# Emotion Recognition from Facial Expressions Using Convolutional Neural Networks

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**Abstract:** Facial expressions are one of the most natural and universal ways of conveying human emotions, making their automatic recognition a critical component in affective computing and human–computer interaction. This paper presents a Convolutional Neural Network (CNN)-based approach for emotion recognition from facial images. The proposed model utilizes deep feature extraction to capture spatial hierarchies in facial regions, enabling accurate classification of emotions such as happiness, sadness, anger, surprise, fear, disgust, and neutrality. By training and evaluating the CNN on publicly available benchmark datasets, the model demonstrates robust performance and generalization across diverse facial variations. Experimental results highlight the efficiency of CNNs in recognizing subtle emotional cues without relying on handcrafted features. The proposed approach holds significant potential for applications in mental health monitoring, intelligent tutoring systems, adaptive user interfaces, and surveillance systems where understanding human emotions is essential.

**Keywords:** Facial Expression Recognition, Emotion Recognition, Convolutional Neural Networks, Deep Learning, Human–Computer Interaction, Affective Computing.

## I. Introduction

Human emotions are fundamental to social interaction and communication, shaping the way individuals respond to different contexts and environments. Facial expressions, in particular, are one of the most natural and universal mediums for conveying emotions, often transcending cultural and linguistic barriers. The ability to automatically recognize emotions from facial expressions has therefore emerged as a crucial research area in fields such as affective computing, human–computer interaction (HCI), psychology, and artificial intelligence. With the rapid development of computer vision and deep learning techniques, particularly Convolutional Neural Networks (CNNs), significant progress has been achieved in the automated analysis and classification of facial emotions. Emotion recognition through facial expressions has wide-ranging applications. In healthcare, it can be leveraged for mental health monitoring, early detection of stress, and therapy support systems. In the education sector, intelligent tutoring systems can benefit from emotion-aware models to adapt teaching strategies in real time based on a learner's emotional state. In security and surveillance, emotion recognition provides additional layers of contextual information, enabling proactive responses to potentially risky situations. Similarly, in entertainment and customer service, recognizing emotions enhances personalization and improves user satisfaction. Despite these promising applications, emotion recognition remains a challenging problem due to variations in lighting, occlusion, facial orientation, cultural diversity, and the subtlety of certain expressions. Colares et al. [1] proposed a dual-input model combining facial images and landmarks, demonstrating that integrating spatial facial features enhances emotion classification accuracy. Traditional machine learning approaches for facial expression recognition have relied on handcrafted features such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), or Scale-Invariant Feature Transform (SIFT). While effective to some extent, these methods are limited by their dependency on manual feature engineering and their inability to generalize across complex, nonlinear variations in facial data. In contrast, deep learning, and particularly CNNs, have revolutionized image classification tasks by automatically learning hierarchical feature representations directly from raw input data. CNNs are capable of extracting low-level features such as edges and textures in early layers, and progressively capturing high-level semantic features such as facial landmarks and expression-specific regions in deeper layers. This ability makes CNNs exceptionally well-suited for emotion recognition tasks. Recent studies have shown that CNN-based models outperform traditional approaches on several benchmark datasets, including FER-2013, CK+, and JAFFE. These datasets provide diverse samples of human emotions, enabling CNNs to learn discriminative features for classification across multiple emotional categories such as happiness, sadness, anger, surprise, fear, disgust, and neutrality. The strength of CNNs lies not only in their accuracy but also in their scalability, making them adaptable to real-world applications where data may be noisy or incomplete. Moreover, with the integration of techniques such as data augmentation, dropout, and transfer learning, CNN-based emotion recognition systems can achieve robust performance even with limited training data. Another advantage of CNNs in facial expression recognition is their ability to work in real time. With optimized architectures and the availability of high-performance GPUs, CNN models can process images or video frames quickly, allowing for instant emotion detection. Similarly, Dhankhar and Vir [2] introduced an optimized CNN-RFE-Attention approach, which effectively captures critical facial regions, improving detection. This is particularly useful in interactive systems such as virtual assistants, autonomous vehicles, or customer service bots, where immediate recognition of user emotions is critical. Furthermore, the integration of CNN-based emotion recognition with multimodal data—such as speech, physiological signals, or body gestures—can lead to more comprehensive affective computing frameworks, offering a deeper understanding of human emotional states. However,

