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Music and Movie Recommendation Based Facial Expression

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ABSTRACT—

In this project, human emotions are complex and influenced by various internal and external factors. However, the use of technology to understand and cater to human emotions has great potential for various applications, including music recommendation systems. The existing systems for music recommendation, such as automatic playlist creation and manual segregation, have limitations and may not always satisfy the user. By incorporating emotions into the recommendation process, the system can better understand and cater to the user's needs and preferences. The proposed system uses deep learning algorithms to classify emotions and generate suitable music recommendations based on the identified emotion. This approach can lead to more accurate and personalized music recommendations, improving the user experience. Additionally, this system opens up opportunities for further research in this area, as emotions are a complex and evolving field of study. Overall, incorporating emotions into music recommendation systems has great potential for improving user experience and paving the way for further research and development in this field.

Keywords—Music recommendation system , Emotion recognition, Convolutional neural networks, Machine learning.

I. INTRODUCTION

Music is an integral part of our daily lives and has the ability to evoke different emotions in individuals. Music recommendation systems have been developed to provide personalized and relevant music suggestions to users. However, most existing systems do not take into account the emotions of the users, which can greatly impact their music preferences.

In recent years, there has been a growing interest in developing emotion-based music recommendation systems that consider the emotional state of the user. These systems aim to provide music suggestions that match the user's emotional state and improve their overall music experience.

Convolutional neural networks (R-CNN) have emerged as a powerful tool for analyzing audio signals and extracting relevant features from them. In the context of music recommendation systems, R-CNNs can be used to analyze the emotional content of music and match it with the user's emotional state.

In this paper, we propose an emotion-based music recommendation system using convolutional neural networks.

The system takes into account the emotional state of the user and recommends music that matches their emotions. We use a deep learning approach to extract features from the audio signals and train a R-CNN model to classify the emotional state of the user. The model then recommends music that matches the user's emotions, providing a personalized and enjoyable music experience.This paper presents the architecture and implementation of the proposed system, as well as the experimental results and evaluation of its performance. We demonstrate the effectiveness of our system in providing accurate and relevant music recommendations based on the emotional state of the user.

II. LITERATURE SURVEY

In [1] 1.For Automatic Facial Expression recognition this research paper [1] uses three phases. These three phases are 1. Face detection2. Feature Extraction and 3. Expression recognition. In the First Phase, YCbCr Colour model are used for face detection, lighting compensation for obtaining face and morphological operations for holding required features of the face i.e. eyes, eyebrows and mouth. This System also uses Active Appearance Model Method (AAM) for facial feature extraction. In this method the features on the face like eye, eyebrows and mouth are located and a data file is created which gives information about the model points detected. Different facial expressions are given as input to the AAM Model which changes according to expression.

Three different ways are used in this paper [2] for emotion classification and context- based music recommendation. They are 1. Emotion State TransitionModel (ESTM) 2. Context-based music recommendation (COMUS) 3. Nonnegative matrix factorization (NMF). ESTM is predominantly used to model various human emotions and their transition to music. It acts like a bridge between an individual's mood and low-level music features. With the help of ESTM the most legitimate music can be recommended to the client for travelling to the ideal state.COMUS ontology is utilized for demonstrating user's musical inclinations and setting, and for supporting thinking about the client's ideal feeling and inclinations.

COMUS are a music dedicated ontology developed by including particular classes for music suggestion which incorporates mood, situation and other features. In order to reduce the dimensions data's related to music are gathered after which NMF are applied to map them to ESTM.

The main objective of this paper [3] is to generate a music recommendation system by observing the sentiments of user and polarity of words used in social media. Sentiment intensity metric (Sentimeter-Br2) is used to extract an individual emotion from SocialNetworks.Sentiment-Br2 is a sentiment intensity metric whose main goal is to improve the overall accuracy and efficiency of music recommendation system. The words extracted from social media is ranked positive, negative or neutral based on sentiment intensity, according to which a musical playlist is generated and played to the respective user.A framework is created where the user registers by giving the necessary details creates a login account. Every time the user posts some content the phrases used by him are collected and stored. These words are then analysed on a day to day basis and are classified by the sentiment metric system. Based on the mood of the individual and his/her preference a playlist is generated and played to the user. The results showed that 72.5% of the total number of users considered the proposed recommendation system to be useful than the traditional recommendation system.

The goal of this research paper [4] is torecommend songs that the user likes, songs which are fresh or new to the user's ear and fit the user's listening pattern. The system mainly focuses on behaviour of the user and metadata rather than the content. A Forgetting Curve is used to estimate the freshness of a song and evaluate likeness using user log. The user's behaviour on the song is continuously monitored which is used as feedback for suggesting better songs when the user is not in a good mood or not satisfied. If a user listens to song completely it means that the user likes that song and similar kinds of songs are recommended to the user.On the other hand, if the user skips a song the system infers that the user dislikes that song and is less recommended. Thus, the user's attitude towards a song is evaluated continuously on a long-term basis. The five factors which are important in designing recommendation systems are freshness, year, favour, time pattern and genre. Lesser the feedback better the automatic music recommendation system. Results showthat the recommendation system surpasses the baseline and is proven to be effective.

