International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 143–154
©Cerebration Science Publishing

Article

Machine Learning-Based Music Classification and Recommendation System from Spotify

Nilesh Bhaskarrao Bahadure [1,*], Muktinath Vishwakarma [2], Manish P. Kurhekar [2], Jagdish Chandra Patni [3] and Prasenjeet D. Patil [4]

[1] Symbiosis Institute of Technology Nagpur Campus, Symbiosis International (Deemed University), Pune 412115, Maharashtra, India
[2] Department of Computer Science and Engineering, Visvesvaraya National Institute of Technology Nagpur, Nagpur 440010, Maharashtra, India; muktinathv@gmail.com (M.V.); manishkurhekar@cse.vnit.ac.in (M.P.K.)
[3] CSE, School of Advance Computing, Alliance University, Bengaluru 562106, Karnataka, India; patnijack@gmail.com
[4] MIT School of Engineering, MIT ADT University, Rajbaug, Loni Kalbhor, Pune 412201, Maharashtra, India; prasenjeet.patil@gmail.com
* Correspondence author: nbahadure@gmail.com

Received date: 4 April 2024; Accepted date: 11 June 2024; Published online: 6 January 2025

Abstract: Music holds significant importance in our daily lives, serving as an earnest element. Amidst the vast expanse of available information, our objective lies in sieving through data to present users with relevant music or song content aligning with their interests and objectives. To improve music recommendation accuracy and real-time recommendation ability, we propose a hybrid music recommendation model based on a Popularity-based Song Recommender System, a Personalized Song Recommender System, and a Content-based Music Recommendation System. Our endeavor focuses on constructing a music recommendation system, which operates as a filtering mechanism predicting user preferences in music based on their inclinations. This approach employs content filtering techniques leveraging data characteristics to refine recommendations. Our model, tailored to accommodate diverse instances and datasets, demonstrates robust performance. The devised song recommendation system exhibits notable efficacy and sustained reliability. Encouraging outcomes, boasting an accuracy of 90.4%, furnish novel insights, laying the groundwork for future exploration in song recommendation systems.

Keywords: K-NN; machine learning; elbow method; content-based recommendation; popularity-based recommendation; personalized-based recommendation; generative ai

1. Introduction

Music plays an indispensable role in our lives. There is a chunk of music for all moods and reasoning, and it also acts as a health therapist. There is a considerable amount of information that uses Big Data to advise or recommend extra information to consumers. It is typically connected to Machine Learning based algorithms [1–4].

These may be based on numerous streamers, such as the most recent search, search history, and other constituents. The internet stores our search history, and then the same product (what we search for) is repetitively shown to us; it is very iterative. Sometimes, even though it is irrelevant, the internet has repeatedly shown us the related information. To mitigate this irritation and irrelevance in the recommendation system, the users of our system find new songs and services they may have yet to find on their own, which makes our Music Recommend System quite helpful and easy to use [5,6]. The proposed system makes searching and then recommendations highly commendable and comfortable.

Our system also provides a social aspect, allowing users to share and discover new music with friends and colleagues. Our music recommendation system is the perfect solution for music lovers looking to expand their musical knowledge and discover various artists. With a significant commitment to accuracy, diversity, and personalization, our project provides an unmatched music discovery experience.

The need for personalized music recommendations has become paramount in today's digital era, where music is abundantly available across various platforms. Content-based music recommendation systems offer a promising solution to this challenge by leveraging the intrinsic characteristics of songs and user preferences to generate tailored recommendations.

Traditional recommendation systems rely heavily on collaborative filtering, which analyzes user behavior and preferences to suggest similar items. While effective, collaborative filtering often faces challenges like the cold-start problem, where new users or items need more data for accurate recommendations [7,8].

Content-based song/music recommendation systems analyze factors such as genre/grouping, tempo, instrumentation, and lyrics to understand the musical characteristics of each track. By comparing these attributes with user preferences, listening, and search history, content-based recommendation systems can suggest songs that align closely with the user's flavor [9–11].

One of the critical advantages of content-based recommendation systems is their ability to mitigate the cold-start problem and offer transparency in recommendations, as users can understand why certain songs are suggested by relying on song attributes rather than historical user data alone and based on their explicit features.

Despite their effectiveness, content-based recommendation systems face challenges, such as the limited scope of recommendations based solely on song attributes and the difficulty in accurately capturing nuanced user preferences [12–16].

In this context, our research aims to explore the potential of content-based music recommendation systems in providing users with personalized and relevant song suggestions. By investigating the effectiveness of similarity measures and machine learning algorithms, we seek to enhance the accuracy and usability of content-based recommendation systems in music streaming and discovery. Through our endeavors, we aim to contribute to the advancement of music recommendation technology and enrich the listening experiences of users.

