Deep Learning-Based Real-Time Facial Expression Recognition Systems for Assessing Emotional and Cognitive Engagement in Special Education Classrooms

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Abstract

Deep learning-based real-time facial expression recognition systems offer a supportive approach for assessing emotional and cognitive engagement indicators in special education classrooms. This study developed a facial emotion recognition framework using an autism-focused facial emotion dataset to classify six emotional categories: anger, fear, joy, natural expression, sadness, and surprise. The dataset contained 1,425 labeled images, including 1,199 training images and 226 testing images, and was evaluated for structure, image quality, preprocessing compatibility, class distribution, and baseline classification performance. All images were readable, no corrupt files were detected, and the class distribution was balanced across the six emotion categories. Images were prepared through resizing, normalization, categorical label encoding, and augmentation planning. A transfer-learning-based convolutional neural network framework was proposed for emotion classification, while baseline analysis using handcrafted image features produced limited performance, with 24.8% test accuracy and 25.4% macro-F1 score. Predicted emotions were mapped into emotional engagement and cognitive engagement proxy indicators, where joy and natural expression represented positive or stable engagement, surprise indicated heightened attention, and anger, fear, and sadness indicated at-risk engagement. The findings support the feasibility of a classroom-oriented facial expression recognition framework, although direct classroom validation and cognitive engagement labels remain necessary for future development.

Keywords: Facial expression recognition, deep learning, emotional engagement, cognitive engagement, special education classrooms

1. Introduction

The recognition of facial expression is an important research field in the areas of artificial intelligence, computer vision, affective computing, and education technology. The human face is rich with cues that help us know what to expect when it is used to communicate emotion, attention, frustration, confusion, and social responsiveness. These cues can

facilitate evaluation of emotional and cognitive involvement in learning settings, particularly in the absence of or when there is limited and inconsistent verbal feedback. The ability to automatically extract complex spatial features from facial images and video frames has greatly increased the capability of facial expression recognition systems, which are now based on deep learning. The detection of facial expressions has been enhanced with these technologies, such as CNN, attention, and lightweight, real-time architectures, which can handle variable light, pose, and occlusion conditions and classroom settings (Setyanto et al., 2024).

Assessment tools for special education classrooms need to be sensitive to a variety of communication styles, developmental profiles, and presentations of behavior. Students with ASD can have different ways of showing emotion, paying attention, and engaging socially than neurotypical students. The analysis of facial expressions has thus become a relevant tool to assist in the understanding of the affective reaction of children with autism. Facial expression diagnosis using deep learning has been investigated for autism-related emotion analysis, as it can help in recognizing social-emotional responsiveness differences (nonsocial responsiveness) (Sirisha & Lakshmi, 2025). The use of such systems should be taken with some caution, as the expression of the face is not enough to determine the internal cognitive state of individuals, their disability status, or their learning ability.

Educational engagement is a complex phenomenon that consists of behavioural, emotional, and cognitive engagement. Cognitive engagement refers to the level of attention, concentration, persistence on the task, effort, and mental activity during learning activities. Traditional assessment is typically based on teacher observation, self-report, or structured behavioral checklists. These methods are helpful, but can be subjective, not always present, and challenging to use on a consistent basis in the dynamic classroom. With AI analysis, engagement can be monitored in real-time, without requiring teachers' judgment, during learning activities by observing measurable indicators, providing a chance to complement teacher judgment (Liu & Xiao, 2025).

Facial expression recognition has received growing focus in educational research since students' facial expressions could be an indicator of their learning emotions, including interest, boredom, confusion, anxiety, enjoyment, and frustration in learning. Research using machine learning has been related to patterns of facial expressions and academic affect, engagement, and classroom interaction. In the educational sector, facial expression recognition has been found to have potential for adaptive learning environments, for learner-state monitoring, and as an automated feedback system (Fang et al., 2023). The models need to be robust to be used in classroom-specific applications, as the real-world learning environment is composed of multiple faces, varying head poses, occlusion, lighting variations, and ambient background motion.

