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Facial Image-Based Autism Detection Using Deep Learning: Methods, Challenges, and Future Directions

Mr.Narendrasing Bhikesing Rajput[1], Name Dr.Atul Hiralal Karode[2],

[1]PhD Research Scholar , :0009-0009- 9005-8401
Shram Sadhana Bombay Trust Sanchlit College of Engineering and technology,Bambhori , Jalgaon,India,425001
[2]PhD Research Guide, Associate Professor, ::0000-0001-9384-8075
Shram Sadhana Bombay Trust Sanchlit College of Engineering and technology,Bambhori , Jalgaon,India,425001
narendrasingrajput@gmail.com, atulkarode@gmail.com

Abstract – *Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by impairments in social interaction, communication, and behavior, making early diagnosis crucial for effective intervention. Traditional diagnostic methods rely on behavioral assessments, which are often time-consuming and subjective. In recent years, deep learning-based computer vision techniques have emerged as promising tools for automated and non-invasive autism detection using facial images. This paper presents a comprehensive review of deep learning approaches for facial image-based autism detection, focusing on convolutional neural networks, transfer learning models, and hybrid architectures. The study analyzes commonly used datasets, evaluation metrics, and performance trends, highlighting that modern approaches achieve high accuracy but remain limited by dataset size, diversity, and clinical validation. Furthermore, key challenges such as ethical concerns, generalization issues, and lack of interpretability are discussed. The paper also outlines future research directions, including multimodal learning, explainable artificial intelligence, and the adoption of advanced architectures, to enhance the reliability and applicability of automated ASD detection systems*

Keywords- *Autism Spectrum Disorder, Deep Learning, Facial Image Analysis, Convolutional Neural Networks, Transfer Learning, Computer Vision, Medical Image Analysis, Explainable AI.*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by impairments in social interaction, communication difficulties, and repetitive behavioral patterns. According to the World Health Organization, ASD affects approximately one in every 100 children globally, highlighting the importance of early diagnosis and intervention [1]. Conventional diagnostic approaches rely primarily on behavioral observations and clinical expertise, which are often subjective, time-consuming, and dependent on the availability of trained professionals [2].

In recent years, advances in artificial intelligence (AI), particularly deep learning, have enabled the development of automated systems for medical diagnosis. Computer vision techniques have demonstrated significant potential in analyzing facial images for disease detection. Research indicates that individuals with ASD may exhibit distinct facial morphological characteristics, including variations in facial symmetry and structural proportions [3]. These findings have encouraged the exploration of facial image-based autism detection as a non-invasive and efficient screening tool.

Deep learning models, especially convolutional neural networks (CNNs), have achieved remarkable success in image classification and feature extraction tasks. Architectures such as ResNet have significantly improved performance in visual recognition problems [4]. Additionally, transfer learning techniques allow the reuse of pre-trained models, enabling effective learning even with limited datasets [5]. These approaches have been increasingly applied in medical image analysis, including autism detection.

Despite these advancements, several challenges remain. One major limitation is the lack of large, diverse, and clinically validated datasets, which affects the generalization capability of deep learning models. Furthermore, ethical concerns related to the use of children's facial images and data privacy must be carefully addressed. The broader landscape of AI ethics highlights the importance of transparency, fairness, and accountability in deploying such systems [6]. Moreover, ASD diagnosis is inherently multifaceted and cannot rely solely on facial features, as behavioral and cognitive assessments remain essential components [2].

Motivated by these challenges, this paper presents a comprehensive review of deep learning-based approaches for autism detection using facial images. The study analyzes existing methods, datasets, and performance metrics, while identifying key limitations and research gaps. Additionally, future research directions, including multimodal learning and explainable AI, are discussed to support the development of reliable and ethically responsible ASD detection systems.

2.Related Work

Recent progress in deep learning and computer vision has significantly advanced automated approaches for Autism Spectrum Disorder (ASD) detection. In particular, facial image-based analysis has gained attention as a non-invasive and scalable solution for early screening. This section reviews key contributions in the application of deep learning techniques for facial image-based ASD detection.

