

Countenance Detection using CNN: An end-to-end Real-Time Emotion Recognition Web Application

Akki Eshwar, Shailesh Bhosekar

Department of Computer Science and Engineering

Keshav Memorial Institute of Technology (Autonomous), Hyderabad, India

Kaggle: <https://www.kaggle.com/code/akkieshwar/notebook5c6bb4febe>

GitHub: <https://github.com/akkieshwar/emotion-detection>

Abstract—In this paper, we present an educational, end-to-end implementation of a real-time facial emotion detection system using a Convolutional Neural Network (CNN), deployed as a browser-based web application. The system combines a Keras/TensorFlow model trained on a public facial expression dataset, a Flask backend, and a webcam-enabled frontend. Browser-captured images are sent to the backend for preprocessing and inference, with predictions returned in real time for live display. This project integrates open-source code and tutorials (with attribution), expands them with a custom-trained model, and documents the entire pipeline for educational reproducibility. The solution demonstrates practical integration of standard AI and web technologies, with applications in affective computing, education, and customer service.

Keywords—Emotion detection, computer vision, CNN, Keras, TensorFlow, Flask, real-time web app, affective computing, educational implementation.

I. INTRODUCTION

Accurately interpreting human emotions from facial expressions is an essential task in affective computing, with broad applications in mental health, education, customer service, and human-computer interaction. Deep learning, especially Convolutional Neural Networks (CNNs), has enabled reliable automated emotion recognition from images. This paper describes an end-to-end, real-time emotion detection system: a custom-trained CNN model is deployed as a Flask web service, accessed from a live webcam-enabled browser UI. The project demonstrates how to translate theory into a complete, usable AI application using open-source tools.

II. RELATED WORK

Numerous tutorials and open-source projects exist for facial emotion detection, often demonstrating isolated parts (e.g., only model training or only web deployment). Many systems are based on the FER-2013 dataset [1] and Keras/TensorFlow example models [2]. Our approach adapts and extends these resources, providing a complete, reproducible workflow from data to live application, as well as documenting engineering and deployment decisions for students and practitioners. Prior YouTube and GitHub tutorials are acknowledged for basic frontend/backend code structure.

III. SYSTEM OVERVIEW

A. Architecture

Frontend: HTML, CSS, JavaScript. Captures webcam video, sends image frames to the backend via HTTP POST, and displays predicted emotion live.

Backend: Flask (Python). Receives images, performs face detection and preprocessing (grayscale, resize, normalize), loads and runs the CNN model, and returns predictions.

Model: Keras/TensorFlow CNN trained on a public dataset to classify emotions (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral).

Integration: End-to-end local deployment for live demo.

