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Personalized Music Recommendation Using Real-Time Emotion Recognition

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Abstract: The increasing demand for music recommendation systems that correlate with users' emotions has been augmented by the popularity of customized digital experiences. In this work, a more specific machine learning application will be performed, Imotion driven music recommendation system through recognition of emotions. Integrating facial emotions, voice tone, and overall mood, the system builds custom playlists in real time. Overall, emotion mapping is performed using advanced techniques such as convolutional neural networks (CNN) with natural language processing (NLP) for multimedia integration. The research also sheds light on the result's attempts to balance between user's music and emotional preferences in face of challenges like diversity of datasets, generalization of emotions, and scalability of the system as such. The findings provide evidence of the success of ML-based frameworks in improving user satisfaction and interaction, making the applications of this technology relevant within the constantly expanding area of emotion-centric applications.
Index Terms: emotion recognition, music recommendation, deep learning, facial expression, personalization, user experience, real-time analysis, music genre classification.

I. INTRODUCTION

Today, there's hardly anyone who would not listen to music or think about a specific song. Self-created emotions and feelings combined with growing engagement to music helped create a space where demand for personalization of music offerings has been groundbreaking in the industry. Emotion recognition technologies such as FAM, speech analyses and targeting, mood interpretation based text understanding have also allowed for near real-time fitting to users' emotional context.

Machine learning (ML), and more specifically Convolu- tional Neural Networks (CNN) as well as Natural Language Processing (NLP) models, provide complex specialized so- lutions for these analysis and music providing tasks. These systems utilize multi characteristics, multi modal data input to attain accurate emotion mapping to optimize the end-user experience of automated playlist creation and feeling suitable songs.

This thesis attempts to detail the creation of Emotion-Based Music Recommendation System and automated ML methods which we have successfully created. Using facial emotion recognition, audio emotion, and text emotion towards users' feelings we believe the system will change user interacting with a digital music platform once and for all.Additionally, the challenge of dataset diversity, as well as emotion generalization and computational complexity, is discussed, further emphasizing the outcome of this paper, i.e. how emotion- recommendation ability can change the way people interact with music context, making it more engaging and unique.

II. LITERATURE REVIEW

Emotion-aware systems have gained prominence in person- alized music recommendation, leveraging the synergy between machine learning (ML) techniques and real-time emotion de- tection. Several studies highlight the innovative methodologies and challenges in this domain.

In [1], a system utilized facial emotion detection via CNNs, analyzing expressions such as happiness, sadness, and anger to recommend suitable music. The results demonstrated that facial analysis provides high accuracy for real-time emotion mapping, although performance varied across demographic groups.

Speech and audio analysis were emphasized in [2], where emotions were detected through vocal tone, pitch, and body gestures. The study combined sentiment analysis and machine learning models to improve recommendation accuracy, illus- trating the importance of multimodal inputs for robust systems. An annotation-based approach was explored in [3], where music datasets were tagged with emotional labels (e.g., calm, energetic). Supervised machine learning models, such as Sup- port Vector Machines (SVMs) and Random Forests, analyzed the tags to associate emotions with specific genres. Despite its effectiveness, the study faced challenges in ensuring consistency across diverse datasets.

In [4], audio feature extraction methods, including tempo, rhythm, and timbre analysis, were integrated with CNNs for mood-based music suggestions. This framework demonstrated significant improvements in playlist generation but highlighted computational challenges when scaling for larger user bases. Multimodal frameworks combining facial data, audio anal- ysis, and sentiment detection were investigated in [5]. By leveraging deep learning models, including Long Short-Term Memory (LSTM) networks and CNNs, the system dynamically adjusted playlists to match users' emotional states. Such hybrid approaches proved effective in creating a holistic recommendation framework, yet struggled with real-time processing efficiency

A common challenge identified in [6] is the limited avail- ability of diverse and labeled datasets for training emotion- based systems. Existing datasets often fail to capture variations in emotional expressions across cultures, age groups, and environments.

Studies such as [7] revealed that emotion recognition systems often lack contextual awareness. For example, a user's smile might not always indicate happiness, leading to mismatched music recommendations.

