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Autism Spectrum Disorder Screening Through Behavioral Gaze Trajectories and Electroencephalography Signal Classification

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ABSTRACT

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that needs accurate early screening for early intervention. Early diagnosis is crucial for infants when their neuroplasticity allows treatment that could effectively hinder long-term developmental outcomes. Indeed, traditional methods are employed such as the Modified Checklist for Autism in Toddlers (M-CHAT), Autism Diagnostic Interview-Revised (ADI-R), and Autism Diagnostic Observation Schedule (ADOS). Yet, these approaches are subjective, which makes them susceptible to bias and misdiagnosis. Therefore, this research aims to identify an objective and accurate non-invasive biomarker for early diagnosis of ASD.

Firstly, a machine learning system that analyses Electroencephalography (EEG) signals and outputs binary classification results will be used. This system was developed using EEG Representation learning and an EEG feature extractor that extracts unique and relevant features of EEG signals. In addition, Gaze trajectories, which detect the patient's eye movements, were used. A gaze estimation network was created by obtaining yaw and pitch angles and using eye-tracking technology.

Our proposed system for EEG-based classification recorded an accuracy of 98.29%, sensitivity of 98.29%, precision of 98.34%, and F1-score of 98.32%. This was significantly higher than the baseline CNN model, which achieved 94.54% accuracy, supporting the effectiveness of the proposed system. In addition, the gaze-based classifier achieved 99% classification accuracy.

These findings indicate that EEG representation learning and gaze trajectory analysis provide an accurate and objective approach for ASD screening. The system minimizes subjectivity while allowing rapid binary classification for early diagnosis. This shows strong potential for clinical application in ASD detection by integrating biomarkers.

INTRODUCTION

For the past years, Autism Spectrum Disorder (ASD) has increasingly become a prevalent illness for children(Shaw, 2025). Because it is a disorder that affects a child's future human interaction, communication skills, and social behavior, it is important for ASD to be diagnosed before 2 years of age for treatment to be effective(Zwaigenbaum et al., 2015). Detecting ASD symptoms early may allow more effective and timely intervention, as the brain is most malleable in the first two years of life (Okoye et al., 2023). Moreover, social skills and language abilities develop most rapidly during this period, meaning quick intervention could reduce learning gaps between ASD and normal children(Abualait et al., 2024).

There have been past approaches on the diagnosis of ASD, including Modified Checklist for Autism in Toddlers (M-CHAT) (Dumont‐Mathieu and Fein, 2005), Autism Diagnostic Observation Schedule (ADOS) (Kamp-Becker et al., 2018), and Autism Diagnostic Interview (ADI-R) (Lord et al., 1993). M-CHAT is a set of 20 questions answered by parents based on their child's behavior used to detect common ASD symptoms (Dumont‐Mathieu and Fein, 2005). ADOS is an observation completed by a specialist on paying attention to the child's behavior in a real-world setting (Kamp-Becker et al., 2018). ADI-R is an interview conducted between a specialist and a parent, asking about what the parent has observed from their own child; the results for the diagnosis would be calculated as a number from 0-3, the highest number indicating the severity of ASD (Lord et al., 1993). Nevertheless, traditional methods of ASD diagnosis have had different limitations. These methods can require substantial time for administration and scoring, potentially delaying the completion of the diagnostic assessment. The methods were also not objective as evaluations were conducted by specific individuals, inducing possible bias. Therefore, past diagnoses of ASD lacked efficiency and accuracy.

To address the aforementioned limitations of traditional methods, we propose an alternative approach: a machine learning-based system that processes Electroencephalography (EEG) signals and gaze trajectory analysis. The proposed EEG-based ASD classification system consists of two phases: EEG representation learning and transfer learning for ASD classification. EEG representation learning focuses on extracting robust features from sampled EEG data. To enhance the diagnosis efficiency, we also introduce a gaze trajectory analysis system to detect distinct gaze patterns in ASD patients by extracting yaw and pitch values to train the machine learning model.

METHODS

EEG Signal Classification

In EEG signal classification, the first step is to obtain samples from the patient's EEG signals. It is important to ensure that all samples taken from the EEG data are similar, as it is from one single patient. A sample should be taken from the EEG data because the entire data would be too large for the Convolutional Neural Network (CNN) to process. All the EEG data used in this process were taken from the AI Hub dataset. Only the EEG data of normal and ASD patients were utilised in training the model.

