Facial Emotion Recognition using ResNet-50

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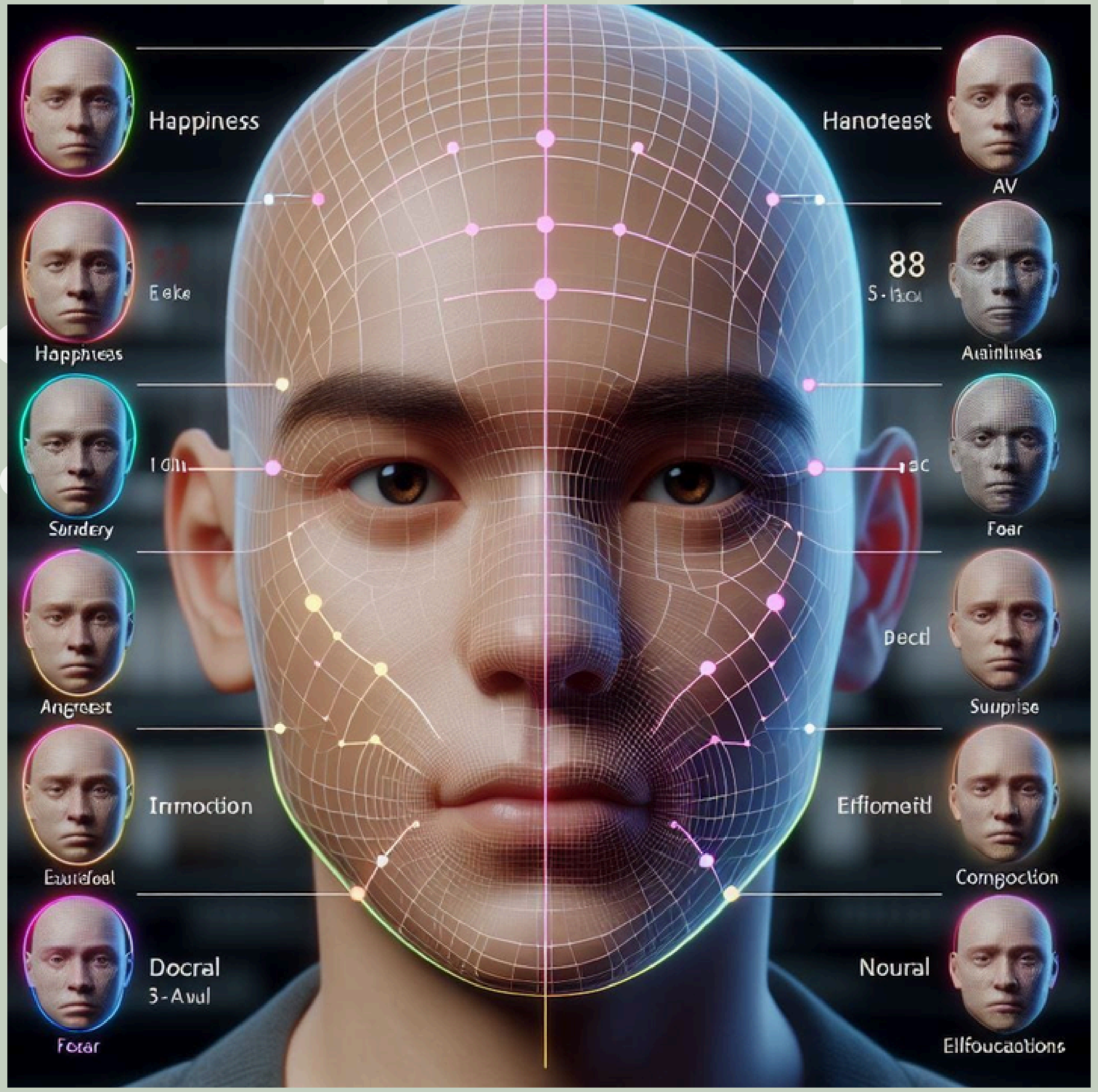
Introduction

Facial expressions play an important role in human communication, as they help us express emotions without words. Automatically recognizing these emotions can improve how machines interact with people and help build emotion-aware systems.

