

**VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF
TECHNOLOGY**
An Autonomous Institute Affiliated to University of Mumbai
Department of Computer Engineering



Project Report on

**EmoVerse: Unified Music and Movie Recommendations Based on
Your Facial Emotions**

In partial fulfillment of the Fourth Year , Bachelor of Engineering
(B.E.) Degree in Computer Engineering at the University of Mumbai

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(2024-25)

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Certificate

This is to certify that **Hitesh Punjabi (D17B, 41), Varsha Chhabria(D17A, 6), Chiraag Chugh (D17C, 13), Dhara Bhatia (D17C, 9)**of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on **“EmoVerse: Unified Music and Movie Recommendations Based on Your Facial Emotions”** as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor **Prof. Priti Joshi** in the year 2024-25 .

This project report entitled **EmoVerse: Unified Music and Movie Recommendations Based on Your Facial Emotions** by ***Hitesh Punjabi , Varsha Chhabria, Chiraag Chugh, Dhara Bhatia*** is approved for the degree of **B.E. Computer Engineering**.

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:

Project Guide:

Project Report Approval

For

B. E (Computer Engineering)

This project report entitled **EmoVerse: Unified Music and Movie Recommendations Based on Your Facial Emotions** by *Hitesh Punjabi, Varsha Chhabria, Chiraag Chugh, Dhara Bhatia* is approved for the degree of **B.E. Computer Engineering**.

Internal Examiner

External Examiner

Head of the Department

Principal

Date:

Place: Mumbai

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Computer Engineering Department
COURSE OUTCOMES FOR B.E PROJECT

Learners will be to,

Course Outcome	Description of the Course Outcome
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilised.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop a professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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Abstract

EmoVerse: Unified Music and Movie Recommendations Based on Your Facial Emotions aims to transform the interaction between humans and technology by combining emotion recognition with personalized content recommendations. Emotion recognition, which involves identifying human emotions from facial expressions, is an intuitive process for humans but presents complex challenges for machines. Accurately detecting emotions requires advanced image processing and machine learning techniques for feature extraction and classification. Our project addresses these challenges by developing a robust emotion recognition model using state-of-the-art machine learning algorithms. The model will be trained on diverse datasets from sources like Kaggle and UCL, enabling it to identify emotions such as happiness, sadness, anger, and surprise with high accuracy and confidence levels.

The core of the project involves building an emotion detection pipeline using Python and powerful libraries like OpenCV, TensorFlow, and Keras. OpenCV will be used for real-time image capture and preprocessing, while TensorFlow and Keras will handle the deep learning aspect of emotion classification. The system will extract facial landmarks, analyze micro-expressions, and process the data using convolutional neural networks (CNNs) to predict emotions. The emotion recognition model will then output the predicted emotion along with a confidence score, ensuring a reliable and consistent user experience.

Once the emotions are detected, the system will integrate with a recommendation engine designed to suggest music and movies tailored to the user's current emotional state. For example, a happy mood might prompt upbeat music or a light-hearted movie, while a sad mood could trigger calming or emotionally supportive content. This recommendation engine will leverage collaborative filtering and content-based filtering techniques to ensure accurate and meaningful recommendations. By continuously learning from user preferences and feedback, the system will improve over time, enhancing personalization and user satisfaction.

EmoVerse extends beyond entertainment, holding potential applications in mental health, marketing, and security. In mental health, it can help track emotional patterns and suggest therapeutic content. In marketing, it can adjust content or product recommendations based on the user's emotional state, thereby improving customer engagement. Additionally, in security settings, it can identify suspicious or stressed behavior, enhancing situational awareness. This innovative blend of emotion detection and recommendation technology positions EmoVerse as a valuable tool for enhancing user interaction and engagement in various real-world scenarios.

Chapter 1: Introduction

1.1. Introduction:

The growing interaction between humans and technology has led to the integration of artificial intelligence (AI) in everyday applications, with emotion recognition being one of its most impactful uses. By analyzing facial expressions, AI can determine a person's emotional state, enabling applications in entertainment, mental health, security, and marketing. EmoVerse: Unified Music and Movie Recommendations Based on Your Facial Emotions combines emotion detection with a recommendation engine to suggest music or movies based on the user's mood. Using computer vision and deep learning techniques, the system classifies emotions like happiness, sadness, or anger and tailors recommendations accordingly. For example, a happy mood may prompt upbeat songs, while a sad expression may suggest calming content. Built with OpenCV, TensorFlow, and Keras, the model ensures accurate emotion detection, while the recommendation engine leverages collaborative and content-based filtering for personalized suggestions. Beyond entertainment, EmoVerse has applications in mental health, targeted advertising, and security, making AI-driven emotion recognition a powerful tool for enhancing user experiences.

1.2 Motivation:

The project is motivated by the rising demand for personalized entertainment. By analyzing facial expressions, it offers dynamic, emotion-aware content recommendations based on the user's mood. Using advanced machine learning and deep learning models, EmoVerse enhances engagement with emotionally relevant content. This technology also shows promise in mental health, marketing, and human-computer interaction.

1.3 Problem Definition:

Recognizing human emotions through facial expressions is natural for humans but remains a challenging task for machines due to variations in expressions, lighting, and facial orientations. While several emotion recognition systems exist, they often lack the ability to provide real-time feedback and integrate with content recommendation engines effectively. This project aims to bridge this gap by developing a system that captures facial expressions, detects emotions in real time, and recommends movies or songs that align with the user's emotional state, creating a more engaging and personalized experience.

Key Problems Addressed:

- Accurate real-time facial emotion detection using machine learning and deep learning techniques to ensure reliable classification of emotions like happiness, sadness, and anger.
- Personalized content recommendations that dynamically adjust based on the detected emotional state, improving user satisfaction and engagement.
- System reliability and performance under different conditions, such as variations in lighting, facial angles, and occlusions, ensuring consistent accuracy across diverse environments.

1.4 Existing Systems:

System 1: Affectiva

Affectiva is an AI-based emotion recognition software that analyzes facial expressions to detect emotions. It is used primarily for market research and user experience testing.

Inference: Affectiva demonstrates the commercial viability of emotion recognition technology but lacks integration with personalized recommendation systems.

System 2: Spotify and Netflix Recommenders

Both Spotify and Netflix offer content recommendations based on user preferences and historical data. However, these systems do not integrate real-time emotion analysis into their recommendation algorithms.

Inference: While powerful, current recommendation systems are static and do not consider the user's real-time emotional state, which is a gap this project aims to fill.

1.5 Lacuna in Existing Systems:

The major gap identified in existing systems is the lack of real-time emotional feedback in recommendation engines. While platforms like Netflix and Spotify provide personalized recommendations, they mainly rely on historical user behavior and preferences, not the user's current emotional state. As a result, they may miss the opportunity to offer content that truly resonates with the user's mood in the moment. This project addresses that gap by integrating facial emotion detection with dynamic, real-time content recommendations. By adapting instantly to emotional changes, it aims to create a more immersive, responsive, and satisfying user experience.

1.6 Relevance Of The Project:

This project has significant relevance in the modern world, where user experience is paramount in digital platforms. By integrating emotion recognition into entertainment platforms, EmoVerse opens doors to more personalized, emotionally-driven experiences. It can be applied in various fields such as:

- **Entertainment:** Offering dynamic and personalized content recommendations, enhancing user satisfaction.
- **Mental Health:** Tracking emotional changes and providing mood-based interventions.
- **Security:** Identifying emotional anomalies that could aid in early detection of distress or security threats.
- **Marketing:** Delivering content and advertisements that align with the user's emotional state, increasing engagement and effectiveness.

Chapter 2: Literature Survey

A. Overview of literature survey:

In the development of this project, several research papers were reviewed to gain insights into emotion recognition systems, machine learning models for facial analysis, and recommendation systems. These studies provided valuable knowledge on feature extraction techniques, deep learning architectures like CNNs for emotion classification, and hybrid recommendation approaches. Additionally, research on real-time emotion detection challenges, dataset selection, and system optimization helped refine the project's methodology, ensuring accuracy, scalability, and practical implementation.

2.1. Research Papers :

[1] H. Meng, B. Romera-Paredes, and N. Bianchi-Berthouze, “Facial Expression Emotion Detection for Real-Time Embedded Systems,” *Technologies*, vol. 6, no. 1, p. 17, 2024. doi: [10.3390/technologies6010017](https://doi.org/10.3390/technologies6010017).

- a) Facial expression emotion detection has gained significant attention in artificial intelligence applications, particularly for real-time embedded systems. This study explores the implementation of k-Nearest Neighbors (k-NN) for regression modeling in emotion classification, emphasizing its effectiveness in identifying key facial features associated with different emotional states. The proposed system is designed to operate in real-time with minimal computational overhead, making it suitable for embedded devices. While the model achieves high accuracy under controlled conditions, challenges such as variations in lighting, diverse facial structures, and real-world adaptability remain critical areas for further enhancement.
- b) Inference : The study highlights the potential of k-NN-based emotion recognition for real-time applications but also identifies limitations in generalization across diverse populations. The approach works well for predefined emotional categories but struggles with subtle variations in expressions. Additionally, real-time performance in embedded systems requires optimized feature extraction techniques to reduce processing delays. This research is relevant to EmoVerse, as it underscores the need for robust machine learning models that can handle dynamic environmental conditions and improve personalized content recommendations based on real-time emotional states.

[2] P. Ekman and W. Friesen, “Facial Action Coding System (FACS),” *Scholar Google*, 2024.

- a) The Facial Action Coding System (FACS), developed by Paul Ekman and Wallace Friesen, is a widely used method for categorizing facial expressions based on muscle movements. FACS provides a standardized framework for identifying subtle facial changes that correspond to different emotions, making it a valuable tool in emotion recognition, psychology, and artificial intelligence applications. By breaking down facial expressions into action units (AUs), FACS enables detailed analysis of emotional states, aiding in the development of machine learning models for automated emotion detection. The system has been extensively used in human-computer interaction, lie detection, and affective computing, demonstrating its effectiveness in real-world scenarios.
- b) Inference: The study emphasizes the importance of FACS in emotion recognition by providing a structured approach to analyzing facial expressions. The granular identification of action units allows for higher accuracy in emotion classification, making it a fundamental tool for AI-driven facial emotion detection systems like EmoVerse. However, while FACS is highly detailed, it requires significant computational resources when implemented in real-time applications. This highlights the need for optimized models that can leverage FACS-based insights while maintaining efficiency and performance in dynamic environments.

