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

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Abstract:

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by impairments in social interaction and communication. Early detection is essential for timely intervention; however, conventional diagnostic methods are often subjective and time-intensive. In this study, a deep learning-based framework is proposed for automated autism detection using facial image analysis. The dataset consists of 2,936 facial images, evenly distributed between autistic and non-autistic classes. A comprehensive preprocessing pipeline is introduced, incorporating multiple base filters such as bilateral filtering, CLAHE, gamma correction, and denoising, along with hybrid combinations including bilateral + CLAHE + unsharp masking. These techniques are applied to enhance feature representation and improve classification performance. Images are resized to 128×128×3 and normalized, and data augmentation is performed to improve model generalization. Five deep learning models CNN, InceptionV3, MobileNetV2, VGG16, and DenseNet—are evaluated under both raw and preprocessed conditions. Experimental results indicate that preprocessing significantly influences model performance. MobileNetV2 achieves the highest accuracy of 79.91% before preprocessing, while DenseNet outperforms other models after preprocessing with a testing accuracy of 79.00% and F1-score of 0.79.

The findings demonstrate that hybrid preprocessing techniques enhance classification performance and that their effectiveness is model-dependent. The proposed framework provides a reliable and non-invasive approach for early autism detection using 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 complex neurodevelopmental condition characterized by impairments in social interaction, communication, and repetitive behavioral patterns. Early detection of ASD is essential for effective intervention and improved developmental outcomes. However, traditional diagnostic methods rely heavily on behavioral assessments conducted by clinical experts, which are often subjective, time-consuming, and require specialized expertise. This limitation has motivated the development of automated and objective diagnostic approaches using artificial intelligence[1], [2], [3], [4].

In recent years, computer vision and deep learning techniques have shown significant potential in medical image analysis, including facial-based diagnosis. Several studies have reported that individuals with ASD exhibit subtle variations in facial morphology, which can be captured and analyzed using deep learning models. Convolutional Neural Networks (CNNs) and transfer learning architectures such as VGG16, InceptionV3, and MobileNetV2 have been widely used for feature extraction and classification tasks due to their ability to learn hierarchical representations from image data[5], [6], [7].

Despite these advancements, the performance of deep learning models in ASD detection is highly dependent on the quality of input images. Variations in lighting, noise, contrast, and background can significantly affect feature extraction and model generalization. While many studies focus on model architecture improvements, limited attention has been given to the role of image preprocessing and enhancement techniques in improving classification performance. In particular, the impact of hybrid filtering techniques combining multiple preprocessing methods—remains underexplored[8], [9], [10], [11].

To address these challenges, this study proposes a comprehensive deep learning-based framework for autism detection using facial images. A diverse set of preprocessing techniques, including bilateral filtering, contrast enhancement, gamma correction, and hybrid filter combinations, is applied to improve image quality and feature representation. The framework evaluates five deep learning models CNN, InceptionV3, MobileNetV2, VGG16, and DenseNet under both raw and preprocessed conditions[12], [13], [14].

The main contributions of this work are threefold. First, a preprocessing-rich pipeline incorporating multiple base and hybrid filtering techniques is developed to enhance facial image quality. Second, a comparative analysis of multiple deep learning models is conducted to evaluate their performance on ASD classification. Third, a detailed investigation of model performance before and after preprocessing is performed, highlighting the model-dependent impact of preprocessing techniques. The remainder of the paper is organized as follows. Section 2 presents the literature review, Section 3 describes the proposed methodology, Section 4 discusses the experimental results, and Section 5 concludes the study with future research directions.

Literature Review:

Recent advancements in deep learning and computer vision have significantly contributed to automated medical diagnosis, including autism spectrum disorder (ASD) detection using facial image analysis. Several studies have explored the use of convolutional neural networks (CNNs) and transfer learning techniques to identify discriminative facial features associated with ASD.

Early work in this domain primarily focused on traditional CNN architectures for binary classification of autistic and non-autistic children. For instance, researchers employed basic CNN models and achieved moderate classification performance, highlighting the feasibility of facial-based ASD detection but also revealing limitations in feature representation and generalization[15]. To overcome these limitations, transfer learning-based models such as VGG16 and InceptionV3 were introduced, leveraging pre-trained weights to improve feature extraction and classification accuracy[16],[17].

