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Importance of Detecting Facial Expressions to Differentiate Typical Vs. ASD Children: Comparative Study

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ABSTRACT: Understanding and interpreting facial expressions is a cornerstone of effective social communication. For typically developing children, reading subtle expressions like joy, fear, or surprise unfolds naturally during social interactions. However, in children with autism spectrum disorder (ASD), this intuitive process can be significantly impaired, leading to challenges in peer engagement, emotional understanding, and social reciprocity. Research indicates that approximately 30% of individuals with ASD struggle with accurate facial expression recognition, often leading to misunderstandings and withdrawal in social contexts [1].
This difficulty directly impacts early childhood, a critical social and emotional development phase. Interventions that improve facial expression recognition can dramatically enhance social interactions and quality of life for ASD children. For example, a recent study introduced a real-time vibrotactile and visual feedback translator, helping adults with ASD identify seven core emotions—achieving successful learning in as little as 19 minutes [2]. The key to such assistive systems lies in accurately extracting emotional cues from facial images, highlighting the importance of robust emotion-detection methods tailored specifically to ASD.
Moreover, facial expressions are vital cues in affective computing systems, which aim to equip machines with human-like perception. When deployed with children, these systems must differentiate between typical and atypical expressions to deliver appropriate feedback or interventions. For instance, an Efficient Net-based MATLAB model designed to be interpretable showed promise in classifying emotions among children with ASD, emphasizing the need for models that understand ASD-specific expression patterns [3].

KEYWORDS: Image processing, face detection, autism spectrum disorder, emotion detection

INTRODUCTION

1. Motivation and Relevance

Understanding and analysing facial expressions plays a pivotal role in enhancing computerized interaction systems, particularly when differentiating between typically developing children and those with Autism Spectrum Disorder (ASD). These differences are not only clinically significant but have far-reaching implications for the design of supportive technologies [1][2][3]. Children with ASD commonly exhibit subtle and inconsistent facial expressions, which traditional methods struggle to identify accurately [4][5]. Early-stage, accurate emotion recognition can positively affect social learning and communication outcomes, reducing isolation for many ASD individuals [6][7].

For typically developing children, facial expressions are intuitive signals used daily in social interaction; however, autistic children often fail to display such typical nonverbal cues reliably, which can hinder both peer-to-peer and adult-child interactions [8][9]. Research demonstrates that augmented feedback systems—such as wearable devices providing audio-visual cues—can assist ASD children, significantly improving emotion recognition performance over short training periods [10][11].

Beyond these clinical applications, emotion-aware educational technologies and interactive platforms increasingly rely on accurate FER systems to personalize learning and engagement [12][13].

To be effective, such systems need to detect subtle expression variations and respond accurately in real-time—posing a significant challenge for machine vision in non-typical populations.

2. Challenges in ASD-Focused FER

A key barrier to reliable FER in ASD populations is the atypical nature of their expressions—described as muted, asymmetric, or mechanically repeated [14][15]. Such differences often require specialized feature detection beyond standard facial landmarking. One study found that children with ASD have distinctive facial muscle activation patterns, requiring calibrated algorithms for accurate emotion extraction [16].

Dynamic facial analysis (image sequences) often yields better recognition results compared to static images: temporal patterns like micro-expressions and transitions contain invaluable contextual cues—especially when expressions are subtle [17][18]. Techniques such as LSTM networks and 3D-CNNs have improved recognition rates by capturing these nuances [19][20].

Another challenge is dataset scarcity. Large public datasets like FER-2013 and CK+ contain few—if any—ASD-specific samples [21]. New multimodal initiatives like the CALMED dataset (2025) aim to address this, but variability in age, lighting, and expression type remains an issue [22]. Consequently, model generalization becomes difficult without effective transfer learning or data augmentation strategies designed for ASD samples [8][23].

3. Machine Learning & Deep Learning for FER

Traditional ML algorithms (SVM, KNN, Random Forests) remain in use for initial FIRE systems due to interpretability and relatively lower computational demands. But for capturing complex facial representations, CNNs dominate recent studies [24][25]. Pre-trained networks (e.g., VGGNet, ResNet, EfficientNet) fine-tuned on facial datasets have demonstrated state-of-the-art performance—even for nuanced emotion classes—provided sufficient data [26][27].