The main objectives of our work are as follows:

1. To create a system for recommending songs.
2. To suggest new songs that the user is likely to appreciate.
3. To make users quickly find new songs they like, it will help them explore, saving time and effort.
4. Make recommendations by looking for music with features similar to the listener's taste.
5. To implement data pre-processing and different algorithms of machine learning.
6. To improve the model's performance and increase accuracy to some extent.

2. Literature Review

One of the best gifts to the human being is music. We are happy, sad, or neutral; whatever the situation, songs play a commanding role in our life. Music is a way to relate our life's journey, so listening to the right music at the right time will boost our mood and concentration. Nowadays, many search options are available through technological advancement, even though the songs are automatically recommended depending on our search history. However, sometimes due to the inaccuracy in the recommendation system, the wrong selection of music will be made. It should be correctly reflected according to our search data, and the keywords we entered should be validated without any mismatch and hurdles.

Ziyang Yu et al. [17] investigated the facial micro-expressions recognition (FER) technique. According to the facial expressions, the algorithm recommends the music. The algorithm has extracted the feature vector, and then the music will be recommended with the help of the cosine similarity index (CSI). The recognition rate of the proposed system is 62.1%.

Yunzhe Dong [18] proposed a machine learning-based music recommendation system using content-based and collaborative filtering techniques. For the new music and to solve the interest drift problem, the real-time recommendation is resolved using a hybrid music recommendation model that uses personalized measurement and game theory [19]. The interest drift problem in the online recommendation and the thorny problem in the offline recommendation are mitigated using a game theory-based recommendation system.

The musical emotion analysis and the performance of emotion prediction are very well integrated by Cao and Park [20] using LSTM networks and IoT-based techniques. This fusion or combined model gives an average of 0.921 absolute error, 0.534 root mean square error, 0.498 R square of Arousal, and an average of 0.902 absolute error, 0.575 root mean square error, and 0.478 R square of Valence. This study reveals significant implications of music emotions and provides high-quality music recommendations.

In Chinese music, the musical vogue patterns are estimated, and informed support for advertising and sponsorships is provided using a Dynamic Incremental Network (DINet) based system [21]. The experimental analysis outperforms the traditional and baseline models by demonstrating superior performance by enhancing musical vogue pattern estimation.

In research [22], a combination of machine learning-based algorithms such as Random Forest, Extra Trees, Gradient Boosting, Multi-Level Perceptron, AdaBoost, Decision tree, Logistic Regression, K-Nearest Neighbors, Nearest Centroidare, Bernoulli Naive Bayes, Quadratic Discriminant Analysis employed, and Radius Neighbors for classification and prediction. This study explores audio features on the Spotify dataset and evaluates the feature's importance for prediction from the playlist in Indonesia. It achieved the highest accuracy, 69.74%, for the Random Forest-based technique, followed by the accuracy for Extra trees with 68.07%.

A popular music dataset, GTZAN, is used for analyzing various types of audio signals and music features. Multiple machine learning algorithms such as naive Bayes, logistic regression, decision trees, and random forests are supported by Apache Spark and explored for music grouping classification. The experimental analysis shows that the random forest-based classifier is outperformed with 90% accuracy, and it also works very well for the mislabelled and distorted dataset [12].

The Internet of Things network and Edge Computing have been investigated for the vocal music signing learning system [13]. This research applies IoT perception to piano technology and uses edge computing-based algorithms for deploying sensors into the system and making the system more humanized and intelligent.

An improved music trend prediction and recommendation system based on LSTM and a random forest-based machine learning algorithm is presented for pop music [9]. The system's performance is analyzed using the evaluation indexes root means square error (RMSE) and mean absolute error index (MAER), and the results indicate better music prediction.

From the enormous song data, selecting the anticipated data is one of the most arduous tasks. Gao Yang [23] presented a technique that predicted the user behavior, and then an automatic tag generation system recommends the music. The low coverage problem is also eliminated by combining depth content with other information. This combined effect improves the tag quality and achieves better classification results of song recommendation accordingly.

Xinglin Wen [24] has investigated the support vector machine (SVM) based classification technique and the multi-scale feature extraction using a fast RCNN algorithm for recommending music to the user. The system uses deep learning and Internet of Things (IoT) based architecture and techniques. A detailed analysis has been done for recommending music in different indoor scenarios such as a bathroom, bedroom, etc. The use of smartphones is now very common; almost 80% of users carry smartphones and listen to music on them. The idea of analyzing mobile accelerometer data and then, based on human activity recognition, the music recommendation system is implemented by Hyoung-Gook Kim et al. [25]. To access the accelerometer data from the smartphone, authors have utilized a deep residual bidirectional gated recurrent neural network. The experimental analysis of real data proves the validity of the proposed system.

Noor Azilah Muda et al. [26] has investigated contents based music recommendation and Modified AIS-based algorithm for music classification system. Based on the features selection, the songs are classified according to the genres. The system is capable to analyzes rhythm, timbre, and pitch-based features for the classification of music genres.