Early investigations into ASD detection primarily relied on behavioral assessments and handcrafted features derived from facial characteristics. Studies have shown that individuals with ASD may exhibit distinct facial phenotypes, including variations in facial symmetry and structural proportions, which can serve as potential biomarkers for detection [3]. However, traditional approaches were limited in capturing complex and subtle patterns present in facial images.

The emergence of deep learning, particularly convolutional neural networks (CNNs), has transformed image-based analysis by enabling automatic feature extraction. Deep architectures such as ResNet have demonstrated superior performance in visual recognition tasks due to their ability to learn hierarchical representations from large-scale datasets [4]. These capabilities have encouraged their application in medical image analysis, including ASD detection.

Transfer learning has further enhanced the applicability of deep learning models in domains with limited labeled data. By leveraging pretrained models and adapting them to specific tasks, researchers can achieve improved performance with reduced computational cost. The effectiveness of transfer learning in knowledge reuse and domain adaptation has been extensively studied in the literature [5]. Additionally, comprehensive surveys on deep learning in medical imaging highlight its growing role in classification and diagnostic applications [9].

Recent studies have specifically explored the use of deep learning models for ASD detection using facial images. For example, approaches based on CNN architectures have demonstrated promising results by learning discriminative facial features associated with ASD [10]. Lightweight models such as MobileNet have also been adopted for efficient and real-time applications, particularly in resource-constrained environments [12].

Despite these advancements, several limitations remain. Many studies rely on relatively small and homogeneous datasets, which restricts model generalization. Furthermore, ethical considerations related to data privacy and the use of children's facial images remain critical challenges in this domain [6]. These issues highlight the need for more robust, scalable, and ethically responsible approaches for facial image-based ASD detection. A comparative summary of key deep learning-based approaches for facial image-based autism detection is presented in Table 1.

Table 1. Comparison of Deep Learning-Based ASD Detection Studies

Study	Method	Dataset	Key Contribution
Tariq et al. [8]	CNN	Facial images	ASD detection using facial features
Litjens et al. [7]	Review	Medical datasets	DL in medical imaging
Howard et al. [9]	MobileNet	ImageNet	Efficient CNN model

3. Review Methodology

This section outlines the methodology adopted to conduct a structured review of deep learning-based approaches for autism detection using facial images. A systematic process was followed to identify, select, and analyze relevant research studies from reputable sources. The methodology ensures that the review is comprehensive, reproducible, and focused on recent advancements in the field.

3.1 Search Strategy

A structured search strategy was adopted to identify relevant studies related to autism detection using facial images and deep learning techniques. Research articles were collected from well-established digital libraries, including IEEE Xplore, Science Direct, Springer, and Google Scholar. The search process was guided by carefully selected keywords such as “autism detection,” “facial images,” “deep learning,” “convolutional neural networks,” and “ASD classification.” These keywords were used individually and in combination to ensure comprehensive coverage of the domain. The objective of this search strategy was to retrieve studies that specifically focus on the application of deep learning methods for facial image-based autism detection.

3.2 Inclusion and Exclusion Criteria

To maintain the quality and relevance of the selected studies, specific inclusion and exclusion criteria were defined. Studies were included if they focused on autism detection using facial images and employed deep learning models such as convolutional neural networks or transfer learning approaches. Only peer-reviewed articles published between 2015 and 2025 were considered to ensure that the review reflects recent advancements in the field. On the other hand, studies were excluded if they were based solely on behavioral, textual, or non-image data, or if they lacked proper experimental validation. Additionally, non-peer-reviewed sources and articles with insufficient technical details were omitted to ensure the credibility of the review.

3.3 Study Selection Process

The study selection process was carried out in multiple stages to ensure that only relevant and high-quality papers were included. Initially, a broad set of research articles was identified through keyword-based searches across the selected databases. In the next stage, the titles and abstracts of these articles were examined to eliminate irrelevant studies. Finally, a detailed full-text review was conducted to select papers that closely align with the objectives of this work. This systematic filtering approach ensured that the final set of studies represents the most relevant contributions in the area of facial image-based autism detection using deep learning.

