompt diagnosis of ASD improves social and communication results and helps parents choose the best course of action for their child's school, home, or clinic (Case-Smith, J., Weaver, L. L., & Fristad, M. A. 2015). Nevertheless, research has shown that the clinical procedures involved in diagnosing ASD are delayed, in addition to the present diagnostic tools' inefficiency in terms of cost (Yuen, T., Carter, M. T., Szatmari, P., & Ungar, W. J. 2018). Several recommendations, particularly the so-called rapid and precise ML-enabled ASD assessment tools, were made in response to these challenges (Shahamiri, S. R., & Thabtah, F.2020).

Department of Computer Science & Engineering, Bipin Tripathi Kumaon Institute of Technology, Dwarahat, Gauchar, Uttarakhand, India

***Corresponding Author:** Archana Verma, Department of Computer Science & Engineering, Bipin Tripathi Kumaon Institute of Technology, Dwarahat, Gauchar, Uttarakhand, India, E-Mail: dr.vermarchana05@gmail.com

**How to cite this article:** Verma, A. (2024). Role of artificial intelligence in evaluating autism spectrum disorder. The Scientific Temper, **15**(2):2404-2409.

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.2.59

**Source of support:** Nil

**Conflict of interest:** None.



**Received:** 04/04/2024 **Accepted:** 05/05/2024 **Published** : 29/06/2024

### *Literature Review*

Children diagnosed with ASD frequently exhibit unpredictable and erratic behaviors. They can't communicate well in their own language most of the time. Rather, they use pointing sentences and hand gestures to communicate (Sundas, A., Badotra, S., Rani, S., & Gyaang, R.2023). As a result of this, it can be challenging for carers to understand the needs of their patients, though this can be greatly simplified with early diagnosis. Communities suffering from a lack of nonverbal and verbal communication can benefit from the Internet of Things and assistive technologies. The IoT-based solutions diagnose patients and improve their quality of life using ML and DL techniques. This paper presents a comprehensive assessment of ASD approaches in the context of IoT devices. The primary objective of this review is to identify important trends in healthcare research involving IoT. Additionally, a technological taxonomy based on many elements, including AI, SS network, ML, and IoT is used to organize the existing publications on ASD algorithms and approaches. The offered statistical and operational studies of the ASD approaches under examination are based on many parameters, including sensitivity and accuracy.

Deficits in social communication associated with ASD can take many different forms, including trouble recognizing faces, difficulty interpreting the intentions of others, and decreased social responsiveness. Moreover, human voices, biological gestures, and social cues are given less consideration (Rafiee, F., Rezvani Habibabadi, R., Motaghi, M., Yousem, D. M., & Yousem, I. J. 2022). An investigation discovered that children with ASD showed hypoactivation in the amygdala and fusiform gyrus when it came to the activity of social brain regions in response to the visual perception of generic faces. These areas are in charge of these responsibilities. But when the faces were known to them, TD controls and ASD patients both exhibited comparable activation. A task was used in another investigation to differentiate between attention to mechanical motions (such as a clock or wheel) and biological motions (such as walking, hand, or mouth movements). This study showed that in comparison to TD controls, children with ASD had less activation in the ventrolateral prefrontal cortex and superior temporal sulcus. According to the research, children with ASD are less able to focus on faces than typically developing children and are more quickly distracted by non-facial stimuli.

As an outcome, a number of researchers have observed that AI is important for the early identification of autism since it speeds up the diagnosis process and produces more precise outcomes for the doctors (Anagnostopoulou, P., Alexandropoulou, V., Lorentzou, G., Lykothanasi, A., Ntaountaki, P., & Drigas, A. 2020). In order to emphasise the use of smart technology in the autism diagnosis process, the research team of this study provides a few applications of AI that are currently in use or are in the early stages of development. Last but not least, it is important to remember that a timely and precise diagnosis is essential to a tailored and effective solution that supports the child's growth both personally and academically.

A disorder called autism prevents a person from developing to their full potential. People with autism struggle greatly to keep up with society's speed, have trouble communicating, and have trouble expressing their emotions. Many medical applications integrate AI, ML, and IoT, and when automated technologies are applied properly, they can help people with autism. A few research studies on the use of AI, ML, and IoT in autism were reviewed in this publication. After collecting state-of-the-art articles, about 58 articles with major contributions to this topic were chosen (Ghosh, T., Al Banna, M. H., Rahman, M. S., Kaiser, M. S., Mahmud, M., Hosen, A. S., & Cho, G. H. 2021). The chosen research projects underwent comparison, analysis, and representation. Lastly, a description of how autistic facilities are integrated into smart city environments is given, along with a list of research problems and gaps and suggestions for more study.

