

Project Proposal: Facial Expression Recognition

Team

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Task Objective

The goal is to perform facial expression classification, identifying emotions from facial images. This task has broad real-world applications—for example, emotion recognition can support targeted advertising strategies, enabling companies to adapt their offerings to customer sentiment.

Dataset

We will use the [FER-2013 Facial Expression Dataset](#) from Kaggle.

A few example images are attached for reference.



Dataset Description

- **Image size:** 48×48 pixels
- **Color channels:** 1 (grayscale)
- **Variation:** The dataset includes a wide range of facial expressions, head poses, lighting conditions, and occlusions.
- **Consistency:** The faces have been automatically registered so that the face is more or less centred and occupies about the same amount of space in each image.

Labels / Emotion Categories

The dataset provides seven emotion categories, defined as below:

- 0 = Angry 😡
- 1 = Disgust 🤢
- 2 = Fear 😨
- 3 = Happy 😊
- 4 = Sad 😞
- 5 = Surprise 😮
- 6 = Neutral 😐

Dataset Composition

Emotion	Training Set (28,709 images)	Public Test Set (3,589 images)
Angry 😡	13.9% (3,995 images)	26.7% (958 images)
Disgust 🤢	1.5% (436 images)	3.1% (111 images)
Fear 😨	14.3% (4,097 images)	28.5% (1,024 images)
Happy 😊	25.1% (7,215 images)	49.4% (1,774 images)
Sad 😞	16.8% (4,830 images)	34.8% (1,247 images)
Surprise 😮	11.0% (3,171 images)	23.2% (831 images)
Neutral 😐	17.3% (4,965 images)	34.4% (1,233 images)

Proposed Approach

1. Traditional Feature Extraction Methods

We will begin with two classical computer vision feature descriptors to establish a strong baseline.

- Histogram of Oriented Gradients (HOG):** Captures edge orientations and overall facial structure (e.g., raised eyebrows, frowns, smiles).
- Local Binary Patterns (LBP):** Captures local texture details such as wrinkles or furrows that reflect micro-expressions and subtle emotional cues.

2. Deep Learning with Transfer Learning

We will leverage pretrained convolutional neural networks (CNNs) for high-level feature extraction.

- ResNet-18:** A neural network with 18 layers that uses skip connections to make training easier. Lightweight and works well on smaller datasets like FER-2013. *Pros: fast to train and reliable; Cons: may miss very complex features.*
- EfficientNet-B0:** A modern neural network that balances layers, width, and image resolution to achieve high accuracy efficiently. *Pros: accurate and resource-efficient; Cons: slightly more complex to fine-tune.*
- Grayscale images will be converted to 3-channel format to match pretrained ImageNet weights.