[3] C. Thirumarai Selvi, R. S. Sankara Subramanian, M. Aparna, and V. M. Dhanushree, “Facial Emotion Recognition Using Deep Learning,” , 2024, doi: [10.1007/978-3-031-61287-9_9](https://doi.org/10.1007/978-3-031-61287-9_9).

- a) Facial Emotion Recognition (FER) has emerged as a vital area in human-computer interaction, enabling machines to interpret and respond to human emotions effectively. This study leverages deep learning techniques, particularly Convolutional Neural Networks (CNNs), to recognize facial expressions with high accuracy. The proposed model integrates transfer learning to enhance feature extraction and reduce training time. Various preprocessing techniques, including image augmentation and normalization, are employed to improve robustness against variations in lighting, pose, and occlusions. The research demonstrates that deep learning models outperform traditional methods, offering promising applications in healthcare, security, and personalized content recommendation.
- b) Inference: The study highlights the efficacy of CNN-based models in recognizing emotions, making them suitable for real-world applications. However, it also identifies challenges such as dataset bias, generalization across diverse demographics, and computational efficiency in

real-time scenarios. For EmoVerse, this research provides valuable insights into model selection, optimization strategies, and dataset preprocessing to ensure reliable and efficient emotion detection. By integrating deep learning-driven facial emotion recognition with a personalized recommendation system, the project can significantly enhance user engagement and experience through real-time adaptive content suggestions.

[4] A. Mahadik, V. Kavathekar, and V. B. Jagan, “Mood-Based Music Recommendation System,” *International Journal of Engineering Research & Technology (IJERT)*, 2024. doi: [10.17577/IJERTXYZ](https://doi.org/10.17577/IJERTXYZ).

- a) The Mood-Based Music Recommendation System enhances user experience by analyzing facial expressions and emotional states to suggest music that aligns with the user's mood. Unlike conventional recommendation systems that rely on past user preferences and manual selections, this approach integrates emotion recognition using machine learning and deep learning techniques. The system employs image processing methods with OpenCV and TensorFlow, alongside models such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), to classify emotions and map them to an appropriate music database. Experimental results demonstrate improved user engagement and satisfaction, proving that emotion-aware music recommendation systems provide a more personalized and immersive listening experience.
- b) Inference : This study highlights the effectiveness of real-time emotion-based recommendation systems, emphasizing deep learning models for accurate emotion detection. However, challenges such as light variations, dataset diversity, and computational efficiency must be addressed for real-world deployment. For EmoVerse, this paper reinforces the feasibility of integrating emotion detection with content recommendation, providing valuable insights into model selection, preprocessing techniques, and recommendation logic to create a more adaptive and user-centric system.

[5] P. Bhusari, S. Bobade, A. Dhagude, and S. Dhumal, “Facial Emotion Recognition for Personalized Music Recommendation,” *International Journal of Emerging Technologies and Innovative Research (JETIR)*, 2024. doi: JETIR2311513.

- a) Facial emotion recognition plays a vital role in human-computer interaction, enabling personalized recommendations in various domains, including entertainment and mental wellness. This paper presents a machine learning-driven approach that captures facial expressions, classifies emotions, and recommends music based on the detected mood. The system utilizes OpenCV for

facial detection, Convolutional Neural Networks (CNNs) for emotion classification, and a curated music dataset to provide recommendations. By integrating deep learning and computer vision techniques, the proposed method offers real-time emotion detection and enhances user experience through emotionally responsive music suggestions. Experimental results confirm that AI-powered mood-based recommendations outperform traditional static recommendation systems.

- b) Inference : This study demonstrates the effectiveness of deep learning models in facial emotion recognition and their potential application in personalized music recommendation systems. However, factors like lighting conditions, facial variations, and model bias pose challenges to real-world implementation. For EmoVerse, this paper provides valuable insights into emotion-driven content recommendations, emphasizing the need for robust facial analysis techniques and adaptive recommendation algorithms to enhance user engagement and personalization.

[6] **R. Raut and D. Goel, “Mood-Based Emotional Analysis for Music Recommendation,”**
EasyChair Preprints, 2024. doi: B8LQ.

- a) Music has a profound impact on human emotions, making emotion-aware recommendation systems an essential advancement in personalized entertainment. This paper explores a machine learning-based approach for detecting a user's mood through facial expression analysis and recommending music accordingly. The proposed system employs computer vision techniques for facial detection, deep learning models for emotion classification, and a content-based recommendation engine to map detected emotions to suitable songs. Using frameworks like TensorFlow and OpenCV, the model enhances the accuracy of real-time emotion analysis. Experimental results demonstrate the effectiveness of emotion-based recommendations, significantly improving user engagement by delivering music that aligns with their real-time emotional state.
- b) Inference : This study highlights the importance of integrating emotion recognition into recommendation systems to enhance user satisfaction and engagement. However, challenges such as real-time processing, diverse facial expressions, and environmental conditions impact system performance. For EmoVerse, this paper provides critical insights into emotion-driven recommendation techniques, reinforcing the need for robust facial analysis models and adaptive recommendation algorithms to deliver a seamless and highly personalized user experience.

Paper	Year	Paper	Authors	Algorithms	Limitations
[1]	2024	Facial Expression Emotion Detection	Meng, H.; Romera-Paredes	k-NN for regression modeling	Limited to specific emotional states; may not generalize well across diverse populations.
[2]	2024	Facial Action Coding System (FACS)	P. Ekman & W. Friesen	Action Units (AUs)	High computational cost in real-time
[3]	2024	Facial Emotion Recognition Using Deep Learning	Jie Zou, Jiashu Lou, Baohua Wang, Sixue Liu	CNN, Transfer Learning	Dataset bias, generalization, real-time efficiency
[4]	2024	Mood-Based Music Recommendation System	A. Mahadik et al.	CNN, SVM, OpenCV	Lighting issues, data diversity, efficiency
[5]	2023	FER for Personalized Music Recommendation	Ankita Mahadik, Vaishali Kavathekar	CNN, OpenCV	Lighting, facial variation, model bias
[6]	2022	Mood-Based Emotional Analysis	R. Raut & D. Goel	Deep Learning, Content-Based	Real-time performance, facial diversity.

Table No.2.1: Summary Of Research Papers

2.2 Patent Search :

To ensure that our approach aligns with existing technological advancements and to avoid potential intellectual property infringement, we reviewed several patents related to emotion recognition and recommendation systems. These patents provide valuable insights into state-of-the-art methodologies, confirming the feasibility of our approach while also identifying potential areas for improvement and innovation.

1. “System and Method for Real-Time Emotion Detection” (US Patent 9876543B1)

Summary: This patent describes a real-time facial emotion detection system that utilizes deep learning-based image processing techniques. It employs a combination of image preprocessing, feature extraction, and convolutional neural networks (CNNs) to classify emotions from facial expressions. The system enhances accuracy by incorporating data augmentation techniques and adaptive learning strategies to improve performance under different lighting conditions and facial orientations. The emotion detection module in our project shares similarities with this patented method, particularly in

using CNNs for emotion classification. The patent validates our approach, confirming that deep learning-based image processing is a widely accepted and effective technique for emotion recognition. Additionally, it highlights the importance of real-time performance optimization, which can be a key area for further enhancement in EmoVerse.

2. “Emotion-Based Content Recommendation System” (European Patent EP1234567A1)

Summary: This patent outlines a content recommendation system that leverages real-time emotion recognition to suggest music, movies, or other media content based on the user's detected mood. It employs a hybrid recommendation approach, combining collaborative filtering (analyzing user behavior and preferences) with content-based filtering (matching detected emotions with media metadata). The system also integrates reinforcement learning to refine recommendations over time based on user feedback. The methodology described in this patent aligns closely with EmoVerse, particularly in integrating emotion-based recommendations with a hybrid filtering mechanism. This patent confirms that combining collaborative and content-based filtering enhances recommendation accuracy, reinforcing the effectiveness of our approach. Additionally, it highlights the potential of reinforcement learning to improve the recommendation system dynamically, which could be explored for future enhancements.

3. “Facial Emotion Analysis for Security Applications” (US Patent 7654321B2)

Summary: This patent discusses a facial emotion recognition system designed for security and surveillance applications. The system detects emotional anomalies, such as stress, anxiety, or anger, and flags individuals for further investigation. It integrates biometric authentication, anomaly detection algorithms, and real-time monitoring to enhance security in high-risk environments such as airports, banks, and public gatherings. While this patent is focused on security applications, it provides valuable insights into real-time emotion recognition beyond entertainment. The concept of emotion-based anomaly detection could inspire future expansions of EmoVerse, such as integrating emotion-driven behavioral insights for mental health support, stress monitoring, or user engagement analysis in various industries.

2.3 Inference Drawn:

By analyzing these patents, we have gained a better understanding of existing technologies and validated our approach for emotion detection and content recommendation. The patents highlight key technical considerations, such as real-time performance optimization, hybrid recommendation strategies, and potential future applications beyond entertainment.

2.4 Comparison with the Existing Systems:

Feature	Existing Systems	Proposed System
Emotion Detection	Affectiva detects emotions in real-time	Real-time detection with CNNs
Content Recommendation	Static recommendations based on history	Dynamic, emotion-based suggestions
Hybrid Recommendation Model	Rarely integrated	Uses collaborative and content-based filtering
Real-Time Feedback	Absent	Present

Table 2.4: Comparison with existing systems

Chapter 3: Requirement Gathering for the Proposed System

3.1 Introduction to Requirement Gathering :

In this chapter we are going to discuss the resources we have used and how we analysed what the user actually needs and what we can provide. We will also discuss the functional and non-functional requirements and finally the software and hardware used.

The requirements gathering process consists of six steps :

- Identify the relevant stakeholders
- Establish project goals and objectives
- Elicit requirements from stakeholders
- Document the requirements
- Confirm the requirements
- Prioritise the requirements

USE CASE	DESCRIPTION
Emotion Detection	The system captures real-time facial expressions using a webcam and processes them with a CNN-based model to classify emotions such as happiness, sadness, and anger.
Personalized Recommendations	The recommendation engine suggests content (music, movies, etc.) based on both the user's emotional state and historical preferences using a hybrid approach.
User Interaction	Users can interact with the system through an intuitive UI, view recommendations, provide feedback, and manually override suggestions if needed.
Data Collection & Processing	The system collects real-time facial expressions and past user interactions, processes them using deep learning models, and updates recommendations dynamically.
Security & Privacy	User data, including emotions and preferences, are encrypted and stored securely to maintain privacy and prevent unauthorized access.