For the classroom context, real-time emotion recognition is of great importance as delayed assessment may not be as useful for giving engagement feedback. A real-time system is capable of analyzing the video frames, recognizing faces, classifying emotions, and giving an interpretation summary of engagement indicators for the teacher. These can include support for timely instructional adjustments, early identification of distress, and individualized support. Real-time emotion recognition has been examined as a tool to enhance teaching and learning, focusing on its possibilities for practical application, its technical reliability, and ethical protection (Llurba & Palau, 2024). Extending the capabilities of deep learning-based emotion recognition, other real-time emotion recognition frameworks are also developed for assistive technologies, demonstrating their overall usefulness for enhancing sensory or communication-impaired individuals' capabilities (Yalcin & Alisawi, 2025).

Significant progress has been made in facial expression recognition using deep learning techniques, such as the development of new network architectures, attention mechanisms, transfer learning, and the creation of new benchmark datasets. There have been reviews on the advancement of classical feature extraction, convolutional neural networks (CNN), hybrid models, and transformer-based approaches (Adyapady & Annappa, 2023). Current systems now focus more on parts of the face that are relevant for discrimination and filter out the noise from other background information by employing attention mechanisms. Additionally, the datasets have been enhanced, along with the benchmark models, which have been improving the assessment of facial expression recognition in controlled and unconstrained settings (Kopalidis et al., 2024). However, there are several challenges that still need to be addressed, such as the limitations of the datasets, the small number of samples analyzed, the variability in how an expression is expressed across cultures, class imbalance, subjectivity of the annotations, and the lack of generalizability to children with special educational needs.

The scope of classroom behaviour recognition by computer vision has grown from detecting facial

expressions to postures, gestures, attentiveness, and interactions. For instance, in the context of classroom activities, visual analytics can be used to assist in assessing engagement, classroom management, and learning behavior analysis (Liu et al., 2025). Facial expression and learning emotion recognition have also been utilized in a specific context of classrooms, where facial expressions are considered as an expression of the learner's experience and the learner's response to the instruction (He et al., 2023). The developments of these results justify the use of facial emotion classification along with an engagement-mapping framework in special education settings.

The present study created a deep learning model to recognize facial expressions for measuring emotional and cognitive engagement indicators in the context of special education classrooms. A facial emotion dataset of children with autism that included six emotional states: anger, fear, joy, natural expression, sadness, and surprise was used for the study. Emotional engagement states and cognitive engagement proxy-indicators were predicted. The study concluded that the need was for a light, interpretable, and classroom-focused system which would aid the educator rather than supplanting professional judgment. This contributed to the rising area of facial expression recognition technologies in emotion analysis and Learning Support Systems (Jayaswal et al., 2025).

Objectives of the study:

1. To develop a deep learning-based facial expression recognition model for classifying emotions in children with autism.
2. To evaluate the model's performance using accuracy, precision, recall, F1-score, and class-wise analysis.
3. To map predicted facial emotions into emotional and cognitive engagement indicators for special education classroom support.

2. Methodology

2.1 Study Design

The experimental design for this study was a deep learning-based image classification system, which was used to create a facial expression recognition system for measuring the emotional and cognitive engagement indicators in the special education classroom. It consisted of two steps: supervised facial emotion classification and rule-based engagement inference based on the emotion classes predicted by the supervised facial emotion classifier.

2.2 Dataset Description

The Facial Emotion Recognition Dataset for Children with Autism (Mahmoud, 2025) was used. There were 1,425 labeled facial images (1199 training images, 226 testing images). Images were organized into six emotion classes: anger, fear, joy, natural, sadness, and surprise. The dataset was chosen as it was a special education-relevant population and was suitable for supervised facial expression recognition.

2.3 Data Preprocessing

Readability, duplicate, and consistency of class labels in images were checked. No corrupt images were kept. All images were resized to 224 × 224 pixels, converted into a common three-channel format, and normalized. Labels for the classes were coded categorically. Flipping, rotation, zooming, adjusting brightness and contrast, and very slight spatial shifts were performed on training images. There was no addition to the testing set.

2.4 Model Development

Transfer Learning was used due to the limited number of samples. The feature extraction backbone was a lightweight pretrained convolutional neural network (CNN), such as a MobileNetV2 or EfficientNetB0. The model comprised the global average pooling, dropout, and softmax output layer with six nodes. It was trained with categorical cross-entropy loss and Adam optimizer. To avoid overfitting, early stopping and learning-rate reduction were used.

