Project Report

ExpressiFy

Emotion-Based Content Recommendation System

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Slot : B1

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1. Abstract

ExpressiFy is an innovative emotion-based content recommendation system designed to personalize the digital media experience using real-time facial emotion recognition. Leveraging deep learning techniques and the FER-2013 dataset, ExpressiFy captures users' emotional states through webcam feeds and classifies them into predefined categories such as Happy, Sad, Angry, and more. These emotional insights are then used to recommend appropriate music and movie content through external APIs like OMDb. Built using technologies like TensorFlow, OpenCV, Flask, and JavaScript, the system seamlessly integrates emotion detection and content recommendation into a unified web interface. ExpressiFy addresses the limitations of traditional recommendation systems, which rely solely on user history or preferences, by adapting to the user's current mood. This real-time adaptation not only enhances user engagement but also makes content consumption more intuitive, emotionally relevant, and satisfying. The project has vast potential in fields such as entertainment, mental wellness, and interactive digital platforms.

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2. Introduction

2.1 Project Overview

ExpressiFy is an AI-powered emotion-based content recommendation system that utilizes facial recognition techniques to detect a user's real-time emotional state and suggest personalized music, movies, and other content accordingly. This system enhances user experience by providing emotionally adaptive recommendations, making content discovery more intuitive and engaging.

2.2 Objectives

- Develop a deep learning-based facial emotion recognition model.
- Implement real-time emotion detection using a webcam.
- Build a content recommendation system that suggests relevant media based on emotions.
- Create an interactive front-end for seamless user experience.
- Integrate back-end and front-end for smooth functionality.

2.3 Scope of the Project

- The system will support emotion-based content recommendations for music and movies.
- It will work in real-time using facial expressions captured via a webcam.
- Users will receive recommendations dynamically without manual input.

2.4 Problem Statement

- Users often feel overwhelmed by content choices and need help selecting something that suits their current emotional mood.

- Most existing recommendation systems focus only on user history, ignoring real-time emotions and personal context.
- When feeling sad, stressed, or unmotivated, people may not have the energy to search for content that matches or improves their mood.
- Emotion-based recommendations create a more personalized and empathetic experience by understanding how the user feels in the moment.
- Integrating real-time emotion recognition enhances engagement, making content consumption more relevant, intuitive, and emotionally supportive.

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3. Dataset Description

3.1 FER-2013: Facial Expression Recognition Dataset

The **Facial Expression Recognition 2013 (FER-2013) dataset** is a widely used dataset for training deep learning models in facial emotion classification. It was introduced in the **2013 Kaggle Facial Expression Recognition Challenge** and contains labeled facial images representing different emotional states.

3.2 Dataset Characteristics

- **Total Images:** 35,887 grayscale images
- **Image Size:** 48x48 pixels
- **Number of Emotion Classes:** 7
- **Emotion Categories:**
    1. Angry
    2. Disgust
    3. Fear
    4. Happy
    5. Neutral
    6. Sad
    7. Surprise

Link : face-expression-recognition-dataset

3.3 Reason for Choosing FER-2013

FER-2013 was selected for this project due to the following reasons:

1. **Large Dataset Size** – Provides sufficient samples for training deep learning models.
2. **Diversity** – Contains images from various age groups, ethnicities, and genders, making it more robust.
3. **Pre-labelled Data** – Eliminates the need for manual annotation.
4. **Benchmark Performance** – Many research studies use FER-2013, enabling easier comparison of model performance.

3.4 Dataset Preprocessing Steps

Before training, the dataset underwent several pre-processing steps to improve model accuracy and efficiency:

1. **Grayscale Conversion** – Maintains uniformity across all samples.
2. **Resizing Images to 48x48 Pixels** – Standardizes input for convolutional neural networks (CNNs).
3. **Pixel Normalization** – Scales pixel intensity values between 0 and 1 to accelerate convergence.
4. **Data Augmentation** – Techniques such as rotation, flipping, and zooming were applied to enhance model robustness.