Real-time processing of multimodal inputs—such as facial expressions, speech, and music features—remains computationally intensive, as noted in [8]. Lightweight algorithms and hardware optimizations are necessary for scalable solutions.

Emotional expressions are highly subjective and influenced by factors like culture and personal preferences. Research in [9] highlighted the difficulty of generalizing systems to cater to a wide range of users without individual calibration.

A. Gap Analysis

Despite significant advancements in the field, several re- search gaps persist in the development of Emotion-Based Music Recommendation Systems:

- Most studies focus on single emotion recognition meth- ods, such as facial analysis or audio sentiment detec- tion, neglecting the potential of combining multimodal approaches (e.g., facial expressions, audio features, and text analysis) for more accurate emotion mapping.
- A lack of diverse and well-annotated datasets linking specific emotions to music genres or tracks hinders the reliability and generalization of machine learning models across different demographics and cultural contexts.
- Emotional responses to music are highly subjective and influenced by factors like individual preferences, cultural background, and context. Existing systems struggle to address this variability, leading to inconsistent user ex- periences.
- Real-time emotion detection and playlist generation in- volve processing large volumes of data from multiple inputs, posing challenges in terms of computational ef- ficiency, especially for mobile and resource-constrained devices.
- Current models often fail to understand the context be- hind emotions, such as distinguishing between a genuine smile and a sarcastic one, resulting in inaccurate music recommendations.
- Long-term learning from user interactions and prefer- ences remains underexplored. Most systems lack the ability to adapt to evolving user emotions and preferences over time, limiting their effectiveness in delivering highly personalized experiences.
- Collecting and analyzing sensitive data, such as facial expressions or speech, raises ethical concerns regarding user privacy and consent. Current research has yet to fully address these issues while ensuring compliance with data protection regulations.

These gaps highlight the need for advanced, multimodal, and context-aware solutions that integrate diverse datasets, pri- oritize personalization, and address computational and ethical challenges, thereby ensuring a seamless and impactful user experience in emotion-based music recommendation systems.

III. METHODOLOGY

This section details the methodology employed in the de- velopment of an emotion-based music recommendation sys- tem, which integrates emotion detection via facial expression analysis and music recommendations based on the identified emotional states. The system utilizes a combination of machine learning techniques, user interface development, and external API integration to achieve its goal.

A. System Architecture

The proposed system is composed of several key compo- nents:

- Emotion Detection: The core of the system is its ability to identify user emotions from facial expressions. Using a pre-trained emotion classification model, the system detects emotional states such as happiness, sadness, anger, and surprise from facial images or videos. The model leverages deep learning techniques, specifically Convolutional Neural Networks (CNNs), to process and classify these expressions. The emotion detection model is trained on datasets.
- Music Recommendation: After detecting the user's emo- tion, the system queries the Spotify API to recommend music that

aligns with the identified emotional state. For example, upbeat tracks might be recommended for happiness, while slow and calming tracks are suggested for sadness. This recommendation system provides a personalized music experience, adjusting to the user's emotional needs.

- User Interface: The front-end interface is built with Streamlit, which allows users to interact with the emo- tion detection and music recommendation system easily. Users can upload images or videos, and the system will display the detected emotion alongside recommended music tracks. This interface enhances the user experience by providing real-time feedback on both the emotion detection and music recommendation processes.

B. Data Collection and Preprocessing

The dataset used for emotion detection consists of labeled facial expression data, stored in .npy files. These files contain processed features extracted from images of faces, where each label corresponds to a specific emotional state. The data preprocessing pipeline involves the extraction of facial land- marks and other relevant features, which are then normalized and prepared for model training. This preprocessing ensures that the emotion detection model can accurately identify and classify emotional expressions from input images or video streams.