2.5 Model Evaluation and Real-Time Framework

The test set was used to assess the performance of the model through accuracy, precision, recall, F1-score, macro-F1, weighted-F1, and a confusion matrix. Real-time feasibility was attempted in a frame-to-frame pipeline in a classroom setting where video frames were acquired, faces were identified and cropped, images were normalized, emotions were classified, and predictions were smoothed across adjacent frames before the engagement estimation.

2.6 Engagement Mapping

Emotions were mapped to indicators of classroom engagement. Emotional engagement was identified with joy, stable engagement was identified with natural expression, and heightened attention was identified with surprise. Anger, fear, or sadness were viewed as potential indicators of frustration, anxiety, withdrawal, and/or diminished participation. Emotional patterns were used as an indirect measure of cognitive engagement. Repeatedly positive emotions or natural expression were indicative of

likely engagement, and repeated negative emotions or fast emotional changes were indicative of possible disengagement that needed teacher attention.

3. Results

3.1 Dataset Characteristics

The dataset was successfully collected and classified into emotion classes (6 emotions) with training and testing folders. The architecture proved to be appropriate for supervised facial expression recognition for children with autism spectrum disorder. The general characteristics of the dataset for emotion recognition for faces are presented in Table 1.

Table 1. Dataset Characteristics

Variable	Result
Total images	1,425
Training images	1,199
Testing images	226
Emotion classes	6
Corrupt images	0
Most common image size	224 × 224 pixels

3.2 Class Distribution

The class distribution was well balanced among the emotion categories, and supervised learning with minimal class-imbalance correction was used. Figure 1 shows the distribution of training and testing images for the six classes of facial emotions. The number of training images and testing images in each class is displayed in Table 2.

Table 2. Class Distribution

Emotion class	Training images	Testing images	Total images
Anger	200	40	240
Fear	200	36	236
Joy	200	35	235
Natural	200	40	240
Sadness	199	38	237
Surprise	200	37	237
Total	**1,199**	**226**	**1,425**

