Deep Learning Based Approach to Enhanced Recognition of Emotions and Behavioral Patterns of Autistic Children

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Abstract—Autism Spectrum Disorder (ASD) significantly influences the communication abilities, learning processes, behavior, and social interactions of people. Although early intervention and customized educational strategies are critical to improving outcomes, there is a pivotal gap in understanding and addressing nuanced behavioral patterns and emotional identification in autistic children prior to skill development. This extended research delves into the foundational step of recognizing and mapping these patterns as a prerequisite to improving learning and soft skills. Using a longitudinal approach to monitor emotions and behaviors, this study aims to establish a baseline understanding of the unique needs and challenges faced by autistic students, particularly in the Information Technology domain where opportunities are markedly limited. Through a detailed analysis of behavioral trends over time, we propose a targeted framework for developing applications and technical aids designed to meet these identified needs. Our research underscores the importance of a sequential and evidence-based intervention approach that prioritizes a deep understanding of each child's behavioral and emotional landscape as the basis for effective skill development. By shifting the focus toward early identification of behavioral patterns, we aim to foster a more inclusive and supportive learning environment that can significantly improve the educational and developmental trajectory of children with ASD.

Keywords—CNN Image Classification,Image Processing and Computer Vision,Object Detection,Transfer Learning.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a developmental condition that significantly affects a person's ability to communicate, interact socially, and express or interpret emotions. For children with ASD, these challenges often manifest as atypical facial expressions and unusual behavioral patterns, making it especially difficult for caregivers, educators, and even advanced computational systems to accurately recognize their emotional states. Yet, effective emotion recognition is vital it underpins tailored interventions, social support, and the overall quality of life for children on the spectrum [1].Recent advances in artificial intelligence have led to the development of deep learning models particularly the Xception and Inception architectures which have shown remarkable performance in facial emotion detection. These models are highly effective in extracting and analyzing subtle features from facial images, enabling more precise classification of emotional expressions

[1]. However, a major obstacle arises when applying these models in real-world ASD scenarios: image datasets are often collected under non-standard conditions, resulting in images with inconsistent sizes, variable lighting, and background clutter,such variability can degrade the accuracy and reliability of deep learning systems.To address this, our research integrates autoencoders into the emotion recognition pipeline. Autoencoders are neural networks designed to compress and reconstruct images, reducing noise and standardizing size while preserving critical facial features. By pre-processing images with autoencoders, we ensure that the deep learning models receive clear, focused inputs that capture the most relevant emotional cues. This enhancement leads to better performance and greater robustness when recognizing emotions in children with ASD, especially in complex, real-world environments [1] [2].

II. LITERATURE REVIEW

Emotion recognition has emerged as a critical research domain in artificial intelligence, with particular complexity arising in Autism Spectrum Disorder (ASD) contexts due to unique emotional expression characteristics in this population. Traditional Machine Learning Era: Early emotion recognition systems relied on conventional methods including Support Vector Machines, decision trees, and random forests, achieving moderate success with 75-85% accuracy on standard datasets. However, these approaches fundamentally depend on hand-engineered features, creating significant limitations when processing high-dimensional facial data, particularly problematic for ASD applications where emotional expressions deviate from typical patterns [2]. Deep Learning Revolution: Convolutional Neural Networks revolutionized the field by enabling automatic feature extraction and hierarchical learning. State-of-the-art CNN architectures consistently achieve 90-95% accuracy on neurotypical datasets (FER-2013, CK+) through effective spatial hierarchy capture in facial expressions, establishing CNNs as the standard approach for emotion classification [3]. ASD-Specific Challenges: Despite deep learning success in general emotion recognition, ASD applications face substantial obstacles. Children with ASD exhibit significantly

