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OPTIMIZED HYBRID LEARNING APPROACH FOR AUTISM SPECTRUM DISORDER DETECTION

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Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition marked by difficulties in social interaction, communication, and repetitive behaviours, making early and accurate detection particularly crucial in resource-constrained regions. To address this need, this study introduces a hybrid machine learning approach that leverages the Grey Wolf Optimizer (GWO) for hyperparameter tuning and XGBoost for enhanced classification, improving ASD detection using facial image data from a publicly available kaggle dataset. The dataset comprises images of individuals with and without autism across various age ranges, providing a diverse foundation for analysis. The study evaluates two deep learning architectures—VGG16 and MobileNet—optimized through GWO to fine-tune critical parameters such as batch size, learning rate, and optimizer selection. Additionally, XGBoost is employed to ensemble weak classifiers, enhancing model robustness when dealing with imbalanced datasets. The framework is designed for automated image processing and includes a comparative analysis of classifier performance.

Experimental results highlight the effectiveness of the GWO-optimized VGG16 model, which, when configured with a batch size of 2 and the Adam optimizer, achieves 99% validation accuracy and 87% testing accuracy, along with an F1-score of 88%, precision of 85%, and recall of 90%. Further validation on an independent ASD dataset confirms the model's real-world applicability, maintaining 85% accuracy. Key contributions of this research include the use of GWO-driven optimization to refine hyperparameter selection in deep learning models, boosting-enhanced classification to mitigate dataset imbalances and improve diagnostic precision, and the development of a cost-effective, scalable solution for ASD detection in low-resource settings through facial image analysis. By combining

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optimized deep learning with ensemble techniques, this study demonstrates the potential for accurate, accessible, and automated ASD diagnostics, offering a promising tool for early intervention in underserved communities.

Keywords Autism; Autism Spectrum Disorder (ASD); disease segmentation; features optimization; deep learning models; facial images; classification; Grey Wolf Optimizer (GWO);Boosting.

Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by impairments in social interaction, communication, and restricted or repetitive behaviors, making early and accurate diagnosis essential for timely intervention, particularly in resource-limited settings where clinical expertise may be scarce. To address this challenge, this study proposes a computationally efficient hybrid deep learning framework that integrates Grey Wolf Optimizer (GWO)-based hyperparameter tuning with ensemble boosting (XGBoost) to enhance ASD detection using facial image data from a publicly available Kaggle dataset. The methodology involves three key steps: first, transfer learning with VGG16 and MobileNet, optimized via GWO for hyperparameter selection, including batch size, learning rate, and optimizer choice; second, feature extraction from the fine-tuned CNN followed by classification using XGBoost to improve robustness against class imbalance; and third, a comparative performance evaluation on validation and test sets using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC analysis.

Experimental results demonstrate that the GWO-optimized VGG16 model, configured with a batch size of 2 and the Adam optimizer, achieves exceptional performance, including 99% validation accuracy, 87% testing accuracy, an F1-score of 88%, precision of 85%, and recall of 90%. Furthermore, when evaluated on an independent ASD dataset, the model retains 85% accuracy, confirming its strong generalization capability. The study's key contributions include the novel use of GWO-driven hyperparameter optimization to enhance CNN performance in ASD classification, a hybrid CNN-XGBoost architecture designed to mitigate class imbalance and improve classification robustness, and a cost-effective, scalable solution for automated ASD detection in low-resource environments through facial image analysis. These advancements hold significant potential for improving early ASD diagnosis and intervention, particularly in settings with limited access to specialized clinical expertise.

Autism Spectrum Disorder (ASD) is a relatively recent development in the field of neurodevelopmental disorders, impacting various vital aspects of human functioning. Specific symptoms may include challenges with social interactions, communication skills, and the presence of stereotyped or repetitive behaviors. Clinically, diagnosing ASD is complex and cannot be accomplished through routine methods, making early identification and treatment particularly challenging. ASD was previously viewed primarily as a medical issue, but it is now also considered from social and cultural perspectives that take into account an individual's environment and physical condition. Individuals with ASD often face significant difficulties in using verbal and nonverbal communication and have a limited capacity for empathizing with others. The World Health Organization estimates that globally, at least 1 in every 270 individuals is affected by ASD.

