Music Recommendation System using Hybrid Approach

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ABSTRACT

In the digital music era, artists and creators on platforms like Spotify seek to engage and connect with their audiences. To facilitate this interaction and promote their playlists, a novel hybrid-based recommendation system is proposed. This project presents a hybrid music recommendation system that combines content-based and collaborative filtering methods to offer personalized song recommendations to users. Leveraging the Spotify API and a rich dataset of song features, this system offers an interactive and user-centric experience for music enthusiasts. The content- based filtering component analyzes audio features of songs, including danceability, energy, acousticness, instrumentals, and more. Users can input their favorite songs, and the system generates recommendations based on the similarity of these features. Additionally, users have the flexibility to fine-tune their preferences using sliders for various audio attributes. The collaborative filtering component employs K-Means clustering to group songs with similar audio characteristics. When users provide input songs, the system calculates a user profile based on the mean audio feature values of those songs. Recommendations are then generated from the cluster that best matches this profile, ensuring contextual relevance. Integration with the Spotify API enriches the dataset with song popularity, explicitness, and additional audio features. Users can listen to recommended songs directly from the interface, enhancing their music discovery experience. This hybrid recommendation system provides a dynamic and adaptable approach to music discovery, catering to diverse user preferences. Its seamless integration of content-based and collaborative filtering techniques empowers users to explore new music while staying connected with their musical tastes.

Keyword : - *Music Recommendation, Hybrid Approach, User Engagement, Spotify, K-means, Streamlet.*

1.Introduction

Music recommendation systems have undergone a remarkable transformation, reshaping the music consumption landscape and redefining how we interact with our favorite tunes. These systems have a fascinating history that unfolds against the backdrop of the digital revolution. Their origins can be traced to the late 20th century when the internet started to pave the way for the digital dissemination of music. Early attempts at music recommendations often reliedon simple collaborative filtering or genre-based approaches, offering users a taste of curated playlists and rudimentary radio stations.The turning point came in the early 2000s with the emergence of pioneering platforms like Pandora and Last.fm. These platforms introduced sophisticated algorithms that analyzed user behavior and music characteristics to create personalized playlists. Pandora's Music Genome Project, for instance, categorized songs based on attributes like tempo, key, and instrumentation, revolutionizing theprecision of music recommendations.

Fast forward to the present day, and music recommendation systems have reached unprecedented levels of sophistication. Streaming giants like Spotify, Apple Music, and YouTube Music have harnessed the power of machine learning and artificial intelligence to dissect user preferences, providing tailored playlists, daily mixes, and song suggestions. These systems continuously adapt and improve, driven by vast data repositories and feedback loops.

In today's digital age[1], where music is accessible at our fingertips, the role of machine learning (ML) in music recommendation has transformed the way we discover and enjoy our favorite tunes. ML algorithms have revolutionized the music listening experience by analyzing user behaviors, dissecting the characteristics of songs, and creating personalized playlists. From humble beginnings in the early days of digital music to the advanced systems we encounter on popular streaming platforms today, ML has been the driving force behind the evolution of music recommendation, enhancing our musical journeys and broadening our horizons in the realm of melodies and rhythms. This exploration delves into how ML has become the maestro behind the symphony of modern music recommendations.

Music[2] streaming applications such as Spotify and Pandora have features to suggest music to users. These characteristics could help in obtaining a list of suitable music from well-known music libraries on the basis of previously heard music. Therefore, the recommender system is crucial to sustaining the streaming music industry. The process of making music suggestions involves comparing songs that aresimilar to each other or ranking users' preferences. The difficulty in developing a music recommender system is in making one that can constantly discover interesting new music and comprehend user musical preferences. This necessitates that the personalized music recommendation system accurately captures the user's preferences. It requires modifications to produce customized suggestions that meet the requirements of various audiences. Then, the music- personalized recommender system is more complicated as compared to the standard recommender system. To extract the music features, it is essential to carefully evaluate user demands and integrate audio processing and music feature identification technology. The objective of the current study is to develop a personalized recommender system that has both practical and significant research value.

