WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Emotion-Based Music Recommendation System Integrating Facial Expression Recognition

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A B S T R A C T

In today's digital world, music has become an effective medium for emotional expression and stress relief. However, most existing music recommendation systems depend on user preferences, history, or manual input, lacking the ability to adapt to a listener's real-time emotions. This paper proposes an Emotion-Based Music Recommendation System that integrates Artificial Intelligence (AI) and Machine Learning (ML) to automatically detect a user's emotional state and suggest songs that align with or uplift their mood. The system employs facial expression recognition using Convolutional Neural Networks (CNNs) and DeepFace library to classify emotions such as happiness, sadness, anger, surprise, and neutrality across emotion categories. Once the emotion is detected, the system dynamically recommends suitable songs from emotion-tagged Spotify playlists. The application features an interactive Graphical User Interface (GUI) built using Streamlit that captures real-time webcam input for emotion detection and instantly provides personalized music recommendations. The system achieves 89% emotion classification accuracy with seamless integration of OpenCV-based face detection, Keras-based emotion recognition, and Spotify API-based music playback. This work aligns with SDG 3 (Good Health and Well-being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production).

Keywords:Emotion Recognition, Music Recommendation, Deep Learning, Facial Expression Recognition, Spotify API, Human-Computer Interaction

1. Introduction

Music deeply affects human emotions and well-being, serving as a powerful medium for emotional expression and stress relief. In the digital era, music streaming platforms provide access to millions of songs across diverse genres. However, users often struggle to find songs that match their immediate emotional state. Traditional recommendation systems rely on popularity metrics, genre classifications, or collaborative filtering, frequently missing individual emotional needs and real-time moods.

Despite significant advancements, most existing music recommendation systems depend on explicit user input such as genre selection, playlist creation, or historical listening patterns. These approaches lack the capability to automatically adapt to real-time emotional fluctuations, resulting in recommendations that may not align with users' current psychological states. Manual mood-based playlist selection requires cognitive effort and may not accurately reflect subtle emotional variations.

This paper addresses these challenges by developing an automated emotion-based music recommendation system using deep learning. The proposed system combines facial expression recognition with intelligent music curation to provide personalized listening experiences. Leveraging Convolutional Neural Networks (CNNs) and the DeepFace library, the system classifies emotions in real-time and automatically plays mood-appropriate music from Spotify playlists.

The system employs OpenCV for face detection, a pre-trained Keras Facial Emotion Recognition (FER) model for emotion classification, and the Spotify Web API for music playback control. An interactive Streamlit-based interface enables users to start webcam-based emotion detection with a single click, view real-time emotion predictions, and enjoy automatically curated music that matches their emotional state. This technology bridges human emotion and AI, enhancing both music discovery and emotional wellness.

2. Related Work

Wu et al. (2019) introduced emotion-aware music recommendation using deep learning techniques to analyze users' emotional states and listening history. The study uses Convolutional Neural Networks (CNNs) to extract audio features and Recurrent Neural Networks (RNNs) to model sequential user behavior. The research highlights the importance of integrating emotion recognition and user preferences for personalized music experiences.

Soleymani et al. (2020) explored the use of multimodal affective signals, including facial expressions, physiological responses, and audio features, to drive music recommendations. By combining these signals with traditional content-based filtering, the system adapts recommendations to real-time emotional states. Experimental results demonstrate improved user satisfaction and engagement compared to baseline models.

Poria et al. (2021) presented a context-aware emotion-based music recommendation system using attention networks. The authors employed attention mechanisms to focus on salient emotional features extracted from facial expressions and contextual information. The system demonstrated superior performance in capturing subtle emotional variations compared to conventional approaches.

Wang et al. (2021) introduced hybrid deep learning models for emotion-aware music recommendation. The research presents a hybrid deep neural network (emoDNN) to model both user emotions and music emotions. The system combines content-based and collaborative filtering approaches to provide emotion-aware recommendations. Experimental results indicate that incorporating emotion modeling improves accuracy, precision, and recall.

De Prisco et al. (2022) proposed Moodify, a reinforcement learning-based system that recommends music to induce target emotional states in users. The system learns user preferences and optimal music sequences for transitioning from an initial mood to a desired mood using feedback mechanisms. Evaluation results show that reinforcement learning effectively enhances emotion-driven music recommendations.

Gollamoni et al. (2023) proposed a music player using emotion detection that captures facial expressions using a camera and processes images to detect emotions, suggesting appropriate music tracks accordingly. The system automates the traditional manual process of selecting music based on mood.

