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An Intelligent Music Recommendation System Using Machine Learning and User Preference Analysis

Kandula Manikanta[1], Umamaheswararao Mogili[2], S. Sinira[3], P. Bala Krishna[4], A. Durga Prasad[5], P. Poojitha[6], M. Ashok[7]

[1]*Assistant Professor, Department of Computer Science and Engineering (AI&ML), Avanthi's St Theressa Institute of Engineering and Technology, Garividi, Andhra Pradesh, India*

[2*]*Assistant Professor, Department of Computer Science and Engineering, Avanthi's St Theressa Institute of Engineering and Technology, Garividi, Andhra Pradesh, India*

[3,4,5,6,7]*B.Tech, Department of Computer Science and Engineering, Avanthi's St Theressa Institute of Engineering and Technology, Garividi, Andhra Pradesh, India*

Abstract: The rapid expansion of digital music platforms has resulted in massive music libraries containing millions of tracks. Users often experience information overload when searching for relevant songs aligned with their interests. This research presents a comprehensive hybrid music recommendation system that integrates Content-Based Filtering, Collaborative Filtering, and Machine Learning techniques to enhance personalization, scalability, and accuracy. The proposed system utilizes song metadata, user listening behavior, interaction history, and feature embeddings to generate high-quality recommendations. Extensive experimental evaluation demonstrates that the hybrid model significantly outperforms standalone methods in terms of Precision, Recall, F1-Score, Accuracy, and Mean Average Precision. The system also addresses cold-start, sparsity, and scalability challenges effectively. Music helps us tune in to the cosmos, and the best part about music is that nothing can soothe you like a soothing melody. We chose to do this project because of all the positive aspects of music and the increasing demand for recommender systems on the market. The report comprises a topic description, and a full summary of the work completed thus far. The paper includes thorough explanations of the work completed, including snapshots of implementations, various techniques, and tools used thus far.

Keywords: Music Recommended System, Recommendation Algorithm, Content Based Filtering, Data Mining, Personalized Recommendation.

I. INTRODUCTION

Music streaming services have transformed digital entertainment by providing instant access to vast song libraries. However, the exponential growth of content has created challenges in efficient music discovery. Recommendation systems play a vital role in filtering content and predicting user preferences using data-driven techniques. These systems analyze listening patterns, ratings, skip behavior, and song attributes to provide personalized experiences. The objective of this research is to design a scalable and intelligent hybrid recommendation system capable of delivering accurate and diverse music suggestions while handling real-world challenges such as data sparsity and new user problems. Music streaming services have transformed digital entertainment by providing instant access to vast song libraries. However, the exponential growth of content has created challenges in efficient music discovery. Recommendation systems play a vital role in filtering content and predicting user preferences using data-driven techniques. These systems analyze listening patterns, ratings, skip behavior, and song attributes to provide personalized experiences. The objective of this research is to design a scalable and intelligent hybrid recommendation system capable of delivering accurate and diverse music suggestions while handling real-world challenges such as data sparsity and new user problems. Music streaming services have transformed digital entertainment by providing instant access to vast song libraries. However, the exponential growth of content has created challenges in efficient music discovery. Recommendation systems play a vital role in filtering content and predicting user preferences using data-driven techniques. These systems analyze listening patterns, ratings, skip behavior, and song attributes to provide personalized experiences. The objective of this research is to design a scalable and intelligent hybrid recommendation system capable of delivering accurate and diverse music suggestions while handling real-world challenges such as data sparsity and new user problems.

