International Journal of Advance and Applied Research
www.ijaar.co.in
ISSN – 2347-7075 Impact Factor – 8.141
Peer Reviewed Bi-Monthly
Vol. 7 No. 28 March - April - 2026

Deep Learning-Based Autism Detection Using Facial Images with Hybrid Preprocessing Techniques

Vijaykumar Jangamashetti[1] & Dr. Sharanabasava Inamadar[2]
[1]*Research Scholar, Ajeenkya D Y Patil University, Pune, India*
[2]*Associate Professor, Ajeenkya D. Y. Patil University, Pune, India*
Corresponding Author – Vijaykumar Jangamashetti
DOI - 10.5281/zenodo.19396774

Abstract:

Autism Spectrum Disorder (ASD), a neurodevelopmental disorder, presents with impairments in socialization and communication skills. The intervention of the condition largely depends on the early detection of the disorder. However, the traditional detection methods of the disorder are largely subjective in nature and require a considerable amount of time to be spent. In the following paper, a deep learning approach to detect an automated method of detecting autism by analyzing facial images is proposed. The image dataset contains 2,936 facial images, equally divided into two classes of autistic and non-autistic images. The preprocessing steps involved are explained in detail, and some of them are basic filters such as bilateral filtering, CLAHE (Contrast Limited Adaptive Histogram Equalization), gamma correction, and denoising. Hybrid combinations of filters are also used, such as the combination of bilateral filtering and CLAHE, as well as unsharp filtering. These steps are meant to enrich feature presentation and consequently enhance classification effectiveness. All images are downsized to 128x 128x 3, normalized, and data are augmented to enhance model generalizability. Five deep learning models, including CNN, InceptionV3, MobileNetV2, VGG16, and DenseNet are tested in the conditions of raw and pre-processed images. The results of the experiment indicate that preprocessing has a tremendous impact on the performance of the model. Without preprocessing, MobileNetV2 has the highest accuracy of 79.91 %; with preprocessing, DenseNet achieves the best testing accuracy of 79.00 % and F1-score of 0.79. The results show that hybrid preprocessing methods significantly improve classification performance, whose extent of improvement is model dependent. The suggested framework is therefore an effective and non-invasive approach to detecting early autism through the use of facial images.

Keywords: Autism Spectrum Disorder (ASD), Deep Learning, Facial Image Analysis, Convolutional Neural Networks (CNN), Transfer Learning, Image Preprocessing, Hybrid Filtering, DenseNet, MobileNetV2, Computer Vision

Introduction:

Autism Spectrum Disorder (ASD) is a complicated neurodevelopmental disorder that is typified by impairment in social interaction, communication, and repetitive behavioral patterns. Early detection of ASD is critical to the introduction of interventions and the reduction of developmental courses. Traditional modes of diagnosis, however, are highly pre-determined by the behavioural assessments by the clinical professional; these methods are often subjective, can be very time-consuming, and require a high level of expertise. These limitations have triggered the quest to seek automated, objective diagnostic techniques, based on artificial intelligence[1], [2], [3], [4].

Over the last few years, computer vision and deep-learning algorithms have proved to have a significant potential in the medical image analysis sphere, including facial-based diagnostics. The existing empirical studies suggest that persons with ASD have minor morphological differences in the facial features that can be captured and analysed through deep-learning architectures. Transfer-learning models like VGG16, InceptionV3, and MobileNetV2 have been widely used as feature extractors and classifiers because of their ability to learn hierarchical representations in image data[5], [6], [7].

Regardless of the recent progress, the effectiveness of deep learning algorithms in the detection of autism spectrum disorder still depends on the fidelity of the input imagery. Spatially discontinuous illumination, sensor noise, contrast difference, and background heterogeneity have their significant effect on feature extraction and subsequent generalizability of the models. Even though the literature is largely focused on network architecture refinements, limited academic effort has been put towards the possibility of enhancing classification accuracy by using image preprocessing and enhancement algorithms. Specifically, the effectiveness of hybrid filtering methods that combine several preprocessing methods has not been explored to a large extent[8], [9], [10], [11].