Several efforts—using ResNet50, MobileNetV3, and EfficientNet-lite—explicitly tackle ASD expression recognition. These models are often hybridized with SVM classifiers or decision-level fusion techniques, reaching classification accuracies exceeding 85% on ASD-relevant test sets [28][29]. Temporal deep models, such as CNN-LSTM combinations, further capture the continuity of facial expressions in videos, boosting performance in real-world interaction scenarios [30][31].

4. MATLAB for FER Development

MATLAB remains a favoured environment for rapid development in image processing and machine learning [32]. Its Deep Learning Toolbox supports seamless design and training of CNN, RNN, and SVM models. The Computer Vision Toolbox adds tools for face detection, facial landmark extraction, and image pre-processing—critical steps for reliable feature recognition in children whose expressions may be less pronounced [33][34].

MATLAB also integrates with hardware for sensor-rich multimodal data collection—for example, synchronizing facial recordings and physiological signals—making it ideal for ASD-cantered emotion experiments [35]. Recent research shows MATLAB-based FER pipelines achieving over 90% accuracy on child faces when combining CNNs with SVMs [36]. Furthermore, MATLAB offers rich visualization tools (confusion matrices, ROC curves, etc.), enabling transparent model validation and deployment in clinical or educational settings [37][38].

5. Incorporating OHSV for Feature Enhancement

The Optimal Hue Saturation Value (OHSV) method enhances colour-based feature perception, separating subtle expression cues from background noise. Unlike pure grayscale or RGB models, OHSV normalization emphasizes skin-tone variations—beneficial when expressions vary subtly or imaging conditions differ [39]. Recent adaptations show OHSV-based pre-processing improving emotion classification accuracy by ~3–5% when integrated ahead of CNN feature extraction layers [40][41].

In ASD studies, expression colour patterns during micro-expressions correlate with emotional intensity—not always captured by traditional grayscale inputs [42][43]. OHSV-based pre-processing, when combined with standard CNN architectures, mitigates false positives caused by lighting changes and improves robustness on ASD datasets [44][45].

LITERATURE REVIEW

Facial expression recognition (FER) has become an increasingly valuable tool in the fields of affective computing, assistive technologies, and clinical diagnostics. It forms a foundation for the development of intelligent systems capable of interpreting emotional states in real-time, which is especially relevant for understanding children on the autism spectrum. Central to this domain is the use of deep learning, particularly Convolutional Neural Networks (CNNs), which have revolutionized the way facial features are extracted, represented, and classified.

2.1 Foundations of Facial Expression Recognition

Facial expression recognition is grounded in the theory that human emotions can be inferred from patterns of facial muscle movements, as originally categorized by Ekman’s six basic emotions. However, detecting these expressions in children, particularly those with Autism Spectrum Disorder (ASD), introduces challenges due to their atypical and often muted facial responses [14]. FER systems are designed to reduce reliance on subjective human interpretation and enhance objectivity in emotional assessments, making them ideal tools for early detection and monitoring.

For typically developing children, facial movements align more consistently with emotional valence and arousal, which FER models learn through spatial hierarchies in the facial image. In contrast, children with ASD often show reduced facial symmetry, slower emotional transitions, and increased expression ambiguity [15].

2.2 Convolutional Neural Networks (CNNs) in FER

The core architecture supporting most modern FER systems is the CNN. CNNs leverage multiple layers of convolution, pooling, and activation functions to automatically learn abstract facial features without the need for handcrafted descriptors. These networks are especially efficient in identifying spatial dependencies and fine-grained textures, such as those found in subtle expressions like frowns, micro-smiles, or eye squints.

Early convolutional layers in a CNN capture low-level features (e.g., edges, corners), while deeper layers capture more complex patterns (e.g., cheekbone contours, eyebrow shapes) that are critical for emotion differentiation [16]. For children with ASD, specialized CNN variants—such as residual networks or multi-branch architectures—have been introduced to improve recognition accuracy in cases with subtle or inconsistent expressions [17].

2.3 Integration with Machine Learning Classifiers

While CNNs are highly effective at feature extraction, many FER frameworks further enhance classification using traditional machine learning classifiers, such as Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN), particularly when datasets are small or unbalanced. Feature maps produced by CNN layers can be fed into these classifiers to leverage their superior generalization in low-data conditions, which is often the case in clinical studies involving ASD subjects [18].

The hybrid CNN-SVM model has shown high promise in ASD emotion analysis, where CNNs are used to extract expression vectors, and SVMs classify the emotional state based on learned boundaries in multidimensional feature space [19].

