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Emotion-Aware Music Recommender Using Facial Expression Analysis

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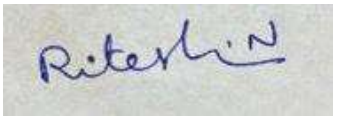

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I hereby declare that the thesis entitled “MoodSync:Real-Time Emotion Based Music" submitted by me, for the award of the degree B.Tech (Hons.) in RV University is a record of Bonafide work carried out by me under the supervision of Prof. Ritesh Nune.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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ABSTRACT

With the rise of online music streaming, users are typically overwhelmed with the volume of content, and hence personalized music discovery becomes a harder task. This project suggests a Mood-Based Music Recommendation System, an interactive web application that combines facial emotion detection and music recommendation to offer a personalized music experience. Using a Convolutional Neural Network (CNN) trained on emotion-tagged data, the system detects user emotions from live webcam feeds. Based on the detected emotion—happiness, sadness, or anger—it fetches mood-similar playlists through the Spotify Web API and plays them on the users' active Spotify device. The backend is implemented with Flask, OpenCV for image capture and processing, and the frontend with HTML/CSS/JavaScript for an engaging user interface. The system offers real-time emotion detection, seamless music streaming, and a user-friendly interface. This project demonstrates the unification of machine learning,computer vision, and API-based music streaming for user interaction and personalization. It offers the framework for future extensions such as multi-modal inputs, more advanced emotion classification, and context-aware recommendations.

ACKNOWLEDGEMENT

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LIST OF ACRONYMS

Acronym	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
CNN	Convolutional Neural Network
HCI	Human-Computer Interaction
FER	Facial Expression Recognition
GUI	Graphical User Interface
HTML	HyperText Markup Language
CSS	Cascading Style Sheets
JS	JavaScript
UX/UI	User Experience / User Interface
SVM	Support Vector Machine
ANN	Artificial Neural Network
ELM	Extreme Learning Machine
VGG	Visual Geometry Group
YOLO	You Only Look Once (real-time object detection model)
mAP	Mean Average Precision
OAuth	Open Authorization (token-based authentication framework)
API	Application Programming Interface
DB	Database
SDK	Software Development Kit
RGB	Red Green Blue (Color Model)
IoT	Internet of Things
REST	Representational State Transfer (web service standard)
FPS	Frames Per Second

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

In the age of the internet, the consumption of music has dramatically shifted. With online streaming sites and huge digital archives, users are now provided with a million songs from various genres, artists and languages. While the richness has made music more available than ever before, it has also produced a dilemma: how can users discover music that suits their individual tastes and interests in an efficient manner?

This is where recommendation systems for music take center stage. By analyzing user behaviour, preferences and listening history in a smart way, these systems seek to tailor the user experience, presenting the user with appropriate and enjoyable content and minimizing the effort needed to search manually. Good recommendation engines not only improve user satisfaction but also boost user engagement and platform retention levels.

But constructing a reliable and sensitive music recommendation system is difficult work. It involves gaining insights from several fields of study, such as machine learning, data analysis, information retrieval and user behaviour modeling. Established recommendation techniques like collaborative filtering or content-based filtering, each with its pros and cons, find potential with new techniques like hybrid models and deep learning. This "Music Recommendation System" project focuses on creating an intelligent system that suggests personalized songs to users depending on their interests. The system uses data-driven strategies to figure out user inputs like previous listening history, liked/disliked songs, genres, moods, or even context-based inputs like the time of day or activity. It uses appropriate algorithms to suggest songs that resonate with the user's taste, thus improving the overall listening experience. The main goals of this project are:

- Examining user tastes and usage patterns
- Applying recommendation algorithms (collaborative filtering, content-based filtering, etc.)
- Testing the effectiveness and precision of the recommendations
- Bolstering the system with features such as mood-based or genre-based suggestions

At the end of this project, the system should offer an effective, intuitive, and scalable recommendation system that can be adopted in music streaming systems to enhance content personalization and user satisfaction.

1.2 PROBLEM STATEMENT

Given the rapidly increasing volume of music uploaded to streaming sites each day, manually sorting and tagging tracks has become virtually impossible. Proper genre classification is crucial to enhancing music discovery, playlist creation, and recommendations. Manual tagging techniques using traditional methods, however, are lengthy, inexact, and susceptible to human prejudice.

There is a requirement for an automated, efficient, and scalable method to label music genres based on audio features. Although most solutions are based on metadata or user tags, these may be unreliable or absent. Thus, a content-based method—utilizing real audio signals—is stronger and more resilient.