Early identification of ASD features can help prevent the illness from developing further. ASD is a neurological disorder that requires extensive testing and expensive medical care. Many items and domain expert criteria form the basis of the current conventional ASD screening procedures, which have drawn criticism for being drawn out and subjective. More importantly, these methods use simple scoring algorithms to identify autistic traits instead of employing complex pattern recognition from cases and controls, which can produce more accurate and efficient findings (Shahamiri, S. R., & Thabtah, F. 2020). To solve the aforementioned issues and speed up ASD assessment referrals, creative AI screening techniques that not only provide accurate pre-diagnostic classifications but also improve the efficiency and accessibility of the screening process may be developed. The novel autism screening system described in this work replaces the traditional scoring functions with DL algorithms in screening methods. The system is made up of a database that allows the CNN to learn new information from system users in the future, an intelligent web service for ASD detection that interacts with a CNN trained on previous ASD cases, and a mobile application that acts as the user interface for gathering data from questionnaires.

ASD is growing more popular now than it has ever been. It is very expensive and time-consuming to identify autism signs using screening tests. The advancement of ML and AI has made it possible to predict autism at a very early level. Even though a lot of studies have been done using different approaches, the results of these studies have not been able to definitively determine how autism traits will manifest in different age groups (Omar, K. S., Mondal, P., Khan, N. S., Rizvi, M. R. K., & Islam, M. N. 2019, February). As a result of this research, a mobile application and an autism forecasting system based on the combination of Random Forest-CART and Random Forest-Id3 were developed. The evaluation's findings demonstrated that, for both types of datasets, the suggested prediction model performed better than the other models in terms of accuracy, specificity, sensitivity, precision, and false positive rate (FPR).

## Research Methodology

Our research primarily focuses on the idea that early diagnosis of ASD is important for both adults and children. Two raw public datasets with various attributes of adults and children were used in this investigation. Furthermore, the combining of these two datasets yields a third dataset, which was made available. Following the preparation phases, the dataset splitting procedures are finished, and missing value handling, duplicate value removal, and significant feature identification using the statistical approach chi-square are completed. The ML algorithms that were employed to complete the classification tasks were then selected using a 5-fold cross-validation technique.

Even though ASD is growing increasingly commonplace worldwide, there aren't many publicly accessible databases that are dedicated to researching the illness. Too few clinical screening datasets are available now for autism, and most of the databases are genetics-oriented. The ASD in Children's and Adults datasets, which comprise 689 occurrences and 19 attributes for the Adult dataset and 301 occurrences and 19 attributes for the Children dataset, were taken from a publicly accessible UCI repository and used in this work.

This children's dataset has 175 observations, with ages ranging from 5 to 10. The most important step in this study to create a successful prediction model is data pre-processing. Before providing the data to the approach, it will assist us in handling missing numbers, eliminating duplicate data, and removing any conflicts. The Pandas library will be used to load the dataset into the data frame "df." All values that are missing and are indicated by '?' will be shown as "NaN." In the adult and children's datasets, there are a total of 90 and 192 missing values, respectively.

Following the treatment of the dataset's missing values, other preparation methods like One-Hot encoding are applied. Additionally, it is evident to us that the data type is non-numeric. We have requirements for things like nationality, residency, and relationship to the case. Even though they are all string data formats, they are all quite predictive. We use one-hot encoding to change these category data into non-categorical values. This is a traditional normalization method where the input values are shifted to fall between 0 and 1.

High dimensionality is a challenge that is reduced using feature selection approaches. Only significant elements are retained during this procedure, and less useful features are eliminated. There are now a lot of feature-selecting methods available. Overfitting, needless noise, excessive temporal complexity, and other problems are some of the consequences of high dimensionality. In this work, the feature selection technique employed is chi-square feature selection.

The independence of events is confirmed using the Chi-Square selection method. The presence of a class and the existence of a feature are the two main events. Determining if a particular trait is dependent on a particular class is its main purpose. We take advantage of the fact that the occurrences are not independent if and only if such is the case. To ascertain if two factors are interdependent, statisticians employ the chi-square test.