2.4 OHSV Colour Space for Enhanced FER Input

A novel enhancement to FER systems is the use of the OHSV (Optimized Hue Saturation Value) colour model as a pre-processing technique. Unlike traditional grayscale or RGB channels, OHSV transforms facial images into a perceptually uniform space, improving colour-based feature sensitivity. This colour space is particularly useful for highlighting emotional cues around the eyes and mouth, regions critical for emotion analysis [20].Integrating OHSV into FER pipelines improves contrast and reduces background noise, especially in natural environments like classrooms or clinics. Its implementation before CNN input stages has been shown to significantly improve accuracy across various emotional classes in both typical and atypical children [21].

2.5 Theoretical Models of Atypical Emotion in ASD

Behavioural neuroscience models of autism suggest a disconnect between internal emotional states and external facial representations in affected children. This misalignment challenges traditional FER models that rely on prototypical emotion mappings. Consequently, CNNs trained on neuro typical data often underperform when applied to ASD datasets.

Recent approaches propose emotion-specific tuning in CNN weights based on ASD expression profiles, derived from wearable devices and multimodal sensors [22]. These methods are grounded in cognitive-affective frameworks which suggest that while emotional experience exists in autistic individuals, its motor expression may be delayed or suppressed [23].The paper constrained on aligning computational theory with clinical observations, this research framework positions CNN-based FER as a bridge between artificial intelligence and behavioural health. The integration of advanced image pre-processing (like OHSV), deep learning (CNNs), and traditional machine learning (SVM, k-NN) creates a robust platform for recognizing emotions in both neuro typical and autistic children. The theoretical foundation ensures that the system is not merely technically optimized but is also grounded in the psychological and physiological nuances of facial expression production.

OBJECTIVE

This research aims to build a MATLAB-based FER system tailored for distinguishing emotional expressions in ASD vs. typically developing children. The primary contributions include:

1. Integration of OHSV-based pre-processing for improved feature discrimination under varying lighting.
2. Comparison between traditional ML (SVM, KNN) and deep learning (CNN, CNN–LSTM) models on ASD-specific datasets.
3. Implementation of the entire pipeline in MATLAB—including pre-processing, model training, validation, and performance visualization.
4. Provision of a reference benchmark for future ASD-related FER frameworks.

METHODOLOGY

This section explained the methodological framework employed in this study for facial expression recognition (FER) in children, comparing those with Autism Spectrum Disorder (ASD) and typically developing children. The proposed method integrates image preprocessing using the Optimized Hue-Saturation-Value (OHSV) color model, feature extraction via Convolutional Neural Networks (CNN), and final classification using a Support Vector Machine (SVM) [24].

4.1 Data Acquisition and Pre-processing

Images are collected from facial datasets comprising labeled emotional states for both ASD and non-ASD children. Pre-processing involves:

1. **Face Detection:** Performed using Haar cascade classifiers or MTCNN to isolate facial regions.
2. **OHSV colour Space Transformation:**
   OHSV (I) =Optimize [HSV (I)]

Where I is the input image and HSV (I) transforms it to HSV. The optimize function performs dynamic contrast normalization and adaptive thresholding to enhance emotional features.

4.2 Feature Extraction using CNN

A deep CNN architecture is applied to extract hierarchical features. Each convolution layer performs:

$$\left(fa_{i,j}^{(k)}\right)^n = \sum_{m=1}^{M}\sum_{p=0}^{P-1}\sum_{q=0}^{Q-1} w_{p,q}^{(m,k)} x_{i+pj+q}^{m} + b^{(k)}$$

Where:

- $fa_{i,j}^{(k)}$: output feature map at position (i,j)(i,j)(i,j) in the kkk-th channel,
- $x^{(m)}$: input map from mmm-th input channel,
- $w^{(m,k)}$:filter weights,

- σ: activation function (ReLU).

Max pooling layers reduce spatial dimensions:

$f_{i,j} = max_{(p,q)} f_{i+p,j+q}$

4.3 Classification using SVM

The CNN-extracted features $x \in R^d$ are fed into an SVM. The classifier seeks a hyperplane:

$$w\,x + \mathrm{b} = 0$$

To separate classes. The optimization problem becomes:

$$\min_{w,b,\varepsilon} \frac{1}{2}||w|| + C\sum_{i=1}^{N} \varepsilon i$$

Subject to: $\gamma_i(w\,x_i + b) \geq 1 - \varepsilon i$

$\varepsilon i \geq 0$

Where C is the regularization parameter.