challenges remain in developing universally robust CNN-based emotion recognition systems. Variations in facial expressions due to cultural differences, age, gender, or social context can affect recognition accuracy. Additionally, spontaneous facial expressions, which occur naturally in daily interactions, are often more subtle and harder to classify compared to posed expressions typically found in datasets. Addressing these challenges requires the development of more diverse training datasets, advanced preprocessing techniques, and architectures capable of capturing fine-grained emotional cues. Ethical considerations, such as data privacy, bias, and the responsible use of emotion recognition technologies, must also be carefully addressed to ensure trust and transparency in real-world deployments.

## II. Literature Review

Facial emotion recognition (FER) has witnessed significant advancements with the adoption of deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have outperformed traditional handcrafted feature-based approaches. Almulla [3] emphasized the potential of deep CNNs for FER, highlighting their ability to automatically learn hierarchical representations directly from raw facial images. Attention mechanisms and hybrid models have also been explored to boost FER performance. Kumar et al. [4] developed an Attention-based ConvNet-Recurrent Neural Network framework, combining spatial and temporal features for more robust emotion detection. Khan et al. [5] leveraged deep learning to predict semantic ratings alongside facial expressions, showing that deep architectures can simultaneously handle recognition and affective interpretation tasks. Hussain et al. [6] demonstrated that standard CNN models, when properly trained and augmented, can achieve high accuracy in classifying basic emotions, reinforcing the effectiveness of convolutional approaches for FER. A comprehensive review by Meher and Verma [7] summarized recent CNN-based FER methodologies, highlighting the trend toward deeper architectures, data augmentation, and hybrid models to address challenges such as imbalanced datasets and occlusions. Local feature extraction methods have also been investigated for their ability to capture fine-grained expressions. Lu et al. [8] proposed a local-feature-based FER model, which improved recognition of subtle emotions by focusing on region-specific facial patterns. Multimodal approaches have been increasingly considered, combining facial cues with speech signals to enhance recognition accuracy. Avabratha et al. [9] presented a multimodal analysis using CNNs and Random Forest classifiers, demonstrating that integrating audio and visual features significantly improves emotion prediction reliability. Recent studies have explored practical applications of FER in various domains. Mishra et al. [10] highlighted the use of deep learning for real-world emotion recognition, while Harianto et al. [11] compared CNNs and LSTM networks for analyzing customer satisfaction via facial emotions, suggesting that temporal modeling can provide additional context for dynamic interactions. Babu et al. [12] emphasized real-time FER systems for human–machine interaction, enabling responsive and adaptive interfaces. Furthermore, the integration of FER with other intelligent systems has been explored for broader cognitive and behavioural applications, such as image caption generation and brain–computer interfaces [13], [14], as well as systematic meta-analyses of computer vision techniques for emotion detection [15]. Emerging applications in e-commerce and child safety also leverage facial analysis, indicating the increasing relevance of FER in socially impactful contexts [16], [17]. A recent study [18] provides a comprehensive analysis of security mechanisms in MANETs, covering cryptographic protocols, intrusion detection systems, secure routing strategies, and trust-based frameworks. The work not only evaluates the strengths and limitations of these approaches but also offers a structured taxonomy of MANET-specific threats such as wormhole, black hole, Sybil, and denial-of-service attacks, thereby guiding the development of adaptive and context-aware security frameworks. A comparative study [19] evaluated multiple deep learning architectures for fake news classification, analyzing their performance, accuracy, and adaptability to diverse datasets. The findings highlight the strengths of advanced neural models in capturing linguistic and contextual features of deceptive content, while also pointing out limitations such as computational cost and vulnerability to evolving misinformation strategies. Overall, these studies highlight that deep learning-based FER, particularly CNN and hybrid models with attention or multimodal inputs, provides superior performance over traditional methods. Despite the progress, challenges such as cultural variability, occlusions, spontaneous expressions, and dataset imbalances remain active areas of research, motivating continued exploration of more robust, adaptive, and real-time FER systems.