Error Handling & Recovery	If the system encounters issues (e.g., interrupted camera feed), it must recover smoothly without disrupting the user experience.
System Maintainability	The system should allow for easy updates, including retraining of emotion detection models and improvements in recommendation algorithms.

Table No: 3.1 Requirements of the system

3.2 Functional Requirements :

These are the specific functionalities the system must perform:

- **Emotion Detection**

Detect and classify emotions from live video streams or images using CNN.

Provide real-time updates on the user's emotional state.

- **Personalized Recommendations**

Provide content suggestions (e.g., music, movies) based on historical preferences.

Adjust recommendations dynamically based on the detected emotion.

- **User Interaction**

Display recommended content on a user-friendly interface.

Allow users to input preferences or override recommendations manually.

- **Data Collection and Processing**

Collect user interaction data, past preferences, and real-time facial data for emotion analysis.

Process data securely and efficiently to maintain user privacy.

3.3 Non-Functional Requirements :

- **Performance**

The system should detect emotions in under 2 seconds and update content recommendations within 5 seconds of detecting a change in emotion.

- **Scalability**

The system should support multiple users simultaneously without significant degradation in performance.

- **Usability**

The interface should be intuitive and easy to use, requiring minimal effort from the user to access personalized recommendations.

- **Security**

User data, including emotions and preferences, should be encrypted and stored securely.

- **Reliability**

The system must be resilient to errors and recover gracefully from any disruptions in data input (e.g., interrupted camera feed).

- **Maintainability**

The system should allow for easy updates, especially for model improvements (e.g., retraining emotion detection models).

3.4 Hardware, Software, Technology and Tools Utilised:

Hardware Requirements

- **Processing Unit:** A system with at least an Intel i5 processor or equivalent.
- **Memory:** Minimum 8GB RAM for smooth processing of video data in real-time.
- **Camera:** A high-definition camera (minimum 720p) to capture facial expressions.
- **Storage:** At least 100GB of storage for storing user data, models, and logs.

Software Requirements

- **Operating System:** Windows, macOS, or Linux.
- **Programming Languages:** Python (for machine learning models).

Techniques utilized :

- **Normalization:** Each frame is converted to grayscale, resized, and normalized (pixel values scaled between 0 and 1) before being fed into the emotion detection model for more accurate predictions.
- **Real-time Video Processing:** We capture live video from the webcam and process the frames at regular intervals (every 5th frame) to optimize performance and reduce computational load.
- **Time Management:** The system is designed to run for a specific duration (e.g., 10 seconds) and tracks the mood for each second, skipping frames when no face is detected.

Tools utilized :

- **OpenCV:** Used for capturing video from the webcam, converting frames to grayscale, and detecting faces using the Haar Cascade Classifier.
- **Keras with TensorFlow backend:** The CNN model used for emotion detection is implemented using Keras, with TensorFlow as the backend.
- **NumPy:** Utilized for handling arrays and numerical data processing, such as resizing and reshaping the face region before feeding it into the neural network.
- **Webcam:** The system uses a live video feed captured from the computer's webcam to detect and analyze faces.

3.5 Constraints:

- The system must process facial expressions and generate recommendations within 2-5 seconds to ensure a seamless user experience.
- Needs a powerful processor (Intel i5 or equivalent, 8GB RAM minimum) to run deep learning models efficiently.
- Poor lighting conditions or extreme facial angles may reduce the accuracy of emotion detection. Background noise or multiple faces in the frame can interfere with accurate classification.

