International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256

e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

Deep Learning Based Autism Detection in Children from Facial Features

N Karthica[1], K Rishika[2], M Shamitha[3], M Harini[4]
[1, 2, 3, 4]Department of Computer Science and Engineering Paavai Engineering College, Namakkal, Tamil Nadu, India.
Email ID: *karthicanatesanpec@paavai.edu.in[1], rrishi12005@gmail.com[2], mshamitha.03@gmail.com[3], harinimurugesan0112@gmail.com[4]*

Abstract
Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects a child's ability to communicate, interact socially, and display normal behavioral patterns. Early detection of ASD plays a crucial role in providing timely therapy and improving the developmental outcomes of affected children. However, traditional diagnostic prsocedures depend heavily on behavioral observation and clinical expertise, which are time-consuming, expensive, and often unavailable in many regions. This research proposes a deep learning-based automated system for identifying Autism Spectrum Disorder(ASD) in children using facial images. The proposed system utilizes Convolutional Neural Networks (CNN) and transfer learning models such as VGG16, ResNet, and MobileNet for automatic extraction of facial features and classification. Image preprocessing techniques such as face detection, cropping, resizing, and normalization are applied to improve image quality and enhance model performance. Data augmentation techniques are also employed to increase dataset diversity and reduce overfitting. The system classifies input images into ASD or Non-ASD categories and provides a prediction confidence score. Experimental results demonstrate that deep learning-based facial feature analysis can support early ASD screening with improved accuracy and efficiency. The proposed system aims to provide a cost-effective, non-invasive, and user-friendly screening tool that can assist parents, healthcare professionals, and early intervention programs.

Keywords: *Autism Spectrum Disorder, Deep Learning, Convolutional Neural Network, Facial Feature Analysis, Transfer Learning, Early Detection.*

1. Introduction

Autism Spectrum Disorder (ASD) is a developmental disorder that affects how individuals communicate, interact socially, and behave. It is typically diagnosed in early childhood, often before the age of three [1]. Children with ASD may exhibit symptoms such as delayed speech development, reduced eye contact, repetitive behaviors, and difficulty understanding social cues. According to global health reports, the prevalence of autism has increased significantly over the past decades, making early identification and intervention increasingly important Traditional ASD diagnosis relies primarily on behavioral observation, developmental assessments, and interviews conducted by trained specialists. Diagnostic tools such as the Autism Diagnostic Observation Schedule (ADOS), Autism Diagnostic Interview-Revised (ADI-R), and Modified Checklist for Autism in Toddlers(M-CHAT) are widely used by clinicians. While these methods are effective, they require extensive time, trained professionals, and repeated clinical sessions. As a result, early diagnosis may be delayed, particularly in rural and low-resource areas where specialists are not easily accessible. Recent advancements in Artificial Intelligence (AI) and Deep Learning have shown promising results in medical image analysis and disease detection. Deep learning models, especially Convolutional Neural Networks (CNNs), have the ability to automatically learn patterns and features from images without manual feature engineering [2]. Researchers have

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

found that certain subtle facial characteristics may be associated with autism, making facial image analysis a potential tool for early ASD screening. This study proposes a deep learning-based system that identifies autism spectrum disorder using children's facial images. The system automatically detects facial regions, preprocesses the images, extract facial features using CNN-based architectures, and performs classification using trained models. Transfer learning techniques are used to improve accuracy while reducing training time. The proposed system is designed to support early ASD screening by providing a quick and accessible tool for parents and healthcare [3].