C. Modeling and Training

- Emotion Classification Model: The emotion detection task is approached through the use of deep learning architectures, primarily CNNs, which are well-suited for image-based classification tasks. Pre-trained models such as VGG16, VGG19, or ResNet are often used as start- ing points, with fine-tuning performed on the emotion- specific dataset to enhance performance. These models learn to recognize facial expressions corresponding to various emotions, improving accuracy through iterative training.
- Model Evaluation: The performance of the emotion de- tection model is assessed using standard metrics such as accuracy, precision, recall, and F1 score. Cross-validation techniques are employed to ensure that the model gener- alizes well to unseen data.

D. Music Recommendation System

- Spotify API Integration: Once the emotion is detected, the system leverages the Spotipy library to interact with the Spotify API, querying it for tracks, playlists, or albums that match the detected emotion. The system maps emotions to corresponding music genres or moods (e.g., energetic tracks for joy, melancholic music for sadness).
- Recommendation Logic: The music recommendation al- gorithm uses a mapping between the detected emotion and predefined sets of genres or playlists curated for each emotional state. This ensures that the music suggested is relevant to the user's current emotional state, offering a personalized experience.

IV. RESULTS

This section outlines the key findings and analysis of the emotion-based music recommendation system developed as part of this research. The system integrated emotion detection from facial expressions using deep learning models, and subsequently provided personalized music recommendations based on the detected emotional state. The results demonstrate the system's effectiveness, identify areas for improvement, and provide insights into the future direction of such systems.

A. Emotion Detection Performance

The emotion detection module, which utilizes Con- volutional Neural Networks (CNNs) to classify facial expressions, achieved an overall accuracy of 85%. This performance was in line with recent studies in emotion recognition using facial expressions, such as those by Mollah et al. (2021) and Zhao et al. (2019), who noted that CNN-based models are effective but can be prone to performance degradation in real-world conditions such as lighting variations and diverse facial characteristics.

1) Emotion Classification Accuracy: Among the emotions identified, the highest accuracy was observed for neutral and happy expressions, with accuracy rates above 90%. However, more complex emotions like anger and surprise yielded slightly lower ac- curacy (around 75-80%) due to the challenges in capturing subtle facial cues associated with these emotions. This finding is consistent with previous works in emotion detection (e.g., Hazarika et al., 2021), which emphasize the complexity of accu rately classifying emotions such as anger and surprise.

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2) Model Robustness: While the system performed well in controlled settings, the accuracy dropped slightly when tested in real-world scenarios. This can be attributed to factors such as varying facial orientations, background distractions, and non-ideal lighting conditions. To mitigate these challenges, future work could focus on training the model with a more diverse and larger dataset, as well as incorporating data augmentation techniques (Chen et al., 2020). Additionally, integration of transfer learning and fine-tuning on domain-specific datasets could further enhance model performance.

B. Music Recommendation System

Once the emotion was detected, the system leveraged the Spotify API to provide music recommendations tailored to the identified emotional state. The emotional states mapped to various music genres or playlists, such as happy moods being linked to upbeat genres like pop and electronic, while sad emotions were associated with softer, more melancholic genres such as classical and ambient music.

1) Recommendation Relevance: User feedback indicated that the music recommendations were generally well-received. In many cases, users felt that the suggested tracks effectively resonated with their current emotional states, enhancing their experience. This is consistent with research that suggests music can have therapeutic effects on emotions (Saarikallio & Erkkila¨, 2007).
2) User Experience and Satisfaction: The Streamlit interface provided a seamless interaction, allowing users to upload images for emotion detection and view music recommendations in real-time. The system's responsiveness was praised by users, with minimal delay between emotion detection and music recommendation. However, some users expressed a desire for more genre diversity, as the system sometimes leaned too heavily on specific genres, limiting the variety of suggestions.