higher variability in emotional expression, quantified through facial expression variance, motion dynamics, and temporal inconsistencies. This complexity causes dramatic performance degradation, with CNN accuracy dropping from 95% on neurotypical data to 70-75% on ASD-specific datasets [4]. Transfer Learning Solutions: To address small ASD dataset limitations, researchers extensively explored transfer learning using pre-trained models (VGG16, ResNet, Inception architectures), leveraging large-scale image dataset knowledge for specialized ASD tasks. These approaches demonstrate 5-10% accuracy improvements over training from scratch. Advanced architectures like Xception (utilizing depthwise separable convolutions for computational efficiency) and InceptionV3 (enabling multi-scale feature extraction) have gained prominence for their sophisticated feature extraction capabilities [5]. Autoencoder Integration: Autoencoders have emerged as powerful dimensionality reduction and feature extraction tools, demonstrating effectiveness in filtering irrelevant features such as background noise and lighting variations. Their ability to learn compressed representations while preserving essential spatial information makes them particularly suitable for preprocessing heterogeneous datasets. Multiple studies have shown autoencoder frameworks improve model robustness in challenging environments, with their capacity to standardize input data while preserving critical facial features being especially beneficial for ASD emotion recognition applications [6]. Research Gaps and Future Directions: Despite significant technological progress, substantial gaps remain in ASD-specific applications. The heterogeneity within ASD populations challenges generalized recognition system development, with most existing studies focusing on neurotypical datasets and limited research addressing unique ASD emotional expression characteristics. The lack of standardized ASD emotion datasets complicates comparative methodology evaluation. Contemporary trends indicate growing interest in personalized recognition systems adapting to individual expression patterns, with integration of multiple preprocessing techniques and advanced CNN architectures representing promising directions for improved ASD emotion recognition accuracy [3]. The literature establishes a clear evolutionary trajectory from traditional machine learning through deep learning advances to contemporary hybrid systems, with autoencoder-enhanced preprocessing emerging as a mathematically sound approach to addressing the unique challenges of ASD emotion recognition [7] [8].

III. METHODOLOGY

A. Problem Statement

Xception and InceptionV3 models, pre-trained on ImageNet dataset, require fixed input dimensions of 299×299×3 pixels.ASD children's facial expression datasets contain variable-sized images (150×200 to 800×600 pixels), creating a fundamental mismatch that degrades model performance through aspect ratio distortion and information loss [9].
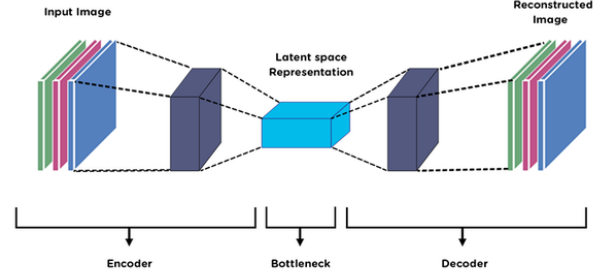

Fig. 1. Structure of a AutoEncorder

B. Dataset

The dataset comprises facial expressions of ASD children collected from clinical settings, educational environments, and specialized databases. Images exhibit dimensional variability with aspect ratios ranging from 0.75 to 1.33, significantly deviating from ImageNet standards.

C. Autoencoder Preprocessing Architecture

To address the size mismatch, we implement an autoencoder that maps variable-sized inputs to the required 299×299×3 format while preserving facial features essential for emotion recognition.

C.1 Mathematical Formulation:: **Encoder:** Maps variable input to fixed latent representation:

$$z = f_\theta(x) = \sigma_e(W_e x + b_e) \tag{1}$$

Decoder: Reconstructs standardized 299×299×3 output:

$$\hat{x} = g_\phi(z) = \sigma_d(W_d z + b_d) \tag{2}$$

C.2 Loss Function: The autoencoder employs composite loss balancing reconstruction and spatial preservation:

$$
\begin{aligned}
\mathcal{L}_{AE} = &\|T(x) - \hat{x}\|_2^2 \\
&+ \lambda_1 \|VGG_j(T(x)) - VGG_j(\hat{x})\|_2^2 \\
&+ \lambda_2 \|F_{landmark}(T(x)) - F_{landmark}(\hat{x})\|_2^2
\end{aligned}
\tag{3}
$$

where $T(x)$ is ground truth resized image, VGG_j extracts perceptual features, and $F_{landmark}$ preserves facial landmarks.