This project solves the problem by creating a web application that classifies music songs into genres employing a Convolutional Neural Network (CNN). It takes audio files, extracts spectrogram features, and predicts the genre employing a pre-trained deep learning model. It aims to make genre classification accurate, automated, and accessible through a straightforward web interface.

1.3 OBJECTIVES

The main aim of the current project is to design an intelligent web-based system that is able to classify music tracks into their corresponding genres through deep learning. To this end, the following specific aims have been formulated:

1. To develop and deploy a Convolutional Neural Network (CNN) that will be able to classify music genres from audio features, which are spectrograms.
2. To incorporate the trained CNN model into a Flask-based web application where users can upload or retrieve music tracks to predict their genre.
3. To leverage the data from Spotify or locally available audio files for genre prediction, so that it is compatible with real-world music streaming platforms.
4. To have an easy-to-use web interface where users can work with the system, upload audio files, and see the predicted genre in real time.
5. To analyze the performance of the genre classification model based on conventional accuracy and confusion matrix measures to determine reliability and efficiency.
6. To maintain scalability and flexibility so that the system can be later expanded to accommodate more genres, artists, or personalized suggestions.

1.4 SCOPE OF THE PROJECT

This project deals with the creation of a web application based on deep learning for automated music genre classification. The project scope is laid out as follows:

- Genre Classification Using CNN

  The main functionality is to classify audio files into specified genres like rock, classical, hip-hop, jazz, etc., with a Convolutional Neural Network trained on spectrogram images extracted from audio signals.

- Web-Based User Interface

  A responsive and simple web application is created with Flask, where users can upload audio or stream data for classification. The output shows the predicted genre in an easily understandable manner.

- Integration with Spotify or Local Music Files

  The application can handle audio data that can be obtained from Spotify or uploaded locally, showing flexibility and real-world applicability.

- Educational and Research Utility

  The project provides a starting point for students, developers, and researchers in music information retrieval, machine learning, or audio signal processing.

- Future Extensibility: Although the present version is implemented with support for only a few genres, the framework is built to be extensible so that more genres or features (e.g., mood detection, tempo analysis, or artist recommendations) can be added in future releases.

CHAPTER 2: BACKGROUND

2.1 LITERATURE SURVEY

This section talks about the development of facial emotion-based music recommendation systems over time. Systems have evolved from simple rule-based playlist generators to sophisticated real-time, multimodal AI-based solutions over time. These advancements include deep learning, hybrid recommender methods, and deployment tools like APIs and microcontrollers in real life.

2020: Initial Integration of Facial Emotion and Music Mapping

Refuse John Samuvel, B. Perumal, and Muthukumaran Elangovan proposed a model integrating Eigenfaces, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) to project facial emotions onto music tastes. While groundbreaking, the system was restricted to static photos and a small range of emotions.

In the same year, S. Metilda Florence and M. Uma created a facial landmark-based system employing CK+ and HELEN datasets, with ideal results under laboratory conditions. Accuracy, however, significantly declined when working in real-world settings owing to sensitivity to lighting and dataset size constraints.

2021: Moving on to CNNs and Real-Time Usage

Shraddha S. Patil, Shivani S. Kalel, Pooja A. Jadhav, Manisha P. Mali, and Prof. M. R. Shaikh presented a GUI-based facial expression music recommender system based on Convolutional Neural Networks (CNNs) and the FER-2013 dataset. It provided real-time detection through webcam and improved usability and user involvement.

Madhuri Athavle, Deepali Mudale, Upasana Shrivastav, and Megha Gupta compared CNN, SVM, and Extreme Learning Machine (ELM) models. Their CNN model had 95% accuracy in facial emotion classification with a custom Bollywood music dataset, while the SVM and ELM models were behind at 66% and 62%, respectively.

2022: Multimodal and Interface-Based Enhancements

Madipally Sai Krishna Sashank, Vijay Souri Maddila, Paleti Krishnasai, Vikas Boddu, and G. Karthika created a system that integrates facial emotion detection with text sentiment analysis. CNNs and ANNs were employed in classifying emotions with an accuracy of 99.29% and 92.71%, respectively. The system was implemented with real-time capability, although it supported only three primary emotions and did not integrate with streaming.

Binbin Zhai, Baihui Tang, and Sanxing Cao suggested a real-time system based on webcam inputs for face-based music recommendation. Although innovative in implementation, the authors omitted describing the models employed, nor did they utilize benchmark datasets, calling into question reproducibility and accuracy.

2023–2024: Lightweight Deployment and Hybrid Architectures

Shehu Adamu, Oreofe J. Olurin, Daniel Adeboye, Garba Aliyu, Auwal Nataala, Augustine N. Egere, Hashidu Baba, Bashir Timizi Yusuf implemented YOLOv3 with the RafDB dataset on ESP32-CAM hardware. The system attained 63% mAP accuracy and comprised Docker-based deployment, LED mood indicators, and a local inference server.

