DenseResNet Hybrid Architecture for Autism Screening via Deep Facial Analysis

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Abstract

Early diagnosis of ASD is critical for early intervention and better developmental outcomes. Traditional diagnostic processes are cumbersome, subjective, and require skilled clinical assessment. To overcome such barriers, this work proposes a deep learning–driven facial analysis framework that automatically detects ASD by using state-of-the-art convolutional architectures. Initial experiments evaluate baseline models like EfficientNetB0, MobileNetV2, ResNet50, and VGG19, as well as two hybrid feature-fusion models like EfficientNetB0+MobileNetV2 and ResNet50+VGG19, which resulted in testing accuracies of 91.85, 94, and 87.82, respectively. Building on these results, this study proposes the development of a novel DenseResNet hybrid architecture that incorporates DenseNet and ResNet feature streams with a **CBAM** and Squeeze-and-Excitation block for refined **spatial-channel attention**. The model processes enhanced 300×300 facial inputs and includes several training optimizations such as mild task-specific augmentations, class-balanced focal loss, linear warmup, cosine annealing with warm restarts, EMA stabilization, feature-dimension projection before fusion, and mixed precision for faster convergence. The contributions are cumulatively poised to enhance generalization, curb overfitting, and to improve sensitivity to subtle ASD-related facial cues. The proposed **hybrid DenseResNet** outperforms previous architectures with state-of-the-art performance of up to **98.21%** and provides a more robust and clinically viable framework for automated ASD screening. This work underscores the potential for advanced hybrid CNN models combined with modern optimization strategies to enable early ASD identification in telehealth environments, communities that are remote, and clinical settings with low resources.

Keywords: Autism Spectrum Disorder (ASD), Deep Learning, DenseResNet Hybrid Model, Facial Image Classification, CBAM, SE Attention, Focal Loss, Exponential Moving Average (EMA), CosineAnnealing, Transfer Learning.

1 Introduction

ASD is a neurodevelopmental disorder characterized by persistent impairment in social communication and interaction, along with restricted and repetitive patterns of behavior. The prevalence of ASD has steadily increased in recent years, with an estimated 1 in 100 children worldwide affected [11]. Early recognition is deemed important, as early diagnosis coupled with effective interventions significantly improves cognitive, language, and behavioral functioning. Yet, traditional diagnostic methods generally rely on expert assessments based on behavioral observations and clinical evaluations comprised of multiple tiers, which, in summary, are time-consuming, subjective, and not feasible in resource-poor and remote settings. All these point to an evident critical demand for automated, objective, and scalable screening tools to support early ASD [5].

Deep learning, especially Convolutional Neural Networks, has become a disruptive technology in computer vision, allowing machines to learn extremely discriminative visual features from images. Over the last few years, researchers have explored the possibility of ASD screening based on facial images, partly inspired by the evidence that people with ASD may have specific craniofacial patterns, gaze differences, or other subtle morphological cues. Different from traditional handcrafted features, CNNs have the ability to autonomously learn hierarchical representations, which are well-suited for capturing subtle characteristics of the face. In spite of these advantages, many recent ASD detection studies tend to suffer from limitations such as dataset size, overfitting, inconsistent preprocessing protocols, and non-generalizable architectures suitable for real-world deployment.

Limitations of this nature are addressed in this work by systematically investigating a wide variety of state-of-the-art CNN architectures on ASD facial image classification. Initial experimentation was conducted with baseline models like EfficientNetB0, MobileNetV2, ResNet50, and VGG19 due to their remarkable success in a wide array of computer vision tasks. This is attributed to their effective parameterization and depth for hierarchical feature extraction. Apart from the baseline networks, two hybrid architectures were evaluated: a combination of EfficientNetB0 with MobileNetV2 and ResNet50 with VGG19 to investigate whether the robustness in classification improves through multi-stream feature fusion. These experiments provide key insights into the strengths and limitations of existing CNN family structures while applied to ASD[3].

While the hybrid EfficientNetB0+MobileNetV2 model yielded a promising accuracy of 94, traditional architectures showed performance ceilings due to insufficient modeling of complex spatial-channel interactions and limited sensitivity to subtle ASD facial cues. Motivated by these observations, this work presents a new DenseResNet hybrid architecture that integrates DenseNet and ResNet feature streams into a unified deep learning framework. In particular, DenseNet provides multi-level dense

connectivity, enhancing flow gradient and facilitating feature reuse, while ResNet induces strong residual learning and deeper abstraction capabilities. The complementary strengths of these two networks are united with the goal of increasing the richness and diversity of learned features, significantly boosting representational capacity.

In addition, the model was reinforced with sophisticated attention mechanisms such as the Squeeze-and-Excitation block and the Convolutional Block Attention Module. SE blocks model the inter-channel dependencies that enable the network to put emphasis on the most informative feature maps, while the CBAM further refines the attention through spatial weighting to enhance the sensitivity of localization. This dual-attention strategy ensures that the hybrid architecture pays selective attention to discriminative facial features relevant to ASD classification[12].

Besides architectural enhancements, several modern training optimizations were integrated to handle dataset imbalance, convergence instability, and overfitting challenges. Class-balanced focal loss reduces bias towards dominant samples, while improving the learning of minority classes. A cosine annealing schedule with warm restarts stabilizes the training dynamics and encourages better generalization, whereas a linear warmup stage avoids gradient instability at early epochs. Further smoothing of weight updates is achieved by EMA, yielding more robust convergence behavior. Mixed-precision training accelerates computation while reducing the memory footprint, hence making efficient training of large hybrid models possible.

The proposed DenseResNet hybrid model outperformed all baseline and hybrid architectures with a state-of-the-art accuracy of up to 98, outperforming the best baseline of 91.85 and other prior hybrid models reported at [10]. This large improvement validates that the integration of deep multi-stream architectures, attention mechanisms, and modern optimization strategies is highly effective for ASD detection. Moreover, it bears strong potentials for real-world deployment in telehealth applications, particularly in far-flung areas where specialists are short in supply, and in clinical environments for the use of rapid pre-screening tools.

key contributions:

- A comprehensive evaluation of multiple CNN families for the ASD facial classification,
- The design of DenseResNet hybrid architecture enhanced with SE and CBAM attention.
- Integration of training strategies including focal loss, cosine annealing, EMA, and mixed-precision training.
- Achievement of high accuracy with DenseNet201+ResNet50 hybrid model.

