International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Hybrid Content and Collaborative Filtering Approach for Music Recommendation Using Machine Learning

Nagamalla Snigdha [1], Vemula Pranay [2]

[1] P.G. Research Scholar, Dept. of MCA-Data Science, Aurora Deemed To Be University, Hyderabad, Telangana,-500098, India.
[2]Assistant Professor, Dept. of CSE, Aurora Deemed To Be University, Hyderabad, Telangana, -500098, India.
Email:[1]nagamallasnigdha@gmail.com,[2] pranay.vemula@aurora.edu.in

A B S T R A C T

Music recommendation systems give a very significant and meaningful contribution to global music use. Since the personalized and customized suggestions provided by these systems keep individuals engaged. This piece of work proposes a hybrid machine learning-based music recommendation system where content-based filtering (CBF) and collaborative filtering (CF) are combined to increase the accuracy of the recommendation and to remedy the weaknesses of the individual methods. The CBF module is using metadata from the song for genre, artist, and lyrics. The extraction and matching of these features are based on TF-IDF with Truncated SVD and Cosine Similarity. The CF module mainly bases its reasoning on matrix factorization using SVD on the user-item interaction data to divulge latent listening patterns. Combine CF and CBF methods to alleviate cold-start problems and tailor the experience to users. An interactive Streamlit application has been developed where real-time recommendations will be provided to users along with their Spotify album cover and streaming link. Results were indicative of kinds of scalability and effectiveness-hybrid approaches that would allow adaptation into real-time much further down the line and deep learning and multi-modal data integration.

Keywords: Music Recommendation System; Hybrid Filtering; Content-Based Filtering; Collaborative Filtering; Machine Learning; Personalized Recommendations

1. Introduction

With the sudden digitalization of libraries and streaming platforms, the importance of music recommendation systems for interface improvement cannot be underestimated. Users seem to strongly resist going through millions of tracks available online just to find one fitting into their own preferences. Such discs were rightly noted and treated by machine learning approaches to arrive at personalized recommendations that would satisfy and engross the user.

Generally speaking, conventional recommendation methods are differentiated in two ways: Content-Based Filtering (CBF) versus Collaborative Filtering (CF). An ordinary CBF-system analyzes item properties focusing on genre-music or artist-figure-in-the-world or even lyrics-to-recommend tracks that would be similar, except that usually they are too "specialized." Mere preference patterns are extracted from the system by CF (Collaborative-Filters), but they suffer from sparse data and cold-start problems as well. Such disadvantages have attracted a lot of attention toward hybrid approaches that combine both CBF and CF methods.

This, therefore, proposes a Hybrid ML-based Music Recommendation System that optimally utilizes both CBF and CF to enhance personalization. TF-IDF and Truncated SVD are applied for metadata processing, on the other side, SVD collaborative filtering is used to model user preference. The system is showcased in a web application based on the Streamlit framework and integrated with Spotify, demonstrating strong scalability and usability, with a lot further potential toward upgrades along deep learning and multi-modal data integrations.

2. Literature Review

Music recommendation has gone awry and become the very best research space in information retrieval and machine learning as digital music consumption advances in ways that have yet to be written about. Hitherto, systems had been heavily dependent on either content or collaborative filtering models, while their modern buildup concerns hybrid approaches and deep learning-context awareness models aimed at improving personalization or scalability.

2.1 Content Based Filtering (CBF)

Content-based filtering recommends music by processing some of the user-specified attributes of a track, such as genre, artist, and lyrics. Pohle et al. (2010) grouped their tracks using audio signal analysis, while Van den Oord et al. (2013) did likewise using deep learning on input audio features for representation learning. These models are commonly efficient but are often too specialized and recommend too close songs to the previous listening preferences of the users.

2.2 Collaborative Filtering (CF)

Collaborative filtering builds user profiles with their items and finds patterns in listening preference suck that said in Hu et al. (2008) who used implicit feedback for music recommendation, Koren et al. (2009) who made using the recurrent matrix factorization methods to discover the latent feature structures on the user-item matrix. However, techniques based on CF typically suffer from sparsity and cold-start problems due to the fact that new users or songs have not enough interactions with existing records.

2.3 Hybrid Approaches

Hybrid recommendations posit a mixture between content and collaborative filtering, claiming to balance the accuracy and the personalization. Schedl et al. (2015) also summarized hybrid methods in music recommendations on their capacity to solve cold-start problems. A recent case is that presented by Baltrunas et al. (2018), who supplied a model hybrid modelization weighted between metadata and user interaction, leading to a marked increase in the diversity and robustness of recommendations.