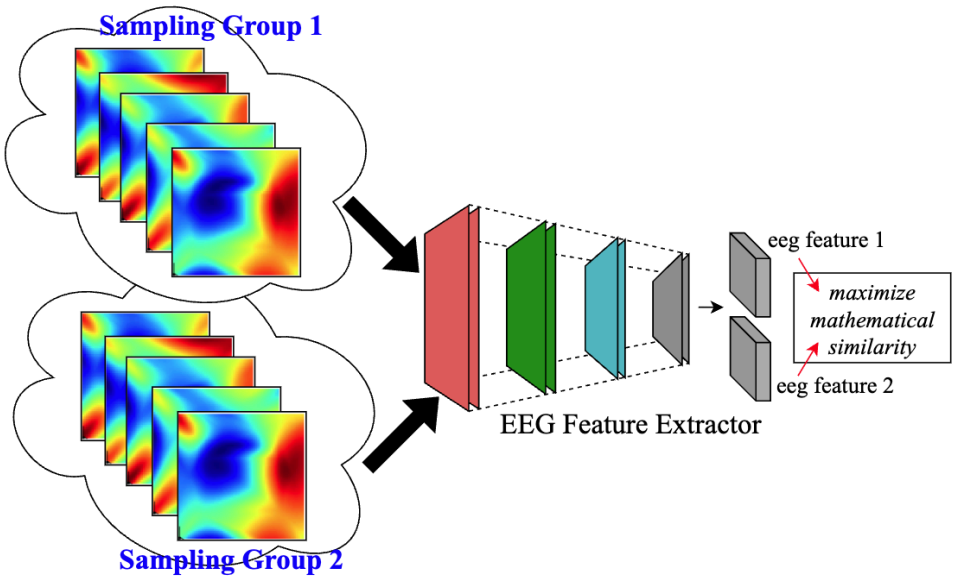


Figure 2. Network architecture of the proposed EEG representation learning

In the EEG signal classification experiment, the independent variable was whether representation learning and similarity function-based sampling were performed. This independent variable was established to compare the dependent variables of accuracy, precision, sensitivity, precision, and F1-score. We first trained the system to ensure that any two samples taken from one patient are similar to one another. This process of training the system was done using a PyTorch library. To train the system, two sampling groups were chosen: Sampling Group 1 and Sampling Group 2. The similarity between the two groups can be determined by using a vector similarity function which produces a numerical value. The numerical value of 1 would indicate that the vectors are identical. A value of -1 would mean that the vectors are opposite. 0 shows the vectors are perpendicular to one another. Assuming that one vector has the coordinate A and another vector has the coordinate B, and i represents the number of pairs the function handles, the similarity is calculated by dividing the dot product by the norm as illustrated in Equation 1.

Subsequently, the similarity score is converted into a probability using the Softmax function. The exponential notation in the Softmax function is used to ensure that even negative similarity values can be converted into a positive value. This process is illustrated in Equation 2. The resulting calculation from the Softmax function can be input into the Cross-entropy loss function to be able to identify how accurately the system obtains consistent results. In a Cross-entropy loss function, the result from the Softmax function becomes the input P and is substituted into the equation -ln P to maximize the loss.

Equation 1: Similarity function

$$Similarity_{A,B} = \frac{\sum_i A_i \times B_i}{\sqrt{\sum_i (A_i)^2} \times \sqrt{\sum_i (B_i)^2}}$$