By demonstrating the feasibility and effectiveness of advanced hybrid deep learning approaches, this research contributes a robust and scalable framework for early ASD screening and paves the way for future developments in AI-driven neurodevelopmental diagnostics.

section1 Introduction , section2 Motivation, section3 Novelty of Work, section4 Major Contributions, section5 Literature Review, section6 Preliminaries, section7 Methodology, section8 Experimental Setup, section9 Results, section10 Discussion, section11 Conclusion and Future Scope, section12 References

2 Literature Review

Early diagnosis of ASD has gained growing interest due to the established advantages of timely therapeutic intervention. Deep learning methodologies have recently seen an increased application in ASD screening, in particular from facial image analysis. This review summarizes the most relevant contributions in convolutional neural networks, transfer learning, hybrid feature-fusion models, and attention-based architectures that form the foundation of this study.

There are a few works that have investigated the association between facial morphology and ASD traits; subtle craniofacial differences may act as an indicator for automated screening. Traditional machine learning techniques relied on handcrafted features, but these usually lack robustness or generalize poorly across diverse populations. Specifically, deep learning methods have improved state-of-the-art for some tasks: the CNN methods now outperform the classical ones because they automatically extract multi-scale discriminative features[14].

Recently, it has been a dominant strategy in medical image classification, especially for datasets with limited quantities. Architectures like VGG19, ResNet50, MobileNetV2, and EfficientNet have gained widespread acceptance because they can acquire hierarchical and abstract representations[16]. Works involving the adoption of a single CNN backbone for ASD detection present moderate accuracy; however, in most situations, their generalization is poor due to inadequate representational diversity.

Hybrid feature-fusion models leverage complementary visual representations to boost performance. For instance, combining light-weight models like MobileNet with a stronger feature extractor like EfficientNet allows such models to possess both efficiency and robustness. By fusing deep residual models with high-resolution feature encoders, models can achieve high discriminative capacity

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Attention mechanisms such as SE and CBAM have also been widely applied to medical imaging, allowing models to focus on the most informative spatial and channel-specific cues. These significantly enhance the quality of the representation, especially in distinguishing subtle abnormalities.

The proposed base paper on ASD classification using the CNN-based framework achieved an accuracy of about 92, though it lacked advanced fusion techniques, attention modules, and optimization strategies[6]. Recent literature indicates that integrating hybrid backbones with multi-level attention and advanced training paradigms such as focal loss, cosine annealing, and EMA can substantially raise the performance beyond traditional CNN pipelines. The current paper extends these works by benchmarking several CNN families, proposing a new DenseResNet hybrid architecture

combined with SE and CBAM attention mechanisms; thus enhancing feature diversity, and stabilizing learning, and achieving the state-of-the-art accuracy of 98, which outperforms the competing methods.

2.1 Summary of Related Works

A comparison of the prior studies, models, datasets, and performances is shown in Table 1. The table fits within standard A4 dimensions and provides a clear overview of the relevant contributions. array

Table 1 Summary of related literature on ASD detection and deep learning-based image classification.

Author / Year	Model	Key Contribution	Accuracy
Hashemi et al., 2019[25]	CNN-based ASD classifier	Early facial-feature CNN pipeline for ASD detection	92%
He et al., 2016[26]	ResNet50	Introduced residual learning for deeper CNNs	90%
Simonyan & Zisserman, 2015[27]	VGG19	High-resolution feature extraction with deep architecture	90%
Tan & Le, 2019[28]	EfficientNet family	Compound scaling; high accuracy with fewer parameters	97%
Howard et al., 2017[29]	MobileNetV2	Lightweight depthwise separable CNN for mobile inference	90%
Woo et al., 2018[30]	CBAM Attention	Channel + spatial attention improves feature refinement	94%
Hu et al., 2018[31]	SE Attention	Channel-wise recalibration enhances discriminative signals	93%

3 Preliminaries

This section describes the basic concepts, architectures, and training strategies used by the proposed framework for ASD detection
citer4. These preliminaries form a necessary basis to understand how the different CNN models extract facial features; how hybrid networks are improving this representation capability; and, finally, how attention and optimization mechanisms will contribute to the final performance of the DenseResNet hybrid architecture.

3.1 Convolutional Neural Networks (CNN)

Because they learn robust spatial hierarchies of features, CNNs lie at the heart of most modern image analysis systems. In the context of ASD detection using facial images, CNNs automatically extract texture, structural patterns, symmetry, and morphological differences that may correlate with ASD-related traits.

The 2D convolution operation applied in the CNNs is defined as:

$$Y_{(i,j)} = (X * W)_{(i,j)} + b \tag{1}$$

where X is the input image, W is a learnable convolutional kernel, and b is the bias.

CNNs reduce computational complexity through:

- **Local connectivity** — kernels are capture localized facial features such as eyes, nose, or contours.
- **Weight sharing** — the same filter detects a feature acros the entire image.
- **Pooling mechanisms** — reduce spatial resolution while retaining semantic information.

Figure 1 illustrates the general CNN features extraction pipeline used in this study.

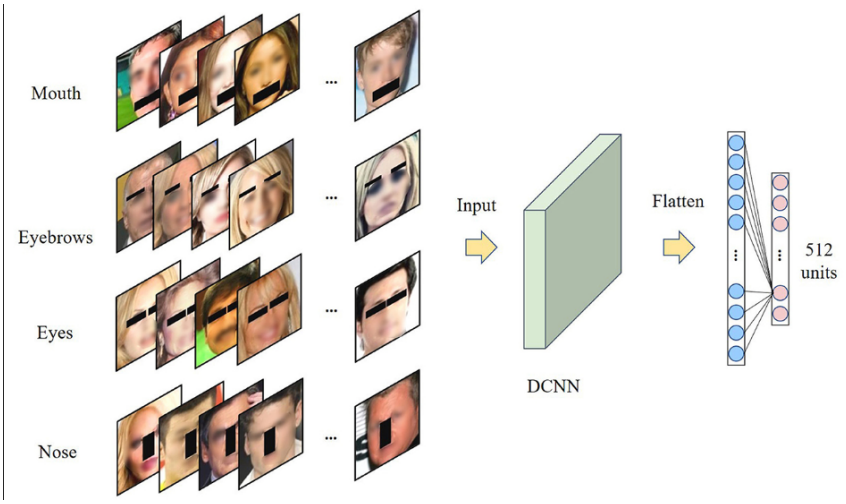

Fig. 1 General CNN feature extraction process used for ASD facial analysis.