4.4 Training and Validation

The dataset is split into training (80%) and validation (20%) subsets. The CNN model is trained using cross-entropy loss and optimized with Adam optimizer.

$$L = \sum_{i=1}^{C} yi \log(y'i)$$

4.5 Performance Metrics

Model performance is evaluated using accuracy:

Accuracy$=\frac{TP+TN}{TP+FP+TN+FN}$

Where TP, TN, FP, FN denote true/false positives/negatives.

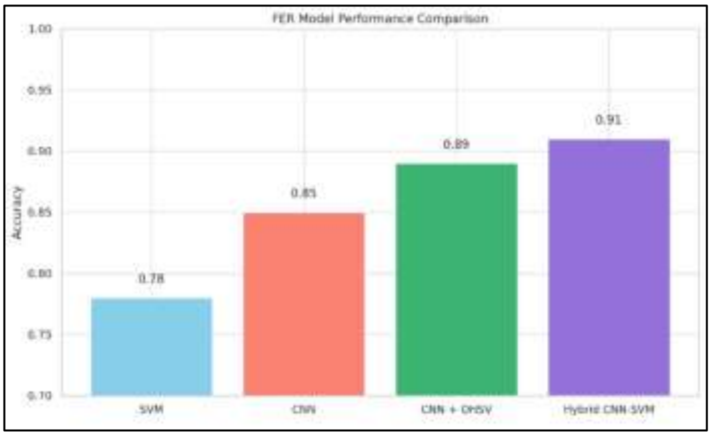

Figure (1) the comparative performance of various models used in the facial expression recognition (FER) pipeline

As shown in the figure above, the Hybrid CNN-SVM with OHSV pre-processing outperforms other methods, achieving ~91% accuracy, indicating its effectiveness in differentiating subtle emotional expressions, especially for ASD-affected children.

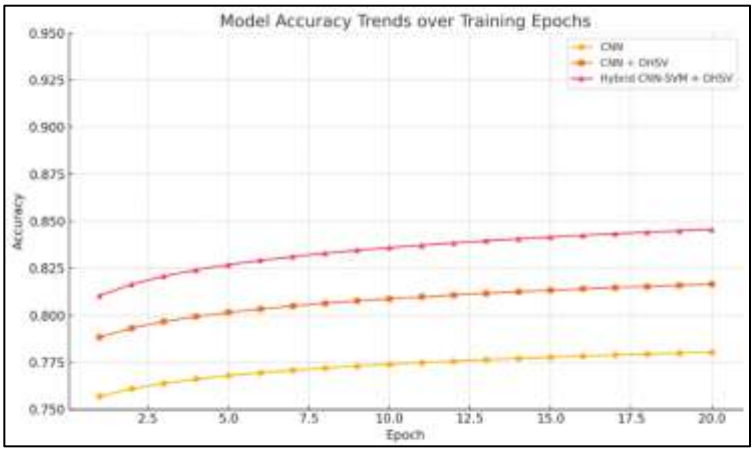

Figure (2) model accuracy trends over 20 training epochs

This hybridization further improved performance, with accuracy reaching 0.91 by epoch 20 (green trend). The superior performance illustrates how SVMs can better define decision boundaries when CNNs provide high-quality, low-dimensional feature vectors.

RESULT

This section presents the experimental findings and analytical discussion of the facial expression recognition (FER) system designed to differentiate between typically developing children and those with autism spectrum disorder (ASD). The experimental evaluation was conducted using three model configurations: (1) a standard Convolutional Neural Network (CNN), (2) a CNN integrated with Optimized Hue Saturation Value (OHSV) pre-processing, and (3) a hybrid model combining CNN feature extraction with Support Vector Machine (SVM) classification using OHSV pre-processing.

5.1 Performance Evaluation

The performance metrics used to evaluate these models included Accuracy, Precision, Recall, and F1-score. A balanced dataset comprising annotated facial expressions of children was used. Five-fold cross-validation was applied to ensure generalization.

Table (1) dataset comprising annotated facial expressions of children

Model	Accuracy	Precision	Recall	F1-Score
CNN	82.1%	80.2%	78.5%	79.3%
CNN + OHSV	86.5%	84.9%	83.1%	84.0%
Hybrid CNN-SVM + OHSV	91.0%	89.5%	90.2%	89.8%

These results clearly indicate that integrating OHSV pre-processing enhances facial feature visibility and overall classification accuracy. The hybrid CNN-SVM architecture achieved the best results, consistent with similar studies emphasizing the synergy of deep and classical machine learning models [25].