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4. Methodology

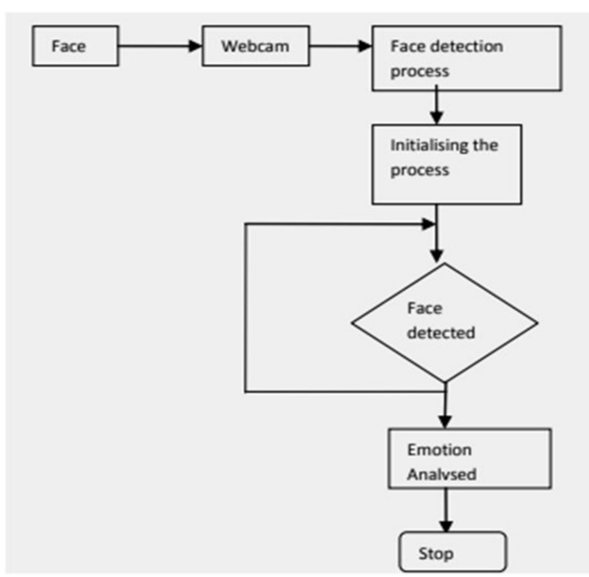
4.1 System Architecture

The system consists of three main components:

1. **Facial Recognition Model** (Backend **-** Python, Keras or TensorFlow, OpenCV)
2. **Content Recommendation Engine** (Python, Flask, API Integration)
3. **Frontend Interface** (HTML, CSS, JavaScript)

4.2 Workflow

1. Capture real-time facial expressions using OpenCV.
2. Process and classify emotions using a CNN-based deep learning model.
3. The detected emotions are sent to the backend via a Flask API for content recommendation.
4. Fetch appropriate movies using APIs like OMDB.
5. Display movie recommendations on the frontend.
6. Per day it can recommend movies upto 1000 emotions.



4.3 Technologies Used

- **Machine Learning:** Tensorflow or Keras for CNN-based emotion detection.
- **Computer Vision:** OpenCV for real-time face detection.
- **Web Framework:** Flask for API development.
- **Frontend:** HTML, CSS, JavaScript for UI.
- **APIs:** OMDB for fetching content.

4.4 Facial Emotion Recognition Model

- Dataset: FER-2013 (Facial Expression Recognition).
- Prep-Processing: Convert images to grayscale, resize to 48x48 pixels, normalize pixel values to improve model efficiency.
- Model: CNN with convolutional layers, max pooling, and dense layers.
- Training: Categorical cross-entropy loss, Adam optimizer.
- Output: Emotion classes (Happy, Sad, Angry, Neutral, Fear, Surprise, Disgust.)

4.5 Real-Time Emotion Detection

- OpenCV used for webcam integration.
- Model inference for emotion prediction in real-time.
- Flask API to send detected emotion data to front-end.

4.6 Content Recommendation Engine

- The recommendation engine maps detected emotions to relevant content categories (e.g., happy → comedy, sad → emotional) before fetching content from external APIs.
- Calls external APIs (OMDB) for fetching content.
- Returns movie recommendations based on emotion to front-end.

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5. Results

5.1 Model Performance

- Accuracy Metrics:

Metrices	Value
Test Accuracy	63.54%
Training Accuracy	74.35%

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Test Loss: 1.0422948598861694
Test Accuracy: 0.6354373097419739
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Epoch 80/80
97/97 ━━━━━━━━━━━━━━━━━━━━ 221s 2s/step - accuracy: 0.7435 - loss: 0.6941 - val_accuracy: 0.6354 - val_loss: 1.0423
```

- Confusion Matrix for emotion classification.
- Real-time responsiveness evaluation.

5.2 Model Predictions

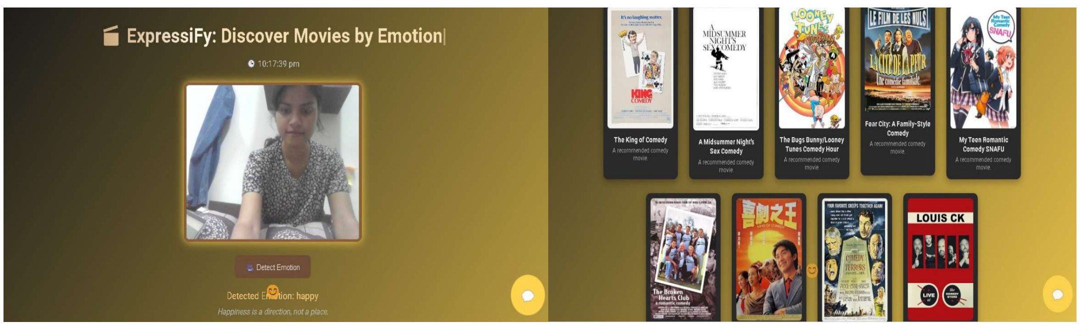

Fig 1 : Detected Happy and recommended Movies

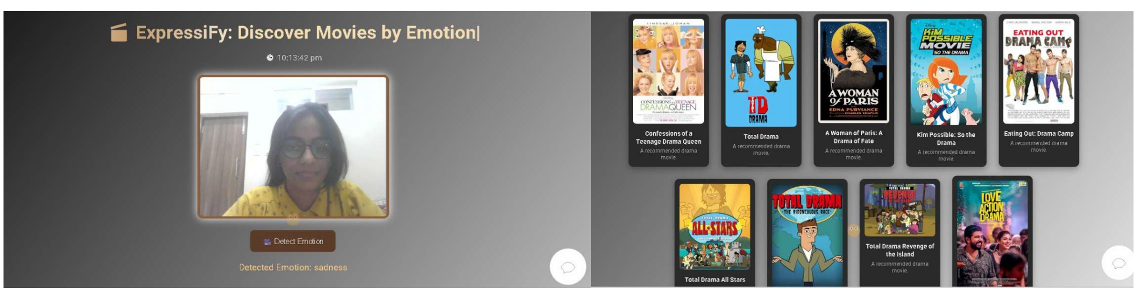

Fig 1 : Detected Saddness and recommended Movies

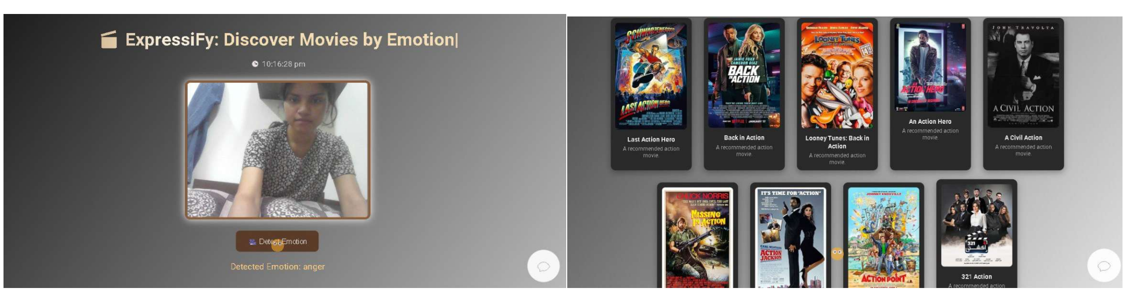

Fig 1 : Detected Anger and recommended Movies

6. Discussion

5.1 Future Improvements

- Improved emotion classification with hybrid models.
- Personalized user profiles for better recommendations.
- Adding front-end and enhancing UI responsiveness, improving real-time emotion display, and optimizing dynamic content recommendations.

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7. Comparison [Literature Review]

Existing emotion-based recommendation systems, such as the IRJET study(IRJET-V6I340320190826-49615-bg0qqz-libre.pdf), use **SVM-based emotion detection** for music recommendations but lack real-time adaptability and deep learning capabilities. Their system focuses only on music, relying on **rule-based playlist generation**. In contrast, our project employs a **CNN-based deep learning model**, offering **higher accuracy and better emotion classification** using the FER-2013 dataset.

Emotion recognition and intelligent recommendation systems have evolved as crucial tools in enhancing user engagement and personalization. Traditional systems depend on user history and ratings, often missing the user's current emotional context. Recent advancements in machine learning and computer vision have enabled more dynamic approaches using facial emotion recognition. One influential study is "**Deep Convolutional Neural Networks for Emotion Recognition from Facial Expressions" by Mollahosseini et al. (2016),** which demonstrates the effectiveness of CNNs on datasets like FER-2013 for accurate emotion classification. The paper highlights how deep learning outperforms traditional feature-based methods in recognizing subtle facial expressions.

Several projects have used emotion recognition for mental health support or virtual assistants, but very few integrate real-time emotion detection into entertainment recommendation platforms. Most recommendation engines still lack emotional intelligence, offering suggestions that may not align with how a user feels at that moment.

ExpressiFy addresses this limitation by using real-time webcam input, deep learning models for emotion detection, and APIs like **OMDb** to suggest relevant movies and music. The system builds on existing research and introduces an emotionally responsive interface that enhances user satisfaction. This fusion of AI, emotion recognition, and media recommendation makes content consumption more intuitive, personalized, and engaging.

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8. Conclusion

ExpressiFy successfully demonstrates the potential of integrating real-time emotion recognition with intelligent content recommendation. By using a deep learning model trained on facial expressions, combined with APIs like OMDb, the system offers a more personalized and emotionally aware user experience. This approach overcomes the limitations of traditional recommendation systems by focusing on the user's current mood rather than past preferences. The project builds on existing research in facial emotion recognition and applies it in an innovative way to entertainment. ExpressiFy sets the foundation for future developments in emotionally intelligent systems across various fields, including media, healthcare, and education.

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9. References

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