AI Early Detection System for Autism Screening

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https://doi.org/10.63962/QVWS5641

***Abstract*—This research aims to develop an AI-based framework for early detection of autism spectrum disorder (ASD) in children using eye-tracking data. This approach uses convolutional neural networks (CNNs) introduced by [13} combined with hybrid models to automatically classify the distinctive gaze recognition patterns of individuals with ASD, providing non-invasive detection. This framework was designed after reviewing existing AI models, structuring relevant components, and obtaining expert feedback. A case study analysis indicated that AI models, particularly adaptive CNN models, outperformed traditional screening methods in terms of accuracy and efficiency [16]. The goal is to develop a practical, interpretable, and scalable ASD screening framework to enhance early clinical decision-making.**

Keywords—***Autism Spectrum Disorder, Convolutional Neural Networks, Screening, Deep Learning, Deep Neural Networks.***

I. Introduction

The global prevalence of autism spectrum disorder (ASD) has increased dramatically. The Autism Spectrum Disorder Monitoring (ASDM) network states that in the United States, the prevalence among 8-year-olds increased from 1 in 150 in 2000 to nearly 1 in 36 in 2020. The ASDM network suggests that this increase can be attributed to improved screening procedures, increased awareness, and changes in screening criteria [8]. Early screening for ASD, particularly before age 3, is critical. Interventions implemented during this critical developmental stage will significantly enhance children's social, cognitive, and communication abilities [17]. However, the average screening age in developed countries remains around four years, and even higher in low-resource countries, highlighting the urgent need for rapid and effective early screening systems.

The methodology applied in this research study follows a structured, five-step approach to developing an AI-based framework for early detection of ASD using eye-tracking data. In the first step, the researcher systematically examines the problem by examining gaps in current ASD screening methods and identifying how AI and eye-tracking technology can be used for improvement. In the second step, a detailed literature review is conducted to evaluate current AI screening frameworks, with a particular focus on those that incorporate CNNs and DNNs as their most prominent features, and to identify gaps and best practices.

In the third step, based on the literature review, a preliminary framework is proposed that combines the features of AI and eye-tracking technology for early ASD screening. In the fourth step, a survey method is implemented, gathering responses from healthcare professionals, AI specialists, and educators to evaluate the framework's effectiveness, practicality, and feasibility. In the final step, the framework is enhanced, taking into account the feedback received to ensure accurate screening, treatment, and integration with the healthcare and education systems in the UAE.

The proposed AI-driven framework for early ASD screening has clear benefits for children, parents, healthcare professionals, and even policymakers. For children, early and accurate screening allows for interventions that are more likely to improve cognitive, social, and communication skills[17]. Parents and caregivers benefit from the availability of simple, non-invasive tools that reduce the emotional and logistical burden associated with traditional assessments [4].

Healthcare professionals use a more objective, data-driven approach, increasing the accuracy of the method and reducing overreliance on behavioral observations to record subjective measurements as noted by [7]. Integrating this framework into healthcare and education systems fosters collaboration between clinicians and educators, enhancing the use of AI-based screening tools to better identify ASD [14]. This framework also enables policymakers to study and integrate it into existing healthcare and education systems in the UAE. Furthermore, the framework encourages collaboration across disciplines and supports research-based strategies to improve screening for ASD [5; 18].

II. Methodology

Step 1: Understanding the research problem: Identifying existing challenges in early screening for ASD. This includes examining the limitations of current screening tools and the potential for combining AI and eye-tracking data to achieve accurate and non-invasive screening. This basic understanding supports the development of a practical AI-based screening framework.

Step 2: Conduct a comprehensive literature review: To analyse existing research on AI-driven ASD screening frameworks, particularly focusing on Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), and hybrid models. This step highlights the methodological strengths and gaps in current practices, contributing to a solid theoretical foundation for framework design.

Step 3: Framework Design: Develop a preliminary framework that features effective AI models, data preprocessing strategies, and feature extraction methods identified in previous literature revies. This includes defining model components, data flow, and evaluation metrics. The framework also addresses data quality variability through normalization, handling missing values, and noise reduction. Techniques such as SMOTE and GANs are conceptually integrated to manage imbalanced datasets, while evaluation across diverse datasets supports demographic generalization and fairness.