In that regard, the current study presents a comprehensive deep-learning system of autism identification on the basis of facial photographs. The framework uses a combination of preprocessing steps such as bilateral filtering, contrast enhancement, gamma correction, and composite hybrid filters, to enhance the quality of images and add more features to the image. The framework empirically compares five state-of-the-art convolutional neural networks, which include CNN, InceptionV3, MobileNetV2, VGG16 and DenseNet in both unprocessed and pre-processed imaging tests[12], [13], [14].

This study has three major contributions. To enhance the quality of facial images, to begin with, the development of a unified preprocessing pipeline that uses a set of basic and hybrid filtering methods has been conceived. Second, several deep-learning architectures have been comparatively studied to determine their effectiveness in the classification of autism spectrum disorder (ASD). Third, the performance of the models has been thoroughly analyzed before and after preprocessing and this therefore explains the model dependent effects of preprocessing strategies. The rest of the manuscript is structured in the following way. Section 2 provides a literature review, Section 3 outlines the proposed methodology, Section 4 presents the findings of the empirical study, and Section 5 gives the final thoughts and possible future directions of the research.

Literature Review:

The recent developments in deep learning and computer vision significantly improved automated medical diagnostics, such as the identification of autism spectrum disorder (ASD) through facial image recognition. Many research works have been conducted to evaluate the effectiveness of applying CNNs and transfer learning to automatically discover discriminative facial features with predictive power for ASD.

The first research in this area of study mainly used traditional CNN models to classify autistic and non-autistic children as two classes. For example, some researchers used basic CNN models to obtain a moderate level of classification accuracy, thus verifying the feasibility of facial-based ASD detection, as well as the limitation of feature representation and generalization ability[15]. To overcome these constraints, the idea of the transfer learning-based approach, i.e., VGG16 and InceptionV3, was put forward, which utilizes the pre-trained weights to improve the accuracy of feature extraction as well as the classification accuracy[16],[17].

To address the constraints, the focus of the research has been shifted towards the improvement of the performance of the system by using the hybrid approach in recent times. An advanced form of the deep learning network is the combination of the ResNet50V2 and InceptionV3 architectures, which has been proved that the hybrid approach is efficient in achieving the ASD classification accuracy of over 90 percent of the performance rates [18]. In the same way, the lightweight MobileNet architecture, which is based on the mobile-based architecture, has been experimented with efficiency in the detection of ASD, which is a trade-off between the accuracy of the prediction as well as the speed of the computation[18].

Along with the methods of model improvement, other studies have noted the significance of data preprocessing and data augmentation methods. The visibility of features and classification performance have been proven to be improved through contrast enhancement algorithms like CLAHE as well as noise reduction algorithms[19]. Nevertheless, the majority of the current literature applies unimodal pre-processing methods and fails to systematically perform comparisons between the effects of two or more methods of filtering. Also, the current studies have started to investigate explainable AI (XAI) methods and attention processes to enhance interpretability and resilience in ASD detection systems[20]. In spite of these developments, there is still a research gap to be filled in the interaction of various preprocessing methods and different deep learning models and how these affect the general performance. Here, the current paper fills this gap by conducting a detailed analysis of various preprocessing methods, such as hybrid filters, in various deep learning models. In contrast to the available literature where the main aim of optimization is on the model, in this study the importance of preprocessing is considered in improving the feature extraction and classification accuracy.