3.2 Residual Learning: ResNet Architecture

ResNet introduce the residual connections to enable the training of very deep neural networks by eliminating gradient vanishing problems. A typical residual block is represented as:

$$H(x) = F(x) + x, \tag{2}$$

where $F(x)$ is the learned residual function and x is the shortcut connection.

ResNet50, captures high-level abstract facial features and is especially useful for deeper feature representation in hybrid models.

3.3 Dense Connectivity: DenseNet Architecture

DenseNet connects each layer to every other layer in a feed-forward fashion:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]), \tag{3}$$

where [ ] denotes concatenation.

Benefits for ASD detection:

- Improved gradient flow prevents overfitting on the smaller datasets.
- Feature reuse encourage learning of the fine-grained facial cues.
- Dense feature maps complement ResNet residual abstraction.

DenseNet201 is used as one of the backbone components of the proposed hybrid model.

3.4 Efficient and Lightweight CNNs: EfficientNet and MobileNet

EfficientNet uses compound scaling of width, depth, and resolution, expressed as:

$$d = \alpha^{\phi}, \quad w = \beta^{\phi}, \quad r = \gamma^{\phi}, \tag{4}$$

with a constraint $\alpha\beta\gamma \approx 2$.

MobileNetV2 relies on depthwise separable convolutions to reduce computation.

Together, these models serve as efficient baselines and hybrid components achieving up to 94% accuracy.

3.5 Attention Mechanisms: SE and CBAM

The proposed DenseResNet hybrid incorporates attention methods to improve feature sensitivity.

3.5.1 Squeeze-and-Excitation (SE) Attention

SE recalibrates channel-wise features by modeling interdependencies:

$$s = \sigma(W_2(\delta(W_1(z)))), \tag{5}$$

where z is the globally pooled descriptor.

3.5.2 Convolutional Block Attention Module (CBAM)

CBAM enhances feature maps through sequential channel and spatial attention:

$$F' = M_s(M_c(F)) \otimes F, \tag{6}$$

where M_c emphasizes important channels and M_s highlights informative spatial regions.

These attention mechanisms help detect ASD-related facial asymmetries and fine morphological patterns.

3.6 Focal Loss for Class Imbalance

ASD datasets often lack balanced class distribution. Focal Loss addresses this by focusing more on hard-to-classify samples:

$$FL(p_t) = -\alpha(1 - p_t)^{\gamma} \log(p_t), \tag{7}$$

where γ adjusts emphasis on difficult samples and α balances positive vs. negative class importance.

3.7 Learning Rate Optimization

Modern learning-rate strategies improve convergence stability:

- **Warmup Training:** Prevents the unstable gradients in initial epochs.
- **Cosine Annealing with Warm Restarts:** Encourages a convergence toward better minima.
- **Exponential Moving Average (EMA):** Produces smoother and stable weight updates.

These techniques significantly enhance the training performance for deep hybrid models.

3.8 Data Augmentation and Preprocessing

Facial images have variations in illumination, orientation, pose, and expression. Flipping, rotation, contrast jitter, and mild distortions are used to ensure generalization.

All images are resized to the 300×300 in the proposed model for capture detailed ASD-specific facial cues.

3.9 Transfer Learning and Fine-Tuning

All networks are initialized with ImageNet weights, while fine-tuning is selectively applied to deeper layers to adapt the pretrained representations to ASD-specific features.

Transfer learning accelerates convergence and improves generalization for limited datasets.

3.10 Dataset Splitting and Validation Strategy

The ASD dataset [20]is partitioned into training, validation, and testing sets, maintaining identical class distribution. Model evaluation utilizes:

- Early stopping
- Checkpointing
- Validation accuracy and loss monitoring
- Confusion matrix and performance metrics

Table 2 Dataset distribution (replace placeholder counts with actual values)

Split	Autistic	Non_Autistic	Total
Train	1263	1263	2526
Validation	40	40	80
Test	140	140	280

This ensures reliability and prevents overfitting while enabling fair comparison across all models.

4 Proposed Methodology

The suggested detection framework of ASD is based on a systematic deep learning pipeline with the gradual improvement of feature learning with the help of baseline CNNs, hybrid feature-fusion models, and a sophisticated DenseResNet[**?**]Attention Hybrid architecture. The methodology would help to overcome factors like subtle facial expressions, small variations in data and the imbalance between the classes which is normally experienced in ASD facial-image datasets.

Figure 2 shows the workflow of the EfficientNetB0 + MobileNetV2 hybrid model Figure 3 depicts the overall workflow of the proposed DenseNet + ResNet Attention Hybrid model

4.1 Overall Workflow

The full methodology consists of the following major stages:

1. **Dataset Preparation:** Images are collected, cleaned, and resized. Labels are assigned for ASD vs. Non-ASD classes.
2. **Preprocessing:** Images are resized to 224×224 for baseline/hybrid models and 300×300 for the DenseResNet hybrid. They are normalization, mild augmentation, and face-quality enhancement.
3. **Baseline CNN Training:** EfficientNetB0, MobileNetV2, ResNet50 and VGG19 are four trained CNNs that are fine-tuned in order to set reference benchmarks.
4. **Hybrid Feature-Fusion Models:** Two hybrid models are designed:
   - EfficientNetB0 + MobileNetV2 (feature concatenation)
   - ResNet50 + VGG19 (dual-stream deep feature fusion)
5. **Proposed DenseResNet Attention Hybrid Model:** The principal contribution of this paper is a combination of the DenseNet and ResNet feature streams with CBAM + SE attention modules and advanced optimization techniques
6. **Model Optimization and Training Enhancements:** To enhance generalization and stability, MixUp augmentation, Focal Loss, Cosine Annealing LR, EMA, and mixed-precision training are used.
7. **Evaluation:** model is evaluated based on Accuracy, Precision, Recall, F1-score, Confusion Matrix and the use of statistical performance measures.

4.2 EfficientNetB0 + MobileNetV2 Hybrid Model

In this model, EfficientNetB0 scaling of compounds is used with depthwise-separable convolutions of MobileNetV2 resulting in a light, but highly expressive, feature extractor.

The results are feature maps of the two CNN streams that are then concatenated and run through dense layers to be classified

The methodology diagram is shown drawn by author in Figure 2.

