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Autism Spectrum Disorder Diagnosis Using Eye-Tracking with Machine and Deep Learning Techniques

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Abstract—Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental disorder characterized by significant impairments in social interaction, communication, and cognitive functions, including linguistic and object recognition abilities. Early diagnosis is crucial as it can significantly improve an autistic child's social communication skills and overall quality of life. One of the characteristic hallmarks of ASD is the difficulty of making or maintaining eye contact. This paper uses Machine Learning (ML) and Deep Learning (DL) approaches to analyze ASD diagnosis through eye-tracking data. This work uses Artificial Neural Networks (ANN), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) to differentiate between ASD and Typically Developing (TD) individuals. This study achieved a notable accuracy of 98% using the Decision Tree (DT) model, marking a significant improvement over previous works. Other models, such as SVM, KNN, and ANN, achieved accuracies of 93.37%, 92.46%, and 73%, respectively.

Keywords—Autism Spectrum Disorder (ASD), Eye tracking, Machine Learning (ML), Deep Learning (DL).

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that typically emerges within the first three years of life. It affects children in various ways, presenting a range of characteristics, including behavioral differences, challenges in communication, and social difficulties [1,2]. In 2020, a study conducted in the USA found that 1 in 36 children aged 8 years were diagnosed with ASD, with boys being 3.8 times more likely to be diagnosed than girls. Prevalence rates were higher among Black (29.3 per 1,000), Hispanic (31.6 per 1,000), and Asian/Pacific Islander children (33.4 per 1,000) compared to White children (24.3 per 1,000) [3]. The lifetime cost of supporting an individual with ASD and intellectual disability is estimated at $2.4 million in the United States, with the highest expenses attributed to special education in childhood and residential care in adulthood [4]. The identification of autism at the early stages of development is very beneficial to achieve common benefits for children and their families [5]. Multiple studies have found that children with ASD tend to avoid making eye contact during social interactions, compared to children without this condition [6]. The diagnosis process of ASD often involves a series of cognitive assessments that may need many hours of clinical evaluations. Moreover, the diversity of symptoms complicates the process of identifying ASD. In this respect, computer-aided technologies have gained importance in assisting in the examination and evaluation process. Electroencephalography, magnetic resonance imaging, and eye tracking are technologies used for the diagnosis of ASD. Eye tracking can be defined as capturing, tracking, and measuring the movement of the eyes or the absolute point of gaze (POG), which refers to the point where the eye gaze is directed in the visual scene [7]. Eye tracking devices are designed to record three fundamental types of eye movements: (1) fixation, (2) saccade, and (3) blink. A fixation is a brief moment when the eyes focus on an object, enabling the brain to interpret visual information. The average fixation duration ranges from 150 to 300 milliseconds [8]. Accurate perception requires continuous scanning through rapid eye movements, known as saccades, which involve quick jumps lasting 30-120 milliseconds each [9]. Various eye-tracking metrics, including pupil size, pupil diameter, pupil position, gaze vectors, Areas of Interest (AOIs), and eye movement categories such as saccades and fixations, are extracted from eye-tracking systems [10]. These features are employed in machine learning and deep learning frameworks for the diagnosis of ASD. This study explores eye-tracking vectors for detecting ASD using machine learning (ML) and deep learning (DL) models, including Artificial Neural Networks (ANN), Decision Trees (DT), k-Nearest Neighbors (KNN), and Support Vector Machines (SVM). Among these, the DT model achieved the highest accuracy of 98%, demonstrating a significant improvement over previous works. The SVM, KNN, and ANN models attained accuracies of 93.37%, 92.46%, and 73%, respectively.

The remainder of this paper is organized as follows: Section II reviews related work in this domain. Section III describes the research methodology, including theoretical analysis and experimental setup. Section IV presents the experimental results and corresponding discussions. Finally, Section V concludes the paper and outlines potential future research directions.

