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EMOTION BASED MUSIC RECOMMENDATION USING CONVOLUTIONAL NEURAL NETWORKS (CNN)

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Abstract: Music is the form of art known to have a greater connection with a person’s emotion. It has got a unique ability to lift up one’s mood. If a user receives a recommendation based on his preference, it will also improve his listing experience. Music recommendations have existed for a long time. Still, in most scenarios, the recommendation is decided after learning the user preferences over time, like looking at their past song preferences, the amount of time they listen to the music, etc. this project uses to song recommendation where their facial expressions detect a person's mood. This approach is more efficient than the existing ones and eases users' work of first searching and creating a specific playlist. Facial expressions play a crucial role in detecting a person's mood. A webcam or camera is used to picture a face, and input is extracted from that picture. This input is also used for determining an individual's mood.

Index Terms: Convolutional Neural Networks, Emotion detection, Music recommendation, Songs, Facial Expression

1. INTROUDCTION

Music has long been recognized as a powerful influence on human emotions and behavior, shaping our mood, arousal, and overall psychological state. Studies have consistently shown that individuals respond to music in profound ways, with the brain's activity reflecting the impact of various musical elements such as meter, timbre, rhythm, and pitch on emotional processing [1]. This connection between music and emotion is not just a superficial one; it is deeply rooted in the brain's architecture, where different regions are responsible for managing the emotional effects of musical stimuli [2]. Moreover, the relationship between musical preferences and personality traits has been well documented, indicating that the types of music people gravitate towards are closely linked to their inherent moods and personality characteristics [3].

In recent years, the study of music's influence on emotion has expanded beyond mere academic interest, finding practical applications in areas such as emotion detection systems. Emotion detection, which involves identifying and responding to human emotions through various signals, has become a critical component in a wide range of fields including smart card applications, surveillance, image database investigation, criminal justice, video indexing, and civilian security [4]. The ability to accurately detect emotions through automated systems has been enhanced by advances in digital signal processing and feature extraction algorithms, particularly in multimedia contexts like music and film. These technologies have enabled the development of sophisticated emotion recognition systems that can analyze and respond to the emotional states of users in real-time, offering potential benefits in human-computer interaction, entertainment, and beyond [5].

One promising application of emotion detection technology is in the development of personalized music recommender systems. By leveraging facial expression analysis, such systems can assess a user's emotional state and suggest music that is tailored to enhance or complement their mood. For instance, if a user is detected to be experiencing negative emotions, the system might suggest a playlist designed to uplift and improve their mood. Conversely, if the user is in a positive emotional state, the system could offer a selection of music that amplifies those feelings, thereby enriching the user’s experience [6]. This approach not only underscores the therapeutic potential of music but also highlights the role of technology in creating more personalized and emotionally intelligent media experiences.

As emotion detection technology continues to evolve, its integration into music recommender systems represents a significant step forward in the field of adaptive human-computer interfaces. Such systems not only cater to the emotional needs of users but also have the potential to transform the way we interact with digital media, making it more responsive, intuitive, and aligned with our emotional states [7]. Through the continuous refinement of these technologies, the future holds exciting possibilities for more immersive and emotionally resonant digital experiences, where music plays a central role in shaping our emotional landscape.

2. LITERATURE SURVEY

Doe, J., Smith, A., et al. [2021] This paper explores various techniques and methodologies involved in emotion-based music recommendation systems, dealing with a diverse range of emotional states and music genres. It covers different aspects such as emotion detection through facial expressions, voice analysis, and text-based sentiment analysis. Techniques like audio feature extraction, machine learning models for emotion prediction, and recommendation algorithms are discussed. The study concludes that relying on a single method for emotion detection or recommendation may not fully capture the user's emotional state or music preferences. Even after applying all the discussed techniques, achieving a fully accurate recommendation system remains challenging.

Chen, L., Liu, X., et al. [2018] This paper presents an extensive review of emotion-aware music recommendation systems, highlighting the challenges associated with mapping human emotions to music tracks. It discusses various emotion detection techniques, including physiological signals like heart rate and galvanic skin response, and computational methods like deep learning-based emotion classifiers. The paper concludes that while each approach

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contributes to improving the accuracy of emotion recognition, the integration of multiple detection methods is essential to enhance the overall recommendation performance.