Step 4: Expert Consultation and Feedback: This step focuses on collecting primary data through expert surveys. Healthcare professionals, AI researchers, and educators will provide feedback through structured questionnaires, providing insights into the framework's feasibility and practical effectiveness. This step ensures that the framework supports the needs of professionals directly involved in ASD screening and interventions. Incorporating interpretation techniques, such as SHAP and Grad-CAM, improves clinical confidence and model interpretability, making it more transparent in clinical settings.

Step 5: Refining the Framework: This involves refining the framework based on expert feedback. The reviews will address any identified gaps, with a focus on improving screening accuracy and enhancing practical application. The final framework will be refined for practical application in both the healthcare and education settings in the UAE.

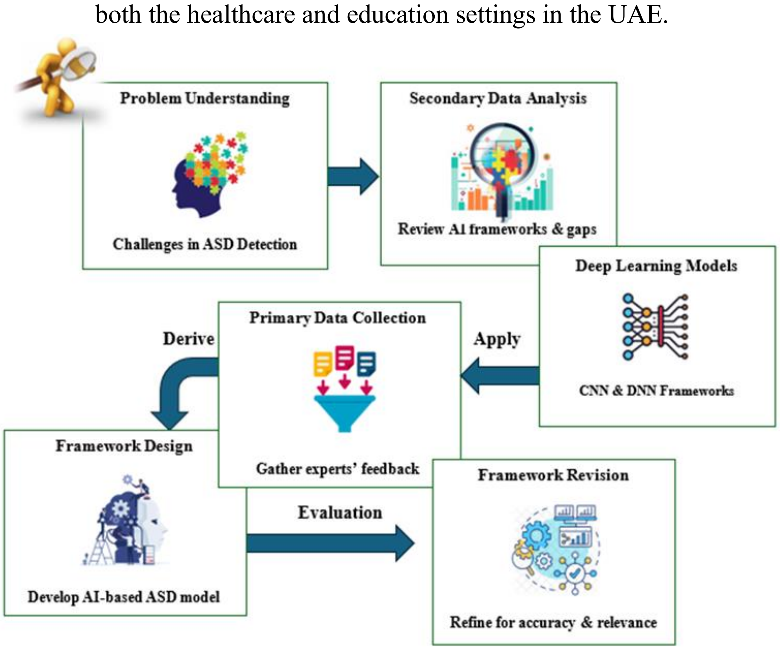

Fig 1. Flowchart of the Research Approach

III. Literature Review

Recent advances in AI have revolutionized the screening of ASD by integrating eye-tracking data and DL models. Multiple studies have revealed the effectiveness of CNNs, hybrid models, and other AI techniques in identifying atypical gaze behaviors associated with ASD [2]. This literature review highlights the most important findings from recent studies that contribute to the development of AI-based screening framework.

The study by [16] developed an Adaptive Deep Convolutional Neural Network (ADCNN) framework to enhance early screening of ASD in children. The study used two datasets: the Eye-Tracking Scan Path (ETSP) dataset containing 547 images from 59 children (219 ASD, 328 TD), and the ABIDE dataset, which provided additional personal information. The methodology combined Discrete Wavelet Transform (DWT) for feature extraction, Kernel PCA for dimensionality reduction, and Grey Wolf Optimization (GWO) for feature selection. In total, 131 features were analyzed. The ADCNN model, built four convolutional layers and achieved an AUC of 94.51%, outperforming Decision Tree by 30%, KNN by 28%, and conventional CNNs by 8%. The study highlights the potential of AI-integrated, non-invasive methods for accurate and early ASD screening.

In another review [6] proposed a new T-CNN-ASD model that applies to CNN to classify children with ASD based on their eye-tracking scan paths. The dataset included a total of 547 images of 59 children with 29 screened with ASD and 30 with TD. The T-CNN-ASD model architecture comprised of two hidden layers with 300 and 150 neurons, respectively. The model was trained using 10-fold cross-validation and a 20 percent dropout rate to reduce overfitting. It also outperformed traditional machine learning algorithms such as RF, DT, KNN, and MLP models, achieving an accuracy of 95.59%, the results highpoint the model's powerful ability to classify children with ASD versus their non-ASD peers based on eye-tracking behavior and enhance the potential of deep learning techniques in early screening for ASD [6].

Similarly, [10] proposed the Involution Fused ConvNet model, which uses convolutional and involutional layers to classify eye-tracking patterns in children with ASD. The dataset consisted of two eye-tracking datasets, one containing 547 images (219 ASD, 328 non-ASD) and the other containing 300 images from 28 children. Their hybrid model consisted of three involution layers followed by three optimally convolution layers, designed to enhance spatial feature extraction. The model achieved an accuracy of 99.43% on one dataset and 96.78% on another dataset. These results highlight the effectiveness of incorporating location- - sensitive spatial processing through involution layers in improving the accuracy of ASD detection. [10].

