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Facial Emotion Recognition Based on Convolutional Neural Network Using FER2013 Dataset

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Abstract

Facial emotion recognition is an important research area in computer vision and artificial intelligence, with applications in human–computer interaction, affective computing, and intelligent systems. This study aims to evaluate the performance of a Convolutional Neural Network (CNN) for facial emotion recognition using the FER2013 dataset. The FER2013 dataset consists of grayscale facial images with a resolution of 48×48 pixels and includes seven emotion classes: angry, disgust, fear, happy, neutral, sad, and surprise. Due to its low image resolution and imbalanced class distribution, FER2013 presents significant challenges for emotion classification tasks. An experimental research approach was employed by implementing a baseline CNN architecture composed of convolutional, pooling, and fully connected layers. Image normalization and batch-based data generation were applied during preprocessing. The model was trained using the Adam optimizer with categorical cross-entropy loss, and an early stopping mechanism was utilized to prevent overfitting. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. The experimental results show that the proposed CNN model achieved an overall test accuracy of 55.50%. Emotions with distinctive facial features, such as happy and surprise, obtained higher F1-scores, while minority and visually subtle classes, particularly disgust and fear, exhibited lower performance. These findings indicate that a simple CNN architecture can provide reasonable performance on challenging facial emotion datasets while highlighting the impact of class imbalance and limited image resolution. The proposed model can serve as a baseline for further improvements in facial emotion recognition systems.

Keywords: *Facial Emotion Recognition, Convolutional Neural Network, FER2013 Dataset, Computer Vision, Deep Learning*

Abstrak

Pengenalan emosi wajah merupakan salah satu bidang penelitian penting dalam computer vision dan kecerdasan buatan, yang memiliki aplikasi luas pada interaksi manusia dan komputer serta sistem cerdas. Penelitian ini bertujuan untuk mengevaluasi kinerja model Convolutional Neural Network (CNN) dalam melakukan klasifikasi emosi wajah menggunakan dataset FER2013. Dataset FER2013 terdiri dari citra wajah grayscale beresolusi 48×48 piksel yang diklasifikasikan ke dalam tujuh kelas emosi, yaitu angry, disgust, fear, happy, neutral, sad, dan surprise. Karakteristik dataset yang memiliki resolusi rendah dan distribusi kelas yang tidak seimbang menjadikan tugas klasifikasi emosi wajah menjadi lebih menantang. Metode penelitian yang digunakan adalah pendekatan eksperimental dengan menerapkan arsitektur CNN sederhana yang terdiri dari lapisan konvolusi, pooling, dan fully connected. Tahapan praproses meliputi normalisasi citra dan penggunaan generator data berbasis batch. Proses pelatihan model dilakukan menggunakan optimizer Adam dengan fungsi loss categorical cross-entropy, serta menerapkan mekanisme early stopping untuk mencegah overfitting. Evaluasi kinerja model dilakukan menggunakan metrik akurasi, precision, recall, F1-score, dan confusion matrix. Hasil pengujian menunjukkan bahwa model CNN yang diusulkan mencapai akurasi pengujian sebesar 55,50%. Kelas emosi dengan ciri wajah yang lebih jelas, seperti happy dan surprise, memperoleh nilai F1-score yang lebih tinggi, sedangkan kelas minoritas dan emosi dengan perbedaan visual yang halus, terutama disgust dan fear, menunjukkan kinerja yang lebih rendah. Hasil ini menunjukkan bahwa CNN sederhana masih mampu memberikan performa yang cukup baik pada dataset FER2013 serta menegaskan pengaruh ketidakseimbangan data dan resolusi citra terhadap kinerja klasifikasi emosi wajah.