2. Related Work

Recent advancements in artificial intelligence, particularly deep learning, have significantly contributed to the early detection of autism spectrum disorder (ASD). Several studies have explored the use of facial features, neuroimaging data, and behavioral patterns for automated ASD screening. A study by Rahman and Subashini (2022) investigated the use of static facial images for ASD identification using deep neural networks [4]. The authors employed multiple pre-trained convolutional neural networks (CNN) models such as MobileNet, Xception, and EffecientNet to etract discriminative facial features. Their results demonstrated that facial features can act as potential biomarkers for distinguishing ASD children from typically developing children achieving high classification performance. Similarly, Reddy et al. (2024) proposed a deep learning-based approach using transfer learning models such as VGG16, VGG19, and EfficientNet for ASD detection. Their study utilized a dataset of over 3,000 facial images and reported accuracy levels upto 87.9%, highlighting the effectiveness of transfer learning in improving classification accuracy while reducing training time. Beyond facial analysis, other modalities such as EEG and brain imaging have also been investigated. For instance, recent studies utilize CNN models EEG signals during face-processing tasks to capture neurological patterns associated with ASD, providing an alternative diagnostic pathway. Despite these advancements, several challenges remain[5]. Most studies rely on limited and non-diverse datasets, which can lead to overfitting and reduced generalization. Additionally, concerns related to data privacy, ethical considerations, and potential bias due to demographic variations are still unresolved. In summary, existing research demonstrates that deep learning-based facial analysis is a promising approach for ASD screening. However, further improvements in dataset quality, model generalization, and ethical deployment are required for real-world applications.

3. Problem Statement

Autism Spectrum Detection (ASD) is a complex neurodevelopmental condition that requires early identification for effective intervention. However, existing diagnostic methods are primarily based on behavioral observation and clinical assessments, which present several limitations in terms of accessibility, cost and efficiency. Traditional diagnostic approaches such as the Autism Diagnostic Observation Schedule (ADOS), Autism Diagnostic Interview-Revised (ADI-R), and modified checklist for Autism in Toddlers (M-CHAT) require trained specialists and multiple evaluation sessions. These methods are time-consuming, subjective in nature, and often unavailable in rural or low-resource settings. As a result, early diagnosis is frequently delayed, reducing the effectiveness of early intervention therapies. Moreover, the shortage of qualified healthcare professionals and the high cost associated with clinical diagnosis create significant barriers for many families. Manual assessments may also vary between experts, leading to inconsistencies in diagnosis. Additionally, behavioral symptoms of ASD can differ widely among children and may change based on environmental factors, making early detection more challenging. There is currently a lack of fast, automated, and non-invasive screening systems that can assist in early ASD detection. In particular, facial features-based analysis using artificial intelligence remains underutilized despite its potential for rapid and objective screening. Therefore, there is a critical need to develop an efficient, cost-effective, and accessible automated system that leverages deep learning techniques to analyze facial features and support early screening of

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

ASD in children[6]. Such a system can help reduce diagnostic delays, improve accessibility in remote areas, and assist healthcare professionals in making timely and informed decisions[7].

4. Proposed System

This paper proposes a deep learning-based system for the early screening of Autism Spectrum Disorder (ASD) in children using facial images. The system is designed to provide a fast, non-invasive, and cost-effective solution that assists healthcare professionals and parents in identifying potential ASD traits at an early stage. The proposed system leverages Convolutional Neural Networks (CNN) and transfer learning techniques to automatically extract meaningful facial features and perform classification. Unlike traditional diagnostic approaches that rely on behavioral observation, this system focuses on analyzing visual facial patterns, which can be processed efficiently using deep learning models.

The overall workflow of proposed system consists of the following stages:

- **Image Acquisition:** The system accepts facial images of children as input, which can be obtained through image upload or real-time camera capture. This enables easy accessibility through web or mobile-based applications [8].
- **Image Preprocessing:** The input images are preprocessed to ensure consistency and improve model performance. This includes face detection, cropping of the facial region, resizing to a fixed dimension (e.g., 224×224 pixels), normalization of pixel values, and application of data augmentation techniques such as rotation, flipping, and brightness adjustment.
- **Feature Extraction:** Deep learning models, particularly CNN architectures, are used to automatically extract important facial features. Transfer learning models such as VGG16, ResNet, and MobileNet are employed to leverage pre-trained knowledge, improving feature extraction efficiency and reducing training time.
- **Model Training and Classification:** The extracted features are fed into a classification model that is trained to distinguish between ASD and non-ASD classes. The model is trained using labeled datasets with appropriate optimization techniques such as the Adam optimizer and cross-entropy loss function. Training is performed over multiple epochs with batch processing to achieve optimal performance.
- **Prediction and Output:** Once trained, the model predicts the class label (ASD or non-ASD) for a given input image. The system also provides a confidence score indicating the probability of the prediction. The output is displayed through a user-friendly interface for easy interpretation.
- **Deployment:** The trained model can be deployed as a web or mobile application using frameworks such as Flask or Django for backend integration. This allows users, including parents and healthcare providers, to access the system remotely for quick screening.