## Results

Results are shown as follows:

Performance matrices are represented in figures as Figure 1, which displays the performance metrics of machine learning (ML) methods for the ASD Detection Children dataset. Figure 2 illustrates the performance metrics of ML models for the ASD Detection Adult dataset, and Figure 3 showcases the performance metrics of ML models for ASD Detection in consolidated dataset.

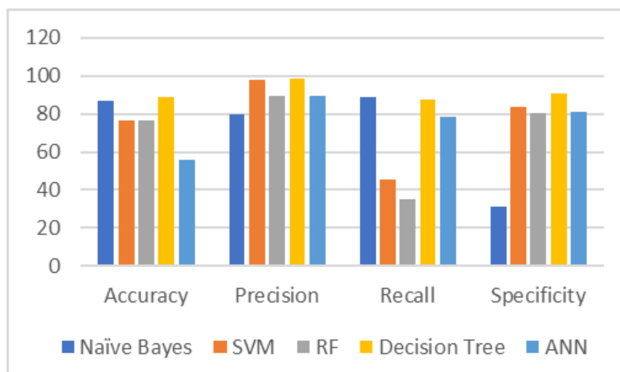


**Figure 1:** Performance metrics of ML methods for ASD Detection Children dataset

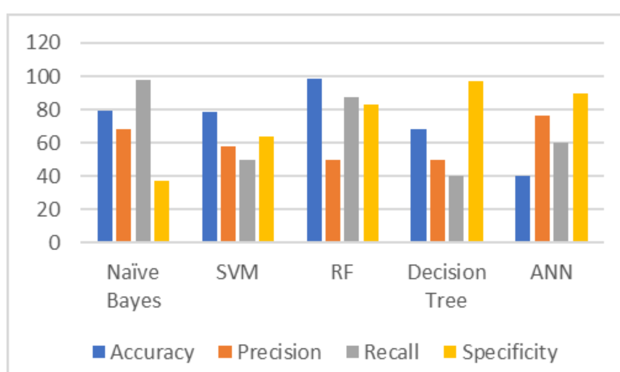


**Figure 2:** Performance metrics of ML models for ASD Detection Adult dataset

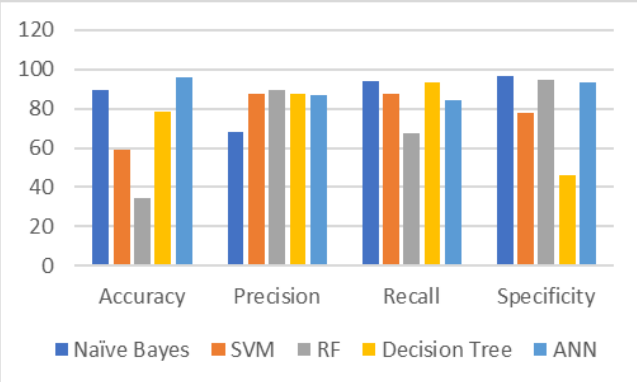


**Figure 3:** Performance metrics of ML models for ASD Detection Combined dataset

**Table 1:** ML methods for ASD detection children dataset

| *Model* | *Accuracy* | *Precision* | *Recall* | *Specificity* |
|---|---|---|---|---|
| Naïve Bayes | 87.23 | 79.65 | 88.65 | 31.5 |
| SVM | 76.8 | 98.07 | 45.78 | 83.54 |
| RF | 76.6 | 89.4 | 34.8 | 80.65 |
| Decision tree | 88.76 | 98.61 | 87.66 | 90.54 |
| ANN | 55.71 | 89.56 | 78.56 | 81.35 |

**Table 2:** ML models for ASD detection adult dataset

| *Model* | *Accuracy* | *Precision* | *Recall* | *Specificity* |
|---|---|---|---|---|
| Naïve Bayes | 79.54 | 68.56 | 98.03 | 36.87 |
| SVM | 78.43 | 57.90 | 49.72 | 63.89 |
| RF | 98.56 | 49.87 | 87.69 | 83.33 |
| Decision tree | 67.90 | 49.80 | 39.87 | 96.77 |
| ANN | 39.89 | 76.56 | 59.78 | 89.43 |