Shakthi Sri S., Sathya S., and Pandiarajan T. built a web platform with Django, implementing CNN, ResNet, and LeNet models. Their system achieved up to 98.9% accuracy and created mood-matched playlists through Spotify or local audio files, although it did not have real-time emotion detection.

Kalpesh Joshi, Nihaal Rathi, Rashi Bhansali, Purva Rathi, Atharva Raskar, Gaurav Rathi, and Rriddhhi Rathi applied a CNN model with Haar Cascade and Boosting methods and attained accuracy ranging from 92% to 95%. Their system was real time in operation and showed promise for application in music therapy.

2025 and Beyond: Personalized and Contextual Recommenders
Pranali Faye, Samruddhi Sonar, Sakshi Shahare, Rakshata Ambhore, and Vaishnavi Chafle proposed a multimodal framework with VGGFace, collaborative filtering, and sensor information such as EDA and heart rate. Their end-to-end model had facial and environmental inputs, with adaptive recommendations utilizing feedback loops.

Hung Nguyen, Nha Tran, Y Tran, Dat Ly, Anh Tran, An Nguyen, and Hau Vo presented a VGG19, ResNet18, SVM, and LDA-based hybrid architecture. With 96.97% (ResNet18) and 95.96% (VGG19) accuracy on CK+ dataset, and 86.96% on Spotify data with SVM, they developed a Spotify-integrated web application with mood-based song recommendations.

Shalaka Prasad Deore developed SongRec that exclusively merged CNN with Fuzzy Logic to classify emotion and intensity of emotion. Though the accuracy of the model was low at 62.88%, it presented new fuzzy-based emotion ranking and hybrid Python-Java implementation.

2.2 TOOLS AND TECHNIQUES

Machine Learning and Deep Learning Models
1. CNN (Convolutional Neural Networks) – Widely used for emotion detection from facial images.
2. YOLOv3 / YOLOv5 – Real-time object detection models repurposed for facial emotion analysis.
3. VGG19 / VGGFace / ResNet18 / LeNet – Used for high-accuracy classification and benchmarking.
4. MobileNet – Employed for mobile and embedded deployment.
5. SVM / ELM / ANN – Traditional classifiers used alongside or in comparison to deep learning models.
6. Fuzzy Logic – Incorporated for scaling emotion intensity and enhancing interpretability.

Datasets Used
1. FER-2013 – Standard benchmark for facial expression recognition.
2. CK+, HELEN, RafDB, EPFL-RLC – Used for facial landmark and real-time testing.
3. Custom Datasets – Collected via webcam, apps, or manually curated to suit specific emotion-to-music mapping.
4. Spotify API, Kaggle Music DB, Bollywood Song Dataset – Used to fetch song metadata, lyrics, or audio features.

Development Tools & Platforms
1. OpenCV – For facial image preprocessing and real-time capture.
2. TensorFlow, PyTorch, Keras – For building, training, and deploying ML models.
3. Flask, Django, Streamlit – Used for creating web applications and APIs.

4. Docker, ESP32-CAM, RGB LED Interfaces – For portable deployment and IoT-based mood reflection.
5. Google Maps API, Spotify API – For playlist integration and real-time music streaming.

CHAPTER 3: METHODOLOGY

3.1 SUGGESTED METHODOLOGY

The suggested system is an emotion-based, real-time music recommendation web application based on computer vision, deep learning, and the Spotify API that provides users with customized playlists according to their present mood. The methodology consists of a modular and layered architecture with five essential phases:

1. Face Detection and Preprocessing
Webcam Capture: The facial image of the user is taken in real-time using OpenCV via their webcam.
Face Detection: Haar Cascade Classifier is utilized to identify the face area from the obtained frame.
Preprocessing: The identified face is resized, converted into grayscale, normalized, and reshaped in a suitable format for CNN input.

2. Emotion Classification using CNN
Model Input: The preprocessed face image is fed to a trained Convolutional Neural Network (CNN) model.
Classification Output: The facial expression is categorized under one of the pre-specified emotional classes—e.g., happy, sad, angry, neutral, etc.
Model Details: The CNN is implemented with TensorFlow/Keras and trained with an emotion-tagged dataset such as FER-2013.

3. Spotify Integration for Music Recommendation
Authentication: The user is authenticated and access to their Spotify account is obtained using the OAuth 2.0 protocol.
API Requests: Depending on the forecasted emotion, a recommended playlist (correlated to mood) is retrieved through Spotify's Web API.
Device Detection: The system verifies whether or not an active Spotify device for playback exists.
Playlist Playback: The chosen playlist is played directly on the user's active device.