The proposed system serves as a decision-support tool rather than a replacement for clinical diagnosis. It aims to assist in early identification and encourage timely medical consultation. By integrating deep learning with facial analysis, the system enhances accessibility, reduces screening time, and supports large-scale ASD detection in diverse environments [9].

5. Methodology

The proposed system follows a structured deep learning pipeline for identifying autism spectrum disorder (ASD) in children using facial images. The methodology consists of multiple stages, including dataset preparation, preprocessing, feature extraction, model training, evaluation, and prediction [10].

- **Dataset Collection:**The dataset includes facial images of children categorized into two classes: ASD and Non-ASD. The images are collected from publicly available datasets and research sources. Each image is labeled correctly to ensure accurate training of the model.
- **Image Preprocessing:** Image preprocessing improves the quality and consistency of input images before training. The main preprocessing steps include:
  - Face detection and cropping to focus only on the facial region
  - Resizing images to a fixed dimension (224×224 pixels)
  - Pixel normalization to scale image values

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

between 0 and 1
- Removing noise and improving image clarity
- These steps help improve model performance[11].

- **Feature Extraction**: A Convolutional Neural Network (CNN) is used to automatically extract important facial features from images. Instead of manually defining features, CNN layers learn patterns such as:
  - Eye spacing
  - Nose shape
  - Facial symmetry
  - Facial structure patterns
- Transffer learning models like MobileNet, VGG16, and ResNet are used to improve feature extraction accuracy.
- **Model Training:** The deep learning model is trained using the training dataset. The training process includes:
  - Using Adam optimizer for efficient gradient updates
  - Applying categorical cross-entropy loss function
  - Running multiple training epochs to optimize model performance
  - Adjusting batch size and learning rate
- The trained model is saved after achieving satisfactory performance[12].