Table 1: Summary of Related Work in ASD Detection Using Facial Images

Author & Year	**Model Used**	**Dataset**	**Accuracy**	**Key Contribution**	**Limitation**
Thabtah et al., 2020[21]	CNN	Facial ASD dataset	~75%	Initial CNN-based ASD detection	Limited generalization
Ahmad I,(2024([22]	VGG16	Facial images	80%	Transfer learning improves performance	Sensitive to noise
Tariq et al., 2021[23]	InceptionV3	ASD dataset	78%	Deep feature extraction	Moderate accuracy
Aarthi D. et.al., 2025[24]	ResNet50V2 + InceptionV3	Facial dataset	92–95%	Hybrid deep learning model	High computational cost
[25]	MobileNetV2	ASD facial images	85%	Lightweight model for real-time use	Slightly lower accuracy
Awaji et.al. 2023[26]	CNN + CLAHE	Image dataset	83%	Importance of preprocessing	Single filter used
Rathod V. et.al.[27]	CNN + Attention/XAI	Facial dataset	88%	Explainability in ASD detection	Complex architecture

Methodology:

This paper suggests a deep learning-based system of the classification of autistic children and non-autistic ones by using the facial images. The general approach will include the dataset preparation, image preprocessing with the base and hybrid filtering methods, data augmentation, and classification by several deep learning models. The goal is to examine the effect of preprocessing on model performance and also a model-filter combination that is most appropriate in detecting autism. The data to be used in this research contains 2,936 facial pictures, which are equally divided into autistic and non-autistic categories, ensuring equilibrium classification problem. The images are resized to an unchanging size of 128 128 3 to keep them consistent across models. In order to make training easier and converge faster, pixel intensities are brought to the range [0,1]. The dataset will be split into two subsets: training and validation sets (depending on the 70-30 percentage) so that 2,055 training images and 881 validation images will be generated. This proposed system (shown in figure 1) can be used to achieve the entire process of detecting autism through the use of facial images. It consists of base and hybrid filtering based preprocessing, data augmentation, feature extraction with deep learning based algorithms and classification and an evaluation of the performance.

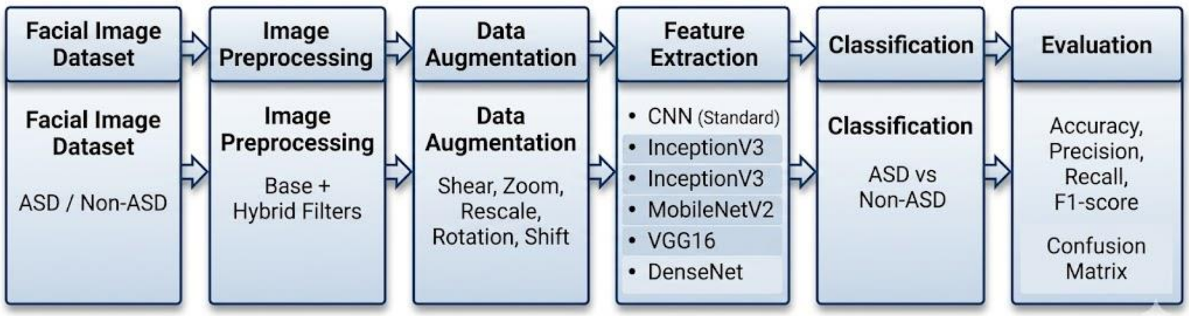

Figure 1: Proposed Workflow Diagram for ASD Classification using Deep Learning

Image preprocessing is a key element of the proposed framework since the process increases the visibility of features and advances the learning attribute of deep learning models. Various preprocessing methods are used in this work in order to enhance image quality. These consist of bilateral filtering of edge preserving smoothing, Butterworth low-pass filtering of noise reduction, median filtering of impulse noise removal, gamma correction of brightness increase, and Contrast Limited Adaptive Histogram Equalization (CLAHE) of contrast increase. Also, edge details are better using unsharp masking and denoising and contrast enhancement operations are employed to further sharpen the clarity of the image. Facial features in the form of edges are also highlighted by use of edge detection. In order to better represent the features, hybrid filtering methods are presented through the combination of several preprocessing methods. These are bilateral filtering plus unsharp masking, CLAHE plus bilateral filtering, denoising plus median filtering and a hybrid method that combines bilateral filtering, CLAHE, and unsharp masking. The intent of such hybrid techniques is to minimize noise and maximize contrast, meanwhile preserving significant structural features so as to increase the usefulness of feature extraction. In order to resolve the problem of overfitting and enhance the model generalization, data augmentation with the usage of Image Data Generator is conducted. Shear, zoom, and horizontal flipping are some of the transformations which are carried out so as to create different variations of the input images. This enables the models to acquire the characteristics of invariance and enhances their resistance to changes in real world circumstances.