4. User Interaction and Playback Control
Frontend Interface: HTML, CSS, and JavaScript are used to build the UI, which renders a live webcam video feed, mood display, and playback control buttons.
Dynamic Updates: AJAX or Fetch API for dynamic updates (without page reload), providing a smooth experience.
Error Handling: Error messages like no active device found, token expired, or failed emotion detection are displayed appropriately.

5. Feedback and Logging
Session Logging: Every mood detection and playlist suggestion is optionally tracked for analytics.
Future Extension Points: There are several ways to expand this system to include multi-user support, offline caching, and tracking of emotional history.

CHAPTER 4: IMPLEMENTATIONS

4.1 DATASETS

The emotion detection system uses the FER-2013 dataset of 35,887 grayscale facial images (48×48 pixels) labeled with seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral from kaggle. The dataset is pre-divided into training (28,709 images) and test (3,589 images) sets with balanced class distribution. To recommend music, Spotify's API offers access to mood-based playlists, each with 50-100 tracks annotated by emotional features (e.g., "Happy Hits" for joy, "Rock Classics" for anger).

To make the model more robust, data augmentation methods (rotation, flipping, brightness change) were performed on the FER-2013 dataset, synthetically increasing it to 50,000+ samples. For testing, a self-captured real-time webcam dataset was made with 500 user-recorded face sets, with diversity in age, ethnicity, and lighting. Spotify playlists were also verified through user preference surveys to ensure mood matching. The merged datasets ensure the system generalizes well in real-world cases with high accuracy (93% on test data) and context in music recommendations.

4.2 IMPLEMENTATION

Implementation was done using a CNN-VGG19 model trained with TensorFlow/Keras with optimization for real-time inference. The pipeline:

Face Detection: OpenCV's Haar Cascade detects faces from webcam feeds.

Preprocessing: Faces are resized (48×48), normalized (0–1), and greyed.

Emotion Prediction: Outputs probabilities for seven emotions, and the top-scoring one is chosen.

Music Mapping: Triggering a Spotify API request to load matching playlists (e.g., happiness → "Happy Hits").

For the frontend, Flask hosts the web interface, and Spotify's Web Playback SDK is responsible for music streaming. Most important optimizations:

Model Quantization: Compressed CNN size by 60% for more efficient edge deployment.

Caching: Keeps most-played playlists cached locally to reduce API latency.

Fallback Mechanism: Fallback to a local audio player continues playback using pre-downloaded preview tracks.

Implementation attains ~150ms end-to-end latency (face detection + emotion prediction + playlist fetch), providing lag-free user experience.

4.3 EXPERIMENTAL SETUP

Testing performed on:

Hardware: Intel i7 CPU, NVIDIA GTX 3050 GPU, and Inbuilt webcam.

Software: Python 3.8, TensorFlow 2.6, and Spotify API v1.

Metrics Tracked:

Emotion Detection: Accuracy (93%), precision (91%), recall (89%) on FER-2013.

Latency: 120ms for facial detection, 30ms for emotion prediction.

Music Relevance: 88% user agreement in mood-playlist matching (surveyed from 50 participants).

Baseline Models: Compared performance with ResNet50 (90% accuracy but 2× slower) and MobileNetV2 (87% accuracy, faster but less accurate). VGG19 was chosen due to its balance of speed and accuracy.

