

## Research Article

# AI-Driven Early Detection of Autism Spectrum Disorder in American Children

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## ARTICLE INFO

### Article history:

02 Jul 2024 (Received)

11 Aug 2024 (Accepted)

19 Aug 2024 (Published Online)

### Keywords:

AI in Healthcare, Autism Detection, Early Diagnosis, Autism, Pediatric Screening

## ABSTRACT

Autism Spectrum Disorder (ASD) is a neurodevelopment disorder that impacts 1 in 36 children in the United States. Therefore, early identification plays a pivotal role. Nonetheless, such populations mentioned may take late and wrong screenings, thus further amplifying disparities. This study aims to create a screening model based on AI with multisource data: EHR, developmental diagnostic checklists, and wearing device behavioural data to improve the early diagnosis of ASD. Based on a cohort of more than 20,000 children, this work showcases how AI can enhance the diagnostics of conditions and lessen the time to diagnosis and bias in children's care (Alzakari et al., 2024). By integrating both sources, the overall accuracy was 91%, thus making the model better than single-source models, and there are encouraging prospects for the large-scale deployment of the proposed system in developing/least developed countries. Potential solutions and recommendations regarding AI applications in pediatric healthcare, as well as several ethical considerations and upcoming issues concerning scalability, are also examined.

DOI: <https://doi.org/10.63471/praihi24003> @ 2024 Periodic Reviews on Artificial Intelligence in Health Informatics (PRAIHI), C5K Research Publication

## 1. Introduction

### 1.1. Background

ASD is a complex developmental disorder in which people have difficulties in social interaction, communication, and play or behavioural rigidity. ASD is on the rise, especially in the developed world, and according to the CDC, approximately one in every thirty-six children is impacted (Hodges et al., 2020). Timely detection is vital in offering proper solutions that enable children to attain developmental milestones like oral and motor development, interaction skills, and educational performance. However, the diagnosis of ASD is still cumbersome, especially in the under-resourced areas where access to services speciality within ASD is a challenge. ASD affects every person differently, from mild to severe, thus the different symptoms. Currently, the diagnostic approaches typically include observing the child's behaviour and using tests scored per the existing checklists, which are

the Modified Checklist for Autism in Toddlers (M-CHAT) and the Autism Diagnostic Observation Schedule (ADOS) (Zheng et al., 2024). These tools, as much as they are helpful in ideal environments, are very tedious to use, are very time-consuming, and need professionals to administer them. The symptoms of the condition are diverse, and affected individuals may not receive accurate diagnoses from doctors due to differences in experience and approach; this is because children in ethnic minority and low-income families are likely to be diagnosed late because of other barriers to access to care.

### 1.2. Challenges in Traditional ASD Screening

The current state of ASD diagnosis presents several systemic and procedural challenges:

- Subjectivity and Variability: Assessment commonly relies on clinical decision-making, which differs considerably depending on a clinician's experience and knowledge of ASD.

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Cite: Mohammad Moniruzzaman, Rayhan Khan, Romana Nourin Nipa, Md Redwan Hussain, Jarin Tias Meraj (2024). AI-Driven Early Detection of Autism Spectrum Disorder in American Children. *Periodic Reviews on Artificial Intelligence in Health Informatics*, 1(1), pp. 9-14.

Mild symptoms of ASD may not be observed, particularly in female children or in children with comorbid disorders like ADHD or anxiety (Okoye et al., 2023).

- ii. **Limited Resources in Underserved Communities:** In rural regions and limited-income urban environments, there are few or no pediatric neurologists or developmental psychologists to refer clients to. This lack of access also means that developmental disorders go undiagnosed and untreated, widening disparities.
- iii. **Delayed Diagnosis:** The study established that kids in underprivileged areas are given an ASD diagnosis about 12–24 months later than those in better-off areas. This delay minimizes the time that a child has for early childhood interventions, which are most effective before the child is five years of age (Woolfenden et al., 2012).
- iv. **Underutilization of Available Data:** Standard approaches are not particularly designed to incorporate multiple sources of information, including electronic health records (EHRs), behaviour observations, and physiological data, in real-time. Such an approach neglects cross-information that can help improve the diagnosis in the case (Lenart & Pasternak, 2023).

