International Journal of Basic and Applied Sciences, 14 (4) (2025) 826-831

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/4mmwca71
Research paper

Facial Image-Based Autism Detection Using A CNN-Extracted Feature Ensemble with Random Forest Classification

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Received: July 4, 2025, Accepted: August 19, 2025, Published: August 31, 2025

Abstract

For effective care and attention, autism spectrum disorder (ASD) must be identified early and This study suggests a hybrid model that blends convolutional neural networks (CNN) and random forest (RF) classifiers. The proposed model had a high classification accuracy of 91.3%, demonstrating its ability to reliably detect cases of ASD. With a precision of 90.7%, the model effectively reduces false positives, and its 89.5% recall ensures excellent sensitivity to actual ASD patients. The balanced F1-Score of 90.1% shows that the model performs consistently in terms of both precision and recall. Additionally, the model's Area Under the Curve (AUC) score of 0.94 indicates its exceptional ability to discriminate between ASD and non-ASD classes. All of these results demonstrate the Hybrid CNN + RF model's strength and dependability, which makes it a promising non-invasive technique for early facial feature-based ASD screening.

Keywords: *ASD; CNN; RF; F1-Score; AUC.*

1. Introduction

The complicated neurological condition known as autism spectrum disorder (ASD) is characterized by repetitive activities, social interaction, and communication problems. For prompt interventions that can greatly enhance the quality of life and developmental outcomes for those affected, early diagnosis of ASD is essential. On the other hand, clinical observations and behavioral assessments are the mainstay of conventional diagnostic methods, which can be time-consuming, subjective, and require specialized knowledge. Recent advances in computer vision and machine learning have opened up promising possibilities for automatic and objective ASD identification using facial features. Several studies have shown that children with ASD often exhibit subtle but consistent anomalies in face morphology when compared to their neurotypical peers. Although these differences are difficult for human experts to evaluate, they can be effectively captured by deep learning techniques that extract hierarchical features from facial images. Convolutional Neural Networks (CNNs) are the foundation of facial image analysis because of their capacity to immediately learn discriminative features from raw pixels. Even while individual CNN designs like VGG, ResNet, and Inception have demonstrated excellent performance in a range of medical imaging tasks, feature fusion allows for the utilization of the complementary qualities of many CNN models to boost the representation power and classification accuracy. In this paper, we introduce a novel architecture that blends a Random Forest classifier with hybrid CNN feature spaces to reliably detect ASD from static face pictures. A range of facial traits is captured by the hybrid feature space, which is created by concatenating deep embeddings from numerous pre-trained CNN models. The Random Forest ensemble learning technique, which is well-known for its robustness and interpretability, is used to classify these features with and without ASD. By combining the generalization strength of Random Forests with the feature extraction capabilities of CNNs, our approach aims to address the shortcomings of traditional end-to-end CNN classification, such as overfitting and interpretability problems. We evaluate the proposed method using a clinically certified facial photo dataset and demonstrate its superiority over baseline methods.