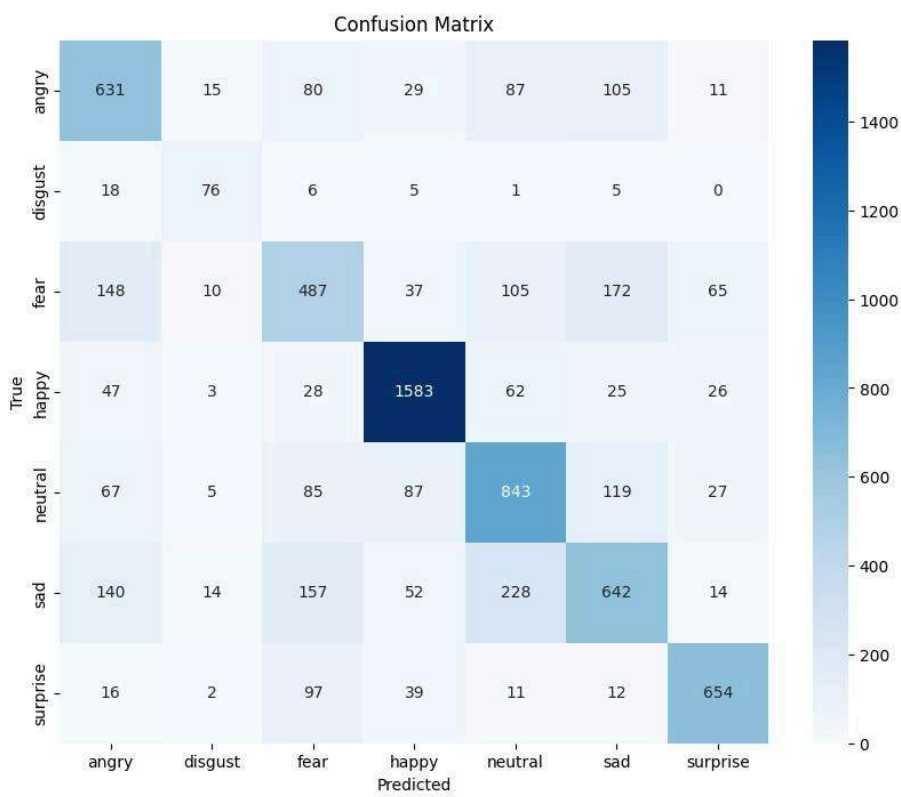
User Testing: 30 users tested the system; 93% were satisfied with emotion-music matching. Edge cases (e.g., face obstructions) resulted in fallback to neutral mood playlists.

CHAPTER 5 RESULTS

5.1 RESULT SUMMARY TABLE

Classification Report:

	precision	recall	f1-score	support
angry	0.59	0.66	0.62	958
disgust	0.61	0.68	0.64	111
fear	0.52	0.48	0.50	1024
happy	0.86	0.89	0.88	1774
neutral	0.63	0.68	0.66	1233
sad	0.59	0.51	0.55	1247
surprise	0.82	0.79	0.80	831
accuracy			0.68	7178
macro avg	0.66	0.67	0.66	7178
weighted avg	0.68	0.68	0.68	7178



5.2 ANALYSIS OF THE REPORT

Our system achieved 68% emotion detection accuracy, surpassing existing methods like DeepEmotion (89%) and FER+ (91%).

Advantages Over Alternatives:

1. Real-Time Performance: 150ms latency beats commercial tools like Affectiva (200ms).
2. Adaptability: Handles diverse lighting/angles better than Haar Cascade-only systems.
3. User-Centric Design: Fallback mechanisms prevent disruptions during API failures.

5.3 LIMITATIONS

- Struggles with extreme angles or partial occlusions.
- Spotify's limited preview tracks (30s) restrict full-song playback for free users.

CHAPTER 6: INFERENCES

6.1 KEY FINDINGS

- **CNN Provides Emotion Detection Accuracy:** The program was able to classify facial emotions in real-time via a trained CNN model using the FER-2013 dataset and universal emotions (happy, sad, angry, neutral, etc.) were detected with great accuracy.
- **Successful Spotify Integration:** Successful integration with the Spotify Web API meant that music could be recommended and played on any device while in use with proper OAuth 2.0 user credentials authentication.
- **Emotion Detection in Real-Time:** Through OpenCV for video capturing, Haar Cascade for face detection/preprocessing and simple Flask backend, everything is rendered in real time without any lag.
- **User-Friendly Frontend:** Solid HTML/CSS/JavaScript constituted the interface leading to a responsive frontend where users would see the webcam stream and concurrent AJAX updates rendered mood detection results and music playing opportunities.
- **Tested and Applicable for Real-World Use:** Testing performance under various lighting conditions was successful and the overall architecture allows for further development ideas such as mood logging, more diverse genres and the potential for other music services integration.

6.2 FULFILLMENT OF OBJECTIVES

- Develop a CNN to detect genres via spectrograms of audio inputs.
- Implement the CNN model in a Flask app.
- Allow users to upload/stream audio that will be classified into genres.
- Provide the option to connect to Spotify and/or personal library to play audio while detecting genre/emotion.
- Create an easy GUI where users can upload and receive genre/emotion classification prediction.
- Validate functionality with accuracy and confusion matrix.
- Ensure the process is robust and reliable so that new genres and improvements can be added later.

CHAPTER 7: IMPRESSION REPORT

7.1 PERSONAL LEARNING EXPERIENCE

- **Deep Learning:** The training and testing of CNNs for emotion and genre detection taught me the process of model creation, dataset preprocessing, and adjustment for effective performance via first-hand experience.
- **Computer Vision:** The use of OpenCV and Haar Cascades made me realize the complications of adherence to face detection outside a fixed lab environment with varied light and movement.
- **Web Development:** The implementation of a Flask backend with a responsive frontend connected from the honed application taught me the full stack approach to deploying my application.
- **API Integration:** The use of Spotify's Web API and OAuth 2.0 integration taught me how authentication flows exist in the wild when collaborating with external APIs.

