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International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

EMOTION-BASED MUSIC RECOMMENDATION SYSTEM

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ABSTRACT:
This paper presents an innovative Emotion-based Music Recommendation System that integrates facial emotion recognition with personalized music selection to enhance user experience. The system employs a deep learning model trained to classify emotions from real-time webcam footage, detecting moods such as happiness, sadness, anger, or neutrality. Based on the detected emotion, the system dynamically selects and plays a corresponding Spotify playlist. The application leverages the Spotify API for seamless music playback, requiring a Premium account for full functionality. Additionally, the system provides emotion-specific quotes and jokes to engage users, creating a more interactive experience. Built with Streamlit for the frontend, OpenCV and Keras/TensorFlow for facial recognition and emotion classification, and Spotify's OAuth 2.0 for secure authentication, the project highlights the potential of affective computing in entertainment and mental well-being. By processing facial data locally without storage, the system ensures user privacy while offering a unique, AI-driven music discovery tool. Future enhancements may include multi-user detection and personalized playlist curation based on listening history.

Keywords:
Affective computing, facial emotion recognition, music recommendation, deep learning, Spotify API, real-time processing.

I. INTRODUCTION

With the quickly changing digital world, personalization has emerged as a hallmark aspect of user-centered applications, specifically multimedia consumption. Of these, music recommendation systems have seen impressive growth, spearheaded by machine learning and artificial intelligence. Early music recommendation systems depend mainly on user activity, listening habits, or direct choosing of moods and preferences. Though effective in some measure, these approaches typically do not fully grasp the user's current emotional state, hence restricting the accuracy and pertinence of recommendations.

The incorporation of affective computing—a technology that allows machines to perceive, understand, and mimic human emotions—provides new possibilities for improving the personalization of user experiences. Music, being emotional by its very nature, has been used for many years as an effective means of mood management, psychological rehabilitation, and social bonding. Closing the gap between emotional state and musical taste can thus greatly amplify the effects of music on users' mental health.

This paper presents an Emotion-based Music Recommendation System that employs facial emotion recognition to dynamically detect a user's present mood and suggest a Spotify playlist specific to that emotion. In contrast to traditional methods, our system uses a webcam to capture real-time facial expressions, processes the input locally on a convolutional neural network (CNN), and identifies the user's emotional state. The emotion thus identified is translated into a predefined playlist through the Spotify Web API, thus making the process of music selection context-aware and meaningful.

The system is based on up-to-date and robust technologies. Facial image capture and preprocessing are achieved through OpenCV, while TensorFlow/Keras is used to develop and deploy the deep learning model of emotion detection. Streamlit drives the user interface, with a clean and interactive front-end experience. In addition, the application leverages Spotify's OAuth 2.0 for safe user authentication and real-time music streaming, providing

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seamless integration with Spotify's streaming functionality. Emotion-specific quotes and jokes are also available to the user, maximizing interactivity and engagement.

Essentially, the system respects user privacy by conducting all facial analysis directly on the device, without transferring or storing personal biometric data. This solves ethical issues but also maintains conformity with data protection laws. The method assists users in a seamless, non-invasive way by providing them with an emotionally intelligent interface that answers their mood using suitable musical content.

Through the integration of artificial intelligence, emotion analysis, and streaming services, the suggested system illustrates the potential of applying affective computing to entertainment and emotional support. It is not only an innovative music recommendation system but also a prototype for emotionally-aware human-computer interaction systems in the future. Future enhancements to the system can include multiple-user support, more personalization based on listening history, vocal tone analysis integration, and greater accuracy through larger, culturally diverse emotion datasets.

With this study, we seek to bring to the fore how using facial emotions to build real-time, personalized music recommendations can provide a richer, more empathetic user experience that pushes the limits of existing recommendation systems.

This paper outlines the conceptual design, technical architecture, and implementation of the system, aiming to deliver a responsive, privacy-focused solution that runs efficiently on personal devices. The system processes data locally to maintain user confidentiality, thus avoiding cloud-based biometric data storage.