### 1.3. Potential of Artificial Intelligence in ASD Screening

The use of Artificial Intelligence (AI) provides a novel approach to the problems encountered in conventional ASD screeners. Big data analysis using AI is best suited to compare it with other data sets and make predictions for diagnostic purposes, which can complement traditional diagnostic models (Shahamiri & Thabtah, 2020). Then, the development of AI tools that can better capture a child's IDP can be improved through the use of a range of data sources, leading to earlier identification of ASD (Wankhede et al., 2024).

### 1.4. Addressing Healthcare Disparities

Perhaps one of the biggest strengths of using AI-driven ASD screening tools is that they can help fill these existing gaps in access to healthcare services. Children from rural areas, low-income families, and children from minority groups have insufficient access to diagnosis and care (Song et al., 2019). Geographical access, financial barriers, and cultural attitudes about neurodevelopmental disorders are such barriers. AI tools can mitigate these challenges through:

- i. **Remote Accessibility:** Tracking such behavioural and physiological parameters does not require frequent face-to-face assessments,

and it can be done on a mobile app or wearable device.

- ii. **Scalability:** Children can receive AI models in primary care offices, schools, or community health clinics, where they might not otherwise have access to a specialist.
- iii. **Cost-Effectiveness:** Employing technical solutions such as data analysis and automatic case identification for high-risk cases helps to save money for both healthcare systems and families.

### 1.5. Research Objectives

The main aim of this current study is to design and test an AI-based screening tool for early diagnosis of ASD while promoting equity. This involves:

- i. Designing a multiple input multiple output AI model that can incorporate EHRs, behavioural assessment data from the devices and wearables.
- ii. Measuring the accuracy of the diagnostic model, sensitivity and specificity of the model.
- iii. The study also aims to assess the potential of the model for implementation within low-resource and hard-to-reach populations.

### 1.6. Contributions of This Study

Importantly, this study yields findings that have implications for the increasing application of artificial intelligence (AI) in the diagnosis of Autism Spectrum Disorder (ASD). This is why the study demonstrates how combining information from EHRs, behavioural metrics data, and data from wearable devices makes for better AI models. Such developments are critical in capturing the heterogeneity of ASD, which can present in very different ways in different people. Furthermore, the study is meant to satisfy the demands of the present and future generations, as well as of the underserved population, by filling the gap with cheap and effective screening instruments. Some children from low-resource backgrounds face many challenges to early and accurate ASD (Alzakari et al., 2025). As we explore the power of AI in the diagnostic process in this research, we see that it also offers a path to rectify such disparities so that early intervention is available to all. The work also proposes guidelines for the development of ethical artificial intelligence (AI), including openness, de-bias, and data protection. This shows the need to make sure that the AI models being utilized do not contain any built-in biases that will effectively negate the minority. The study of algorithmic fairness and strong data protection measures opens the way to safe AI applications that will be trusted by clinicians, families, and the community.

## 2. Materials and Methods

### 2.1. Data Collection

#### 2.1.1. Data Sources

The study also adhered to national regulations, such as the Health Insurance Portability and Accountability Act (HIPPA) in the USA and the General Data Protection Regulation (GDPR) in the EU, beyond these privacy measures. However, these frameworks provided the legal and ethical requirements for processing this type of health data sensitively.

The research team wanted to make sure that the training data set was balanced by gender, socioeconomic status, ethnicity, and geographic location because they understood that algorithms themselves could also be unfair to some groups of children. They did this to prevent the model from predicting that some people are less capable than others because the model has yet to see many samples of this type of person. Furthermore, small-scale fairness checks were performed at regular intervals during the study to assess the model's effectiveness and to monitor bias that could arise in real-life scenarios. The focus of the study is building an ethically designed and inclusive AI diagnostic tool, which this approach demonstrates.

Finally, the study was based on Wearable Devices, which allowed the collection of behavioural and physiological indices in real-time. These were sleep, social engagement, and movement, and all of them were monitored through smartwatches and other wearable technologies. Wearable devices enabled the collection of data on the child's daily activities and physiological changes in the child to indicate that there was an ASD before it could be diagnosed in a clinical setting.