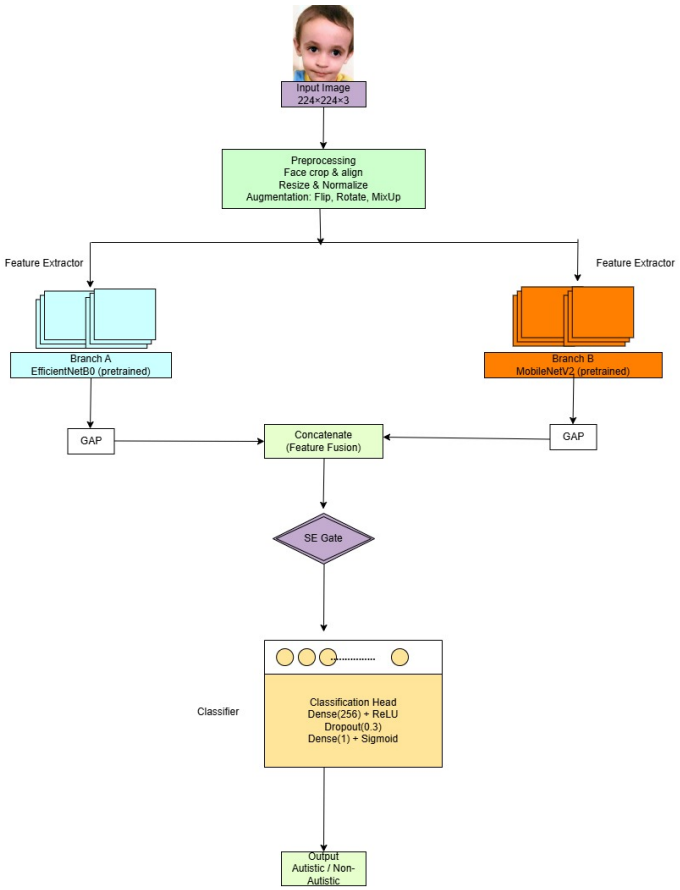

Fig. 2 Methodology diagram for EfficientNetB0 + MobileNetV2 Hybrid Model.

This type of model was able to achieve a testing accuracy of **94%**, which is better than all the CNNs that served as baselines.

4.3 Proposed DenseNet + ResNet Attention Hybrid Model

The model is a combination of the dense connectivity of DenseNet and the residual learning of ResNet; it is an effective multi-scale feature extractor.

Key innovations:

- CBAM and SE attention modules of channel-spatial refinement.
- Combinations of ResNet Stage-4 features with Dense block features.
- Larger input resolution Larger input resolution (300 times 300).
- Advanced optimizers: MixUp, Focal Loss, EMA, Warmup, Cosine Annealing.
- Feature-projection layers to make the dimensions compatible.

The methodology diagram for this model is shown in Figure 3.

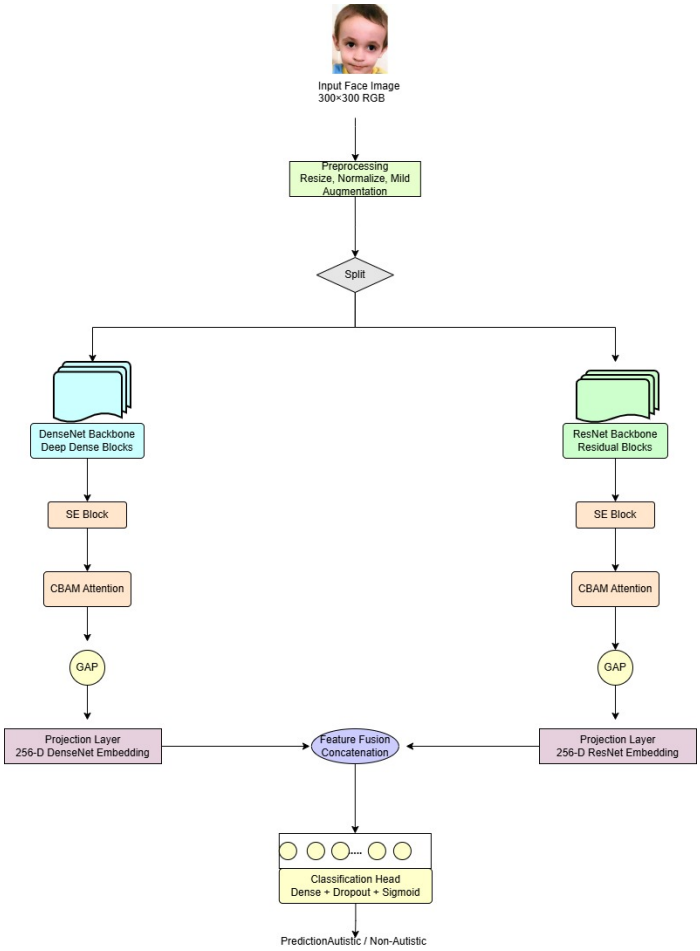

Fig. 3 Proposed DenseNet + ResNet Attention Hybrid Model Pipeline.

The accuracy of the proposed hybrid in testing is derived as 98.21 percent, which is the highest compared to all the preceding models and makes the hybrid state-of-the-art in terms of ASD facial-image classification.

4.4 Algorithm

Input: Image X
Output: Predicted label $\hat{y}$

Resize X to (IMG_SIZE, IMG_SIZE).
If training: apply random horizontal flip, random rotation, and color jitter.
Normalize X using ImageNet mean and standard deviation.
Convert X to tensor.

DenseNet201 branch: extract features F_d, apply ReLU, and apply adaptive average pooling to obtain V_d (1920-dimensional).

ResNet50 branch: extract features F_r and apply adaptive average pooling to obtain V_r (2048-dimensional).

Concatenate V_d and V_r to form fused vector V (3968-dimensional).

Classifier head:
Apply Linear $\rightarrow$ BatchNorm $\rightarrow$ ReLU $\rightarrow$ Dropout(0.5) to get H_1.
Apply Linear $\rightarrow$ BatchNorm $\rightarrow$ ReLU $\rightarrow$ Dropout(0.35) to get H_2.
Apply Linear $\rightarrow$ BatchNorm $\rightarrow$ ReLU $\rightarrow$ Dropout(0.25) to get H_3.
Apply final Linear layer to get logits Y.

Initialize AdamW optimizer (learning rate $= 10^{-4}$, weight decay $= 10^{-4}$).