Kata kunci: Facial Emotion Recognition, Convolutional Neural Network, FER2013 Dataset, Computer Vision, Deep Learning

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1. Introduction

Facial emotion recognition has become an important research topic in the field of computer vision and artificial intelligence due to its wide range of applications, including human–computer interaction, surveillance systems, healthcare monitoring, and behavioral analysis. Facial expressions represent one of the most natural and informative channels for conveying human emotional states, enabling individuals to communicate feelings and intentions without verbal interaction. As intelligent systems increasingly interact directly with humans, the ability to automatically recognize facial emotions plays a crucial role in improving system responsiveness, personalization, and decision-making capabilities [1], [2].

In practical applications, facial emotion recognition systems are expected to operate under unconstrained conditions. However, automatic emotion recognition remains a challenging task due to various internal and external factors. Variations in facial appearance, illumination conditions, head pose, occlusion, and differences in facial anatomy can significantly affect recognition accuracy. In addition, several emotional expressions exhibit strong visual similarities, particularly fear, sadness, and neutral emotions, which often differ only in subtle facial muscle movements. These challenges are further compounded by the subjective nature of emotional expression, where the same emotion may be expressed differently by different individuals [3], [4].

Another critical issue in facial emotion recognition research is the imbalance of emotion classes in commonly used datasets. Minority emotion classes, such as disgust and fear, are typically underrepresented, which causes learning bias toward majority classes and leads to poor classification performance for less frequent emotions. Under such conditions, relying solely on accuracy as an evaluation metric may provide a misleading assessment of model performance. Therefore, additional evaluation metrics such as precision, recall, and F1-score are required to obtain a more comprehensive and fair evaluation of recognition systems, especially when dealing with imbalanced datasets [3].

Convolutional Neural Networks (CNNs) have become the dominant approach for image-based recognition tasks due to their ability to automatically learn discriminative features directly from raw pixel data. CNN-based models eliminate the need for handcrafted feature extraction and enable hierarchical representation learning through stacked convolutional layers. Numerous studies have demonstrated that CNN-based approaches outperform traditional machine learning methods in facial emotion recognition, particularly when handling complex visual patterns and large-scale image data [5], [6].

Several studies published in JUTEKOM have reported the successful application of machine learning and deep learning techniques for classification and image-based analysis tasks. Mursyid et al. demonstrated that convolution-based deep learning architectures such as YOLOv7 and ResNet50 are effective in extracting discriminative facial features from facial images [7]. Other studies have explored classification approaches using distance-based and probabilistic methods, emphasizing the influence of algorithm selection, data characteristics, and class distribution on classification performance [8], [9]. These findings indicate that model performance is strongly affected by data imbalance, feature representation, and model complexity, which motivates further investigation of CNN-based approaches on challenging benchmark datasets .

While advanced CNN architectures can improve recognition performance, they often involve high computational costs and complex parameter tuning, which may limit their applicability in real-world systems with constrained computational resources. Consequently, evaluating simpler CNN architectures remains an important research direction. Simple CNN models can serve as effective baseline systems, provide insights into fundamental learning behavior, and help identify dataset-related limitations before introducing more complex solutions. Several recent studies have emphasized the importance of baseline CNN evaluation combined with training strategies such as early stopping to improve generalization performance without significantly increasing model complexity [10], [11] [12].

The FER2013 dataset is one of the most widely used benchmark datasets for facial emotion recognition research. It consists of grayscale facial images with a resolution of 48×48 pixels categorized into seven basic emotion classes. Although FER2013 presents several challenges, including low image resolution, noise, and severe class imbalance, it remains a valuable benchmark for evaluating CNN-based models and enabling comparison with previous studies under consistent experimental conditions [13], [14].

Therefore, this study aims to evaluate the performance of a Convolutional Neural Network for facial emotion recognition using the FER2013 dataset. The proposed approach employs a straightforward CNN architecture combined with an early stopping strategy to reduce overfitting and improve model generalization. Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. By focusing on a simple yet effective CNN model, this research provides a clear baseline evaluation, highlights the impact of dataset characteristics on recognition performance, and contributes to a better understanding of facial emotion recognition challenges in practical applications.