3.4 Analysis Framework

The selected studies were analyzed using a structured framework to enable meaningful comparison and interpretation. Each study was evaluated based on the type of deep learning model used, the characteristics of the dataset, and the performance metrics reported, such as accuracy, precision, and recall. In addition, the strengths and limitations of each approach were examined to identify common trends and research gaps. This analytical framework provides a foundation for the comparative analysis presented in subsequent sections and supports the identification of future research directions.

The overall workflow of facial image-based autism detection using deep learning, including stages such as data acquisition, preprocessing, feature extraction, and classification, is illustrated in **Fig. 1**.

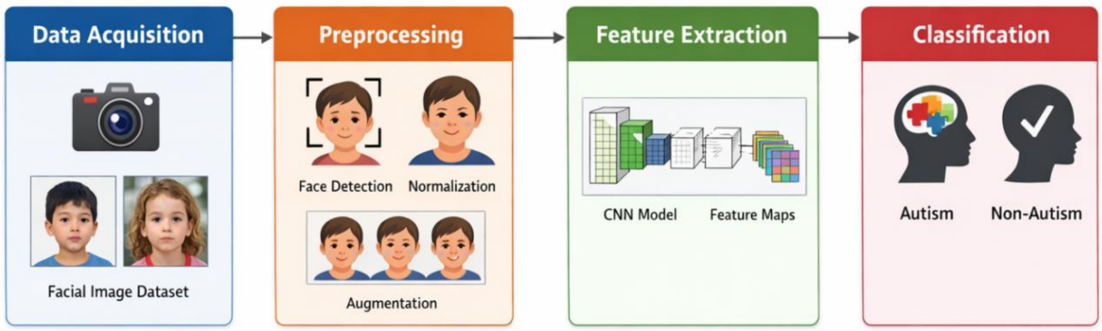

Fig. 1- General pipeline of deep learning-based autism detection using facial images

4.The **Deep Learning Methods for Autism Detection**

This section discusses the various deep learning techniques that have been employed for autism detection using facial images. With the advancement of computer vision and neural network architectures, deep learning models have demonstrated significant capability in extracting discriminative features from facial data. This section provides an overview of commonly used models and approaches, including convolutional neural networks, transfer learning techniques, and hybrid frameworks.

4.1 Convolutional Neural Network (CNN)-Based Approaches

Convolutional Neural Networks (CNNs) are the most widely used deep learning models for image classification tasks [10], [11], [12]. These networks automatically learn hierarchical feature representations from input images through multiple convolutional and pooling layers. In the context of autism detection, CNNs are used to extract facial features such as structural patterns, symmetry, and spatial relationships.

CNN-based approaches eliminate the need for manual feature extraction, which was a limitation in earlier machine learning methods. By learning directly from raw pixel data, CNNs can capture subtle variations in facial morphology that may be associated with ASD. The effectiveness of CNN architectures in image recognition tasks has been well established in the literature [4] ,[13], [14], making them a suitable choice for facial image-based autism detection.

4.2 Transfer Learning-Based Models

Transfer learning has emerged as a powerful technique for improving model performance, particularly when the available dataset is limited. In this approach, models pretrained on large-scale datasets such as ImageNet are fine-tuned for specific tasks, including ASD detection.

Popular pretrained architectures such as ResNet, VGG, and MobileNet are commonly used in this domain. These models provide robust feature extraction capabilities and reduce the need for extensive training data. The concept of transfer learning that enables knowledge reuse across domains, has been widely studied and applied in various machine learning applications [5]. Additionally, lightweight models such as MobileNet are particularly useful for real-time and mobile-based applications due to their reduced computational complexity [9].

4.3 Hybrid and Ensemble Models

To further enhance classification performance, recent studies have explored hybrid and ensemble approaches that combine multiple deep learning models. These methods aim to leverage the strengths of different architectures to improve accuracy and robustness.

Hybrid models may integrate CNNs with other machine learning techniques or combine multiple CNN architectures to form ensemble systems. Such approaches can reduce overfitting and improve generalization, especially when dealing with limited or imbalanced datasets. Ensemble learning techniques have been shown to enhance predictive performance by aggregating outputs from multiple models, thereby providing more reliable results [7].