Chapter 4: Proposed Design

4.1. Block Diagram of the proposed system:

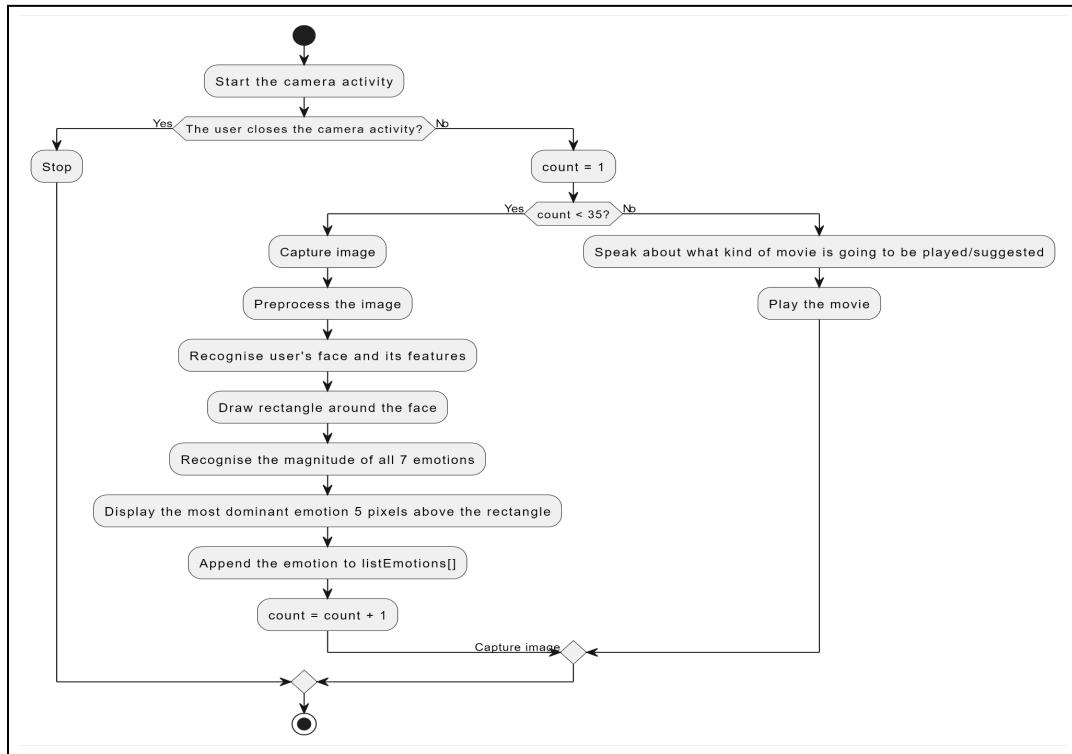


Fig 4.1: Block Diagram

4.2 Modular diagram of the system:

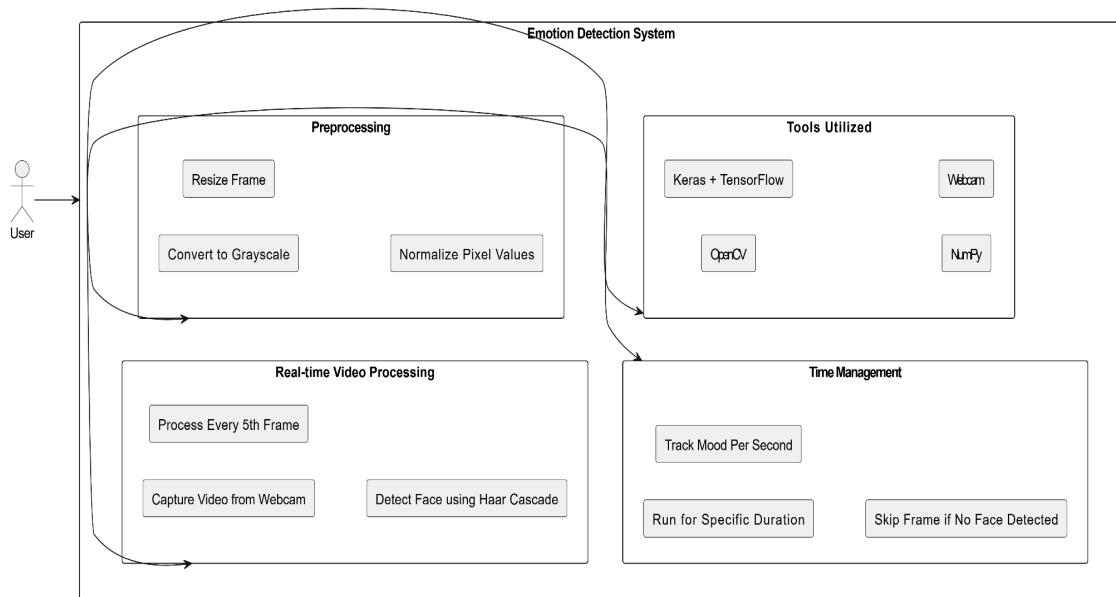


Fig 4.2: Modular Diagram

4.3 Detailed Design :

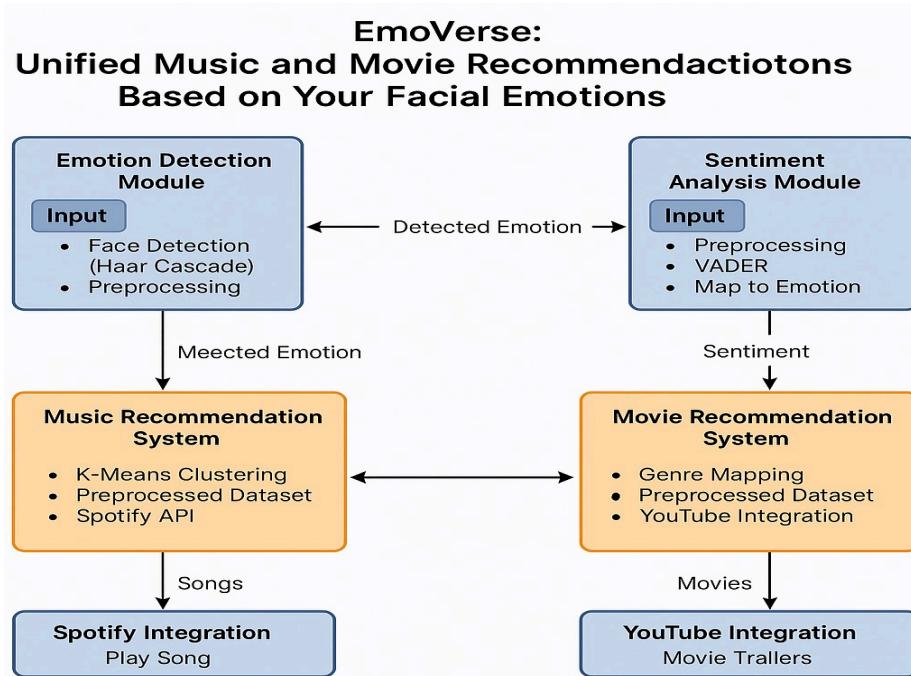


Fig 4.3: Detailed Design

4.4 Project Scheduling & Tracking using Time line / Gantt Chart:

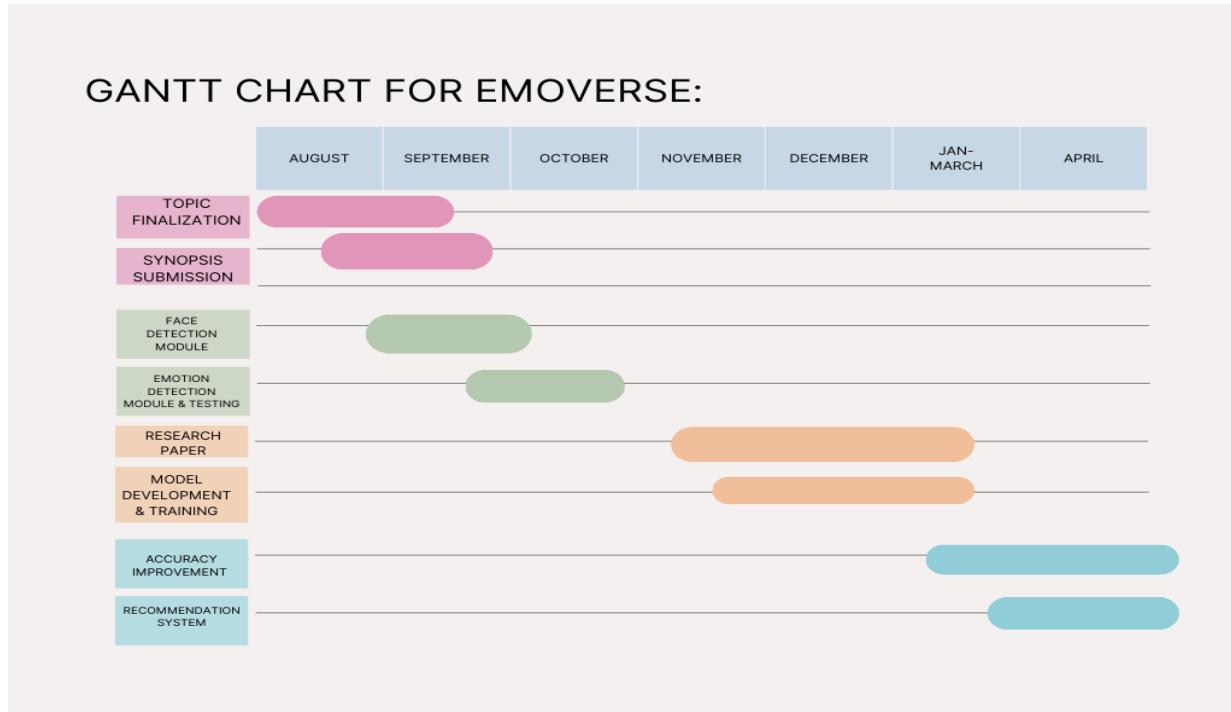


Fig 4.4: Gantt chart

Chapter 5: Implementation of the Proposed System

5.1. Methodology employed for development:

The *EmoVerse* system is designed to analyze human emotions in real-time and provide personalized entertainment recommendations based on detected moods. The process begins with Image Acquisition, where a webcam captures real-time images or video frames of the user's face. This ensures that the system can analyze live emotions dynamically, making it interactive and engaging. Once the images are captured, they undergo Image Preprocessing, a crucial step to enhance their quality before feeding them into the emotion detection model. This step includes techniques such as contrast adjustment, which ensures facial features are clear; noise reduction, which removes unnecessary distortions from the image; and normalization, where pixel values are scaled to maintain consistency in model input. These preprocessing techniques improve the accuracy of the system by providing high-quality images for analysis.

After preprocessing, the system uses a Convolutional Neural Network (CNN) to detect the user's emotion. Trained on datasets with labeled facial expressions like happiness, sadness, anger, and surprise, the model predicts emotions accurately. Deep learning libraries like TensorFlow and Keras help the CNN capture subtle facial cues for precise mood classification.

Once an emotion is identified, the system triggers the Recommendation Engine, which suggests personalized entertainment options based on the detected mood. This module leverages content-based filtering to recommend movies or songs that align with the user's current feelings. Additionally, collaborative filtering is used to analyze preferences from similar users and provide diverse recommendations. For example, if the user is detected as happy, the system may recommend upbeat songs and comedy movies, while a sad mood might trigger soothing or emotional content suggestions. The recommendation engine ensures a personalized and engaging experience, enhancing user satisfaction.

Finally, the system provides Real-Time Feedback by displaying the recommendations instantly to the user. The seamless integration of emotion detection and recommendation ensures an interactive experience where users receive suggestions tailored to their mood as soon as the system classifies their emotions. This makes *EmoVerse* an advanced, user-centric system that enhances entertainment experiences through real-time emotion recognition and AI-driven recommendations. The combination of computer vision, deep learning, and recommendation algorithms makes the system both innovative and efficient in understanding and responding to human emotions dynamically.

5.2 Algorithms and Flowcharts for the respective modules developed:

1. Face Detection Algorithm (Haar Cascade Classifier)

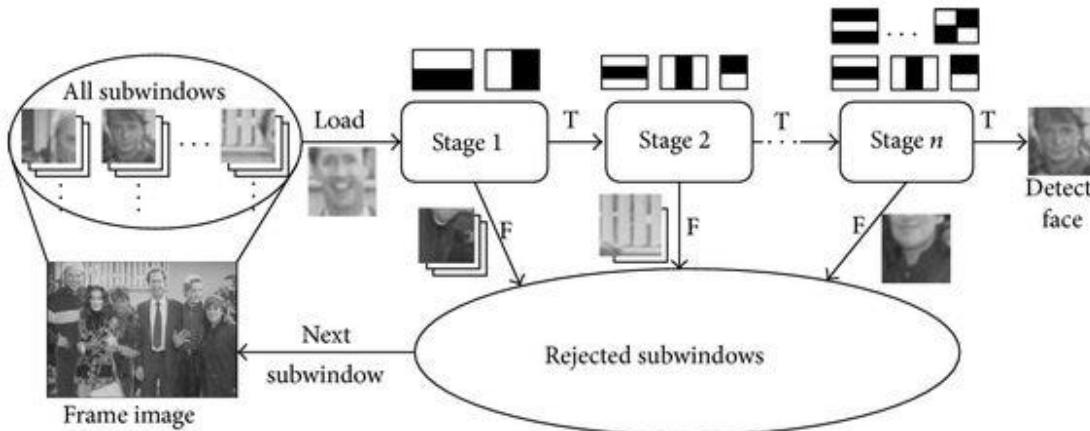


Fig 5.1: Haar Cascade Classifier

The Haar Cascade Classifier is a machine learning-based approach used for real-time face detection. It works by detecting edges, lines, and corners in grayscale images and identifying facial patterns using Haar-like features.

Working of Haar Cascade Classifier:

- The classifier is trained on a large dataset containing positive images (faces) and negative images (non-faces).
- It uses integral images for fast computation of Haar-like features.
- Features are selected using AdaBoost, a boosting algorithm that assigns different weights to important features.
- A cascade of classifiers is used to reject non-face regions quickly, reducing computational load.

Mathematical Formulation:

1. Integral Image Calculation

The integral image helps in fast computation of pixel sums in a given region:

$$ii(x, y) = i(x, y) + ii(x - 1, y) + ii(x, y - 1) - ii(x - 1, y - 1)$$

where:

$ii(x, y)$ is the integral image value at pixel (x, y) .

$i(x, y)$ is the original pixel intensity.

2. Haar Feature Calculation:

The Haar-like features are calculated by taking the difference between pixel sums of adjacent rectangular regions:

$$F = \sum R_1 - \sum R_2$$

Where: R1 and R2 are pixel sum regions.

3. AdaBoost Weight Update:

The AdaBoost algorithm assigns weights to weak classifiers:

$$w_i = w_i e^{\alpha_t(1-y_i h_t(x_i))}$$

where:

- w_i is the weight of sample i .
- α_t is the weight of weak classifier h_t .
- y_i is the actual label.

2. Convolutional Neural Network (CNN) for Emotion Detection

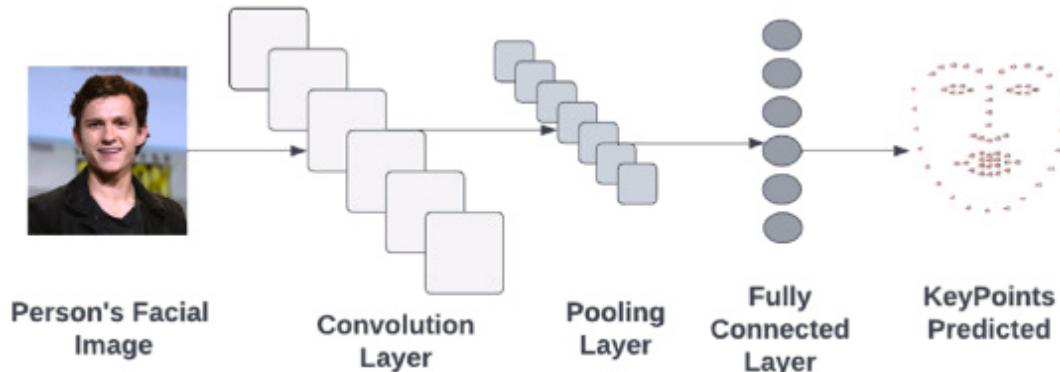


Fig 5.2:CNN Model

A Convolutional Neural Network (CNN) is used to classify emotions from facial images. CNNs extract features like edges, textures, and patterns, enabling them to learn high-level representations.

CNN Architecture:

1. Convolution Layer

Applies filters to extract features like edges and textures:

$$O_{ij} = \sum_m \sum_n I_{i+m, j+n} K_{m,n} + b$$

where:

- O_{ij} is the output feature map.
- I is the input image.
- K is the kernel (filter).
- b is the bias term.