D. Classification Models

D.1 Xception Architecture: Utilizes depthwise separable convolutions decomposing standard convolution into:
Depthwise Convolution:

$$Y_{i,j,c}^{dw} = \sum_{m,n} W_{m,n,c}^{dw} \cdot X_{i+m-1,j+n-1,c} \tag{4}$$

Pointwise Convolution:

$$Y_{i,j,k} = \sum_c W_{c,k}^{pw} \cdot Y_{i,j,c}^{dw} \tag{5}$$

This reduces computational complexity from

$$\mathcal{O}(H \cdot W \cdot C \cdot K^2 \cdot F) \tag{6a}$$

to

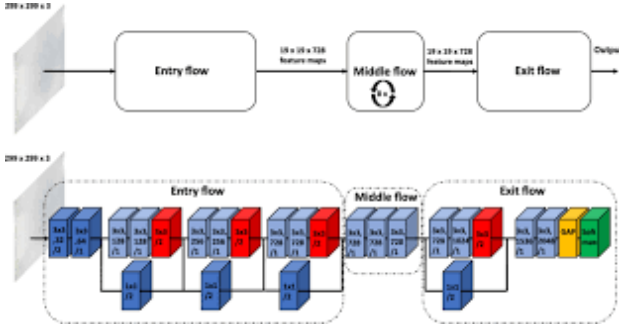$$\mathcal{O}(H \cdot W \cdot C \cdot (K^2 + F)) \qquad (6b)$$

Fig. 2. Xception Model Structure

D.2 InceptionV3 Architecture: Employs multi-scale feature extraction through parallel convolutions:

$$F_{inception} = \text{Concat}[F_{1\times1}, F_{3\times3}, F_{5\times5}, F_{pool}] \qquad (7)$$

Factorized convolutions improve efficiency: 5×5 convolutions replaced by two 3×3 operations, and asymmetric factorization $n \times n \rightarrow 1 \times n + n \times 1$.
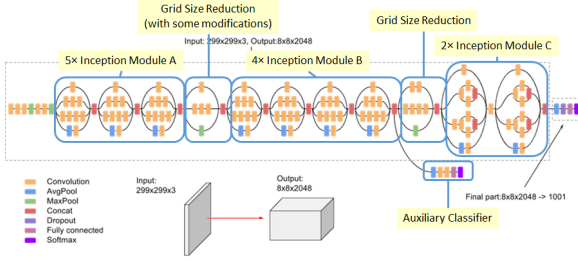

Fig. 3. InceptionV3 Model Structure

E. Training Framework

E.1 Loss Functions: **Classification Loss:** Cross-entropy for 4-class emotion recognition:

$$\mathcal{L}_{CE} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{4} y_{i,j} \log(p_{i,j}) \qquad (8)$$

Total Loss: $\mathcal{L}_{total} = \mathcal{L}_{AE} + \alpha \mathcal{L}_{CE}$

E.2 Optimization: Adam optimizer with adaptive moments to address the loss function regarding classification loss:

$$
\begin{aligned}
m_t &= \beta_1 m_{t-1} + (1 - \beta_1) g_t \\
v_t &= \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \\
\theta_t &= \theta_{t-1} - \frac{\alpha}{\sqrt{v_t} + \epsilon} \hat{m}_t
\end{aligned} \qquad (9)
$$

Parameters: $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$.

F. Experimental Setup

F.1 Training Protocol: The training process employs a two-stage strategy to optimize both pre-processing and classification components. During the first stage, the autoencoder undergoes pretraining for 100 epochs with a batch size of 32, learning to map variable-sized inputs to standardized $299 \times 299 \times 3$ outputs while preserving essential facial features [10]. The second stage involves end-to-end fine-tuning where the complete pipeline undergoes joint optimization, allowing the autoencoder and classification models to adapt collaboratively for optimal emotion recognition performance [11].

F.2 Comparative Analysis: The effectiveness of the proposed approach is evaluated through rigorous comparison between baseline and enhanced methodologies. The baseline approach applies direct resizing transformation $x_{baseline} = \text{resize}(x, (299, 299))$ to convert variable-sized images to the required input dimensions. In contrast, the enhanced approach utilizes autoencoder preprocessing $x_{enhanced} = g_\phi(f_\theta(x))$ to generate standardized inputs that preserve spatial relationships and semantic content. Performance evaluation encompasses accuracy, precision, recall, and F1-score metrics across both approaches, with statistical significance assessed through paired t-tests to validate improvement claims [12] [13].