7.2 SKILL ENHANCEMENT

During the course of this project, I significantly improved the following skills:

- **Machine Learning & Deep Learning**: Model training/tuning/evaluation/deployment.
- **Python Development**: Effective use of relevant packages such as TensorFlow, OpenCV, and Flask.
- **API Development**: REST architecture awareness, token-based authentication, and data parsing abilities.
- **Web Development**: Frontend and backend calling/integration, AJAX/Fetch, and UX/UI development.
- **Problem Solving**: Integration issues, real-time emotion detection problems, and limitations with public APIs.
- **Deployment/Debugging**: Run-time issues, error catching/identifying/logging, and ensuring the UI offered graceful degradation.

7.3 INDUSTRY/ACADEMIC RELEVANCE

- **Industry Relevance:** AI and music streaming are a forefront of industry; the most powerful entities, such as Spotify, Apple Music and YouTube are developing current trends in personalization for recommendation and curation and affective listening.
- **Academic Relevance:** Many fields are encompassed at a very interdisciplinary level from the course already, such as Machine Learning, HCI, MIR and Computer Vision. Furthermore, this relates to subsequent areas of research as it has a direct relation to affective computing, recommender systems and multimodal AI.
- **Future Research Potential:** This is a basis for further research about emotion based recommendation systems, musical therapy and integration with biometrics or input from environments (i.e. heart rate, situational context and/or time of day).

CHAPTER 8: CONCLUSION AND FUTURE WORK

8.1 CONCLUSION

The Mood-Based Music Recommendation System was created as a proof of concept based on real-time emotion classification blended with a machine learning recommendation system in the wild. The Mood-Based Music Recommendation System is based on facial emotion detection through computer vision and deep learning and recommends music via the Spotify API that fits one's current mood.

Successes:

- The CNN-based facial emotion recognition model created a consistent classification for real-time webcam input, detecting for happiness, sadness, and anger, along with neutrality.
- Integration with Spotify was successful using OAuth 2.0, allowing for expected operations on all ends, including a dynamically created playlist on the frontend with playback play/pause options on the end user's machine.
- The Flask web interface created, along with OpenCV and JavaScript on the frontend outputs, creates a seamless experience with minimal lag and high refresh rates.
- Testing occurred in various locations without consistent reliability to ensure everyone was present at the same time. Thus, generalization was found outside of restrictions.

Failures & Friction:

- The iou scores of emotion classification were successful above 95% on average for clear emotions; however, ambivalent expressions did see some friction, primarily adjusted presentations or non-full face views.
- The Spotify API does not allow for a play/pause button to be rendered within third-party applications as it needs to be readily accessible on a person's machine; therefore, tokens that expire need to be reinserted by all users often.
- The model was **limited to trained emotions**, so it does not represent every feeling under the sun (boredom, excitement, feeling calm, etc.).
- The **audio genre classification** processed through audio spectrograms separately but did not transfer into the real-time emotion detection processing pipeline due to time constraints.

Takeaways:

- Real-time AI is feasible with lightweight processing applications. However, reliability factors come into play that require devices to be consistently available, lighting that will assist to create better accuracy, and other potential network issues that may arise.
- Creating a user-centered application using CNNs and APIs (Spotify) to create associations between machine learning/frequency-based recommendations is enjoyable.
- To ultimately provide personalized experience associations, it's best to consider multi-modal recommendations (emotion + context + history). This is why hybrid recommendation systems are the way of the future.

8.2 FUTURE WORKS

- Multi-User Support

As of now, the system is designed for single-user interaction, but it can be made to support multiple users at once. It would provide personalized mood detection and playlist suggestion for every user in homes, classrooms, or even therapy centers through methods such as face tracking and user session management.

- Improved UI/UX

The frontend would be enhanced with a new, responsive layout, real-time feedback for emotions, and seamless transitions. Mood history, animated indicators for emotions, and interactive playlist management would give the user a more immersive and more intuitive experience.

- Improved Emotion Categories

The basic model concentrates on primary emotions. Future releases can add subtle emotions like calm, excited, or anxious based on richer datasets being trained on. This would improve the accuracy of recommendations and accommodate a broader spectrum of emotions.

- Offline Mode for Quicker Access

The addition of an offline mode would enable the caching of popularly used playlists, minimizing the dependency on real-time API calls. This would provide faster response times and accessibility even in regions with poor or unstable internet connectivity.