4.4 Feature Extraction and Classification Strategies

In deep learning-based autism detection systems, feature extraction and classification are typically performed in an end-to-end manner. The convolutional layers are responsible for extracting relevant features from facial images, while fully connected layers perform classification into categories such as ASD and non-ASD.

In some approaches, deep features extracted from pretrained models are further processed using traditional classifiers such as Support Vector Machines (SVM) or Random Forests. This combination of deep feature extraction and classical classification can improve performance in certain scenarios. The choice of feature extraction and classification strategy depends on factors such as dataset size, computational resources, and application requirements.

5. Datasets and Performance Evaluation

This section presents the datasets commonly used for facial image-based autism detection and discusses the evaluation metrics employed to assess the performance of deep learning models. The effectiveness of any deep learning approach largely depends on the quality and diversity of the dataset, as well as the selection of appropriate evaluation measures.

5.1 Datasets Used for Autism Detection

Facial image-based autism detection studies primarily rely on publicly available datasets and curated image collections. Most datasets consist of facial images of children categorized into autistic and non-autistic classes. However, the availability of large-scale, clinically validated datasets remains a significant challenge in this domain.

Typically, datasets used in existing studies contain a few thousand images, often collected from online sources or research repositories. These datasets may suffer from issues such as class imbalance, limited diversity, and lack of standardized annotations. As a result, data preprocessing techniques such as normalization, augmentation, and resizing are commonly applied to improve model performance and generalization capability

Table 2. Summary of Commonly Used Datasets

Dataset Type	**Description**	**Limitation**
Public ASD Facial Dataset	Contains labeled autistic and non-autistic facial images	Limited size
Kaggle-based datasets	Widely used in research experiments	Lack of clinical validation
Custom datasets	Collected by researchers	Small and biased samples

5.2 Performance Evaluation Metrics

The performance of deep learning models for autism detection is evaluated using several standard metrics. Accuracy is the most commonly reported metric, representing the proportion of correctly classified samples. However, accuracy alone may not provide a complete picture, especially in imbalanced datasets.

Precision and recall are important metrics that measure the correctness and completeness of classification results, respectively. The F1-score, which is the harmonic mean of precision and recall, provides a balanced evaluation. These metrics are widely used in medical image classification tasks to assess the reliability and robustness of models. The overall data processing and evaluation workflow for facial image-based autism detection is illustrated in Fig. 4.

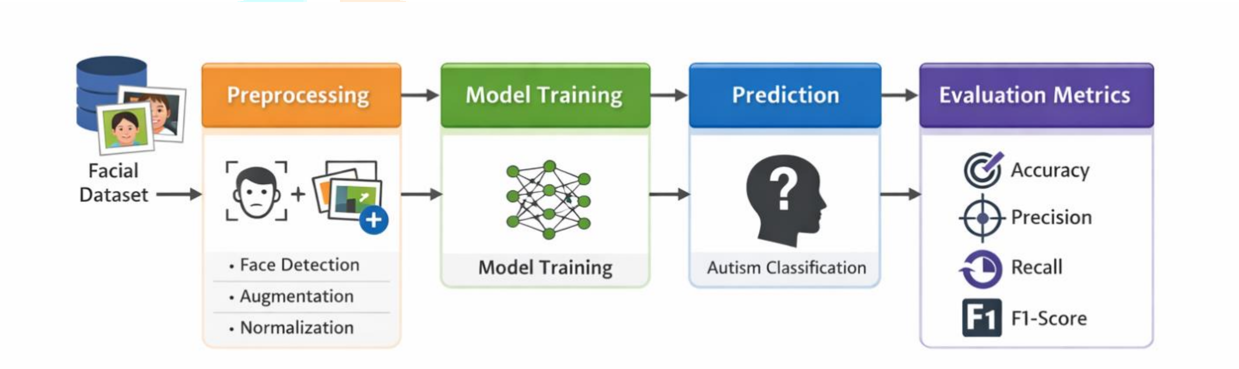

Fig. 2. Dataset processing and performance evaluation pipeline for facial image-based autism detection

5.3 Comparative Performance Analysis

Different deep learning models exhibit varying levels of performance depending on their architecture and training strategy. CNN-based models provide strong baseline performance, while transfer learning approaches such as ResNet and MobileNet offer improved accuracy due to pretrained feature representations. Ensemble models further enhance performance by combining predictions from multiple models.