II. RELATED WORK

Eye-tracking technology has significantly advanced the diagnosis of ASD. This section summarizes key research on eye-tracking-based approaches, focusing on how ML and DL techniques are utilized to analyze eye movements and associated metrics for ASD diagnosis. In a study [11], researchers utilized eye-tracking technology to investigate and compare the gaze patterns of autistic children with those of typically developing children. The study involved 65 participants, comprising 34 children diagnosed with ASD and 31 Typically Developing (TD) children. The average age of the participants was 8 years. Data was gathered using the Tobi X2 eye tracker as the children sat in front of the device and viewed objects such as tomato, football, banana, and an image of a child. The eye fixation data was recorded for analysis. The study revealed that autistic children spent less time fixating on the eyes and showed more interest in looking at the mouth compared to typically developing children. Using machine learning algorithms, a method [12] was designed to extract and classify eye-tracking features. These features, derived from display behavior, image content, and scene centers, demonstrated strong performance in distinguishing children with autism spectrum disorder from their typically developing children. In a study [13], researchers proposed a system for tracking eye movements, extracting key features, and applying machine learning classifiers. This system was evaluated on a group of 71 participants, comprising 31 autistic individuals and 40 typically developing individuals, using multiple stimuli to determine its performance. A study investigated gaze patterns of children with autism towards other children using a Tobii T120 eye tracker. The participants included 39 children with autism and 28 typically developing (TD) children. They watched a video of two young children playing with a toy and engaging in nonverbal communication. The study achieved a classification accuracy of 0.91 [14]. Another study examined disengagement and orientation of attention in children with autism, developmental delay, and typically developing children, aged 4–13 years. Eye movements were recorded using a Tobii X120 Eye Tracker, and a web camera was used to capture facial expressions and looking behavior. The children, seated on their parent's laps and positioned 60 cm from the device, viewed non-social stimuli with engaging visual and auditory features. Analysis of the eye-tracking data, converted to CSV, showed that children with autism were slower to disengage from dynamic stimuli compared to static ones, demonstrating delays in attention disengagement compared to the other groups [15]. A study utilized Convolutional Neural Networks (CNNs) to classify children with ASD and TD based on scanpaths of fixation points. The dataset, sourced from the Saliency4ASD grand challenge, comprised 300 images collected from 14 children with ASD and 14 TD children. The classification achieved an accuracy of 74.22% [16]. A study [17] utilized eye movement patterns during face scanning to identify autism in children. The experiment involved 29 children with ASD and 29 typically developing (TD) children, aged 4 to 11 years, using a Tobii T60 eye tracker with a 60 Hz sample rate. During the procedure, the children were asked to memorize six faces and later tested on their recognition of 18 faces. Eye-tracking data were clustered using the K-means algorithm, and features were represented in a histogram and classified via an SVM model. The study achieved an accuracy of 88.51%, demonstrating the potential of eye-movement patterns in differentiating children with ASD from TD children. A study [18] of ASD and TD children based on gaze fixation times, involving 37 participants in each group, aged 4 to 6 years. Using a portable eye-tracking system (SMI RED250), the participants viewed a 10-second silent video of an Asian woman reciting the English alphabet on a widescreen LCD. An SVM classifier achieved an accuracy of 85.1%, revealing that children with ASD exhibited significantly shorter fixation durations across various facial areas compared to TD children.

III. Research Methodology

A. Data Description

In this study, a CSV-formatted dataset derived from the research titled *"Eye-Tracking Dataset to Support the Research on Autism Spectrum Disorder [10]"* was utilized for analysis. The dataset includes key participant metadata such as age, gender, and diagnostic classification (ASD or TD), along with 17 eye-tracking features capturing spatial and temporal aspects of eye movement. These features include fixations, saccades, blinks, pupil characteristics (diameter, size, position), gaze vector, point of gaze (POG), stimulus type, category groups, and eye position. The data records responses to specific visual stimuli, with session times documented for temporal analysis. This dataset enabled the application of ML and DL models to effectively differentiate between ASD and TD participants, supporting early diagnosis efforts. While the image dataset from this research [10] has been explored for ASD detection, the CSV-formatted dataset remains largely unexplored, making this the first study to analyze it for autism spectrum disorder detection.

Table 1: Summary of participants

Count of Participants (TD, ASD)	59 (30, 29)
Gender (Female, Male)	21 (≈ 36%), 38 (≈ 64%)
Age (Mean, Median)	7.88, 8.1 years

Table 1 summarizes the study participants, including 59 individuals (30 TD, 29 ASD), with a gender distribution of 36% females and 64% males. The mean and median ages are 7.88 and 8.1 years, respectively [10].