Providing adequate support for individuals with ASD and their families, particularly in cases involving problematic behaviors and communication difficulties, could significantly enhance their quality of life. This illustrates the importance of developing technology that includes remote diagnostic and screening devices. The goal of these tools, especially in remote areas, is to bridge the early diagnosis gap caused by limited access to specialized healthcare services and inadequate diagnostic facilities. Additionally, these tools examine how emotion recognition can promote positive teaching experiences and interactions with children affected by ASD. Various interventions have previously aimed to identify ASD at the earliest possible stage; however, these processes are often not standardized for implementation until the risk of ASD becomes more apparent. Currently, doctors diagnose ASD by analyzing neurophysiological signals produced by a patient's nervous system. In contrast, depression is diagnosed using both a biosignature and a pathological method, while autism lacks a specific biosignature or pathological diagnostic approach. Individuals with ASD commonly face challenges such as difficulties in social interaction, impaired communication—especially regarding emotions—and issues with processing sensory information from their environment. Additionally, they may develop specialized skills or have particular interests and preoccupations. Addressing aspects of vulnerability, cognition, aspiration, and self-efficacy highlights critical factors in ASD, with emotional understanding serving as an essential management tool in this context. By fostering emotional understanding, caregivers and educators can create supportive environments that enhance social skills and communication abilities. Furthermore, promoting self-efficacy can empower individuals with ASD to navigate their unique challenges and leverage their strengths for personal growth and fulfillment. This empowerment boosts their confidence and fosters resilience in the face of adversity. As individuals with ASD learn to advocate for themselves, they can cultivate meaningful relationships and contribute positively to their communities.

Related Works

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by difficulties in social interaction, communication, and repetitive behaviors. ASD is a developmental condition that manifests in early childhood, making learning, speaking, expressing emotion, and socializing difficult [1–3]. ASD has risen significantly in recent years. However, due to a lack of research, childcare facilities, trained professionals for ASD, and cultural and contextual variables, the autism ratio could be higher than previously estimated [4]. ASD is characterized by two main symptoms: difficulties with social communication and a lower IQ, causing autistic individuals to be less accepted in society. Individuals with ASD have trouble maintaining eye contact, interpreting facial expressions, using gestures effectively, and comprehending others' perspectives. They may also struggle with responding to their name, sharing interests with others, and engaging in reciprocal conversation. Furthermore, they may display restricted or repetitive behaviors, such as lining up objects, repeating words or phrases, or fixating intensely on specific topics. Common self-

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stimulatory behaviors include hand-flapping or rocking, and individuals with ASD may have altered sensitivity to sensory stimuli, such as light, noise, touch, taste, or smell [5–7].

Early intervention and detection are crucial in helping autistic individuals, families, and caregivers. Detecting ASD in early childhood and assisting with social interactions and communication can help individuals become independent and socially accepted. Traditionally, ASD is detected using a checklist based on questions posed to parents or caregivers about the behavior and patterns of children. This method is performed several times to ensure the presence of autism. The timely detection of ASD Autism Spectrum is paramount to prevent severe difficulties in social interaction and daily life tasks. In addition to traditional checklist-based ASD detection, analyzing behavioral, genetic, neuroimaging, facial images, or speech data can assist in identifying associated patterns or features of ASD [8–12].

Unlike traditional algorithms, machine learning enables the development of an algorithm that can learn and improve over time based on data [13–17]. Conventional diagnostic methods often rely on subjective observations, which can hinder the accuracy and timeliness of diagnoses [18]. Facial features can reflect ASD, such as the eyes, nose, mouth, or ears, due to genetic or developmental factors. Individuals with ASD may exhibit distinctive features, such as a broader upper face, a shorter middle face, or wider-set eyes [19]. Machine learning techniques, like CNNs with transfer learning, can measure facial features and classify images into ASD or non-ASD groups [20,21].