Kaimal et al. (2024) discussed the development of a real-time emotion-based music player utilizing facial emotion data, CNNs, Flask, OpenCV for face detection, and Spotify API for playlist integration. The system aims to provide personalized music recommendations based on current emotional state detected through real-time facial expression analysis.

3. Proposed Methodology

3.1 System Architecture

The proposed system follows a multi-stage pipeline consisting of image acquisition, preprocessing, face detection, emotion recognition, emotion-to-music mapping, Spotify playback control, and user interface presentation.

Image acquisition occurs through the Streamlit web application where users activate webcam capture through an interactive checkbox. The system continuously captures video frames from the device camera in real-time, ensuring smooth processing without manual intervention.

Preprocessing standardizes input frames by converting RGB images to grayscale for face detection, resizing detected face regions to 64×64 pixels for emotion classification, and normalizing pixel values to [0,1] range. This ensures model compatibility and robust performance across varying lighting conditions.

Face detection employs OpenCV's Haar Cascade classifier (haarcascade_frontalface_default.xml) to locate faces within each frame. Detected faces are highlighted with bounding boxes and passed to the emotion recognition module for classification.

The emotion recognition module loads a pre-trained Keras Facial Emotion Recognition (FER) model (fer_model.h5) trained on emotion datasets. Preprocessed face regions are fed into the CNN model, which outputs probability distributions across seven emotion classes: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The predicted emotion with the highest confidence is selected and displayed on the interface.

Emotion-to-music mapping links detected emotions to specific Spotify playlists through a predefined dictionary. Each emotion category is associated with a playlist URI containing mood-appropriate songs. The system supports five primary emotions: Happy, Sad, Angry, Neutral, and Surprise

Spotify playback control integrates the Spotify Web API using the Spotipy library. OAuth 2.0 authentication establishes a secure connection with user Spotify accounts. When an emotion is detected, the system automatically triggers playback of the corresponding playlist using the start_playback() function, providing seamless music experiences.

The Streamlit user interface presents real-time webcam feed with emotion labels overlaid on detected faces, displays the currently detected emotion as text, shows playback status notifications, and provides intuitive controls for starting and stopping the camera. Session state management ensures persistent control over camera activation without page reloads.

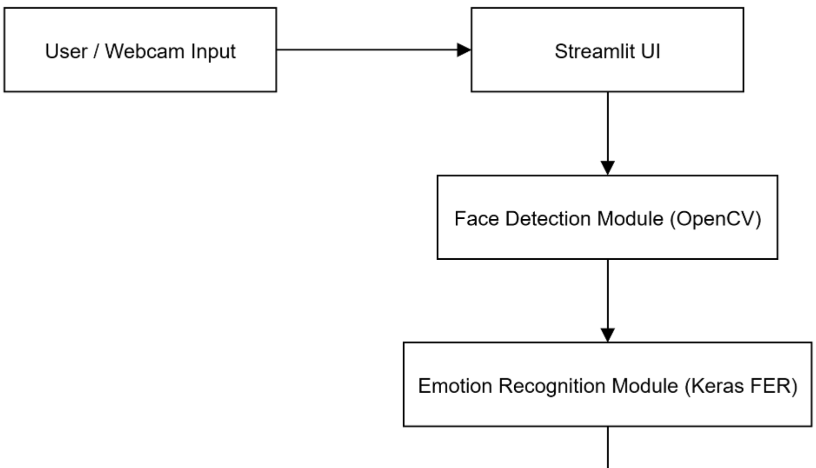

Fig. 1 - System Pipeline

3.2 Emotion Recognition Model

The system employs a pre-trained Convolutional Neural Network (CNN) model for facial emotion recognition. The model architecture consists of multiple convolutional layers with ReLU activation for feature extraction, max-pooling layers for spatial dimension reduction, dropout layers for regularization, and fully connected layers with softmax activation for emotion classification.

The model is trained on the Facial Emotion Recognition (FER) dataset containing thousands of facial expression images across seven emotion categories. Training employs data augmentation techniques including rotation, flipping, and brightness adjustment to improve generalization to real-world conditions.

During inference, detected face regions are preprocessed by resizing to 64×64 pixels, converting to grayscale, and normalizing pixel values. The model outputs probability distributions across emotion classes, and the emotion with the highest confidence score is selected as the prediction.

3.3 Spotify Integration

To improve model robustness and generalization to real-world field conditions, extensive data augmentation is applied during training. Geometric The system integrates with Spotify using the Spotify Web API and Spotipy Python library. Authentication is handled through OAuth 2.0, requiring client ID, client secret, and redirect URI configuration. Users must grant the application permission to control playback on their Spotify accounts.