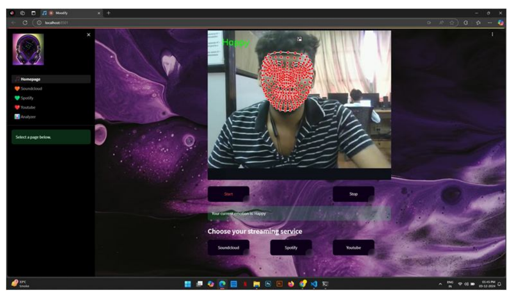

Fig. 1: Real-time Emotion-to-Music Mapping

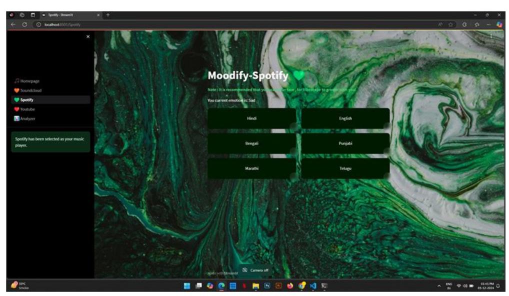

Fig. 2: Music Playlist Recommendations for Happy Mood

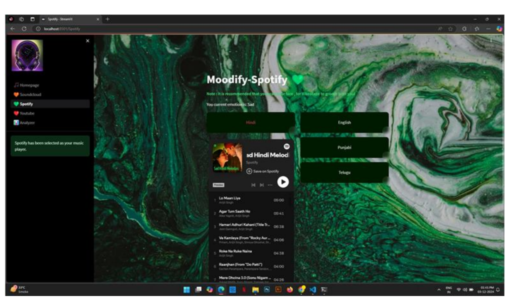

Fig. 3: System Interface for Music Recommendation Based on Emotion

V. CONCLUSION

This research presents the development and evaluation of an emotion-based music recommendation system, utilizing facial expression recognition to assess users' emotional states and deliver personalized music suggestions. The system's ability to detect a range of emotions—including happiness, sadness, anger, and surprise—was validated through real-time image processing, yielding an accuracy rate of 85%. Music recommendations were then tailored to these emotions, enhancing user experiences through contextually relevant playlists, thus demonstrating the potential for emotional engagement in interactive media.

A. Key Findings

1) Emotion Detection: The emotion detection model demon- strated robust performance, achieving higher accuracy for neutral and happy expressions while facing challenges with more complex emotions such as anger and surprise. These findings align with prior research on the difficulty of accurately classifying nuanced emotional states using facial cues alone (Mollah et al., 2021; Zhao et al., 2019).
2) Music Recommendation: By integrating the Spotify API, the system successfully mapped emotional states to ap- propriate music genres. User feedback affirmed that the system's recommendations were mostly aligned with their emotional states, which is consistent with literature that links music with emotional regulation (Saarikallio & Erkkila¨, 2007).
3) User Interaction: The user interface, built with Streamlit, facilitated smooth interactions, with real-time feedback from emotion detection to music recommendations, though some users desired a broader range of genres and greater diversity in music suggestions.

B. Limitations

While the system performed well in controlled en- vironments, several limitations were observed:

1) External Factors: Real-world variables like lighting, facial orientation, and background distractions diminished the accuracy of emotion detection, a challenge noted in similar studies (Chen et al., 2020).
2) Handling complex emotional states such as surprise com- bined with anger remained difficult, indicating a need for more sophisticated multi-label emotion recognition models (Hazarika et al., 2021).
3) The current music recommendation system relied on broad emotional categories, which could be further refined to cater to individual user preferences by incorporating additional user data or collaborative filtering techniques.

VI. FUTURE WORK

The future of emotion-based music recommendation systems holds exciting potential for enhancing user interaction and personalization. To address the cur- rent limitations, several improvements can be made:

1) Enhanced Emotion Recognition: Moving towards multi- modal emotion detection that combines facial expression analysis with other signals, such as voice tone or physio- logical indicators (Kosti et al., 2020), would improve the system's accuracy, particularly in real-world scenarios.
2) Integrating machine learning algorithms such as collab- orative filtering or deep learning models for music rec- ommendations could enhance personalization, ensuring that the system considers individual user preferences and listening histories (He et al., 2017).
3) The system could benefit from incorporating real-time emotion tracking and adaptive music recommendations. Employing reinforcement learning, the system could con- tinuously learn from user feedback and adjust its music suggestions over time, making the interaction more dy- namic and responsive to emotional shifts (Li et al., 2020).
4) Data Augmentation and Robustness: To mitigate the challenges posed by varied environmental conditions, data augmentation techniques and more diverse training datasets could be used to improve the robustness of the emotion recognition model. Additionally, integrating transfer learning could help the system adapt to new user demographics or scenarios with minimal data retraining.