Equation 2: Softmax function

$$P^A = \frac{e^{Similarity_{A,B}}}{\sum_{i \neq A} e^{Similarity_{A,i}}}$$

Equation 3: Cross-entropy loss function

$$L_{FEAT} = -log_e(P)$$

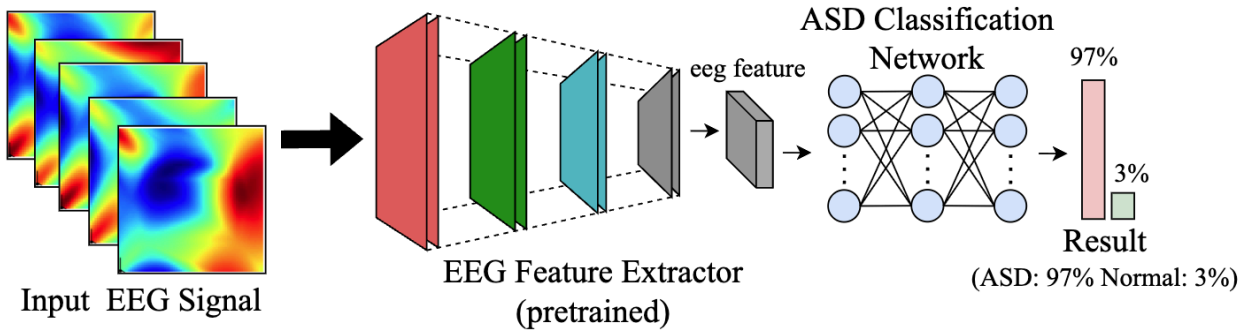


Figure 3. Network architecture of the proposed ASD classifier

The ASD classifier undertakes a number of processes. Firstly, EEG signals from the patient are obtained. The EEG Features Extractor that has been pretrained by using a number of sampling groups is used to output a feature. This feature contains only the relevant parts of the EEG signal that contribute to detecting the presence of ASD. The EEG feature that has been extracted enters the ASD classification network. This network is a two-layer Convolutional Neural Network which classifies the feature into either of the two categories: ASD or Normal. The system outputs the classification result, also providing a numeric probability on the presence of ASD.

Equation 4: Binary cross entropy loss function

$$L_{ASD} = -(y \times log_e(p) + (1 - y) \times log_e(1 - p))$$

Equation 4 is used to measure the performance of the ASD classifier and further improve it by minimizing the error. The variable y represents the actual status of the patient (0 is Normal, 1 is ASD) while variable p represents the probability previously calculated by the ASD classifier. During supervised training, if the ground-truth label indicates ASD, y=1 is used in the loss function; this label is used only to calculate training loss and is not provided to the model as an input feature. Conversely, if the ground-truth label indicates a neurotypical individual, y=0 is used in the loss function. Overall, the Binary cross entropy loss function uses either 0 or 1 to determine how much the prediction deviates from the actual diagnosis. Continuation of the process trains the neural network to minimise loss and produce a more accurate result.

Behavioral Gaze Trajectories Analysis

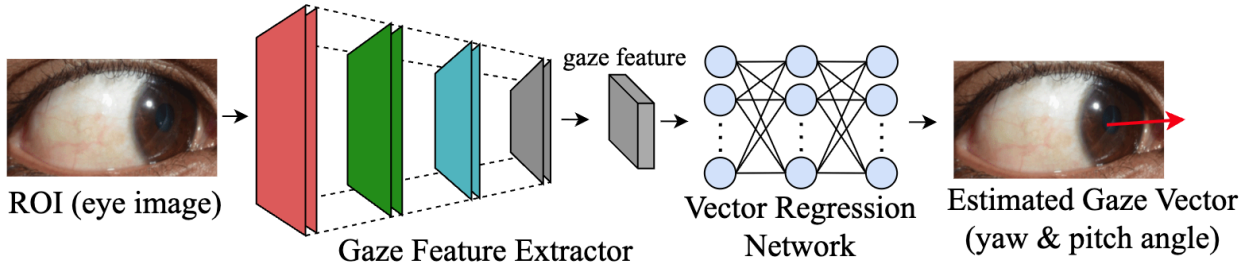


Figure 4. Network architecture of the proposed gaze estimation network

The second part of the experiment utilizes gaze tracking, which is the analysis of eye movement, as a biomarker for ASD diagnosis. The system involves the input of an eye image (Region of Interest). Then, a Gaze Feature Extractor is used to extract relevant features of the eye that could be used to identify important gaze characteristics from the image. The resulting gaze feature is then transferred to the Vector Regression Network, which analyses the feature to estimate yaw, the horizontal angular direction of gaze (left-right), and pitch, the vertical angular direction of gaze (up-down). The final output is the estimated gaze vector which shows the direction of the gaze in terms of yaw and pitch angles. The independent variable in this study was whether the vector regression network for extracting yaw and pitch angles and the gaze feature extractor were implemented for ASD screening. The dependent variables were true positives and false positives to compare the accuracy of the gaze estimation network.

