Machine Learning and Deep Learning Techniques for the Prediction of Autism Spectrum Disorder: A Comprehensive Review

Gaurangkumar Patel[1*], H.B. Pandya ,B.H. Trivedi[2]

Student, Computer Engineering Department, L.D. College ofEngineering, Ahmedabad, India[1]
AssistantProfessor, Computer Engineering Department, L.D. College of Engineering, Ahmedabad, India[2]
pthunder309@gmail.com, hetalbpandya@ldce.ac.in, bhoomitrivedi@ldce.ic.in

Abstract: Early identification of Autism Spectrum Disorder (ASD) is crucial for enabling timely intervention and improving developmental outcomes. Conventional diagnostic methods rely heavily on behavioral observation and expert judgment, often leading to delayed diagnosis. In recent years, machine learning and deep learning techniques have been increasingly explored to support early ASD prediction using facial images, behavioral videos, neuro imaging data, and clinical datasets. This review presents a comparative analysis of recent approaches for early ASD prediction, focusing on methodologies, datasets, predictive performance, and key limitations. The findings indicate that deep learning-based approaches, particularly those using facial images and behavioral video analysis, generally achieve higher accuracy compared to traditional machine learning models. However, challenges such as limited dataset diversity, reduced cross-dataset generalization, lack of interpretability, and insufficient clinical validation remain prevalent across studies. In addition to the review, this work includes the implementation of an existing deep learning-based facial image classification method to validate reported findings. Overall, this critical review highlights current progress and emphasizes the need for robust, interpretable, and clinically validated approaches to support early ASD screening and complement traditional diagnostic practices.

Keywords: Autism Spectrum Disorder, Machine Learning, Deep Learning, Facial Image Analysis, Behavioral Analysis

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neuro developmental condition that affects how a person communicates, interacts socially, and behaves. In India, approximately 1 in 100 children are affected by Autism Spectrum Disorder, according to the Indian Council of Medical Research (ICMR)[1]. People with ASD often find it difficult to read social signs, struggle to communicate, and may follow the same patterns or behaviors repeatedly. These signs usually start appearing when a child is quite young and continue throughout their life, which can affect their performance in school, their jobs, and their general well-being [2], [3].

Even though signs can be seen early, autism is often found much later, which means children miss out on the best time to get help. This late finding usually happens because doctors have to make a choice based only on what they see and because there are not enough expert specialists available [4], [5].

Finding autism early is vital because a young child's brain is very flexible and can learn quickly. Providing support during this time is known to help with thinking, social life, and behavior [4]. However, the usual ways of testing, like observing children or interviewing parents, are often slow, cost too much, and need an expert to make the final call. This makes it hard to provide these tests to everyone who needs them [5].

New improvements in computer science and smart technology allow us to build systems that automatically search for signs of autism. These computational models analyze many types of information, including images of the brain, videos of behavior, photos of faces, recorded voices, and signals from the body. The goal is to build screening tools that are more objective and more accessible than traditional diagnostic methods doctors have used for a long time [6], [7].

Many new studies show that multimodal deep learning models are very effective at finding tiny patterns in behavior and biology. These advanced systems often have higher predictive accuracy than traditional machine learning methods[5], [8]. Even

http://doi.org/10.63766/spujstmr.26.000078

with these good results, there are still big problems with using them in clinics. These include dataset variability, a lack of common testing standards, and the hidden logic of these models, which makes it hard for doctors to see exactly how they reach their final decision [6].

The purpose of this study is to provide a detailed comparison of the various methods currently used to predict Autism Spectrum Disorder at an early stage. This review highlights the specific algorithmic frameworks used, the nature of the information collected, and how accurately these systems perform.

By examining the pros and cons of current techniques, the analysis seeks to identify existing knowledge gaps and future directions. In addition to reviewing existing approaches, this study also implements a previously published deep learning-based method for ASD detection using facial images to validate its effectiveness.