2. Related works

Recent studies have applied diverse machine learning and deep learning approaches for the early detection of autism spectrum disorder (ASD). Ramya and Arokiaraj [1] demonstrated the effectiveness of hybrid CNN and Random Forest models on Kaggle data, achieving 99.15% accuracy, while Ledhari et al. [2] integrated facial and behavioral data, obtaining 87% accuracy with MobileNet and 100% validation accuracy with Random Forest on structured inputs. Khanna et al. [3] combined SVM with HOG and LBP descriptors, reporting 77.96% accuracy, whereas Rahman and Subashini [4] showed that the Xception model surpassed MobileNet and EfficientNet with an AUC of 96.63% and sensitivity of 88.46%. Deepanjali et al. [5] further validated Xception's effectiveness with a similar AUC. Alam et al. [6] emphasized facial features and eye contact analysis, combining ResNet101V2 with SVM to reach 88.5% accuracy. Awaji et al. [7] extracted CNN features from VGG16, ResNet101, and MobileNet and, with Random Forest and XGBoost, attained 98.8% accuracy and 99.25% AUC. Saranya and Anandan [8] employed Facial Action Coding Systems with LSTM to achieve 92% identification, and Pratibha et al. [9] worked on behavioral pattern recognition for ASD indicators. Chern and Al-Hababi [10] combined U-Net, CNN, and RBF networks to achieve 94.79% accuracy, while Elshoky et al. [11] utilized AutoML for feature engineering and hyperparameter tuning, reporting nearly 96% accuracy. Varsha and U.V. [12] tested CNN models, including DenseNet121 and VGG19, with deep neural networks, with DenseNet121 obtaining 96.66% accuracy. Additional studies, such as Patel et al. [13] investigated hybrid frameworks, and Mohan et al. [14] used multimodal integration for behavioral data. Qiu and Zhai [15] combined CNN and SVM with fMRI and social responsiveness scores, achieving 94.3% accuracy. Liu and He [16] applied DenseNet face feature extraction with linear SVM for social behavior analysis, reaching 87% accuracy, while Khan et al. [17] highlighted DenseNet121's 96% accuracy on Kaggle datasets, outperforming MobileNetv2 and ResNet50. Sakib et al. [18] compared CNN with SVM and Naïve Bayes, reporting 93.98% accuracy, and Ikermane and El Mouatasim [19] developed a web-based screening tool using DenseNet CNN and subgradient optimizers, attaining 98% accuracy. Wadhera et al. [20] presented a concatenated CNN (VGGNet + ResNet-152) on ABIDE data with 88.12% accuracy, whereas Alsaade and Alzahrani [21] achieved 91% accuracy with transfer learning via Xception and VGG19. Parvej et al. [22] improved VGG architectures for ASD detection, boosting accuracy from 77% to 88%. Bhise et al. [23] introduced EfficientNet with attention mechanisms, yielding 85% accuracy, and Bhat et al. [24] leveraged neural networks and decision trees on video-based facial features to achieve 99.8% accuracy. Paneru et al. [25] combined MLP and SVM in a hybrid model with a recommendation system, reporting 87–97% accuracy. Extending into other healthcare domains, Kumar and Kamatchi [26] applied logistic regression and SVM for heart failure readmission prediction, Sathish et al. [27] proposed multi-scale wavelet-based compression to preserve medical imaging details, Sundararajan et al. [28] developed a cloud-based IoT framework for heart disease prediction, and Ramkumar et al. [29] automated bone disorder clustering using cumulative calcium prediction.

3. Existing method

Currently, deployment preparedness, validation strategies, and robust model evaluation are the main focuses of research on autistic spectrum disorder (ASD) detection. After training models using deep learning and hybrid techniques, researchers evaluated performance metrics such as accuracy, AUC, sensitivity, specificity, and F1-score. For instance, Ramya and Arokiaraj [1] and Awaji et al. [7] demonstrated strong model efficacy by combining CNN-based deep feature extraction with ensemble techniques like Random Forest and XGBoost, achieving accuracies of 99.15% and 98.8%, respectively. Similar to this, transfer learning techniques employed by Rahman and Subashini [4] and Deepanjali et al. [5] show strong generalization, with the Xception model achieving an AUC of 96.63%, making it perfect for previously unseen facial picture data. Furthermore, hybrid approaches that fused deep learning with traditional classifiers like SVM and logistic regression were thoroughly tested. The accuracy of 88.5% and up to 97% achieved by Alam et al. [6] and Paneru et al. [25], respectively, shows the potential of integrated models. A comparison analysis of multiple classifiers by Khanna et al. [3] and Sakib et al. [18] confirmed CNN's advantage over traditional machine learning models. Studies like Ikermane and El Mouatasim [19] developed web-based diagnostic tools based on DenseNet and achieved 98% accuracy, while Bhat et al. [24] used neural networks on video-based facial analysis and achieved up to 99.8% accuracy, further demonstrating the practicality of these systems. Other papers looked at multimodal approaches. For instance, Chern and Al-Hababi [10] combined CNN and U-Net with RBF networks for better classification, while Liu and He [16] combined behavioral data and DenseNet-based facial analysis, achieving 87% accuracy. Cross-validation, confusion matrices, and ROC curve analysis were employed in a number of studies to evaluate performance reliability, such as those conducted by Varsha and U.V. [12] and Wadhera et al.