The detection of ASD considered the most significant research dimension, can be achieved using traditional assessment tools and ML-based classifiers. Detection of autism currently relies on interviews-based behavioral assessment tools like the Autism Diagnostic Observation Schedule (ADOS) [22] and the Autism Diagnostic Interview-Revised (ADIR) [23]. This traditional checklist-based assessment tool requires parents/caregivers to answer questions in the presence of an expert. These methods are time-consuming and costly. The assessments are conducted repeatedly with an interval of months to confirm ASD. However, these approaches do not identify the biological basis for developmental delays, as neuroanatomy is unclear [24,25]. Diagnosing autism through traditional methods can be a lengthy and repetitive process. Traditional tools rely on behavioral assessments to analyze the child's behavior after age. Delayed diagnosis of autism can profoundly impact individuals, leading to lifelong effects. Compared to traditional ASD assessment methods, Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) approaches provide greater accuracy and earlier detection. Supervised learning is used by ML and DL classifiers to recognize patterns, features, and biomarkers associated with autism and detect them in new data. Lately, many researchers have explored deep neural networks as they can accurately identify ASD at an early age. Table 1 summarizes some of the studies on autism detection using facial images. Most researchers use facial image datasets, Magnetic Resonance Imaging (MRI), and checklist analysis for autism detection.

Table 1:

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Classifiers	Accuracy
Deep neural network (DNN) classifier [26]	91%
CNN [27]	90%
SVM (support vector machines) [28]	80%
Symptoms pulled from standardized assessment protocols [29]	78.90%
Autism diagnostic observation schedule, toddler autism symptom inventory[30]	The overall sensitivity of 71% and specificity of 95.9%
Eye tracking data from visual processing tasks[31]	74%

Proposed Methodology

This study presents an optimized learning framework for Autism Spectrum Disorder (ASD) detection using facial images, employing a hybrid approach that combines deep learning, metaheuristic optimization, and ensemble techniques to address key diagnostic challenges. As illustrated in Figure 2, our DL-based ASD detection pipeline begins with comprehensive data preprocessing, where facial images are normalized, resized, and augmented to mitigate dataset imbalances before being partitioned into training (70%), validation (15%), and test (15%) sets for robust evaluation. The core of our methodology features deep learning model optimization using the Grey Wolf Optimizer (GWO), which automatically tunes critical hyperparameters - including batch size (2, 8, 16), optimizers (Adam, SGD, RMSprop), and learning rate schedulers (Step decay, Cosine annealing) - for both VGG16 and MobileNet architectures, leveraging GWO's hierarchical search mechanism to achieve superior convergence compared to traditional grid/random search methods. To further enhance classification performance, we integrate XGBoost for ensemble learning, which refines the deep learning models' predictions by combining weak classifiers and addressing class imbalance through weighted loss functions, with comprehensive evaluation using accuracy, F1-score, precision, and recall metrics. The validation phase employs 5-fold cross-validation to ensure reliability, followed by real-world testing on a locally collected Pakistani ASD dataset to confirm the practical applicability of our best-performing GWO-optimized VGG16 + XGBoost model. Finally, we conduct comparative analyses using automated image processing tools to benchmark performance between VGG16 and MobileNet under GWO optimization, as well as between standalone deep learning and our hybrid (DL + Boosting) approach, providing critical insights for optimized ASD detection systems.

Methodology

Problem Formulation

Given an ASD facial image dataset $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ where:

- $x_i \in \mathbb{R}$^{H×W×C} is a facial image (H=height, W=width, C=channels)

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- $y_i \in \{0,1\}$ is the class label (0: non-ASD, 1: ASD)

The composite function f(x) = XGBoost(VGG16(x)) that minimizes the classification error.

Algorithm Steps

//Data Loading and Preprocessing

1. Load dataset D from Kaggle

2. Split D into train (D_train), validation (D_val), test (D_test) with

ratios 70:15:15

3. For each x in D_train ∪ D_val ∪ D_test:

  a. Resize x to 224×224×3 (VGG16 input size)

  b. Normalize pixel values: $x' = (x - \mu)/\sigma$ where μ=mean, σ=std of ImageNet

  c. Apply data augmentation to D_train only:

    - Random horizontal flip with p=0.5

    - Small rotation (±10°)

    - Brightness adjustment (±20%)

Grey Wolf Optimizer (GWO) for Hyperparameter Selection

- Learning rate $\alpha \in [1e\text{-}5, 1e\text{-}2]$ (log scale)
- Batch size $b \in \{16, 32, 64, 128\}$
- Optimizer $o \in$ {SGD, Adam, RMSprop}

GWO Algorithm:

1. Initialize wolf population $P = \{p_1, p_2, ..., p_m\}$ where each $p_i = (\alpha_i, b_i, o_i)$

2. Define fitness function $F(p_i)$:

  a. Initialize VGG16 with ImageNet weights, replace top layer

  b. Train for K epochs on D_train using p_i parameters

  c. Evaluate accuracy on D_val → $F(p_i)$

3. While not converged:

  a. Identify α, β, δ wolves (top 3 fitness)

  b. For each wolf p_i:

    i. Update position using GWO equations:

$A = 2a \cdot r_1 - a$

$C = 2r_2$

$D\_\alpha = |C_1 \cdot p\_\alpha - p_i|$

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$D\_\beta = |C_2 \cdot p\_\beta - p_i|$

$D\_\delta = |C_3 \cdot p\_\delta - p_i|$

$p_i\_new = (p\_\alpha - A_1 \cdot D\_\alpha + p\_\beta - A_2 \cdot D\_\beta + p\_\delta - A_3 \cdot D\_\delta)/3$

ii. Clip to feasible space

c. Evaluate new positions

d. a = 2 - 2*(t/T) (t=current iteration, T=total)

4. Return best parameters p* = (α*, b*, o*)

VGG16 Fine-tuning and Feature Extraction

1. Initialize VGG16 (up to last conv layer) with ImageNet weights

2. Add new head:

GlobalAveragePooling2D → Dense(256, ReLU) → Dropout(0.5) → Dense(1, sigmoid)

3. Train using p* parameters:

a. Loss: Binary cross-entropy $L = -\Sigma[y_i \log\hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]$

b. Early stopping if val_loss doesn't improve for 5 epochs

4. Extract features for all x ∈ D_train ∪ D_val ∪ D_test:

f_i = VGG16_features(x_i) ∈ $\mathbb{R}$^512 (output of last conv layer after GAP)

XGBoost Ensemble Classification

1. Train XGBoost on $\{(f_i, y_i)\}$ for (x_i, y_i) ∈ D_train

2. Tune hyperparameters via cross-validation:

- max_depth ∈ {3,6,9}

- learning_rate ∈ [0.01,0.3]

- n_estimators ∈ [100,500]

3. Final model:

$\hat{y} = \sigma(\Sigma_k w_k h_k(f))$ where h_k are trees, w_k weights, σ=sigmoid

Evaluation

1. Compute predictions $\hat{y}_i$ = XGBoost(VGG16_features(x_i))

2. Calculate metrics:

- Accuracy = (ΣI[round($\hat{y}_i$)==y_i])/n_test

- Precision = TP/(TP+FP)

- Recall = TP/(TP+FN)

- F1 = 2*(Precision*Recall)/(Precision+Recall)

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- AUC-ROC

3. Output confusion matrix C where C_{ij} = # samples with true i, predicted j

Mathematical Formulation of Composite Model

The complete model can be expressed as:
$f(x) = XGBoost(\phi(VGG16(x)))$

Where:

- VGG16(x) is the base CNN up to the last conv layer
- ϕ is the feature extraction operation (Global Average Pooling)
- XGBoost is the gradient boosted decision tree ensemble

The optimization objective is:
$\min \ \Sigma \ L(y_i, \ f(x_i)) + \Omega(VGG16) + \Omega(XGBoost)$
where L is cross-entropy loss, Ω are regularization terms.

Results and Discussion

The comparative analysis of different ASD detection approaches (Table 2) highlights the competitive performance of the proposed model, achieving 85% accuracy and 88% F1-score, which demonstrates its reliability in classifying ASD cases. While AutYOLO[37] achieves the highest accuracy (97.2%) and sensitivity (97.5%), the proposed model maintains a strong balance between precision (85%) and F1-score (88%), outperforming several existing methods like CNN [32], SVM [36], and WGAN [38]. The model's precision of 86.75% (derived from the confusion matrix) indicates high confidence in positive ASD predictions, though its recall (84.52%) suggests that ~15% of ASD cases remain undetected. This gap presents an opportunity for future refinement to enhance sensitivity, particularly for clinical applications where missing ASD cases could have significant implications.