1.1 Literature Review

In a paper titled "A Novel Mathematical Model for the Classification of Music and Rhythmic Genre Using Deep Neural Networks," [3] Thirupathi Rao Komati,G. Pradeepini,and Swati A. Patil have introduced an innovative approach to Music Genre Classification (MGC) that transcends conventional methods. Their three-stage system, comprising data readiness, feature mining, and categorization, represents a paradigm shift in MGC. Instead of traditional feature engineering, the authors utilize spectrographs from short song clips as inputs to a neural network, enabling automated feature extraction and categorization. Extensive experimentation on diverse datasets, including GTZAN, IMG (“Indian Music Genre”), HMR (“Hindustan Music Rhythm”), and Tabala, showcases the superiority of their strategy over existing methods. Notably, their approach excels in both music genre classification and the classification of Indian rhythmic patterns, underscoring its potential as a transformative advancement in music classification.

In another paper "Enhancing Music Discovery: A CNN- Based Music Recommendation System"[4] This literature review delves into an innovative approach to music recommendations using Convolutional Neural Networks (CNNs), exemplified by the study focusing on digital piano music. The system's core methodology involves creating comprehensive features from spectrum and notes, implementing CNNs for classification and recommendation, and optimizing network model design and parameters. Leveraging historical user behavior data and Mel feature extraction from audio data, the recommendation algorithm distinguishes itself by shifting away from traditional similarity-based methods. Comparative experiments reveal that CNN-driven single-category user feature recommendations achieve a remarkable 50.35% accuracy rate, while multi-category user feature recommendations further enhance the music discovery process. This work represents a substantial leap toward enriching the music- listening experience and underscores the transformative potential of CNNs in shaping the future of music recommendation systems.

In the paper "Music recommendation using collaborative filtering with MLP"[5] by K. Ram Babu and Nagendra Kumar Chilakalapalli. Deep neural networks are being harnessed to extract latent factors from audio signals and metadata, as well as to learn sequential patterns within listening sessions or music playlists. These latent item factors are then effectively integrated into hybrid MRS and content- based filtering, enhancing music recommendations. Furthermore, sequence models are employed for tasks like automatic playlist continuation. This review paper provides insights into the unique aspects of music recommendation within the realm of Recommender Systems (RS) research. It offers a comprehensive overview of the state-of-the-art techniques that utilize DL ("Deep Learning") for music recommendation, categorizing the discussion based on neural network forms, input data sources, recommendation approaches (collaborative filtering, content-based filtering, or a combination), and tasks (sequential or standard music recommendation). Additionally, the review highlights the major challenges confronted by MRS, particularly in the context of ongoing research efforts, shedding light on the complexities of this dynamic field.

The paper titled "Music Recommendation System Using Machine Learning" [6] aims to develop a recommendation system that suggests songs to users based on their historical song preferences. This recommendation system is built usingPython libraries such as NumPy, Pandas, and Scikit-learn. Additionally, it incorporates Cosine similarity and Count Vectorizer techniques for song correlation analysis. The project also includes a Flask-based frontend to display recommended songs to users .

The research paper titled "Music Recommendation System Based on Usage History and Automatic Genre Classification" [7] K. Yoon, S. -J. Jang, D. Jang, S. Shin, and J. Lee explores the development of a personalized music recommender system that aims to recommend user-favorite songs from a vast music database. To achieve this, the study focuses on two key aspects: managing user preference information and automating genre classification. The author also introduces a novel approach where a concise feature vector, derived from low-dimensional projection techniques and pre-existing audio features, is utilized for the classification of music genres. This approach ensures efficient genre classification while maintaining a small feature vector size, thereby enhancing computational efficiency.

1.2 Methodology

Data Collection: The dataset consists of music-related information with various features. These features include the track name (track_name), the album to which the track belongs (album), the name of the artist who created the track (artist_name), the release date of the track (release_date), the duration of the track in milliseconds (duration_ms), the track's popularity (popularity), its danceability (danceability), acoustic quality (acousticness), energy level (energy), instrumentalness (instrumentalness) indicating the presence of vocals, liveness (liveness) which suggests whether the track was recorded live, loudness (loudness) indicating audio volume, speechiness (speechiness) which relates to spoken words or vocals, tempo (tempo) indicating the speed of the music in BPM (Beats Per Minute), and valence (valence) measuring the emotional positivity or happiness of the music. These features give a comprehensive overview of the characteristicsand attributes of each music track in the dataset, making it suitable for various music analysis and research purposes.

Setup Spotify API Credentials: Log in to the Spotify Developer Dashboard with your account credentials. Click on the "Create an App" button or a similar option to create a new application. Provide a name and description of the application. Retrieve the Client ID andClient Secret.