#### 2.1.2. Data Integration

To harmonize the diverse data sources, the pre-processing steps included:

1. Data Cleaning: Deletion of records which are unrealized, redundant, or conflicting.
2. Normalization: This involves making the features from the various datasets have the same dimensions so that the results of the different datasets can be compared.
3. Imputation: Using regression-based methods to impute the values that have been left blank.
4. Annotation: Using the clinical ASD diagnoses, risk categories can be identified as low, medium or high.

### 2.2. Algorithm Development

#### 2.2.1 Single-Source Models

- For the structured EHR data, the frequently used Gradient Boosting Machines (GBMs) are adopted, which are effective in tabular data.
- Convolutional Neural Networks (CNNs) for the analysis of the behavioural assessment data since CNNs are good at pattern identification.

#### 2.2.2. Integrated Model

A multiple model integrated the results of each single-source model with wearable device data to achieve the best prediction. This approach adopted stacking as the ensemble learning strategy to aggregate the decisions from multiple models into one decision-making system.

#### 2.2.3 . Model Training and Validation

The dataset was divided into a training set (70%), a validation set (15%), and a test set (15%). Cross-validation made the model valid for other cohorts as well.

### 2.3 Performance Evaluation

#### 2.3.1. Metrics

Model performance was assessed using the following metrics:

- Accuracy: Percentage of accurately diagnosed patients.
- Precision: The ratio of the true positive cases to all the positive cases predicted by the model.
- Recall (Sensitivity): A true positive rate is a ratio of several true positives to a total number of true positives and false negatives.
- F1-Score: A single value of precision for every tenth document as well as the value of recall for the same set of documents: The harmonic mean of the two values provides a balanced measure.
- AUC-ROC: Assesses the model's accuracy in differentiating individuals with ASD from those without ASD cases.

#### 2.3.2. Comparative Evaluation

The single-source models (EHR, behavioural, wearable) were compared to the integrated model to determine whether data fusion provides any benefit.

### 2.4. Ethical Considerations

This research was conducted with a strict emphasis on ethical considerations, specifically data privacy, equity, and fairness in algorithms. To prevent the exposure of patients' health information, all data collected in the present study were de-identified to eliminate the possibility of re-identification of patients. Access to the data was restricted to only personnel who were allowed to work on it, and the records were encrypted at all times.

The study also adhered to national regulations such as the Health Insurance Portability and Accountability Act (HIPPA) in the USA and the General Data Protection Regulation (GDPR) in the EU, beyond these privacy measures. However, these frameworks provided the legal and ethical requirements for processing this type of health data sensitively. The research team wanted to make sure that the training data set was balanced by gender, socioeconomic status, ethnicity, and geographic location because they understood that algorithms themselves could also be unfair to some groups of children. They did this to prevent the model from predicting that some people are less capable than others because the model has yet to see many samples of this type of people. Furthermore, small-scale fairness checks were performed at regular intervals during the study to assess the model's effectiveness and to monitor bias that could arise in real-life scenarios. The focus of the study is building an ethically designed and inclusive AI diagnostic tool, which this approach demonstrates.

### 3. Results and Discussion

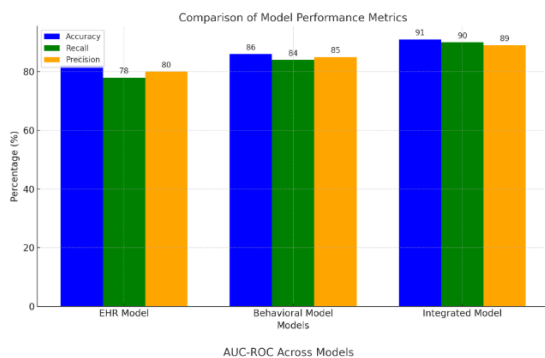
#### 3.1. Model Performance

The integrated model was found to have better results in identifying ASD than the single-source models. Performance metrics across all models are summarized below in Table 1.