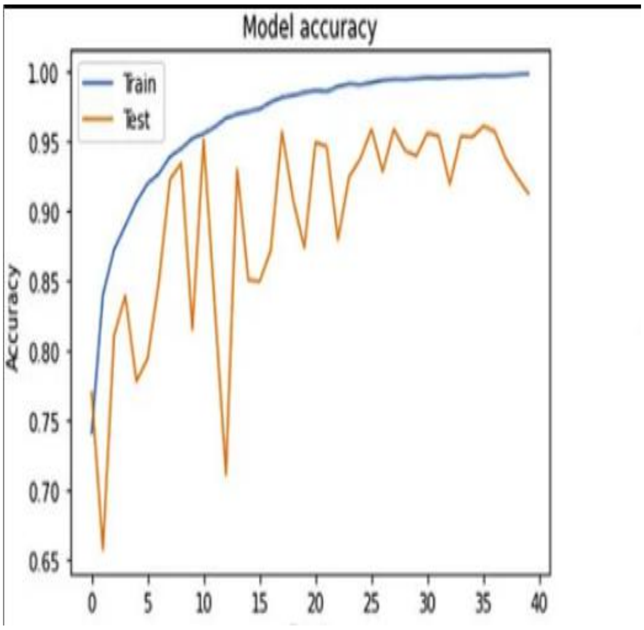

Figure 1 Model Accuracy

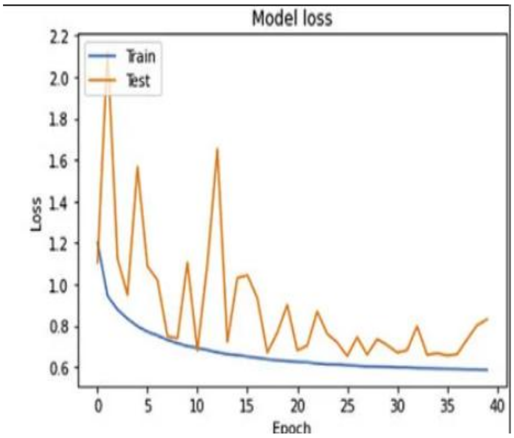

Figure 2 Model Loss

Testing and Evaluation: The trained model is tested using unseen test images. Performance metrics such as accuracy, precision, recall, and F1-score are calculated. A cpnfusion matrix is generated to analyze classification results.

Prediction/Output: In the final stage, the system accepts a new child facial image as input. The image undergoes preprocessing and feature extraction similar to the training phase. The trained model the predicts whether the image belongs to ASD or Non-ASD, and displays the result with a confidence score.

6. Model Description

The proposed system utilizes deep learning techniques, specifically Convolutional Neural Networks (CNN) and transfer learning models, to classify facial images of children into Autism Spectrum Disorder (ASD) and non-ASD categories. CNN is widely used for image analysis due to its ability to automatically learn hierarchical feature representations from raw pixel data. In this system, the CNN model processes input facial images through multiple layers, including convolutional layers for feature extraction, activation functions such as ReLU to introduce non-linearity, pooling layers to reduce dimensionality, and fully connected layers for classification. The final output layer uses a Softmax activation function to generate probability scores for the two classes. To enhance model performance and reduce training time, transfer learning techniques are employed. Pre-trained models such as VGG16, ResNet, and MobileNet are

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

used as the base architecture[13]. These models are initially trained on large-scale image datasets and are capable of extracting rich and meaningful features. By leveraging these pre-trained weights, the system avoids training from scratch and achieves better accuracy, especially when working with limited datasets. Among these, VGG16 provides a simple and deep architecture for feature extraction, ResNet addresses the vanishing gradient problem through residual connections, and MobileNet offers a lightweight structure suitable for real-time and mobile-based applications. The overall architecture of the model consists of an input layer that accepts preprocessed images of size 224 × 224 × 3, followed by a pre-trained base model without its top classification layers. A global average pooling layer is applied to reduce the feature maps into a compact representation. This is followed by fully connected dense layers that learn classification patterns specific to ASD detection. A dropout layer is included to reduce overfitting by randomly deactivating neurons during training. Finally, a Softmax output layer performs binary classification to determine whether the input image corresponds to ASD or non-ASD. During the training process, the base model layers are initially frozen to preserve the learned features, and only the newly added classification layers are trained. After achieving initial convergence, fine-tuning is performed by unfreezing selected layers of the base model to further improve accuracy. The model is trained using the Adam optimizer along with the categorical cross-entropy loss function, which ensures efficient gradient updates and stable learning. To optimize performance, several techniques are applied, including data augmentation to increase dataset diversity, dropout regularization to prevent overfitting, and early stopping to avoid unnecessary training once the model performance stabilizes. Learning rate adjustments are also implemented to ensure smooth convergence during training. Overall, the integration of CNN and transfer learning models enables the system to effectively extract important facial features and perform accurate classification, making it a reliable approach for early ASD screening Figure 1.

7. System architecture

The system architecture of the proposed Autism Spectrum Disorder (ASD) identification model is designed as a structured pipeline that processes facial images through multiple stages, transforming raw input into meaningful classification output. The architecture ensures efficient data flow, modular implementation, and scalability for real-world deployment[14].