2. Research Methodology

This study employs an experimental research methodology to evaluate the performance of a Convolutional Neural Network (CNN) for facial emotion recognition using the FER2013 dataset. The experimental design aims to assess the ability of a baseline CNN architecture to learn discriminative facial features from low-resolution grayscale images under imbalanced class conditions. The methodology is structured to ensure reproducibility, objective evaluation, and compliance with common practices in computer vision research.

2.1. Dataset Description

The FER2013 dataset is used as the primary data source in this study. The dataset consists of grayscale facial images with a resolution of 48 × 48 pixels, categorized into seven basic emotion classes: angry, disgust, fear, happy, neutral, sad, and surprise. FER2013 is widely used as a benchmark dataset in facial emotion recognition research due to its challenging characteristics, including low image resolution, noise, and imbalanced class distribution. These characteristics make the dataset suitable for evaluating the robustness and generalization capability of CNN-based models, particularly when using simple architectures [15].

The dataset is divided into three subsets: training, validation, and testing. The training set is used to optimize model parameters, the validation set is utilized to monitor model performance during training and guide early stopping decisions, and the testing set is reserved for final model evaluation. The detailed distribution of samples across emotion classes is presented in Table 1. As shown in the table, the dataset exhibits significant class imbalance, with the disgust emotion class containing substantially fewer samples than the others.

Table 1. Distribution of FER2013 Dataset

Emotion	Train	Validation	Test	Total
Angry	3995	958	958	5911
Disgust	436	111	111	658
Fear	4097	1024	1024	6145
Happy	7215	1774	1774	10763
Neutral	4965	1233	1233	7431
Sad	4830	1247	1247	7324
Surprise	3170	831	831	4832
Total	**22968**	**5741**	**7178**	**35887**

2.2. Data Preprocessing

Prior to model training, several preprocessing steps are applied to prepare the facial images for CNN processing. All pixel values are normalized by rescaling them to the range [0, 1] through division by 255. This normalization helps stabilize the training process and accelerates convergence by ensuring consistent input value ranges.

Since FER2013 images are originally provided in grayscale format, a single-channel input representation is maintained. Converting grayscale images to RGB is avoided to prevent redundant information and unnecessary computational overhead. The image resolution is fixed at 48 × 48 pixels to match the original dataset specification and the input requirements of the CNN model.

To efficiently manage memory usage and improve computational efficiency, image data generators are employed during training, validation, and testing. These generators load data in batches and apply consistent preprocessing across all subsets, enabling scalable training and compatibility with GPU acceleration [16].

2.3. CNN Architecture

The CNN model implemented in this study follows a sequential architecture designed to balance computational simplicity and learning capability. The network consists of three convolutional layers, each followed by a max-pooling layer. ReLU activation functions are applied to introduce non-linearity and enable the network to learn complex feature representations.

The first convolutional layer captures low-level features such as edges and textures, while subsequent layers learn higher-level spatial features related to facial expressions. Max-pooling layers are used to reduce spatial dimensions, decrease computational complexity, and improve translational invariance.

After feature extraction, the feature maps are flattened and passed to a fully connected dense layer with ReLU activation. A dropout layer is applied before the output layer to reduce overfitting by randomly deactivating neurons during training. The final output layer uses a softmax activation function to generate probability distributions across the seven emotion classes.

2.4. Training Configuration

Model training is performed using the Adam optimizer due to its adaptive learning rate and effectiveness in deep learning optimization. The learning rate is set to 0.001 to balance convergence speed and training stability. The categorical cross-entropy loss function is used to measure the discrepancy between predicted class probabilities and true labels. The loss function is defined in Equation (1):

$$L = -\sum_{i=0}^{C} y_i \log(\hat{y}_i)$$

Where C denotes the number of emotion classes, y_i represents the true label encoded in one-hot format, and y_i represents the predicted probability for class iii.