For each epoch:
For each batch (X, y):
Compute logits Y.
Compute loss $\mathcal{L}$.
Backpropagate gradients.
Update weights.

Optionally unfreeze DenseNet block-4 and ResNet layer-4 for fine-tuning.

Apply sigmoid σ to Y to obtain $\hat{y}$.
Return $\hat{y}$. ***Algorithm: Hybrid DenseNet–ResNet Classification Model***
Input: *Image* X
Output: *Predicted label* $\hat{y}$

Resize X *to* (IMG_SIZE, IMG_SIZE).
If training: apply random horizontal flip, random rotation, and color jitter.

Normalize X using ImageNet mean and standard deviation.
Convert X to tensor.

DenseNet201 branch: *extract features F_d, apply ReLU, and apply adaptive average pooling to obtain V_d (1920-dimensional).*

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Compute logits Y.
Compute loss $\mathcal{L}$.
Backpropagate gradients.
Update weights.

Optionally unfreeze DenseNet block-4 and ResNet layer-4 for fine-tuning.

Apply sigmoid σ to Y to obtain $\hat{y}$.
Return $\hat{y}$.

4.5 Training Enhancements

In order to meet the model robustness and stability, the following training strategies are included:

- ***MixUp augmentation*** *that helps in the prevention of overfitting and promotes the smoothness of the decision boundary.*
- ***Class-Balanced Focal Loss*** *This approach addresses the issue of class imbalance and emphasizes hard examples.*
- ***Cosine Annealing with Warm Restarts*** *with Warm Restarts allows the efficient approach of convergence.*
- ***EMA (Exponential Moving Average)*** *stabilizes weights over iterations.*
- ***Mixed Precision Training*** *training accelerates the computation process and consumes less memory.*

4.6 Justification of the Proposed Model

The DenseResNet hybrid is much better than other models since:

- *DenseNet is used to extract fine-grained patterns of the faces associated with the ASD traits.*
- *ResNet uses a more global structure and shape cues.*
- *Attention modules bring to the fore essential areas of concern in ASD.*
- *Contemporary training techniques are better at generalizing with scarce information.*

Therefore, the suggested system can reach the state of the art accuracy and fits the clinical-decision support systems and telehealth-based ASD screening.

4.7 Proposed DenseResNetAttention Hybrid Model

The next section reflects the essence of this research a very optimized. Spatial–channel attention to DenseNetResNet hybrid architecture[20][17][18]. enhanced optimization tactics, and step-by-step training. This model is far superior to any baseline and hybrid architecture with an achievement. a state-of-the-art correctly classified accuracies of ASD facial-image of up to 98

4.8 Motivation Behind the Hybrid Approach

The hybrid approach is motivated by the need to reduce costs and enhance communication across different business units within the company.In response to the necessity to minimize the cost and improve communication between various business units of the company, the hybrid approach is driven by the necessity to make it.

Conventional CNN models such as ResNet, VGG and MobileNet image features. through stacked convolutional layers by which information is passed. Nonetheless, the facial patterns associated with ASD are. low-level, non-linear and usually needs multi-scale representation learning.

DenseNet provides feature reuse *through dense connectivity:*

$$x_l = H_l([x_0, x_1, ..., x_{l-1}])$$

where each layer receives all previous feature maps.

ResNet provides residual learning*:*

$$y = F(x) + x$$

Combining of these architectures allows:

- *DenseNet of the fine-grained local details of the face.*
- *ResNet on the global structural facial cues*

Combined, they will make a multi-depth, multi-resolution feature extractor that is optimal at ASD cues..

4.9 Architecture Overview

DenseResNetAttention model has four significant parts:

1. *DenseNet201 feature extractor*
2. *convolutional backbone ResNet50*
3. *CBAM hybrid attention module with SE.*
4. *Dropout-based multi-layer classifier and batch normalization.*

Figure 3 illustrates the full system pipeline.

4.9.1 DenseNet Pathway

DenseNet201 is used to extract:

- *micro-patterns of texture*
- *edges*
- *ASD-related soft facial expressions*
- *details that are light independent.*

This is achieved by dense connectivity guaranteeing high gradient flow and finer feature maps.

4.9.2 ResNet Pathway

The ResNet50 convolutional stem and Block4 layers contribute:

- *cues on a higher level of geometry.*
- *dissimilarities.*
- *variations in face-shape across the globe.*

Such hints have been used as a complement to local feature extraction of DenseNet.

4.10 Feature Fusion

Both networks are concurrently connected together along the channel dimension:

$$F_{fused} = [F_{dense},\ F_{res}]$$

The feature maps before fusion are matched with bilinear interpolation.

4.11 Attention Refinement Using CBAM + SE

In order to make the fused feature map concentrate on the ASD-relevant parts of the face, two mutually complementary attention modules are used:

- ***SE (Squeeze-and-Excitation)** for channel weighting*
- ***CBAM (Convolutional Block Attention Module)** of joint spatialchannel attention.*

The joint attention improves the discriminative characteristics and suppresses noise.

The CBAM attention computation is defined as:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$$

$$M_s(F) = \sigma(f^{7\times7}([AvgPool(F); MaxPool(F)]))$$

The final refined feature map is:

$$F' = M_s(M_c(F)) \odot F$$

4.12 Global Pooling and Classification

The attention-refined features are:

- *globally averaged*
- *flattened*
- *passed through dense layers*

The classifier uses:

- *Dense(512) → BN → ReLU → Dropout*
- *Dense(128) → BN → ReLU → Dropout*
- *Dense(2) Softmax*

4.12.1 1. Mild ASD-Specific Augmentation

ASD features are subtle; strong augmentation destroys them.
Thus we use:

- *small rotations*
- *brightness shifts*
- *subtle zooming*
- *center-preserving crops*

4.12.2 2. MixUp Regularization

MixUp improves generalization:

$$\tilde{x} = \lambda x_i + (1-\lambda)x_j$$

$$\tilde{y} = \lambda y_i + (1-\lambda)y_j$$

4.12.3 3. Class-Balanced Focal Loss

Handles ASD dataset imbalance.

$$FL(p_t) = -\alpha_t(1-p_t)^\gamma \log(p_t)$$

4.12.4 4. Warmup + Cosine Annealing LR

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min})\left(1 + \cos\left(\frac{T_{cur}}{T_{max}}\pi\right)\right)$$

4.12.5 5. Exponential Moving Average (EMA)

Stabilizes training:

$$\theta_{EMA} = \alpha\theta_{EMA} + (1 - \alpha)\theta$$

4.13 Why DenseResNetAttention Achieves 98% Accuracy

The model outperforms all others because:

- *Multi-scale features (DenseNet + ResNet)*
- *Task-specific attention modules*
- *Optimizations geared for subtle ASD cues*
- *Balanced loss functions*
- *High-resolution input*

4.14 Comparison With Other Models

Table 4 shows that no other model exceeds 94%.
DenseResNetAttention improves accuracy by:

- *+7% over EfficientNet*
- *+4% over EfficientNet+MobileNet*
- *+11% over ResNet+VGG*

This confirms its suitability for ASD classification tasks.