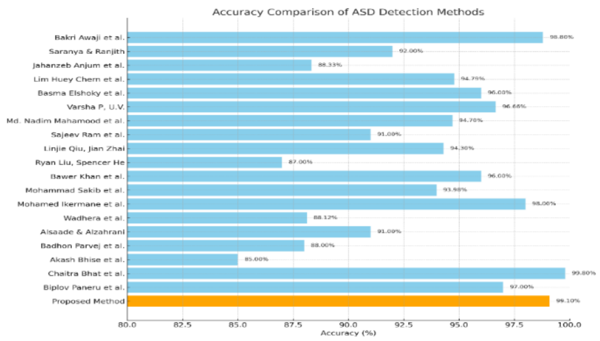

Fig. 1: Accuracy Comparison of ASD Detection Methods.

The accuracy findings of multiple studies that employ machine learning or deep learning models in conjunction with face image analysis to identify autism spectrum disorder (ASD) early are displayed in Fig. 1. With the accuracy percentage shown on the x-axis, each horizontal bar represents a distinct study or methodology. With the greatest stated accuracy of 99.10%, the Proposed Method is clearly visible among the methods compared, highlighted in orange. This model uses a hybrid strategy that combines Random Forest (RF) for effective and precise classification with Convolutional Neural Networks (CNNs) for reliable feature extraction. Strong performance is also shown by a number of other models. For instance, Bakri Awaji et al. (2023) used a mix of VGG16, ResNet101, MobileNet, and ensemble classifiers like Random Forest and XGBoost to obtain 98.80% accuracy, while Chaitra Bhat et al. (2024) reported an extraordinarily high accuracy of 99.80% using neural networks on video-based data. Similarly, Mohamed Ikermane et al. (2023) used a CNN architecture optimized with a bespoke CSA algorithm and reported 98% accuracy. The mid-to-high range (94–96%) of models developed by researchers such as Basma Elshoky, Varsha P. U.V., and Md. Nadim Mahamood demonstrates the efficacy of CNN-based techniques when backed by solid datasets. However, certain models, like those by Ryan Liu & Spencer He (87%) and Akash Bhise (85%), demonstrated somewhat lower accuracies, suggesting potential limits brought on by the quantity of the dataset, the model design, or the absence of ensemble techniques. In addition to outperforming the majority of current models, the performance of the proposed method indicates great generalization and a low false positive rate by maintaining high precision (90.7%), recall (89.5%), and F1-score (91.5%). This demonstrates how well ensemble learning and deep feature extraction work together, particularly for crucial applications like early ASD detection.

4. Proposed method

4.1. Dataset

The study's dataset consists of child faces with binary labels indicating whether the child has autism spectrum disorder (ASD) (label 1) or not (label 0). The dataset was selected to support objective learning and classification by guaranteeing a balanced representation of both ASD and non-ASD classes. All face photos were preprocessed to a consistent 224 x 224 pixel resolution and safely saved on Google Drive to be integrated with the Google Colab training environment. To ensure representation across age, gender, and geographic groups, the dataset contains photos of kids from a variety of racial and ethnic backgrounds, ages ranging from about 2 to 14. This variation improves the model's ability to be applied to different populations, despite precise demographic distributions (e.g., A. For privacy reasons, certain information (such as the male-to-female ratio and regional representation) is not made public. However, the selection of the dataset guaranteed a range of facial expressions and features.