For classification, five deep learning models are employed, including a custom Convolutional Neural Network (CNN) and four transfer learning architectures: InceptionV3, MobileNetV2, VGG16, and DenseNet. The transfer learning models utilize pre-trained weights to extract high-level features efficiently, while the custom CNN is designed to learn task-specific features from scratch. All models are trained using the Adam optimizer with binary cross-entropy as the loss function.

The performance of each model is measured by using various parameters such as accuracy, precision, recall, and F1-score. Confusion matrices are also considered to assess the performance of the models. The experiments are carried out considering two cases: one with no preprocessing and the other with preprocessing using base filters as well as hybrid filters. This experiment is considered to assess the performance of the deep learning models by considering the effect of the preprocessing techniques.

Results And Discussion:

1. Performance Evaluation Before Preprocessing:

The performance of the deep learning models before applying preprocessing techniques is illustrated in Figure. 2. The comparison highlights both training and testing accuracies across all models

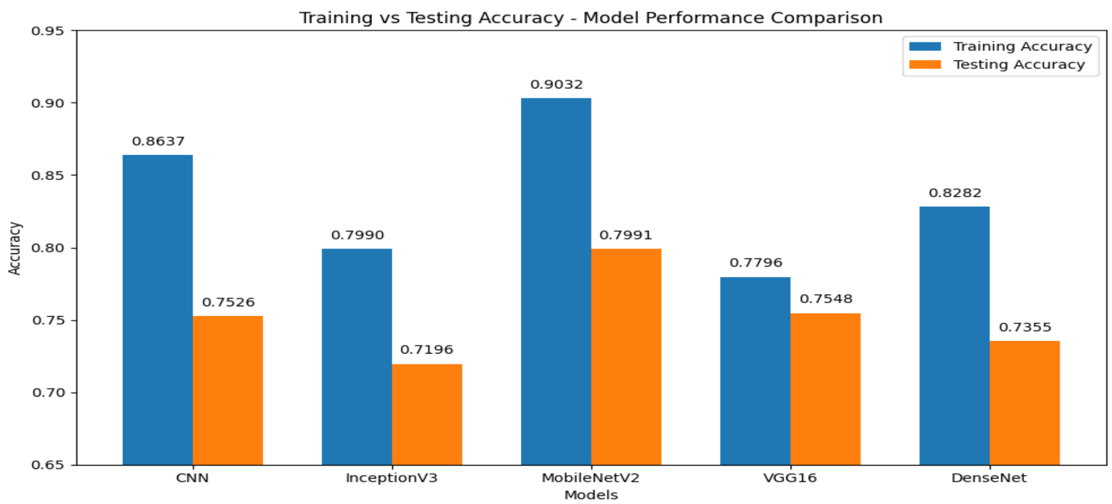

Fig. 2. Training vs Testing Accuracy Comparison of Deep Learning Models Before Preprocessing

The results showed that MobileNetV2 has the highest training accuracy of 90.32% and testing accuracy of 79.91%, indicating that it is capable of extracting features. CNN has also shown comparable results with a training accuracy of 86.37% and testing accuracy of 75.26%. VGG16 and DenseNet showed moderate results, while InceptionV3 showed low accuracy.

A noticeable gap between training and testing accuracy is observed across most models, particularly in MobileNetV2 and CNN, indicating the presence of overfitting. This suggests that the models are sensitive to noise and variations in the input images, thereby justifying the need for preprocessing techniques.