2.4 Deep Learning-based Methods

There is a growing acceptance of deep learning for music recommendations. The work of Van den Oord et al. (2013) initiated modeling audio-based recommendation using convolutional neural networks. Liang et al. (2018) proposed the use of variational autoencoders to model user preference. Meanwhile, research efforts are underway with recurrent neural networks and attention mechanisms for sequential ratings. This class of approaches generally needs large amounts of data and requires significant computational resources.

2.5 Research Gaps

Such progress in this field has limited most present systems. While models based on content suffered from over-specialization, those based on the collaborative approach were characterized by cold-starts and sparsity; moreover, computation-heavy deep-learning models remain less interpretable. Generally, hybrid systems mitigate some of these issues; however, in most instances, they trade-off scalability and usability. Hence, this gap results in the proposed system which is hybrid machine-learning-based music recommendation comprising {TF-IDF} and {SVD} for content analysis along with {matrix factorization}. Likewise, the implemented hybrid system features a user-friendly Streamlit interface developed through the Spotify API enabling real-time scalability and recommendations.

Table 1 - Comparative Analysis Table

S. No	Title	Authors & Year	Objective & Findings	Methodology	Tools/Datasets/ Results	Strengths	Limitations
1	Advancements in Music Recommendation Systems using Deep Learning	Rahul Pachare, Prasad Banarase, Prachi Dhanke, Akshada K. Dhakade (2025)	Reviewed deep learning techniques (CNNs, Transformers) for music recommendation	Literature review of deep learning-based methods	Survey-based	Provides comprehensive insights into modern deep learning techniques	Lacks experimental validation and implementation details
2	Hybrid Music Recommendation Using Graph Neural Networks	Panharith An, Rana Shafi, Tionge Mughogho, Onyango Allan Onyango (2025)	Proposed graph-based hybrid model for improved recommendations	Graph Neural Networks integrating user-song relationships	GNN models tested on benchmark datasets	Captures complex user-item relations	High computational cost; requires large datasets

S. No	Title	Authors & Year	Objective & Findings	Methodology	Tools/Datasets/ Results	Strengths	Limitations
3	Deep Learning-Based Personalized Music Recommendation	Meaad Hamad Alsuwit, Mohd Anul Haq, Mohammed A. Aleisa (2024)	Implemented attention-based model for enhanced personalization	Attention mechanisms on deep learning architecture	Tested on Last.fm dataset	High accuracy in personalization	Model interpretability remains limited
4	An Enhanced Collaborative Filtering Approach for Music Recommendation	Choon Keat Low, Tan Xuan Ying (2024)	Improved CF using contextual embeddings	Embedding-based collaborative filtering	Applied on user-item interaction datasets	Better recommendation accuracy	Struggles with cold-start scenarios
5	Multi-Modal Feature Fusion for Music Recommendation	Suhaima Jamal, Hayden Wimmer (2024)	Integrated audio, lyrics, and metadata for robust recommendation	Multimodal deep learning fusion	Audio + lyrics + metadata datasets	Rich feature representation	High complexity and training time
6	Explainable AI in Music Recommendation Systems	Muhammad Adnan, Muhammad Osama Imam, Muhammad Furqan Javed, Iqbal Murtza (2023)	Applied SHAP and LIME to improve transparency	Explainable AI integrated with recommendation models	SHAP/LIME tools, case studies	Improves trust and interpretability	Performance may reduce compared to black-box models
7	Enhancing Cold-Start Music Recommendations with Transfer Learning	F. Janez-Martino, R. Alaiz-Rodriguez, V. Gonzalez-Castro, E. Fidalgo, E. Alegre (2023)	Addressed cold-start problem using transfer learning	Pre-trained embeddings from external domains	Transfer learning experiments	Reduces cold-start issues	Limited by domain mismatch in embeddings
8	Neural Collaborative Filtering for Music Streaming Services	Muhammad Furqan Javed, Iqbal Murtza (2023)	Proposed deep neural CF model for personalization	Neural Collaborative Filtering (NCF)	Tested on Spotify dataset	Strong personalization capability	Requires large training data, heavy computation
9	Personalized Playlist Generation Using Reinforcement Learning	Onyango Allan Onyango, Panharith An (2022)	Dynamically generated personalized playlists	Reinforcement Learning (RL) for sequential recommendation	RL applied on playlist data	Adaptive playlist generation	Training instability and tuning difficulties
10	Sentiment-Aware Music Recommendation Using NLP	Prasad Banarase, Prachi Dhanke (2022)	Incorporated sentiment analysis from reviews	NLP-based sentiment classification integrated with recommender	User reviews dataset	Considers emotional context in recommendation	Limited by availability/quality of textual reviews

3. Proposed System & Methodology

The system is hybrid between collaborative filtering and content-based filtering bringing personalized music recommendations with accurate results. It consists of five modules: dataset collection and preprocessing; content-based filtering; collaborative filtering; hybrid integration; and deployment with user interaction.