II. REVIEW METHODOLOGY

To gather relevant research, we performed a systematic search across major academic databases, including IEEE Xplore, SpringerLink, Elsevier, MDPI, and Google Scholar. The search was built around key phrases such as “early detection of autism spectrum disorder,” “machine learning for ASD,” “deep learning in autism,” “behavioral tracking,” and “multimodal diagnostic tools.” We specifically selected peer-reviewed articles written in English and published between 2018 and 2024. Our criteria focused on papers discussing early screening and automated identification techniques. The resulting collection of research features a variety of methods, including those based on brain imaging, behavioral patterns, facial recognition, combined data sources, and adaptive learning models.

III. OVERVIEW OF EARLY PREDICTION APPROACHES

A. Neuroimaging-Based Approaches

Neuroimaging-based approaches utilize structural and functional brain data, such as MRI and fMRI, to identify neural biomarkers associated with ASD. Deep learning models trained on large datasets such as ABIDE have demonstrated promising classification accuracy by learning complex brain connectivity patterns [9].

More recent studies extend neuroimaging approaches to severity-aware prediction by mapping brain regions to behavioral domains using machine learning frameworks, achieving classification accuracies exceeding 90% [5]. However, the high cost of data acquisition and limited accessibility restrict the applicability of these methods for large-scale early screening.

B. Machine Learning-Based Clinical and Behavioral Approaches

Traditional machine learning models, such as support vector machines (SVM), random forests, and logistic regression, are frequently used with clinical data and survey results to identify early risks of ASD [10]. These methods require less computing power and are relatively inexpensive, which allows them to be used effectively in areas with fewer medical resources.

Modern developments have introduced specialized systems that go beyond a simple "yes or no" result; they can now estimate the intensity of ASD across different behavior types, making the results much more useful for doctors. However, the success of these models still relies heavily on the quality of the input data and how well the specific features of that data are chosen and organized.

C. Behavioral Video-Based Approaches

Analyzing behavioral videos has become a very successful and gentle way to identify signs of ASD early. These systems use deep convolutional and recurrent neural networks to automatically spot repetitive actions, such as spinning, head banging, or hand flapping.

Modern approaches that track body movements over time, such as pose estimation and spatiotemporal modelinghave set new records for accuracy on shared research databases [8]. While these behavioral methods are great for early checks, they still need a massive amount of high-quality, clearly labeled video data to work correctly.

D. Facial and Multimodal Approaches

Facial feature-based approaches exploit morphological differences between ASD and typically developing children using deep convolutional neural networks and transfer learning. Studies consistently report classification accuracies above 90%, highlighting their scalability and ease of deployment. Multimodal approaches integrate facial images, behavioral videos, and

ISSN: 3049-1479(Online)

depth information to enhance robustness and generalization. Recent work demonstrates that multimodal fusion outperforms single-modality models but introduces increased system complexity and computational cost [7].