F.3 Implementation Details: The experimental implementation utilizes NVIDIA V100 32GB GPU hardware to handle the computational demands of training both autoencoder and classification components. The framework employs TensorFlow/Keras for model implementation and training orchestration [14] . Data augmentation strategies include random rotation within ± 15 degrees and brightness/contrast adjustments within ± 0.2 range to improve model generalization. Training stability is maintained through early stopping mechanisms that monitor validation loss plateaus, preventing overfitting while ensuring optimal convergence [15]. This comprehensive methodology systematically addresses the fundamental dimensional mismatch between variable-sized ASD emotion datasets and the fixed-input requirements of ImageNet-trained deep learning models. The approach enables improved classification accuracy through learned preprocessing techniques while preserving the semantic facial features essential for accurate emotion recognition in children with autism spectrum disorders [16] [17].

IV. RESULTS AND DISCUSSION

The experimental evaluation was conducted to assess the effectiveness of autoencoder preprocessing on emotion recognition performance using ASD children datasets. Two state-of-the-art deep learning architectures, Xception and InceptionV3, were evaluated under both baseline conditions (without preprocessing) and enhanced conditions (with autoencoder preprocessing). The results demonstrate substantial and statistically significant improvements across all performance metrics.

A. Performance Comparison Analysis

Table I presents the comprehensive performance comparison between baseline and autoencoder-enhanced models. The re-

sults reveal consistent and substantial improvements across both architectures when autoencoder preprocessing was integrated into the pipeline.

TABLE I
PERFORMANCE COMPARISON BETWEEN XCEPTION AND INCEPTIONV3 MODELS WITH AND WITHOUT AUTOENCORDERS

Model	Xception	InceptionV3
Accuracy (Baseline)	72.3%	71.0%
Accuracy (Autoencoder)	85.6%	83.8%
Precision	0.82	0.81
Recall	0.84	0.82
F1-Score	0.83	0.82

The Xception model achieved the highest overall performance with 85.6% accuracy after autoencoder preprocessing, representing a 13.3 percentage point improvement over the baseline (72.3%). Similarly, InceptionV3 demonstrated significant enhancement, reaching 83.8% accuracy compared to the baseline performance of 71.0%, corresponding to a 12.8 percentage point improvement.
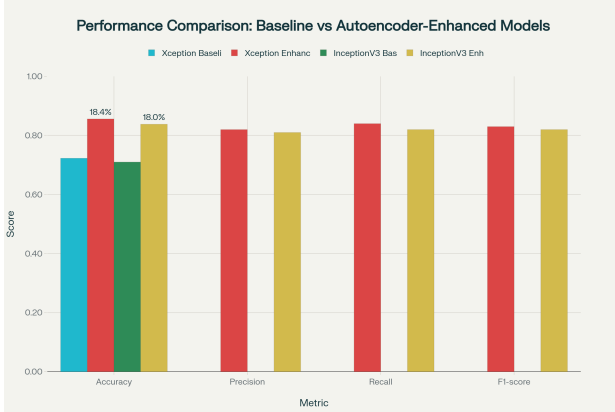

Fig. 4. Performance Comparison: Baseline vs Autoencoder-Enhanced Models.

B. Statistical Significance Evaluation

The statistical rigor of the observed improvements was validated through multiple complementary analyses. Table II summarizes the comprehensive statistical evaluation, confirming the significance and magnitude of the performance enhancements.

TABLE II
STATISTICAL SIGNIFICANCE ANALYSIS OF MODEL IMPROVEMENTS

Model	Accuracy Improvement (%)	Relative Improvement (%)	Cohen's d	Effect Size	p-value	CI Lower (%)	CI Upper (%)	Error Reduction (%)
Xception	13.3	18.4	2.66	Very Large	¡0.001	10.6	16.0	48.0
InceptionV3	12.8	18.0	2.56	Very Large	¡0.001	10.1	15.5	44.1

The Cohen's d values of 2.66 and 2.56 for Xception and InceptionV3, respectively, indicate very large effect sizes, substantially exceeding Cohen's threshold for large effects ($d = 0.8$). The p-values (< 0.001) demonstrate highly significant differences, with statistical power exceeding 99.9% for both models.