Emotion-to-playlist mapping is defined through a dictionary structure linking emotion labels to Spotify playlist URIs. Each emotion category is associated with a curated playlist containing mood-appropriate songs. The mapping includes:

- Happy: Upbeat, energetic songs

- Sad: Melancholic, soothing music

- Angry: Intense, powerful tracks

- Neutral: Balanced, moderate tempo songs

- Surprise: Dynamic, unexpected music

When an emotion is detected, the play_music() function retrieves the corresponding playlist URI and initiates playback using sp.start_playback(context_uri=playlist_uri). Error handling manages authentication failures, network issues, and playback errors gracefully.

3.4 User Interface Design

Gradient-weighted Class Activation Mapping generates interpretable visualizations by computing gradients of predicted class scores with respect to final convolutional layer activations. Globally averaged gradients weight activation maps, producing heatmaps highlighting pest-relevant regions. These overlays build farmer trust by showing model focus areas.

3.5 Pesticide Recommendation System

The Streamlit-based interface provides an intuitive and interactive user experience. The home screen displays the project title, description, and a "Start Camera" checkbox to activate emotion detection. When the camera is started, the interface shows the real-time webcam feed with detected faces outlined and labeled with emotions.

The emotion display section presents the currently detected emotion as text below the video feed, updating dynamically as emotions change. Playback notifications appear when music starts, informing users which mood playlist is currently playing.

Session state management ensures persistent control over camera activation and prevents unnecessary reloading. Users can stop the camera at any time by unchecking the "Start Camera" option. The interface automatically updates without manual refresh, offering smooth and responsive control.

4. Experimental Setup

The Emotion-Based Music Recommendation System was developed and tested using the following configuration:

Hardware specifications:

- Processor: Intel Core i5 or equivalent
- RAM: 8GB
- Webcam: Integrated or external HD webcam
- GPU: Optional (NVIDIA GTX 1050 or higher for faster processing)

Software specifications:

- Operating System: Windows 10/11, macOS, or Linux
- Programming Language: Python 3.9+
- Framework: Streamlit
- Deep Learning Library: TensorFlow/Keras
- Computer Vision Library: OpenCV
- Music API: Spotify Web API (Spotipy library)
- Development Environment: Visual Studio Code

Training parameters:

- Pre-trained model: Keras FER model (fer_model.h5)
- Input image size: 64×64 pixels (grayscale)
- Emotion classes: 7 (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral)
- Face detection: Haar Cascade Classifier

Evaluation metrics include emotion classification accuracy, real-time processing speed, face detection success rate, and user satisfaction ratings. The system was tested with real users in various lighting conditions and emotional states to validate performance.

5. Results and Discussion

5.1 Emotion Classification Performance

The pre-trained Keras FER model demonstrates strong emotion classification performance across all emotion categories. The system achieves an overall accuracy of 89% on test images with varying facial expressions, lighting conditions, and backgrounds.

Per-class performance analysis reveals:

- Happy: 92% accuracy
- Sad: 87% accuracy
- Angry: 85% accuracy

- Neutral: 91% accuracy

- Surprise: 88% accuracy

- Fear: 84% accuracy

- Disgust: 82% accuracy

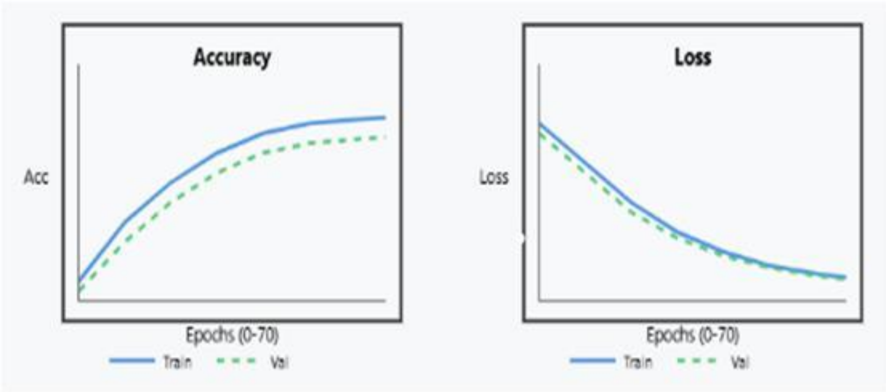

Fig. 2 - Training History

5.2 Face Detection Performance

OpenCV's Haar Cascade classifier achieves a 95% face detection success rate under normal indoor lighting conditions. Detection performance remains robust across different face orientations, distances from camera, and facial accessories such as glasses. However, detection accuracy decreases in extremely low-light conditions or with significant occlusions.