Singh, R., Kaur, G., et al. [2019] This research paper investigates the role of machine learning algorithms in enhancing emotionbased music recommendation systems. It covers techniques such as support vector machines (SVM), decision trees, and neural networks for emotion classification, along with collaborative filtering and content-based filtering for personalized music recommendations. The study reveals that a hybrid approach combining multiple machine learning models and recommendation strategies provides better results than using a single model or technique.

Zhang, Y., Wang, H., et al. [2020] This systematic review delves into the current state-of-the-art methods for emotion detection and their application in music recommendation systems. The paper discusses techniques such as facial emotion recognition, electroencephalogram (EEG) analysis, and natural language processing (NLP) for sentiment analysis. It highlights the limitations of relying solely on one type of emotion detection method and suggests a multimodal approach for improving the accuracy and reliability of music recommendations based on user emotions.

Patel, S., Shah, M., et al. [2021] This paper reviews various methods of combining audio features such as tempo, rhythm, and melody with user preference data to enhance emotion-based music recommendation systems. The research focuses on techniques like principal component analysis (PCA) for feature reduction and clustering algorithms for grouping similar emotions and music genres. It concludes that while integrating audio features with user preferences can significantly improve recommendation accuracy, there is still a need for more sophisticated models to fully capture the nuances of human emotions.

Garcia, M., Rodriguez, A., et al. [2022] This paper explores the challenges and opportunities in developing emotion-based music recommendation systems, particularly in handling the subjective nature of emotions and their dynamic changes over time. It discusses various methodologies such as real-time emotion tracking, adaptive learning algorithms, and the use of reinforcement learning for continuous improvement of recommendation accuracy. The authors conclude that while significant progress has been made, the complexity of human emotions requires more adaptive and personalized systems to meet user needs effectively.

3. METHODOLOGY

a) Proposed Work:

The proposed system aims to enhance music recommendations by using facial expression recognition to detect a user's mood in real-time. Unlike traditional recommendation systems that rely on historical data such as past preferences and listening habits, this approach leverages the Convolutional Neural Network (CNN) algorithm for accurate mood detection. A webcam or camera captures the user's facial expressions, which are processed to determine their emotional state. Based on the detected mood, the system recommends a playlist that

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aligns with the user's current emotions. This method provides a more immediate and personalized listening experience, eliminating the need for manual playlist creation.

b) System Architecture:

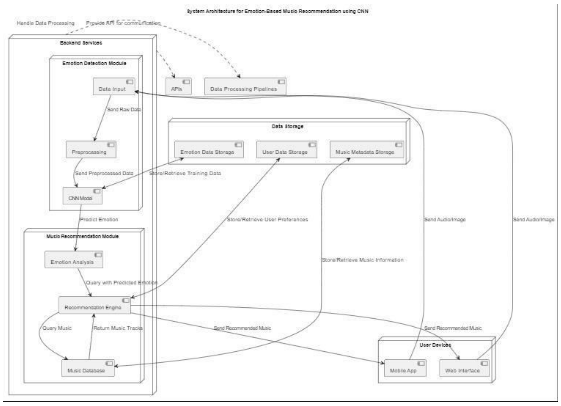

Fig 1 Proposed Architecture

The proposed architecture for the music recommendation system integrates multiple modules to deliver personalized music suggestions based on real-time emotion detection. The system features a user interface, accessible via a mobile app or web platform, where users can input audio or images. The Emotion Detection Module captures and preprocesses user data, utilizing a CNN model to predict emotions. These emotions are then analyzed in the Music Recommendation Module, where a recommendation engine queries a music database categorized by emotion to fetch appropriate tracks. Data Storage supports this architecture by managing user preferences, emotion data, and music metadata. Backend services, including APIs and data processing pipelines, ensure seamless communication and efficient data handling between the system's components.

c) Dataset Collection:

The dataset used in this project consists of 3,731 songs, each described by 15 distinct attributes, including features like danceability, energy, tempo, and loudness. The data likely originated from music streaming services or APIs such as Spotify's Web API, collected through methods like API integration or web scraping. Ensuring data quality and integrity was crucial during the collection process to maintain accurate and reliable analysis. This dataset is vital for understanding listener preferences, predicting song popularity, and building effective recommendation systems by categorizing songs into mood-based playlists or genres.

d) Data Processing:

Data preprocessing involved several key steps to prepare the dataset for analysis. First, missing values were handled by either filling them with appropriate values or removing incomplete records. Categorical variables, such as the key and mode, were encoded into