This research paper [5] uses real time datasets for music recommendation system. A TV music program's audience were requested to rate the music of the participants based on their music preference and emotional feelings. The developers targeted low- level music features which triggered human emotions among the audience. In addition to this a personalized music recommendation system was implemented using low- level music features, listener's history and content analysis.For selection of low-level music features which are responsible for triggering emotions, preference analysis method is used which is based on empirical evaluation scores.

Once the features are selected a design is created based on the selected features, listening history which are combined with environmental information. The design shows the subjective validity and accuracy of audience evaluation. Though aural aspect affected a large part of the evaluation, by extracting more features and increasing the size of dataset better results with high accuracy can be obtained.

III. METHODOLOGY

The proposed methodology for the emotion-based music recommendation system using convolutional neural networks can be divided into several stages:

a) ***Data Collection:*** The first stage involves collecting a large dataset of audio files along with their corresponding emotional labels. This dataset can be obtained from various sources such as online music platforms or curated by the researchers.

b) ***Feature Extraction:*** In the next stage, audio features such as Mel Frequency Cepstral Coefficients (MFCCs) and Spectral Contrast are extracted from the audio files using a pre-processing step. These features are commonly used in music analysis and provide valuable information about the emotional content of the music.

c) ***R-Convolutional Neural Network Model:*** A R-CNN model is designed to classify the emotional state of the user based on the extracted features. The model can have multiple convolutional and pooling layers with varying filter sizes to capture different features of the audio signals. The output layer of the model predicts the emotional state of the user based on the extracted features.

d) ***Training and Validation:*** The R-CNN model is trained on the collected dataset of audio files and their emotional labels. The dataset is divided into training, validation, and testing sets. The model is trained on the training set and validated on the validation set to ensure that it is not overfitting. The model is then evaluated on the testing set to measure its performance.

e) ***Music Recommendation:*** Once the R-CNN model is trained and validated, it is used to recommend music to the user based on their emotional state. When a user interacts with the system, their emotional state is detected using the R-CNN model, and the system recommends music that matches their emotional state. The recommended music can be chosen from the dataset or obtained from online music platforms.

f) ***User Feedback:*** Finally, user feedback is collected to improve the performance of the system. The system can collect feedback on the recommended music, user emotions, and overall user experience to refine the recommendations in the future.

Overall, the proposed methodology for the emotion- based music recommendation system using convolutional neural networks involves collecting a dataset of audio files, extracting audio features, designing a R-CNN model, training and validating the model, recommending music based on the user's emotional state, and collecting user feedback to improve the system's performance.

IV. HAAR-CASCADE CLASSIFIER

The Haar-Cascade classifier is a machine learning algorithm used for object detection in images or videos. The algorithm works by detecting objects based on patterns of pixel intensities in a given image or video frame.

The Haar-Cascade classifier is a widely used algorithm for object detection and has been used for a variety of applications, including face detection, pedestrian detection, and object tracking.

V. WORKING PRINCLIPLE

The working principle of the emotion-based music recommendation system using convolutional neural networks (R- CNNs) can be summarized in the following steps:

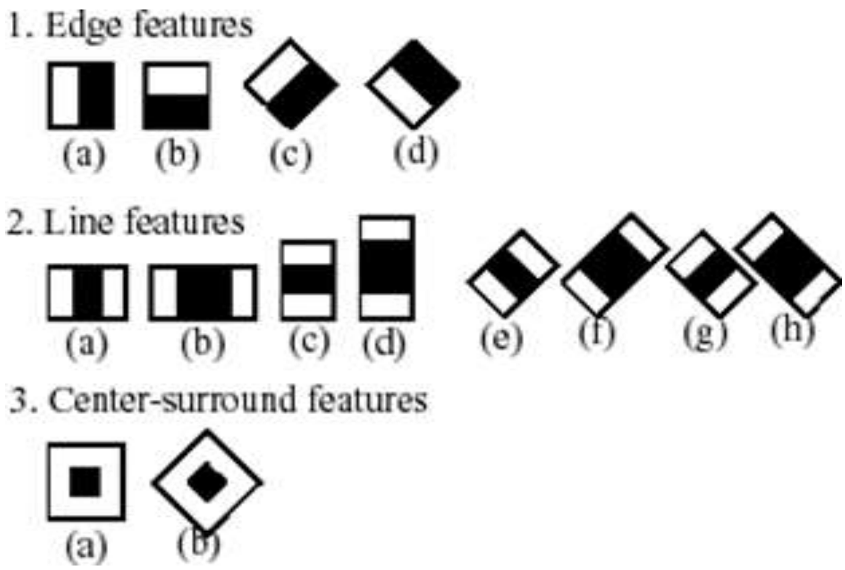

Fig 1:Haar-Cascade Classifier process

The process for using the Haar-Cascade classifier is as follows:

a) ***Collect and Prepare Training Data:*** The first step is to collect and prepare a dataset of positive and negative images for training the classifier. Positive images contain the object of interest, while negative images do not.