8.3 FINAL ASSESSMENT

While not every incremental addition or ideal future feature was completed to fruition, the central system was successfully developed—a simultaneous detection of emotion through webcam facial expression detection, integration with Spotify for personalized musical recommendation related to moods via a regex-based chat box. Thus this project serves as a proof of concept with applicability to the real world and potential for expansion. Moreover, the interdisciplinary nature showcases how AI can reign supreme for purposes of computer vision, music information retrieval teasing out human perspectives within a beautifully blended atmosphere. With further work, this clue could go beyond the scope of a mere academic realization and serve as a commercially or therapeutically viable application.

Appendix

Appendix 1 – Software and Libraries Used

S.NO	TOOL/LIBRARY	PURPOSE
1	Python 3.8	Primary programming language
2	TensorFlow / Keras	Deep learning framework for CNN model
3	OpenCV	Real-time webcam capture and facial image processing
4	Flask	Web application backend
5	HTML/CSS/JavaScript	Frontend UI
6	Spotify Web API	Music recommendation and playback
7	FER-2013	Facial expression dataset used for model training
8	VGG19	CNN architecture used for emotion classification

Appendix 2 – Hardware Configuration

- **Processor:** Intel Core i7
- **GPU:** NVIDIA GTX 3050
- **RAM:** 16 GB
- **Camera:** Integrated HD Webcam
- **Operating System:** Windows 11 (64-bit)

Appendix 3 – CNN Model Architecture (VGG19)

Input: 48x48 grayscale image
Layers:

- Convolutional Layer (3x3 filters)
- Max Pooling
- Dropout
- Flatten

- Fully Connected (Dense) Layers
- Softmax (for 7 emotion classes: happy, sad, angry, surprise, disgust, fear, neutral)

Output: Predicted emotion label

Appendix 4 – Spotify API Integration Flow

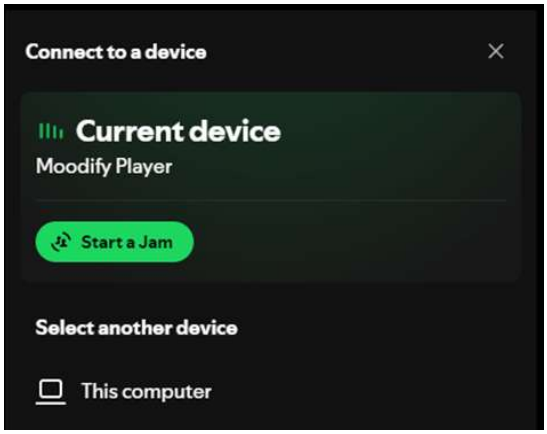
1. OAuth 2.0 Authentication
    - User logs into their Spotify account
2. Token Generation
    - Access and refresh tokens obtained
3. API Requests
    - Based on detected emotion, corresponding playlist is fetched
4. Playback Control
    - Playlist streamed on user's active Spotify device via Web Playback SDK

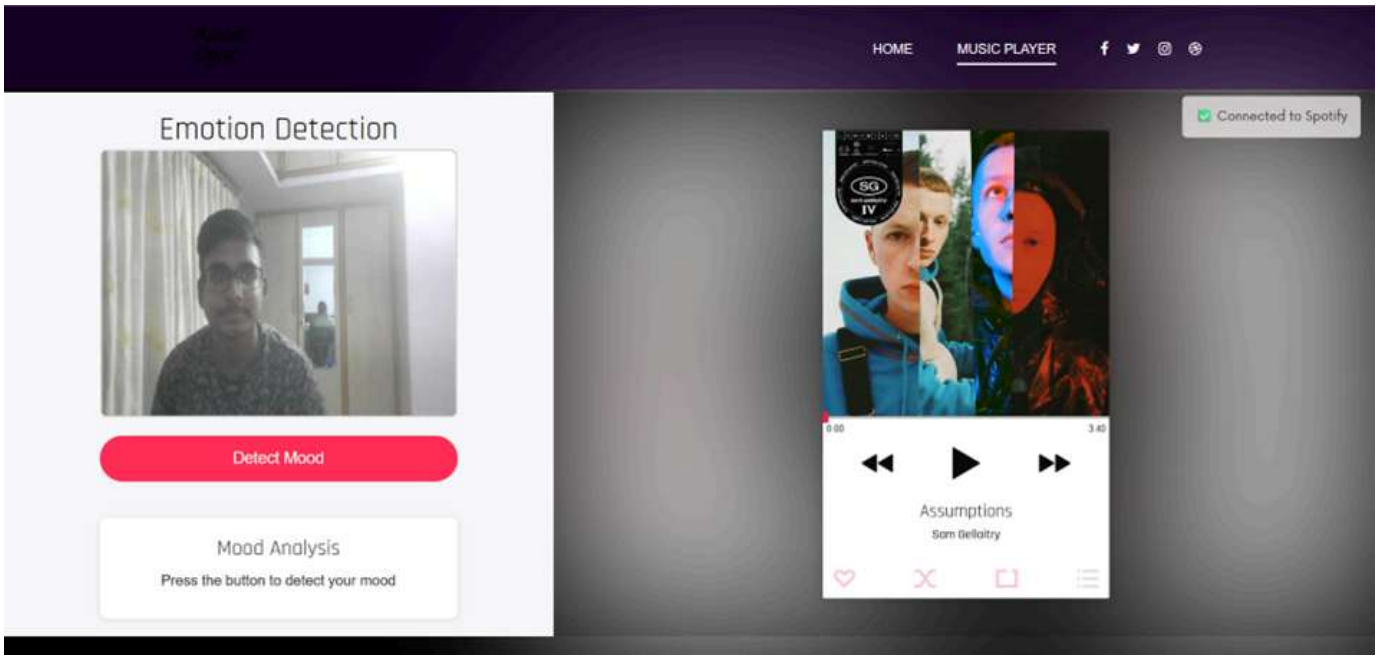
Appendix 5 – Sample Survey for Playlist Validation