IV. COMPARATIVE ANALYSIS OF SELECTED STUDIES

TABLE I

COMPARATIVE SUMMARY OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES FOR ASD PREDICTION

Reference	Technique Category	Methodology	Dataset	Accuracy	Limitations/Future work
[9]	Deep Learning (Neuroimaging)	CNN on fMRI data	ABIDE (Autism Brain Imaging Data Exchange)	70%	• High computational cost • Depends on neuroimaging (expansive & not easily accessible)
[8]	Deep Learning (Behavioral Video)	RGBPose-SlowFast Network with skeleton heatmaps and RGB frames	SSBD	98% (limb), 94% (keypoints)	• Struggles with fast hand flapping • Lower accuracy for lying posture
[11]	Deep Learning (Behavioral Video)	Two-stage pipeline: YOLOv7 + VGG19 for detection, Movenet + CNN for classification	SSBD+ (SSBD + 35 new videos)	81%	• Highly unbalanced dataset
[12]	Deep Learning (Behavioral Video)	Two-stage temporal action localization and classification	SSBD, ESBD	88.3% (SSBD), 88.6% (ESBD)	• Dependent on complex video segmentation
[10]	Machine Learning	Decision Tree, Random Forest, SVM, Logistic Regression	Kaggle ASD for toddlers Dataset	Random Forest achieved ~97% accuracy	• Limited use of visual and behavioral information
[6]	Deep Learning (Facial Images)	Active learning + transfer learning (ResNet50V2, Xception CNNs) with domain adaptation	Kaggle ASD dataset & YTUIA dataset	Xception: 95% (Kaggle ASD) ResNet50V2: 96% (YTUIA) With domain adaptation: ~80% (cross-dataset)	• Accuracy drops when combining datasets, still needs larger and more diverse data for clinical reliability.
[13]	Deep Learning (Facial Images)	MobileNetv2,Xception, ResNet-50,VGG16,and DenseNet-121 with CNN and transfer learning.	Kaggle ASD Dataset	DenseNet-121: 96% accuracy	• Integrate models with the Internet of Medical Things (IoMT) to enhance early detection and intervention

Reference	Technique Category	Methodology	Dataset	Accuracy	Limitations/Future work
[14]	Machine Learning & Deep Learning	Multilayer Perceptron (MLP), Random Forest (RF), Gradient Boosting Machine (GBM), AdaBoost (AB), and Convolutional Neural Network (CNN)	Kaggle ASD Dataset	CNN: 92.31% accuracy	• Expand dataset and enable cloud-based diagnosis
[15]	Deep Learning (Facial Images)	Transfer learning with MobileNetV2 and hybrid VGG19, combined with classifiers such as logistic regression, linear SVC, and random forest.	Kaggle ASD Dataset	MobileNetV2 92% accuracy	• Improve model accuracy using advanced AI algorithms. • Use the model to assist physicians in validating in
[16]	Deep Learning (Facial Images)	VGG16 transfer learning with VGGFace,	Kaggle ASD Dataset & East Asian Dataset	95% accuracy	• Combine image-based and video-based methods to detect both facial and behavioral traits, reducing misclassifications.

Table I presents a comparative analysis of representative machine learning and deep learning techniques for the early prediction and detection of Autism Spectrum Disorder (ASD). The reviewed works employ a wide range of methodologies, including neuroimaging-based deep learning, behavioral video analysis, facial image classification, and classical machine learning techniques.

Early neuroimaging-based approaches, such as the study utilizing convolutional neural networks on functional MRI data from the ABIDE dataset, demonstrate the potential of deep learning to identify neurological patterns associated with ASD. However, the reported accuracy remains relatively moderate, and the approach is limited by high computational requirements and the dependence on expensive neuroimaging data, which restricts large-scale clinical applicability[9].

Behavioral video-based methods show significantly stronger performance for early ASD screening. Techniques using RGBPose-SlowFast networks with skeleton heatmaps and RGB frames achieve very high accuracy for limb and key-point detection, highlighting the effectiveness of spatiotemporal modeling for identifying stereotypical behaviors [8]. However, challenges remain in accurately detecting fast hand movements and certain body postures. Similarly, two-stage pipelines combining object detection and classification networks demonstrate reasonable performance but are affected by dataset imbalance and complex video segmentation requirements [11], [12].

Machine learning classifiers applied to questionnaire-based datasets, such as decision trees and random forests, report high accuracy but rely on non-visual features, which may limit their ability to capture real-world behavioral cues [10].Several studies focus on facial image-based ASD detection using transfer learning and deep convolutional neural networks. Deep learning models trained on facial images consistently achieve strong performance, with architectures such as DenseNet-121, MobileNetV2, Xception, and VGG-based models reporting accuracies above 90% [13], [14], [15], [16].