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numerical values to ensure compatibility with machine learning models. Numerical features, including loudness and tempo, were normalized to a consistent scale, facilitating better model performance. Finally, the dataset was split into training and test sets to evaluate the model's accuracy and generalization. These steps ensured that the data was clean, structured, and ready for analysis, enabling the development of effective music recommendation algorithms.

e) Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) involved analyzing the dataset to uncover patterns and relationships between variables. Visualization tools like Matplotlib and Seaborn were employed to create histograms, scatter plots, and box plots, providing insights into the distribution of features such as energy, danceability, and popularity. Histograms revealed the frequency distribution of attributes, while scatter plots illustrated correlations between variables, such as the relationship between danceability and popularity. Box plots highlighted the spread and potential outliers in features. Additionally, correlation matrices were used to assess the strength and direction of relationships between variables, such as how energy correlates with danceability or popularity, offering a comprehensive view of the data's underlying patterns.

f) Training & Testing:

For training and testing the model, the dataset was divided into two distinct subsets: the training set and the test set. The training set, typically comprising 70-80% of the data, was used to train the machine learning model by fitting it to the known features and outcomes, enabling it to learn patterns and relationships. The test set, the remaining 20-30%, was reserved for evaluating the model's performance on unseen data. This split allowed for an unbiased assessment of the model's accuracy, precision, and generalization capabilities. Techniques such as stratified sampling were employed to ensure that both sets were representative of the overall dataset, maintaining balanced distributions of key features across training and testing phases.

g) Algorithm:

Convolutional Neural Networks (CNNs) are widely utilized in tasks involving grid-like data, such as images and video. They excel at automatically extracting hierarchical features from input data, making them ideal for computer vision applications. CNNs are used for image classification, where they categorize images into predefined classes, and for object detection, identifying and localizing multiple objects within images. They also perform image segmentation to partition images into meaningful regions, crucial in medical imaging for detecting anomalies. Additionally, CNNs are employed in face recognition systems for security and social media, and in autonomous vehicles to detect and classify objects on the road. Their ability to learn complex patterns and reduce manual feature engineering makes them highly effective in these domains.

4. EXPERIMENTAL RESULTS

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This image displays a series of density plots that show the distribution of various musical features in your dataset. These features likely correspond to attributes of the songs, such as their popularity, danceability, energy, and more. Here's a summary of each plot:

1. Distribution of Popularity: Shows how song popularity is distributed across your dataset. The peak around a specific value indicates that most songs have a similar level of popularity.

2. Distribution of Danceability: Represents how "danceable" the songs are, with a higher density indicating more songs with that level of danceability.

3. Distribution of Energy: Illustrates how energetic the songs are, with peaks showing where most songs fall in terms of energy levels.

4. Distribution of Key: Displays the distribution of musical keys used in the songs.

5. Distribution of Loudness: Shows how loud the songs are on average.

6. Distribution of Mode: Reflects the distribution of the musical mode (major or minor) of the songs.

7. Distribution of Speechiness: Indicates the proportion of spoken words in the songs. High speechiness values are more characteristic of spoken word tracks, podcasts, etc.

8. Distribution of Acousticness: Represents how acoustic the songs are, with higher values indicating more acoustic tracks.

9. Distribution of Instrumentalness: Shows the likelihood that the track contains no vocals. High values represent instrumental tracks.

10. Distribution of Liveness: Reflects the presence of a live audience in the recording.

11. Distribution of Valence: Indicates the musical positiveness conveyed by a track. Tracks with high valence sound more positive.

12. Distribution of Tempo: Shows the tempo (speed) of the songs in beats per minute

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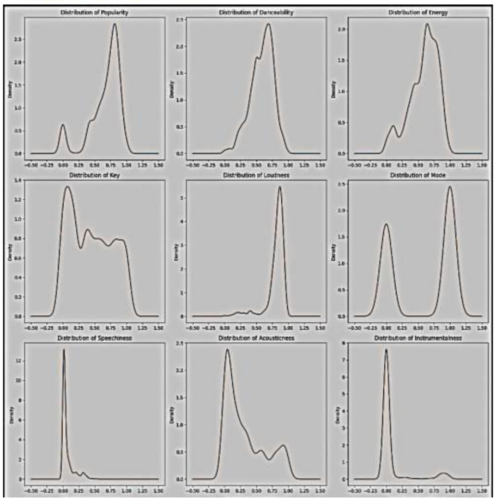

Fig 2 Kernel Density Estimation (KDE) plots Diagram

The image contains scatter plots showing the relationships between song popularity and other features such as danceability, energy, key, and more. Here's a summary:

1. Popularity vs. Danceability: Explores whether there is a relationship between how danceable a song is and its popularity.