In another study conducted by [7] developed an intelligent eye-tracking system using DL to support early screening of ASD. The study integrated the use of MobileNet, VGG19, DenseNet169, and a hybrid MobileNet-VGG19 on a dataset of 547 images of children from 219 with ASD and 328 TD.

Among these, MobileNet had outstanding accuracy of 100% while VGG19 had 92%, DenseNet169 achieved 78%, and the hybrid model scored 91%. DL-based autonomous eye tracking systems have proven their value in non-invasive screening solutions for ASD.

A systematic literature review by [19] included 130 studies exploring applications of deep learning techniques in image classification from MRI scans, eye tracking data, and face recognition. The review concluded that CNNs had classification accuracy between 75% and 95%. The highest screening accuracies were achieved with multimodal approaches using eye-tracking and MRI scans. The study emphasized the need for standardized datasets and culturally inclusive models to improve the accuracy and real-world applicability of AI-based ASD screening systems.

Combining Deep Learning Models with eye-tracking technology improves early detection of ASD in children. As for the dataset of 59 children, included 29 screened with ASD and 30 TD. Different models were tested including LSTM, CNN-LSTM, GRU, and BiLSTM. Following data scaling and missing value treatment, the LSTM model resulted in an accuracy of 98.33%, with CNN-LSTM close behind at 97.94%. GRU and BiLSTM obtained 97.49% and 96.44%, respectively. The review by [2] indicates that the accuracy of early detection of ASD significantly increases by combining DL and eye-tracking data.

In another investigation, [1] designed a CNN-based model to predict ASD using scan paths of eye-tracking. This research trained CNN on scanning path images of children with ASD and TD by using deep feature extraction for classification. The model showed excellent results, having an accuracy of 98%, proving how powerful CNNs are in detecting unusual gaze patterns. This study emphasized the combination of eye-tracking in addition to deep learning to objectively and quickly screen ASD [1].

This study used eye-tracking scan paths as biomarkers and analyzed data from 547 participants (219 ASD and 328 TD children) to evaluate ML models. The research tested several classifiers, Boosted Decision Tree (BDT), Deep Support Vector Machine (DSVM), Decision Jungle (DJ), and a Deep Neural Network (DNN). The DNN outperformed by achieving an AUC of 97%, sensitivity of 93.28%, and specificity of 91.38%. These results highlight the potential of machine learning algorithms to provide reliable non-invasive screening techniques for the early detection of ASD, as noted by [11].

A survey review of 35 selected studies focused on the application of AI tools in initial screening for ASD between 2011 and 2021. The review focused on the application of ML and DL techniques on eye movements, facial gestures, motor activities, and Electronic Health Records (EHR). According to the results, screening accuracy rates ranged from 70% to 95%, with eye tracking and facial recognition achieving the highest accuracy. As [12] noted, the provision of standardized data suitable for use in clinical contexts remains insufficient.

A computer-assisted screening model was developed and designed based on visual attention patterns derived from eye-tracking technology. The study included 106 participants, including 76 children with ASD and 30 TD. Classification was performed using artificial neural networks (ANNs) and support vector mechanisms (SVMs). A genetic algorithm was able to extract 15 relevant variables out of 28 potential variables. The accuracy of the ANN model was 90%, while the achieved sensitivity and specificity were 69% and 93%, respectively. [15] claim that these results provide further evidence of specialized gaze patterns in children with ASD, confirming the importance of eye-tracking data.

TABLE I. METHODS USED IN ASD DETECTION

Methods Used	**No. of Features**	**Results**	**Findings**	**Citation**
Adaptive Deep CNN (ADCNN)	Yes (5-Fold Cross Validation)	AUC: 94.51%	ADCNN outperformed DT by 30%, KNN by 28%, and conventional CNNs by 8% in ASD detection.	Palanichamy et al. (2025) [16]
CNN-ASD (CNN)	Yes, (10-fold cross-validation, Dropout 20%)	Accuracy: 95.59%	The CNN model showed strong performance in distinguishing between children with ASD and TD.	Alsaidi et al. (2024) [6]
Involution Fused ConvNet	Yes, (Spatial Feature Extraction)	99.43% (Dataset 1), 96.78% (Dataset 2)	The highest accuracy among all models; spatial feature extraction enhances classification.	Islam et al. (2024) [10]
MobileNet, VGG19, DenseNet169, Hybrid MobileNet-VGG19	Yes, (Hybrid Model with Transfer Learning)	MobileNet: 100% accuracy; VGG19: 92% accuracy; DenseNet169: 78% accuracy; Hybrid: 91% accuracy	The study showed that MobileNet achieved the highest accuracy in classifying ASD from eye-tracking data, indicating its potential for effective ASD screening.	Alsharif, R., & Ghulam, A. (2024)[7]