b) ***Feature Extraction:*** The next step is to extract features from the positive and negative images. The Haar-Cascade classifier uses Haar-like features, which are simple rectangular features that can be computed quickly. These features are computed at various scales and positions in the image.

c) ***Training the Classifier:*** The Haar-Cascade classifier is trained using a machine learning algorithm such as Adaboost. During training, the algorithm iteratively adjusts the weights of the features to minimize the classification error.

d) ***Creating the Cascade:*** Once the classifier is trained, it is converted into a cascade of classifiers. The cascade is a series of stages, each consisting of multiple weak classifiers. The cascade is designed to quickly reject regions of the image that are unlikely to contain the object of interest.

e) ***Object Detection:*** To detect objects in a new image, the Haar-Cascade classifier slides a window of fixed size over the image and applies the cascade of classifiers to each window. If the window passes all stages of the cascade, it is classified as containing the object of interest.

f) ***Post-Processing:*** After object detection, post-processing steps can be applied to refine the results. These steps may include non-maximum suppression, which removes overlapping detections, and bounding box regression, which adjusts the bounding boxes to more accurately fit the object.

The first step is to collect a dataset of music tracks with their corresponding emotional labels. The emotional labels can be obtained through various means such as crowd-sourcing, surveys, or self-reporting.The audio files are preprocessed by converting them into a suitable format for analysis. This includes audio feature extraction using various techniques such as Mel Frequency Cepstral Coefficients (MFCCs) and chroma features. These features represent the characteristics of the audio signal such as its spectral content, timbre, and rhythm. The preprocessed audio data is then used to train a R-CNN model. The R-CNN model is designed to learn the features that are most relevant to each emotion. The model architecture consists of multiple layers of convolutional, pooling, and fully connected layers. The weights of the model are learned through a backpropagation algorithm that minimizes the difference between the predicted and actual emotion labels. The trained R-CNN model is then tested on a separate dataset of music tracks to evaluate its performance. This involves predicting the emotional label for each test track and comparing it to the actual label. The performance of the model is measured using various metrics such as accuracy, precision, and recall.The final step is to develop a music recommendation system that takes the emotional state of the user as input and recommends music tracks that match their emotional state. The emotional state can be obtained through various means such as facial expression analysis, speech analysis, or self-reporting. The recommended tracks are selected based on their emotional labels and the similarity to the user's emotional state.

Overall, the emotion-based music recommendation system using R-CNNs is designed to provide personalized music recommendations based on the emotional state of the user. The R- CNN model is able to learn the relevant features of the music tracks that are most closely associated with each emotional label and use this knowledge to recommend suitable music tracks to the user.

VI. ANACONDA TOOL

Anaconda is a popular distribution of Python and R programming languages for data science and machine learning tasks. Anaconda includes a wide range of pre-installed packages and libraries for data analysis, including NumPy, Pandas, Matplotlib, and Scikit-learn.

It provides a convenient and user-friendly graphical interface, called Anaconda Navigator, for managing packages and launching applications.Anaconda also includes Jupyter Notebook, an interactive web-based environment for creating and sharing documents that contain live code, equations, and visualizations.

It supports virtual environments, which allow users to create isolated environments with different packages and configurations.Anaconda can be easily installed on various operating systems, including Windows, macOS, and Linux. It includes tools for managing data and files, such as Anaconda Prompt, Anaconda PowerShell Prompt, and Anaconda File Explorer.Anaconda also supports collaboration and sharing through its Anaconda Cloud platform, which enables users to publish and share their packages and notebooks.It provides extensive documentation and resources for learning and troubleshooting, including online courses, tutorials, and a community forum.Anaconda is open-source and free to use, with the option of upgrading to a paid version for additional features and support.

Overall, Anaconda is a comprehensive and powerful tool for data science and machine learning that simplifies the setup and management of environments and packages, while also providing a range of useful features and resources for users.