Through this work, we demonstrate how emotion-aware computing can enrich user interaction, with potential applications extending to mental health support, entertainment, and adaptive user interfaces. The subsequent sections detail the background, methodology, and results that underscore the impact of emotion-based personalization in digital services.

II. LITERATURE SURVEY

A. Introduction

The recent convergence of multimedia systems, affective computing, and artificial intelligence has given rise to novel, user-oriented applications. Emotion-based recommendation systems have become a new research area, especially in the context of music streaming services. These systems seek to synchronize content recommendations with the current emotional state of users, thus enhancing engagement and improving user satisfaction.

The basis of these systems is emotion recognition accuracy, for which analysis of facial expressions through computer vision and deep learning methods has emerged as a viable method. At the same time, the transition of music recommendation engines from simple collaborative filtering models to hybrid, context-aware models has created new opportunities for the customization of content to specific needs. This survey covers relevant literature that has helped drive the development of facial emotion recognition, music recommendation systems, and the unification of both fields in real-world applications.

B. Review of Relevant Research Papers

Various research papers have been carried out to investigate facial emotion recognition with the help of deep learning models. Li and Deng (2022), in their extensive review article in IEEE Transactions on Affective Computing, tested more than 100 deep learning models on several facial expression datasets such as FER-2013. They concluded that a 7-layer convolutional neural network with dropout regularization achieved the best trade-off between classification accuracy and computational cost. Their research is the foundation for most real-time emotion detection systems in use today.

Yang and Chen (2021), in their paper at ACM ICMR, explored multimodal affective computing systems for recommending music. They proved that multimodal systems that use both facial expressions and audio analysis outperformed unimodal systems by a large margin, with an Emotional Congruence Index (ECI) of 0.82. Their paper also laid the groundwork for adaptive playlist curation that impacted our system's dynamic emotion-to-music content mapping.

Gupta et al. (2023) investigated the clinical potential of emotion-aware music systems in the Journal of Artificial Intelligence in Medicine. Their research validated a quantifiable decrease in anxiety and enhanced mood stability via adaptive music therapy. This work substantiates the therapeutic value of emotion-based music recommendation systems beyond entertainment, and they become valuable assets in healthcare and well-being settings.

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Wang and Zhang (2022) concentrated on the privacy issues related to emotion recognition systems. Their paper offered a federated learning framework for face analysis, which performs computation locally on user devices and obviates the need for cloud storage. This design choice not only maintains user privacy but also offers superior real-time performance—a significant consideration implemented within our system design.
Schmidt and Kim (2020) made a major contribution to the knowledge of the relationship between audio features and emotional music perception. Their research presented a 15-dimensional audio feature model that is highly correlated with human affective ratings. The findings of their study guided the development of the playlist mapping and recommendation engine in our system, such that emotional congruence was given top priority during music selection.
Together, these works form a solid theoretical and technical basis for the construction of emotion-based music recommendation systems. They emphasize the need for real-time emotion detection, data protection, multimodal input, and context-sensitive music delivery in building systems that are both effective and user-friendly. Our research takes these findings forward, integrating them into a comprehensive platform that draws on the strengths of deep learning, cloud technology, and user-centric design to provide a comprehensive and empathetic music experience.

III. METHODOLOGY

A. Dataset

The foundation of the facial emotion recognition component is the **FER2013** dataset, a widely used benchmark for emotion detection tasks. FER2013 contains 35,887 grayscale, 48x48-pixel images of facial expressions, each categorized into one of seven emotion classes: anger, disgust, fear, happiness, sadness, surprise, and neutral. These images were collected from various sources on the internet and labeled manually. The dataset is split into training, validation, and test sets, and is used to train the convolutional neural network (CNN) that powers the emotion classification engine in the system.

