

MULTIMODAL EMOTION RECOGNITION AND EMOJI MAPPING USING FACIAL EXPRESSION AND TEXT ANALYSIS

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A close-up photograph of a highly articulated, metallic robotic hand. It is positioned as if it is interacting with a futuristic, circular digital interface. The interface features several concentric rings and a central glowing blue area, suggesting a touch-sensitive or scanning function. The background is a dark, textured blue.

Introduction

This project combines real-time facial emotion recognition and text-based sentiment analysis to enhance digital communication. Using CNNs with the FER2013 dataset, it identifies seven emotions from facial expressions and maps them to emojis via a Flask. For text input, an LSTM model predicts emotions, offering an interactive interface through flask. The system bridges the emotional gap in virtual interactions with applications in healthcare, education, social media, and beyond.

About the dataset



Images of Faces Dataset:

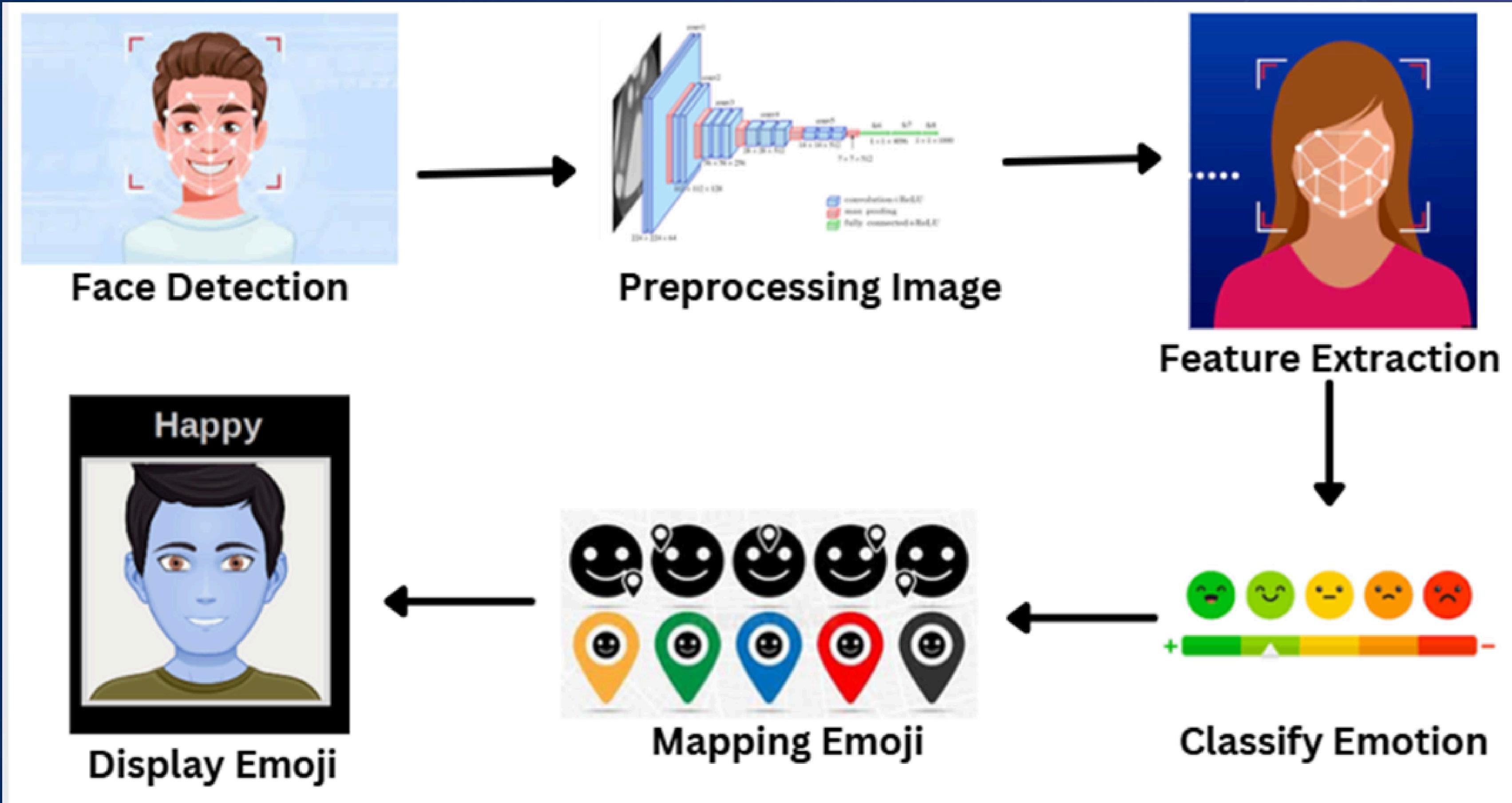
This dataset contains 48x48 pixel grayscale images of faces, centered and uniformly scaled. It includes 28,709 training images and 7,178 test images, each categorized into one of seven emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The dataset is used for facial emotion recognition tasks.