Data exploration and preprocessing: Drop columns that are not needed for clustering and classification. One of the primary purposes of PCA is dimensionality reduction. In datasets with a large number of features (high-dimensional data), it can be challenging to visualize and analyze the data effectively. PCA helps reduce the number of features while preserving as much of the variance in the data as possible. This reduction can aid in visualization and computational efficiency. The original features are changed by PCA into a new set of principal components, which are uncorrelated features. This decorrelation is useful because it simplifies the interpretationof data and can remove multicollinearity. K-Means is an unsupervised learning algorithm utilized for clustering data points into clusters or groups on the basis of their similarity. Unlike PCA, K-Means focuses on finding clusters within thedata without any prior labels or target variables.

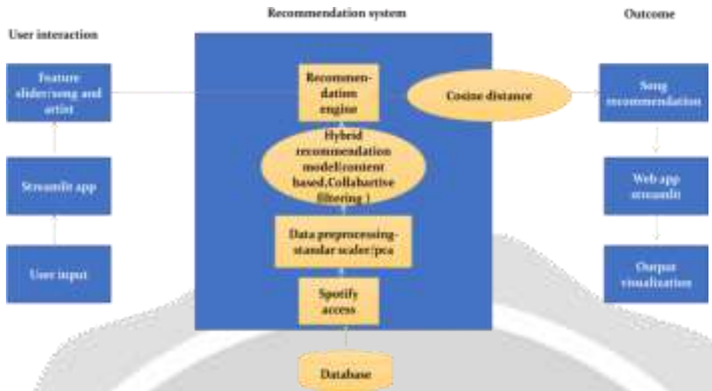

Fig-1:Block Diagram

K-Means is applied to the audio features of songs to group similar songs together based on their feature similarities. This can be useful for music recommendation systems, as songs within the same cluster tend to have similar audio characteristics. K-Means also provides a way toreduce the dimensionality of the data and visualize it in two dimensions using PCA. By reducing the data to two dimensions, it becomes easier to plot and visualize the song clusters in a scatter plot.

In datasets with many audio features such as valence, acousticness, tempo, etc. It can be challenging to work with all the features directly. PCA is used to decrease the data dimensionality by transforming the original features into a smaller set of uncorrelated principal components. This simplifies the subsequent analysis.

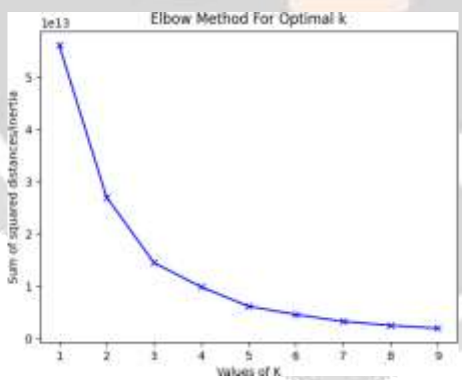

Fig-2: Elbow method graph

The next implementation of the Elbow Techniques is to examine the optimal number of clusters (K) for the K-Means clustering algorithm. The Elbow Technique is graphical technique used to find the point at which the within-cluster sum of squares (inertia) starts to decrease at a slower rate, indicating an appropriate number of clusters.

In the above case by using the elbow method graph shows 2 and 3 as potential optimal points. To decide between K=2 and K=3 (or any other potential values), validation should be done.