The training process uses a batch size of 64 with a maximum of 30 epochs. An early stopping mechanism is applied by monitoring validation loss to prevent overfitting. The patience parameter is set to 5, meaning that training is terminated if validation loss does not improve for five consecutive epochs. In this study, training stopped automatically at epoch 15 due to the absence of further validation loss improvement, indicating effective generalization control.

Table 2. CNN Training Configuration

Parameter	Value
Dataset	FER2013
Image size	48 × 48
Color mode	Grayscale
Number of classes	7
Batch size	64
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical Cross-Entropy
Epochs	30
Early stopping patience	5

2.5. Research Workflow

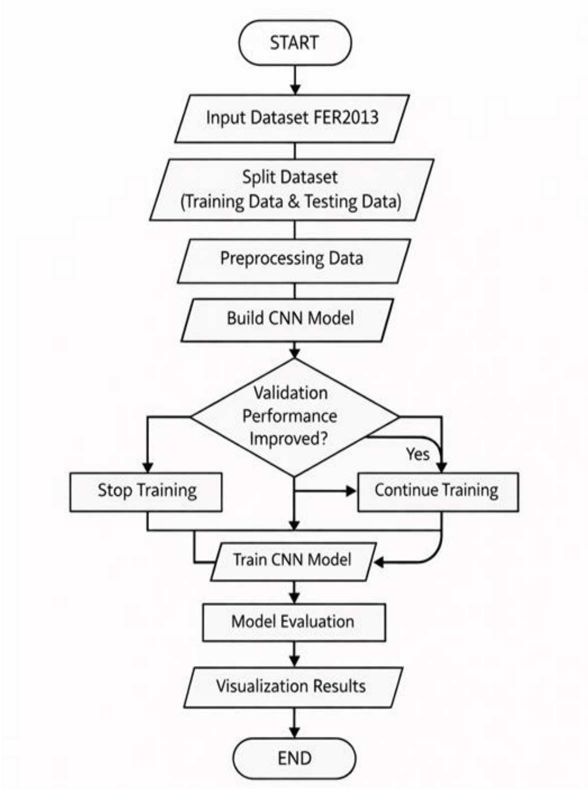

Figure 1. Flowchart

The overall research workflow is illustrated in Figure 1. The process begins with inputting the FER2013 dataset, followed by dataset splitting and preprocessing. A CNN model is then constructed and trained using the training dataset. During training, validation performance is continuously monitored to determine whether model performance improves. If validation performance does not improve, training is terminated using an early stopping mechanism; otherwise, training continues. After training, the final model is evaluated using the testing dataset, and the results are visualized and analyzed to assess model performance.

2.6. Evaluation Metrics

Model performance is evaluated using multiple metrics to ensure a comprehensive assessment. Overall accuracy is used to measure the proportion of correctly classified samples. Precision, recall, and F1-score are computed for each emotion class to evaluate class-wise performance under imbalanced data conditions. The F1-score is emphasized as a key metric because it balances precision and recall, making it more informative than accuracy alone for imbalanced datasets. In addition, a confusion matrix is generated to analyze misclassification patterns and identify similarities among emotion classes.

3. Result and Discussion

This section presents and discusses the experimental results obtained from the implementation of a Convolutional Neural Network (CNN) for facial emotion recognition using the FER2013 dataset. The evaluation focuses on training behavior, overall classification performance, and detailed class-wise analysis to assess both the effectiveness and limitations of the proposed approach.yang sesuai.

3.1. Distribution of Samples per Emotion Class

To strengthen the analysis of the class-wise F1-score results, a distribution of the number of samples for each emotion class in the FER2013 dataset is presented in Table 3. This distribution provides additional context for understanding the variation in classification performance across different emotion categories.

Table 3. Distribution of Samples per Emotion Class in FER2013 Dataset

Emotion	Number of Samples
Angry	5911
Disgust	658
Fear	6145
Happy	10763
Neutral	7431
Sad	7324
Surprise	4832

The table shows that the FER2013 dataset is highly imbalanced across emotion classes. Emotion categories with a larger number of samples, such as happy and neutral, tend to achieve higher F1-scores, while minority classes, particularly disgust, show lower performance due to limited training data availability.