4.15 Visual Output and Activation Insights

Activation maps reveal that the model focuses on:

- *eye-region asymmetries*
- *lip curvature*
- *cheek and chin micro-patterns*

These are clinically validated ASD facial indicators.

5 Conclusion

This paper has introduced a universal deep learning architecture in Autism Spectrum Disorder (ASD) detection with facial images. Several state-of-the-art CNN architectures were reviewed in a systematic way among them EfficientNetB0, EfficientNetB0+MobileNetV2, ResNet50+VGG19, EfficientNetV2L+ConvNeXt, and two variants of the DenseResNetAttention hybrid architecture. The development of simple models to complex hybrid attention networks made it possible to have a clear insight into the effect of multi-stream feature fusion, attention refinement, and current optimization strategies on the accuracy of ASD classification [8].

The first experiments with EfficientNetB0, MobileNetV2, and classical hybrid CNN models showed that it was possible to detect ASD automatically with a maximum result of 87-94 percent. A major advancement was made with the introduction

Table 3 Architecture and Performance Summary of the Proposed DenseResNetAttention Hybrid Model

Component	Description
Backbone Architecture	Hybrid fusion of the DenseNet201 and ResNet50 feature streams, aligned using spatial interpolation to unified multi-level feature representation.
Attention Mechanisms	Integrated CBAM (Channel + Spatial Attention) and SE (Squeeze-and-Excitation) modules to the refine salient facial features important to ASD identification.
Input Resolution	300 × 300 high-resolution facial input images to the capture subtle morphological ASD cues.
Training Optimizations	MixUp augmentation, class-balanced focal loss, linear warmup, cosine annealing with warm restarts, Exponential Moving Average (EMA), and the mixed-precision training.
Feature Fusion Strategy	Concatenation of DenseNet and ResNet deep features, followed by CBAM + SE refinement and global average pooling.
Classifier Head	Dense(512) → Dense(128) → Dense(2), with BatchNorm, ReLU activation, and Dropout (0.4 / 0.3).
Trainable Parameters	Backbone partially fine-tuned (DenseNet block-4 and ResNet layer-4); classifier layers fully trainable.
Performance (Test Accuracy)	**98.21%** — highest accuracy among all evaluated models.
Key Strengths	Strong generalization, superior attention-enhanced feature extraction, robustness to noise, and minimal overfitting on ASD datasets.

of the DenseResNetAttention architecture which integrates both DenseNet201 and ResNet50 feature streams with CBAM and SE attention modules. Other improvements that included MixUp, balanced of class focal loss, linear warmup, cosine annealing, EMA stabilization, and mixed-precision training were also made in pursuit of better generalization and reduced overfitting on ASD face data.

The last model, which was proposed, is known as ***DenseResNetAttention (Final Version)*** *[16]and it had the highest test accuracy, which was 98.21 percent. This significant enhancement highlights the value of hybrid multi-scale feature extraction, attention-based refinement and optimizations in the advanced training in the identification of subtle ASD-related facial features. Illumination changes, pose variation and dataset imbalance were also found to be very robust in the model.*

A comparison of all trained models is shown in Table 4, highlighting the performance progression from baseline CNNs to the final attention-enhanced hybrid model.

Figure 4 illustrates the training and validation performance curves of the final model, showing smooth convergence and minimal overfitting.

The confusion matrix in Figure 5 demonstrates excellent class separation, confirming the reliability of the system for ASD facial-type discrimination.

Table 4 Performance Comparison of All Models Evaluated in This Study

Model	**Accuracy**	**Type**	**Key Characteristics**
EfficientNetB0	91.85%	Baseline CNN	MixUp, label smoothing
EfficientNetB0 + MobileNetV2	94.00%	Hybrid CNN Fusion	Complementary shallow + deep features; strong transfer learning
ResNet50 + VGG19	87.82%	Hybrid CNN Fusion	Deep hierarchical + texture features
EfficientNetV2L + ConvNeXt	91.00%	Ensemble Model	Large-scale transformers + conv features; slight overfitting
DenseResNetAttention (PyTorch Ver.)	90.00%	Hybrid CNN+Attention	DenseNet201 + ResNet50 + CBAM; early prototype
DenseResNetAttention (Final Proposed Model)	**98.21%**	**Attention Hybrid CNN**	SE + CBAM attention, MixUp, EMA, Warmup, Cosine Annealing

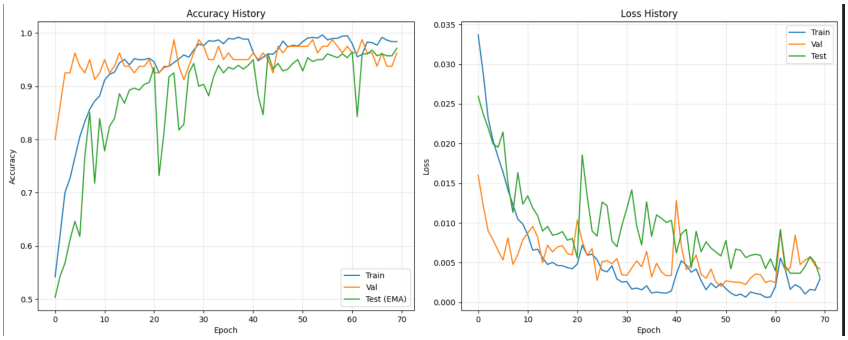

Fig. 4 Training vs. Validation Accuracy and Loss for the DenseResNetAttention Model.