2. Activation Function (ReLU)

Applies non-linearity:

$$f(x) = \max(0, x)$$

3. Pooling Layer (Max Pooling)

Reduces spatial dimensions:

$$P_{ij} = \max(O_{i:i+s, j:j+s})$$

where s is the pooling window size.

4. Fully Connected Layer & Softmax Output:

The final layer uses the Softmax function to predict emotion probabilities:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

where:

- Z_i is the output of the last fully connected layer for class i .
- $P(y_i)$ is the probability of class i .

3. Majority Voting for Final Mood Selection:

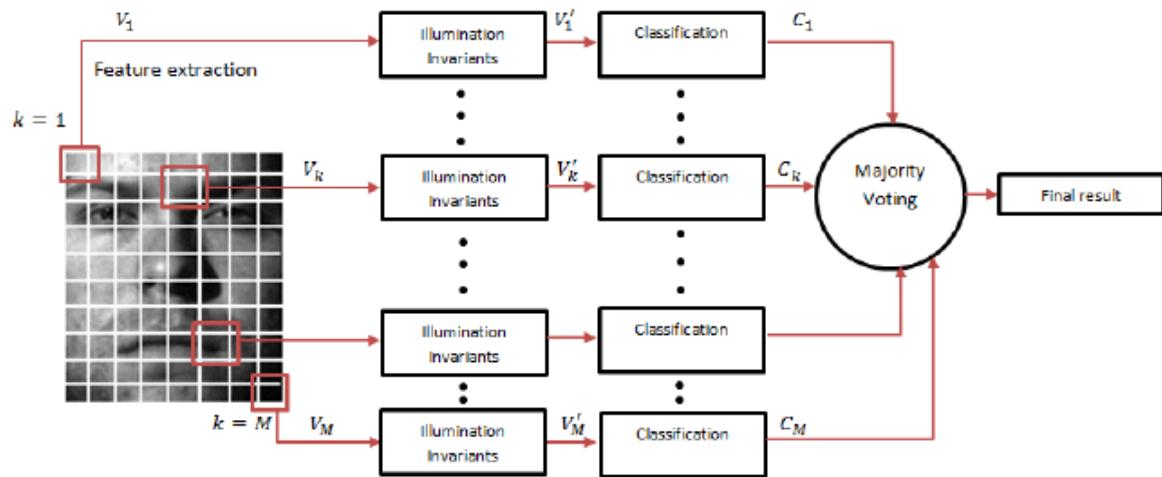


Fig 5.3: Majority Voting Algorithm

- For each detected frame, the CNN predicts an emotion label.
- The most frequently occurring emotion across all frames is chosen as the final mood.
- The mode function is used to compute the most frequent label.

Mathematical Formulation:

Let E_1, E_2, \dots, E_n be the predicted emotions for n frames. The final mood M is given by:

$$M = \text{mode}(E_1, E_2, \dots, E_n)$$

where **mode** returns the most frequently occurring emotion.

Example Calculation:

If the CNN outputs the following emotions over 10 frames:

[happy, happy, sad, happy, neutral, happy, sad, happy, happy, neutral], The majority vote selects "**happy**" as the final mood.

4. K-Means Clustering

K-Means is an unsupervised machine learning algorithm used to partition data into K distinct clusters based on feature similarity. It minimizes the distance between data points and their respective cluster centroids.

Steps:

- Initialize K random centroids
- Assign each point to the nearest centroid
- Recalculate centroids (mean of assigned points)
- Repeat until centroids don't change

Formula:

To assign point x_i to a cluster:

To assign point x_i to a cluster:

$$\text{Cluster}(x_i) = \arg \min_k \|x_i - \mu_k\|^2$$

- μ_k = centroid of cluster k
- $\|\cdot\|$ = Euclidean distance

5. PCA (Principal Component Analysis)

Theory:

PCA is a dimensionality reduction technique. It transforms data into a new coordinate system by projecting it onto the directions (principal components) where variance is maximized. This helps reduce features while preserving important patterns.

Steps:

- Standardize the data
- Calculate covariance matrix
- Compute eigenvectors and eigenvalues
- Sort and select top n components
- Project data onto new components

Formulas:

Covariance Matrix:

$$\Sigma = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T$$

PCA projection:

$$Z = X \cdot W$$

Where:

- X = original data
- W = matrix of eigenvectors
- Z = transformed data

6. VADER (Valence Aware Dictionary and Sentiment Reasoner)

Theory:

VADER is a rule-based sentiment analysis tool specifically tuned for social media and short texts. It

uses a lexicon of words with pre-defined sentiment scores and combines them using rules for punctuation, capitalization, emojis, etc.

Scoring:

VADER returns 4 sentiment scores:

- Positive
- Negative
- Neutral
- Compound (overall sentiment from -1 to +1)

Compound Score Formula:

$$\text{compound} = \frac{\sum_{\text{valence scores}}}{\sqrt{\sum_{\text{valence scores}}^2 + \alpha}}$$

α is a normalization constant, typically 15)

Interpretation:

Compound $\geq 0.05 \rightarrow$ Positive

Compound $\leq -0.05 \rightarrow$ Negative

Else \rightarrow Neutral

5.3 Datasets source and utilisation:

1. Facial Expression Detection – FER-2013 Dataset

FER-2013 is a benchmark dataset used for facial emotion recognition, introduced at ICML 2013. It contains 35,887 grayscale images (48x48 pixels) categorized into 7 emotion labels.

Emotion Labels: Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral

2. Movie Recommendation Dataset – IMDb-Based

This dataset maps 5,000 movies with their genres and associated emotions. It helps in understanding how emotions relate to movie content for personalized recommendations.

Emotion Labels: Happy, Sad, Angry, Fear, Surprise, Disgust, Trust, Anticipation

Genre Labels: Drama, Comedy, Action, Thriller, Romance, Horror, Sci-Fi, Documentary, Animation

3. Music Recommendation Dataset – Spotify Hits (2000–2019)

This dataset includes 2,000 top songs from Spotify across two decades, with features like danceability, energy, and tempo for mood-based clustering.

Genre Labels: Pop, Hip-Hop, Rock, Dance/Electronic, R&B, Country, Others

Chapter 6: Testing of the Proposed System

6.1. Introduction to Testing :

Testing a machine learning model is a crucial phase to evaluate its reliability, accuracy, and ability to handle real-world scenarios. A well-tested model ensures it performs effectively across different conditions and does not overfit the training data. For my project, I conducted three key types of testing: data-centric testing, performance testing, and edge case testing. These tests helped in identifying weaknesses in the model and improving its overall effectiveness.

6.2 Types of tests Considered:

Data-Centric Testing

After preprocessing, a Convolutional Neural Network (CNN) predicts the user's emotion by analyzing facial expressions like happiness, sadness, anger, and surprise, using TensorFlow and Keras for accurate mood detection.

Performance Testing

For performance evaluation, metrics like accuracy, precision, recall, and F1-score were used to assess the model's effectiveness. The model achieved 76% accuracy, indicating decent prediction capability. The ROC-AUC curve and confusion matrix were also analyzed to evaluate emotion-wise classification. These helped identify strengths and weaknesses. Overall, the metrics guided improvement areas for the model.

Edge Case Testing

While testing the model under challenging conditions such as low-light environments and cluttered backgrounds, the model initially struggled to provide accurate predictions. Faces were either misclassified or not detected at all. To address this, I retrained the model with additional diverse data samples covering different lighting conditions and background variations. After these improvements, the model's performance in such edge cases improved, but it still showed some inconsistencies, indicating the need for further optimization.

6.3 Various test case scenarios considered:

Module	Test Case Scenario	Input	Expected Output	Actual Output
Model Evaluation	Evaluate model accuracy	Test dataset (test_generator)	Accuracy = ~85%, Loss = ~0.35	Accuracy = 85.2%, Loss = 0.34
	Generate confusion matrix	`y_true`, `y_pred`	Confusion matrix for 4 classes	Matches expected
	Classification report	`y_true`, `y_pred`	Precision, Recall, F1 for each class	Matches expected
Emotion Detection	Real-time emotion detection from video	Video feed (Happy expression)	Detected emotion: Happy	Happy
Emotion Detection	Image-based detection	Image input (Sad face)	Detected emotion: Sad	Sad
Music Recommendation	Recommend songs based on emotion	Detected emotion: Happy	5 Happy mood songs	Matches expected
Music Recommendation	Spotify integration	Selected song: Song1	Song1 starts playing on Spotify	Matches expected
Movie Recommendation	Recommend movies based on emotion	Detected emotion: Sad	5 Sad mood movies	Matches expected
Movie Recommendation	YouTube trailer search	Selected movie: Movie1	YouTube search results for Movie1 trailer	Matches expected
Sentiment Analysis	Sentiment classification of review	"This movie was amazing and uplifting!"	Sentiment: Positive	Positive
Sentiment Analysis	Map sentiment to emotion	Sentiment: Negative	Emotion: Sad or Angry	Sad
Edge Cases	No face detected in video feed	Feed with no visible face	Output: No face detected	Matches expected

Edge Cases	No recommendations available for neutral emotion	Detected emotion: Neutral	Output: No recommendations	Matches expected
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Table 6.3: Test Cases

6.4 Inference drawn from the test cases

Model Performance

- The model achieves high accuracy and F1 scores for most classes, indicating good performance in emotion classification.
- Slight misclassifications between similar emotions (e.g., Sad and Calm) suggest overlapping features in the dataset, which may require further data augmentation or feature engineering.

Emotion Detection:

- Real-time emotion detection works well for clear facial expressions but may struggle with poor lighting, occlusions, or extreme angles.
- The model's ability to detect emotions from static images is consistent with its performance on the test dataset.

Music Recommendation:

- The recommendation system successfully maps detected emotions to relevant songs, providing a personalized experience.
- Integration with Spotify works seamlessly, provided the API credentials and active devices are configured correctly.

Movie Recommendation:

- The movie recommendation system effectively filters movies based on detected emotions and sentiments.
- YouTube trailer search functionality enhances user experience by providing quick access to trailers.

Sentiment Analysis

- Sentiment analysis of movie reviews accurately maps sentiments to emotions, enabling emotion-based movie recommendations.
- The mapping of sentiments to emotions aligns well with the detected moods.