Recent advances incorporate active learning and domain adaptation to improve cross-dataset generalization. While these approaches achieve high accuracy within individual datasets, performance decreases when models are evaluated across different datasets, indicating the need for more diverse and representative data for clinical reliability [6].Overall, the comparison reveals that deep learning-based approaches, particularly those utilizing facial images and behavioral videos, generally achieve higher predictive accuracy than traditional machine learning and neuroimaging-based methods. Behavioral video-based models are highly effective in detecting stereotypical actions associated with ASD, whereas facial image-based approaches offer a non-invasive and scalable solution for early screening. In contrast, machine learning methods provide greater interpretability and lower computational complexity but may be limited in capturing complex behavioral and visual patterns. Neuroimaging-based approaches offer valuable neurological insights; however, their practical deployment is constrained by the high cost and limited accessibility of imaging equipment. Despite their promising performance, challenges related to dataset diversity, cross-dataset generalization, model interpretability, and real-world clinical validation remain common across studies, highlighting important directions for future research

V. IMPLEMENTATION OF THE EXISTING METHODOLOGY

This study includes the implementation of an existing deep learning-based method for ASD detection using facial images. The purpose of this implementation is not to propose a novel model, but to reproduce and evaluate the effectiveness of a previously published approach under a controlled experimental setting.

A. Source of the Existing Methodology

The implemented method is adopted from the research paper titled "Autism Spectrum Disorder Detection in Children via Deep Learning Models Based on Facial Images", published in Bulletin of Business and Economics in 2024. This study was selected because it focuses on non-invasive early ASD screening using facial images and reports strong classification performance using transfer learning-based convolutional neural networks [13].

B. Reason for Selecting the Existing Methodology

Facial image-based approaches are particularly suitable for early ASD prediction as they rely on easily obtainable data and do not require specialized medical equipment. The selected study evaluates multiple pretrained deep learning models and demonstrates that DenseNet-121 achieves superior performance compared to other architectures. Re-implementing this method allows for validation of the reported findings and provides practical insights into the strengths and limitations of facial feature-based ASD detection.

C. Dataset and Preprocessing

The implementation uses the publicly available Kaggle Autism Image Dataset, which consists of 2,940 facial images of children aged between 2 and 8 years, categorized into autistic and non-autistic classes. Prior to model training, standard preprocessing steps were applied, including image resizing to a fixed resolution of 224 × 224, normalization of pixel values to the range [0,1], and data augmentation techniques such as rotation and horizontal flipping to reduce overfitting and improve generalization, as described in the original study[13].

For model development and evaluation, the dataset was organized into separate training, validation, and testing subsets. The training set consisted of 2,540 images (1,270 autistic and 1,270 non-autistic), the validation set contained 100 images (50 autistic and 50 non-autistic), and the testing set contained 300 images (150 autistic and 150 non-autistic). This balanced distribution ensured equal representation of both classes across all subsets and enabled reliable model training and performance evaluation.

TABLE II

DATASET DISTRIBUTION USED FOR TRAINING, VALIDATION, AND TESTING

Dataset Subset	**Autistic**	**Non-Autistic**	**Total Images**
Training	1270	1270	2540
Validation	50	50	100
Testing	150	150	300
Total	1470	1470	2940

D. Model Architecture and Training

The implemented framework uses DenseNet-121 with ImageNet-pretrained weights as the backbone, with the original classification layers removed. Input facial images are resized to 224 × 224 × 3. A custom classification head is added consisting of batch normalization, flattening, two Dense (512, ReLU) layers, dropout (0.2), and a final Softmax layer with two outputs for autistic and non-autistic classification. The complete architecture is shown in Fig.1.