The comparative performance of commonly used models is illustrated in Fig. 3, which shows the variation in classification accuracy across different architectures.

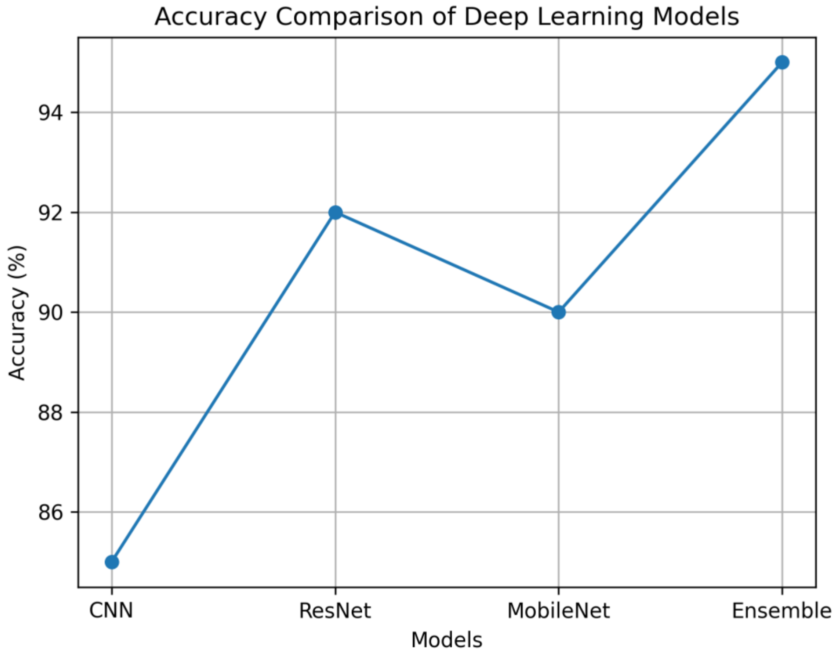

Fig. 3. Accuracy Comparison of Deep Learning Models

The comparison of precision and recall values across different models is shown in Fig. 4. These metrics provide deeper insight into model reliability, particularly in medical applications where false predictions can have significant consequences.

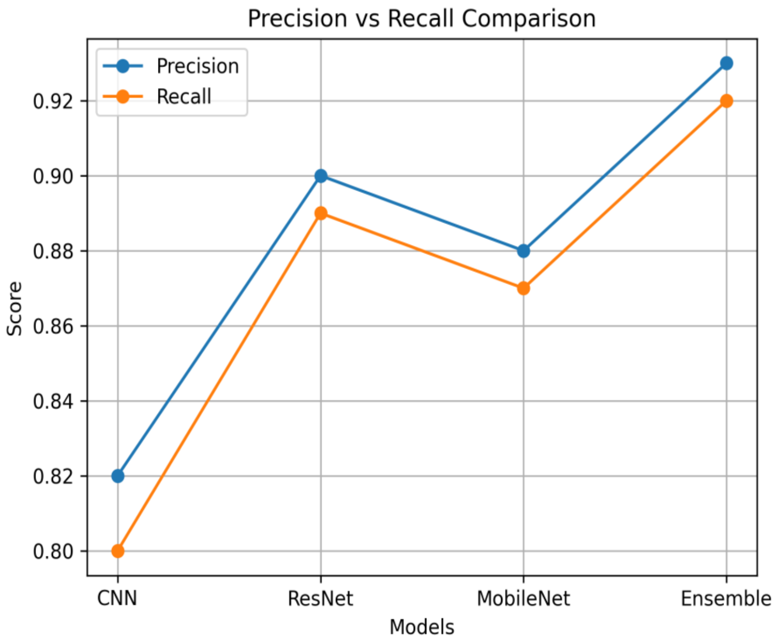

Fig. 4. Precision and Recall Comparison

5.4 Discussion

The analysis indicates that while deep learning models can achieve high accuracy, their performance is highly dependent on dataset quality and diversity. Transfer learning and ensemble approaches generally outperform standalone CNN models, especially in scenarios with limited training data. However, the lack of standardized datasets and evaluation protocols remains a key limitation, making it difficult to compare results across studies. Addressing these challenges is essential for developing robust and clinically reliable autism detection systems