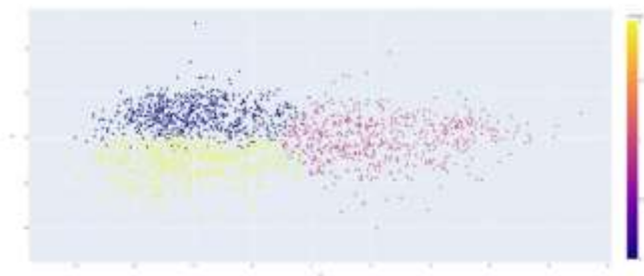

Fig-3: K-Means 3 cluster Graph

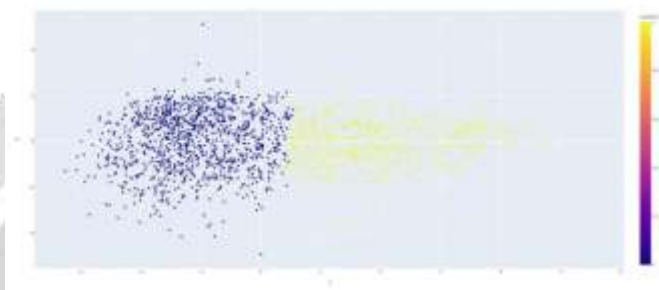

Fig-4: K-Means 2 cluster Graph

Validation metrics for optimal k: Consider cluster 2 as the dependent variable and evaluate the metrics. Logistic Regression is used as a classification method used to predict binary outcomes. A model was built and trained on standardized training data. The model made predictions on both training and testing data. Metrics like F1 score, accuracy, recall, precision, and ROC AUC score were calculated to assess performance. Confusion matrices were displayed to visualize the distribution of true positives, true negatives, false positives, and false negatives. Results of the classification model were presented, indicating its performance on training and testing data. These metrics help assess how effectively the model can classify songs into the two clusters defined by K-Means.

Testing Metrics Precision Score: 0.97

Recall Score: 0.97

Accuracy Score: 0.98

F1 Score: 0.97

Precision measures how many of the songs predicted as belonging to a cluster were correctly classified into that cluster. In this case, 97% of the songs predicted to be in a specific cluster were indeed in that cluster. It indicates a high level of accuracy in positive predictions. Recall assesses the model's ability to correctly identify all relevant songs in a specific cluster. A recall of 97% means that the model successfully identified 97% of all songs that belong to the cluster. It suggests that the model is good at capturing most of the relevant songs. Accuracy provides an overall measure of how well the model performed in terms of correct predictions. An accuracy of 98% indicates that the model made correct predictions for 98% of all songs, regardless of whether they were in the cluster or not. It suggests high overall accuracy. The F1 Score combines recall and precision into a single metric. A score of 0.97 implies that the model achieves a balanced trade-off between precision (the accuracy of positive predictions) and recall (the ability to find actual positives). It suggests that the model's positive predictions are accurate, and it captures most of the positive instances. However, cluster 3 validation results show an accuracy of 84%. So finally fix cluster2 for deployment. Below is the confusion matrix for training and testing data with k cluster value 2.

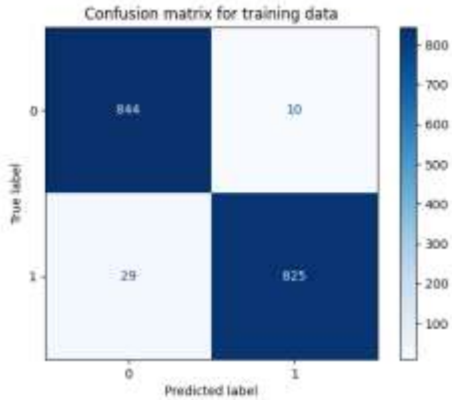

Fig-5: Confusion matrix of training data

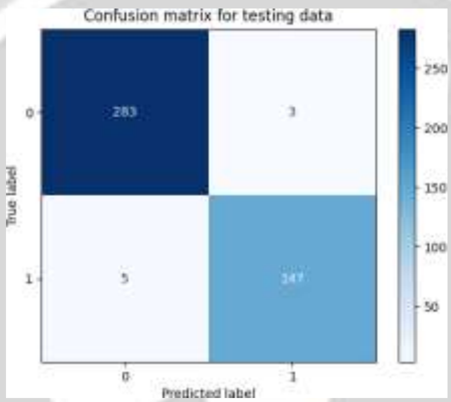

Fig-6: Confusion matrix of testing data

RECOMMENDATION ENGINE: The content-based filtering component of the algorithm relies on audio features and metadata of songs to makerecommendations. The user can provide input in the form of one or more songs. The algorithm extracts audio features such as energy,danceability,tempo,speechiness,loudness,liveness, instrumentalness, acousticness, and valence from these input songs. These audio features are used to create a profile of the user's musical preferences. The algorithm then finds songs from the dataset that are most similar to the user's profile on the basis of these audio features. It calculates the similarity between the user's profile and each song in the dataset, typically using measures like cosine similarity. The top most similar songs are recommended to the user based on their input.

The collaborative filtering component of the algorithm clusters songs in the dataset using K-Means clustering based on their audio features. It assigns each song to one of several clusters. When a user provides input songs, the algorithm calculates the mean audio feature values for those songs.It then scales and transforms these mean values using the same scaler used for the clustering step. The cosine distance between the transformed mean values (user profile) and all songs in the dataset is computed. The algorithm recommends songs from the cluster that are most similar to the user's profile, ensuring that the recommendations are more contextually relevant.