Hiromu Yakura et al. [27] proposed a music recommendation system with matching user preferences while working. The system considers the user's concentration level. Then it prioritizes the unplayed songs, estimates the preference level, and recommends the music. The entire system works based on the Focus Music Recommender system. Table 1 gives summary of related works.

Table 1. Summary of related works.

Authors	Technique Used	Findings
Aldiyar Niyazov et al. [28]	Deep learning and computer vision	The main idea to develop this recommendation system is based on the external features of musical compositions, such as genre, artist, title, tags, etc., but on the acoustic similarity of musical compositions.
Adiyansjah et al. [29]	Convolutional Recurrent Neural Networks	Recommendation from the music database has been given based on the similarity of features in audio signals.
Qiu and Jia [30]	Internet of Things & CNN	Western music recommendation system is investigated using the Internet of Things and CNN-based classifier and achieved an accuracy rate of 96.7% and a user satisfaction ratio of 98.6%.
Meng Lu et al. [31]	Deep learning	The proposed system integrates two methods for interlinking a content-based music recommendation system, and the entire methodology of extracting music audio features has been improved using deep learning techniques.
Chen Chen [32]	Deep learning	The author has presented a two-layer attention mechanism by considering music names through textual CNN and music label text data. The overall quality and normalized discount cumulative gain (NDCG) is improved with a high standard characterization ability.
Rushabh Chheda et al. [33]	Transfer learning and CNN	This study deals with a music recommendation from emotion matching through image visuals.
Bhavyajeet Singh et al. [34]	Natural language processing	In this study, Reddit, a social media platform, is used to analyze mood in the context of depression and recommend music accordingly.
Vijay Prakash Sharma et al. [35]	Neural network	This paper talks about how the music recommendation system that is being existed for a long time, in most of them, the recommendation is decided once the user's preferences over time. It also suggests a neutral network-based approach to song recommendation where their facial expressions helps detect mood of a person.
Wang and Wang [36]	Deep belief network and probabilistic graphical model	It talks about the two-stage approach of content-based music recommendation system, where first they extract traditional audio content features and then predict user preferences.
Singh and Dembla [37]	Transfer learning	Emotions based music system is recommended. Webcam is used to extract facial traits and is then recognized using transfer learning techniques. Spotify songs dataset is used for experimental analysis.

3. Proposed Methodology

Big Companies like Spotify and Apple Music use a hybrid approach to recommendation, applying more than one method to recommend user songs and artists. Their model includes content-based as well as collaborative filtering methods. A hybrid recommendation is conventionally used in companies that manage large databases like Amazon. There are other works done to analyze the accuracy of music recommendation, one of which is using deep learning to enhance the quality of music recommended to the user and increase accuracy that cannot be otherwise increased through traditional filtering methods.

Our Music Recommendation System uses unsupervised learning which uses machine learning to analyze and cluster unlabeled datasets [38]. It uses the K-means clustering model. Using k-means we can group similar data points into k- distinct clusters. It is based on how far two data points are, the points are said to be similar if the distance between the two points are closer to each other. Implementation of k-means can be done using centroids which are the center of the data points. The proposed system has six stages, as shown in Figure 1.