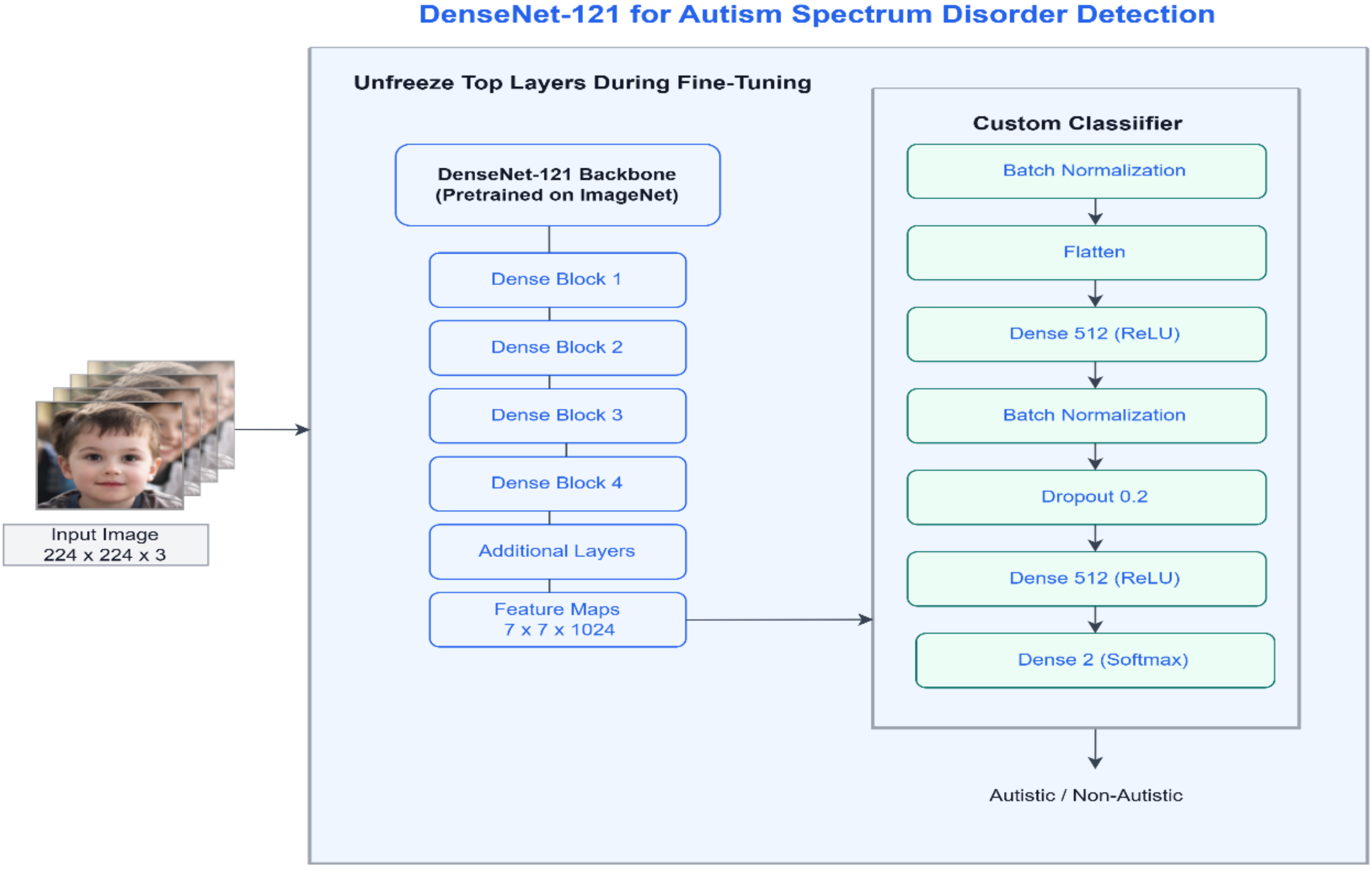

Fig. 1 Architecture of the implemented DenseNet-121–based model with custom classification layers for autism spectrum disorder detection (redrawn and adapted from [13]).