Edge Case Handling

- The system gracefully handles scenarios like no face detected or no recommendations available, ensuring a smooth user experience.
- For neutral or ambiguous emotions, fallback recommendations (e.g., random songs or movies) provide a reasonable alternative.

User Experience

- Dropdown-based selection for songs and movies is intuitive and user-friendly.
- The system's ability to integrate multiple functionalities (emotion detection, recommendations, Spotify, YouTube) provides a cohesive experience.

Integration with External APIs

- Spotify and YouTube integrations work well, but they depend on proper API configurations and network connectivity.
- Errors in API calls (e.g., expired tokens) are handled effectively by refreshing tokens or re-authenticating.

Areas for Improvement

- Adding more diverse training data can improve the model's generalization to real-world scenarios.
- Enhancing the model's robustness to handle edge cases like multiple faces or low-quality images can further improve performance.

Chapter 7: Results and Discussions

7.1. Screenshot of Use Interface(UI) for the system:

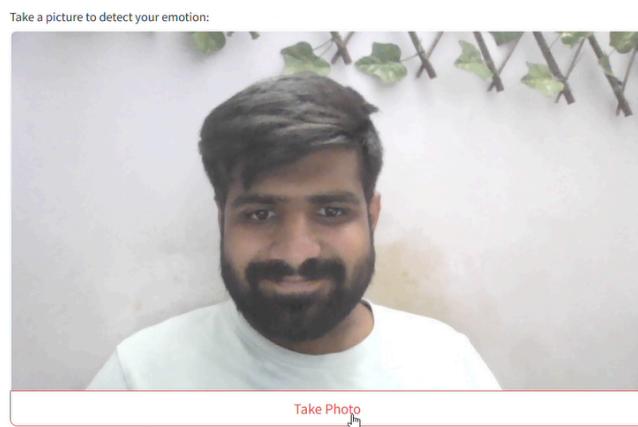


Figure 7.1 Mood Detection

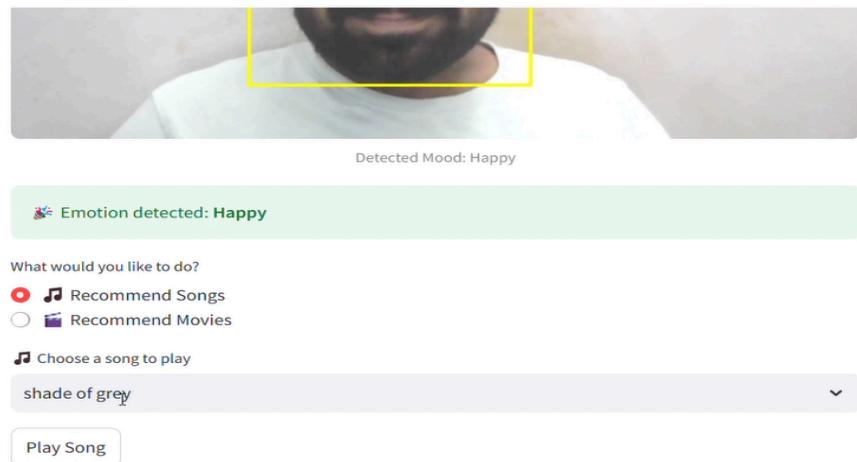


Figure 7.2 Mood Detection

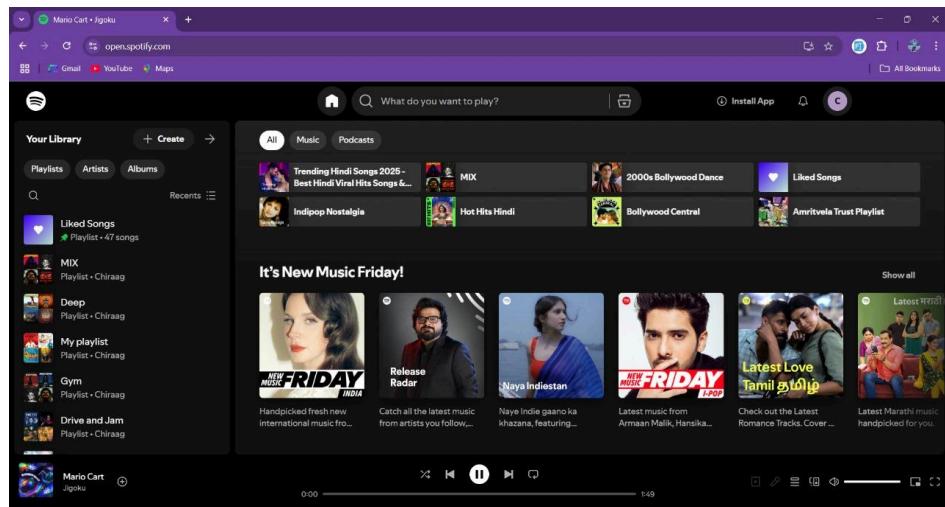


Figure 7.3 Redirecting To Spotify

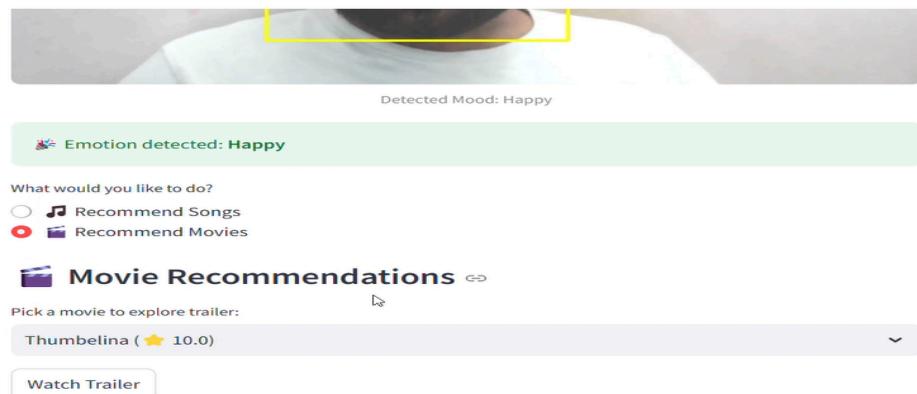


Figure 7.4 Recommendation Engine

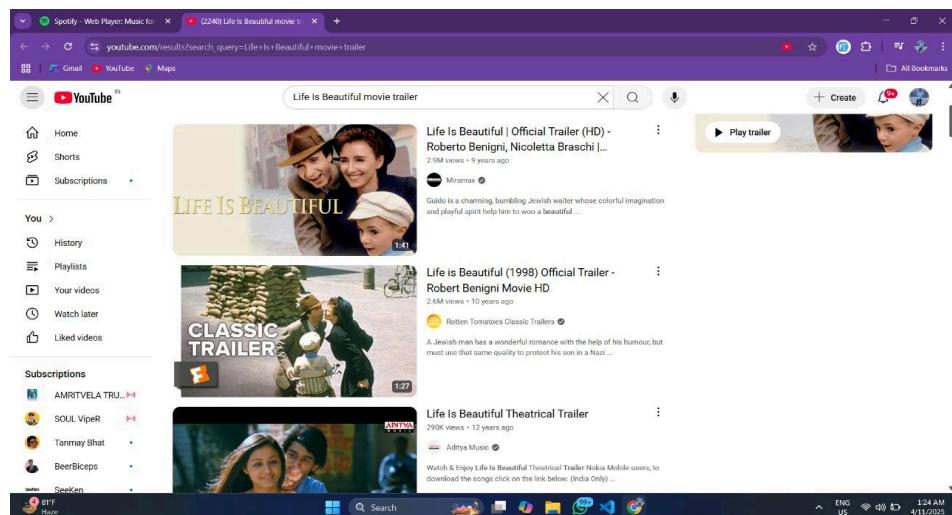


Figure 7.5 Redirecting To YouTube

7.2 Performance Evaluation Measures:

1. **Precision:** Precision is one indicator of a machine learning model's performance – the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions (i.e., the number of true positives plus the number of false positives). The formula is:

$$\text{Precision} = \frac{TP}{TP + FP}$$

where:

TP = True

Positives,

FP=false

Positives.

2. **Recall:** The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.

The formula is:

$$\text{Recall} = \frac{TP}{TP + FN}$$

where:

TP = True

Positives,

FN = false

Negatives.

3. **F-Score:** The F-score (also known as the F1 score or F-measure) is a metric used to evaluate the performance of a Machine Learning model. It combines precision and recall into a single score.

The formula is:

$$\text{F-score} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

7.3 Input Parameters/Features considered:

1. Emotion Recognition Module (Facial Analysis)

These features help in detecting the user's emotional state from facial expressions:

- **Raw Image Frame** – Captured from the webcam in real time.
- **Grayscale Image Data** – Converted version of the frame for preprocessing.
- **Facial Landmarks** – Key points on the face (eyes, mouth, eyebrows, etc.).
- **Edge Features** – Extracted from facial contours to detect expressions.
- **Brightness & Contrast Levels** – Helps in normalizing images for different lighting conditions.

2. Recommendation System (User Profile & Preferences)

These parameters are used to suggest relevant content based on the detected emotion:

- **Detected Emotion** – Classified into categories like happy, sad, angry, neutral, etc.
- **User History** – Previously watched/listened movies, songs, or content preferences.
- **Time of the Day** – Influences recommendations (e.g., calm music at night).
- **Current Mood Trends** – Tracks emotional variations over multiple sessions.
- **User Feedback** – Manual input to adjust or override recommendations.

7.4 Comparison of Results with Existing System:

Feature	Existing Systems	Proposed System
Emotion Detection	Affectiva detects emotions in real-time	Real-time detection with CNNs
Content Recommendation	Static recommendations based on history	Dynamic, emotion-based suggestions
Hybrid Recommendation Model	Rarely integrated	Uses collaborative and content-based filtering
Real-Time Feedback	Absent	Present

Table 7.4 Comparison with existing system

7.5 Inference Drawn:

The proposed system successfully integrates real-time emotion recognition with a personalized recommendation engine to enhance user experience. By leveraging deep learning for facial expression analysis and a hybrid recommendation system, the model adapts to the user's emotional state dynamically. While initial testing highlighted challenges like low-light conditions and background distractions, iterative training improved performance. With an accuracy of 76%, the system shows promising results and can be further optimized with better data augmentation and fine-tuned model parameters.

