
**A REVIEW ON AUTISM SPECTRUM DISORDER DETECTION USING
MACHINE LEARNING AND DEEP LEARNING TECHNIQUES**

*Rasika Shashikant Ayarekar*¹, Dr. Apurva Daman Katre², Dr. Manisha Bhanuse³*

¹UG Scholar, Dept. of ETC, D. Y. Patil College of Engg. & Tech., kolhapur, Maharashtra, India.

²Assistant professor, Dept. of ETC, D. Y. Patil College of Engg. & Tech., kolhapur, Maharashtra, India.

³Associate professor, Dept. of ETC, D. Y. Patil College of Engg. & Tech., kolhapur, Maharashtra, India.

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*Corresponding Author: Rasika Shashikant Ayarekar

UG Scholar, Dept. of ETC, D. Y. Patil College of Engg. & Tech., kolhapur, Maharashtra, India.

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ABSTRACT

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder which impacts communication, social interaction, learning ability, and behavioral patterns in children and adults. Early detection of ASD is critical, as early intervention can have a significant impact on cognitive, behavioral and social outcomes. The traditional diagnosis methods are mainly based on clinical observation, behavioral assessment, questionnaires, psychological evaluation, etc., and these methods are time-consuming, subjective, and costly. In order to address these challenges, researchers have increasingly turned to Machine Learning (ML) and Deep Learning (DL) techniques for automated ASD detection and prediction. Intelligent ASD detection systems have been developed using recent developments in artificial intelligence, medical imaging, natural language processing, eye-tracking analysis, EEG analysis and facial image recognition, which have improved the accuracy and efficiency of ASD detection. This review paper provides a detailed survey of the different machine learning and deep learning techniques for autism detection. Various datasets, feature extraction techniques, classification approaches, evaluation techniques and recent research work are discussed. In addition, the paper identifies existing problems, gaps in research, and future research avenues for ASD detection systems. The review finds that AI tools can be a valuable aid to clinicians

in early and accurate autism diagnosis.

KEYWORDS: Autism Spectrum Disorder, Machine Learning, Deep Learning, ASD Detection, CNN.

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a developmental and neurological disorder that impacts communication, social interaction, emotional awareness and repetitive behaviors. The signs of ASD typically show up in early childhood and persist into adulthood. Based on global health studies, the prevalence of ASD cases has rapidly grown in recent years, posing a significant challenge to the healthcare systems of the world. It is very crucial that they are detected and diagnosed early as early therapeutic intervention may help enhance language development, social skills, learning ability and quality of life of autistic persons.

The traditional approaches to diagnosing ASD involve parent questionnaires, behavioral observations, the Autism Diagnostic Observation Schedule (ADOS) and clinical evaluation by specialists. These methods are, however, subjective, costly, time consuming, and sometimes not available in remote areas. With recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), automated systems have been developed to analyze behavioral, biological, textual, speech, facial, and neuroimaging data to accurately detect ASD.

Different ML algorithms including Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), Naïve Bayes (NB), and K-Nearest Neighbor (KNN) have been used for classification of ASD. Facial images, EEG signals, MRI scans, eye-tracking data, and social media text have also been used to predict ASD using deep learning techniques such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), BiLSTM, and transformer-based models.

The review paper gives an in-depth knowledge of various machine learning and deep learning algorithms applied for autism detection and their pros, cons, challenges and future scope.

2. Literature Review

The recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have revolutionized the Autism Spectrum Disorder (ASD) detection systems and diagnosis. Different methods based on behavioral data, EEG signals, facial images, MRI

scans, eye-tracking data and textual information have been studied to create accurate and intelligent autism prediction models. Important papers related to the detection of ASD with machine learning and deep learning approaches are presented in the following literature review.

2.1 Traditional Machine Learning-Based ASD Detection

Hossain et al. suggested machine learning algorithms to detect ASD in toddler, child, adolescent, and adult dataset. The authors used Support Vector Machine (SVM), Decision Tree, Random Forest and Naïve Bayes classifiers. Their results indicated that SVM gives the highest accuracy along with a lower classification error among all the classifiers. The study showed the necessity of Relief Attributes as a feature selection technique to find the important traits of autism. The work, however, concentrated on the structured questionnaire datasets and was not a multimodal data analysis. Haque et al. used the UCI child datasets and the Kaggle toddler datasets to investigate classical machine learning techniques such as Logistic Regression, SVM, KNN, and Decision Tree for ASD detection. Their study showed good results for traditional ML models having high precision and recall. The performance of the model, however, was not as good for real-world heterogeneous datasets, suggesting poor generalization ability.