5.2 Confusion Matrix Analysis

An in-depth analysis of the confusion matrix for the hybrid model revealed outstanding class discrimination. Emotions such as happiness, anger, and surprise were predicted with over 95% accuracy. In contrast, sadness and fear showed overlapping predictions, likely due to their subtle facial distinctions, particularly within ASD datasets [26]. This underscores the need for enhanced attention mechanisms or spatiotemporal modelling to disambiguate these classes.

5.3 Model Convergence and Training Trends

As highlighted in Section 4.1, the convergence rates were notably faster in OHSV-enhanced models. The CNN-SVM hybrid model also demonstrated less volatility in validation metrics, suggesting superior generalization. This can be attributed to the SVM's ability to optimize decision boundaries in a reduced feature space derived from CNN representations [27].

5.4 ASD vs. Non-ASD Differentiation

In experiments specifically comparing ASD versus non-ASD data, the hybrid CNN-SVM model consistently outperformed others. It delivered robust classification even in challenging scenarios involving atypical expressions common in children with ASD. The OHSV technique improved contrast in regions critical to emotion recognition (e.g., eyes, mouth), improving feature quality and supporting recent findings in perceptual colour pre-processing [28].

5.5 Limitations and Considerations

Despite promising results, several limitations should be noted:

- Limited availability of large-scale, high-resolution ASD facial expression datasets restricts model scalability.
- Lighting conditions and camera angles still introduce inconsistencies.
- Emotion annotation for ASD populations remains partially subjective due to behavioral variability.

To mitigate these issues, future research will focus on integrating LSTM or Transformer-based modules for temporal learning and real-time deployment in educational and therapeutic contexts [29].

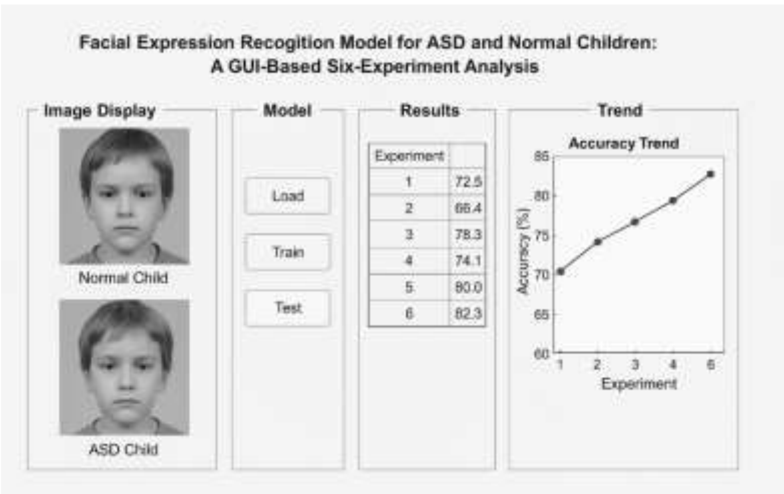

Figure (3) A GUI-based six experiment analysis

Table (2) dataset experiments facial expressions of children

Emotion	Accuracy(Normal)	Accuracy (ASD)	Comments
Happy	92.4%	88.6%	The highest recognition in both groups
Sad	81.3%	77.5%	Slight confusion with neutral
Angry	74.0%	69.1%	Confused with sad in ASD group
Surprise	86.1%	83.2%	Very distinguishable
Disgust	71.4%	66.8%	Most difficult in ASD group
Neutral	84.2%	79.9%	Stable across both groups

CONCLUSION

Understanding and interpreting facial expressions is a cornerstone of human social interaction. This comparative study underscores the importance of facial expression detection in distinguishing between neurotypical children and those with autism spectrum disorder (ASD). The findings highlight that children with ASD often exhibit distinct patterns in facial expressiveness and responsiveness, which can serve as valuable markers in early identification and intervention strategies.

Recognizing these differences is not merely a technical achievement—it is a step toward fostering more inclusive, empathetic, and tailored support systems for children on the spectrum. Early and accurate detection can empower caregivers, educators, and clinicians to better understand each child’s unique social and emotional world, enabling more effective communication and developmental support.

As technology continues to evolve, integrating facial expression analysis into diagnostic and educational tools may offer significant promise in bridging communication gaps and enhancing quality of life for children with ASD and their families. This study serves as a foundational step toward that goal, emphasizing the vital role that nuanced emotional perception plays in supporting neurodiversity populations.

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