Equation 5: Gaze loss function

$$L_{GAZE} = |yaw - \widehat{yaw}| + |pitch - \widehat{pitch}|$$

The Vector Regression Network is optimized using a Gaze loss function. To improve the model's accuracy, the function compares predicted values against actual data. The actual values of the yaw and pitch are given, and numerical calculations allow us to perceive how accurate the network is. The difference between the actual yaw and the yaw calculated by the Vector Regression Network is calculated, then put in an absolute form. Similarly, the difference between the actual pitch and the pitch calculated by the Vector Regression Network is put in an absolute form. Two absolute values are added together to calculate the total loss of the network.

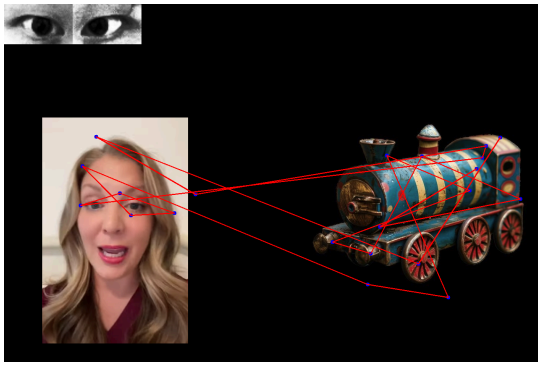


Figure 5. Gaze trajectory example

To test the effectiveness of the model, we conducted an experiment on 12 participants: 6 ASD patients and 6 neurotypical individuals. A computer was used for each trial, and each subject was instructed to look at a computer screen. On one side of the screen, a video of a talking person was played while geometric shapes like train images often preferred by ASD patients, were placed intermittently on the opposite side. A gaze tracking technology created by OpenCV was used to track the subject's eye movement throughout the experiment. The gaze estimation network created previously was then used to gather the gaze trajectories of each subject. This experiment confirmed that gaze trajectory is a distinguishing factor of ASD patients.

Dataset

The data for the meta-analysis were drawn from the Pediatric EEG data released by AI-Hub (AI Hub 2025), which is managed by the Ministry of Science and ICT. The data included a total of 1500 brainwave data sets that consist of 750 EEG data sets from clinical information data and 750 EEG data sets among three groups: normal, ADHD, and ASD. The data is composed of 33.33% normal, 33.33% ADHD, and 33.33% ASD individuals. 40.27% of the data was drawn from infants and toddlers (under 7 years old), 32.93% of the data was drawn from school-age (7-12 years old), and 26.80% was drawn from youth (13-18 years old). During our research, we only utilised the EEG data of normal and ASD individuals.

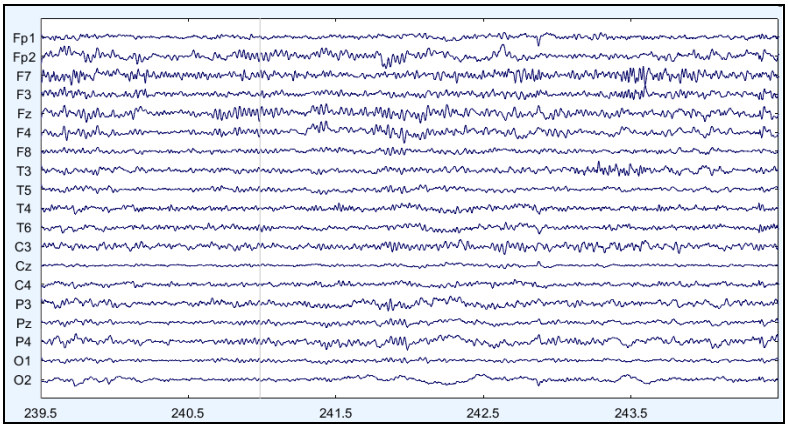


Figure 6. EEG sample (AI Hub 2025)

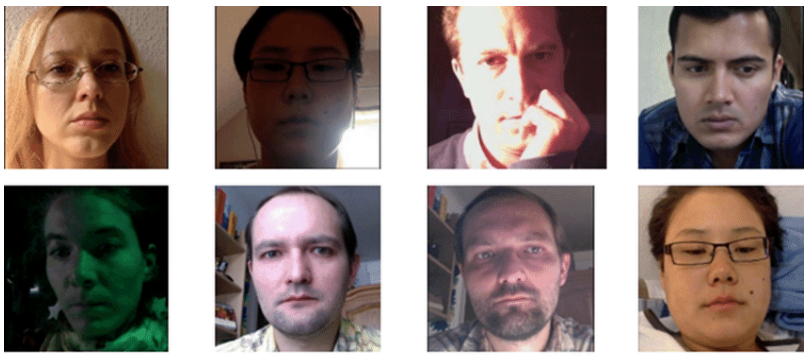


Figure 7. MPII gaze dataset (Zhang et al., 2017)