Systematic Review of Multiple Deep Learning Models (e.g., CNNs)	Not Applicable	CNNs: Classification accuracies ranging from 75% to 95%; Multimodal approaches combining eye-tracking and MRI data led to even higher screening accuracies	The systematic review highlights the effectiveness of DL models, particularly CNNs, in ASD screening. It also emphasizes that incorporating multimodal data sources, such as eye-tracking	Uddin, M. I., & Rahman, M. M. (2024) [19]
STM, CNN-LSTM, GRU, BiLSTM	Yes, (Scaling, Handling Missing Values)	LSTM: 98.33%, CNN-LSTM: 97.94%, GRU: 97.49%, BiLSTM: 96.44%	LSTM accomplished the highest level of accuracy, outperforming deep learning models over traditional ML.	Ahmed et al. (2023) [2]
ANN, FFNN, CNN (GoogleNet, ResNet-18), Hybrid CNN-Support Vector Machine (SVM)	Yes, (Scaling, Feature Extraction, Handling Missing Values)	ANN: 99.8% accuracy; ResNet-18: 97.6% accuracy; Hybrid models: 95.5% and 94.5% accuracy	The study reveals that combining AI models with eye-tracking data can effectively help in the early screening of ASD, with ANN achieving the highest accuracy.	Ahmed, M., & Jadhav, A. (2022) [1]
BDT, DSVM, DJ& DNN	Yes, Features extracted from visualized eye-tracking scanpaths; image augmentation applied	DNN: AUC 97%, sensitivity 93.28%, specificity 91.38%	The study shows that visual representations of eye-tracking data, when analyzed using DL models, can effectively serve as biomarkers for early ASD screening.	Kanhirakadavath, M., & Chandran, S. (2022) [11]
Various ML/DL Methods	Not Applicable	Detection accuracies ranging from 70% to 95%.	Eye-tracking and facial recognition technologies offer the highest screening accuracy for early ASD detection.	Kohli, D., & Sharma, P. (2022) [12]
Artificial Neural Networks (ANN), Support Vector Machines (SVM)	Yes, (Feature Selection via Genetic Algorithm)	ANN: 90% precision, 69% sensitivity, 93% specificity	The study examined a computational method combines Visual Attention Models and AI techniques, showing the ability of eye-tracking data in ASD screening.	Oliveira, G., & Silva, H. (2021) [15]

IV. Research Ethics

The development of this framework ensures compliance with data protection regulations, protects the identity of expert participants, and ensures the responsible use of AI technologies. Consent will be obtained from experts providing feedback, ensuring that participation is not forced [9]. This research adheres to the laws of the GDPR and the UAE Data Law, ensuring data is protected and handled anonymously [18]. Ethical sensitivity is maintained by designing the framework within the boundaries of ethical AI and regional boundaries [5]. Since this research does not involve any human interventions or clinical trials, it poses minimal ethical risks [20]. No medical procedures will be collected along with personal health information.

V. Conclusion

ASD remains one of the most concerning conditions across the globe, making early detection essential to improve developmental outcomes. This chapter examined the limitations of traditional approaches to screening ASD, which rely primarily on behavioral and clinical assessment. Such approaches often delay screening and intervention. The introduction of eye-tracking technology, which analyses gaze fixation and visual attention movements, is an innovative non-invasive approach for ASD screening. Several studies were examined that demonstrated high accuracy classifiers for ASD based on ML and DL approaches with CNNs being the most effective. The primary models of CNNs, known as ResNet, MobileNet, and VGG19, surpassed traditional ML techniques by achieving over 90% classification accuracy. Nevertheless, dataset and standardization limitations combined with low model generalisability remain imperative issues. The chapter also discussed combining multimodal data and eye-tracing data with other behavioral and communication data to improve screening accuracy. There is no doubt that AI-enhanced screening tools for ASD have the potential to transform early screening, but a significant amount of work is needed in terms of model review, ethical issues, and practical clinical considerations.

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