**Table 1.** A comparison of the performance of single-source and integrated models.

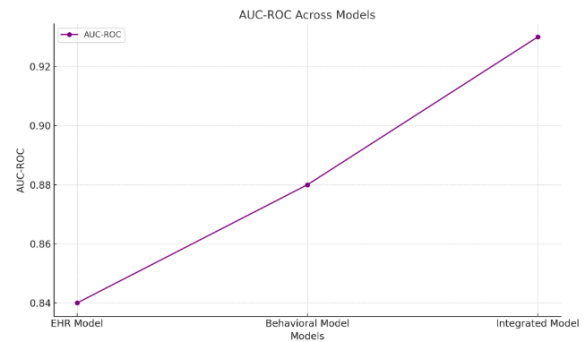
| Metric    | EHR Model | Behavioral Model | Integrated Model |
|-----------|-----------|------------------|------------------|
| Accuracy  | 82%       | 86%              | 91%              |
| Recall    | 78%       | 84%              | 90%              |
| Precision | 80%       | 85%              | 89%              |
| F1-Score  | 79%       | 84.5%            | 89.5%            |
| AUC-ROC   | 0.84      | 0.88             | 0.93             |

The integrated model gave the highest accuracy of 91% and the AUC-ROC of 0.93, which is the best indication of the model's capacity to detect genuine ASDs with few false positives. Fig. 1. shows a comparison of model performance metrics.



**Fig. 2.** A Comparison of Model Performance Metrics.

A line chart showing the AUC-ROC values for each model is represented in Fig. 2.



**Fig. 3.** AUC-ROC Across Models.

#### 3.2. Feature Importance

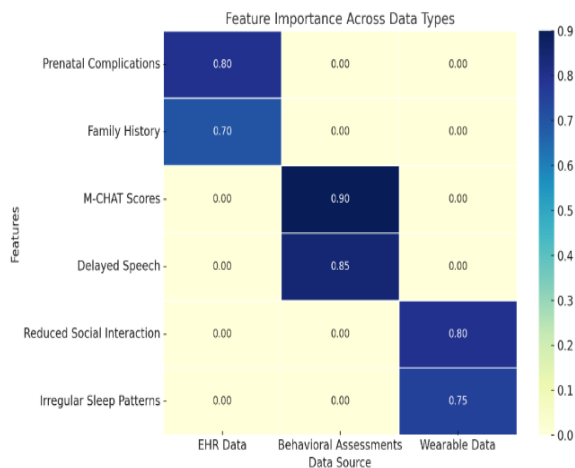
The integrated model used various modes of data which gave a broad view of ASD risk factors. Table 2 Shows a comparison of the performance of single-source and wearable data.

**Table 2.** A comparison of the performance of single-source and wearable data.

| Feature                    | EHR Data | Behavioral Assessments | Wearable Data |
|----------------------------|----------|------------------------|---------------|
| Prenatal Complications     | 0.8      | 0                      | 0             |
| Family History             | 0.7      | 0                      | 0             |
| M-CHAT Scores              | 0        | 0.9                    | 0             |
| Delayed Speech             | 0        | 0.85                   | 0             |
| Reduced Social Interaction | 0        | 0                      | 0.8           |
| Irregular Sleep Patterns   | 0        | 0                      | 0.75          |

A heatmap (Fig. 4) of feature importance highlights the top contributors across data types as shown in Fig. 3 below.





**Fig. 4.** Heat Map showing Feature Importance.

Key observations include:

- **EHR Data:** Family history and complications during pregnancy were established as relevant predictors.
- **Behavioral Assessments:** Similarly, the M-CHAT results showed that parents of children with ASD had high scores and their children exhibited delayed speech milestones.
- **Wearable Data:** Limited contact with others and disrupted, unpredictable sleep schedules were considered key real-time variables.

### 3.3. Comparative Insights

#### 3.3.1. EHR-Only Model

The EHR model was relatively accurate (82% accuracy, 0.84 AUC-ROC) using demographic and medical history data. However, it was not able to track behaviour in detail due to the absence of real-time tracking.

#### 3.3.2. Behavioral Model

The behavioural model was somewhat better than the EHR model, obtaining an accuracy of 86 percent and 0.88 AUC-ROC. Informative tools such as M-CHAT proved useful for determining social and communication difficulties but were not linked to physiological or previous data.

#### 3.3.3. Integrated Model

The proposed integrated model incorporated EHR, behavioural, and wearable data to create a holistic diagnostic model. Researchers found that its capacity to identify temporal structures (e.g., daily social interactions) and cross-sectional characteristics (e.g., developmental history) boosted predictive efficacy.