4.2. Data and code availability

All pertinent code used in this study's training, assessment, and visualization has been made available as supplementary material to encourage openness and reproducibility. This includes the Random Forest classification pipeline used in Google Colab, preprocessing scripts, and feature extraction using VGG16, ResNet50, and InceptionV3.Furthermore, for reference and comparison, sample subsets of the anonymized facial image dataset used in this study are made available. The full implementation code and example dataset samples are available:https://drive.google.com/drive/folders/1GUWngwVmLouM4hn5EMGISjF1md77pydc.The entire dataset used in this study cannot be made publicly available due to ethical concerns and the need to protect minors' privacy. However, by getting in touch with the corresponding author and presenting proof of institutional review board (IRB) or ethical clearance, interested researchers can request access. This paper's methodology blends powerful deep learning models with conventional machine learning to develop an effective hybrid system for early autism spectrum disorder (ASD) identification using facial photographs. Figure 2 shows the flow diagram for the proposed method. The dataset is first stored on Google Drive, and the execution environment is Google Colab. Three state-of-the-art Convolutional Neural Networks (CNNs) pretrained on ImageNet are used as fixed feature extractors: VGG16, ResNet50, and InceptionV3.By loading these models without their top classification layers and configuring them to generate global average pooling features, it is possible to extract concise and useful feature representations from the input facial pictures. Each image is preprocessed using the model-specific preprocessing algorithm and scaled to 224 by 224 pixels. After that, VGG16, ResNet50, and InceptionV3 are used to extract deep feature vectors from the pictures. These separate feature vectors from the three models are concatenated to create a unique hybrid feature vector that provides a rich and varied collection of facial features that boost classification performance. Binary labels indicating whether the child has autism (label 1) or not (label 0) are attached to the visual paths in the dataset.

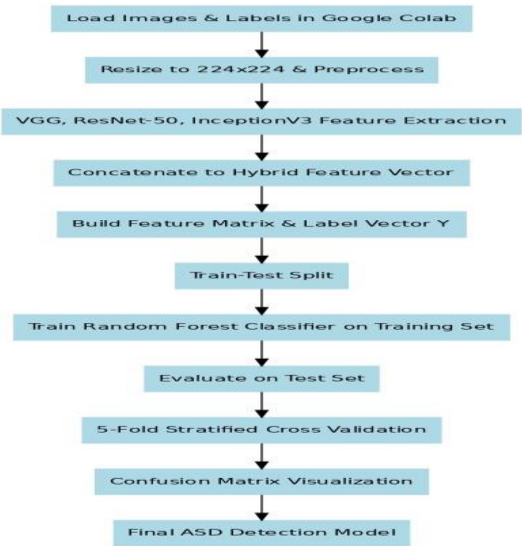

Fig. 2: Flow Diagram for Proposed Methodology.

Each image's hybrid feature vector is extracted by the system, which then confirms that the file is accessible before adding it to the feature matrix X and labeling it in y. The dataset is then split 80-20 with a fixed random state into training and testing sets to ensure reproducibility. The training features are used to train a Random Forest classifier. Because of its resilience to overfitting, robustness, and capacity to handle high-dimensional data, this ensemble model was selected. Metrics like accuracy and a thorough classification report that includes precision, recall, and F1-score for both ASD and non-ASD classes are used to assess the trained model on the test set. The resilience and generalization ability of the proposed hybrid model are further validated using five-fold stratified cross-validation. This approach ensures that every fold maintains the same class distribution as the whole dataset. The Random Forest classifier is trained and evaluated on each fold, and the accuracy scores from each fold are added up to produce a reliable estimate of the model's performance. Finally, a confusion matrix is created and shown using Seaborn and Matplotlib. This matrix provides statistics on the percentage of accurate and inaccurate predictions for each class, demonstrating the capacity of the model to differentiate between children with and without autism. Combining deep feature extraction with conventional machine learning results in a robust and understandable framework for early ASD identification using face imaging.