Integration:The hybrid model combines the recommendations from both content-based and collaborative filtering methods. For content-based recommendations, it recommends songs similar to the user's input songs based on audio features. For collaborative filtering recommendations, it recommends songs from the cluster that best match the user's profile. The final list of recommended songs is a combination of these two sets of recommendations.

The algorithm uses the Spotify API to obtain additional song data, such as track popularity and explicitness. It also retrieves audio features for songs not present in the original dataset. Users can input songs and artists they like, and the algorithm generates recommendations based on those inputs. Users can also adjust various audio feature sliders to fine-tune their recommendations, giving them more control over the recommendation process.

DEPLOYMENT: Finally Streamlet web application with various components, such as sliders for adjusting audio features (e.g., danceability, energy), text input fields for specifying songs and artists, buttons for generating recommendations, and an embedded Spotify playlist for listening to music. Users can input up to three songs and artists or adjust audio feature sliders to fine-tune their preferences. The application allows users to receive song recommendations based on their input.

Fig-7: User Interface

2. CONCLUSION

By seamlessly integrating content-based and collaborative filtering techniques and harnessing the Spotify API's capabilities, the system provides a holistic music exploration experience. Users can effortlessly input their favorite songs, fine-tune preferences, and receive recommendations that strike a balance between familiarity and novelty. The direct listening feature adds an immersive element, allowing users to immediately engage with suggested tracks. Overall, this system not only simplifies theprocess of finding new music but also enhances user engagement and satisfaction, making it a valuable tool for music enthusiasts seeking a tailored and enriching musical journey.

3. REFERENCES

[1]. ALESSANDRO B. MELCHIORRE and MARKUS SCHEDL, Johannes Kepler University and Linz Institute of Technology, Linz, Austria “Explainability in Music Recommender Systems” 2022 .

[2]. Adiyansjah, Alexander A S Gunawan , Derwin Suhartono “MusicRecommender System Based on Genre using Convolutional Recurrent Neural Networks”.

[3]. Adiyansjah, Alexander A S Gunawan, Derwin Suhartono “Music Recommender System Based on Genre using Convolutional Recurrent Neural Networks.

[4]. Yezi Zhang, "Music Recommendation System and Recommendation Model Based on Convolutional Neural Network", Mobile InformationSystems, vol. 2022, Article ID 3387598, 14 pages, 2022.

[5]. k.ram babu (m.tech), Nagendra Kumar Chilakalapalli “Music recommendation using collaborative Filtering with mlp”

[6]. Verma, Varsha & Marathe, Ninad & Sanghavi, Parth & Nitnaware, Dr. (2021). Music Recommendation System Using Machine Learning. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 80-88. 10.32628/CSEIT217615.

[7]. J. Lee, S. Shin, D. Jang, S. -J. Jang and K. Yoon, "Music recommendation system based on usage history and automatic genre classification," *2015 IEEE International Conference on Consumer Electronics (ICCE)*, Las Vegas, NV, USA, 2015, pp. 134-135, doi: 10.1109/ICCE.2015.7066352.

[8]. Bull, M.: Investigating the culture of mobile listening: from Walkman to iPod. In: O'Hara, K., Brown, B. (eds) Consuming music together: social and collaborative aspects of music consumption technologies, Springer, Dordrecht, Netherlands, 131–149, (2006).

[9]. Canali, D., Lanzi, A., Balzarotti, D., Kruegel, C., Christodorescu, M., Kirda, E.: A quantitative study of accuracy in system call-based malware detection. In: Proceedings of the 2012 International Symposium on Software Testing and Analysis, ACM, New York, NY, 122–132, (2012).

[10]. Cardoso, J.P.V., Pontello, L.F., Holanda, P.H.F., Guilherme, B., Goussevskaia, O., da Silva, A.P.C.: Mixtape: direction-based navigation in large media collections. In: Proceedings of the 17th International Society for Music Information Retrieval Conference, ISMIR, Montreal, Canada, 454–460, (2016)

[11]. Charuvaka, A., Rangwala, H.: HierCost: improving large scale hierarchical classification with cost-sensitive learning. In: Proceedings of the 2015 European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, Springer, Cham, Switzerland, 675–690, (2015)

[12]. Liang, D., Zhan, M., Ellis, D.P.W.: Content-aware collaborative music recommendation using pre-trained neural networks. In: Proceedings of the 16th International Society for Music Information Retrieval Conference, ISMIR, Montreal, Canada, 295–301, (2015)