The data for the Gaze Estimation Network was derived from the MPII Gaze Dataset (Zhang et al., 2017) published by the Max Planck Institute for Informatics. This dataset contains 213,659 full-face images that were collected over 3 months. The images were based on 15 different participants. The images of the participants vary by race, gender, lighting conditions, and daily environments, which considers real-world variability. This variance in the dataset extends the AI application to gaze trajectory analysis, as it allows the model to conclude with generalized outcomes across the population. In terms of gaze analysis, the dataset is gauged with yaw and pitch analysis of the eye movement that corresponds to horizontal and vertical measures of the eye's angle, respectively.

RESULTS

Evaluation Metric

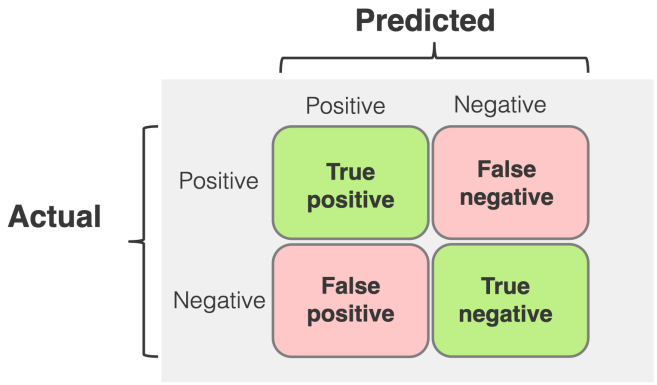


Figure 8. Confusion matrix (Evidently AI 2025)

Accuracy refers to the proportion of correct predictions (both positive and negative) out of all proportions. The numerator has the sum of all correct predictions, while the denominator consists of the total number of predictions involving correct and incorrect results. This measures the correctness of the model.

Precision is the proportion of true positive predictions out of all of the positive predictions made by the model. High precision would mean that there are fewer false positives. Low precision would mean a higher number of false positives.

Recall is the proportion of actual positives that are correctly identified. The denominator calculates the number of data that are actually positives, and the numerator shows the number of positives that were correctly predicted. High recall would indicate that there are few false negatives. Low recall means there are high false negatives.

F1-Score is used when we need one metric to balance precision and recall. The two metrics are in an inverse relationship as precision is affected by false positives while recall is affected by false negatives. The F1-score is derived from the harmonic mean of precision and recall.

Performance Comparison

EEG-based ASD Classification

Method	EEG Representation	Accuracy	Sensitivity	Precision	F1-Score
Baseline	X	94.54	93.87	94.14	94.01
Proposed System	O	98.29	98.29	98.34	98.32

Table 1: Ablation study result

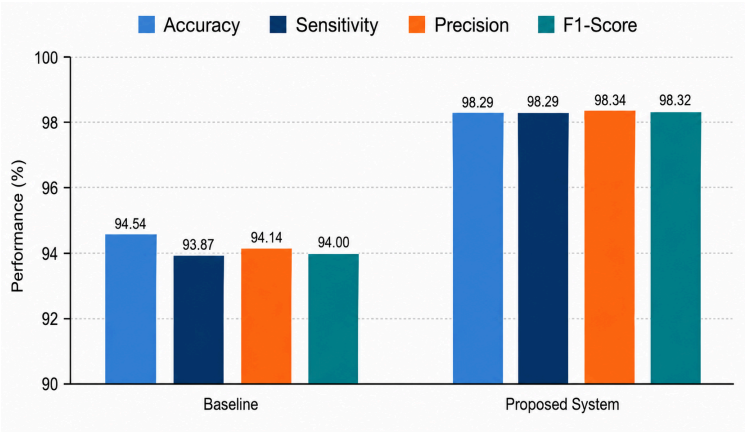


Figure 9. Ablation study result

To assess the performance of the proposed method, an ablation study was conducted. Two models were trained. The first was trained using the original CNN method, serving as the baseline, and the second was trained using the proposed EEG representation learning approach. We then compared four evaluation metrics, as described in Section 4.2. Table 1 and Figure 9 summarize the comparison results. The experimental results reveal a significantly higher performance of the proposed method compared to that of the baseline.