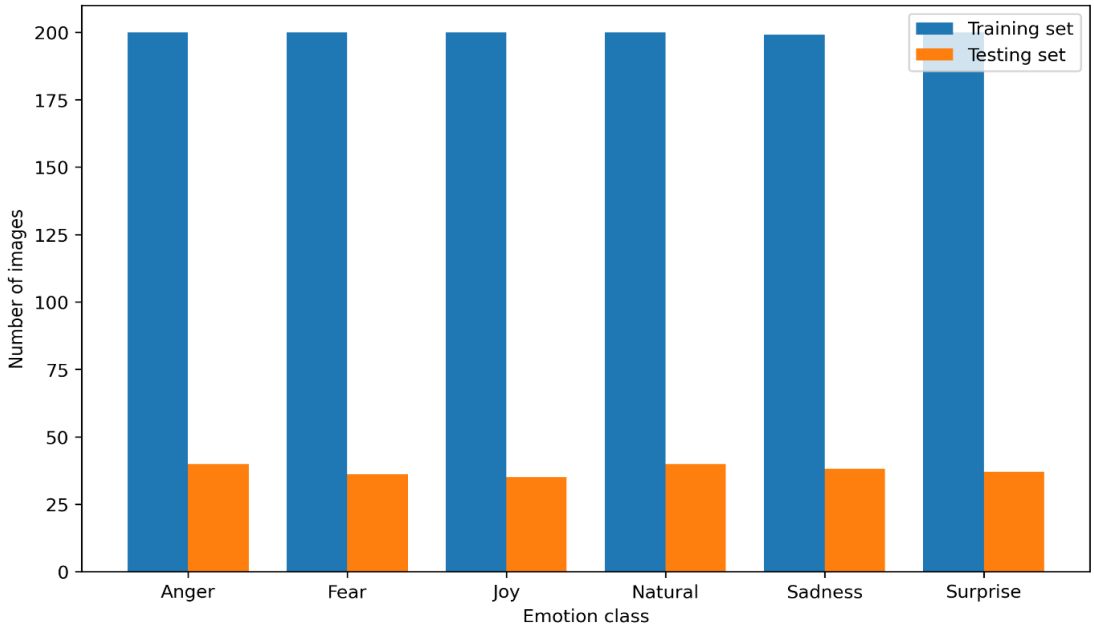

Figure 1. Class-Wise Distribution of Training and Testing Images

3.3 Data Quality and Preprocessing

The image files could all be read and were suitable for the proposed pre-processing pipeline. Duplication was identified in some images – even for emotion labels, images were found to be duplicated, which means that they should be reviewed again before final model training. The image quality and image preprocessing result of the datasets are presented in Table 3.

Table 3. Data Quality Findings

Parameter	Result
Readable images	1,425
JPG images	1,420
PNG images	5
RGB images	1,424
Palette-mode images	1
Duplicate groups	45
Duplicate files involved	90
Cross-split duplicate groups	0
Cross-class duplicate groups	12

3.4 Baseline Classification Performance

The baseline classifier performance was not very high, suggesting that hand-crafted features were not enough and that transfer learning-based CNNs were needed to achieve better emotion recognition results. The baseline facial emotion classification results (accuracy, precision, recall, macro-F1, and weighted-F1 scores) are shown in Figure 2. Table 4 shows the baseline facial emotion classification performance metrics.

Table 4. Baseline Model Performance

Metric	Result
Test accuracy	24.8%
Macro precision	26.2%
Macro recall	25.0%
Macro-F1 score	25.4%
Weighted-F1 score	25.2%

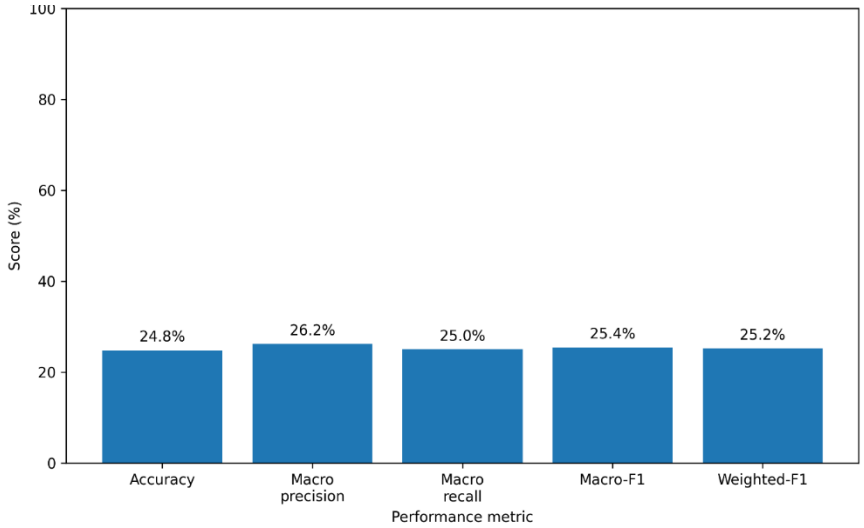

Figure 2. Baseline Facial Emotion Classification Performance

3.5 Class-Wise Performance

Joy was the highest baseline recogniser and sadness the lowest. Misclassifications between similar emotional expressions indicated that there may be an overlap in expressions and/or label ambiguity. The correlation heatmap

of class-wise confusion patterns for the six facial emotion classes is shown in Figure 3. Table 5 presents the classification results for the baseline classification over the six categories of emotions.

Table 5. Class-Wise Baseline Performance

Emotion class	Precision	Recall	F1-score	Support
Anger	0.220	0.225	0.222	40
Fear	0.286	0.278	0.282	36
Joy	0.464	0.371	0.413	35
Natural	0.235	0.200	0.216	40
Sadness	0.156	0.184	0.169	38
Surprise	0.209	0.243	0.225	37