E. Training Strategy and Hyperparameters

Model training was performed using a two-phase transfer learning strategy. In Phase 1, the DenseNet-121 backbone was frozen and only the added classification layers were trained using RMSprop with a learning rate of 1e-4. In Phase 2, fine-tuning was applied by unfreezing the last 40 layers of DenseNet-121 and reducing the learning rate to 1e-5 for stable convergence. ReduceLROnPlateau was used to automatically adjust the learning rate when validation loss stopped improving. The model was trained using categorical cross-entropy, a batch size of 32, and a total of 50 epochs across both phases, with weights carried forward between phases.The validation dataset was used to monitor model convergence and support hyperparameter tuning, while the independent test dataset was used exclusively for final performance evaluation.

F. Implementation Results

The performance of the implemented DenseNet-121 model was evaluated on a test dataset using standard classification metrics. The model achieved an overall classification accuracy of 86%, demonstrating reliable performance for facial image–based Autism Spectrum Disorder detection.

TABLE III

CLASSIFICATION METRICS (PRECISION, RECALL, F1-SCORE, ACCURACY, AUC)

Model	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)	AUC (%)
DenseNet-121[13]	96	96	96	96	98
Reproduced DenseNet-121	86	86	86	86	93.53

As shown in Table III, the reference study reported 96% accuracy, while thereproduced DenseNet-121 implementation achieved 86% accuracy and an AUC of 93.53%. The performance difference may be due to variations in preprocessing, training configuration, and the sensitivity of deep learning models to dataset characteristics and hyperparameter settings.

The confusion matrix, shown in Fig. 2, illustrates the distribution of correct and incorrect predictions on the test dataset. Out of 300 test samples, 258 were correctly classified, with misclassifications evenly distributed between autistic and non-autistic classes, indicating consistent decision behavior.

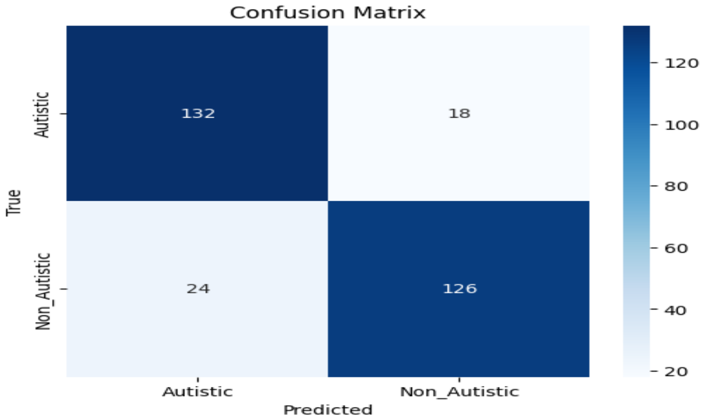

Fig. 2 Confusion matrix of the reproduced DenseNet-121 Model (generated by the authors from experimental results).

As illustrated in Fig. 3, the model achieved an Area Under the Curve (AUC) value of 93.53%, demonstrating strong separation between autistic and non-autistic facial images across varying classification thresholds.

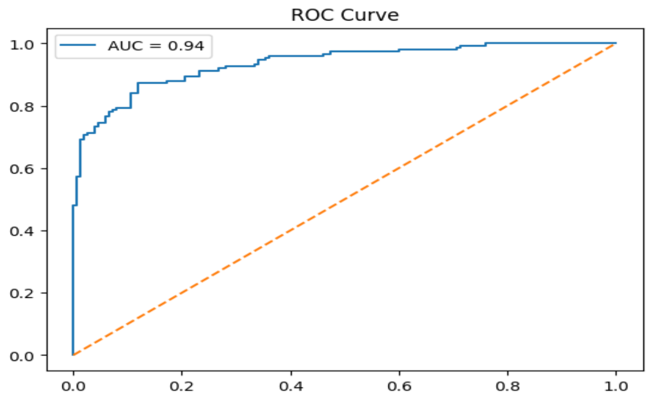

Fig. 3 ROC curve of the reproduced DenseNet-121 model for ASD classification (generated by the authors from experimental results).