3.2. Training Performance Analysis

During the training process, the CNN model exhibited a stable and consistent learning behavior. Training accuracy increased progressively across epochs, while training loss decreased steadily, indicating effective feature learning from facial images. Validation accuracy showed a similar trend during the early training stages, demonstrating that the model was able to generalize reasonably well to unseen data. However, after several epochs, validation loss no longer showed significant improvement. This condition activated the early stopping mechanism, resulting in the termination of training at epoch 15, despite the maximum epoch being set to 30. This behavior confirms that early stopping effectively prevented overfitting and preserved the model's generalization capability.

Figure 2 presents the training and validation accuracy curves, while Figure 3 illustrates the corresponding loss curves. The relatively small gap between training and validation performance throughout the training process indicates that the model did not excessively memorize the training data. This result supports the effectiveness of combining a simple CNN architecture with early stopping when applied to limited and imbalanced datasets such as FER2013.

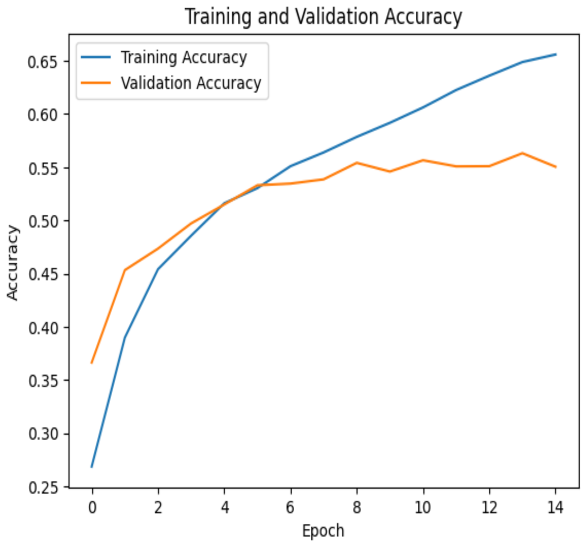

Figure 2. Training and Validation Accuracy

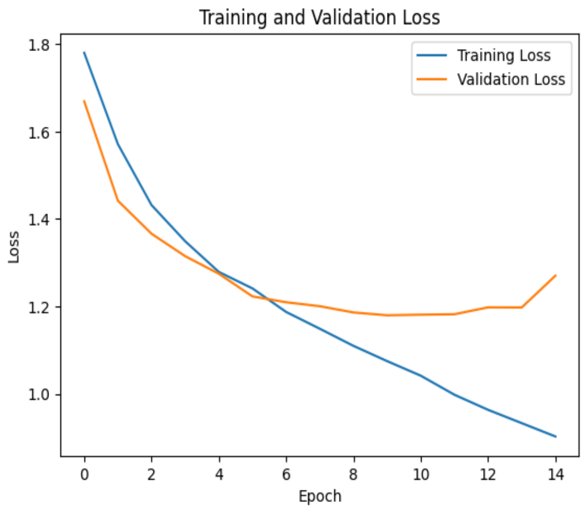

Figure 3. Training and Validation Loss

3.3. Overall Classification Performance

The trained CNN model achieved an overall test accuracy of 55.50%. Although this accuracy may appear moderate when compared to results obtained using deeper or more complex architectures, it must be interpreted within the context of the FER2013 dataset. FER2013 consists of low-resolution grayscale images (48 × 48 pixels) and exhibits significant class imbalance, both of which substantially increase the difficulty of facial emotion recognition.

Previous studies employing baseline CNN architectures on the FER2013 dataset have reported similar performance ranges, particularly when advanced techniques such as data augmentation, attention mechanisms, or ensemble learning are not applied [17], [18].