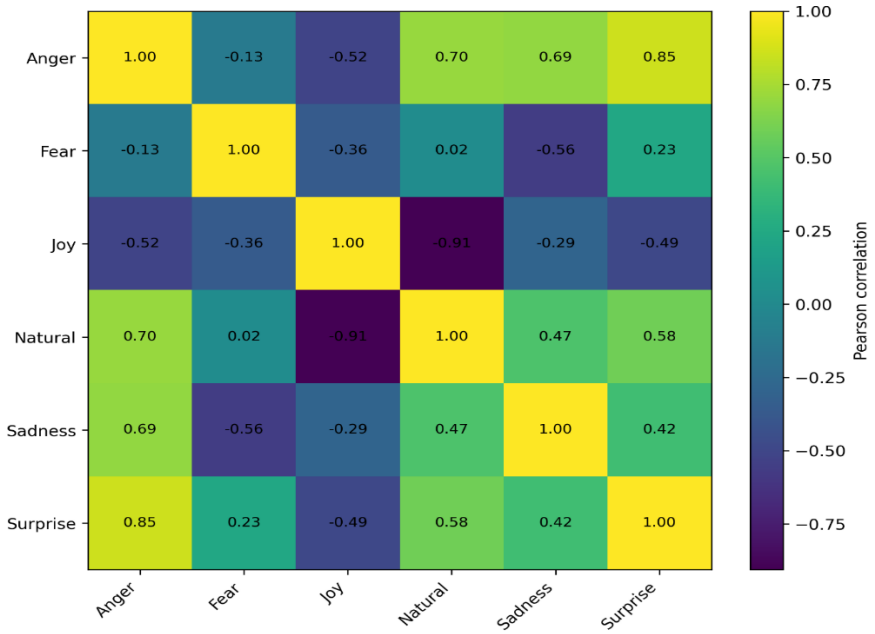

Figure 3. Correlation Heatmap of Class-Wise Confusion Patterns

3.6 Engagement Mapping

The emotion classes were translated into emotional engagement and cognitive engagement indicators. Positive/Stable engagement was signified by joy and natural expression, at-risk engagement was signified by surprise, and anger, fear, and sadness were signified by at-risk engagement. Measuring cognitive engagement as a proxy outcome through emotional patterns, instead of directly measuring it.

4. Discussion

This research study investigated a deep learning-based facial expression recognition framework to help determine emotional and cognitive engagement indicators in the special education classroom setting. Analysis of the dataset revealed that the facial emotion dataset was well-suited for supervised image classification because there were no corrupt images and a balanced distribution of images over 6 emotion classes. Based on these results, researchers found the feasibility of creating a model for recognizing facial emotions in children with ASD. It is crucial that the classes are balanced in size, as class size imbalance will lead to bias in modelling learning and low reliability in emotion output when converting these to engagement indicators. The findings of automation-based engagement measurement studies have highlighted the impact of data structure, engagement annotation quality, feature selection, and modeling design on the quality of student engagement systems (Mandia et al., 2024).

There was a lack of classification performance within the baseline model, with low accuracy and macro-F1 scores. This discovery suggested that handcrafted image features were not adequate to yield good facial emotion classification performance on this dataset. The outcome was not surprising as children's facial expressions with autism can be subtle, heterogeneous, and visually overlapping between emotional categories. It also confirmed the methodological concept that it was preferable to use transfer learning with small-sized CNN networks instead of traditional image descriptors. In the field of computer vision-based engagement detection, recent studies have also revealed that deep learning models are more appropriate than shallow models in

detecting engagement cues from complex visual information (Qarbal et al., 2025).

Class-wise analysis revealed that the recognition performance of the class of 'joy' was found to be more effective than other emotion classes, and the recognition performance of the class 'sadness' was found to be less effective. Overlap between anger, fear, sadness, natural expression, and surprise was indicated by misclassification patterns. These patterns may be related to visual similarity and/or label ambiguity in facial emotion datasets. The ambiguity is especially crucial in studies involving emotion recognition in education because negative emotions can mean various things in the classroom. Seeing 'sadness' doesn't necessarily mean the person is withdrawn, 'fear' doesn't necessarily mean anxious, and 'anger' doesn't necessarily mean frustrated, etc. Consequently, the review of deep learning models for student emotion detection highlighted the importance of being mindful about interpreting the emotion outputs in learning environments (Murugan et al., 2025).