More recent studies have focused on improving performance through hybrid and ensemble approaches. A hybrid deep learning model combining ResNet50V2 and InceptionV3 demonstrated significant improvement in ASD classification accuracy, achieving performance levels exceeding 90% [18]. Similarly, MobileNet-based lightweight architectures have been explored for efficient and real-time ASD detection, offering a balance between computational efficiency and accuracy [19].

In addition to model improvements, some studies have emphasized the importance of data preprocessing and augmentation techniques. Contrast enhancement methods such as CLAHE and noise reduction techniques have been shown to improve feature visibility and classification performance [20]. However, most existing works utilize single preprocessing techniques and do not systematically evaluate the impact of multiple or hybrid filtering approaches.

Furthermore, recent research has begun exploring explainable AI (XAI) techniques and attention mechanisms to improve interpretability and robustness in ASD detection systems [21]. Despite these advancements, there remains a research gap in understanding how different preprocessing techniques interact with various deep learning models and influence overall performance.

In this context, the present study addresses this gap by providing a comprehensive evaluation of multiple preprocessing techniques, including hybrid filters, across different deep learning architectures. Unlike existing works that focus primarily on model optimization, this study emphasizes the role of preprocessing in enhancing 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[22]	CNN	Facial ASD dataset	~75%	Initial CNN-based ASD detection	Limited generalization
Ahmad I,(2024([23]	VGG16	Facial images	80%	Transfer learning improves performance	Sensitive to noise
Tariq et al., 2021[24]	InceptionV3	ASD dataset	78%	Deep feature extraction	Moderate accuracy
Aarthi D. et.al., 2025[25]	ResNet50V2 + InceptionV3	Facial dataset	92–95%	Hybrid deep learning model	High computational cost
[26]	MobileNetV2	ASD facial images	85%	Lightweight model for real-time use	Slightly lower accuracy
Awaji et.al. 2023[27]	CNN + CLAHE	Image dataset	83%	Importance of preprocessing	Single filter used
Rathod V. et.al.[28]	CNN + Attention/XAI	Facial dataset	88%	Explainability in ASD detection	Complex architecture

Methodology:

This study proposes a deep learning-based framework for the classification of autistic and non-autistic children using facial image analysis. The overall methodology consists of dataset preparation, image preprocessing using both base and hybrid filtering techniques, data augmentation, and classification using multiple deep learning models. The objective is to analyze the influence of preprocessing on model performance and to identify the most suitable model–filter combination for autism detection.

The dataset used in this study comprises 2,936 facial images, evenly distributed between autistic and non-autistic classes, ensuring a balanced classification problem. All images are resized to a fixed dimension of 128×128×3 to maintain uniformity across models. To facilitate efficient training and faster convergence, pixel intensities are normalized to the range [0,1]. The dataset is divided into training and validation sets in a 70:30 ratio, resulting in 2,055 training images and 881 validation images.

The proposed framework described in figure 1 illustrates the complete pipeline for autism detection using facial images. It includes preprocessing using base and hybrid filtering techniques, data augmentation, deep learning-based feature extraction, and classification followed by performance evaluation.

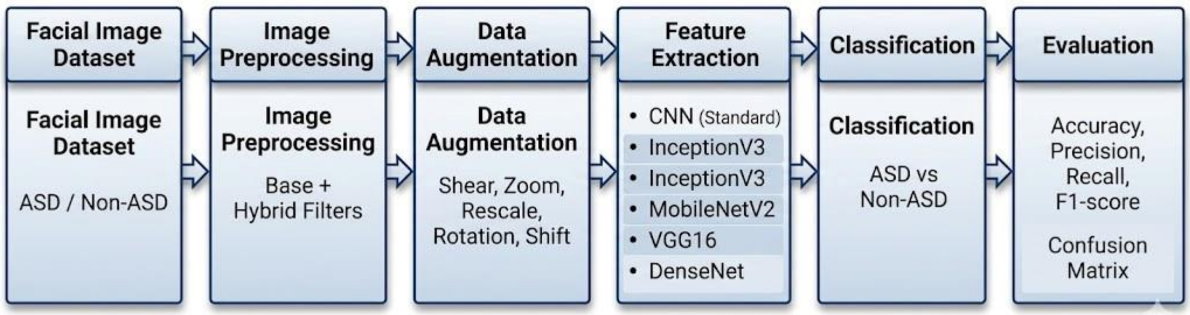

Figure 1: Proposed Workflow Diagram for ASD Classification using Deep Learning

Image preprocessing is a critical component of the proposed framework, as it enhances feature visibility and improves the learning capability of deep learning models. In this work, multiple preprocessing techniques are applied to improve image quality. These include bilateral filtering for edge-preserving smoothing, Butterworth low-pass filtering for noise reduction, median filtering for impulse noise removal, gamma correction for brightness adjustment, and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement. Additionally, unsharp masking is used to enhance edge details, while denoising and contrast enhancement techniques are applied to further improve image clarity. Edge detection is also employed to highlight structural facial features.