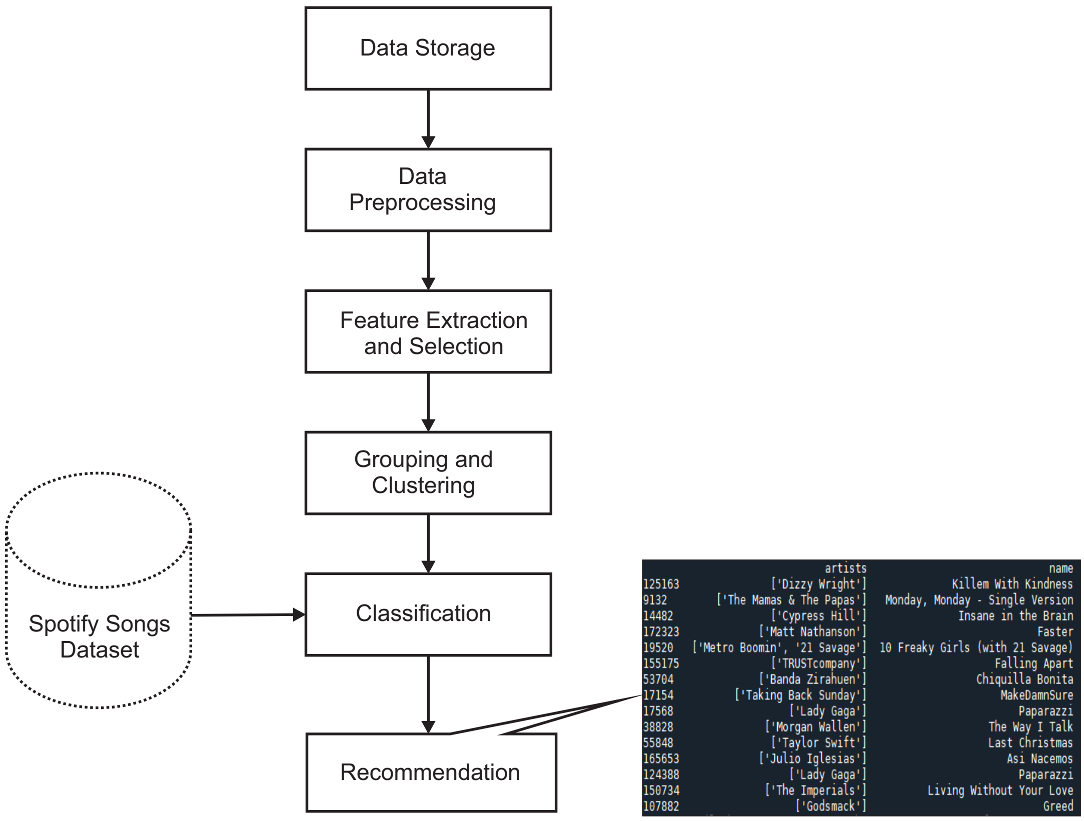

Figure 1. Proposed system.

3.1. Data Storage and Pre-Processing

The data used to implement our algorithm is taken from the Kaggle dataset with the file Spotifyfeatures.csv. This CSV file is extracted from Kaggle. The pre-processing is applied to ensure the dataset data are free from any noses and other oddities and also to ensure no data or information is missing. Pre-processing is a process to get a clean dataset from filthy data. The results are also validated without pre-processing, but the system's accuracy is compromised. In Python programming, using Pandas data frame and using basic commands such as `df.head()` and `df.isnull().sum()` are used for getting the overview of the data and getting the number of missing values by reading each column of a data frame.

3.2. Feature Extraction and Selection

We have used a correlation matrix to find the correlation between various features. Suppose the value is less than 0, i.e., negative. In that case, it indicates that the particular features are inversely related, meaning one feature increases, the other will decrease. In contrast, if the value is positive, it indicates that the features are directly related, and if one increases, others will also increase. We need to determine which features are correlated with each other. They will form clusters of similar features, which will then be used to recommend [39–41].

3.2.1. Min-Max Scaler

The MinMaxScaler class from `sklearn.preprocessing` module is imported, which provides many methods for normalizing data. The min-max scaler is the method where the data has a scale range of 0 and 1. This scaler is done by subtracting the minimum value from each value and dividing by the range. It creates a list of datatypes that will be normalized. It includes the following data types: int16, int32, int64, float16, float32, and float64.

Now, the loop over the columns gives us normalized columns using MinMaxScaller class. The output will be a new Data Frame called normalization which contains the normalized data. The min-max scaler is the method where the data has a scale range of 0 and 1. This scaler is done by subtracting the minimum value from each value and dividing by the range.

Normalized data refers to a dataset in which the values have been adjusted or rescaled to fall within a specific range or distribution. Normalization is commonly applied to ensure that different variables or features in a dataset have a similar scale [42].

3.3. Clustering and Grouping

To determine the optimum number of clusters, we employed the elbow method. The elbow method uses the within-cluster sum of squares (WCSS) that counts the sum of squares of the distance between the data and the centroids of the clusters. The more the number of clusters, the less the value of the WCSS and the point on the x-axis where there is a sharp drop in the graph, considered the optimal number of clusters [43–45]. The only problem with the elbow method we encountered was that it could not give a sharp point of the elbow; in that case, we used another way to find out the number of clusters, or we considered one of the values of the graph. The optimum value of clusters using the elbow method is shown in Figure 2.