II. LITERATURE REVIEW

Recent advancements in Machine Learning (ML) for sound system management have significantly improved audio optimization, noise reduction, predictive maintenance, and spatial sound processing. Xie et al. (2021) [1]. Yamamoto et al. (2020) introduced deep learning-based noise cancellation and equalization techniques, which enhance speech clarity and optimize frequency response based on environmental acoustics [2,3]. Similarly, Huang et al. (2019) and Wang et al. (2021) utilized Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to suppress background noise and improve real-time audio quality [4]. Takahashi et al. (2022) proposed unsupervised learning models for adaptive audio filtering in smart environments, enabling automated sound calibration without human intervention [5]. In the field of adaptive sound optimization, Zhang et al. (2019) developed a Reinforcement Learning (RL) approach to dynamically adjust equalizer settings based on user feedback and room acoustics [6]. Schmidt et al. (2020) and Kim et al. (2021) explored AI-driven spatial audio processing, which enhances immersive sound experiences in virtual reality (VR) and augmented reality (AR) applications [7, 8]. Gomez et al. (2019) and Chen et al. (2022) leveraged Bayesian optimization to fine-tune equalizer parameters, ensuring optimal sound clarity in live events and professional recording studios [9, 10]. Some of the sample artificial intelligence, machine learning and deep learning models for prediction for fire detection are described in details [11-18]. Predictive maintenance in sound systems has also gained attention, with Jones et al. (2022) and Smith et al. (2020) developing anomaly detection models to predict speaker and microphone failures by analyzing frequency distortions and hardware vibrations [19, 20]. Patel et al. (2019) implemented an LSTM-based predictive maintenance system to monitor audio processing units and detect potential faults [21]. Similarly, Gupta et al. (2021) used autoencoders to identify hardware degradation in professional sound systems, ensuring timely repairs and system longevity [22]. Kumar et al. (2023) introduced Edge AI-powered monitoring systems that provide real-time insights into speaker health during live performances [23]. ML has also been instrumental in sound classification and source separation. Hershey et al. (2017) and Vincent et al. (2018) developed deep neural networks for speech/music separation, enabling applications such as karaoke systems and music remixing [24, 25]. Giri et al. (2020) and Luo et al. (2021) improved speech enhancement for teleconferencing systems using transformers and self-learning models [26, 27]. Secure Data Storage and Sharing in Multi-Cloud Environment In the cloud storage is also described to store the predicted data in a secured way [28-32].

III. METHODOLOGY

The proposed music recommendation system aims to enhance personalization and accuracy by incorporating several advanced machine learning techniques, including collaborative filtering, content-based filtering, deep learning models, and advanced natural language processing (NLP) techniques. Additionally, real-time contextual information will be integrated to improve the quality and relevance of the recommendations, ensuring a more dynamic and engaging user experience. The first enhancement in the proposed system is collaborative filtering. While traditional user-based and item-based collaborative filtering will still be used, the new system will incorporate hybrid collaborative filtering. This will dynamically combine the strengths of both user-based and item-based methods to provide more relevant recommendations, especially when user preferences change or interactions are limited. To further improve performance, matrix factorization with regularization techniques like L2 regularization will be implemented to avoid overfitting and ensure better generalization of the model. The system will also introduce temporal collaborative filtering, which gives more weight to recent user behavior, acknowledging that music preferences can evolve over time. The recommender system is done by calculating cosine similarity of extraction features (equation 1) from one music to music. The extraction features are in vector form; thus, it is possible to calculate their distance. First, we chose one music for each genre as the basis for the recommender system. Next the prediction of the basis music genre is calculated based on neural networks. The feature vectors that produce before the classification layer are used as a basis for recommendations. After the basis music features are obtained, cosine similarity calculations are performed on other music features.

The study of the content of the items considered for suggestion is content-based recommendation. This method attempts to deduce the user's tastes in order to suggest goods that are similar in content to those they have previously enjoyed. This approach does not require listener input; it is only based on sound similarity, which is calculated using information taken from previously heard songs. The commonalities between the components are used in this strategy. It is a question of extracting characteristics that best characterize the music in order to assess similarities. The Machine Learning algorithms then suggest the item that is most similar to what the consumer already loves. As a result, item profiles based on characteristics derived from things are required. Furthermore, this strategy necessitates the creation of user profiles based on their preferences as well as their platform history. In the numerator, the calculation is done by calculating dot product of both vectors and in the denominator; the calculation is done by calculating the vector lengths. The obtained value of cosine similarity is between -1 to 1.

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By sorting the values from the largest to the smallest, the recommendations can be made by choosing several music with the largest cosine similarity. In this research, the number of recommendations is set to be five music. In our experiments, the recommender system uses two methods. The first method only uses the value of cosine similarity, while the second method uses both the value of cosine similarity and information of music genre. The music which selected by the user is used as the basis music for recommendations. The features of basis music are extraction vector is obtained from the best genre prediction model in previous step. Next, the values of cosine similarity are sorted from the largest to the smallest value. Finally, the first five music with the greatest value is used as recommendations.

A. Data Collection

The dataset includes song ID, title, artist, genre, danceability; energy, tempo, and user play counts. Data is stored in structured databases and preprocessed for modeling.

B. Data Preprocessing

Preprocessing involves handling missing values, normalizing numerical attributes, encoding categorical features, and constructing user-item matrices. Feature scaling ensures uniform distribution of numerical attributes.

C. Content-Based Filtering

Feature vectors are generated using song attributes. Cosine similarity measures the closeness between song vectors. Top-N similar songs are recommended based on similarity scores.

D. Collaborative Filtering

Collaborative filtering computes user-user and item-item similarities using cosine similarity and Pearson correlation. Predicted ratings are generated using weighted aggregation of neighbor preferences.