Emotion_final.csv Dataset:

This dataset contains 21,459 text samples labeled with corresponding emotions, such as sadness, anger, love, fear, happiness, and surprise. The "Text" column provides sentences or phrases, while the "Emotion" column categorizes the emotional context, supporting text-based sentiment analysis.

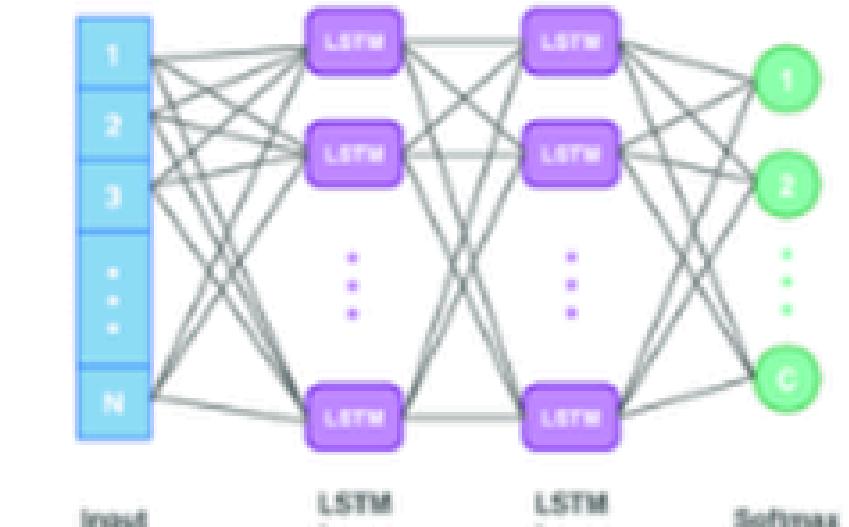


System Architecture of Emoji Mapping



System Architecture of Text analysis

Text
Input



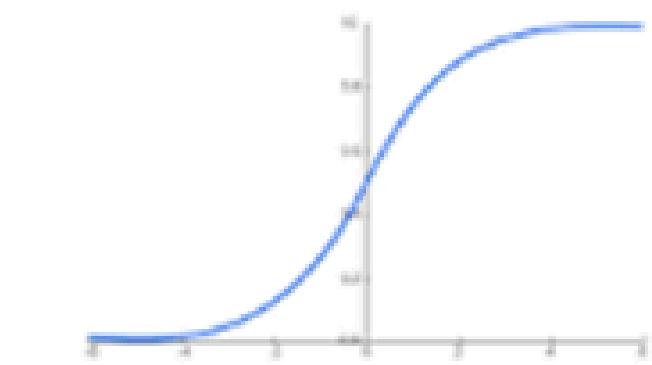
LSTM Layers



Output

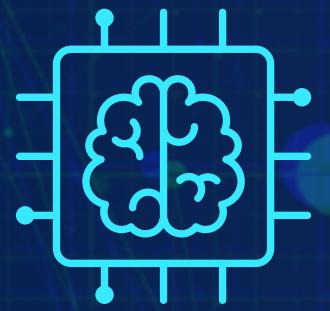


Predicted Emotion



Dense Layer with
Softmax Activation

Libraries used



NumPy

Array processing



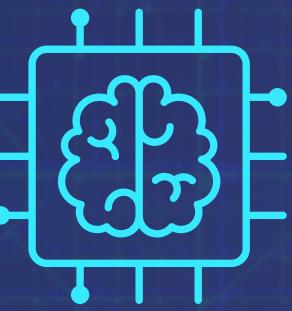
OpenCV

Real-time face
detection



Haar Cascade Classifier

Face detection



Flask

Web development



PIL (Pillow)