To further enhance feature representation, hybrid filtering techniques are introduced by combining multiple preprocessing methods. These include combinations such as bilateral filtering with unsharp masking, CLAHE with bilateral filtering, denoising with median filtering, and a composite approach integrating bilateral filtering, CLAHE, and unsharp masking. These hybrid approaches aim to simultaneously reduce noise, enhance contrast, and preserve important structural features, thereby improving the effectiveness of feature extraction. To address the issue of overfitting and improve model generalization, data augmentation is performed using an Image Data Generator. Transformations such as shear, zoom, and horizontal flipping are applied to generate diverse variations of the input images. This allows the models to learn invariant features and improves their robustness to variations in real-world conditions.

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 evaluated using multiple metrics, including accuracy, precision, recall, and F1-score. Confusion matrices are also analyzed to understand class-wise performance and misclassification patterns. The experiments are conducted under two conditions: without preprocessing and with preprocessing (including both base and hybrid filters). This setup enables a comprehensive evaluation of the impact of preprocessing techniques on the performance of different deep learning models.

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.

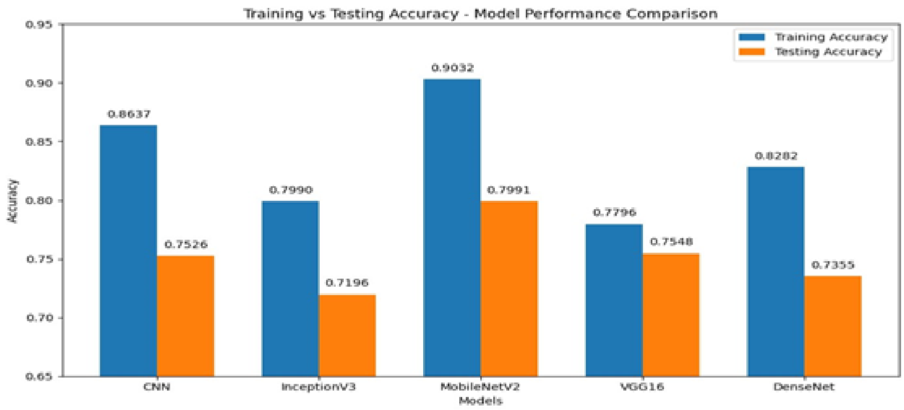

Fig. 2. Training vs Testing Accuracy Comparison of Deep Learning Models Before Preprocessing

The results indicate that MobileNetV2 achieved the highest training accuracy of 90.32% and testing accuracy of 79.91%, demonstrating strong feature extraction capability and generalization. CNN also performed competitively, achieving a training accuracy of 86.37% and testing accuracy of 75.26%. VGG16 and DenseNet showed moderate performance, while InceptionV3 achieved comparatively lower 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.

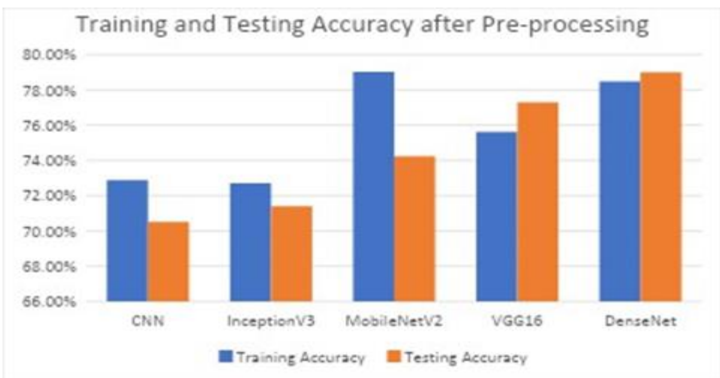

Fig. 3. Training vs Testing Accuracy Comparison of Deep Learning Models After Preprocessing

2. Model-wise Classification Analysis:

A detailed analysis of classification performance reveals that different models exhibit varying behavior in identifying autistic and non-autistic classes.