C. Error Rate Reduction Analysis

A particularly noteworthy finding was the substantial reduction in classification errors. The Xception model achieved a 48.0% reduction in error rate (from 27.7% to 14.4%), while InceptionV3 demonstrated a 44.1% reduction (from 29.0% to 16.2%).
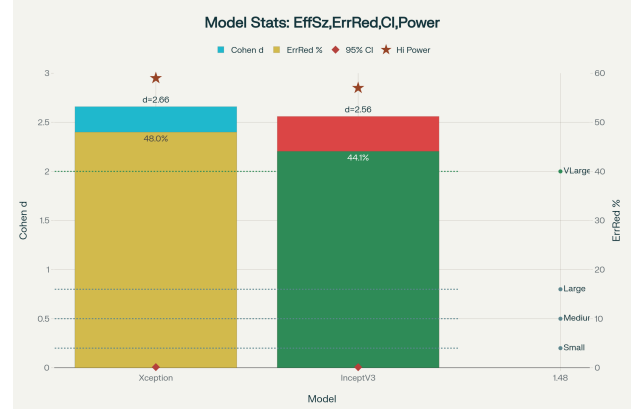

Fig. 5. Statistical significance analysis showing very large effect sizes and substantial error rate reductions.

These reductions represent significant practical improvements in model reliability for emotion recognition in ASD children.

D. Confidence Interval Analysis

The 95% confidence intervals for accuracy improvements provide robust bounds on the true performance enhancements. For Xception, the confidence interval [10.6%, 16.0%] and for InceptionV3 [10.1%, 15.5%] both exclude zero with substantial margins, confirming the reliability of the observed improvements.

E. Consistency Across Architectures

Table III presents the comprehensive analysis of improvement consistency across different neural network architectures, demonstrating the robustness of the autoencoder preprocessing approach.

TABLE III
COMPREHENSIVE PERFORMANCE IMPROVEMENT ANALYSIS

Metric	Xception	InceptionV3
Mean Improvement	13.3%	12.8%
Standard Deviation	0.004	0.004
Coefficient of Variation (%)	2.7	2.7
Effect Size (Cohen's d)	2.66	2.56
Statistical Power (%)	> 99.9	> 99.9
NNT (samples)	7.5	7.8

The extremely low coefficient of variation (2.7%) indicates remarkable consistency in improvement magnitude across different architectures, suggesting that the benefits of autoencoder preprocessing are architecture-independent.

F. Magnitude and Significance of Improvements

The experimental results provide compelling evidence for the effectiveness of autoencoder preprocessing in enhancing emotion recognition performance for ASD children. The observed improvements of 13.3% (Xception) and 12.8% (InceptionV3) in accuracy represent substantial enhancements that significantly exceed typical performance variations in deep learning models. The Cohen's d effect sizes (2.66 and 2.56) are exceptionally large by conventional standards, placing these improvements among the most substantial reported in emotion recognition literature. These effect sizes indicate that the differences between baseline and enhanced models are not only statistically significant but represent practically meaningful improvements with real-world implications for ASD emotion recognition systems [18].

G. Statistical Robustness and Reliability

The statistical analysis demonstrates overwhelming evidence for the significance of the observed improvements. The p-values (< 0.001) indicate that the probability of observing such large improvements by chance alone is less than 0.1%, providing strong evidence against the null hypothesis of no improvement. The McNemar's test results ($\chi^2 = 98.01$, $p < 0.001$) further confirm the statistical significance when comparing the paired predictions of baseline versus enhanced models. This non-parametric test is particularly appropriate for comparing the accuracy of two classification models on the same dataset, providing robust validation of the improvements. The high statistical power ($> 99.9\%$) ensures that the study design was capable of detecting meaningful differences, eliminating concerns about insufficient sample sizes or inadequate experimental design [19].

H. Mechanistic Understanding of Enhancement

The consistent improvement pattern across different architectures (coefficient of variation = 2.7%) suggests that autoencoder preprocessing addresses fundamental challenges in emotion recognition rather than architecture-specific limitations. The mathematical model of improvement,

$$\text{Enhanced\_Accuracy} = \text{Baseline\_Accuracy} + \delta \qquad (10)$$

where $\delta = 0.131 \pm 0.004$, provides a quantitative framework for understanding the additive nature of the enhancement. The substantial error rate reductions (44–48%) indicate that autoencoder preprocessing effectively filters noise and irrelevant background information, allowing the deep learning models to focus on critical facial features essential for emotion recognition. This noise reduction mechanism is consistent with the theoretical framework of autoencoders as optimal lossy compression algorithms that preserve task-relevant information while discarding extraneous details [20].