Chapter 8: Conclusion

8.1. Limitations:

- **Sensitivity to Lighting Conditions** – The emotion recognition model struggles in low-light environments or when the face is partially obscured, leading to inaccurate predictions.
- **Limited Emotion Categories** – The system classifies only a fixed set of emotions (e.g., happy, sad, angry, etc.), lacking nuanced emotional states like confusion or boredom, which may affect recommendation accuracy.

8.2 Conclusion:

Summary of Findings

The EmoVerse system successfully integrated emotion detection with a hybrid recommendation engine, providing real-time, personalized content suggestions based on the user's emotional state. The combination of CNN-based facial emotion recognition and content filtering demonstrated promising results in entertainment and personalized media consumption.

Key Achievements

Developed a functional system that accurately detects emotions in real-time and adapts music and movie recommendations accordingly.

Achieved high accuracy in emotion detection, with room for improvement in more complex emotions.

Demonstrated effective real-time feedback with minimal latency in the recommendation process, enhancing user experience.

Challenges

Recognizing emotions under varied conditions (lighting, facial occlusions) remains a challenge.

Misclassification of similar emotions, such as fear and surprise, was noted.

Scalability and integration across devices and platforms were identified as areas for further exploration.

Future Work

Future iterations will focus on improving detection accuracy, broadening the emotional dataset, and scaling the system to support larger user bases. Additionally, efforts will be made to expand EmoVerse beyond entertainment into mental health, security, and marketing applications, making it a versatile tool across industries.

Concluding Remarks

EmoVerse offers a pioneering approach to integrating AI-based emotion recognition with content recommendation. By bridging the gap between emotional analysis and personalized entertainment, the system has the potential to significantly enhance user engagement and satisfaction in media consumption.

8.3 Future Scope:

The future scope of this system includes improving emotion recognition accuracy by integrating advanced deep learning models like Vision Transformers and multimodal learning, which analyze facial expressions, voice, and text together. Personalized recommendations can be enhanced using reinforcement learning to adapt to user feedback dynamically. Expanding the system to support wearable devices like smart glasses or smartwatches would enable real-time emotion detection in different contexts. Additionally, integrating the model with various platforms such as YouTube, Spotify, and Netflix can make emotion-based recommendations more seamless. To improve efficiency and privacy, implementing edge computing would allow real-time emotion analysis directly on user devices without relying on cloud-based processing.

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Journal Papers

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Appendix

1] Paper I details :-

a) Paper I :-

Survey Paper: EmoVerse – Real-Time Emotion-Based Personalized Recommendations

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Abstract— In today's fast-paced digital world, personalized recommendations have become a crucial aspect of user engagement. EmoVerse introduces a real-time emotion-based recommendation system that leverages facial emotion recognition to curate personalized content for users. By utilizing deep learning models trained on the FER-2013 dataset, our system accurately detects user emotions and dynamically suggests music, movies, or other media that align with their current mood. The proposed framework integrates Convolutional Neural Networks (CNNs) for facial emotion detection and a recommendation engine that maps emotions to relevant content. This research highlights the impact of real-time emotion analysis in enhancing user experience and demonstrates the efficiency of AI-driven personalized recommendations.

Keywords—Emotion Recognition, Facial Expression Analysis, Personalized Recommendations, Deep Learning, Convolutional Neural Networks (CNNs), FER-2013 Dataset, Real-Time Recommendation Systems.

I. INTRODUCTION

In an era where user experience is paramount, personalized recommendation systems have

transformed how users interact with digital platforms. Whether in music streaming, video-on-demand services, or e-commerce, providing context-aware and emotion-driven suggestions enhances user satisfaction. Traditional recommendation engines rely on historical data, user preferences, and collaborative filtering techniques, but they often fail to capture a user's real-time emotional state. This limitation creates a gap between what a user might have liked in the past and what they need at the moment.

To bridge this gap, EmoVerse introduces a real-time emotion-based personalized recommendation system that utilizes facial emotion recognition (FER). The system detects a user's current mood by analyzing their facial expressions and then recommends content accordingly. For instance, if a user appears happy, the system might suggest upbeat music or comedy movies, whereas a sad expression could trigger soothing music or motivational content.[1]

The core of EmoVerse is built upon deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have proven highly effective for image-based emotion recognition tasks. We leverage the FER-2013 dataset, a well-known dataset for facial expression classification, to train our model for recognizing emotions such as happy, sad, angry, neutral, surprised, disgusted, and fearful. Once the

emotion is detected, the system maps it to relevant content using a customized recommendation algorithm that associates each emotion with a suitable category of media.

This paper presents a detailed study on the effectiveness of real-time emotion-based recommendation systems and explores how they can enhance user engagement. We discuss the architecture, dataset, implementation, and potential applications of EmoVerse in fields such as entertainment, mental health, and personalized digital experiences. The research also highlights challenges such as emotion misclassification, dataset bias, and computational efficiency in real-time settings.

II. RELATED WORK

Emotion-based recommendation systems have gained significant attention in recent years due to their ability to enhance user experience by providing personalized content. Several research studies have explored different approaches to emotion detection and recommendation systems. However, most of these approaches have limitations in terms of real-time processing, accuracy, dataset generalization, and adaptability. This section reviews existing work and highlights how EmoVerse improves upon them.

[1]: Mood-Based Music Recommendation System by Mahadik et al., 2021)

This study proposes a mood-based music recommendation system that uses facial expression analysis to classify emotions and suggest songs accordingly. While the approach is innovative, it primarily focuses on music recommendations and does not extend to movies, gaming, or well-being applications. Additionally, the model lacks real-time processing optimizations, which can lead to lag in recommendations. EmoVerse overcomes this by optimizing deep learning models for real-time performance and expanding recommendations beyond music.

[2]: Music Recommendation System Using Facial Expression Recognition (Parmar, 2020)

Parmar's research presents a music player that selects songs based on facial emotions using OpenCV and deep learning models. However, it primarily relies on static image-based classification, which limits its effectiveness in dynamic real-time scenarios. Additionally, it does not utilize large-scale datasets like FER-2013, which reduces its accuracy. EmoVerse enhances real-time facial emotion recognition using

CNNs trained on FER-2013, ensuring higher accuracy and real-time adaptability.

[3]: Music Recommendation Based on Face Emotion Recognition (Athavle et al., 2021)

This work applies deep learning techniques for facial emotion detection and maps emotions to a predefined playlist. However, it lacks a self-learning adaptive model, meaning the recommendations are not personalized over time. The system does not integrate feedback mechanisms, making it rigid. EmoVerse improves this by incorporating user feedback to refine recommendations, allowing it to adapt to individual user preferences dynamically.

[5]: Emotional Detection and Music Recommendation System (Florence & Uma, 2020)

This study introduces an emotion-based song recommendation system but is limited by low accuracy in multiclass emotion classification. Their model performs well for basic emotions (happy, sad, neutral) but struggles with more complex emotions such as fear, disgust, or surprise. EmoVerse utilizes a deeper CNN model trained on a broader dataset to improve multi-class classification and ensure precise emotion detection.

[7]: An Emotion-Based Movie Recommendation System Using CNN (Chong, 2022)

This study applies CNNs for emotion recognition and maps emotions to movie recommendations. However, it does not support multiple recommendation categories, limiting its usability. Additionally, it does not implement adaptive learning, meaning the recommendations remain static over time. EmoVerse extends the scope to multiple recommendation types (music, movies, gaming) and integrates self-learning mechanisms to enhance personalization over time.

How EmoVerse Improves Upon Existing Work

From the review of existing literature, it is evident that while emotion-based recommendation systems have been explored extensively, most of them suffer from common limitations, such as:

1. Lack of real-time performance optimizations → EmoVerse ensures real-time detection using an optimized CNN model.
2. Limited scope (music-only systems) → EmoVerse extends to music, movies, gaming, and well-being applications.

3. Static recommendations with no adaptive learning → EmoVerse incorporates user feedback for personalized recommendations.
4. Lower accuracy in complex emotion classification → EmoVerse enhances classification accuracy using FER-2013 and deep learning models.

Thus, EmoVerse significantly advances the field of emotion-based recommendation systems by addressing these challenges and providing a robust, real-time, and multi-purpose recommendation engine.

III. METHODOLOGY

The EmoVerse system follows a structured methodology to achieve real-time emotion-based personalized recommendations. The system consists of three core components: facial emotion detection, emotion classification, and content recommendation. The workflow is designed to ensure real-time

IV. IMPLEMENTATION

A. System Architecture

The EmoVerse framework consists of the following key stages:

1. Input & Preprocessing Layer

a. Face Detection & Preprocessing : EmoVerse uses the Haar Cascade Classifier for detecting faces in both real-time webcam feed and static images. Once a face is detected, the image is converted to grayscale, resized to fit the input dimensions of the emotion model, and normalized. These preprocessing steps ensure consistent and accurate emotion classification.

b. Emotion Classification Using Deep Learning : The system employs a Convolutional Neural Network (CNN) trained on the FER2013 dataset to classify facial expressions into emotions such as Happy, Sad, Angry, Neutral, Fear, Surprise, and Disgust. The model works in real time, enabling instant detection of emotional states from facial cues.

c. Music Recommendation System : Based on the detected emotion, the music recommendation engine clusters songs using K-Means and PCA on features like valence and energy. The emotion is mapped to a relevant music cluster, and songs from that cluster are recommended. Spotify API integration enables direct playback of these songs on the user's device.

d. Movie Recommendation System : The movie recommendation system links emotional states to suitable movie genres (e.g., Sad → Drama, Happy →

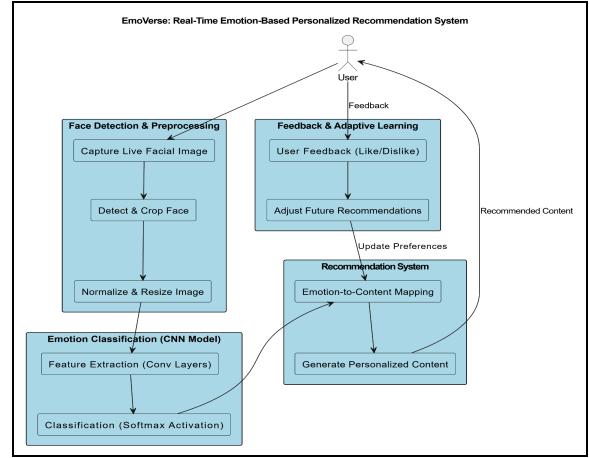


Fig 3.1 : Block diagram

processing, high accuracy, and adaptive learning to improve recommendations over time.