**Table 3:** ML models for ASD detection combined dataset

| *Model* | *Accuracy* | *Precision* | *Recall* | *Specificity* |
|---|---|---|---|---|
| Naïve Bayes | 89.67 | 67.89 | 94.32 | 96.45 |
| SVM | 58.90 | 87.69 | 87.65 | 78.09 |
| RF | 34.67 | 89.76 | 67.54 | 94.67 |
| Decision tree | 78.56 | 87.67 | 93.33 | 45.89 |
| ANN | 95.67 | 86.78 | 84.56 | 93.54 |

**Table 4:** Clustering methods for ASD detection child dataset

| *Model* | *NMI* | *ARI* | *SC* |
|---|---|---|---|
| k-means | 0.678 | 0.548 | 0.289 |
| GMM | 0.879 | 0.689 | 0.575 |
| Spectral | 0.378 | 0.489 | 0.389 |
| BIRCH | 0.538 | 0.851 | 0.624 |

With the use of tables, the results are presented as follows: ML methods for the detection of autism spectrum disorder (ASD) in children are presented in Table 1, while ML models for the detection of ASD in adults are presented in Table 2. Table 3 presents ML models for the detection of ASD in a combined dataset. Table 4 presents clustering methods for the detection of ASD in children, Table 5 presents clustering methods for the detection of ASD in adults, and Table 6 presents clustering methods for the detection of ASD in combined datasets.

**Table 5:** Clustering methods for ASD detection adult dataset

| *Model* | *NMI* | *ARI* | *SC* |
|---|---|---|---|
| k-means | 0.589 | 0.478 | 0.189 |
| GMM | 0.631 | 0.845 | 0.178 |
| Spectral | 0.845 | 0.413 | 0.187 |
| BIRCH | 0.671 | 0.932 | 0.534 |

**Table 6:** Clustering methods for ASD detection combined dataset

| *Model* | *NMI* | *ARI* | *SC* |
|---|---|---|---|
| k-means | 0.623 | 0.912 | 0.734 |
| GMM | 0.743 | 0.178 | 0.532 |
| Spectral | 0.768 | 0.945 | 0.745 |
| BIRCH | 0.167 | 0.854 | 0.687 |

## Discussion

An increasing number of people are interested in using AI to diagnose ASD. The field of AI in medical diagnostics is growing quickly. DTI is a neuroimaging method that evaluates the white matter's microstructure in the brain, while fMRI uses variations in blood flow to estimate brain activity. Due to its ability to shed light on the neural underpinnings of ASD, DTI and fMRI have both demonstrated promise in the identification of the condition. This paper highlights the various machine learning approaches that have been used in the review of investigations on the use of fMRI and DTI in ASD diagnosis and the outcomes that have been reported. We also discuss the benefits and drawbacks of different approaches and offer suggestions for additional research.

Similar to mental illnesses, the use of AI models in radiomics is thought to represent a major breakthrough in precision medicine research (Cui, L. B., Xu, X., & Cao, F. 2021). This encourages the creation of a thorough analysis of radiomic utilization in the diagnosis of ASD. There are just two classes that the general public can attend: ASD and HC, and none of them can examine every ASD subtype. As previously mentioned, when we included all of the ABIDE sites, bias developed because of the texture characteristics' reliance on the MRI sites. These days, assistive devices with domain adaptation algorithms can mitigate this difficulty, but when these algorithms are used in real-world scenarios, the problems still exist.

This study illustrated the several applications of radiomic models, as well as their advantages and disadvantages, in the diagnosis and categorization of ASD. We've talked about and examined key instances of radiomic pipelines for ASD that include accurate classification, a variety of assessment metrics, and the identification of key features, along with their methods and dataset sources. However, there are still certain problems that need to be solved, such as how to classify data from imbalanced datasets and apply the XAI in radiomic analysis, how to consider improper sampling techniques, and how to learn from limited data. Not only would incorporating AI in clinical settings increase our understanding of ASD, but it would also facilitate medical professionals to use these techniques as clinical decision support systems for screening and diagnosis procedures.