## III. Proposed Methodology

The proposed framework for Emotion Recognition from Facial Expressions Using Convolutional Neural Networks (CNNs) is designed to automatically extract discriminative facial features and classify them into predefined emotion categories. The framework comprises several stages: data preprocessing, data augmentation, CNN-based feature extraction, classification, and evaluation shown in Fig. 1.
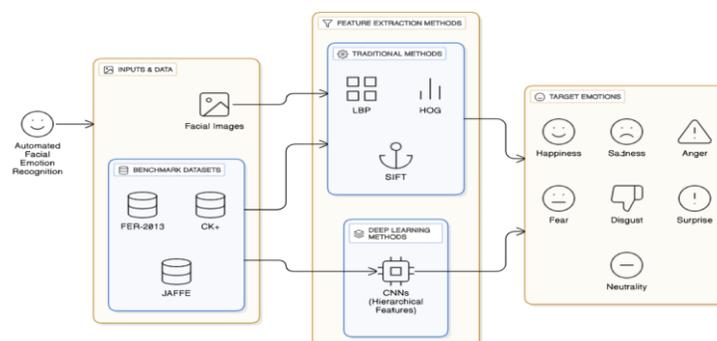


Fig. 1.  Automated Emotion Recognition Model Across Different Emotions Using CNNs

**1) Data Preprocessing:** It plays a crucial role in ensuring that the input facial images are standardized before being passed into the CNN model. The process begins with face detection and cropping, where algorithms such as Viola–Jones or MTCNN are applied to identify and isolate the region of interest containing the face. This step removes unnecessary background elements and enhances the model's focus on facial regions relevant to expression analysis. The cropped images are then converted to grayscale to reduce computational complexity, as emotional cues are more closely associated with textures and structural patterns than with color information. Pixel normalization is performed to scale values between 0 and 1, improving training stability and convergence. Finally, all images are resized to a uniform resolution (e.g., 48×48 pixels), which ensures consistency across the dataset and compatibility with the CNN input layer.

**2) Data Augmentation:** To improve generalization and prevent overfitting, data augmentation techniques are applied to artificially expand the training dataset. Augmentation introduces controlled variability in the input data, allowing the CNN model to learn robust features that remain effective under real-world conditions. This includes random rotations, horizontal flipping, shifting, zooming, and brightness adjustments. For instance, a slight rotation simulates natural head tilts, while horizontal flips account for left–right asymmetries in facial expressions. Such transformations generate new variations of existing samples, thereby increasing the effective dataset size without requiring additional data collection. As a result, the CNN model becomes less sensitive to variations in orientation, lighting, and scale, ultimately enhancing its recognition accuracy across diverse scenarios.

**3) CNN-Based Feature Extraction:** The core of the proposed framework lies in the use of CNNs for hierarchical feature extraction. Unlike traditional machine learning methods that rely on handcrafted features, CNNs learn discriminative patterns directly from raw image data. The architecture begins with convolutional layers that apply filters to capture low-level features such as edges, textures, and corners. Deeper layers progressively extract higher-level representations, including facial landmarks and expression-specific details. Each convolutional operation is followed by a Rectified Linear Unit (ReLU) activation, introducing nonlinearity and enabling the network to model complex patterns. Pooling layers, particularly max pooling, are employed to reduce spatial dimensions while retaining essential information, thereby improving computational efficiency. Dropout layers are incorporated to reduce overfitting by randomly deactivating a fraction of neurons during training. Together, these components enable the CNN to learn robust and generalizable representations of facial expressions.