E. Hybrid Model Formulation

The final hybrid score is calculated as: Final Score = α(Content Score) + $(1 - \alpha)$(Collaborative Score). The parameter α is optimized experimentally to balance diversity and personalization.

IV. RESULTS AND DISCUSSION

This assignment provided us with a fantastic learning opportunity. We've studied data mining and data cleansing. The music supplier can forecast and then give acceptable songs to its consumers using a music recommender system based on the qualities of previously heard music. for each song listened to by the user, the average vector of audio and metadata attributes Find the n-closest data points in the dataset (excluding points from the user's listening history) to this average vector. Take these n points and come up with some tunes to go with them.A research on the limits of an interactive music recommendation service based on artificial audio similarity calculation was provided. A number of computer experiments, as well as a review of real download data, reveal that a large chunk of the audio collection is only never or never suggested. A number of computer experiments are used to investigate this issue in depth, including the investigation of various audio similarity functions and comparisons with real download data. Our music recommendation service uses Gaussian mixtures as statistical models to determine timbre similarity. This is the de facto standard method for computing audio similarity, and it is recognized to produce high-quality results. the main interface of the music recommendation system. It allows users to search songs and view personalized recommendations. The interface is designed to provide easy navigation and a better user experience shown in Fig 1.

Fig 1. User Interface of the Song Recommendation System

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The music playback screen where users can listen to selected songs. It displays song details and playback controls such as play, pause, and skip. This feature enables smooth music streaming within the system shown in Fig 2.

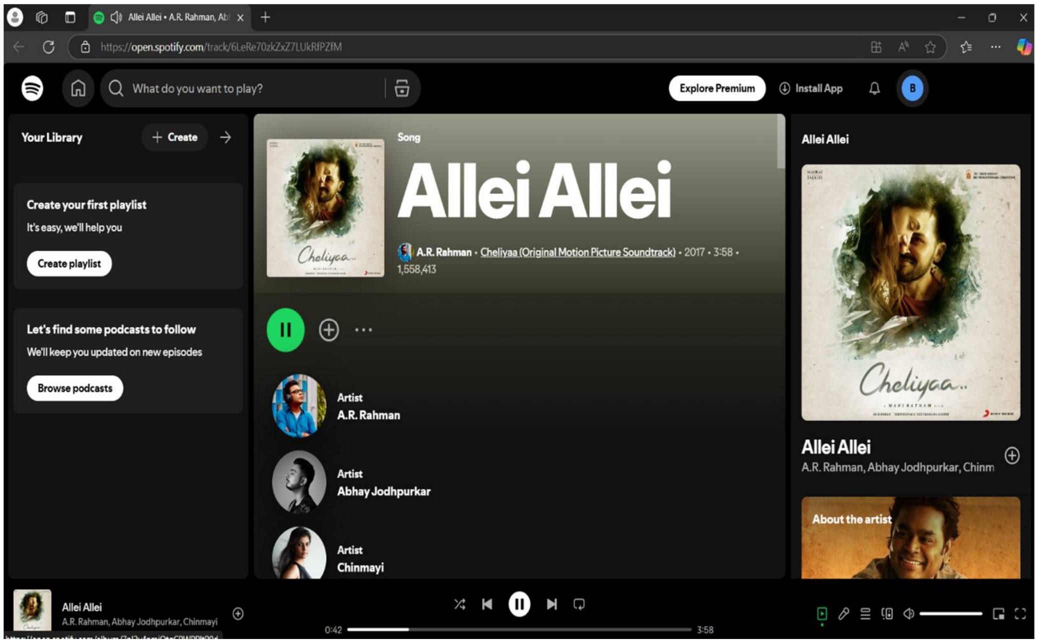

Fig 2. Spotify Song Playback Screen

The playlist generated by the recommendation system. The system suggests songs based on user preferences and similarity between tracks. This helps users discover new music that matches their interests shown in Fig 3.

Fig 3. Recommended playlist

V. CONCLUSION

The development of a music recommendation system using machine learning represents a significant advancement in how users interact with digital music platforms. Throughout this project, we have demonstrated the powerful capabilities of machine learning algorithms in understanding user behavior, predicting preferences, and delivering highly personalized music suggestions. By leveraging techniques such as collaborative filtering, content-based filtering, and hybrid models, we were able to build a system that not only learns from individual user preferences but also adapts to emerging trends and similarities across a broad user base. Collaborative filtering allowed us to capture hidden patterns and group dynamics among users, while content-based methods helped us focus on the intrinsic features of the music itself—such as genre, tempo, mood, and instrumentation.