## Conclusions

Understanding autistic features and expediting referrals for additional evaluation in a clinical context are two key goals of autism screening. Nevertheless, many of the screening instruments currently in use, including AQ, Q-CHAT, and many more, rely on straightforward computations employing scoring functions to total the scores of each respondent's replies. These scoring functions, which were created during the screening process based on manually created norms, may be viewed as subjective. Thus, streamlining the screening procedure to provide people and their families with quicker, more accurate services is one of the most important issues in ASD screening research. This can be achieved by using machine learning (ML)-based automated techniques that create precise categorization systems using past examples and controls. This study presents a novel machine learning technique called RML that provides automatic classification in addition to rich rule sets for educators, patients and their families, carers, and physicians.

It is currently necessary to diagnose an ASD condition only on the basis of visible behavioral traits. On the other hand, pupils will be able to correctly identify this activity in schools thanks to the processing speed and duration. Any evaluation of an activity must be understood to include some interpretive bias. Behavior analysis can be done in a number of ways, with a variety of sources, technology, and methods. Each has pros and cons in terms of technique, accuracy, cost, and time.

These technologies have not been subjected to much independent testing despite their potential. This work has demonstrated that early ASD detection in schools may be accomplished safely, quickly, accurately, and precisely through the application of ML to analyze face image data. Diagnostic methods provide a number of benefits and drawbacks that are typical to ML and big data. They can be used for closed-circuit television and even diagnosis in schools to prevent the leakage of private information about the individual. Simplified models perform worse than ML algorithms trained on large data sets. To prevent developing models that are consistently skewed, it is imperative that the data collection be representative of the intended audience. Even if ML models have a high prediction accuracy, inferential inference is not always possible with them. The usage of ML models requires additional processing power due to their complexity. DL requires large volumes of data for both categorization and training. Subsequent studies will examine several classification schemes for ASDs based on facial features and Down syndrome in school environments, as well as techniques for merging information from various diagnostic instruments. In the future, we want to improve our AI and IoT-based models to help diagnose autism in kids and adults more quickly. AI-driven algorithms can analyze speech, body language, and facial expressions to identify indicators of autism spectrum condition. In the upcoming study, we will also employ IoT devices to track children's behavioral patterns and identify indicators of autism.

ML has been used extensively in the behavioral evaluation of ASD. Multiple data sources are used by machine learning as input for data-intelligence algorithms. It is usual practice to use inputs from screening instruments such as ADI-R and ADOS-G. Neural networks, SVMs, random forests, and decision tree variants are popular machine-learning techniques. Nevertheless, the proposed ML technologies have not yet solved the myriad of issues with accurate ASD diagnoses. More specifically, the clinical use of ML algorithms has not been ensured by the high metrics acquired by data intelligence techniques. Thus, a thorough comprehension of the logical underpinnings of data-intelligence approaches and the clinical foundation of assessment tools should result in fruitful investigations into the real-world implementation of low-cost ASD assessment systems. This study carried out a comprehensive evaluation of the literature and provided a conclusive analysis of the findings' applicability for the real-world application of machine learning-based assessment systems. This study differs from others because previous studies concentrated on the efficacy of various data-intelligent techniques on various types of data. The results of this comprehensive literature review, according to the authors, should help inform future developments in machine learning for ASD evaluation for academics, carers, and other pertinent stakeholders.

However, a number of the shortcomings of the current effort include failing to take into account other materials that are not in English. As a result, it's likely that good research published in other languages was overlooked. Secondly, the four scientific databases indicated were the only ones included in the ten-year search filters. Moreover, only a few search phrases included in the query were sufficient to yield the documents that were found. As a result, expanding the search parameters to include more databases may turn up more pertinent research. Finally, only full-text online journal publications were taken into consideration in our evaluation. As such, the results are restricted to the selected studies. Future studies will concentrate on loosening the search criteria and including additional academic databases to get more comparative findings. Additional investigation may allow for the inclusion of books and other items in the search parameters. Notably, future studies should examine data-intelligence approaches that will yield both high-quality evaluation metrics and adhere to the theoretical framework utilized by professionals to diagnose ASD in order to improve upon or duplicate the results given.

### *Limitations*

The fact that DTI and fMRI are usually only offered at specialized centers and might not be easily accessible to all patients is one drawback of utilizing them to diagnose ASD. These methods can also be expensive and time-consuming, which might prevent them from being used widely. Another drawback is that research on DTI and fMRI in ASD has produced results that are frequently contradictory, and opinions regarding the precise brain abnormalities linked to the disorder are divided. This may be partially explained by the fact that ASD is a heterogeneous condition and that various ML approaches and sample sizes have been used in different research.