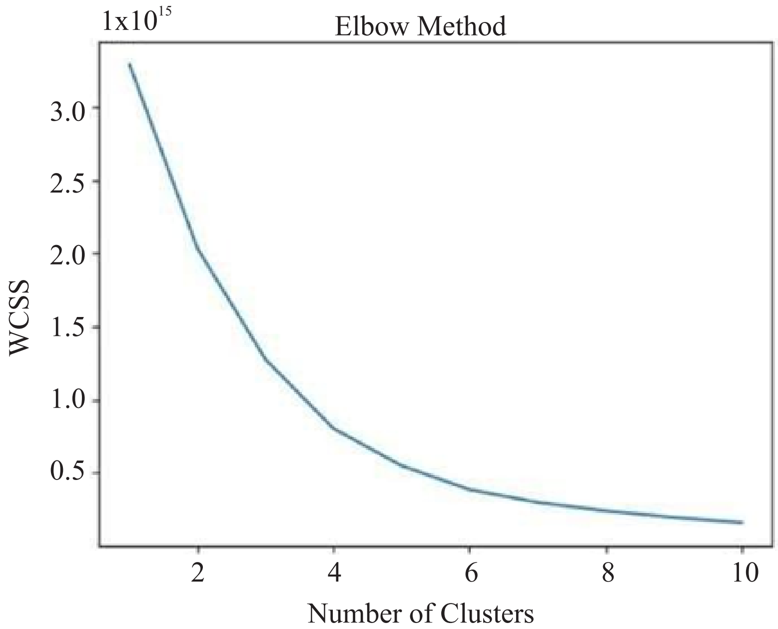

Figure 2. Elbow method for clustering.

3.4. Classification

This study investigates three techniques for classification based on the popularity-based song recommendation system, personalized song recommendation system, and content-based music recommendation system. The results are validated through excessive experimentation and found that the content-based music recommendation system outperforms the other methods. A content-based music recommendation system is commonly used to solve search and optimization problems for data with constrained and unconstrained relativity.

3.4.1. Popularity-Based Song Recommender System

We will utilize the popularity_recommender_py class from the recommenders library to implement a popularity-based recommender system. This approach allows the system to recommend items with universally demonstrated appeal across the user base without tailoring the recommendations to individual user preferences. The core idea is to recommend universally popular items among all users without personalizing these recommendations based on individual user preferences. This approach is simple and effective for scenarios where personalized data is sparse or when the goal is to increase the visibility of the most popular items across the entire user base.

3.4.2. Personalized Song Recommender System

We now create an item similarity based collaborative filtering model that allows us to make personalized recommendations to each user. For this, we will utilize the item_similarity_recommender _py class from the recommenders library.

The item similarity-based collaborative filtering model represents a tailored approach to recommendations, leveraging user-item interactions to identify similarities between items and personalize suggestions for each user. By analyzing patterns in user behavior, this model discerns which items are often liked, rated similarly, or interacted with in comparable ways, using these insights to predict a user's affinity for items they have yet to encounter. The core principle revolves around the notion that if a user has shown a preference for specific items, they are more likely to appreciate similar items. This method adapts to individual tastes, delivering bespoke recommendations that align closely with each user's unique preferences. It shines in environments rich in user interaction data, allowing for nuanced understanding and prediction of user interests. This personalized approach enhances user engagement by suggesting items with a higher likelihood of resonating with the user's taste, contrasting with broader, popularity-based strategies by focusing on individual users' specific interests and behaviors.

3.4.3. Content-Based Music Recommendation

The item_similarity_recommender _py class from the recommenders library also provides a function get_similar_items(), which gives content-based recommendations.

Content-based recommendation systems utilize item attributes and metadata to personalize suggestions, matching users with new items similar to those they have previously enjoyed. By analyzing specific features like genre or tags, it crafts user-specific recommendations based on content similarity. This method offers tailored suggestions that closely align with individual preferences, leveraging detailed item information to enhance user engagement.

The model using a content-based music recommendation system is validated on the Spotify dataset with the following parameters:

no. of unique songs in the training set: 8,169

Non-zero values in cooccurence_matrix:1,567

The top ten most popular songs from the training dataset of 8169 songs are also analyzed, shown in Table 2. The percentage obtained is based on the most frequently to the least frequently access of the songs from the similar grouping of the songs.

Table 2. Most popular ten songs in the dataset.

Song	Play Count	Percentage
Bjork-Undo	7,032	0.430419
Dwight Yoakam-You're The One	6,412	0.392470
Kings Of Leon-Revelry	6,145	0.376127
OneRepublic-Secrets	5,841	0.357520
Charttraxx Karaoke-Fireflies	4,795	0.293495
Cartola-Tive Sim	4,548	0.278377
Kings Of Leon-Use Somebody	3,976	0.243366
Usher featuring will.i.am-OMG	3,947	0.241591
Train-Marry Me	3,578	0.219005
Coldplay-The Scientist	3372	0.206396

4. Results and Discussion

Here, We build a KMeans class instance with the desired number of clusters set to 4. We can tell the algorithm how many clusters to look for using the n_clusters option. The dataset's normalized form is represented by normalization. Prior to using K-means clustering, it is typical to normalize the data using a method like Min-Max scaling or standardization (mean = 0, standard deviation = 1). The `fit_predict()` method is once more invoked to cluster the normalized data and determine the cluster assignments.

A dataset is subjected to Min-Max scaling using the class MinMaxScaler from the Sklearn package. We applied the scaling operating, created a MinMaxScaler object, fit it to the data, and then used the scaler to alter the data to apply Min-Max scaling to the "features" column.