Overall, the obtained results validate the effectiveness of the implemented DenseNet-121 framework and confirm the reproducibility of the reference method under a rigorous experimental protocol.

VI. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite strong performance reported in recent studies, several limitations restrict the real-world application of data-driven approaches for early prediction of Autism Spectrum Disorder. A key challenge is the limited diversity and scale of datasets, as many models are trained on single-source facial or behavioral datasets, reducing generalizability across populations and environments [10], [13], [14], [15], [16]. Future research should prioritize larger and more diverse datasets. Another major issue is poor cross-dataset generalization, where model accuracy decreases significantly when evaluated on unseen datasets due to domain shift and data bias [6]. Techniques such as domain adaptation and federated learning offer promising solutions to improve robustness. The lack of model interpretability remains a barrier to clinical adoption, as deep learning systems often operate as black boxes [13], [15]. Incorporating explainable AI methods could enhance trust and usability in healthcare settings. Additionally, most existing approaches rely on single data modalities, limiting robustness to noise and missing information [8],

[11]. Future systems should explore multimodal integration of facial, behavioral, and contextual data.Finally, clinical applicability and real-world validation remain important challenges for ASD prediction systems. Although many machine learning and deep learning models report high accuracy on publicly available research datasets, their practical deployment in healthcare settings is still limited [6], [10]. Facial image-based and behavioral video-based approaches have significant potential as non-invasive screening tools that can assist pediatricians and healthcare professionals in the early identification of children at risk of ASD. However, real-world environments introduce challenges such as variations in image quality, lighting conditions, ethnicity, age distribution, and behavioral diversity, which may affect model performance. Furthermore, many studies lack external validation across multiple datasets and clinical centers, raising concerns about their generalizability and reliability. Future work should focus on multi-center clinical studies, cross-dataset evaluation, prospective clinical trials, and explainable artificial intelligence techniques to improve trust, transparency, and practical adoption in routine healthcare settings.

VII. CONCLUSION

This review analyzed recent machine learning and deep learning approaches for early prediction of Autism Spectrum Disorder using neuroimaging, behavioral, and facial information. The comparison shows that deep learning methods, particularly those based on facial images and behavioral videos, generally achieve higher accuracy than traditional machine learning techniques and are more suitable for scalable screening.However, challenges such as limited dataset diversity, reduced cross-dataset generalization, limited model interpretability, and insufficient clinical validation remain. Addressing these issues through larger datasets, improved transparency, and real-world evaluation is essential for developing reliable tools that can support early ASD screening alongside conventional diagnostic methods.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to our guide and co-guide for their valuable guidance and continuous support throughout this research work. We also thank our institution for providing the necessary resources and environment to successfully complete this study.

REFERENCES

[1] Indian Council of Medical Research (ICMR), “ICMR Annual Report 2023–24,” 2024, Accessed: Mar. 24, 2026. [Online]. Available: https://www.icmr.gov.in/icmrobject/uploads/Documents/ 1744706555_icmr_annualreport_2023-24_78804328_1.pdf, 2024

[2] F. W. Alsaade and M. S. Alzahrani, “Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms,” *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/8709145.

[3] A. Rashid and S. Shaker, “Autism spectrum Disorder detection Using Face Features based on Deep Neural network,” *Wasit Journal of Computer and Mathematics Science*, vol. 2, no. 1, pp. 74–83, Mar. 2023, doi: 10.31185/wjcm.100.

[4] J. Wang *et al.*, “Early markers of neurodevelopmental disorders based on general movements for very preterm infants: Study protocol for a multicentre prospective cohort study in a clinical setting in China,” *BMJ Open*, vol. 13, no. 5, May 2023, doi: 10.1136/bmjopen-2022-069692.

