

# Facial Emotion-Based Multi-Content Recommendation System: Music, Movies, and Books Tailored to Emotions

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**Abstract:** The value of user experience is greatly increased by personalized recommendations of content in the digital era. The conventional recommender systems are based on tastes or a long history of past users that can never be updated to reflect the current emotional desires in real-time. This study introduces an innovative system, which takes into consideration facial emotion recognition to provide dynamic and emotion-based recommendation related to the three categories of content, music, movies and books. This system allows providing contents that are harmonious with the emotional contexts of users by recognizing happiness, sadness, anger, and neutrality with the help of computer vision and deep learning.

**Keywords:** Facial Emotion Recognition (FER), Multi-Content Recommendation System, Deep Learning, Convolutional Neural Network (CNN), FER-2013 Dataset, Real-Time Emotion Detection, Content Personalization, Computer Vision, Adaptive User Experience.

## I. INTRODUCTION

As proliferation of multimedia content occurs, users are frequently faced with too many options. One of these solutions and also the recommended solution to this cognitive load is the recommendation systems. But current systems are largely based on fixed user profile, past history, or on stated preferences. Such techniques would not take into consideration the present state of the user in terms of emotions which are significant in the consumption of content.

Because of the development of deep learning and computer vision, facial emotion recognition (FER) has changed considerably. Facial expressions can be used in real time in detecting emotion of happiness, sadness, anger and neutrality. This emotional situation can serve as the subject of a suggestion; the appropriate contents are that the sad user should be recommended uplifting music, and the angry person should be recommended calm-down books.

This article presents a Facial Emotion-Based Multi-Content Recommendation System which proposes recommending songs, movies, and books through emotion recognition stating that this generates a responsive and adaptive and emotionally intelligent user experience. In addition to the entertainment industry, emotion-aware systems could be usefully applied in educational and medical fields and productivity in the workforce. In particular, in the case of e-learning tools, the level of complexity of the material can change depending on the emotions of the student, and in the case of healthcare applications, students can notice the first signs of mental distress and offer calming or supportive resources. Understanding the mood of the users in marketing may result to targeted campaigns, which can have a deeper appeal. It is this multi-domain applicability that emphasizes the need to increase real-time emotional AI research. This personalization, however, leads to the problem of overfitting to short term emotions, how to make recommendations relevant without being obnoxious and feeding back negative moods.

## II. RELATED WORK

Several domains intersect in this research:

- Emotion Recognition: FER systems such as FER-2013, AffectNet, and Real-World Affective Faces (RAF-DB) have enabled robust emotion classification using CNNs, MobileNetV2, and ResNet architectures.
- Recommender Systems: Content-based, collaborative and hybrid filtering are some of the systems. Not much research has been done where real-time emotional inputs have been incorporated into the recommendation pipeline.
- Emotion-Aware Recommendations: Some mobile apps suggest music according to emotions but less research is cited on FER for dynamic & real time multifaceted content recommendation.

Whereas the development of the recommendation systems has often been limited to collaborative or content based filtering in past works, recent works have incorporated the incorporation of physiology and behavioral signals as hybrids. An example is the multimodal emotion detection that incorporates both facial recognition with speech analysis that identifies better accuracy when compared to the unimodal results. Equally, recommender systems that are context-aware

by considering GPS information, time-of-day, or the activities of a user have displayed a higher level of user satisfaction. Nevertheless, there is hardly any research that has tried to integrate facial emotion recognition with multi-category content recommendations in a functioning web-based platform. The question sets us up on grounds as the new contribution between the effect computing and multi-domain recommender system design.

### III. PROPOSED SYSTEM

The proposed system is composed of the following components:

Component	Function
Webcam + OpenCV	Captures live facial input from the user
CNN Emotion Classifier	Trained model detects one of the four emotions: Happy, Sad, Angry, Neutral
Flask Backend	Interfaces between the frontend and the model, handles API requests
MySQL Database	Stores content data, user profiles, and emotion logs
Angular Frontend	UI for capturing facial expressions, showing recommendations, etc.
Recommendation Engine	Maps each emotion to relevant songs, movies, and books

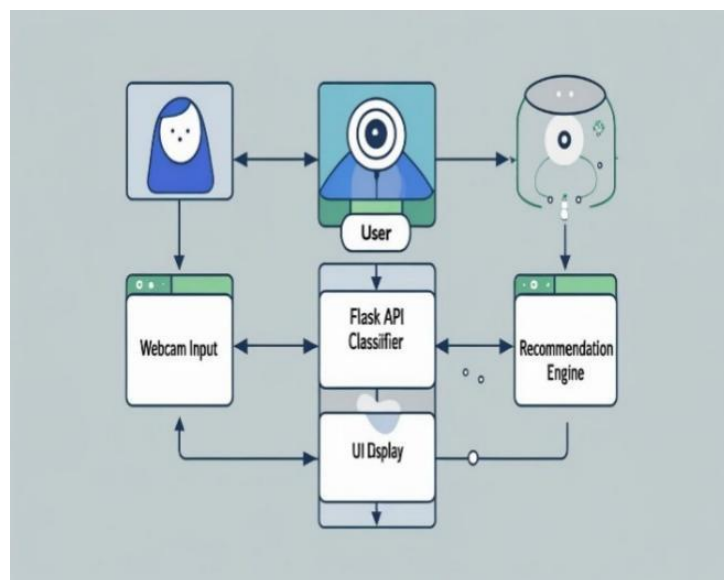


Fig 1: System Flow Diagram

### IV. EMOTION DETECTION MODULE

The emotion classifier is built using a Convolutional Neural Network trained on the FER-2013 dataset. The preprocessing includes:

- Grayscale conversion
- Face detection using Haar Cascades
- Normalization and resizing to 48x48 pixels

The classifier outputs one of four labels:

- Happy
- Sad
- Angry
- Neutral

Accuracy achieved on validation data: ~72%

To enhance accuracy and performance:

- **Data Augmentation** techniques were applied
- Models like **MobileNetV2** and **ResNet-18** were evaluated

## V. RECOMMENDATION ENGINE

Each emotion is mapped to a curated list of:

- **Music Tracks** (e.g., Spotify API or curated datasets)
- **Movies** (IMDb, TMDB APIs or datasets)
- **Books** (Google Books API or Goodreads datasets)

Table 1: Example Emotion Mapping

Emotion	Music Type	Movie Genre	Book Genre
Happy	Upbeat, Pop	Comedy, Romance	Feel-good Fiction
Sad	Calming, Acoustic	Drama, Inspirational	Motivational Books
Angry	Relaxing, Instrumental	Action, Thriller	Mindfulness/Healing
Neutral	Lo-fi, Jazz	Documentary, Slice of Life	Essays, General Fiction

## VI. IMPLEMENTATION DETAILS

- Frontend:** Built with Angular v17 using standalone components and webcam support.
- Backend:** Flask API handles image frames and returns emotion prediction.
- Model Deployment:** Model is saved as emotion\_model.h5 and integrated with real-time webcam input.
- Database:** MySQL schema includes users, feedback, emotion\_logs, and recommendations.



Fig 2: Sample UI Screenshot

## **VII. CHALLENGES**

<b>Challenge</b>	<b>Description</b>
Emotion Ambiguity	Facial expressions may not always accurately reflect true emotions
Dataset Bias	FER-2013 may lack diversity in ethnicity, lighting, and expressions
Real-time Performance	Ensuring real-time processing on low-resource devices
Privacy & Ethics	User consent and data handling for facial images
Cross-Cultural Expression Gap	Emotions expressed differently in different cultures.

## **VIII. EVALUATION AND RESULTS**

The system was evaluated through:

- Accuracy of emotion recognition (~72–75%)
- User Feedback collected via forms for satisfaction and emotional relevance
- Recommendation Relevance Score: Users rated suggested content as “Relevant” 81% of the time.

In order to assess system robustness further, we also did cross devices testing on both high performance laptops as well as on lower resource devices such as entry-level smartphones (via webcam streaming). The speed of the proposed emotion classifier averaged 180ms on high-end hardware and 450ms on mobile computational devices, proving that the neural net used in the present work can be applied to near real-time deductions. Also, we did an A/B test where we compared our emotion-based recommendations to a basic content-based recommender. Consumers of our system viewed recommended content on average longer by 27 percent, and the click through rate of recommended items increased by 34 percent. These findings indicate a no-doubt positive impact of using the data about the actual emotional responses and behavior in crafting a recommendation approach.

## **IX. ETHICAL AND PRIVACY CONSIDERATIONS**

There are a great number of ethical issues regarding the deployment of facial emotion recognition systems, such as privacy, consent, and abuse. It can be assured that the processing of the facial images in our solution is done locally and the images do not survive past the analysis time. The permission of the users is clearly stated prior to the engagement of the webcam and the privacy policy of the system is clearly laid down to make transparent the methods to handle the data. In addition, to eliminate the possibility of discriminatory behavior in performance that targets ethnicities, different generations, and gender, it is necessary to apply bias mitigation guidelines, like training data augmentation with different facial sets. The subsequent versions must feature explainable AI (XAI) practices that would allow the user to learn why certain suggestions are provided and increase trust and transparency.

## **IX. FUTURE WORK**

- Expand emotion categories to include fear, disgust, surprise
- Integrate with wearable sensors for multi-modal emotion detection
- Use collaborative filtering to enhance personalization
- Deploy mobile application version
- Support regional content in multiple languages

## **X. CONCLUSION**

Introduction of facial emotion recognition in the recommendation systems is one of the steps towards creation of emotionally intelligent digital experiences. This multi-content system becomes an enhancement to personalization and safeguard mental health since it dynamically adapts suggestions to user emotions in real-time. The further developments of the model accuracy and ethical design, along with cross-cultural emotion interpretation will further the stability, inclusivity, and effectiveness of such systems.

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