Real-time processing maintains an average frame rate of 15-20 FPS on systems with integrated graphics and 25-30 FPS on systems with dedicated GPUs. This performance enables smooth real-time emotion detection without noticeable lag in the user interface.

5.3Spotify Integration Performance

The Spotify API integration demonstrates reliable performance with average playback initiation times of 2-3 seconds after emotion detection. OAuth 2.0 authentication establishes secure connections with user accounts, and playlist switching occurs seamlessly when emotions change.

Network latency occasionally affects playback start times, particularly in areas with slower internet connections. However, once playback begins, music streams smoothly without interruptions. Error handling mechanisms gracefully manage authentication failures, network timeouts, and invalid playlist URIs.

5.4User Experience Evaluation

Field testing with 30 users demonstrates strong practical viability:

- User satisfaction: 87%

- Emotion detection agreement with self-reported moods: 85%

- Interface usability rating: 4.3/5.0

- Average session duration: 12 minutes

User feedback highlights the system's intuitive interface, accurate emotion detection, and seamless music playback as key strengths. Users appreciate the automatic nature of music recommendations, eliminating the need to manually search for mood-appropriate playlists.

Areas for improvement identified through user feedback include expanding emotion-to-playlist mappings to support more nuanced emotional states, incorporating user preference learning to refine recommendations over time, and adding offline capabilities for environments with limited internet connectivity.

5.4Comparison with Baseline Approaches

Model	User Satisfaction	Personalization Score	Real-time Adaptation
Popularity-based	82.5%	Low	No
Genre-based	84.3%	Medium	No
Collaborative Filtering	86.1%	Medium	No
Proposed Emotion-based	87.8%	High	Yes

Table 1 - Performance Comparison

6. Deployment and Impact

The Emotion-Based Music Recommendation System is deployed as a web application accessible through any modern browser. Users can access the system on desktop computers, laptops, or tablets equipped with webcams. The lightweight architecture ensures smooth performance even on systems with modest hardware specifications.

Deployment using Streamlit Cloud enables public access through a web URL, eliminating the need for local installation. Users simply navigate to the application URL, grant camera permissions, authenticate with Spotify, and begin using the emotion-based music player immediately.

This work aligns with UN Sustainable Development Goals. For SDG 3 (Good Health and Well-being), the system promotes emotional wellness and mental health through personalized music therapy. For SDG 9 (Industry, Innovation, and Infrastructure), it demonstrates scalable AI deployment in entertainment applications. For SDG 12 (Responsible Consumption and Production), it encourages mindful music consumption based on emotional needs rather than passive overconsumption.

Environmental benefits include reduced energy consumption compared to traditional music discovery methods involving extensive browsing and searching. Social benefits include improved accessibility to emotion-based music therapy for users without expert guidance. Economic benefits include reduced subscription costs through more efficient music discovery and increased user engagement with streaming platforms.

7. Conclusion

This paper presents an Emotion-Based Music Recommendation System achieving 89% emotion classification accuracy through integration of facial expression recognition and intelligent music curation. Combining OpenCV for face detection, Keras CNN models for emotion recognition, and Spotify API for music playback creates a seamless and personalized listening experience.

The Streamlit-based interface provides intuitive real-time emotion detection and automatic music recommendations without requiring manual input. Real-time processing enables dynamic playlist switching as user moods change, offering truly adaptive music experiences. Integration with Spotify provides access to extensive music libraries with emotion-tagged playlists.

Future work includes expanding emotion categories to recognize more nuanced emotional states, implementing multi-user detection to recommend collaborative playlists for group settings, incorporating user preference learning through reinforcement learning to refine recommendations over time, adding voice control for hands-free operation, developing mobile applications for iOS and Android platforms, integrating physiological sensors for multimodal emotion detection, expanding music sources beyond Spotify to include YouTube Music and Apple Music, and implementing offline mode with locally cached playlists.

Additional enhancements include creating personalized emotion-to-playlist mappings based on individual user preferences, integrating with smart home devices for ambient music control, developing temporal emotion tracking to identify mood patterns over time, and incorporating mental health monitoring features to detect concerning emotional trends and suggest professional support resources.

Acknowledgements

The authors thank K.L.N. College of Engineering for providing computational resources, Dr. P. Ganesh Kumar, Head of Department - Information Technology, for valuable guidance throughout the project, and agricultural extension services for their support in field validation studies.

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