[5] M. T. Ali *et al.*, “A personalized classification of behavioral severity of autism spectrum disorder using a comprehensive machine learning framework,” *Sci. Rep.*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-43478-z.

[6] M. S. Alam, E. A. A. Elsheikh, F. M. Suliman, M. M. Rashid, and A. R. Faizabadi, “Innovative Strategies for Early Autism Diagnosis: Active Learning and Domain Adaptation Optimization,” *Diagnostics*, vol. 14, no. 6, Mar. 2024, doi: 10.3390/diagnostics14060629.

[7] M. M. Rashid, M. S. Alam, M. Y. Ali, and S. Yvette, “Developing a multi-modal dataset for deep learning-based neural networks in autism spectrum disorder diagnosis,” in *AIP Conference Proceedings*, American Institute of Physics, Aug. 2024. doi: 10.1063/5.0229867.

[8] S. Jeba Berlin, D. Pandian, S. S. Rajagopalan, and D. B. Jayagopi, “DETECTING A CHILD’S STIMMING BEHAVIOURS FOR AUTISM SPECTRUM DISORDER DIAGNOSIS USING RGBPOSE-SLOWFAST NETWORK,” in *Proceedings - International Conference on Image Processing, ICIP*, IEEE Computer Society, 2022, pp. 3356–3360. doi: 10.1109/ICIP46576.2022.9897867.

[9] A. S. Heinsfeld, A. R. Franco, R. C. Craddock, A. Buchweitz, and F. Meneguzzi, “Identification of autism spectrum disorder using deep learning and the ABIDE dataset,” *Neuroimage Clin.*, vol. 17, pp. 16–23, 2018, doi: 10.1016/j.nicl.2017.08.017.

[10] K. Vakadkar, D. Purkayastha, and D. Krishnan, “Detection of Autism Spectrum Disorder in Children Using Machine Learning Techniques,” *SN Comput. Sci.*, vol. 2, no. 5, Sep. 2021, doi: 10.1007/s42979-021-00776-5.

[11] V. Lokegaonkar*et al.*, “Introducing SSBD+ Dataset with a Convolutional Pipeline for detecting Self-Stimulatory Behaviours in Children using raw videos,” Nov. 2023, [Online]. Available: http://arxiv.org/abs/2311.15072

[12] C. H. Yoo, J. H. Yoo, M. K. Back, W. J. Wang, and Y. G. Shin, "A unified framework to stereotyped behavior detection for screening Autism Spectrum Disorder," *Pattern Recognit. Lett.*, vol. 186, pp. 156–163, Oct. 2024, doi: 10.1016/j.patrec.2024.10.001.

[13] B. Khan, S. M. Bhatti, and A. Akram, "Autism Spectrum Disorder Detection in Children Via Deep Learning Models Based on Facial Images," *Bulletin of Business and Economics (BBE)*, vol. 13, no. 1, Mar. 2024, doi: 10.61506/01.00241.

[14] M. F. Rabbi, S. M. M. Hasan, A. I. Champa, and M. A. Zaman, "A Convolutional Neural Network Model for Early-Stage Detection of Autism Spectrum Disorder," in *2021 International Conference on Information and Communication Technology for Sustainable Development, ICICT4SD 2021 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., Feb. 2021, pp. 110–114. doi: 10.1109/ICICT4SD50815.2021.9397020.

[15] H. Alkahtani, T. H. H. Aldhyani, and M. Y. Alzahrani, "Deep Learning Algorithms to Identify Autism Spectrum Disorder in Children-Based Facial Landmarks," *Applied Sciences (Switzerland)*, vol. 13, no. 8, Apr. 2023, doi: 10.3390/app13084855.

[16] A. Lu and M. Perkowski, "Deep learning approach for screening autism spectrum disorder in children with facial images and analysis of ethnoracial factors in model development and application," *Brain Sci.*, vol. 11, no. 11, Nov. 2021, doi: 10.3390/brainsci11111446.