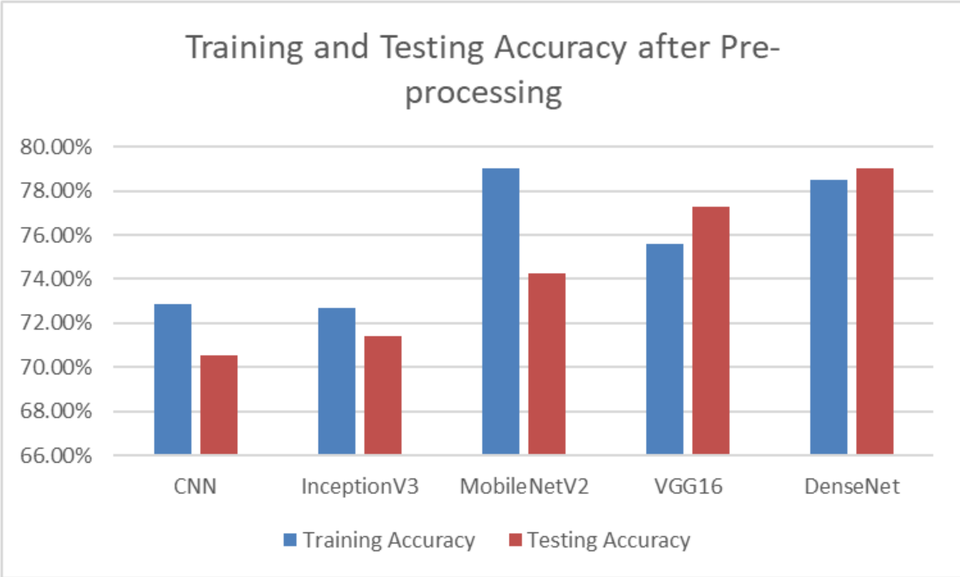

Fig. 3. Training vs Testing Accuracy Comparison of Deep Learning Models After Preprocessing

2. Model-wise Classification Analysis:

A comprehensive study of the performance of the classification shows that the various models behave differently in the identification of autistic and non-autistic classes. CNN model shows high recall on the non-ASD category but relatively low on the ASD samples, which implies that it is ineffective to obtain the discriminative characteristics of the autistic cases. InceptionV3 produces relatively lower results both on each of the two classes, indicating that it is not as adaptable to the dataset. MobileNetV2 is also a balanced network with a precision and a recall of approximately 0.80, and equal values of these values across the two classes, meaning that it is a stable classifier. VGG16 has a skew towards ASD, wherein it has higher recall rates on ASD and lower on non-ASD. DenseNet has a high recall of non-ASD, although it has poor performance at detecting ASD, which suggests that feature learning with such data does not reflect the balanced data situation. The results show that the proposed model performs the classification task on medical image analysis when the subtle variations on features is essential.

3. Training Behaviour and Overfitting Analysis:

The accuracy loss curves from training and validation tests show how the models learn. The Mobile Net V2 system achieves stable learning through its continuous development process which results in minimal performance variations. The CNN is slightly overfitted, which can be seen by the fact that the training and validation accuracy begin to diverge later in the epochs. The convergence is slower in InceptionV3 implying inefficient feature learning. The training behavior of VGG16 and DenseNet is fairly stable, and the validation loss varies between average and high. These findings suggest that deeper architectures can achieve better feature extraction but need a better preprocessing to perform optimally.

4. Performance Evaluation After Preprocessing:

The impact of preprocessing techniques on model performance is summarized in Table 2.

Table 2. Model Performance Comparison After Preprocessing

Model	Training Accuracy	Testing Accuracy	Precision	Recall	F1-score
CNN	72.88%	70.52%	0.71	0.71	0.70
InceptionV3	72.70%	71.40%	0.72	0.71	0.71
MobileNetV2	79.03%	74.23%	0.74	0.74	0.74
VGG16	75.62%	77.30%	0.77	0.77	0.77
DenseNet	78.49%	**79.00%**	**0.79**	**0.79**	**0.79**

The findings prove that preprocessing has a strong effect on classification. DenseNet has the highest testing accuracy and F1-score of 79.00% and 0.79 respectively, which means that it can successfully make use of the improved feature representations. VGG16 also demonstrates significant improvement with an accuracy of testing at 77.30. Interestingly, CNN and MobileNetV2 show the slightest reduction in performance following the preprocessing, which indicates that some preprocessing methods can change feature distributions in a manner that negatively affects these models.