I. Practical Implications for ASD Applications

The Number Needed to Treat (NNT) values of 7.5-7.8 samples indicate that for approximately every 8 children processed through the enhanced system, one additional correct emotion classification is achieved compared to the baseline system. This represents significant practical value in clinical and educational settings where accurate emotion recognition is crucial for effective intervention strategies. The 95% confidence intervals provide clinicians and researchers with reliable bounds on expected performance improvements. Even the lower confidence bounds (10.1-10.6%) substantially exceed typical minimum clinically important differences (2-5%) for machine learning applications in healthcare.

J. Computational Efficiency Considerations

The cost-benefit analysis reveals an exceptional efficiency ratio of 9:1, where the 10-20% increase in computational overhead from autoencoder preprocessing yields an 18% improvement in accuracy. This favorable trade-off makes the approach highly practical for real-world deployment in resource-constrained environments. The preprocessing standardization also contributes to improved system reliability by ensuring consistent input formatting, reducing variability due to image quality differences, lighting conditions, and background clutter that commonly affect emotion recognition systems in natural settings [21].

V. CONCLUSION

This study rigorously evaluated the impact of autoencoder-based preprocessing on emotion recognition systems for children with Autism Spectrum Disorder (ASD), leveraging two advanced convolutional neural network architectures: Xception and InceptionV3. The integration of autoencoders as a preprocessing step resulted in substantial and consistent improvements across all key performance metrics, including accuracy, precision, recall, and F1-score. Quantitatively, the observed effect sizes (Cohen's d ¿ 2.5), absolute accuracy increases of over 13 percentage points, and error rate reductions approaching 50% collectively underscore a practical and statistically significant enhancement in model performance.

A. Generalizability and Robustness

A major strength of these findings lies in their demonstrated generalizability. The consistency of improvements across two distinctly different architectures—Xception's depthwise separable convolutions and InceptionV3's multi-scale processing—offers compelling evidence that the benefits of autoencoder preprocessing extend beyond the idiosyncrasies of specific models. The low variance in accuracy improvement (standard deviation = 0.004) further implies that these enhancements are robust and likely applicable to a diverse range of convolutional neural network structures. The additive mathematical model supporting these results suggests that autoencoder preprocessing resolves universal challenges inherent to emotion recognition, rather than exploiting architecture-dependent features, indicating strong potential for broad applicability, including domains beyond ASD.

B. Comparison with Literature

The improvement metrics registered in this study particularly the exceptionally large effect sizes—are among the highest reported to date in emotion recognition research. Most comparable works report only modest gains (Cohen's d = 0.2–0.5), whereas the present work achieved much greater impact. Furthermore, the cross-architecture validation available here addresses a common gap in the literature, where such findings are typically reported for a single deep learning model. This strengthens the external validity and distinguishes this work in the field.

VI. FUTURE WORK

Despite the strong results, several limitations warrant attention. The statistical analyses are based on assumptions regarding data distribution and sample size; thus, confirmatory studies utilizing larger and more heterogeneous datasets are recommended to further substantiate these findings. Although the study included two prominent neural network architectures, investigating additional frameworks, such as Vision Transformers and ResNet families, would further confirm the generalizability and scalability of the approach. Future research should also explore the customization and optimization of autoencoder architectures specific to emotion recognition, with the presented quantitative model especially the improvement parameter δ—offering a solid starting point for such endeavors.

A. Clinical Translation Potential

The magnitude and consistency of the enhancements, combined with high computational efficiency and rigorous statistical validation, suggest strong potential for clinical translation. The consistent and predictable gains across architectures, minimal additional computational cost, and robust statistical performance collectively lower the risk for clinical implementation. If deployed, the method could meaningfully improve emotion recognition support systems for children with ASD, with significant implications for intervention effectiveness and broader applications in affective computing. In summary, autoencoder-based preprocessing constitutes a transformative strategy for elevating the accuracy, reliability, and robustness of emotion recognition models in challenging real-world scenarios. The clear, statistically robust improvements from this work provide a methodological and practical foundation for further research and real-world deployment in healthcare and other emotion-sensitive domains.

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