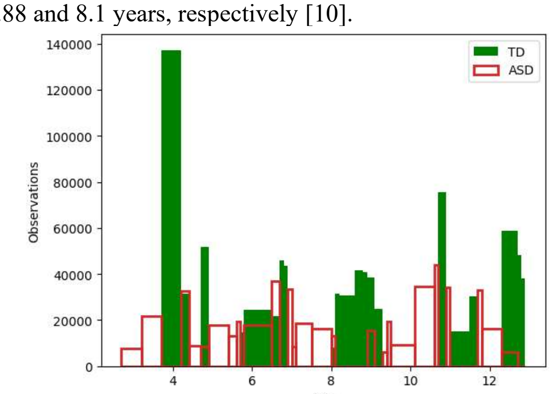

Figure 1: Distribution of observations by age for TD and ASD participants.

Figure 1 illustrates the distribution of observations across different ages for TD and ASD participants. It highlights a significant concentration of TD observations at age 4, while ASD observations are more evenly distributed across various age groups. This visualization emphasizes the demographic differences in the dataset used for analysis.

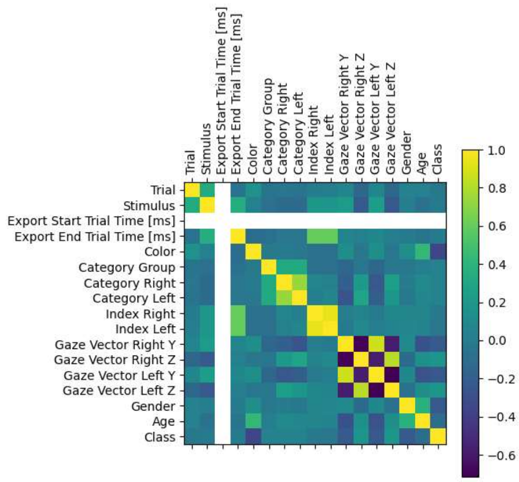

Figure 2: Correlation Analysis of Eye-Tracking Features Using Heatmap

The heatmap in Figure 2 illustrates the correlation between various eye-tracking features and demographic variables in the dataset. Features such as gaze vectors, category indices, trial times, and demographic attributes (e.g., age and gender) are compared. The color intensity indicates the strength and direction of their relationships, helping to identify patterns or dependencies that may be relevant for detecting ASD.

B. Data Preprocessing

The preprocessing phase involved merging individual participant data into a unified dataset and removing irrelevant columns to streamline the analysis. Missing values were handled using forward and backward filling techniques and categorical variables like gender and diagnostic classification were numerically encoded for compatibility with machine learning models. Duplicate records were eliminated to ensure data integrity, and the dataset was split into training and testing subsets, maintaining the class distribution. This preprocessing ensured the data's consistency, cleanliness, and readiness for model training and evaluation.

C. Training and Testing

The dataset was split into training (75%) and testing (25%) subsets using stratified sampling to preserve class distribution. Four models—DT, SVM, KNN, and ANN—were trained and fine-tuned on the training set, while the testing set assessed their accuracy and robustness in ASD classification.

D. Model Selection

This study employs four machine learning models—Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN)—selected for their effectiveness in classification tasks. Using eye-tracking metrics like fixations, saccades, and pupil characteristics, these models were evaluated for ASD detection, demonstrating high accuracy and suitability for this application.

IV. Result And Discussion

The performance of several classification algorithms was evaluated on a given dataset. The Decision Tree (DT) model achieved the highest accuracy of 98%, significantly exceeding this target range and demonstrating its exceptional effectiveness for this dataset. This suggests that the data's features allow for clear and effective partitioning.

Table 2: Accuracy Rate of Different Algorithms

Algorithms	**Accuracy Rate (%)**
Artificial Neural Network (ANN)	73
Decision Tree (DT)	98
Support Vector Machine (SVM)	93.365
K-Nearest Neighbor (KNN)	92.462

The SVM model achieved 93.37% accuracy, effectively separating classes but slightly trailing the DT model. KNN performed similarly at 92.46%, indicating the usefulness of neighboring points for classification. ANN, however, lagged with 73% accuracy, suggesting limitations in network architecture, training, or dataset suitability for deep learning