It is crucial to keep improving and testing machine learning techniques in addition to standardizing the collection and handling of neuroimaging data if we are to overcome these constraints and raise the accuracy of ASD diagnosis using DTI and fMRI. In addition to determining the precise brain abnormalities most closely linked to ASD, future research should concentrate on creating more reliable and accurate biomarkers for the illness.

Although there is still much to learn about the neurological foundations of ASD and to create precise and dependable diagnostic techniques, the use of AI for DTI and fMRI-based ASD diagnosis has a lot of potential. To validate, improve, and ascertain the clinical value of these approaches, more study is required. More precisely, prior to commercialization, optimized software prototypes must be created and evaluated on sizable datasets obtained from various labs and organizations. One of the biggest potential obstacles is thought to be the availability and expense of these datasets, particularly in light of the dearth of MRI data pertaining to infants and toddlers that are required to show how effective these diagnostic imaging-based techniques are at diagnosing autism in its early stages.

## References


Ap Association. (2000). Diagnostic and statistical manual of mental disorders (DSM-IV-TR), text revision. (No Title).

Anagnostopoulou, P., Alexandropoulou, V., Lorentzou, G., Lykothanasi, A., Ntaountaki, P., & Drigas, A. (2020). Artificial intelligence in autism assessment. International Journal of Emerging Technologies in Learning (iJET), 15(6), 95-107.

Baio, J. (2018). Prevalence of autism spectrum disorder among children aged 8 years—autism and developmental disabilities monitoring network, 11 sites, United States, 2014. MMWR. Surveillance Summaries, 67.

Cui, L. B., Xu, X., & Cao, F. (2021). Building the precision medicine for mental disorders via radiomics/machine learning and neuroimaging. Frontiers in Neuroscience, 15, 685005.

Chaddad, A., Toews, M., Desrosiers, C., & Niazi, T. (2019). Deep radiomic analysis based on modeling information flow in convolutional neural networks. IEEE Access, 7, 97242-97252.

Chauhan, A., Sahu, J. K., Jaiswal, N., Kumar, K., Agarwal, A., Kaur, J.,& Singh, M. (2019). Prevalence of autism spectrum disorder in Indian children: A systematic review and meta-analysis. Neurology India, 67(1), 100-104.

Case-Smith, J., Weaver, L. L., & Fristad, M. A. (2015). A systematic review of sensory processing interventions for children with autism spectrum disorders. Autism, 19(2), 133-148.

Duda, M., Zhang, H., Li, H. D., Wall, D. P., Burmeister, M., & Guan, Y. (2018). Brain-specific functional relationship networks inform autism spectrum disorder gene prediction. Translational psychiatry, 8(1), 56.

Ghosh, T., Al Banna, M. H., Rahman, M. S., Kaiser, M. S., Mahmud, M., Hosen, A. S., & Cho, G. H. (2021). Artificial intelligence and internet of things in screening and management of autism spectrum disorder. Sustainable Cities and Society, 74, 103189.

Omar, K. S., Mondal, P., Khan, N. S., Rizvi, M. R. K., & Islam, M. N. (2019, February). A machine learning approach to predict autism spectrum disorder. In 2019 International conference on electrical, computer and communication engineering (ECCE) (pp. 1-6). IEEE.

Parekh, V. S., & Jacobs, M. A. (2019, April). Radiomic synthesis using deep convolutional neural networks. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) (pp. 1114-1117). IEEE.

Rafiee, F., Rezvani Habibabadi, R., Motaghi, M., Yousem, D. M., & Yousem, I. J. (2022). Brain MRI in autism spectrum disorder: narrative review and recent advances. Journal of Magnetic Resonance Imaging, 55(6), 1613-1624.

Sundas, A., Badotra, S., Rani, S., & Gyaang, R. (2023). Evaluation of autism spectrum disorder based on the healthcare by using artificial intelligence strategies. Journal of Sensors, 2023(1), 5382375.

Shahamiri, S. R., & Thabtah, F. (2020). Autism AI: a new autism screening system based on artificial intelligence. Cognitive Computation, 12(4), 766-777.

Yuen, T., Carter, M. T., Szatmari, P., & Ungar, W. J. (2018). Cost-effectiveness of universal or high-risk screening compared to surveillance monitoring in autism spectrum disorder. Journal of Autism and Developmental Disorders, 48, 2968-2979.