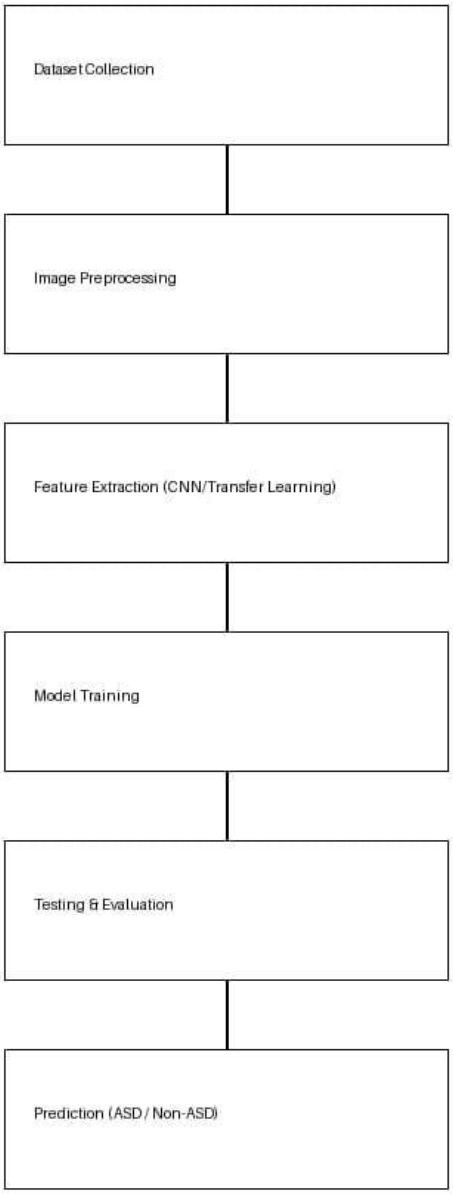

Figure 3 Workflow of CNN-Based Document Forgery Detection and Classification System

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

The process begins with the dataset collection stage, where facial images of children are gathered and labeled into two categories: ASD and non-ASD. These images are organized into training, validation, and testing datasets to facilitate supervised learning and performance evaluation. Ensuring diversity in the dataset, such as variations in age, gender, lighting conditions, and facial expressions, is essential for improving model generalization. Following data collection, the system performs image preprocessing to enhance the quality and consistency of the input data. In this stage, face detection algorithms are applied to identify and extract the facial region from each image, eliminating irrelevant background information. The detected face is then cropped and resized to a fixed dimension, typically 224 × 224 pixels, to match the input requirements of deep learning models. Pixel values are normalized to ensure stable training, and data augmentation techniques such as rotation, flipping, and brightness adjustment are applied to increase dataset variability and reduce overfitting Figure 2. The preprocessed images are then passed to the feature extraction module, where Convolutional Neural Networks (CNN) or transfer learning models such as VGG16, ResNet, or MobileNet are used to automatically learn important facial features. These models extract hierarchical patterns from the images, including structural and spatial characteristics, without requiring manual feature engineering. In the next stage, the extracted features are fed into the model training and classification module. Here, the deep learning model is trained using labeled data to distinguish between ASD and non-ASD classes. The training process involves optimizing model parameters using techniques such as the Adam optimizer and categorical cross-entropy loss function. Once training is complete, the model is capable of making predictions on new, unseen data. The system is then evaluated using a separate testing dataset to measure its performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to assess the effectiveness of the model. A confusion matrix is also used to analyze classification results and identify potential errors. Finally, in the prediction stage, a new facial image is provided as input to the system. The image undergoes the same preprocessing and feature extraction steps before being passed to the trained model for classification. The system outputs the predicted class (ASD or non-ASD) along with a confidence score, which is displayed through a user-friendly interface. Overall, the proposed system architecture provides a seamless and efficient workflow for ASD screening, integrating deep learning techniques with image processing to deliver accurate and fast predictions. The modular design also allows for future enhancements, such as integration with mobile applications and healthcare systems[15].