The baseline model scored an accuracy of 94.54%, sensitivity of 93.87%, precision of 94.14%, and F1-Score of 94.01%. In contrast, the proposed method which utilized EEG representation learning and similarity-based sampling demonstrated higher performance with an accuracy of 98.29%, sensitivity of 98.29%, precision of 98.34%, and F1-Score of 98.32%. These results suggest that the proposed method enhances the model's ability to accurately diagnose ASD and achieve higher sensitivity and precision. The improved performance is largely due to the utilization of EEG Representation learning, which was used to extract relevant robust features from the EEG samples.

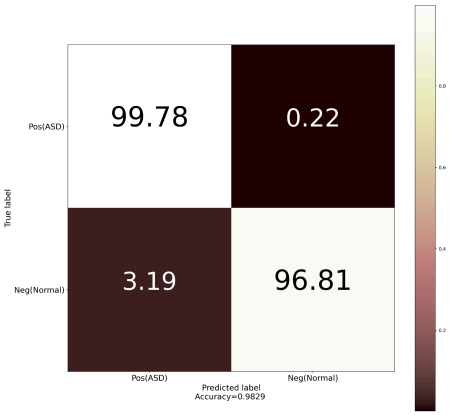


Figure 10. Confusion matrix for the proposed method.

The proposed method achieved a true positive rate of 99.78% and a true negative rate of 96.81%, demonstrating accurate performance. However, the method recorded a false positive rate of 3.19%, incorrectly classifying some normal cases as ASD cases. This limitation can be addressed by incorporating a larger sample size to train the model in future studies.

Gaze-based ASD Classification

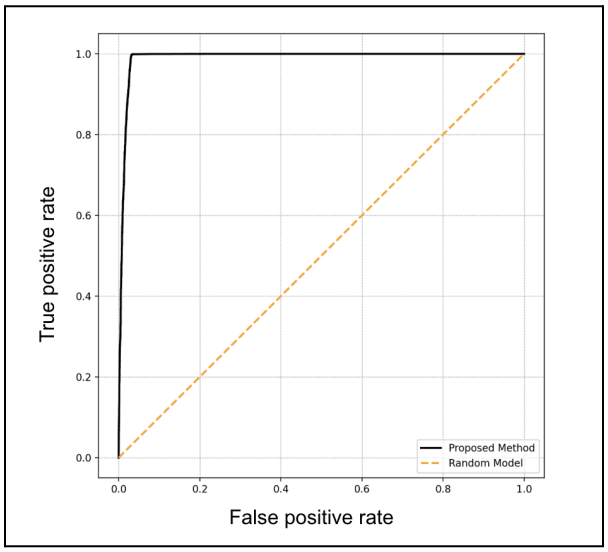


Figure 11. ROC curve of the proposed method

Figure 11 presents the ROC (Receiver Operating Characteristic) curve for the proposed gaze-based ASD classification system. The gaze estimation network was previously trained using data from 12 individuals as stated in the methodology. The trained model was tested on a separate group of 6 individuals' videos accessed from a public dataset in order to assess the performance of the model. The video data comprised 3 ASD and 3 neurotypical individuals. As shown in Figure 11, the proposed method (solid black line) achieved a nearly perfect performance, as it showed a true positive rate of 1.0 and a low false positive rate, yielding an area under the curve (AUC) close to 1.0. To illustrate the effectiveness of the proposed method, a random model was used in comparison (orange dashed line). The random model yields an AUC of approximately 0.5, significantly lower than that of the proposed method. This significant difference demonstrated the feasibility of using the gaze-based ASD classification system for early autism diagnosis.

Discussion

The results of our research indicate that Electroencephalography (EEG) representation learning and behavioral gaze trajectory would offer a highly accurate and objective model of Autism Spectrum Disorder (ASD) screening. The proposed EEG-based classifier had 98.29% accuracy which was much higher than the accuracy of 94.54% of the supervised baseline, and the gaze-based classifier had an accuracy of 99% with an almost perfect ROC curve. The improvement of the performance in the ablation

study shows that the EEG representation learning is successful in extracting the required feature of sampled brain wave signals, which confirms the hypothesis that abnormal neural connectivity patterns in ASD cases are effective biomarkers.