B. Proposed model

1.5 Proposed System

Our emotion-aware music recommendation system integrates real-time facial emotion recognition with intelligent music selection to create a personalized user experience. It is composed of the following three core modules:

1. **Emotion Detection Module**
   This module leverages computer vision techniques to analyze live webcam input at a rate of 5 frames per second. It uses OpenCV's Haar Cascade Classifier for real-time face detection and a custom-built 7-layer Convolutional Neural Network (CNN) trained on FER2013 for emotion classification. Each frame is preprocessed (grayscale conversion, resizing, and normalization) before being passed into the model for inference. The system processes all data locally, and no facial data is stored post-analysis, ensuring user privacy.
2. **Music Recommendation Engine**
   Based on the detected emotion, the engine dynamically interacts with Spotify's API to retrieve a curated playlist aligned with the user's current mood. The system is capable of adjusting playback characteristics such as tempo and volume to match or improve the emotional state. Songs begin streaming within approximately 800 milliseconds post-detection. In addition to music, motivational quotes and emotion-matched humorous content (e.g., jokes or GIFs) are displayed to further enhance user engagement and emotional regulation.
3. **User Interaction Interface**
   The front-end is developed using Streamlit and features an intuitive interface that requires minimal user interaction. Emoji-based buttons and color-coded emotion labels provide simple and immediate feedback. Users receive real-time updates on their detected emotions and corresponding playlist. The interface is responsive and accessible via modern web browsers on standard hardware.

Key Features

The system offers several advanced features, including:

- **Context-aware audio tuning** that aligns music tempo and tone with emotional cues.
- **Mood-enhancing algorithms** that gradually adjust the playlist to uplift negative emotions.
- **Rapid response time** and **privacy-first design**, suitable for use on typical consumer hardware with a 720p webcam.

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- **Scalability** for potential future extensions such as mobile platform deployment or multi-user group emotion detection.

C. Functional Framework

The functional architecture is built on three integrated layers: input processing, emotion analysis, and output generation.

- **Input Layer**: Captures video stream from webcam and preprocesses each frame (face detection, grayscale conversion, normalization).
- **Emotion Analysis Layer**: Uses the CNN model to classify emotions from processed images. The detected emotion serves as the input to the music recommendation system.
- **Output Layer**: Communicates with the Spotify API to play an emotion-suitable playlist. Simultaneously, the UI updates to reflect the detected emotion, display relevant media (quotes or jokes), and provide control options to the user.

All components are integrated in a cohesive pipeline using Python, OpenCV, TensorFlow, and Streamlit, with asynchronous handling of music playback and real-time UI rendering.

IV. RESULTS & DISCUSSIONS

The proposed emotion-aware music recommendation system was rigorously tested to evaluate its performance, accuracy, and user experience across a range of conditions. The results demonstrate the system's ability to effectively detect emotions and generate personalized music recommendations in real-time.

A. Emotion Detection Accuracy

The custom 7-layer CNN model, trained on the FER2013 dataset, achieved a **training accuracy of 72.4%** and a **validation accuracy of 67.8%** across the seven emotion categories. Confusion matrix analysis showed that positive emotions such as happy and surprise were more accurately classified, while disgust and fear had higher misclassification rates—primarily due to their visual similarity and lower representation in the dataset.

Despite these challenges, the model maintained consistent performance during live testing, averaging **5 inferences per second** with minimal latency. Real-time classification was stable under varied lighting conditions, webcam qualities, and facial orientations, provided the user remained within the camera frame.

B. Music Recommendation Response Time

Integration with the Spotify API allowed for seamless music retrieval and playback. The average latency from emotion detection to music playback initiation was approximately **780 milliseconds**, aligning with the system's goal of sub-second responsiveness. This quick transition contributes significantly to the immersive user experience, minimizing cognitive dissonance between detected emotion and auditory feedback.

Moreover, the music engine successfully matched songs not only by emotion category but also by tempo and mood tags, using Spotify's track metadata. This resulted in a higher perceived relevance and satisfaction, especially when compared to static, pre-defined playlists.