Image conversion



Scikit-learn

Dataset splitting,
evaluation



TensorFlow

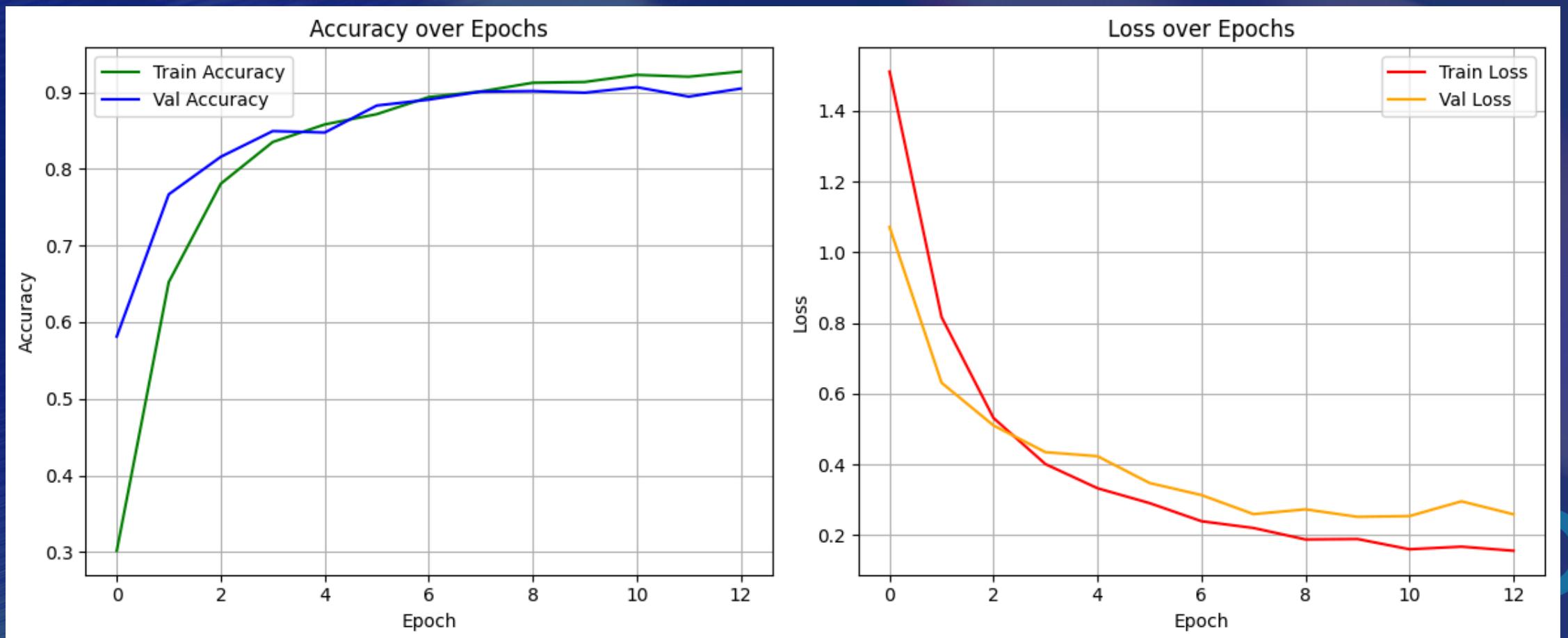
Deep learning
models



Seaborn/Matplotlib

Data visualization

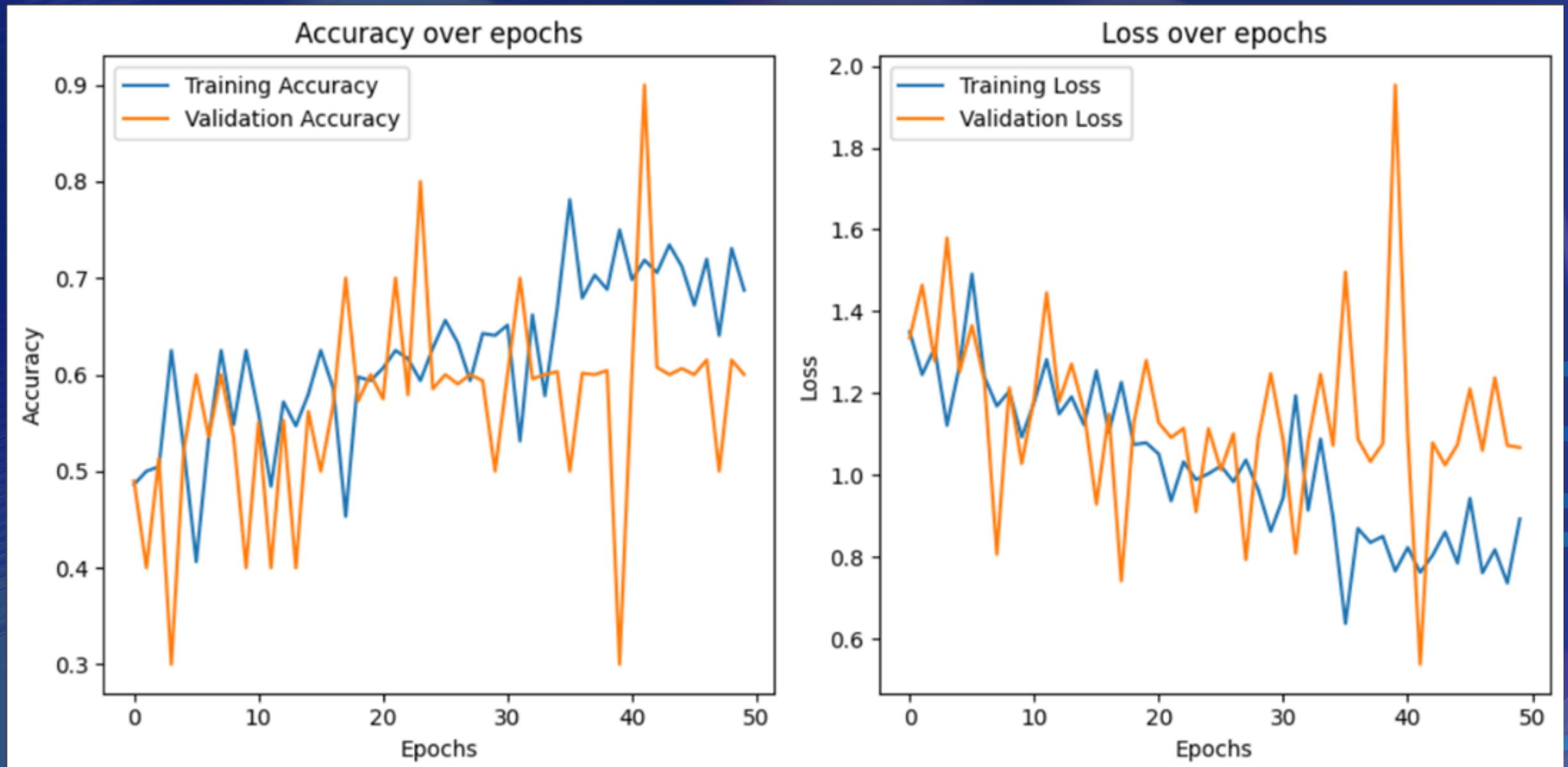
TEXT EMOTION RESULTS



Classification Report:				
	precision	recall	f1-score	support
angry	0.90	0.92	0.91	617
fearful	0.84	0.93	0.88	531
happy	0.96	0.89	0.92	1381
love	0.78	0.94	0.85	318
sad	0.95	0.93	0.94	1277
surprised	0.79	0.75	0.77	168
accuracy				4292
macro avg	0.87	0.89	0.88	4292
weighted avg	0.92	0.91	0.91	4292

- ✓ Overall Accuracy: 91% on the test set.
- 🎯 Highest Precision: Happy (96%) and Sad (95%) classes.
- ⌚ Best Recall: Love (94%) and Fearful (93%).
- ⚠ Lowest Scores: Surprised class had lowest precision (79%) and recall (75%).
- 📊 Macro F1-score: 0.88 – good balance across all 6 classes.

FACE EMOTION RESULTS



- ✓ Achieved 73.6% Training Accuracy – strong learning capability
- 🎯 60% Validation Accuracy – decent generalization with room for improvement
- ⟳ Loss Reduced to 0.72 – model is learning effectively
- ⚠ Slight Overfitting Observed – validation loss ~1.07
- 📊 Next Step: Fine-tune with better data, dropout, or deeper CNN

Applications

- **Mental Health Monitoring:** Track emotional well-being through facial and text analysis for better mental health support.
- **Customer Service:** Enable empathetic and personalized responses in chatbots and support systems.
- **Educational Tools:** Adapt learning materials dynamically based on students' emotions to enhance engagement.
- **Virtual Communication Platforms:** Add real-time emotion detection and emoji mapping for richer interactions.
- **Gaming Industry:** Create immersive experiences by incorporating emotion-based interactions into gameplay.



Conclusion



This project redefines emotion recognition by seamlessly integrating text and facial analysis into a unified system. With cutting-edge NLP and computer vision technologies, it not only deciphers emotions in real-time but also transforms them into visually intuitive emojis, enhancing digital communication. From mental health monitoring to smarter interfaces in education and customer service, this innovation bridges the emotional gap in virtual interactions, making technology more human-centric and engaging.

Thank You