The recommendation method takes a song name as input and returns a list of songs most similar to the input song. The algorithm works as follows:

1. The method first finds the row in the numeric_df corresponding to the input song.
2. The method then creates a new DataFrame that contains all of the songs in the numeric_df except for the input song.
3. The method then calculates the Euclidean distance between the input song and each in the new DataFrame.
4. The method then sorts the new DataFrame by distance and returns the top amount of songs.
5. The Euclidean distance metric is a simple way to measure the similarity between two points in a vector space. The distance between two points is calculated as the square root of the sum of the squares of the differences between their corresponding coordinates. In this case, the coordinates of the points are the values of the different features in the numeric_df.
6. The Spotify_Recommendation class is a simple but effective way to recommend songs to users. The class is easy to use and can be customized to recommend songs based on different features.

The proposed classification algorithms have been validated through experimentation. The response to the top 10 popular songs for the 1st user, 50th user, and 100th user has been checked. It was noticed that the output for all the users is the same in the case of the Polularity-Based Song Recommender System and Content-Based Music Recomendation. However, it is different in all cases for the Personalized Song Recommender System. The responses using the Polularity-Based Song Recommender System, Personalized Song Recommender System, and Content-Based Music Recomendation for the top ten recommended songs are shown in Tables 3–5. The score and the rank are produced based on the most recommended to the least recommended from the similar grouping of the songs.

The responses from the Personalized Song Recommender System and Content-Based Music Recommendation System are validated from excessive experimentation, and it is found that for the different users, the output for all the users is the same. It is also noticed that the score obtained using the Personalized Song Recommender System has ambiguity. However, there are no such things in Content-Based Music recommendations, so Content-Based Music recommendations outperform the two.

Table 3. Most popular ten songs using popularity-based song recommender.

Song	Score	Rank
Björk-Undo	0.7032	1.0
Dwight Yoakam-You're The One	0.6412	2.0
Kings Of Leon-Revelry	0.6145	3.0
OneRepublic-Secrets	0.5841	4.0
Charttraxx Karaoke-Fireflies	0.4795	5.0
Cartola-Tive Sim	0.4548	6.0
Kings Of Leon-Use Somebody	0.3976	7.0
Usher featuring will.i.am-OMG	0.3947	8.0
Train-Marry Me	0.3578	9.0
Coldplay-The Scientist	0.3372	10.0

Table 4. Most popular ten songs using personalized song recommender.

Song	Score	Rank
Fleet Foxes-Quiet Houses	0.050211	1
Fleet Foxes-Tiger Mountain Peasant Song	0.048733	2
Fleet Foxes-White Winter Hymnal	0.048470	3
Fleet Foxes-Your Protector	0.048036	4
Fleet Foxes-Sun It Rises	0.047604	5
Fleet Foxes-Heard Them Stirring	0.046229	6
Fleet Foxes-Meadowlarks	0.046217	7
Fleet Foxes-Oliver James	0.045491	8
Foo Fighters-No Way Back	0.041123	9
Fleet Foxes-Drops In The River	0.040744	10

Table 5. Most popular ten songs using content-based song recommender.

Song	Score	Rank
Fleet Foxes-Quiet Houses	0.304233	1
Fleet Foxes-Your Protector	0.286962	2
Fleet Foxes-He Doesn't Know Why	0.281250	3
Fleet Foxes-Meadowlarks	0.258095	4
Fleet Foxes-Heard Them Stirring	0.234336	5
Fleet Foxes-Tiger Mountain Peasant Song	0.228992	6
Fleet Foxes-Sun It Rises	0.215946	7
Fleet Foxes-White Winter Hymnal	0.188730	8
Fleet Foxes-Ragged Wood	0.175576	9
Pearl Jam-Got Some	0.166667	10

When the keyword 'Saw You In A Dream' is entered with cluster size 15, then the 15 songs of similar genres are recommended from the dataset of Spotify. The result obtained for the recommended songs for 'Saw You In A Dream' is shown in Figure 3.

	artists	name
125163	['Dizzy Wright']	Killem With Kindness
9132	['The Mamas & The Papas']	Monday, Monday - Single Version
14482	['Cypress Hill']	Insane in the Brain
172323	['Matt Nathanson']	Faster
19520	['Metro Boomin', '21 Savage']	10 Freaky Girls (with 21 Savage)
155175	['TRUSTcompany']	Falling Apart
53704	['Banda Zirahuen']	Chiquilla Bonita
17154	['Taking Back Sunday']	MakeDamnSure
17568	['Lady Gaga']	Paparazzi
38828	['Morgan Wallen']	The Way I Talk
55848	['Taylor Swift']	Last Christmas
165653	['Julio Iglesias']	Asi Nacemos
124388	['Lady Gaga']	Paparazzi
150734	['The Imperials']	Living Without Your Love
107882	['Godsmack']	Greed

Figure 3. Recommended songs for 'Saw You In A Dream'.