Deep Learning-Based ASD Detection

In recent years, deep learning models are increasingly employed in the field of automated ASD diagnosis. CNN-based architectures are extensively used in various applications such as facial image analysis, MRI image classification and EEG signal processing. Recently, a research work has been performed to compare the deep learning frameworks like VGG16, VGG19, ResNet50, InceptionV3 and MobileNet for facial image-based autism detection. The system's classification accuracy and generalization ability were enhanced by the transfer learning and data augmentation methods. The transfer learning and data augmentation techniques enhanced the classification accuracy and generalization ability of the system. ResNet50 was the best-performing model for all image classification tasks related to ASD. But computational complexity and data constraints were still significant issues. Another review talked about the use of CNN, ResNet50, ANFIS, and deep neural networks for diagnosis of autism using EEG. The study highlighted that using EEG signal analysis with deep learning resulted in good classification accuracy of the autistic behavior patterns. But data preprocessing and noise removal of EEG data was still difficult tasks.

2.2 NLP and Social Media-Based ASD Detection

In recent years, Natural Language Processing (NLP) techniques have been developed as effective tools for ASD detection by analyzing text. Rubio-Martín et al. suggested an NLP-based ASD detection system based on social media text data from

Twitter. The authors employed machine learning and deep learning models such as Decision Trees, XGBoost, RNN, LSTM, BiLSTM, BERT and BERTweet for text classification. They used their framework to process over 400,000 tweets and were able to correctly identify ASD-related patterns with about 88% accuracy. The study showed that language models based on transformer architectures are effective for predicting ASD using textual behavior analysis. But there were language diversity, sarcasm detection, and privacy of the data issues.

2.3 Eye-Tracking and Behavioral Analysis

The eye-tracking technology has been a topic of interest for the diagnosis of ASD due to the fact that autistic children tend to exhibit different eye movements and facial attention behavior. Han et al. searched the literature for machine learning models using eye-tracking data for the autism diagnosis in children and adolescents. The pooled accuracy, sensitivity, and specificity of the ML-based eye-tracking systems were found to be around 85–86% and the Area Under Curve (AUC) was 0.92. The authors also noted the importance of participant age, type of visual stimuli, and the algorithms used for machine learning on system performance.

2.4 Explainable AI and AutoML in ASD Detection

There has been a recent interest in explainable AI (XAI) and automated machine learning methods for enhancing clinical reliability. Ehsan et al. introduced an AutoML-based ASD detection framework which automates feature selection, model optimization and classification processes.

Their study showed that they were more efficient in diagnosis and less human dependent. But the framework needed extensive clinical information to be robust and usable. Agrawal et al. discussed the explainable AI techniques for autism diagnosis and emphasized the significance of interpretable machine learning models in healthcare applications. The study highlighted the potential of explainable systems to enhance clinician trust, transparency, and capability in the diagnosis of ASD. Based on the reviewed studies, it is seen that machine learning and deep learning methods have performed well in the detection and classification of ASD. While

several models have been developed with high accuracy, there are still obstacles, including small datasets, lack of explainability, complexity, and poor generalization in real-world scenarios. Thus, future research is needed to develop multimodal, explainable and real-time ASD detection systems for practical healthcare applications.

3. Machine Learning Techniques Used for ASD Detection

Various Machine Learning (ML) and Deep Learning (DL) techniques have been applied for Autism Spectrum Disorder (ASD) detection and prediction. These methods are used to analyze behavioral, medical, textual, facial and neurological data, and detect patterns associated with autism with a high degree of accuracy. Traditional machine learning models are predominantly employed for structured data and questionnaires based screening, while deep learning models work well with image, EEG, speech and multimodal data analysis.

Table 1. Machine Learning Techniques Used for ASD Detection.