In this project, we built a Facial Emotion Recognition system using deep learning model. We used a pre-trained ResNet50 model and trained it on the FER2013 dataset, which contains facial images labeled with seven emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.
By using transfer learning, our model can accurately predict emotions from facial images. This kind of system can be useful in areas like mental health support, security, customer experience, and AI-based interactions.



Aim and Objective

Aim:

- To design and develop a robust and accurate facial emotion recognition system using deep learning techniques.

Objectives:

- Utilize the **FER2013 dataset**, which consists of 48x48 grayscale images of facial expressions.
- Build a convolutional neural network model using **ResNet50** architecture for feature extraction.
- Train the model to classify facial emotions into **seven categories**: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.
- Evaluate and visualize model performance using metrics and plots.
- This system aims to reduce manual effort in emotion analysis and provide real-time emotion recognition capabilities.

System Requirement Analysis

Platform Used:

- Google Colab – a cloud-based Jupyter Notebook environment providing free access to GPUs.

Programming Language:

- Python – for its simplicity and vast library support in AI/ML development.

Libraries & Frameworks:

- TensorFlow & Keras – for building and training deep learning models.
- OpenCV – for image handling and preprocessing.
- NumPy & Pandas – for data manipulation.
- Matplotlib & Seaborn – for visualizations and data exploration.
- The system requires basic internet access, a browser, and a Google account to run on Colab, making it accessible and easy to deploy.

Methodology

Data Collection & Preprocessing

- Used FER2013 dataset with grayscale facial images and 7 emotion labels.
- Converted pixel strings to 48×48 NumPy arrays, then resized to 224×224 using OpenCV.
- Normalized pixel values to [0, 1]; applied one-hot encoding to labels.

Data Exploration & Visualization

- Visualized class distribution using bar plots.
- Displayed sample images from each class to analyze visual clarity and diversity.

Model Architecture (Transfer Learning)

- Used pre-trained ResNet50 with include_top=False to remove original classifier.
- On top of ResNet50's output, we added:
    - A Global Average Pooling layer to reduce dimensions.

Methodology

- A Dense layer followed by BatchNormalization and Dropout to improve generalization and avoid overfitting.
- A final Dense layer with Softmax activation to predict the 7 emotion classes.
- Initially, all layers of ResNet50 were frozen to use its learned features.
- Later, the last 50 layers were unfrozen and fine-tuned to adapt to our dataset.

Model Training

- The dataset was split into training and validation sets.
- Model trained for 30 epochs with batch training to ensure efficient learning.
- Training and validation accuracy/loss were monitored each epoch to detect overfitting or underfitting.