A. Performance Analysis of Decision Tree (DT)

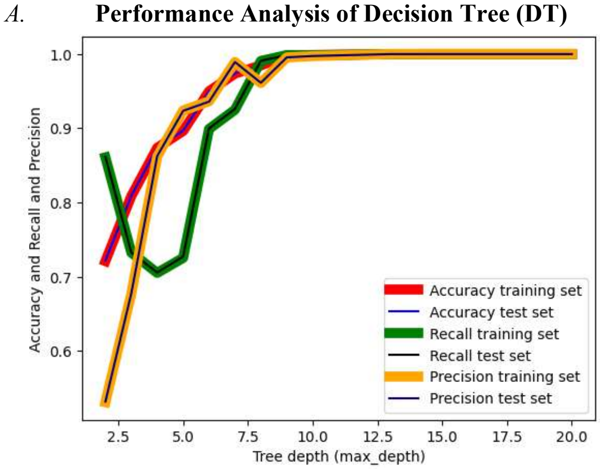

Figure 3: Changes for accuracy, recall, and precision metrics by increasing max depth for the Decision Tree Classifier

The relationship between decision tree depth (max_depth) and performance metrics on training and test sets is illustrated in Figure 3. A general increase in accuracy and recall is observed with increasing tree depth for both sets, with training set performance consistently exceeding test set performance. This divergence indicates increasing overfitting as the tree depth grows. Precision also initially improves with depth but may subsequently plateau or decline. This suggests a trade-off between model complexity and generalization, with optimal performance achieved at a tree depth balancing high accuracy and recall with controlled overfitting.

B. Performance Analysis of Artificial Neural Network (ANN)

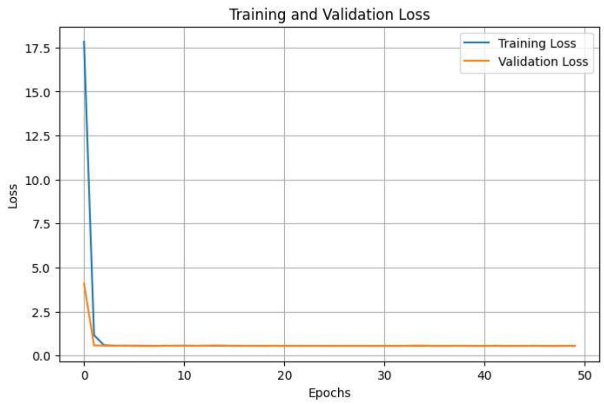

Figure 4: Training and validation loss curves over 50 epochs

The graph illustrates the training and validation loss over 50 epochs. A rapid initial decline indicates effective early learning, followed by convergence around epoch 5. The small, consistent gap between the curves suggests good generalization and no overfitting, demonstrating a successful training process.

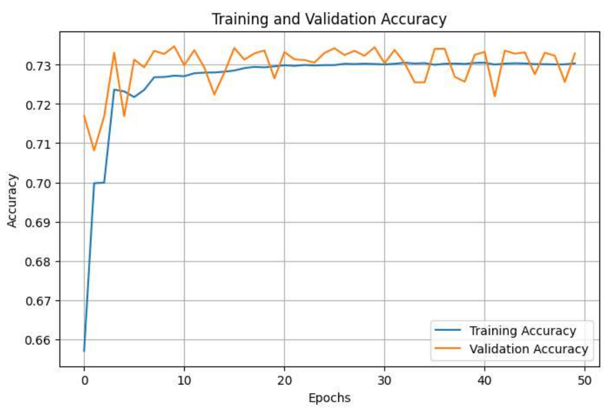

Figure 5: Training and validation accuracy over 50 epochs

Figure 5 illustrates the training and validation accuracy of an ANN model over 50 epochs. Initially, both accuracies rise rapidly, indicating effective early learning. The curves then stabilize, with training accuracy around 0.73 and validation accuracy slightly lower with minor fluctuations. The small gap suggests good generalization, though fluctuations indicate some sensitivity to the validation set. Further training is unlikely to yield significant improvements.

V. Conclusion and Future Scope

This study demonstrates improved ASD detection using eye-tracking data and ML models. The DT model achieved the highest accuracy (98%), followed by SVM (93.37%), KNN (92.46%), and ANN (73%). These results highlight ML's potential in ASD detection, with DT proving highly effective. The future research aim is to develop a simple web-camera-based eye tracker and create a local dataset of children both typically developing and with ASD. This could further enhance model performance. Moreover, integrating these models into practical diagnostic tools could provide valuable support to healthcare personnel in the early and accurate detection of ASD.

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