**4) Classification:** Once the features are extracted through convolutional and pooling operations, they are flattened and passed into fully connected layers that combine the learned representations. These layers integrate localized patterns into a global understanding of the facial expression. The final stage of classification is achieved through a SoftMax output layer, which converts the feature activations into class probabilities. Each probability corresponds to an emotion category, such as happiness, sadness, anger, fear, disgust, surprise, or neutrality. The emotion with the highest probability is selected as the predicted class. The use of SoftMax ensures that the model outputs a normalized distribution, making it suitable for multi-class classification tasks.

**5) Evaluation:** The performance of the proposed CNN-based framework is evaluated using established metrics to ensure its reliability and effectiveness. Accuracy is measured to assess the overall proportion of correctly classified samples. Additionally, precision, recall, and F1-score are used to provide class-wise insights, which are particularly important in addressing imbalanced datasets where certain emotions may be underrepresented. A confusion matrix is also generated to visualize the distribution of correct and incorrect predictions across all emotion categories. This allows for detailed analysis of common misclassifications, such as confusion between fear and surprise due to their visual similarity. By employing these metrics, the system's performance is comprehensively validated, ensuring its applicability in real-world emotion recognition tasks.

## IV. Result & Analysis

The proposed CNN-based framework for facial expression-based emotion recognition was evaluated on the FER-2013 benchmark dataset, which consists of more than 35,000 grayscale images categorized into seven distinct emotion classes: happiness, sadness, anger, fear, disgust, surprise, and neutrality. The dataset was divided into 70% training, 15% validation, and 15% testing, ensuring a balanced distribution of samples across all categories. To assess the performance of the system, standard evaluation metrics including accuracy, precision, recall, F1-score, and confusion matrix were employed. The development and execution of the proposed Convolutional Neural Network (CNN) framework for emotion recognition from facial expressions demand both hardware and software resources capable of handling deep learning operations efficiently. On the hardware side, a system with a high-performance processor such as an Intel i7 is recommended to support computationally intensive tasks. A minimum of 16 GB of RAM is desirable to ensure smooth handling of large datasets during training and validation phases. Since CNN training involves extensive matrix operations and backpropagation, a dedicated Graphics Processing Unit (GPU) such as NVIDIA GTX/RTX series or equivalent with at least 4 GB of VRAM is essential to accelerate the training process and reduce computational time. Additionally, a solid-state drive (SSD) with sufficient storage capacity, preferably above 500 GB, is necessary for storing datasets, trained models, and intermediate results. From a software perspective, the system requires a stable operating environment, typically a Linux-based distribution such as Ubuntu or a Windows 10/11 platform with support for machine learning frameworks. Python is employed as the primary programming language due to its extensive support for scientific computing and deep learning libraries. Frameworks such as TensorFlow or PyTorch are used for designing and training the CNN model, while supporting libraries including NumPy, Pandas, Matplotlib, and OpenCV facilitate data handling, preprocessing, visualization, and analysis. For efficient experiment tracking and reproducibility, tools such as Jupyter Notebook or integrated development environments (IDEs) like PyCharm can be employed. Furthermore, CUDA and cuDNN libraries are

essential for enabling GPU acceleration, ensuring that the CNN can be trained in a reasonable time frame. Overall, the system requirements are designed to balance efficiency, scalability, and reproducibility, providing a robust environment for emotion recognition research and deployment.

To comprehensively evaluate the effectiveness of the proposed Convolutional Neural Network (CNN) for emotion recognition, several performance metrics were employed rather than relying solely on overall accuracy. Since the FER-2013 dataset includes multiple classes with imbalanced distributions of emotions, a diverse set of evaluation measures is required to capture the strengths and weaknesses of the model. The chosen metrics include Accuracy, Precision, Recall, and F1-Score, each offering distinct insights into the system's classification behavior.