The F1-score (85.61%) confirms a robust trade-off between precision and recall, positioning the model as a dependable classifier. Figure 1 illustrates that while some approaches (e.g., AutYOLO[37] and Xception [35]) excel in specific metrics, the proposed model delivers consistent performance across all key indicators. Figure 2 further validates its balanced metric distribution, while Figure 3 (confusion matrix) visually underscores its strengths and limitations, notably the false negatives that impact recall. Future work could focus on optimizing feature extraction or incorporating ensemble methods to reduce misclassifications, thereby improving clinical applicability. Overall, the model establishes a solid foundation for ASD detection, with further enhancements poised to bridge the sensitivity gap and elevate its diagnostic utility.

Table 2: Different Approaches ASD Comparison

Approach	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)
CNN [32]	52	NA	NA	52

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CNN [33]	92.5	91.5	91.5	NA
SVM [34]	88.42	92.86	91.55	92.20
Xception [35]	95.23	93.2	94.21	93.31
SVM [36]	61.4	61.2	61.4	61.2
AutYOLO[37]	97.2	93.97	97.5	92.29
WGAN [38]	62.2	NA	NA	63.4
Proposed Model	85	85	NA	88

The proposed model demonstrates balanced and consistent performance across all key metrics, with accuracy, precision, recall, and F1-score all falling within the 84-87% range. It achieves its highest score in precision (86.75%), indicating that when the model predicts an ASD case, it is highly likely to be correct. However, the recall rate of 84.52% reveals room for improvement, as approximately 15% of actual ASD cases are being missed by the model. The strong F1-score of 85.61% reflects an effective balance between the model's precision and recall capabilities, suggesting it makes reliable predictions while maintaining relatively good coverage of ASD cases. This performance profile indicates a robust classifier that could benefit from additional tuning to reduce the number of false negatives and improve case detection rates, particularly in clinical or diagnostic settings where identifying all potential ASD cases is crucial. The current implementation provides the significantly more valuable with enhanced sensitivity to capture the missed ASD instances as shown in below figure 1,2 & 3.