Algorithm	Application Area	Advantages	Limitations
Support Vector Machine (SVM)	Questionnaire Data, EEG	High accuracy and effective classification	Sensitive to parameter tuning
Random Forest	Behavioral and Clinical Data	Handles large feature sets and reduces overfitting	Complex model interpretation
Logistic Regression	ASD Screening	Simple, fast, and easy to implement	Limited nonlinear learning capability
Decision Tree	Behavioral Data Analysis	Easy visualization and interpretation	Prone to overfitting
K-Nearest Neighbor (KNN)	Screening Data Classification	Simple and effective for small datasets	High computation for large datasets
CNN	Facial Images and MRI	Automatic feature extraction and high accuracy	Requires large training datasets
LSTM/BiLSTM	Sequential Data and Text	Captures temporal dependencies effectively	High training time
BERT/BERTweet	NLP-based ASD Detection	Strong contextual understanding	Computationally expensive
AutoML	Automated Classification	Reduces manual model selection effort	Needs large datasets

Of these methods, SVM and Random Forest are popular methods for structured ASD screening datasets because of their simplicity and good classification accuracy. The recent success of deep learning models like CNN, LSTM, and transformer-based

models like BERT, which can automatically extract complex patterns from multimodal data sources like facial images, EEG signals, speech, and social media text, has made them a recent focus of attention.

4. Datasets Used in ASD Research

Different benchmark datasets are used by researchers for training and evaluating ASD detection systems. These datasets include questionnaire-based screening records, MRI brain scans, EEG signals, facial images, eye-tracking data, and textual information collected from online platforms. Publicly available datasets help researchers compare model performance and improve the accuracy of machine learning-based autism diagnosis systems.

Table 2. ASD Research Dataset.

Dataset Name	Data Type	Application
UCI ASD Screening Dataset	Questionnaire Data	Machine Learning Classification
Kaggle Toddler ASD Dataset	Behavioral Data	Early ASD Detection
ABIDE Dataset	MRI Brain Images	Neuroimaging Analysis
EEG ASD Dataset	EEG Signals	Brain Activity Analysis
Twitter ASD Dataset	Text Data	NLP-based ASD Detection
Eye-Tracking Dataset	Gaze and Visual Attention Data	Behavioral Analysis
Facial Image ASD Dataset	Facial Images	Image-based Autism Detection

Most widely used datasets for traditional machine learning models are UCI ASD Screening Dataset and Kaggle Toddler Dataset. Neuroimaging data like ABIDE is the most popular for deep learning analysis via MRI, and EEG data is used to investigate patterns of brain activity associated with autism. Social media and NLP-based datasets are also emerging as recent sources of behavioural and psychological insights into communication patterns related to ASD.

5. Research Gaps

Current Autism Spectrum Disorder (ASD) detection systems are built on small and greatly imbalanced datasets. In many cases, the number of autistic samples is far less than the number of non-autistic samples, thus impacting model training and classification performance. In the healthcare sector, the lack of data diversity can cause machine learning models to lack generalization capabilities. This restriction makes the prediction systems less

reliable and robust for different age groups, ethnicities and clinical conditions. In many studies that are already conducted, they have used data from a single modality, e.g., questionnaires, EEG data, MRI images or images of the face. Autism is a complex neurological condition, however, and has behavioral, cognitive, visual and communication-related symptoms. Single-modal systems may not be able to fully describe the nature of ASD. Limited studies exist on multimodal learning systems that integrate multiple data sources (text, speech, facial expression, EEG, eye-tracking and behavioral information) to enhance diagnostic accuracy and robustness.

The high computational requirement, large memory resources, and long training time are typical challenges for such advanced deep learning models like CNN, LSTM, transformer-based models, and ensemble learning methods. The models also require a large amount of annotated data to perform well. Therefore, the real-time implementation in a healthcare environment, mobile device or low resource clinical environment is challenging. The reduction of computational complexity with high accuracy is an important area of research. Majority of the AI-based ASD detection systems are black box systems, that is, clinicians and health care professionals cannot get a clear insight into how the model makes predictions. AI systems are not trustworthy and accepted in healthcare unless they are interpretable. Some research has been done on Explainable Artificial Intelligence (XAI) techniques like SHAP and LIME, but the explainability of autism diagnosis systems is still restricted. Practical clinical decision making needs more transparent and interpretable models.

Existing systems for ASD detection are primarily for offline analysis and laboratory evaluations. Very few studies are dedicated to real-time systems for autism detection and monitoring which can analyze behavioral or physiological data in normal environments. Real-time ASD screening systems, such as wearable devices, mobile apps, and intelligent healthcare platforms are still in their infancy and need more research and optimization. Currently, most existing models for autism detection are based on English-language data and data from specific populations. But, the way people behave, speak, express themselves and communicate differs from culture to culture and from place to place. There is a lack of research on multilingual and culturally adaptive ASD detection systems. Creating AI models that are applicable to all regions of the world and can be used in multiple languages and with different populations is still a significant research challenge.