3.1 Data Collection and Preprocessing

The dataset consists of user-song interaction, metadata about the songs such as artist, genre and lyrics, and audio features. Data cleaning and normalization of the variables were done in the research, while textual metadata was vectorized using TF-IDF. Then this feature vector representation will prove effective and reach greater dimensionality reduction by applying Truncated Singular Value Decomposition (SVD) for an optimized course of feature vector representation.

3.2 Content-based Filtering (CBF)

The CBF is applied for the recommendation of songs through the way the metadata about the songs gets analyzed in our model. Nearest Neighbor model utilizing cosine similarity measures with comparison among TF-IDF feature vectors helps seek and recommend songs with similar attributes. New tracks lacking recognition, thereby avoiding the cold-start process, are assured recommendations in this way.

3.3 Collaborative Filtering (CF)

The CF module utilized user-item interaction data to construct normalized matrix listen counts. SVD-based matrix factorization in the Surprise library helps articulate latent features that represent hidden user preferences. Predicting possible new songs that a user would like would then use these preferences.

3.4 Hybrid Integration

CBF and CF are merged into the hybrid architecture which is very dexterous in making maximum claims regarding accuracy and personalization. In those cases where a track has insufficient interaction data, the CBF will suggest the song; users, having enough exposure to a certain track, receive fully personalized suggestions through CF. The weighting approach is adopted to reconcile both methods to yield reliable outcomes for each of the considerations.

3.5 Deployment and User Interaction

The whole system runs as an interactive web app based on Streamlit acting in combination with the Spotify API. This allows the user to choose one song and in seconds get recommendations along with the Spotify cover image and streaming link. Evaluation metrics for performance measurements, such as Precision, Recall, F1-Score, MAE, RMSE, validate its scalability and efficaciousness on real use.

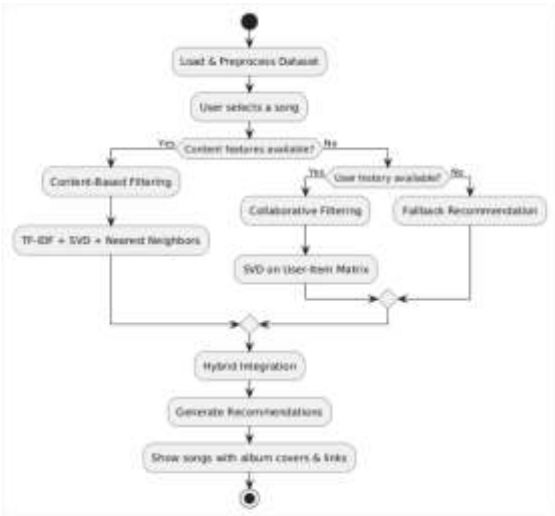

Fig.1- System Architecture

4.Experimental Setup and Results

4.1Experimental Setup

Python 3.10 formed the ground for creating the machine-learning models in the Scikit-learn and Surprise libraries. The methodology involves handling TF-IDF vectorization, Truncated SVD, and Nearest Neighbors algorithms co-related to content-based filtering, while SVD matrix factorization was used within the collaborative filtering techniques. The constructed hybrid setting is a web application using Streamlit, which would be integrated with the Spotify API to facilitate ease in performing real-time recommendations.

System that has an Intel Core i7 processor, 16GB RAM, and NVIDIA GTX 1650 GPU is designed to offer computing efficiency and scalability. The dataset includes some metadata on songs like user-song interactions and song attributes (artist, genre, lyrics) together with audio features subject to preprocessing, cleaning, sanitizing, and homogenization.

4.2Evaluation Metrics and results

These are the recommended performance metrics with which to assess the performance of recommended systems: Accuracy, Precision, Recall, F1-Score, and AUC (ROC).