VII. APPLICATION

The emotion-based music recommendation system using convolutional neural networks (R-CNNs) has several potential applications in various industries, including:

- ***a)*** ***Music Streaming Platforms:*** The system can be integrated into music streaming platforms like Spotify, Pandora, and Apple Music to provide personalized music recommendations based on the user's emotional state. This can improve user engagement and satisfaction with the platform.
- ***b)*** ***Marketing:*** The system can be used by marketers to create personalized advertisements and content based on the emotional state of the target audience. This can improve the effectiveness of marketing campaigns by creating more emotional connections with the audience.
- ***c)*** ***Healthcare:*** The system can be used in healthcare settings to provide music therapy to patients based on their emotional state. For example, the system can recommend calming music for patients with anxiety or upbeat music for patients with depression.
- ***d)*** ***Entertainment Industry:*** The system can be used by the entertainment industry to create more immersive experiences for viewers by incorporating music that matches the emotional tone of the content. For example, a movie with a suspenseful scene can have music that enhances the tension and fear in the audience.
- ***e)*** ***Psychology and Neuroscience Research:*** The system can be used by researchers in psychology and neuroscience to study the relationship between music and emotions. The system can provide insights into how music affects different emotional states and how these emotions are represented in the brain.

Overall, the emotion-based music recommendation system using R-CNNs has a wide range of potential applications that can benefit various industries and fields.

VIII. RESULT

Fig 2:Result In fig 2,The above figures these are the result of project using Pytthon.

The result of an emotion-based music recommendation system using convolutional neural networks (R-CNNs) can be evaluated using various metrics such as accuracy, precision, recall, F1 score, and mean squared error. The performance of the R-CNN model can be compared to other machine learning models such as support vector machines (SVMs) and decision trees to determine its effectiveness.

The user's satisfaction with the music recommendations can also be evaluated through surveys and feedback. User engagement metrics such as click-through rate (CTR), time spent listening to recommended songs, and the number of songs added to the user's playlist can also be measured.

Overall, a successful emotion-based music recommendation system using R-CNNs should provide personalized music recommendations that match the user's current emotional state with high accuracy and user satisfaction.

The system should also be scalable and able to handle large datasets of music tracks with corresponding emotional labels.

IX. ALGORITHM

The steps involved in building an emotion-based music recommendation system using convolutional neural networks (R- CNNs) can be summarized as follows:

Step 1: Collect a dataset of music tracks with corresponding emotional labels. The emotional labels can be obtained through surveys, self-reporting, or crowd-sourcing.

Step 2: Preprocess the audio files by converting them into a suitable format for analysis. This includes audio feature extraction using techniques such as Mel Frequency Cepstral Coefficients (MFCCs) and chroma features.

Step 3: Split the dataset into training, validation, and test sets.

Step 4: Design a R-CNN model architecture that consists of multiple layers of convolutional, pooling, and fully connected layers. Train the model using the preprocessed audio data and the emotional labels.

Step 5: Evaluate the performance of the trained model on the validation set. This involves predicting the emotional label for each validation track and comparing it to the actual label. Measure the performance of the model using various metrics such as accuracy, precision, and recall.

Step 6: Tune the hyperparameters of the model to improve its performance on the validation set. This includes adjusting the learning rate, batch size, and number of epochs.

Step 7: Test the performance of the trained model on the test set. This involves predicting the emotional label for each test track and comparing it to the actual label.

Step 8: Integrate the trained model into a music recommendation system that takes the emotional state of the user as input and recommends music tracks that match their emotional state.

Step 9: Test the music recommendation system with real users to evaluate its effectiveness in providing personalized music recommendations based on the user's emotional state.

Overall, building an emotion-based music recommendation system using R-CNNs requires collecting and preprocessing the audio data, designing and training a R-CNN model, evaluating its performance, and integrating it into a music recommendation system. The system can then be tested with real users to ensure its effectiveness in providing personalized music recommendations based on the user's emotional state.

X. CONCLUSION

In conclusion, the use of convolutional neural networks (R-CNNs) in building an emotion-based music recommendation system can greatly improve the user's experience and satisfaction. By analyzing the audio features of music tracks and predicting the emotional state associated with them, the system can provide personalized music recommendations that match the user's current emotional state.

The R-CNN model can be trained on a dataset of music tracks with corresponding emotional labels and evaluated using various metrics to ensure its effectiveness in predicting the emotional state. Hyperparameter tuning can be applied to improve the model's performance.

Integrating the trained R-CNN model into a music recommendation system can allow users to input their current emotional state and receive personalized music recommendations that match their mood. The system can be tested with real users to evaluate its effectiveness and refine it for better performance.

Overall, an emotion-based music recommendation system using R-CNNs has the potential to provide personalized music recommendations and improve the user's emotional well- being through the power of music.

XI. FUTURE ENHANCEMENT

The current system is limited to a set number of basic emotion labels. Future enhancements can explore the addition of more nuanced and complex emotion labels to improve the accuracy and personalization of music recommendations. Integrating multiple modalities such as facial expression, physiological signals, and voice patterns can provide a more comprehensive understanding of the user's emotional state, improving the accuracy of the music recommendations.

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