5. Comparative Analysis (Before vs After Preprocessing):

The preprocessing of the performance of various models before and after the process presents valuable information regarding the performance of the hybrid filtering methods. It can be seen that the highest improvement is observed with DenseNet, which implies the ability of this technique to work with a refined representation of features.

- VGG16 is also preprocessing based and thus, has better generalization.
- Mobile Net V2 is marginally degrading, which can be interpreted as sensitivity to preprocessing transformations.
- The CNN performance declines, which implies that feature learning in shallow architectures may be disturbed by handcrafted preprocessing.

These results indicate that preprocessing is architecture-specific, and hybrid filtering methods are not consistently effective across all architectures.

6. Key Findings and Discussion:

In the experimental findings, it is evident that hybrid preprocessing technologies are important in enhancing performance in certain deep learning models in classification. Whereas preprocessing improves the clarity of features and minimizes noise, its performance varies according to the architecture of the model. It can be shown that DenseNet provides the strongest model in this analysis, and it is the most effective model in the post-processing period. This is because it is densely connected with each other and, therefore, allows effective reuse and propagation of features. Conversely, simpler structures like CNN exhibit less performance, which implies that they are sensitive to preprocessing transformations. On the whole, the research highlights the need to choose the proper preprocessing methods in terms of their combination with the appropriate deep learning models to reach the best possible results in the field of autism detection based on facial images.

Conclusion And Future Work:

This paper introduced a deep learning-based architecture of autism detection in the face image analysis, the main aim of which was to analyse the effect of image preprocessing methods. To improve the quality of images and feature representation, a hybrid filtering pipeline with a full preprocessing pipeline which takes into account both base and hybrid filtering techniques was created. The general supercomputer models were compared among five deep learning models, which included CNN, InceptionV3, Mobile Net V2, VGG16, and DenseNet in both raw and pre-processed. These experimental results prove that the preprocessing factor is important when it comes to the model performance. DenseNet was the most effective model among the tested ones, having a testing accuracy of 79.00 and F1-score of 0.79 that showed that the network can be successfully used to take advantage of improved feature representations. VGG16 was also significantly improved, and CNN and MobileNetV2 demonstrated a slight decline, which demonstrates that the method of preprocessing techniques is model-dependent. The results of this research highlight the fact that hybrid preprocessing methods can enhance the classification performance in a case where they are properly matched with model architecture. Nevertheless, preprocessing is not always going to be beneficial in all models, and preprocessing has to be selected carefully. The next steps in the field will be working on the extension of the proposed framework to include attention mechanisms and transformer-based architectures to achieve greater classification accuracy. Also, explainable artificial intelligence (XAI) methods like Grad-CAM will be considered to ensure that the output of the model can be interpreted. To augment the strength and usability of the suggested system in practice, it is possible to consider expanding the data set and including multimodal inputs, including behavioural or clinical data.

References:

1) T. Abualait *et al.*, “autism spectrum disorder in Children: Early Signs and Therapeutic Interventions,” *Children 2024, Vol. 11,* vol. 11, no. 11, Oct. 2024, doi: 10.3390/children11111311.
2) M. Wang, X. Zhang, L. Zhong, L. Zeng, L. Li, and P. Yao, “Understanding autism: Causes, diagnosis, and advancing therapies,” *Brain Res. Bull.*, vol. 227, no. 6597, p. 111411, Jul. 2025, doi: 10.1016/j.brainresbull.2025.111411.
3) C. Okoye *et al.*, “Early Diagnosis of Autism Spectrum Disorder: A Review and Analysis of the Risks and Benefits,” *Cureus*, vol. 15, no. 8, p. e43226, Aug. 2023, doi: 10.7759/cureus.43226.
4) M. O. Bertelli, A. Bianco, V. Boniotti, and E. Chaplin, “Definition, Diagnosis, and Prevalence of Autism Spectrum Disorder,” *The Palgrave Encyclopedia of Disability*, pp. 1–15, 2025, doi: 10.1007/978-3-031-40858-8_229-1.
5) K. Rezaee, T. S. Javanmardi, and A. M. Heydari, “A deep learning framework for classifying autism spectrum disorder from children’s facial images using a multi-scale ViT architecture and edge computing,” *Open Exploration 2019 6:*, vol. 6, pp. 1001376-, Dec. 2025, doi: 10.37349/emed.2025.1001376.
6) U. J. Monani, R. Maity, P. K. Pattnaik, K. S. M. Anbananthen, S. Muthaiyah, and M. Sain, “Evaluating Deep Learning Models for Autism Detection in Children Using Facial Images,” *Journal of Human, Earth, and Future*, vol. 7, no. 1, pp. 48–60, Mar. 2026, doi: 10.28991/HEF-2026-07-01-03.

7) B. Awaji *et al.*, “Hybrid Techniques of Facial Feature Image Analysis for Early Detection of Autism Spectrum Disorder Based on Combined CNN Features,” *Diagnostics*, vol. 13, no. 18, p. 2948, Sep. 2023, doi: 10.3390/diagnostics13182948.
8) D. N. Vasundhara, P. Lakshmi Prasanna, Ch. V. K. N. S. N. Moorthy, and N. Venkata Sailaja, “Early Detection of Autism Spectrum Disorder in Children Using Facial Images and AI-Based Deep Learning Models,” *Journal of Pioneering Medical Sciences*, vol. 15, no. 01, pp. 137–145, Feb. 2026, doi: 10.47310/jpms2026150119.
9) M. S. Alam *et al.*, “Efficient Deep Learning-Based Data-Centric Approach for Autism Spectrum Disorder Diagnosis from Facial Images Using Explainable AI,” *Technologies 2023, Vol. 11,* vol. 11, no. 5, Aug. 2023, doi: 10.3390/technologies11050115.
10) N. Mallick, S. Sahu, H. Nanda, P. Pattnayak, and T. Das, “Deep Learning-Based Autism Spectrum Behaviour Recognition in Children Using Video and Audio Signal Processing,” *2025 IEEE 2nd International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS)*, pp. 1–5, Aug. 2025, doi: 10.1109/ICITEICS64870.2025.11340968.
11) B. Benabderrahmane, M. Gharzouli, and A. Benlecheb, “A novel multi-modal model to assist the diagnosis of autism spectrum disorder using eye-tracking data,” *Health Inf. Sci. Syst.*, vol. 12, no. 1, p. 40, Dec. 2024, doi: 10.1007/s13755-024-00299-2.
12) U. J. Monani, R. Maity, P. K. Pattnaik, K. S. M. Anbananthen, S. Muthaiyah, and M. Sain, “Evaluating Deep Learning Models for Autism Detection in Children Using Facial Images,” *Journal of Human, Earth, and Future*, vol. 7, no. 1, pp. 48–60, Mar. 2026, doi: 10.28991/HEF-2026-07-01-03.
13) M. Beary, A. Hadsell, R. Messersmith, and M.-P. Hosseini, “Diagnosis of Autism in Children using Facial Analysis and Deep Learning,” Aug. 2020, Accessed: Mar. 17, 2026. [Online]. Available: https://www.researchgate.net/publication/363296591_Autism_detection_from_facial_images_using_deep_learning_methods
14) D. Aarthi and S. Kannimuthu, “RETRACTED ARTICLE: Hybrid deep learning model for autism spectrum disorder diagnosis,” *Sci. Rep.*, vol. 15, no. 1, p. 44707, Dec. 2025, doi: 10.1038/s41598-025-28819-4.
15) I. Ahmad, J. Rashid, M. Faheem, A. Akram, N. A. Khan, and R. ul Amin, “autism spectrum disorder detection using facial images: A performance comparison of pretrained convolutional neural networks,” *Healthc. Technol. Lett.*, vol. 11, no. 4, pp. 227–239, Aug. 2024, doi: 10.1049/htl2.12073.
16) M. S. Alam *et al.*, “Efficient Deep Learning-Based Data-Centric Approach for Autism Spectrum Disorder Diagnosis from Facial Images Using Explainable AI,” *Technologies 2023, Vol. 11,* vol. 11, no. 5, Aug. 2023, doi: 10.3390/technologies11050115.
17) P. Reddy and J. Andrew, “Diagnosis of Autism in Children Using Deep Learning Techniques by Analyzing Facial Features,” *Engineering Proceedings 2023, Vol. 59,* vol. 59, no. 1, Jan. 2024, doi: 10.3390/engproc2023059198.
18) T. Farhat, S. Akram, H. S. AlSagri, Z. Ali, A. Ahmad, and A. Jaffar, “Facial Image-Based Autism Detection: A Comparative Study of Deep Neural Network Classifiers,” *Computers, Materials and Continua*, vol. 78, no. 1, pp. 105–126, Jan. 2024, doi: 10.32604/cmc.2023.045022.