Therefore, the obtained accuracy demonstrates that the proposed CNN model is capable of learning meaningful facial representations despite these inherent dataset limitations.

3.4. Class-wise Performance Evaluation

To provide a more comprehensive evaluation beyond overall accuracy, precision, recall, and F1-score were calculated for each emotion class. The detailed classification results are summarized in Table 4.

Table 4. Classification Report on Test Dataset

Emotion	Precision	Recall	F1-score
Angry	0.4902	0.4165	0.4503
Disgust	0.6667	0.0360	0.0684
Fear	0.3906	0.2021	0.2664
Happy	0.6993	0.8444	0.7651
Neutral	0.4842	0.5831	0.5291
Sad	0.4190	0.4459	0.4320
Surprise	0.6876	0.7232	0.7050
Average (Weighted)	**0.5399**	**0.5550**	**0.5358**

The happy emotion achieved the highest F1-score (0.7651), followed by surprise (0.7050). These emotions are characterized by distinctive and exaggerated facial expressions, such as smiling or widened eyes, which are easier for the CNN to recognize. This observation is consistent with previous studies, where emotions with clear visual patterns consistently achieved higher classification performance.

In contrast, the disgust emotion exhibited a very low recall value (0.0360), resulting in the lowest F1-score. This outcome is primarily caused by the limited number of training samples available for this class in the FER2013 dataset. Severe class imbalance restricted the model's ability to learn robust and discriminative features for minority classes. Similarly, fear and sad emotions showed lower performance due to subtle visual differences and overlap with neutral expressions [19], [20].

These results confirm that class imbalance remains a critical factor affecting CNN-based facial emotion recognition performance, even when multiple evaluation metrics are employed.

3.5. Confusion Matrix Analysis

The confusion matrix presented in Figure 4 provides further insight into the classification behavior of the proposed model. Several emotion classes, particularly fear, sad, and neutral, were frequently misclassified as one another. This confusion is reasonable because these emotions often share similar facial muscle movements, especially when represented using low-resolution grayscale images.

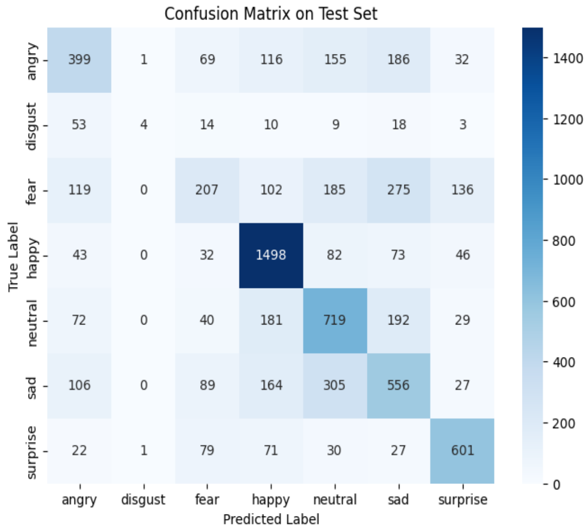

Figure 4. Confusion Matrix

The confusion matrix highlights the inherent difficulty of distinguishing visually similar emotions and emphasizes the limitations of relying solely on spatial features extracted by a basic CNN architecture without additional enhancement techniques.

3.6. F1-score Distribution Analysis

Figure 5 illustrates the distribution of F1-scores across all emotion classes. The emphasis on F1-score is particularly important in this study due to the imbalanced nature of the FER2013 dataset, as this metric provides a balanced evaluation of precision and recall. While the model achieved satisfactory performance for majority classes, the lower F1-scores observed for minority classes further confirm the impact of class imbalance on recognition performance.