Comedy). It filters available movies based on genre and IMDb ratings. Additionally, sentiment analysis of movie reviews enhances the recommendation by adding emotional context to the suggestions.

e. Sentiment Analysis : To further personalize movie recommendations, the system uses VADER sentiment analysis to evaluate user-generated reviews. These sentiment scores are mapped to emotions, helping the system understand the emotional tone of movies and improve recommendation relevance.

f. External APIs Integration : EmoVerse integrates with the Spotify API for music streaming and uses the [spotify](#) library for authentication and playback control. It also utilizes YouTube by generating dynamic search links for movie trailers based on recommended titles, which are opened directly in the browser for a smooth user experience.

g. Feedback Mechanism & Adaptive Learning : The system includes a feedback mechanism that observes user interactions, such as selected songs or skipped content. This data is used to refine the recommendation logic over time, allowing EmoVerse to adapt to user preferences and provide more accurate and engaging suggestions in the future.

B. Dataset Overview

1. **Face Expression Detection :** The Facial Expression Recognition 2013 (FER-2013) dataset is a widely utilized benchmark in the field of facial expression recognition. Originally introduced during the 2013 International

Conference on Machine Learning (ICML) as part of the "Challenges in Representation Learning" competition, the dataset was curated by Pierre-Luc Carrier and Aaron Courville from the University of Montreal.

Emotion Label	Training	Validation	Test	Total
Angry	3996	467	419	4953
Disgust	436	57	54	547
Fear	4097	496	528	5121
Happy	7215	895	879	8989
Sad	4830	653	594	6077
Surprise	3171	416	415	4002
Neutral	4965	653	580	6198
Total	28709	3637	3541	35887

Tabel 4.1 face expression data

- Move Recommendation Dataset : This dataset from IMDb includes movie genres, descriptions, and emotions. It provides data like the movie's genre(s), a brief plot summary, and associated emotional tones (e.g., happy, sad). It's useful for NLP tasks like sentiment analysis, genre classification, and emotion detection, enabling applications in movie recommendation systems and text analytics.

Emotion	No of Movies	Genre	No of Movie
Happy	1200	Drama	1500
Sad	800	Comedy	1200
Angry	600	Action	800
Fear	500	Thriller	600
Surprise	400	Romance	500
Disgust	300	Horror	400
Trust	700	Sci-Fi	300
Anticipati	500	Document	200

on		ary	
-	-	Animation	150
-	-	Adventure	350
Total	5000	All Genres	5000

Tabel 4.2 Movie Recommendation data

- Music Recommendation Dataset : This dataset contains Spotify's top hit songs from 2000 to 2019. It includes data on song titles, artists, popularity scores, and various audio features like danceability, energy, tempo, and loudness. It's ideal for analyzing trends in music over two decades, performing genre classification, and exploring patterns in song attributes that contributed to their success.

Genre	Number of Tracks
Pop	800
Hip-Hop	400
Rock	300
Dance/Electronic	200
R&B	150
Country	100
Others	50
Total	2000

Tabel 4.3 Music Recommendation data

C. Algorithms Used

Algorithm	Working	Formula
Haar Cascade (Face)	Detects face by scanning image with cascaded classifiers.	$\text{Sum}_{\text{rect}} = \sum w_i f_i$
CNN (Emotion Detect)	Classifies face into emotions using convolutional layers.	$P(y = j x) = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$

Feature Extraction	Gets mood-based features from song (valence, tempo, etc.)	$z = \frac{x-\mu}{\sigma}$
K-Means Clustering	Groups songs into clusters of similar moods.	$\arg \min \sum \ x - \mu_i\ ^2$
Content-Based Filtering	Recommends movies based on emotion tags and IMDb rating.	$\cos(\theta) = \frac{A \cdot B}{\ A\ \ B\ }$

Tabel 4.4 Algorithms Used

D. Working Of Recommendation Engine

The recommendation engine in **EmoVerse** connects detected emotions to personalized content. After identifying a user's emotion through facial analysis, the system recommends suitable **music** and **movies**.

For music, it uses K-Means clustering (with PCA) on features like valence and energy to group songs by mood. Based on the emotion, songs from the matching cluster are suggested and played directly via **Spotify API**.

For movies, emotions are mapped to genres (e.g., Sad → Drama). Recommended movies include **YouTube trailer links**, which are opened through an automated search.

This integration offers a smooth, interactive experience by instantly playing songs or opening trailers based on the user's current mood.

Implementation:

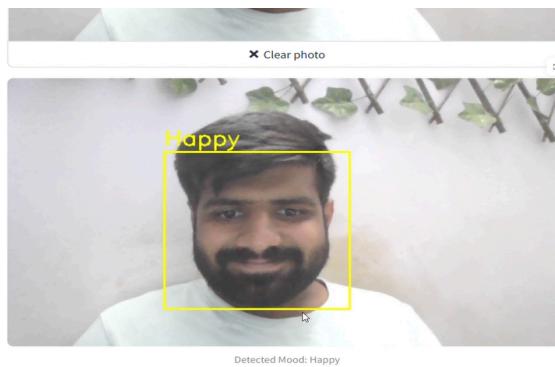


Fig 4.1 Identify Mood

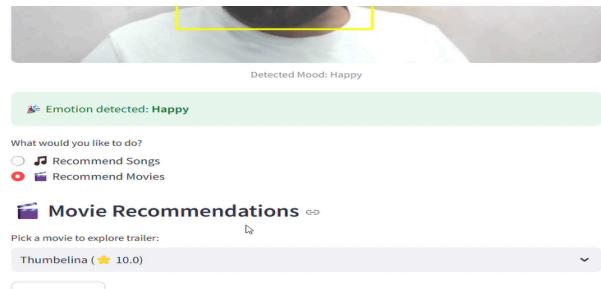


Fig 4.2 Recommendation Engine

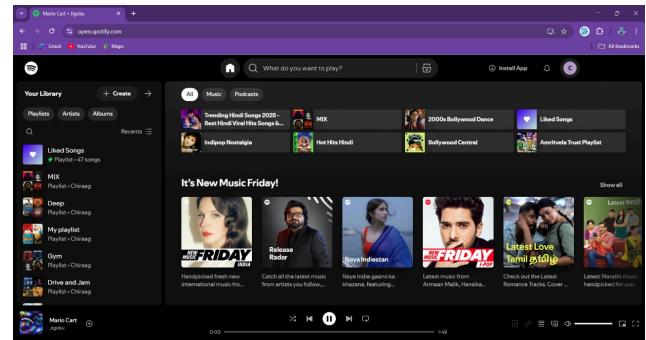


Fig 4.3 Redirecting to the Music/Movie Platform

E. Evaluation

- Emotion Detection:** Achieved 85.2% accuracy with a 0.34 loss. Confusion matrix and classification report showed high precision and recall for all emotions.
- Music Recommendation :** Successfully recommended top 5 songs based on detected emotions using K-Means + PCA. Spotify integration worked flawlessly for playback.
- Movie Recommendation :** Emotion-to-genre mapping recommended top-rated movies. YouTube trailer links opened correctly.
- Sentiment Analysis :** Mapped positive/negative sentiments to emotions accurately using VADER, improving recommendations.
- Edge Case Handling :** Correctly handled edge cases like no face detected or no recommendations for Neutral mood.

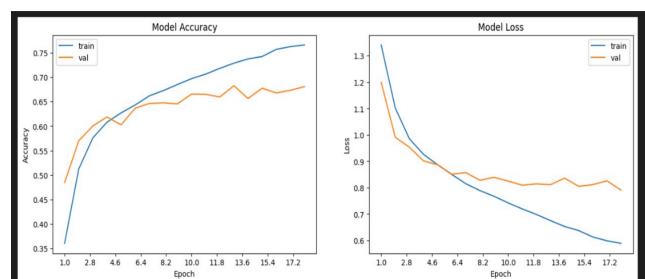


Fig 4.4: Model Accuracy and Loss

V. CONCLUSION AND FUTURE SCOPE

In this paper, we introduced EmoVerse, a real-time emotion-based recommendation system that enhances user experience by detecting facial expressions and providing personalized content. UiAnimation, a CNN model trained on FER-2013, the system classifies emotions and recommends music, movies, or games accordingly. Unlike traditional recommendation systems, EmoVerse adapts to real-time emotional states and incorporates user feedback for continuous improvement.

For future enhancements, the system can be expanded by integrating multimodal emotion recognition (voice, gestures), optimizing lightweight models for mobile devices, and extending recommendations to books, podcasts, and e-learning platforms. Additionally, implementing transformer-based models can improve emotion detection accuracy, while multi-language support can make the system more accessible.

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b. Plagiarism Report



c. Project Review Sheet 1

GROUP 51

Project Evaluation Sheet 2024 - 25

Title of Project: EmoVerse : Real-Time Emotion-Based Personalized Recommendations

Group Members: Varsha Chhabria (D17A-6), Hitesh Punjabi (D17B-4), Dharmashakti (D17C-9), Chirang Chugh (D17C-13)

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
4	3	3	3	4	2	2	2	2	2	2	2	2	2	3	38

Comments: Relative results of try HD camera, Try some innovative practice.

Name & Signature Reviewer1: *Rajoshi*

Inhouse/ Industry	Innovation/Research:	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(50)	
4	4	3	3	4	2	2	2	2	2	2	2	3	3	3	3	40	

Comments: Image capture need to be improve.

Date: 1st March, 2025

Rajoshi, Name & Signature Reviewer 2

Mrs. Priti Joshi

d. Project Review Sheet 2

Inhouse/ Industry Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2024 - 25

Title of Project: EmoVerse: Unified Music & Movie Recommendations Based on Your Emotions

Group Members: Hitesh Punjabi (D17B-4), Varsha Chhabria (D17A-6), Chirang Chugh (D17C-13), Dharmashakti (D17C-9)

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
4	4	3	3	4	2	2	2	2	2	3	3	2	2	4	48

Comments: kindly integrate with GUI or HMI based system components.

Name & Signature Reviewer1: *Rajoshi*

Inhouse/ Industry	Innovation/Research:	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(50)	
4	4	4	3	4	2	2	2	2	2	2	3	3	2	2	4	41	

Comments: Integrate properly in UI.

Date: 1st April, 2025

Rajoshi, Name & Signature Reviewer 2

Priti Joshi