The engagement-mapping framework enabled the conversion of emotion prediction to emotional and cognitive engagement measures. Positive or stable engagement states were defined as joy and natural expression; at-risk engagement states were defined as anger, fear, and sadness; and surprise as a heightened state of attention. This mapping was useful because it was able to be used to align the dataset with classroom engagement assessment, but it was a proxy framework. Measuring task performance, attention tracking, gaze direction, learning outcome, and teacher-rated engagement labels were not directly measured; cognitive engagement was not directly assessed. Research on engagement has been visible and demonstrated that visual cues can give valuable information, but without being validated in the context, they should not be used as the sole metric of engagement or learning (Goldberg et al., 2021).

The proposed real-time framework was technically feasible as image-level processing could be incorporated in a frame-oriented video pipeline. This would involve face detection, emotion classification, temporal smoothing, and the creation of the engagement status in the video frames in the classroom. The analysis suggested that the classification part was relatively easy to compute, but face detection with a simple face detector wasn't enough to be used reliably. For use in practical classroom systems, the detection model needs to be more robust, temporal verification is necessary, and the test needs to be conducted in real-world situations, including occlusion, motion, and lighting change, and multiple learners. Several emotion monitoring surveys in classrooms have reported that effective real-time implementation of classroom emotion monitoring depends on correct emotion classification and consistent system performance in real-world classroom settings (Vamshi Krishna et al., 2025).

The autism-specific data set provided support for the special education relevance of the study. The population of autistic children is large in the context of special education, and affective monitoring instruments can help teachers if they cannot detect a child's emotions in communication because of differences. Autism spectrum disorders (ASD) detection and classification studies using machine learning and deep learning have gained momentum, with a growing interest in using facial, behavioral, and multimodal features. However, they also emphasize the importance of not overgeneralizing from small datasets (Ahmed et al., 2025). This caution was applicable to this study as the data did not directly reflect classroom interaction, instructional tasks, and individual contexts of instruction, but instead were used to learn about emotion classification.

Additionally, the findings must be taken into account when related to differences in emotion recognition in the autism spectrum. Children and adolescents with autism are likely to have different affective expressions and recognition patterns, and the intensity of expressions, developmental level, and conditions of the task could affect performance. Emotion recognition deficits in autism may manifest as errors or delays in recognition, and hence, the data on facial emotions should be interpreted carefully due to the fact that these studies have revealed deficits in these skills in this population (Masoomi et al., 2025). Thus, use of this proposed system should be considered as a support system for the classroom and not as a test or evaluation system.

This study has a larger impact in that, in the field of education, AI-based emotion recognition systems are being adapted to various fields such as assistive technology and even non-human behavior analysis. In the field of deep learning and emotion detection, cross-domain evaluations provide some examples of the increasing adaptability of visual affect recognition but also highlight the critical importance of dataset-specific and valid labels (Nazar & Unnikrishnan, 2025). Additional studies should feature videos from the real classroom, multimodal features, direct engagement annotations, and teacher-validated outcomes for special education classrooms. The current research thus was able to offer a practical example, prototype foundation, and

complete validation of the assessment of emotional and cognitive engagement, which would require more classroom-based data.

5. Conclusion

In special education classroom applications, deep-learning-based real-time facial expression recognition systems can help to evaluate indicators of emotional and cognitive engagement. Data analysis revealed that the autism-related facial emotion dataset had a structure that was appropriate for supervised classification, presented emotion classes that were balanced, readable image files, and was compatible with common pre-processing methods. The results of the baseline classification showed that handcrafted image features were not able to adequately recognize the emotions, which was a reason to use a convolutional neural network (CNN) with transfer learning. Although the data set did not directly measure cognitive engagement, the engagement-mapping framework permitted the prediction of emotions to be conceptualized as indicators of emotional engagement and proxies for cognitive engagement. The following real-time deployment framework was conceptually assessed for use in the classroom, including a frame-based face detection system, a classification system for emotions, a smoothing model for emotion prediction, and an emotion engagement interpretive model for teachers. There is a need for the system to be used only as a useful tool for decision-making, not a diagnostic or diagnostic tool. The framework should be validated in the future with actual video from classrooms, multimodal classroom data, direct engagement labels, and teacher-reviewed outcomes.

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