6.Comparative Analysis

This section presents a comparative analysis of various deep learning approaches used for facial image-based autism detection. The objective is to evaluate different models based on their performance, computational complexity, and suitability for real-world applications. By systematically comparing existing methods, this section highlights the strengths and limitations of current approaches and provides insights into their practical applicability.

6.1 Model Comparison

Different deep learning architectures have been employed for autism detection, each offering unique advantages. Convolutional Neural Networks (CNNs) provide a strong baseline for image classification tasks due to their ability to learn hierarchical feature representations. However, their performance is often limited by the availability of large datasets.

Transfer learning-based models such as ResNet and MobileNet have demonstrated improved performance by leveraging pretrained knowledge. These models are particularly effective when working with limited datasets, as they reduce the need for extensive training while maintaining high accuracy. Lightweight architectures such as MobileNet are especially suitable for real-time applications due to their lower computational requirements.

Ensemble and hybrid models combine multiple learning approaches to enhance prediction accuracy and robustness. These methods are capable of reducing overfitting and improving generalization, making them suitable for complex classification tasks such as autism detection.

1.2 Comparative Table of Existing Approaches

To provide a clearer understanding of the performance and characteristics of different deep learning approaches, a comparative summary of commonly used models is presented in Table 3. The comparison highlights key aspects such as accuracy, advantages, and limitations of each model. This facilitates an objective evaluation of their suitability for facial image-based autism detection.

Table 3. Comparative Analysis of Deep Learning Models for ASD Detection

Model	Accuracy (%)	Advantages	Limitations
CNN	80–88	Simple architecture, effective feature extraction	Requires large dataset
ResNet (Transfer Learning)	88–93	High accuracy, deep feature learning	Computationally intensive
MobileNet	85–91	Lightweight, fast inference	Slightly lower accuracy
Ensemble Models	90–95	High robustness, improved generalization	Complex implementation

6.3 Discussion

The comparative analysis indicates that transfer learning and ensemble-based approaches generally outperform traditional CNN models in terms of accuracy and robustness. ResNet-based models achieve high performance due to their deep architecture, which enables effective feature extraction. However, their computational complexity can limit their deployment in resource-constrained environments.

MobileNet provides a balance between performance and efficiency, making it suitable for real-time applications such as mobile-based autism screening tools. On the other hand, ensemble models achieve the highest accuracy by combining predictions from multiple architectures, but they introduce additional complexity in training and deployment.

Overall, the choice of model depends on the specific application requirements. For high-accuracy clinical support systems, ensemble models are preferable, whereas for real-time and portable applications, lightweight architectures such as MobileNet are more suitable.

7. Challenges in Facial Image-Based Autism Detection

This section discusses the key challenges associated with deep learning-based autism detection using facial images. Despite significant advancements in this domain, several technical, ethical, and practical issues limit the reliability and real-world applicability of existing approaches. Understanding these challenges is essential for developing robust and clinically acceptable solutions.

7.1 Dataset Limitations

One of the major challenges in facial image-based autism detection is the limited availability of large-scale and high-quality datasets. Most existing datasets contain a relatively small number of samples, which can lead to overfitting and reduced generalization capability of deep learning models. In addition, many datasets lack diversity in terms of age, ethnicity, and environmental conditions, further affecting model performance in real-world scenarios. The absence of standardized and clinically validated datasets also makes it difficult to compare results across different studies.