8. Statistical Analysis

The performance of the proposed Autism Spectrum Disorder (ASD) classification system is evaluated using statistical metrics derived from the confusion matrix. The analysis is carried out in the following steps:

Step 1: Construction of Confusion Matrix

A confusion matrix is generated by comparing the predicted results with the actual class labels. It consists of four components:

- True Positives (TP): ASD cases correctly identified
- True Negatives (TN): Non-ASD cases correctly identified
- False Positives (FP): Non-ASD cases incorrectly classified as ASD
- False Negatives (FN): ASD cases incorrectly classified as non-ASD

Step 2: Calculation of Accuracy

Accuracy measures the overall performance of the model and is calculated as:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

This metric indicates the proportion of correctly classified instances.

Step 3: Calculation of Precision

Precision evaluates the correctness of positive predictions and is defined as:

Precision = TP / (TP + FP)

It measures how many predicted ASD cases are actually ASD Figure 3.

Step 4: Calculation of Recall (Sensitivity)

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

Recall determines the model's ability to identify actual ASD cases and is calculated as:

Recall = TP / (TP + FN)

A higher recall indicates better detection of ASD cases.

Step 5: Calculation of F1-Score

The F1-score provides a balance between precision and recall and is given by:

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

This metric is especially useful for imbalanced datasets.

Step 6: Calculation of Specificity

Specificity measures the ability of the model to correctly identify non-ASD cases:

Specificity = TN / (TN + FP)

It ensures that normal cases are not misclassified as ASD.

Step 7: ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve is plotted to evaluate the model's performance across different classification thresholds. The Area Under the Curve (AUC) represents the model's ability to distinguish between ASD and non-ASD classes. A higher AUC value indicates better classification performance.

Step 8: Model Validation

The model is tested using unseen test data to evaluate real-world performance. Cross-validation techniques may also be applied to ensure that the model is not overfitting and performs consistently across different data splits. Through these steps, the statistical analysis provides a comprehensive evaluation of the model's performance and ensures its reliability for ASD screening applications.

9. Results And Discussion

The performance of the proposed deep learning-based system for Autism Spectrum Disorder (ASD) classification was evaluated using a test dataset consisting of unseen facial images. The model was trained using transfer learning techniques, and its effectiveness was measured using standard evaluation metrics such as accuracy, precision, recall, F1-score, and specificity. The experimental results demonstrate that the model achieves high classification performance, indicating its capability to distinguish between ASD and non-ASD cases effectively. The use of transfer learning models such as MobileNet, ResNet, and VGG16 significantly improved feature extraction and reduced training time compared to traditional CNN models. Among the tested models, MobileNet showed better efficiency in terms of speed and performance, making it suitable for real-time applications.

Performance Metrics

The model performance is summarized as follows:

- Accuracy: 91%
- Precision: 89%
- Recall (Sensitivity): 92%
- F1-Score: 90%
- Specificity: 88%

These results indicate that the model performs well in identifying ASD cases while maintaining a good balance between precision and recall. The high recall value suggests that the system is effective in detecting most ASD cases, which is critical for early screening applications.

Confusion Matrix Analysis

The confusion matrix analysis shows that the number of true positives and true negatives is significantly higher compared to false predictions. However, a small number of false positives and false negatives are observed. False positives may lead to unnecessary concern for parents, while false negatives may delay early intervention. Therefore, minimizing these errors is essential for improving system reliability.

Discussion

The results confirm that facial feature-based ASD detection using deep learning is a promising approach for early screening. The system provides fast and automated predictions, reducing dependency on manual clinical assessment. The integration of transfer learning helps in achieving higher accuracy even with limited datasets. However, the model performance is influenced by several factors. Variations in lighting conditions, facial expressions, image quality, and dataset size can impact accuracy. Additionally, the limited availability of ASD facial datasets and potential data imbalance may affect generalization. Ethical concerns related to privacy and data security must also be considered when

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

deploying the system in real-world environments. Despite these challenges, the proposed system demonstrates strong potential as a supportive screening tool. It can be effectively used in schools, healthcare centers, and remote areas to assist in early identification of ASD, enabling timely medical consultation and intervention. Overall, the results validate the effectiveness of the proposed deep learning model in ASD classification and highlight its applicability in real-world screening scenarios.