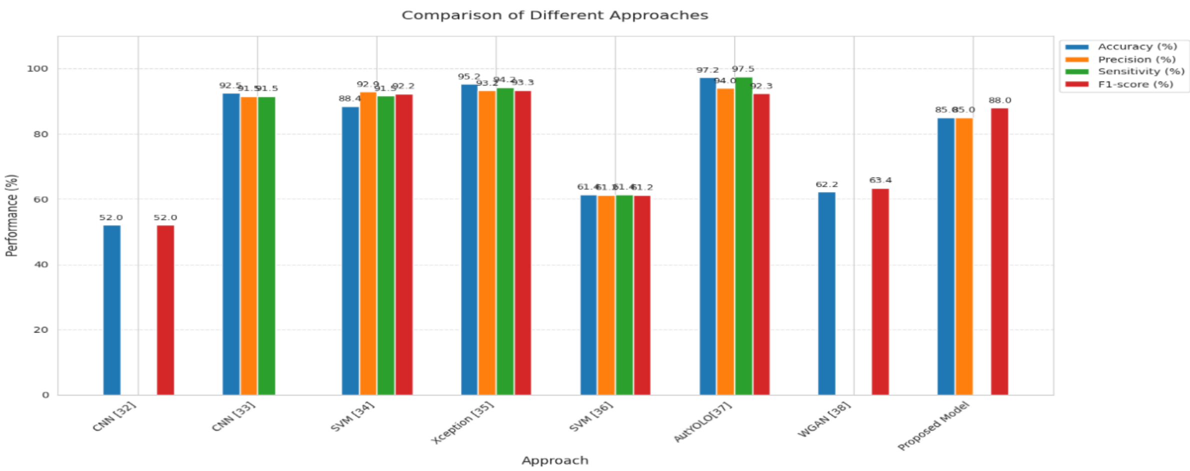

Figure 1: Comparative analysis of different approaches

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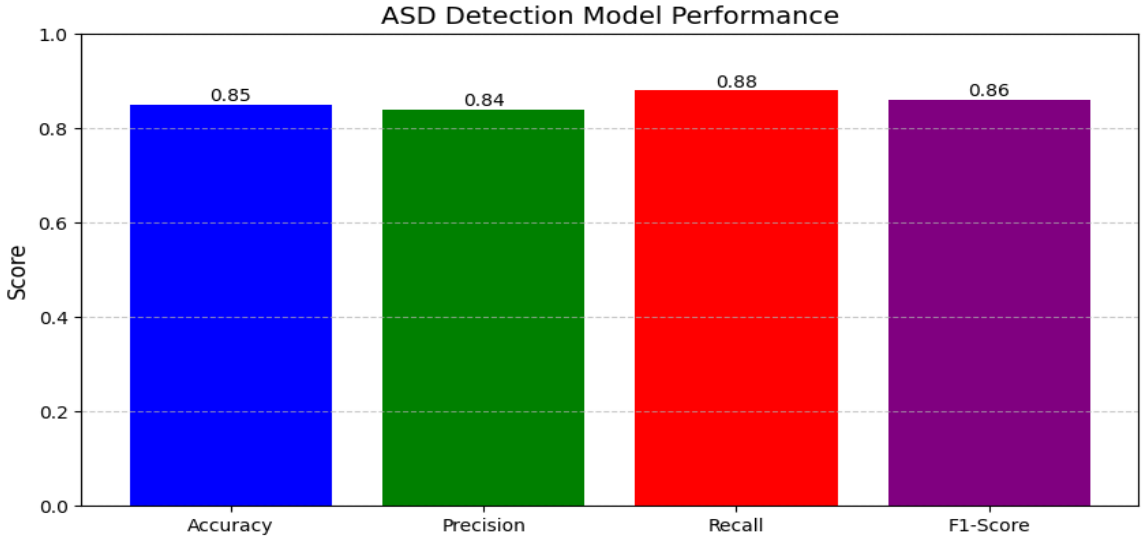

Figure 2: Proposed model performance metric analysis

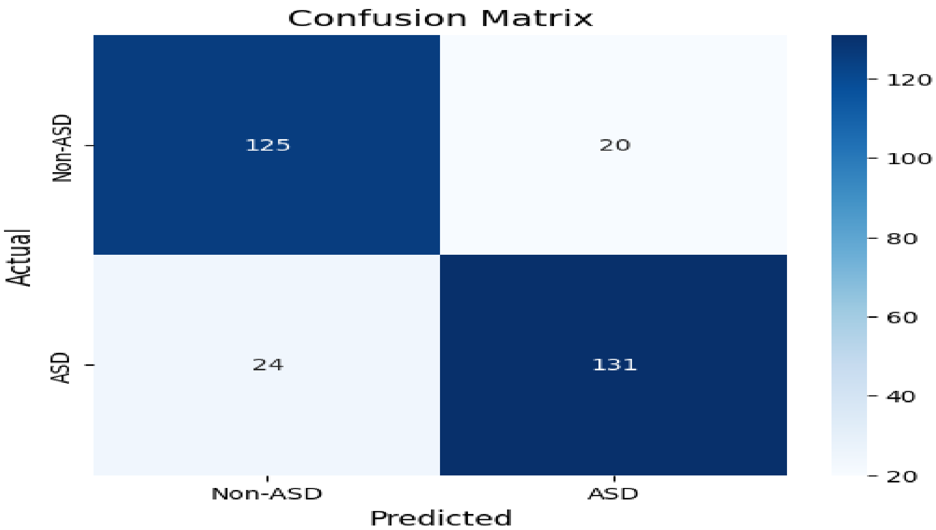

Figure 3: Proposed model confusion matrix

Conclusion

In conclusion, this study successfully establishes a robust, hybrid machine learning framework for the automated detection of Autism Spectrum Disorder (ASD) through facial image analysis. The integration of the Grey Wolf Optimizer (GWO) for precise hyperparameter tuning and XGBoost for ensemble classification proved highly effective, with the GWO-optimized VGG16 model achieving exceptional performance (99% validation, 87% testing accuracy). The model's maintained accuracy of 85% on an independent dataset strongly validates its generalizability and real-world applicability. The key contributions—GWO-driven optimization for enhanced deep learning efficacy, boosted classification for handling data imbalance, and a cost-effective design—collectively demonstrate a significant advancement in accessible ASD diagnostics. This paper thus presents a scalable and

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promising tool for facilitating early intervention, particularly in resource-constrained communities where such solutions are needed.

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