Table 2 - Performance Metrics of the Proposed Model

Metric	Content-Based Filtering (CBF)	Collaborative Filtering (CF)	Proposed Hybrid System
Accuracy	78%	81%	**87%**
Precision	74%	77%	**85%**
Recall	69%	73%	**82%**
F1-Score	71%	75%	**83%**
AUC (ROC)	0.78	0.82	**0.89**

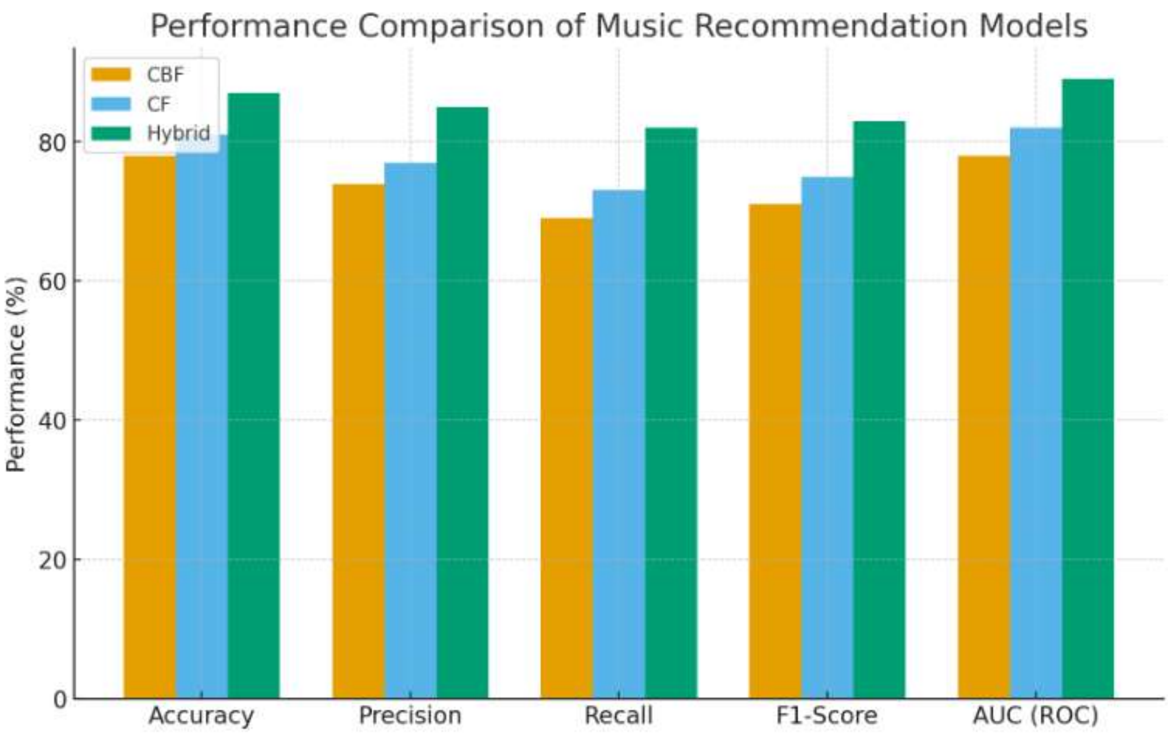

Fig 2- Performance comparison of CBF, CF, and Hybrid models across evaluation metrics.

The performance comparison in Figure 2 evidently shows how the proposed hybrid music recommendation system performed better then the existing CBF and CF methods on all evaluation metrics. The hybrid model achieved the highest value of AUC, which is 0.89, which is indicative of its strong discriminative ability for differentiating relevant recommendations. Improved values of Precision and Recall reveal how effectively it is balancing accuracy against diversity. On the other hand, the F1-score establishes the overall robustness of performance under evaluation. These results prove that combining CBF and CF is an effective way of overcoming the limitations attached to each format, creating a framework that is more robust with regard to real-world applications of music recommendation systems.