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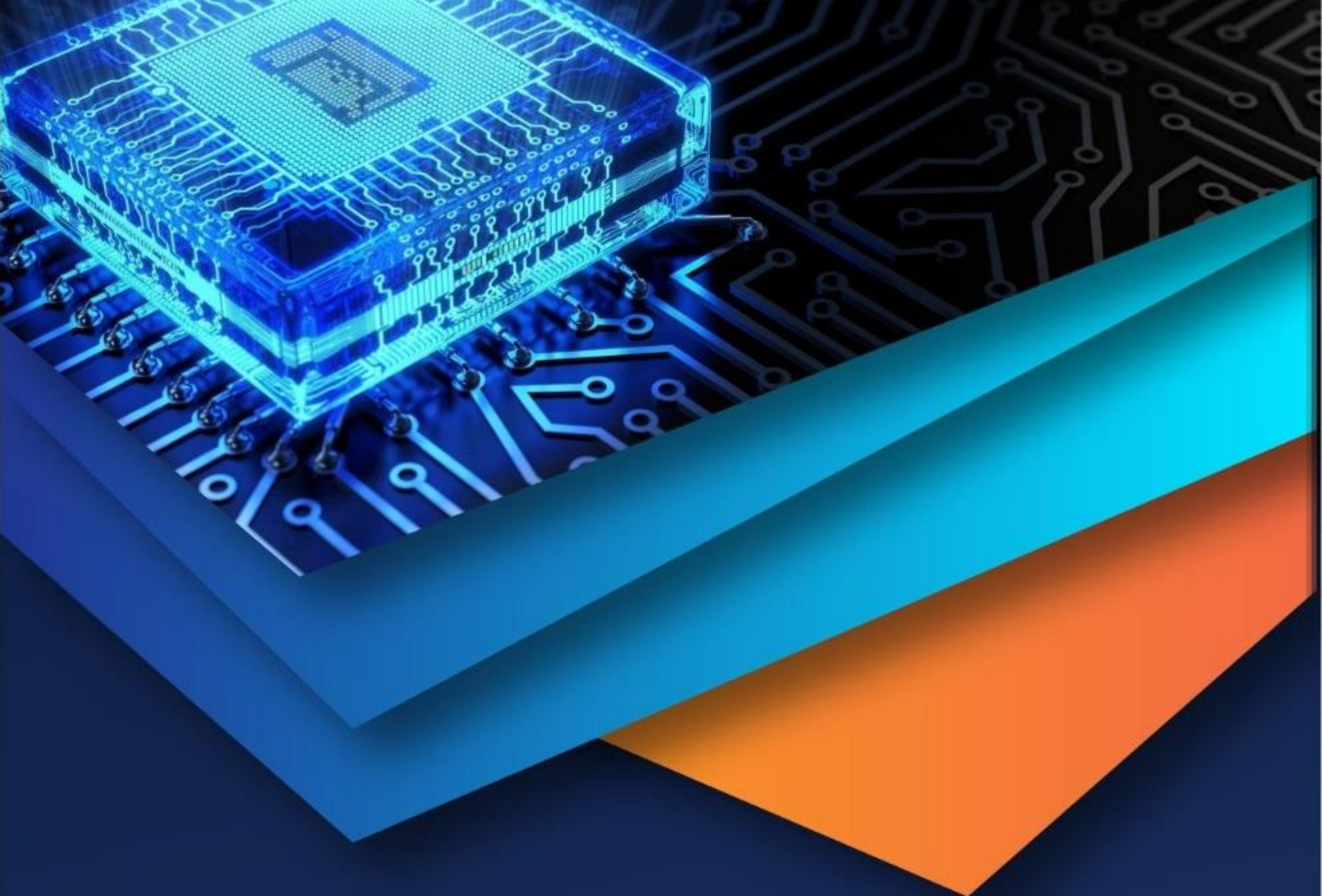

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