The accuracy of EEG-based representation learning supports the previous studies showing that the EEG coherence and connectivity was altered in people with ASD, especially in the frontal and temporal areas (Hankus et al., 2025). These studies are consistent with the current findings, which also indicate that representation learning improves stability and generalization in contrast to traditional supervised training. The accuracy obtained in this study is more consistent and has much higher accuracy compared to the earlier published EEG-based ASD classification studies that reported the accuracy between 63% and 95%. This enhancement could be due to balanced data composition, the application of similarity function between sampling groups as well as the application of the representation learning.

The findings of the gaze trajectory analysis are also aligned with other existing research that has shown that face fixations of the eyes and attention to geometric images are lower in children with ASD (Jones and Klin, 2013). This strong ROC performance in this study suggests that gaze trajectory representations capture meaningful behavioral patterns on ASD patients consistent with prior findings. The proposed framework provides binary classification in a relatively short period of time, in comparison with the usual diagnostic tools like ADI-R, which requires extensive clinician training and time-intensive behavioral evaluation (Lord et al., 1993).

Despite promising results, there are a number of limitations and possible sources of error that need to be taken into consideration. The false positive rate of the EEG-based classifier was 3.19% and this can be attributed to leftover EEG artifacts that might arise like motion or muscle movement. Neural feature consistency might have been also affected by developmental variations in age groups. Also, the gaze-based classifier presented a high level of performance, but the sample of participants was rather limited, raising concerns about limited generalizability. Additionally, the lighting conditions, head motion and the calibration precision may also create an uncontrolled variability during gaze recording and this indicates that larger datasets and standardized protocols are required when testing. Machine-learning-based screening also carries risks of false classifications, dataset bias, and reduced consideration of the broader clinical context; therefore, such systems should support rather than replace evaluation by trained clinicians.

Further research is needed to not only increase the database used but also to direct the experiment on infants aged 6-24 months to be more consistent with the objective of early diagnosis, as well as improving the model to minimize false positives and to test the system in a more varied population to improve its generalizability and clinical applicability. The explainability methods of AI can enhance clinical interpretability as well, since it can determine which neural or gaze features have the strongest effect on classification decisions.

CONCLUSION

This paper proposed a new machine learning-based method to screen Autism Spectrum Disorder (ASD) at an early stage by combining Electroencephalography (EEG) signal classification and gaze trajectory analysis. The suggested system overcame the constraints of the conventional approaches to ASD diagnosis, subjectivity and slow feedback, and used strong feature extraction of EEG data and specific gaze patterns as behavioral biomarkers. The experimental results showed a significantly higher performance on the proposed method than the baseline model with the accuracy of 98.29%, the sensitivity of 98.29%, the precision of 98.34% and the F1-Score of 98.32%, whereas the baseline showed the accuracy of 94.54%, the sensitivity of 93.87%, the precision of 94.14% and F1-score of 94.01%. The confusion matrix also demonstrated the reliability of the system having a true positive rate of 99.78% and a true negative rate of 96.81% but false positive rate of 3.19% indicates the need to increase sample sizes in subsequent studies. The gaze-based classification system included in ROC curve analysis proved the viability of the application of gaze trajectory patterns as a biomarker to screen ASD by showing a large AUC.

The findings provide direct responses to the research question that aims to find out how the integration of neural and behavioral biomarkers with the use of machine learning can enhance the objectivity and accuracy of early screening of ASD. Our hypothesis is supported by the learned results that the EEG representation learning through similarity function based sampling together with the gaze trajectory analysis yields better classification performance compared to the traditional methods of supervised methodology and traditional methods of behavioral assessment. Compared to the available literature, the proposed model was capable of outcompeting the default model and could outperform the conventional diagnostic instruments like ADOS, ADI-R, and M-CHAT. This paper builds on this study by showing that a multimodal framework can provide high classification performance within the evaluated datasets.

This research combines EEG representation learning and gaze trajectory analysis to establish a framework for ASD diagnosis particularly for infants aged 6–24 months. If corroborated with further research, this system could be applied in real medical settings such as pediatric clinics to be used as a rapid pre-diagnostic screening tool. Subsequently, the system could contribute to early ASD detection and induce timely intervention for autistic individuals. With further validation in larger and more diverse clinical populations, this approach could complement clinician-led assessment by providing a more objective and efficient method for early ASD screening.

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