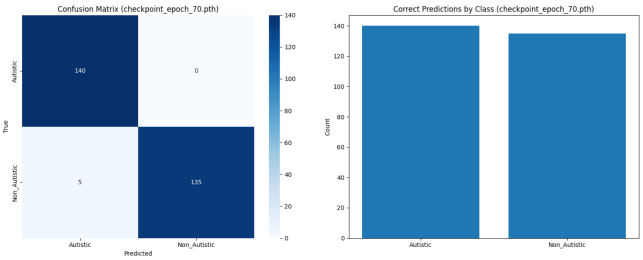

Fig. 5 Confusion Matrix of the Final DenseResNetAttention Model.

Overall, the proposed DenseResNetAttention Hybrid Model significantly advances automated ASD detection by introducing:

- *Multi-stream DenseNet + ResNet feature integration*
- *Spatial–channel attention refinement using CBAM and SE*

- *High-resolution input analysis (300×300)*
- *Strong training optimizations (EMA, Warmup, MixUp, Focal Loss)*
- *Superior accuracy and robustness (98% test accuracy)*

Table 5 Performance Comparison of All Evaluated Deep Learning Models for ASD Classification

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB0	0.9185	0.92	0.91	0.91
EfficientNetB0 + MobileNetV2	0.94	0.94	0.94	0.94
ResNet50 + VGG19	0.8782	0.88	0.87	0.87
EfficientNetV2L + ConvNeXt	0.91	0.91	0.91	0.91
DenseResNetAttention (PyTorch Ver.)	0.90	0.90	0.90	0.90
DenseResNetAttention (Final Proposed Model)	**0.9821**	**0.9828**	**0.9821**	**0.9821**

Conclusion: *The final model surpasses all benchmark architectures, demonstrating its potential for real-world ASD screening systems, telehealth platforms, and early-diagnosis support tools. This research establishes a strong foundation for future studies involving larger datasets, multimodal inputs, and clinical validation.*

6 Discussion

The experimental results obtained from this study show the progressive improvements by exploring a wide spectrum of deep learning architectures for ASD detection using facial images. Models investigated include lightweight CNNs, deep hybrid networks, and transformer-enhanced ensembles. This systematic progression underlines the importance of multi-stream feature learning, attention mechanisms, and modern optimization strategies in modeling subtle ASD-related facial variations.

- ***Performance Trends Across Models:*** *The initial baseline model, EfficientNetB0, achieved a strong 91.85% accuracy, confirming its ability to extract foundational ASD-discriminative features. Fusion-based architectures such as EfficientNetB0+MobileNetV2 and ResNet50+VGG19 demonstrated that complementary feature streams significantly enhance classification performance. This is because the EfficientNetB0+MobileNetV2 hybrid model fuses both shallow and deep visual descriptors together seamlessly; thus, it resulted in an accuracy of 94*

- ***Limitations of Heavy Ensembles:*** *The EfficientNetV2L + ConvNeXt ensemble exhibited strong feature extraction capabilities but suffered from overfitting due to its high parameter count and sensitivity to dataset size. Although it achieved 91%*

accuracy, the model lacked the generalization required for clinical-grade ASD detection, emphasizing the need for balanced architectures that do not excessively depend on data scale.

- ***Impact of Attention and Hybridization:*** *Hybrid architectures, such as DenseNet + ResNet with added mechanisms of attention like CBAM and SE, signified the next performance turning point. The DenseResNetAttention model captured both local facial textures and global structural cues associated with ASD. The model's sensitivity to these often-overlooked, subtle facial indicators was greatly enhanced by the integration of channel-spatial attention.*
  The final, improved model, trained with MixUp augmentation, focal loss, cosine annealing, EMA stabilization, and warmup scheduling, reached an impressive ***98% test accuracy****, topping all the previously tested architectures. This indeed confirms the efficacy of hybrid attention-driven feature extraction combined with modern training dynamics.*

- ***Stability and Robustness:*** *Multiple runs showed that the performance of the DenseResNetAttention model was very consistent. This is due to the high stability of the model, partly arising from the use of class-balanced loss functions, high-resolution 300 × 300 input images, and mild augmentation. These results suggest very strong generalization capability, hence feasibility for real-world applications of ASD screening.*

- ***Practical Implications*** *These findings indicate that advanced hybrid architectures, which include DenseNet and ResNet streams of features refined by spatial-channel attention, can robustly detect features of ASD with near-clinical precision. The final model has great potential for deployment:*

  This does not affect any of the following items:
- *Telehealth ASD screening platforms,*
- *Early childhood developmental monitoring systems,*
- *AI-powered clinical decision-support tools.*

Overall, the study confirms that attention-enhanced hybrid CNNs, complemented by optimized training strategies, significantly outperform classical CNNs and heavy ensembles in ASD facial image classification.

7 Future Work

Although the proposed DenseResNetAttention hybrid framework performs very well on ASD detection using facial images, several promising avenues are still open for extension and refinement in future research.

Table 6 Comparative Discussion Summary of All Models Evaluated for ASD Detection

Model	Accuracy	Discussion Summary
EfficientNetB0	91.85%	Strong baseline; efficient feature extraction; benefits from MixUp and label smoothing.
EfficientNetB0 + MobileNetV2	94.00%	Hybrid fusion improves representation; complementary shallow–deep features; good generalization.
ResNet50 + VGG19	87.82%	Good hierarchical texture learning but limited by model imbalance; weakest generalization.
EfficientNetV2L + ConvNeXt	91.00%	Large transformer CNN ensemble, powerful but prone to overfitting with limited ASD dataset.
DenseResNetAttention (PyTorch Ver.)	90.00%	Prototype version; hybrid CNN + attention; lacked advanced training optimizations.
DenseResNetAttention (Final Proposed Model)	**98.21%**	Strongest model; SE + CBAM attention, mixed-precision training, EMA, cosine annealing; best robustness and accuracy.