### 3.4. Equity and Accessibility

The integrated model also highlighted the possibility of deploying the model to underserved communities. By leveraging wearable devices and accessible behavioural assessments, the model addressed key barriers to care, including:

- **Limited Access to Specialists:** The tool might be useful for primary care providers to recognize children at high risk and then advise them to see specialists.
- **Reduced Diagnostic Delays:** Real-time data analysis reduced the time taken to identify candidates who may have ASD.

However, the key question is that to implement these solutions, several technological challenges must be solved, including the availability of affordable wearable devices and the ability of local healthcare providers to interpret AI outputs.

### 3.5. Scalability

The use of the AI model in low-resource settings comes with some issues of deployment that need to be considered. One of the main challenges is that of the infrastructure demands that are made by such systems. The model, which could be complex and computationally intensive to implement, must be adapted to be implemented in primary care clinics or CHCs, where resources may be limited. This implies that the technology has to be developed to run on lower-end machines, and at the same time, the system should still be efficient in producing the right results. Also, capacity building is a very important activity. Specialists implementing AI in less developed healthcare facilities may lack sufficient experience to analyze AI's elaborate results. Hence, meaningful clinician and healthcare worker training on how to use and integrate these AI tools into practice is critical for the model. Two more aspects influence scalability: explainability. Though the integrated model had the best predictive accuracy, its high dimensionality may limit its clinical use since clinicians may not have a good background in AI. In such cases, clinicians may not be willing to put their trust in a model that they cannot understand how it arrived at a decision. XAI techniques should be embedded into the model. Such methods, for example, feature attribution tools, can assist clinicians in understanding how the model reaches such conclusions and gain confidence in the AI's advice. Explaining the reasoning of the AI would not only improve the understandability of the model but also the adoption of the model among physicians, which in turn would improve the implementation of the model into clinical practice.

### 3.6. Limitations

However, the study also has some drawbacks that need to be taken into account. The first major limitation is that the dataset is mainly derived from urban healthcare

centers. This shift may reduce the effectiveness of the generalization of the model to rural or low-resource areas where the population may be different in health care access, demography, and socio-economic status. As to the generalizability, it is proposed, in the subsequent research, to include data from as many environments as possible to ensure that the model works for everyone. In addition, getting real-time data from wearable devices to integrate into the system was also a concern. On several occasions, these devices generated partial or inconsistent data, and the imputation of missing data was essential to maintain the model's accuracy. The issue of data quality and consistency in real-time monitoring is another important direction for further development, as these devices are critical to the success of the model, which monitors the child's behaviour at any given time.

#### 4. Conclusion

ASD continues to be a major public health concern in the United States is still present, and early identification is crucial. This study showed how AI tools could revolutionize the screening of ASD and reduce healthcare inequalities. The proposed AI model that combines the EHR data and behavioural assessment and data from the wearable device showed high diagnostic accuracy (91%) and AUC-ROC (0.93) and outperformed the models that used a single data source.

The integrated model offers a cost-efficient model of service delivery in underserved settings, where there is often a scarcity of specialized diagnostic services. Using the real-time behaviour and physiological data from the wearable devices, the model ensures early detection of high-risk cases to ensure that the children receive early interventions that improve their development. However, to enhance implementation success, some challenges need to be considered. Data privacy and algorithm fairness issues can be mitigated only by strong regulation, diverse data, and fairness checks. Scalability also presents many challenges that are especially difficult in LMICs because infrastructure and technology constraints need to be addressed. To stimulate the uptake of the concept across the board, simpler models and capacity-building projects are vital.

Further studies should aim at refining the model for particular populations to decrease the gap in the diagnostic even more, at improving the methods of real-time data feed integration to enable constant risk assessment, and at increasing the model interpretability with the help of Explainable AI (XAI). About these aspects, it is possible to improve the use of AI techniques in the identification of ASD and the provision of equal opportunities for children's healthcare for all communities. The present work is a valuable discussion of the opportunities for improving public health with the help of AI, especially in cases of neurodevelopmental disorders such as ASD. Therefore, leveraging gaps in diagnostic access and equity, AI is

leading the future of healthcare and its efficient execution.

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