7.2 Ethical and Privacy Concerns

The use of facial images, particularly those of children, raises significant ethical and privacy concerns. Collecting and storing such sensitive data requires strict adherence to data protection regulations and ethical guidelines. Issues related to consent, data misuse, and identity protection must be carefully addressed. Furthermore, the broader challenges associated with ethical AI deployment emphasize the need for transparency, accountability, and fairness in such systems [6].

7.3 Generalization and Bias Issues

Deep learning models trained on limited or biased datasets may fail to generalize well to new and unseen data. Bias in training data can lead to inaccurate predictions, especially when applied to diverse populations. This is particularly critical in medical applications, where incorrect predictions can have serious consequences. Ensuring model robustness and fairness across different demographic groups remains a significant challenge.

7.4 Clinical Reliability and Interpretability

Autism diagnosis is a complex process that involves behavioral, cognitive, and developmental assessments. Relying solely on facial features for diagnosis may not provide sufficient clinical accuracy. Moreover, deep learning models often operate as “black boxes,” making it difficult to interpret their decisions. The lack of explainability can reduce trust among medical professionals and limit the adoption of such systems in clinical practice.

7.5 Computational and Deployment Challenges

Advanced deep learning models, particularly deep CNNs and ensemble methods, require significant computational resources for training and inference. This can limit their deployment in real-time or resource-constrained environments such as mobile devices or rural healthcare settings. Additionally, integrating these models into practical healthcare systems requires careful consideration of scalability, efficiency, and usability.

Table 4. Summary of Challenges in ASD Detection

Challenge	**Description**
Dataset limitations	Small, non-diverse datasets
Ethical concerns	Privacy and data protection issues
Generalization	Poor performance on unseen data
Clinical reliability	Lack of medical validation
Computational cost	High resource requirements

8. Future Directions

This section outlines potential research directions for improving deep learning-based autism detection using facial images. Although significant progress has been made, several limitations identified in previous sections highlight the need for more advanced, reliable, and ethically responsible approaches. Future research should focus on enhancing model robustness, improving data quality, and integrating multidisciplinary perspectives.

8.1 Multimodal Learning Approaches

One promising direction is the integration of multiple data modalities for autism detection. Instead of relying solely on facial images, future systems can combine visual data with behavioral, speech, and physiological signals to improve diagnostic accuracy. Multimodal learning frameworks can capture complementary information, enabling a more comprehensive understanding of ASD characteristics. Such approaches are expected to significantly enhance the reliability of automated detection systems.

8.2 Explainable Artificial Intelligence (XAI)

The adoption of explainable artificial intelligence techniques is essential for increasing trust and transparency in deep learning models. Current models often function as black-box systems, making it difficult to interpret their predictions. Future research should focus on developing interpretable models that provide insights into the features influencing classification decisions. This is particularly important in medical applications, where clinicians require clear justifications for automated diagnoses.

8.3 Development of Standardized and Large-Scale Datasets

The availability of high-quality datasets remains a critical challenge in this domain. Future efforts should aim to develop standardized, large-scale, and clinically validated datasets that include diverse populations. Collaborative initiatives between research institutions, healthcare organizations, and regulatory bodies can facilitate the creation of such datasets. Standardization will also enable fair comparison of models and promote reproducibility in research.

8.4 Advanced Deep Learning Architectures

Emerging deep learning architectures, such as vision transformers and attention-based models, offer new opportunities for improving feature extraction and classification performance. These models can capture global contextual information more effectively than traditional CNNs. Future research should explore the application of these advanced architectures to facial image-based autism detection.

8.5 Real-World Deployment and Edge Computing

For practical adoption, deep learning models must be optimized for real-world deployment. Lightweight architectures and edge computing solutions can enable real-time autism screening on mobile and embedded devices. This is particularly beneficial for remote or underserved regions where access to specialized healthcare services is limited. Future work should focus on developing efficient, scalable, and user-friendly systems for real-world applications.

8.6 Ethical and Regulatory Considerations

As AI-based diagnostic systems become more prevalent, addressing ethical and regulatory concerns will be crucial. Future research should emphasize the development of frameworks that ensure data privacy, informed consent, and fairness in model predictions. Compliance with regulatory standards and ethical guidelines will be essential for the safe and responsible deployment of such technologies.