The different keywords (songs) are hit 500 times, and 452 times, the results are matched. Hence the accuracy of the proposed system is 90.4%. However, from the 37 mismatched results, total eleven times 60% to 75% of the recommended songs are correctly shown, and only 26 times, it is less than 60%, which is not recommended. So effectively, the overall accuracy of the proposed system is 94.8%.

5. Conclusions and Future Scope

The music recommendation system has significant potential for future development and enhancement. Our proposed system shows adoptable accuracy, and the results are highly encouraging; these open new avenues of song recommendation systems using machine learning and other advanced techniques. Here are some potential future scopes of the system:

1. Integration with new music platforms: The music recommendation system could be integrated with new and emerging music platforms, such as social media platforms, online music stores, or streaming services. This could expand the range of available music data and provide new opportunities for user engagement.
2. Use of advanced machine learning techniques: The recommendation system could be enhanced with more specialized machine learning techniques, such as deep learning techniques or sentimental analysis.
3. Integration with other recommendation systems: The music recommendation system could be integrated with other recommendation systems, such as movie recommendation systems or book recommendation systems, to provide a more comprehensive and personalized recommendation experience for users.
4. Expansion of social interaction features: The social interaction module of the system could be expanded with new features, such as live chat, group discussions, or virtual events. This could enhance user engagement and create a more interactive community of music listeners.

Spotify's dataset is used in this study, with 76,353 unique users and 100,000 unique songs. We have also checked if any value is missing or not. If any value is missing, we have to delete that row with that missing value. Missing values or entries will affect the algorithm's performance. In a future study, instead of deleting the missing value, the new value generation technique by finding the mean of the nearby values will be considered using the K-NN-based technique. Through the experimental analysis, a cross-check was done to ensure no empty value in the table.

Author Contributions
Conceptualization, N.B.B. and M.V.; methodology, M.P.K.; software, J.C.P.; validation, P.D.P., and N.B.B.; formal analysis, N.B.B.; investigation, N.B.B.; resources, M.V.; data curation, M.K.; writing-original draft preparation, N.B.B.; writing-review and editing, J.C.P.; visualization, M.V.; supervision, P.D.P. All authors have read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Conflicts of Interest
Author declares no conflict of interest.

Data Availability Statement
The datasets used and/or analyzed during the current study available from the corresponding author on request.

References

1. Bahadure, N.B., Patil, P.D., Kalbande, S., Pipalatkar, S., Nagar, S., Kuhikar, O: Machine learning based music recommendation system from spotify. In *Proceeding of the 15th World Congress on Nature and Biologically Inspired Computing (NaBIC 2023)*, (2023)
2. Karishma, M: Music recommendation system using machine learning. *International Journal of Research Publication and Reviews* **5**(1), **2024**, 20–24
3. Schedl, M: Deep learning in music recommendation systems. *Frontiers in Applied Mathematics and Statistics* 5, **2019**,
4. Sharma, V., Bajaj, A., Abraham, A: Machine learning techniques for electronic health records: Review of a decade of research. *International Journal of Computer Information Systems and Industrial Management Applications* 15, **2023**, 595—604
5. Chirasmayee, B.V.S., Sharmila, G., Sahithi, D., Prabhakar, V: Song recommendation system using tf-idf vectorization and sentimental analysis. *International Journal for Research in Applied Science & Engineering Technology* 10(VI), **2022**, 2475–2483
6. Fathollahi, M.S., Razzazi, F: Music similarity measurement and recommendation system using convolutional neural networks. *International Journal of Multimedia Information Retrieval* 10 **2021**, 43–53
7. Ferilli, S., Redavid, D., Pierro, D.D., Loop, L: An ontology-driven architecture for intelligent tutoring systems with an application to learning object recommendation. *International Journal of Computer Information Systems and Industrial Management Applications* 14, **2022**, 297–312