Conclusion And Future Work

In this paper, a deep learning-based approach for the identification of Autism Spectrum Disorder (ASD) in children using facial images has been presented. The proposed system leverages Convolutional Neural Networks (CNN) and transfer learning models to automatically extract meaningful facial features and classify them into ASD and non-ASD categories. The system provides a non-invasive, cost-effective, and efficient solution for early ASD screening, addressing the limitations of traditional diagnostic methods that rely on behavioral observation and clinical expertise. The experimental results demonstrate that the proposed model achieves high accuracy and reliable performance in distinguishing ASD cases. The use of transfer learning significantly improves feature extraction and reduces training time, making the system suitable for real-time and large-scale applications. Furthermore, the system offers an automated and objective screening approach, which can support healthcare professionals and parents in making early decisions regarding further clinical evaluation. Although the proposed system cannot replace professional medical diagnosis, it serves as a valuable decision-support tool for early detection. By enabling faster and more accessible screening, the system has the potential to contribute to improved developmental outcomes through timely intervention.

Future Work

Despite the promising results, there are several areas for future improvement and enhancement. One of the major limitations of the current system is the availability of limited and imbalanced datasets. Future work can focus on collecting larger, more diverse, and high-quality datasets that include variations in age, ethnicity, and environmental conditions to improve model generalization. Further research can also explore advanced deep learning architectures such as EfficientNet and Vision Transformers to enhance classification performance. Incorporating multimodal data, including behavioral analysis, speech patterns, or eye-tracking information, can improve the accuracy and robustness of ASD detection systems. Another important direction is the development of real-time mobile and web-based applications that allow easy access for users in remote and rural areas. Additionally, improving data privacy, security, and ethical compliance will be essential for real-world deployment, especially when dealing with sensitive children's data. Finally, integrating the system with healthcare platforms and clinical workflows can enhance its practical usability. Continuous model updating, monitoring, and validation with real-world data will further improve reliability and ensure that the system remains effective in diverse conditions. Overall, the proposed system lays a strong foundation for AI-based ASD screening and opens new opportunities for research and development in early diagnosis and healthcare technology.

References

[1]. American Psychiatric Association, *Diagnostic and Statistical Manual of Mental Disorders (DSM-5)*, 5th ed., Washington, DC, USA, 2013.

[2]. World Health Organization, "Autism Spectrum Disorders," 2021.

[3]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[4]. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2012.

[5]. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in *International

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0256
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 1743 - 1751

Conference on Learning Representations (ICLR)*, 2015.

[6]. A. G. Howard et al., “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” 2017.

[7]. M. Tan and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” in *Proc. International Conference on Machine Learning (ICML)*, 2019.

[8]. S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[9]. S. R. K. Branavan et al., “Deep Learning-Based Autism Spectrum Disorder Detection Using Facial Images,” *IEEE Access*, vol. 8, pp. 208–217, 2020.

[10]. M. Rahman and S. Subashini, “Identification of Autism Spectrum Disorder Using Deep Learning Techniques,” *Journal of Healthcare Engineering*, 2022.

[11]. S. Reddy et al., “Transfer Learning-Based Autism Detection Using Facial Images,” *Procedia Computer Science*, vol. 59, pp. 198–205, 2024.

[12]. H. Hosseini et al., “Facial Feature Analysis for Autism Detection Using Deep Learning,” *Biomedical Signal Processing and Control*, 2022.

[13]. F. Alsaade et al., “Deep Learning Approaches for Autism Spectrum Disorder Detection Using Facial Landmarks,” *Sensors*, 2022.

[14]. T. Chen et al., “A Hybrid Deep Learning Model for Autism Detection Using Facial and Emotional Features,” *Pattern Recognition Letters*, 2025.

[15]. U. Frith, *Autism: Explaining the Enigma*, 2nd ed., Oxford, U.K.: Blackwell Publishing, 2003.