9. Conclusion

This paper presented a comprehensive review of deep learning-based approaches for autism detection using facial images, highlighting the effectiveness of convolutional neural networks, transfer learning models, and hybrid techniques in extracting discriminative facial features for classification. The analysis demonstrates that while these methods achieve promising accuracy, their performance is significantly influenced by the availability and quality of datasets. Key challenges such as limited data diversity, ethical concerns, generalization issues, and lack of clinical validation continue to restrict real-world deployment. The study also identified important future directions, including multimodal learning, explainable artificial intelligence, and the adoption of advanced architectures, which can enhance the reliability and applicability of such systems. Overall, deep learning-based facial analysis holds strong potential for early and non-invasive autism detection, provided that existing limitations are addressed through continued research and responsible implementation.

REFERENCES

1. *World Health Organization, Autism spectrum disorders, 2023.*
2. *American Psychiatric Association, Diagnostic and Statistical Manual of Mental Disorders (DSM-5), 5th ed. Washington, DC, USA, 2013.*
3. *K. Aldridge, L. George, C. Cole, et al.,"Facial phenotypes in subgroups of prepubertal boys with autism spectrum disorders,"Journal of Autism and Developmental Disorders, vol. 41, no. 10, pp. 1307–1316, 2011.*
4. *K. He, X. Zhang, S. Ren, and J. Sun,"Deep residual learning for image recognition," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 770–778.*
5. *S. J. Pan and Q. Yang,"A survey on transfer learning,",IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, pp. 1345–1359, 2010.*
6. *A. Jobin, M. Ienca, and E. Vayena,"The global landscape of AI ethics guidelines,"Nature Machine Intelligence, vol. 1, pp. 389–399, 2019.*
7. *G. Litjens et al.,"A survey on deep learning in medical image analysis,"Medical Image Analysis, vol. 42, pp. 60–88, 2017.*
8. *S. Tariq et al.,"Detecting autism spectrum disorder using facial features,"IEEE Access, vol. 7, pp. 26118–26128, 2019.*

9. *A. G. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications,"arXiv:1704.04861, 2017.*
10. *Chetan Gode, Bhushan Marutirao Nanche, Dharmesh Dhabliya, Rahul Dnyanoba Shelke, , Rajendra V Patil. & Shushma Bhosle, "Dynamic neural architecture search : A pathway to efficiently optimized deep learning models" , Journal of Information and Optimization Sciences, 46:4-A, 1117–1127, 2025, DOI: 10.47974/JIOS-1896*
11. *R. M. Patil, R. V. Patil. U. B. Pagare, R. K. Navandar, R. Mapari, M. Bhowmik, S. S. Deore, "Anomaly Detection in Network Security: Deep Learning for Early Identification", International Journal of Intelligent Systems and Applications in Engineering, 12(19s), 133–144, 2024*
12. *Jayasimha S R, Rajendra V. Patil, Yashashwini S, Prabu M, Srisathirapathy S, R Maranan, "Spilled Deep Capsule Neural Network with Skill Optimization Algorithm for Breast Cancer Recognition in Mammograms", 8th International Conference on Inventive Computation Technologies [ICICT 2025], April. 2025*
13. *R. V. Patil, M. P. Patil, G. M. Poddar, A. L. Wakekar, D. Y. Bhadane and S. R. Patil, "Hybrid Convolution with Dilated EfficientNet for Plant Disease Classification," 2025 2nd Asian Conference on Intelligent Technologies (ACOIT), KOLAR, India, pp. 1-6, 2025.*
14. *M. Motghare, V. K. Joshi, M. Jamal, M. Shanmugam, R. V. Patil and N. J. Rawool, "Leveraging Deep Learning for Nutritional Profiling: A Comparative Analysis of EfficientNetB0, MobileNetV2, and ResNet50 for Healthy and Unhealthy Food Classification," 2025 IEEE International Conference on Recent Advances in Computing and Systems (REACS), Gwalior, India, 2025, pp. 1-10, 2025*