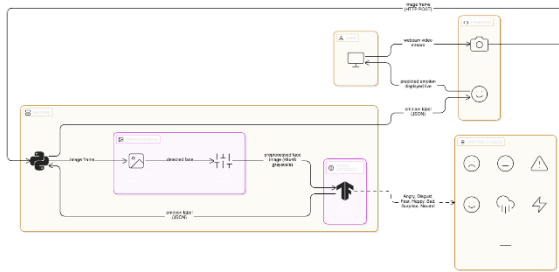


Fig. 1. Architecture of the Proposed Emotion Detection System

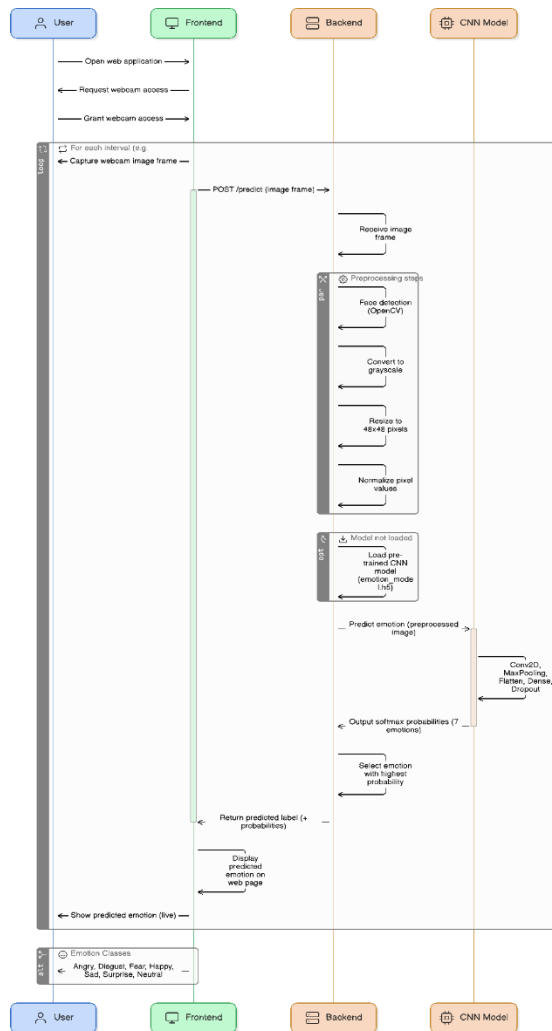


Fig. 2. Component flow design

IV. DATASET AND MODEL

A. Dataset

- Public facial expression dataset.
- Preprocessing: face detection, grayscale conversion, resize to 48x48, normalization (pixel values scaled to [0,1]), data augmentation for robustness.

B. Model

- Keras Sequential CNN with multiple Conv2D, MaxPooling, Flatten, Dense, Dropout layers.
- Activation: ReLU (hidden), Softmax (output).
- Trained with categorical cross-entropy loss and Adam optimizer.
- Achieved 63.5% accuracy on validation set.

V. IMPLEMENTATION DETAILS

A. Backend (Flask, Python)

- app.py handles image upload, loads emotion_model.h5, preprocesses images, predicts emotion, and returns result as JSON
- Uses OpenCV for face detection and image handling
- Fast API response times (<150 ms per image)

B. Frontend (HTML/JS/CSS)

- index.html, script.js, styles.css: accesses webcam with navigator.mediaDevices.getUserMedia, captures frames, sends to /predict endpoint via AJAX, receives and displays predicted emotion

VI. RESULTS AND DISCUSSION

The application delivers real-time emotion detection in a standard browser environment.

Softmax probabilities are returned for each class, with the label of highest probability shown live.

Performance: System predicts emotions within 100–150 ms per frame on a standard PC

Limitations: Accuracy depends on dataset quality and lighting; edge cases (occluded faces, low light) are more challenging; no transfer learning from larger face models (could be a future upgrade)

Test Image	sad	neutral	surprise	fear	happy	angry	disgust	Predicted Label
1	0.0629	0.0079	0.0748	0.4764	0.2288	0.0903	0.0589	fear
2	0.1475	0.0035	0.4871	0.0059	0.0455	0.0485	0.2619	surprise
3	0.0177	0.0001	0.2047	0.0089	0.0055	0.0080	0.7550	disgust
4	0.0126	0.0002	0.0098	0.4952	0.4581	0.0199	0.0043	fear
5	0.0314	0.0002	0.3001	0.0015	0.0191	0.0164	0.6314	disgust

Table 1. Sample Prediction Outputs and Model Decision

Live Emotion Detection



Happiness

Image 1

Live Emotion Detection



Angry

Image 2

VII. LIMITATIONS AND FUTURE WORK

Model Improvements: Upgrade to modern architectures (e.g., ResNet, EfficientNet), or use transfer learning for higher accuracy

Real-time Video: Streamline for higher FPS and better latency

Multimodal Emotion Recognition: Combine facial, vocal, and text cues

Deployment: Create a portable/mobile version or cloud deployment

VIII. CONCLUSION

This project demonstrates the practical, educational implementation of an end-to-end real-time facial emotion detection system using modern AI and web technologies. The codebase, model, and documentation are provided for reproducibility and as a teaching tool for students entering AI, computer vision, and full-stack engineering.

IX. REFERENCES

- [1] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.
- [2] F. Chollet, Deep Learning with Python. Manning Publications, 2018.
- [3] FER-2013 Kaggle Dataset, 2013. [Online]. Available: <https://www.kaggle.com/datasets/msmbare/fer2013>
- [4] TensorFlow Documentation. [Online]. Available: <https://www.tensorflow.org>
- [5] OpenCV Documentation. [Online]. Available: <https://opencv.org>
- [6] [YouTube Author], "Tutorial Title," YouTube, [Online]. Available: <https://youtube.com/link-to-tutorial>
- [7] [GitHub Author], "Repository Title," GitHub, [Online]. Available: <https://github.com/link-to-repo>.