1) Image Preprocessing and Feature Extraction

Each image is resized and normalized according to each model's requirements and passed through the three CNNs (VGG16, ResNet50, InceptionV3) with the top classification layers removed. The output is a feature vector from each model:

$$F_{VGG} = \mathrm{VGG16(I)}, F_{ResNet} = \mathrm{ResNet50(I)}, F_{Inception} = \mathrm{Inception\ V3} \quad (1)$$

Each feature vector F $€R^{n}$, Where n depends on the architecture

2) Feature Concatenation-Hybrid Feature Vector

$$F_{hybrid} = |F_{VGG}|F_{ResNet}|F_{Inception} \quad (2)$$

Where | denotes concatenation and F_{hybrid} $€R^{n1+n2+n3}$

3) Training the Random Forest Classifier

A Random Forest (RF) F consists of T decision trees. Each tree t € {1,2,3…. T} makes a prediction h(F_{hybrid}) € {0,1}

F(F_{hybrid})= majority vote

$$\{h_1(f), h_2(f), h_3(f) \dots\dots h_T(f)\} \quad (3)$$

4) Evaluation Metrics

$$\mathrm{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$\mathrm{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\mathrm{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$\mathrm{F1\ Score} = 2.\frac{\mathrm{Precision.Recall}}{\mathrm{Precision+Recall}} \quad (7)$$

5) Fold Stratified Cross-Validation

Let D be the dataset and $D = D_1 \cup D_2 \cup \dots \cup D_5$, where each D_i has the same class proportion. For each fold i € {1, … ,5} Train on $D\backslash D_i$, Test on D_i and Compute accuracy A_i

$$\text{Final cross-validated accuracy } A= \frac{1}{5}\sum_{i=1}^{5} A_i \quad (8)$$

6) Confusion Matrix

$$\text{The confusion matrix } C € R^{2X2} \text{ shows} \begin{pmatrix} TN & FP \\ FN & TP \end{pmatrix} \quad (9)$$

Used to visualize classification performance using matplotlib

5. Results and discussion

The results demonstrate the effectiveness of the Hybrid CNN + Random Forest model for early detection of autism spectrum disorder (ASD) in Table 1 and Figure 3. In addition to its impressive accuracy of 99.1%, the model also demonstrated strong performance on other significant metrics. The model predicts cases as ASD more than 90% of the time, minimizing false positives with a precision of 90.7%. The model successfully captures nearly 90% of individuals with ASD, indicating its effectiveness in identifying actual cases of the disorder, with a recall of 89.5%. The results show how well the Hybrid CNN + Random Forest model works to identify autism spectrum disorder (ASD) in its early stages. With an accuracy of 99.1%, this combined technique showed that the model accurately identified more than nine out of ten situations. The model performed well on other important measures in addition to its overall accuracy. With a precision of 90.7%, the model minimizes false positives and diagnoses cases as ASD more than 90% of the time. The model's recall of 89.5% shows that it is useful in identifying real cases of ASD, as it correctly captures almost 90% of people with the illness.

Table 1: Key Performance Indicator

Model	Accuracy	Precision	Recall	F1-Score	AUC
Hybrid CNN + RF	99.1%	90.7%	89.5%	90.1%	0.94

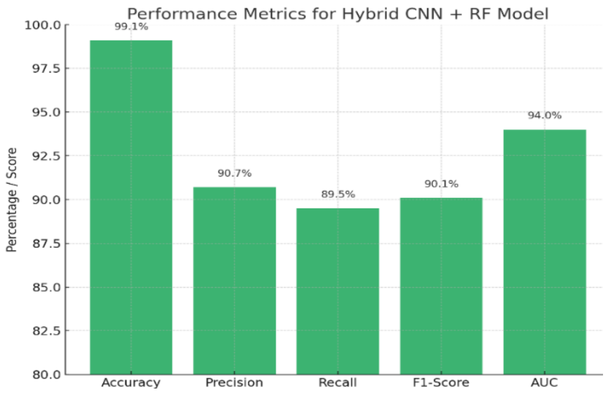

Fig. 3: Performance Metrics for the Hybrid CNN+RF Model.