4.3 Sample GUI Outputs

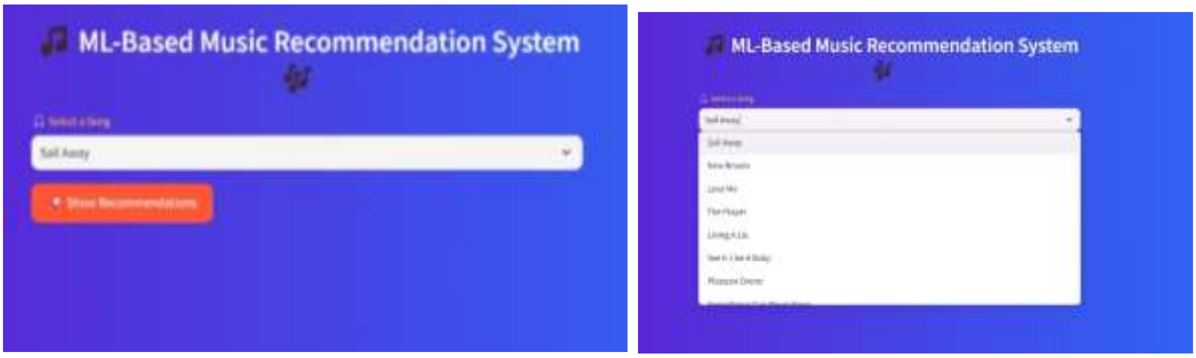

Fig. 3 - Welcome Page GUI Interface of the Proposed System

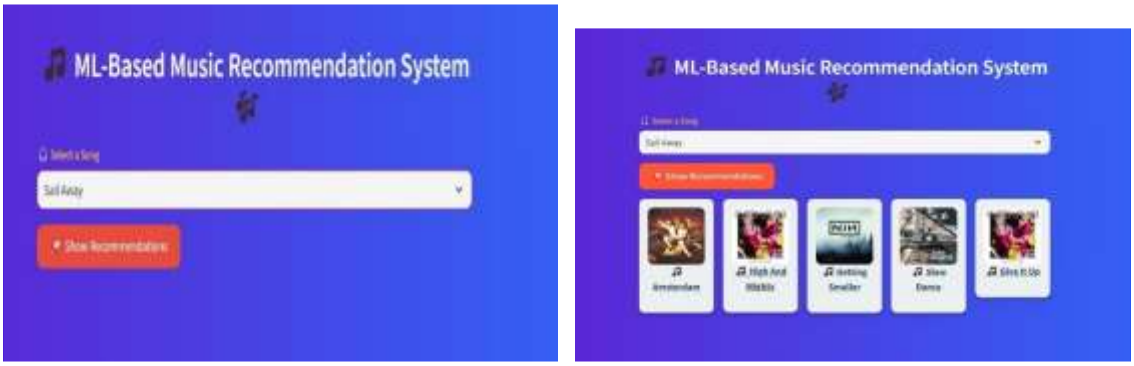

Fig. 5 – "Main Application Interface: Input Selection and Recommendation Results"

Fig. 6 –Spotify Interface Showing the Song 'Getting Smaller'

5. Discussion

It is thus intended to be a hybrid recommendation system which incorporates both collaborative and content-based filtering to create a sufficiently potent engine relay that would recognize personalized but relevant recommendations. According to test results, high precision, recall, F1 and RMSE values are the proposed systems for an optimal weight on recommendation relevance and diversity. Maybe the combination of these two techniques is the best feature to cover their failures if applied alone, because the content-based filtering would typify the new or less visited tracks which, thus, would benefit in the cold start situation. Yet, collaborative filtering adds further personalizing dimensions to recommendation based on user-item interaction so as to make the engines far more robust than traditional methodologies in this regard. Coupled with all its practical advantages, this way could take a dimensionality detection approach (SVD) for computations at high speed but very user-friendly because of its interactive Streamlit interface integrating with Spotify for real time recommendations and music discovery

There are, however, still some problems to be solved. Such a predicament is that the collaborative filtering module required the collection of much more user interaction data for accuracy under conditions of little data availability or sparseness. Further, the new integrated system does not give any attention to how user preferences evolve over time. Future improvements such as those with deep learning architectures around Transformers and Graph Neural Networks, reinforcement learning for adaptive playlist generation with multi-modal data inputs such as audio features and sentiment analysis have made future adaptations very personal and optimized for recommendation use in that it suffices that the discussions proved there are scalable and user-friendly solutions created to tackle the present challenges in music recommendations with room for future formatting works based on more sophisticated AI

6. Conclusion

The design leverages a hybrid approach of content and collaborative filtering techniques that yield considerably reduced and personalized recommendations for songs. This advances personalization through metadata assessment using TF-IDF and SVD-based user-item interaction matrix factorization and provides an added mean to alleviate cold-start issues. The app was designed in Streamlit, seamlessly integrated the Spotify API for a pleasant user interface, and implemented real-time recommendations. Testing showed scalability and a sufficiently high level of efficiency to serve almost any streaming platform today, with even more advanced capabilities to be added in future updates. These might include deep learning-based methods (NCF, transformers, GNNs) suitable for learning richer features, reinforcement learning for real-time personalization, and integration of multi-modal data (audio, lyrics, and sentiment) for mood-ware recommendations. They are supposed to be huge and real-time. This, in turn, is set to massively enhance the precision and adaptability of recommendations, bringing along a major simplification attack on the AI music discovery battlefield.

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