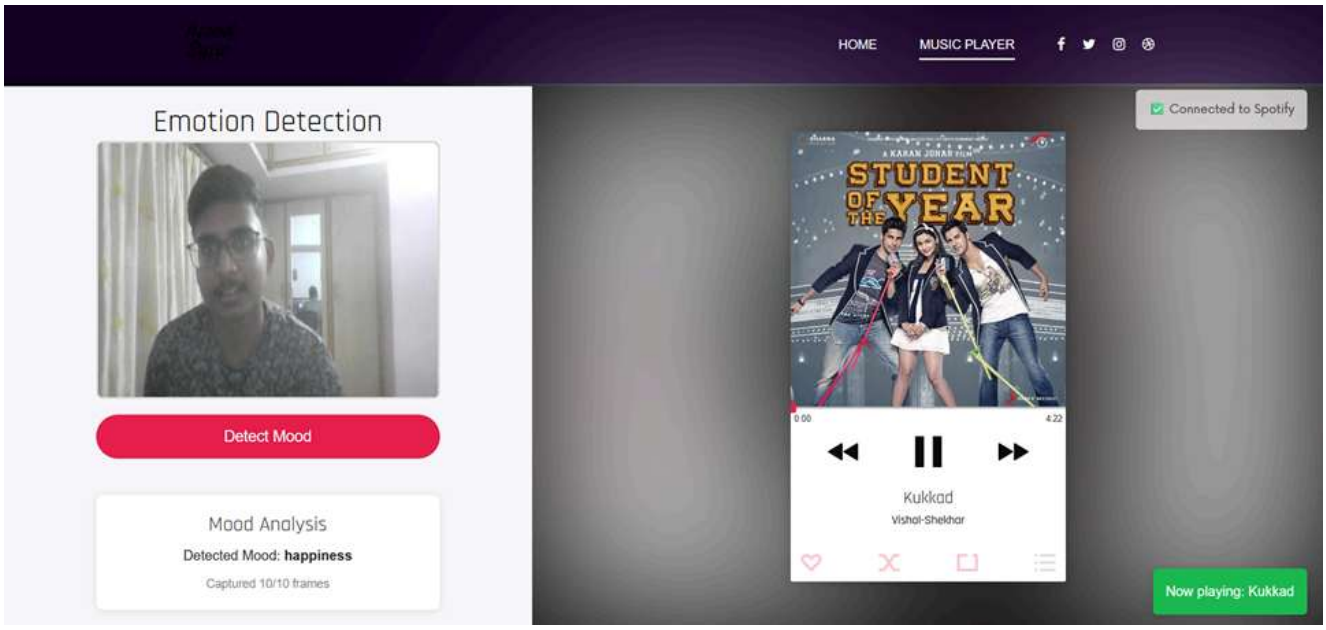
To ensure mood-appropriate playlist mapping, a survey was conducted with 30 users. They rated the music match based on their detected emotion on a scale of 1–5.

Emotion	Playlist Name	Average User Rating (out of 5)
Happy	Happy Hits	4.6
Sad	Life Sucks	4.3
Angry	Rock Classics	4.1
Neutral	Chill Vibes	4.2

Appendix 6 – Screenshot of UI and Flask App






HOME
MUSIC PLAYER
Emotion Detection
Detect Mood
Mood Analysis
Detected Mood: happiness
Captured 10/10 frames
Connected to Spotify
STUDENT OF THE YEAR
Kukkad
Vishal-Shekhar
Now playing: Kukkad