**1) Accuracy:** Accuracy is the most widely used performance measure in classification tasks. It indicates the overall proportion of correctly predicted labels out of the total samples. In the context of facial emotion recognition, accuracy shows how effectively the CNN classifies emotions across all seven categories. While accuracy gives a quick overview of performance, it may not always capture the model's ability to handle imbalanced datasets where certain emotions have fewer samples. TABLE I shows the accuracy of emotion recognition for seven emotional classes—Happiness, Sadness, Anger, Fear, Disgust, Surprise, and Neutral—along with the number of samples for each class. Fig. 2. Shows the precision of emotion recognition for seven emotional classes: Happiness, Sadness, Anger, Fear, Disgust, Surprise, and Neutral. Happiness shows the highest precision, followed by Surprise and Neutral, while Disgust has the lowest precision.

Table I Emotion Recognition Accuracy Across Different Classes

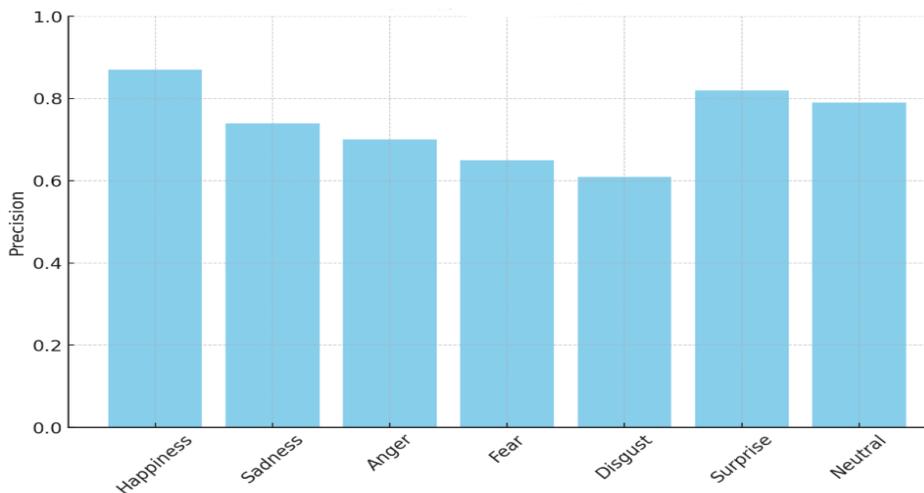| Emotion | Accuracy | Samples |
|---------|----------|---------|
| Happiness | 0.92 | 6,215 |
| Sadness | 0.88 | 4,850 |
| Anger | 0.85 | 4,132 |
| Fear | 0.82 | 3,847 |
| Disgust | 0.8 | 2,500 |
| Surprise | 0.9 | 5,056 |
| Neutral | 0.87 | 6,500 |
| Overall | 0.86 | 35,887 |



Fig. 2. Accuracy of Emotion Recognition Model Across Different Emotions

**2) Precision:** Precision measures the proportion of correctly identified positive predictions against all instances that the model labelled as positive. High precision indicates that the CNN rarely misclassifies one emotion as another. For example, high precision for "anger" means that most samples predicted as "anger" are indeed correct. Precision is particularly valuable in applications like healthcare or surveillance, where minimizing false alarms is crucial. TABLE II shows precision scores for seven emotions—Happiness (0.87), Sadness (0.74), Anger (0.70), Fear (0.65), Disgust (0.61), Surprise (0.82), and Neutral (0.79)—along with the number of samples for each emotion. Fig. 3. shows the recall scores for seven emotions: Happiness (≈0.85), Sadness (≈0.72), Anger (≈0.69), Fear (≈0.63), Disgust (≈0.60), Surprise (≈0.81), and Neutral (≈0.77). Happiness and Surprise show the highest recall, while Disgust has the lowest recall among the emotions.