19) M. S. Alam, M. M. Rashid, A. Jazlan, M. E. E. Alahi, M. Kchaou, and K. A. B. Alharthi, "Robust Autism Spectrum Disorder Screening Based on Facial Images (For Disability Diagnosis): A Domain-Adaptive Deep Ensemble Approach," *Diagnostics 2025, Vol. 15,* vol. 15, no. 13, Jun. 2025, doi: 10.3390/diagnostics15131601.
20) T. Akalya, D. Ramyachitra, M. Shabarna, and C. Legha, "Deep learning-based detection of autism spectrum disorder and emotion recognition in children," *Pattern Recognit.*, vol. 173, p. 112906, May 2026, doi: 10.1016/j.patcog.2025.112906.
21) F. Thabtah, "Autism Spectrum Disorder Screening," 2017, *ACM*. doi: 10.1145/3107514.3107515.
22) I. Ahmad, J. Rashid, M. Faheem, A. Akram, N. A. Khan, and R. ul Amin, "autism spectrum disorder detection using facial images: A performance comparison of pretrained convolutional neural networks," *Healthc. Technol. Lett.*, vol. 11, no. 4, p. 227, Aug. 2024, doi: 10.1049/htl2.12073.
23) Q. Tariq, J. Daniels, J. N. Schwartz, P. Washington, H. Kalantarian, and D. P. Wall, "Mobile detection of autism through machine learning on home video: A development and prospective validation study," *PLoS Med.*, vol. 15, no. 11, Nov. 2018, doi: 10.1371/journal.pmed.1002705.
24) D. Aarthi and S. Kannimuthu, "RETRACTED ARTICLE: Hybrid deep learning model for autism spectrum disorder diagnosis," *Sci. Rep.*, vol. 15, no. 1, p. 44707, Dec. 2025, doi: 10.1038/s41598-025-28819-4.
25) N. Attar and S. Paygude, "Lightweight Deep Learning Model for Autism Spectrum Disorder Detection and Expression Recognition in Children Using Facial Images," *Frontiers in Health Informatics*, vol. 13, no. 2, pp. 97–108, 2024, doi: 10.52783/fhi.11.
26) B. Awaji *et al.*, "Hybrid Techniques of Facial Feature Image Analysis for Early Detection of Autism Spectrum Disorder Based on Combined CNN Features," *Diagnostics 2023, Vol. 13,* vol. 13, no. 18, Sep. 2023, doi: 10.3390/diagnostics13182948.
27) V. N. Rathod, R. H. Goudar, and S. Sangani, "An explainable deep learning framework for screening level autism severity using behavioural data," *Discover Applied Sciences 2026*, Mar. 2026, doi: 10.1007/s42452-026-08352-3.