Evaluation & Saving

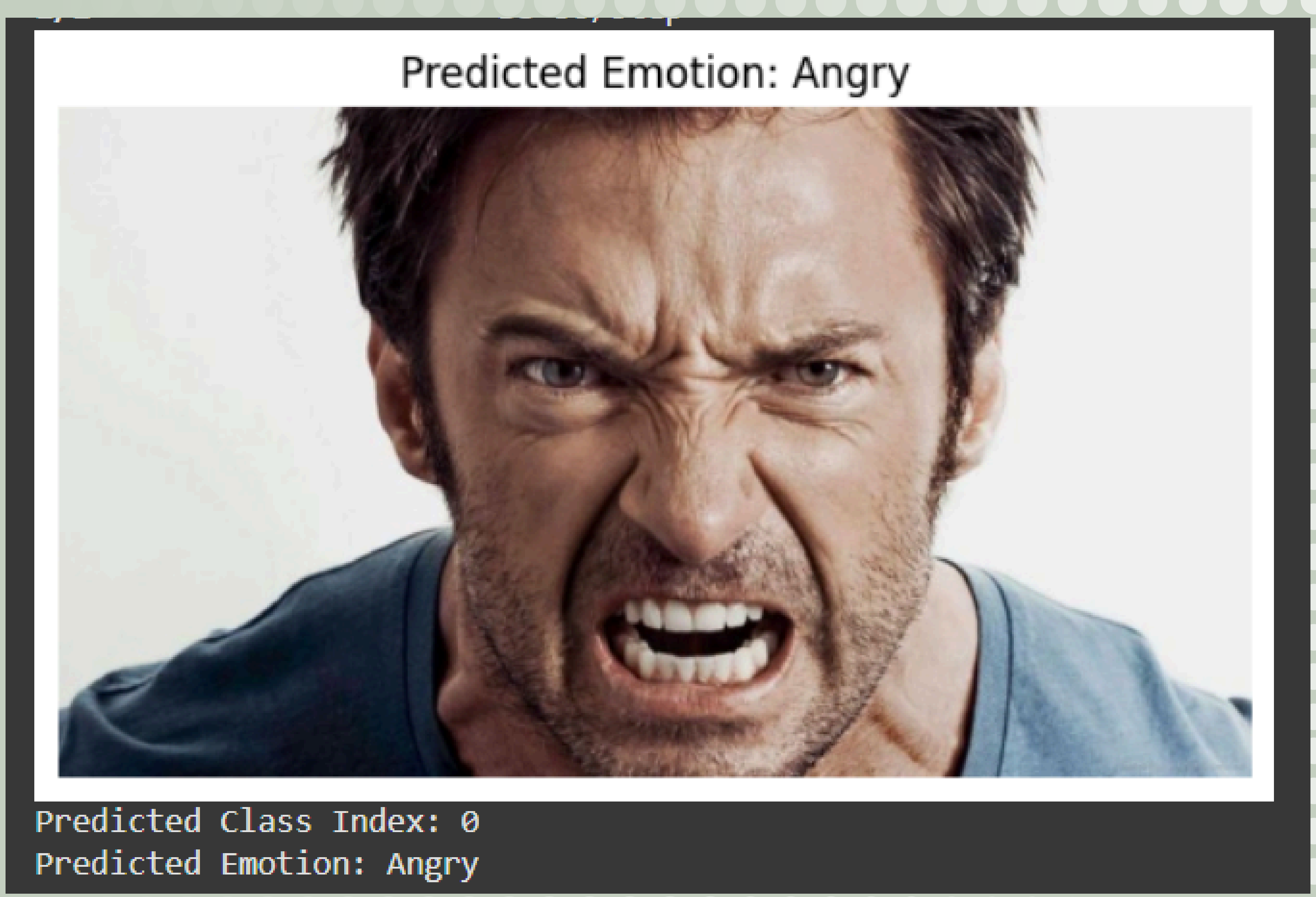
- Model performance was evaluated on a separate test set.
- Used accuracy, confusion matrix, and classification report to measure performance across all emotion classes.
- The trained model was saved in .h5 format for future use or deployment in real-world emotion recognition systems.

Model Prediction

- Input: A facial image displaying an angry expression

- Model Output:
  - Predicted Class Index: 0
  - Predicted Emotion: Angry

The model correctly identifies the emotion as Angry.



The model achieved over 80% accuracy on the training set, With a validation accuracy of 70.01%

Applications

Mental Health Monitoring
Detects emotional changes to assist in early diagnosis and therapy support.

Human-Computer Interaction
Enhances user interaction by enabling emotion-aware intelligent systems.

Customer Feedback Analysis
Analyzes real-time emotional reactions to improve user experience and services.

Education
Tracks student emotions to adjust teaching pace or content dynamically.

Conclusion

In this project, a deep learning model based on ResNet50 was successfully implemented to classify facial emotions using the FER2013 dataset.

Key Takeaways:

- Achieved efficient classification of seven emotion categories.
- Demonstrated the strength of transfer learning in feature extraction.
- Provided a scalable solution for real-world applications.
- This system can serve as a base for building more advanced emotion-aware applications that promote better interaction between humans and machines.

Future Scope

Facial emotion recognition can be extended and enhanced in several ways:

Mobile Deployment:

- Convert the model to TensorFlow Lite for use in mobile apps, enabling real-time facial analysis.

Advanced Architectures:

- Implement CNNs with attention mechanisms or emotion-specific fine-tuning for better accuracy.

Data Enhancement:

- Use data augmentation and Generative Adversarial Networks (GANs) to increase dataset diversity.

Application Integration:

- Integrate into video conferencing, e-learning platforms, and smart cars for emotion-aware systems.

Multimodal Emotion Recognition:

- Combine audio and text data along with facial cues for holistic emotion detection.

THANK YOU