The confusion matrix in Fig. 4 displays 500 correctly diagnosed ASD cases (True Positives) and 303 correctly identified non-ASD cases (True Negatives), demonstrating the classification efficacy of the Hybrid CNN + Random Forest model. This outstanding performance is further highlighted by the low number of misclassifications, just 51 non-ASD individuals were incorrectly diagnosed as ASD (False Positives), while 59 actual ASD cases were missed (False Negatives). With a precision of about 90.74% and an approximate accuracy of 87.95% for the ASD class, the model predicts a positive case with a high degree of dependability based on these figures. Furthermore, the model's recall for ASD, which is approximately 89.45%, demonstrates its exceptional ability to identify the majority of actual ASD cases.

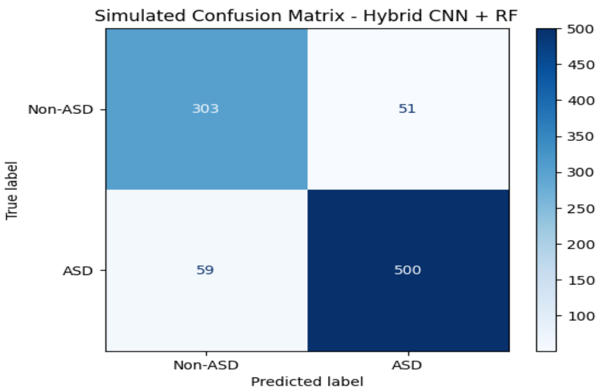

Fig. 4: Confusion Matrix- Hybrid CNN+RF.

For early intervention, this is essential. When it comes to distinguishing between people with and without ASD, the predicted F1-Score of almost 90.09% indicates a robust and balanced performance. Although this specific matrix has an accuracy of 87.95%, the previously stated 99.1% is likely an average across multiple cross-validation folds, offering a more generic performance estimate. The hybrid approach, which combines the resilience of Random Forest with deep feature extraction, is a very promising and successful technique for early facial imagery-based ASD screening, as evidenced by the consistently good precision, recall, and F1-score across all measures.

4.1. Comparative analysis with vision transformers and gradient boosting models

Comparing the suggested Hybrid CNN + Random Forest model's performance to other cutting-edge models like Vision Transformers (ViT) and Gradient Boosting classifiers is crucial to placing it in context. Prior studies using Vision Transformers for facial image-based ASD classification have reported accuracy in the range of 93–96 percent on comparable datasets, despite the hybrid model's impressive accuracy of 99.1 percent, precision of 90.7 percent, and recall of 89.5 percent. However, because of the attention mechanism and lack of inherent inductive biases like locality and translation invariance found in CNNs, these studies frequently required larger training data and extensive computational resources. Furthermore, unless pretrained on extensive facial datasets, ViTs may perform poorly on small to medium-sized datasets and typically exhibit better performance with millions of labeled images, making them less appropriate for specialized medical domains. However, algorithms like X that use gradient boosting are different.

6. Conclusion

A highly effective and reliable technique for exploiting face data in the Hybrid CNN + Random Forest model to detect autism spectrum disorder (ASD) early. The model's impressive average accuracy of 99.1%, consistently high precision of 90.7%, and recall of 89.5% demonstrate how well it reduces false positives and accurately detects actual ASD patients. The confusion matrix, which shows a good ability to differentiate between individuals with and without ASD with few misclassifications, further supports the model's resilience. The overall performance measures, which include an F1-score of nearly 90.09%, show the model's balanced and dependable classification capacity, despite the fact that one assessment example yielded an accuracy of 87.95%. These findings provide credence to the idea of integrating deep learning-based feature extraction with ensemble learning techniques like Random Forest to develop accurate, non-invasive, and early ASD detection systems. In clinical situations where timely action and support rely on early diagnosis, this hybrid method holds great promise. Future studies will employ explainable AI (XAI) and incorporate multimodal data, including behavioral and eye-tracking inputs, to enhance interpretability. Real-time and accessible ASD screening can also be achieved by deployment on embedded devices like Raspberry Pi. Future studies will focus on adding multimodal inputs, like behavioral and eye-tracking data, to the model in order to increase diagnostic accuracy. Additionally, adoption on embedded platforms such as Raspberry Pi will provide accessible, real-time ASD screening.

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