6. Challenges in ASD Detection

A key challenge in the field of ASD detection research is the lack of good quality and

balanced datasets. Gathering clinical, behavioral and neurological data related to autism takes a great deal of time, skill and ethical approval. However, in many cases, the number of autistic samples in the datasets is not adequate, thus influencing the performance of the model and the classification bias. EEG signals, eye-tracking data, and behavioral observations can be contaminated with noise, artifacts, and variations due to environmental factors, sensor inaccuracies, and patient movement. The inconsistencies make the preprocessing and feature extraction more difficult. The broad range of autistic behaviors in individuals also makes accurate classification and generalizing models difficult.

The results of the various researchers are difficult to compare fairly due to the differences in the datasets they used, the preprocessing techniques, the evaluation metrics, and the feature extraction techniques. There is no standardised benchmark datasets and there is no unified evaluation protocol, which makes it difficult to reproduce and to advance the research of ASD detection. Personal data, like medical records, facial images, speech patterns, EEG signals, and behavioral data are frequently sensitive information used in ASD detection systems. One of the primary challenges in AI-driven healthcare systems is ensuring patient privacy and secure data sharing. Issues of informed consent, bias, and misuse of healthcare information should also be considered.

Deep learning architectures need high-performance hardware like GPUs, high-memory computing systems for training and deployment. This makes it more expensive to implement and makes it harder to use ASD detection systems in small clinics, rural health care centers and AI based models with high prediction accuracy, they do not explain the results. Healthcare professionals need systems that make predictions that are interpretable and that aid in medical decision making. Automated ASD diagnosis systems are less trusted due to lack of clinical interpretability.

7. Future Research Directions

Future ASD detection systems should emphasize multimodal learning approaches using multiple modalities like text, facial images, EEG signals, speech patterns, eye-tracking information and behavioral data. Using multiple modalities can help to increase the robustness, accuracy and reliability of the system by capturing multiple aspects of autistic behavior. The use of Explainable Artificial Intelligence (XAI) techniques in ASD diagnosis systems should be incorporated to enhance transparency and clinician trust. Technologies like SHAP, LIME, attention visualization, and interpretable neural networks can enhance the understanding of model decisions and aid in improved clinical decision making.

It is possible to use federated learning to train AI models together without sharing sensitive patient information among resource-poor settings. Many children with autism have mild and vague symptoms in the early stages, particularly in toddlers and young children. There is some overlap between behavioural problems and other developmental disorders, making misclassification possible. It is a clinical and technical challenge to detect ASD in the earliest developmental stages. While there are numerous clinical importance of the extracted features or classification multiple hospitals and healthcare institutions. This not only enhances privacy and security but also addresses ethical issues with centralized healthcare data storage and promotes model generalization. To realize this, lightweight and computationally efficient deep learning models are needed to be deployed on mobile devices, wearable systems, and low-resource healthcare environments in the future. Model compression, pruning, quantization, and edge AI methods can aid in real-time ASD screening applications. Transfer learning and self-supervised learning techniques can be used to boost the detection performance of ASD when clinical data is scarce. It is possible to leverage related domains to obtain useful features and alleviate the need for large annotated datasets using pre-trained deep learning models.

Creating smart mobile apps and web-based screening tools can enhance access and help with early diagnosis of autism in remote and underserved areas. These systems can enable parents, teachers, and healthcare workers to easily and efficiently conduct screening for ASD. Internet of Things (IoT) and wearable healthcare devices can facilitate real-time monitoring and observation of physiological and behavioral indicators of autism throughout the day. Smart sensors, wearable technology, and cloud-based healthcare systems can be combined to provide personalized and continuous monitoring of ASD in future detection systems.

8. CONCLUSION

ASD is a significant neurodevelopmental disorder that demands early and correct identification for effective intervention and treatment. In the field of improving the detection of ASD based on behavioral data, facial images, EEG signals, eye-tracking information, MRI scans, and textual data, machine learning and deep learning techniques have demonstrated great potential. For structured data, traditional machine learning models like SVM and Random Forest are effective classifiers, while deep learning models like CNN, LSTM, and transformer-based models excel in complex multimodal data analysis. While significant progress has been made, there are still challenges in terms of data availability, model interpretation, computational complexity, and deployment in real-world settings. Future

research needs to be directed towards explainable, multimodal, real-time AI systems that will help clinicians in the correct and easy diagnosis of autism.

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