The CNN model demonstrates high recall for the non-ASD class but comparatively lower recall for ASD samples, indicating difficulty in capturing discriminative features for autistic cases. InceptionV3 shows relatively weaker performance across both classes, suggesting limited adaptability to the dataset. MobileNetV2 achieves a balanced performance with precision and recall values around 0.80 for both classes, indicating stable classification capability.

VGG16 shows a bias toward ASD classification, achieving higher recall for ASD but lower performance for non-ASD. DenseNet exhibits strong recall for non-ASD but struggles with ASD detection, indicating class imbalance in feature learning despite balanced data.

These observations highlight that model architecture significantly influences classification behavior, particularly in medical image analysis tasks where subtle feature variations are critical.

3. Training Behavior and Overfitting Analysis:

The training and validation accuracy-loss curves provide insights into the learning behavior of the models. MobileNetV2 demonstrates smooth convergence with minimal fluctuations, indicating stable learning. CNN exhibits slight overfitting, as evidenced by divergence between training and validation accuracy in later epochs. InceptionV3 shows slower convergence, suggesting suboptimal feature learning.

VGG16 and DenseNet demonstrate relatively stable training behavior, with moderate fluctuations in validation loss. These results indicate that deeper architectures benefit from structured feature extraction but may require enhanced preprocessing for optimal performance.

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 results demonstrate that preprocessing significantly influences classification performance.

DenseNet achieves the highest testing accuracy of 79.00% and F1-score of 0.79, indicating its ability to effectively utilize enhanced feature representations. VGG16 also shows noticeable improvement, achieving a testing accuracy of 77.30%.

Interestingly, CNN and MobileNetV2 exhibit a slight decrease in performance after preprocessing, suggesting that certain preprocessing techniques may alter feature distributions in a way that negatively impacts these models.

5. Comparative Analysis (Before vs After Preprocessing):

A comparative analysis of model performance before and after preprocessing reveals important insights into the effectiveness of hybrid filtering techniques.

- DenseNet shows the most significant improvement, indicating its compatibility with enhanced feature representations.
- VGG16 also benefits from preprocessing, demonstrating improved generalization.
- MobileNetV2 shows slight degradation, suggesting sensitivity to preprocessing transformations.
- CNN performance decreases, indicating that handcrafted preprocessing may interfere with learned features in shallow architectures.

These findings highlight that preprocessing is model-dependent, and hybrid filtering techniques do not uniformly improve performance across all architectures.

6. Key Findings and Discussion:

The experimental results clearly demonstrate that hybrid preprocessing techniques play a crucial role in improving classification performance for certain deep learning models. While preprocessing enhances feature clarity and reduces noise, its effectiveness varies depending on the model architecture.

DenseNet emerges as the most robust model in this study, achieving the highest performance after preprocessing. This can be attributed to its dense connectivity, which enables effective feature reuse and propagation. On the other hand, simpler architectures such as CNN show reduced performance, indicating their sensitivity to preprocessing transformations.

Overall, the study emphasizes the importance of selecting appropriate preprocessing techniques in conjunction with suitable deep learning models to achieve optimal performance in autism detection using facial images.

Conclusion And Future Work:

This study presented a deep learning-based framework for autism detection using facial image analysis, with a primary focus on evaluating the impact of image preprocessing techniques. A comprehensive preprocessing pipeline incorporating both base and hybrid filtering methods was developed to enhance image quality and improve feature representation. Five deep learning models—CNN, InceptionV3, MobileNetV2, VGG16, and DenseNet—were evaluated under both raw and preprocessed conditions.

The experimental results demonstrate that preprocessing plays a significant role in influencing model performance. Among the evaluated models, DenseNet achieved the best performance after preprocessing, with a testing accuracy of 79.00% and F1-score of 0.79, indicating its ability to effectively leverage enhanced feature representations. VGG16 also showed noticeable improvement, while CNN and MobileNetV2 exhibited slight performance degradation, highlighting the model-dependent nature of preprocessing techniques.

The findings of this study emphasize that hybrid preprocessing techniques can improve classification performance when appropriately aligned with model architecture. However, preprocessing does not universally enhance performance across all models, and careful selection of preprocessing strategies is required.

Future work will focus on extending the proposed framework by incorporating attention mechanisms and transformer-based architectures to further improve classification accuracy. Additionally, the integration of explainable artificial intelligence (XAI) techniques such as Grad-CAM will be explored to provide interpretability of model decisions. Expanding the dataset and incorporating multimodal inputs, such as behavioral or clinical data, can further enhance the robustness and applicability of the proposed system in real-world scenarios.

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