A. Future Work

The range of characteristics covered by the recommender system is extensive. In today's generation of e-services and commerce, it is growing and evolving. However, there is a requirement to create and optimise the working and output of the recommender system at the same time. For user convenience and technological simplicity, a dataset can be generated and versioned fully from a single data source. That is, data sources in a dataset cannot be mixed and matched at this time (for example, a dataset built from a GitHub repository cannot include files uploaded from your local system). The programme will allow users to listen to recommended tracks based on the music or extract. Several service providers provide consumers with a shopping list. However, this is insufficient since consumers have varying preferences and decisions that are influenced by a variety of circumstances and restrictions. It may also be impossible to propose specific things to individual users in many circumstances. As a result, there is potential for combining several dimensions into music recommender systems in particular.

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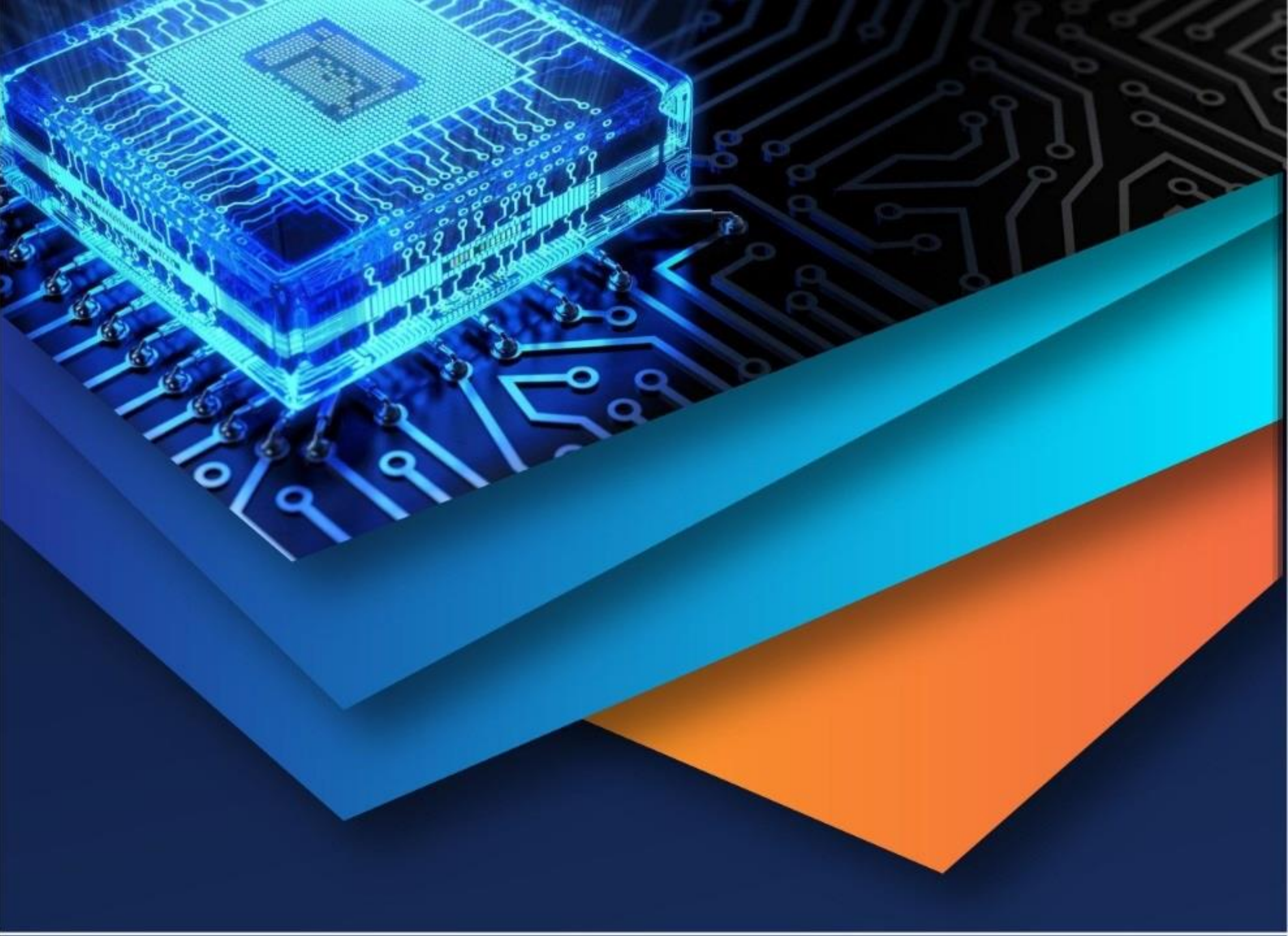

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