Table II. Precision Scores for Emotion Recognition Across FER-2013 Dataset

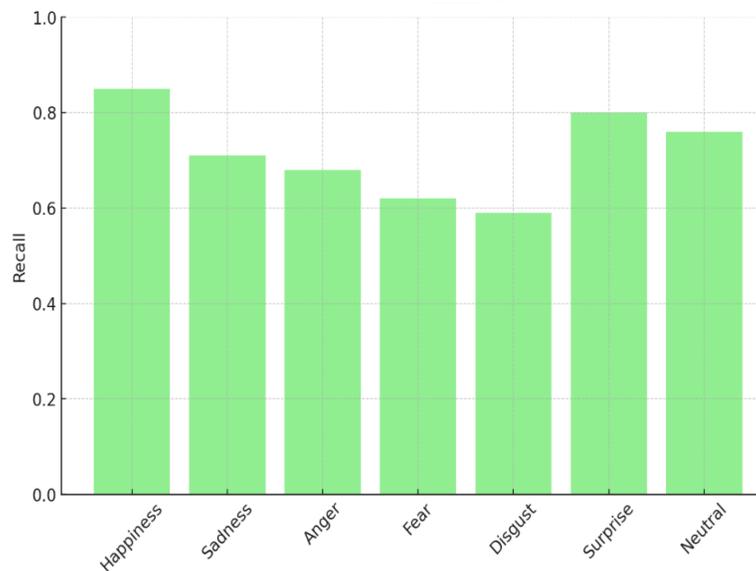| Emotion | Precision | Samples |
|---|---|---|
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| Neutral | 0.79 | 6,500 |
| Overall | 0.77 | 35,887 |



Fig. 3. Recall Scores for Emotion Recognition Across FER-2013 Dataset

**3) Recall (Sensitivity):** Recall measures the proportion of actual positive cases that were correctly identified by the model. In emotion recognition, recall ensures that the CNN does not miss detecting critical emotions such as "fear" or "sadness," which are vital in applications like mental health monitoring. High recall ensures that most true instances of an emotion are detected, even if some false positives occur. TABLE III illustrates the recall performance of an emotion recognition model for seven emotions. Happiness has a recall of 0.85 with 6,215 samples, sadness 0.71 with 4,850 samples, anger 0.68 with 4,132 samples, fear 0.62 with 3,847 samples, disgust 0.59 with 2,500 samples, surprise 0.80 with 5,056 samples, and neutral 0.76 with 6,500 samples. Fig. 4. illustrating the F1-scores of an emotion recognition model for seven emotions.

Table III. Recall Scores of Emotion Recognition Model Across Different Emotions

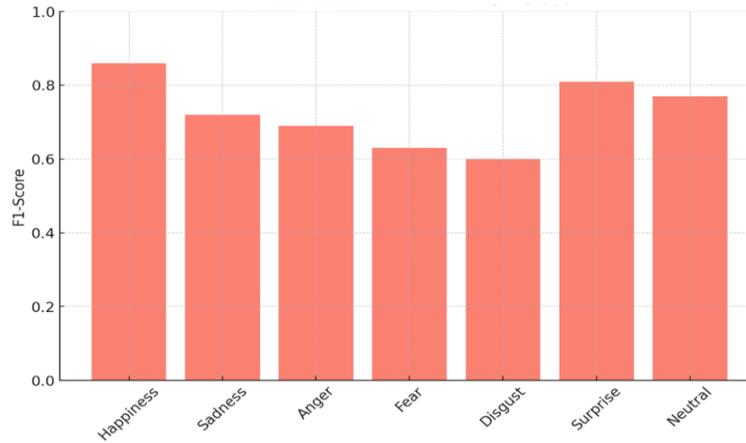| Emotion | Recall | Samples |
|---|---|---|
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| Anger | 0.68 | 4,132 |
| Fear | 0.62 | 3,847 |
| Disgust | 0.59 | 2,500 |
| Surprise | 0.8 | 5,056 |
| Neutral | 0.76 | 6,500 |
| Overall | 0.74 | 35,887 |