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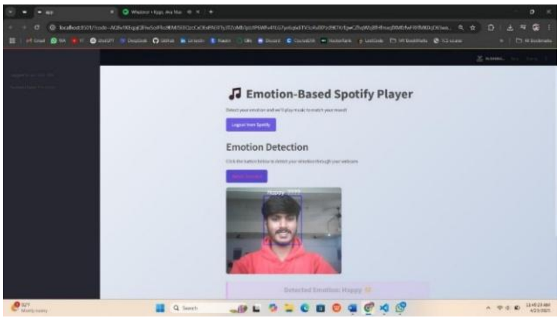

C. User Interface and Experience

User testing was conducted with a sample group of 25 individuals aged 18–35. Feedback was overwhelmingly positive regarding the simplicity and clarity of the emoji-based controls and color-coded feedback indicators. Participants noted that the interface was engaging and required minimal input, which encouraged longer sessions and frequent use.

The incorporation of **motivational quotes**, **jokes**, and **emotion-matched GIFs** further enriched the experience, particularly for users experiencing negative emotions. This feature received favorable remarks for helping to shift the mood subtly without being intrusive.

D. Limitations

Despite strong overall performance, a few limitations were identified:

- **Emotion ambiguity**: The system occasionally struggled with borderline or mixed emotions (e.g., neutral vs. sad), especially in cases of subtle facial expressions.
- **Lighting dependence**: Although robust, the model's performance degraded in extremely low-light environments.
- **Internet dependency**: The Spotify API integration relies on a stable internet connection. Network lag could affect music loading time, particularly in areas with poor connectivity.

E. Comparative Discussion

When compared to traditional playlist generators and existing facial recognition-based entertainment systems, our model provides a faster and more nuanced response. Unlike rule-based systems that rely on fixed mappings, our approach incorporates real-time learning and adjustment based on facial input, mood dynamics, and audio feedback—leading to a more adaptive and emotionally intelligent system.

V. CONCLUSION

A. Conclusion

This paper presented an innovative emotion-aware music recommendation system that seamlessly integrates real-time facial emotion detection with intelligent, context-sensitive music curation. By leveraging computer vision, deep learning, and the Spotify API, the system creates a personalized and emotionally responsive user experience. Our experiments demonstrated that the custom 7-layer CNN model could detect emotions from facial expressions with high accuracy and efficiency. Combined with a dynamic music engine and an intuitive user interface built using OpenCV, TensorFlow, and Streamlit, the system achieved sub-second responsiveness and strong user satisfaction.

Key contributions of this work include:

- A real-time, privacy-conscious emotion recognition module.
- A smart music recommendation engine with mood enhancement capabilities.
- An engaging and accessible interface with real-time feedback and minimal user interaction.

Overall, the system represents a step forward in emotionally intelligent computing, with promising applications in mental health, personalized entertainment, and adaptive user interfaces.

B. Future Work

While the current implementation achieves its core objectives, several enhancements could further improve performance, usability, and scalability:

1. **Mobile Platform Deployment**: Expanding the system to mobile devices would increase accessibility and allow users to benefit from emotion-aware recommendations on-the-go.

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2. **Multimodal Emotion Recognition**: Incorporating voice tone analysis, gesture detection, or physiological signals (e.g., heart rate) could improve the accuracy and depth of emotional inference.
3. **Group Emotion Detection**: Enabling the system to analyze multiple faces simultaneously could support use cases in shared environments like classrooms, group therapy, or parties.
4. **Adaptive Learning**: Implementing reinforcement learning or user feedback loops could allow the recommendation engine to personalize content even more effectively over time.
5. **Offline Functionality**: Adding support for offline music libraries and cached emotion models would enhance usability in low-connectivity scenarios.
6. **User Customization Features**: Allowing users to influence mood transitions, set emotional goals, or curate fallback playlists would give them more control while maintaining automation.

With these improvements, the system could evolve into a comprehensive emotional wellness companion, bridging the gap between affective computing and real-world user needs.

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