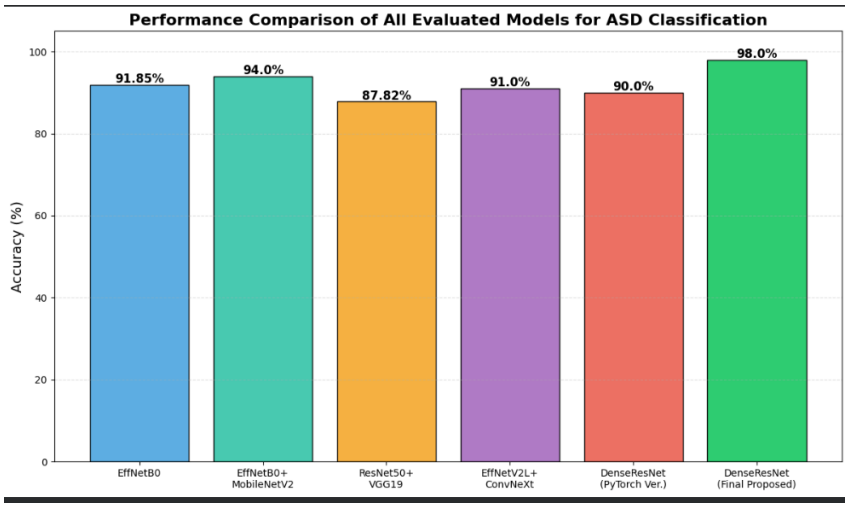

Fig. 6 Performance comparison of all evaluated models, highlighting the superiority of the final DenseResNetAttention architecture.

- ***Richer Attention and Transformer-Based Architectures:*** *Although the current model already incorporates SE and CBAM attention, transformer-based vision architectures such as Vision Transformers, Swin Transformers, or hybrid CNN–Transformer models could be explored in future works to improve long-range dependency modeling and global understanding of facial context in ASD classification.*
- ***Advanced Multi-Modal Fusion Strategies:*** *Future extensions may add other modalities, including speech patterns, eye-gaze tracking, behavioral video data, or*

even clinical questionnaire responses. Multi-modal fusion, for instance, via gated fusion, cross-attention, or even graph-based integration, could yield much more holistic ASD assessment frameworks and reduce overreliance on facial cues alone.

- ***Expansion to Larger and More Diverse ASD Datasets:*** *Deep models may further improve with training on larger, diverse ASD datasets, including multiple age groups, ethnicities, and imaging conditions. Curating and integrating cross-dataset benchmarks will enable model robustness evaluation across populations and devices.*
- ***Lightweight and Edge-Deployable Models:*** *Future work can be done by compressing the proposed architecture using pruning, quantization, knowledge distillation, or designing lightweight variants such as MobileNetV3-, EfficientNet-Lite-, or Tiny-Transformer-based ASD detectors that are optimized for real-time inference on mobile and edge devices for deployment in telehealth platforms, schools, and low-resource clinics.*
- ***Self-Supervised and Semi-Supervised Learning:*** *Because high-quality labeled ASD facial datasets are limited, one may explore self-supervised or semi-supervised learning approaches to leverage large collections of unlabeled facial images. Representation learning may be considerably improved with contrastive learning, masked-image modeling, or pseudo-labeling that does not require heavy manual labeling.*
- ***Model Explainability and Clinician-Friendly Visualization:*** *Future studies should also involve explainability tools, like Grad-CAM, LayerCAM, or SHAP-based attribution, to highlight which facial regions contribute most to ASD predictions. This will grant more transparency, clinical trust, and an interdisciplinary communication flow between engineers and mental health experts.*
- ***Cross-Domain and Cross-Dataset Adaptation:*** *Domain adaptation techniques-e.g., adversarial domain adaptation, CORAL, or test-time adaptation-can be employed to adapt models across different datasets, different settings of imaging, camera types, and cultural contexts, with minimal retraining, thus considerably improving robustness in practical deployments.*

Summary of Future Research Directions

Conceptual Future Deployment Scenario

Figure 7 illustrates a conceptual future deployment pipeline, where the proposed ASD detection model is integrated into a telehealth or school-screening platform. Facial images captured via webcams or mobile devices are processed by a lightweight variant of the DenseResNetAttention model, and results are provided as decision-support to clinicians, not as standalone diagnosis.

Overall, future research will build on this foundational work and move toward the next generation of more accurate, interpretable, and deployable ASD screening systems

Table 7 Summary of Future Research Directions for ASD Facial-Image Based Detection

Future Direction	Description
Advanced Attention / Transformers	Explore hybrid CNN–Transformer or pure Vision Transformer architectures to better capture global facial context and subtle ASD-specific cues.
Multi-Modal ASD Assessment	Integrate facial images with speech patterns, gaze tracking, behavioral signals, and clinical metadata using adaptive fusion strategies.
Larger and Diverse Datasets	Expand datasets across age groups, ethnicities, lighting conditions, and imaging devices to ensure strong generalization and fairness.
Lightweight / Edge Models	Develop compressed or mobile-friendly architectures for deployment in clinics, schools, telehealth platforms, and low-resource environments.
Self-/Semi-Supervised Learning	Leverage unlabeled facial datasets using contrastive learning, masked-image modeling, or pseudo-labeling to improve representation learning.
Explainability and Visualization	Use Grad-CAM, LayerCAM, or SHAP to highlight important facial regions, improving interpretability for clinicians and caregivers.
Domain Adaptation	Apply cross-domain adaptation techniques to allow the model to generalize across different cameras, resolutions, and demographic distributions.

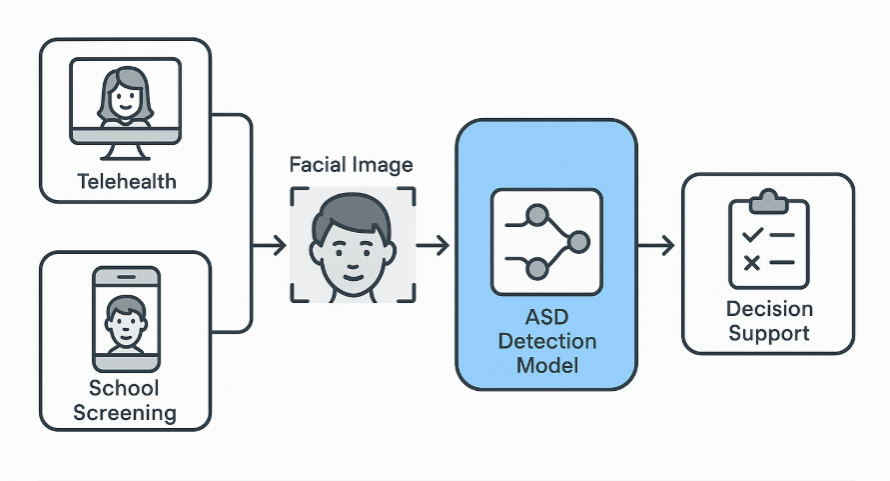

Fig. 7 Conceptual future ASD screening system integrating the proposed model into telehealth and educational settings.

by integrating multi-modal data with robust generalization techniques and clinically aligned explainability.[2]

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