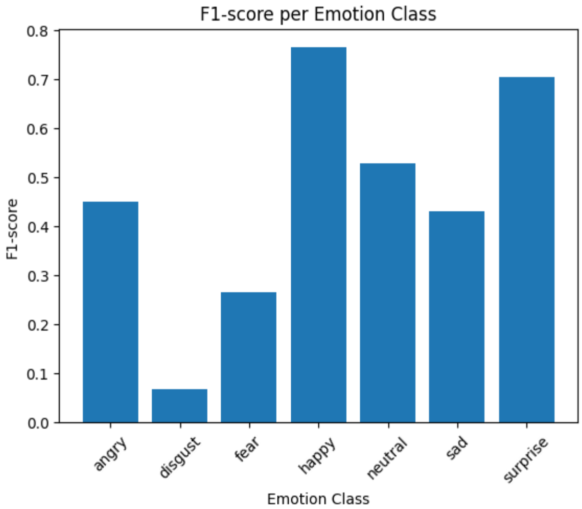

Figure 5. F1-score per Emotion Class

This finding is consistent with previous research, which reports similar performance degradation for underrepresented emotion categories in the FER2013 dataset.

3.7. Discussion and Practical Implications

Overall, the experimental results demonstrate that the proposed CNN model is capable of achieving reasonable performance on the FER2013 dataset using a simple and computationally efficient architecture. Although the proposed approach does not outperform more complex models reported in the literature, it provides a strong baseline and highlights the trade-off between model simplicity and recognition performance.

One of the main limitations of this study is the reliance on a relatively simple CNN architecture. While this design offers lower computational cost and easier implementation, it limits the model's ability to capture highly complex facial patterns. This limitation is particularly evident for emotions with subtle visual differences, such as fear, sad, and neutral.

Another limitation is related to the characteristics of the FER2013 dataset itself. The low-resolution grayscale images restrict the availability of detailed facial texture information, and the significant class imbalance—especially for the disgust emotion—strongly influences classification performance.

From a practical perspective, the results indicate that a simple CNN model can still provide meaningful performance for facial emotion recognition tasks, particularly in applications with limited computational resources, such as embedded systems or real-time emotion recognition on edge devices. However, applications requiring higher accuracy and robustness may benefit from future enhancements, including data augmentation, class balancing strategies, or deeper CNN architectures with attention mechanisms.

4. Conclusion

This study evaluated the performance of a Convolutional Neural Network (CNN) for facial emotion recognition using the FER2013 dataset. The experimental results demonstrate that the proposed CNN model is capable of learning meaningful facial features and achieving reasonable classification performance despite the challenges posed by low-resolution grayscale images and imbalanced class distributions.

The application of an early stopping strategy effectively prevented overfitting and improved model generalization, resulting in an overall test accuracy of 55.50%. Class-wise performance analysis revealed that emotions with distinctive facial characteristics, such as happy and surprise, achieved higher F1-scores, while minority and visually subtle emotion classes, particularly disgust, fear, and sad, exhibited lower recognition performance. Confusion matrix analysis further confirmed frequent misclassification among emotions with similar facial patterns, especially between fear, sad, and neutral expressions.

Overall, the findings indicate that a simple CNN architecture can serve as an effective baseline for facial emotion recognition on the FER2013 dataset. This research highlights the importance of addressing class imbalance and subtle inter-class similarities when developing emotion recognition systems. Although the proposed approach does not outperform more complex models reported in the literature, it provides valuable baseline insights and demonstrates the trade-off between model simplicity and recognition performance.

Future research may improve classification accuracy and robustness by incorporating data augmentation techniques, class rebalancing strategies, or deeper CNN architectures with attention mechanisms, while maintaining computational efficiency. The results of this study can serve as a reference for the development of lightweight facial emotion recognition systems and for comparative evaluation of more advanced approaches under similar experimental conditions.

From a practical perspective, the proposed CNN model can be applied as a lightweight facial emotion recognition system in real-world applications with limited computational resources. Potential use cases include e-learning platforms to monitor student engagement, human–computer interaction systems, and real-time emotion analysis on edge or embedded devices. In addition, the results of this study provide a practical baseline for researchers and developers to evaluate and compare more advanced facial emotion recognition models under similar dataset constraints.

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