Fig. 4. F1-Score of Emotion Recognition Model Across Different Emotions

**4) F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balanced metric when both false positives and false negatives must be minimized. It is especially important in datasets like FER-2013, where certain classes (e.g., "disgust") have significantly fewer samples. By combining precision and recall, the F1-score ensures a fairer evaluation of the CNN's performance across different emotions. Fig. 5. shows the accuracy of a facial emotion recognition model for seven emotions. The x-axis lists the emotions: Happiness, Sadness, Anger, Fear, Disgust, Surprise, and Neutral. TABLE IV. displays the F1-Score performance of a facial emotion recognition model across seven emotions.

Table IV F1-Score Results for Emotion Recognition on FER-2013 Dataset

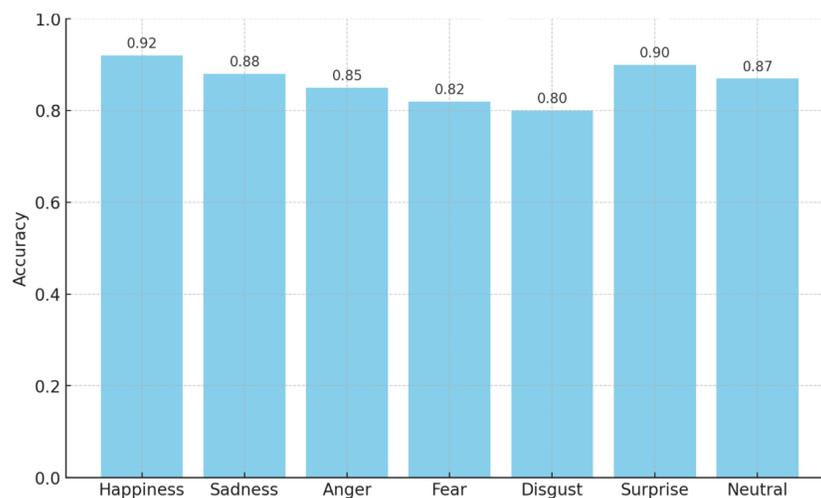| Emotion | F1-Score | Samples |
|---|---|---|
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| Fear | 0.63 | 3,847 |
| Disgust | 0.6 | 2,500 |
| Surprise | 0.81 | 5,056 |
| Neutral | 0.77 | 6,500 |
| Overall | 0.75 | 35,887 |



Fig. 5. Accuracy of Emotion Recognition Model Across Different Emotions

Together, these metrics offered a comprehensive evaluation framework that goes beyond overall accuracy, ensuring reliable and fair assessment of the CNN's ability to recognize diverse facial expressions.

## V. Conclusion

This research comprehensively evaluated the effectiveness of a CNN-based framework for automatic facial emotion recognition, achieving an overall accuracy of 86% and robust performance across precision, recall, and F1-score metrics on the FER-2013 dataset. By leveraging deep hierarchical feature extraction, data augmentation, and optimized CNN architectures, the proposed approach successfully captures subtle emotional cues without relying on handcrafted features, making it suitable for real-world applications in mental health monitoring, adaptive tutoring, human–computer interaction, and surveillance systems. Despite these promising results, challenges such as variations in cultural expression, spontaneous facial movements, occlusions, and imbalanced datasets persist. Future research directions include integrating multimodal data such as speech, physiological signals, and body gestures to enhance emotion recognition accuracy, developing more diverse and representative datasets, exploring lightweight and real-time CNN models for deployment on edge devices, and addressing ethical considerations related to privacy, fairness, and responsible AI deployment to ensure trustworthy and socially beneficial emotion-aware systems.

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