

FACIAL EMOTION RECOGNITION USING RESNET-18 MODEL

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ABSTRACT

Facial Emotion Recognition (FER) is a growing field in computer vision that enables machines to detect and classify human emotions through facial expressions. With the advent of deep learning, particularly Convolutional Neural Networks (CNNs), the performance of FER systems has significantly improved, surpassing traditional handcrafted methods. This paper presents a customized ResNet-18 architecture tailored for FER tasks. The proposed model is evaluated on the FER-2013 using various performance metrics such as accuracy, precision, recall, and F1-score. Our results demonstrate that ResNet-18 provides a strong balance between accuracy and computational efficiency.

1. INTRODUCTION

Human facial expressions are among the most powerful non-verbal cues used in communication. The ability to automatically interpret these expressions has vast implications in domains such as human-computer interaction, mental health assessment, intelligent tutoring systems, and driver fatigue detection [1]. Facial Emotion Recognition (FER) aims to classify facial expressions into predefined emotional states such as happiness, sadness, anger, fear, surprise, and disgust [14].

Traditional FER systems utilized handcrafted features such as Gabor filters, Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT) descriptors [2]. These methods, however, were limited in scalability and generalization across real-world environments. Deep learning models have demonstrated superior performance in extracting hierarchical and spatial features directly from raw pixel data, reducing the need for manual feature engineering [3]. These networks can learn complex patterns that correspond to subtle variations in facial expressions, even in the presence of noise or occlusions. CNNs in particular have demonstrated remarkable success due to their hierarchical learning of spatial patterns in images.

The emergence of deep learning, especially CNNs, has transformed FER by enabling models to learn hierarchical features directly from pixel-level data [4]. This research explores state-of-the-art deep learning methods in FER, focusing on architecture design, dataset utilization, and evaluation metrics.

2. RELATED WORK

Early approaches in FER involved extracting geometric and appearance-based features manually before feeding them into classifiers like Support Vector Machines (SVMs) or k-Nearest Neighbors (k-NN) [5]. These techniques suffered in uncontrolled environments, where variations in lighting, head pose, and occlusion negatively impacted performance.

With the rise of deep learning, CNNs began to outperform traditional models by automatically learning spatial features from images. Mollahosseini et al. [3] developed deep neural networks trained on AffectNet and demonstrated robust performance under real-world conditions. One of the early CNN-based FER models were introduced by Tang [6], who used a shallow CNN to win the FER-2013 Kaggle competition. This demonstrated the feasibility of deep learning in emotion recognition tasks. Other works, such as those by Kim et al. [7], combined CNNs with Recurrent Neural Networks (RNNs) to capture temporal dependencies in video-based FER tasks. Zhao et al. [8] designed transformer-based facial expression recognition with self-supervised learning. Song et al. [9] utilized GANs to generate synthetic facial expressions, helping to balance emotion classes and improve model robustness. Author developed deep learning based efficient emotion recognition technique for facial images [15]. Author presented efficient facial emotion recognition model using deep convolutional neural network and modified joint trilateral filter [16]. Author developed saliency map and deep learning based efficient facial emotion recognition technique for facial images [17]. Author presented comparative Study and Analysis of Various Facial Emotion Recognition Techniques [18]. Author used residual neural network for Facial emotion detection [19]

Recent developments include the use of attention mechanisms and Transformer-based architectures to enhance spatial awareness and feature localization in FER systems [10].

3. METHODOLOGY

3.1 Dataset

We employ the FER-2013[11] benchmark dataset for emotion recognition. It consists of 35,887 grayscale images, each 48x48 pixels, labeled into seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral.

3.2 Preprocessing

To enhance model generalization, the following preprocessing steps are applied:

- **Histogram equalization:** Histogram equalization is a contrast enhancement technique used to improve the global contrast of an image by redistributing the intensity values. It spreads out the most frequent intensity values to use the full range of possible intensities, making features in the image more distinguishable. Histogram is used to normalize lighting conditions.
- **Data augmentation:** Data augmentation is a technique to artificially increase the size and diversity of your training dataset by applying various transformations to existing data samples. This helps improve the model's ability to generalize and reduces overfitting. including rotation, flipping, and scaling

3.3 Model Architecture

Our proposed model is based on a modified **ResNet-18** architecture:

- Input Layer: 48x48 grayscale image.
- 5 convolutional blocks with batch normalization and ReLU.
- Global Average Pooling.
- Fully Connected Layer with Softmax for classification.

Dropout (0.5) is added to prevent overfitting.

3.4 Training Setup

- Optimizer: Adam
- Learning Rate: 0.0001
- Epochs: 50
- Batch Size: 64
- Loss Function: Categorical Cross-Entropy

Training and validation are conducted on an 80/20 split of the FER-2013 dataset.

4. RESULTS AND EVALUATION

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM + LBP [2]	47.6	0.46	0.45	0.45
VGGNet [6]	65.4	0.63	0.64	0.63
Proposed ResNet-18	77.9	0.76	0.75	0.74

Our model achieves high accuracy with notable improvements for facial emotion recognition.

5. DISCUSSION

The results confirm that deep learning models, particularly CNNs with residual connections, are highly effective for FER. However, certain limitations remain:

- **Class imbalance:** Emotions like “disgust” are underrepresented in most datasets [12].
- **Cultural and contextual variation:** Expressions differ across cultures, affecting generalization [13].
- **Real-time performance:** Lightweight models are required for embedded and mobile systems.

Future work includes exploring multi-modal FER by integrating audio and physiological signals, and implementing Transformer-based models for enhanced attention to facial regions.

6. CONCLUSION

This paper presents a deep learning-based approach to facial emotion recognition using a customized ResNet-18 model trained on the FER-2013 dataset. This study confirms that ResNet-18, a relatively shallow residual network, is a strong candidate for FER tasks. When trained with appropriate augmentation techniques and evaluated on benchmark datasets, it achieves high accuracy. Future work will focus on extending the model for video-based FER and integrating temporal information.

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