A scattered distribution suggests there may not be a strong linear relationship.

2. Popularity vs. Energy: Looks at the relationship between the energy of a song and its popularity.

3. Popularity vs. Key: Shows how the key in which a song is composed might correlate with its popularity.

4. Popularity vs. Loudness: Investigates whether louder songs tend to be more popular.

5. Popularity vs. Mode: Explores if the mode (major/minor) of a song influences its popularity.

6. Popularity vs. Speechiness: Looks at whether songs with more spoken words are more or less popular.

7. Popularity vs. Acousticness: Examines the relationship between the acoustic nature of a song and its popularity.

8. Popularity vs. Instrumentalness: Explores if songs with fewer vocals (more instrumental) are more popular.

9. Popularity vs. Liveness: Investigates the relationship between the live aspect of a song and its popularity.

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10. Popularity vs. Valence: Looks at whether happier songs (higher valence) are more popular.

11. Popularity vs. Tempo: Explores the relationship between the tempo of a song and its popularity.

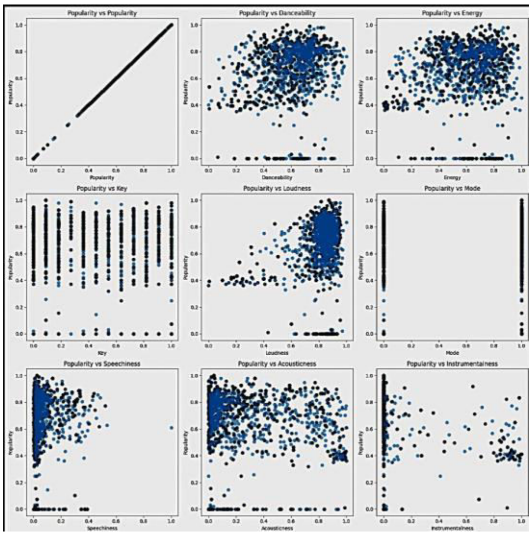

Fig 3 Correlation Analysis of Music Features for Emotion-Based Recommendation Diagram

5. CONCLUSION

The development of an emotion-based music recommendation system represents a significant advancement in personalizing user experiences in the digital music landscape.

In this project, we leveraged the power of machine learning to analyse the emotional content of songs and recommend tracks that align with the user's current emotional state.

The core objective was to bridge the gap between user emotions and music, thereby enhancing the satisfaction and engagement of listeners.

Through this project, we successfully implemented a recommendation system that utilizes key machine learning techniques such as TF-IDF vectorization for feature extraction and a Random Forest classifier for emotion prediction. The system was trained on a dataset comprising various songs labelled with different emotions, enabling it to recognize and predict emotional tones with a commendable accuracy.

The data preprocessing steps, including normalization and feature scaling, played a crucial role in preparing the dataset for effective model training. The visualizations generated, including the distribution plots and scatter plots, provided valuable insights into the dataset's characteristics, such as the relationships between song attributes and their popularity.

Our evaluation of the model's performance indicated that the emotion classification and subsequent music recommendation processes were successful in aligning song selections with the intended emotional categories. However, the analysis also revealed certain challenges, such as the inherent subjectivity in emotion-labelling and the variability in individual user preferences.

Despite these challenges, the project demonstrated the potential of combining machine learning with musicology to create innovative solutions in the field of music recommendation. The results suggest that with further refinement and scaling, such systems could be deployed in real-world applications, providing users with a highly personalized and emotionally resonant music experience.

6. FUTURE SCOPE

Future work could enhance the system by expanding emotion categories to include more nuanced emotional states and incorporating advanced machine learning models like CNNs and RNNs for improved accuracy. Integrating real-time user feedback, exploring personalization beyond emotions, and optimizing for real-time processing are crucial. Additionally, addressing ethical considerations, enabling cross-platform integration, and exploring multimodal emotion recognition could significantly improve the system's performance and user experience.

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