8. Nirban, V.S., Shukla, T., Purkayastha, P.S., Kotalwar, N., Ahsan, L: A machine learning perspective on fake news detection: A comparison of leading technqiues. *International Journal of Computer Information Systems and Industrial Management Applications* 15, **2023**, 59–68
9. Liu, X: Music trend prediction based on improved lstm and random forest algorithm. *Journal of Sensors* **2022**, (Article ID 6450469), 1–10
10. Shokrzadeh, Z., Feizi-Derakhshi, M.R., Balafar, M.A., Mohasefi, J.B: Graph-based recommendation system enhanced by community detection. *Scientific Programming* **2023**, (Article ID 5073769) 1–12
11. Yu, K., Lim, K., Kim, P: Deep learning-based business recommendation system in intelligent vehicles. *Mobile Information Systems* **2023**, (Article ID 3704217) , 1–12
12. Chaudhury, M., Karami, A., Ghazanfar, M.A: Large-scale music genre analysis and classification using machine learning with apache spark. *Electronics*, 11(16), (2022)
13. Li, Q., Liu, H., Zhao, X: Iot networks-aided perception vocal music singing learning system and piano teaching with edge computing. *Mobile Information Systems* **2023**, (Article ID 2074890), (2023) 1–9
14. Song, Y., Jiao, X: A real-time tourism route recommendation system based on multitime scale constraints. Mobile Information Systems **2023**, (Article ID 4586047), 1–10
15. Wang, X., Liu, C: Design of personalized news recommendation system based on an improved user collaborative filtering algorithm. *Mobile Information Systems* **2023**, (Article ID 9898337), 1–9
16. Wu, H., Yang, T., Li, H., Zhou, Z: Air quality prediction model based on mrmr–rf feature selection and issa–lstm. *Scientific Reports* 13(12825), **2023**, 1–15
17. Yu, Z., Zhao, M., Wu, Y., Liu, P., Chen, H: Research on automatic music recommendation algorithm based on facial micro-expression recognition. In *Proceedings of the 2020 39th Chinese Control Conference (CCC)*. **2020**, 7257–7263
18. Dong, Y: Music recommendation system based on machine learning. *Highlights in Science, Engineering and Technology* 47, **2023**, 176–182
19. Yun, W., Jian, L., Yanlong, M: A hybrid music recommendation model based on personalized measurement and game theory. *Chinese Journal of Electronics* 32(6), **2023**, 1319—1328
20. Cao, Y., Park, J: The analysis of music emotion and visualization fusing long short-term memory networks under the internet of things. *IEEE Access* 11, (2023), 141192–141204
21. Hou, P., Zhang, X: Dynamic incremental network for estimating chinese musical vogue patterns of a given artist over time. *IEEE Access* 12, **2024**, 18028–18040
22. Saragih, H.S: Predicting song popularity based on spotify's audio features: insights from the indonesian streaming users. *Journal of Management Analytics* 10(4), **2023**, 693–709
23. Yang, G: Research on music content recognition and recommendation technology based on deep learning. *Security and Communication Networks* **2022**, (Article ID 7696840), 1–8
24. Wen, X: Using deep learning approach and iot architecture to build the intelligent music recommendation system. *Soft Computing* 25(02), **2021**, 1–10
25. Kim, H.G., Kim, G.Y., Kim, J.Y: Music recommendation system using human activity recognition from accelerometer data. *IEEE Transactions on Consumer Electronics* 65(3), **2019**, 349–358
26. Muda, N.A., Choo, Y.H., Ahmad, N: Content-based feature selection for music genre classification. *International Journal of Computer Information Systems and Industrial Management Applications* 14, **2022**, 001–009
27. Yakura, H., Nakano, T., Goto, M: An automated system recommending background music to listen to while working. *IEEE Transactions on Consumer Electronics* 32, **2022**, 355–388
28. Niyazov, A., Mikhailova, E., Egorova, O: Content-based music recommendation system. In *Proceedings of the 2021 29th Conference of Open Innovations Association (FRUCT)*. **2021**, 274–279
29. Adiyansjah, Gunawan, A., Suhartono, D. Music recommender system based on genre using convolutional recurrent neural networks. *Procedia Computer Science* 157, **2019**, 99–109
30. Qiu, H., Jia, X: Western music history recommendation system based on internet-of-things data analysis technology. *Mobile Information Systems* **2022**, (Article ID 8920599), 1–12
31. Lu, M., Pengcheng, D., Yanfeng, S: Digital music recommendation technology for music teaching based on deep learning. *Wireless Communications and Mobile Computing* **2022**, (Article ID 1013997) 1–8
32. Chen, C: Design of deep learning network model for personalized music emotional recommendation. *Security and Communication Networks* **2022**, (Article ID 4443277) (2022) 1–8

33. Chheda, R., Bohara, D., Shetty, R., Trivedi, S., Karani, R: Music recommendation based on affective image content analysis. *Procedia Computer Science* 218 **2023** 383–392; International Conference on Machine Learning and Data Engineering.
34. Singh, B., Vaswani, K., Paruchuri, S., Saarikallio, S., Kumaraguru, P., Alluri, V: "help! i need some music!": Analysing music discourse & depression on reddit. *PLoS ONE* 18(07), **2023**, e0287975
35. Sharma, V.P., Gaded, A.S., Chaudhary, D., Kumar, S., Sharma, S: Emotion-based music recommendation system. In *Proceedings of the 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*. (2021) 1–5
36. Wang, X., Wang, Y: Improving content-based and hybrid music recommendation using deep learning. In *Proceedings of the 22nd ACM International Conference on Multimedia. MM '14, New York, NY, USA*, Association for Computing Machinery (2014), 627–636
37. Singh, K., Dembla, P: A study on emotion analysis and music recommendation using transfer learning. *Journal of Computer Science* 19(06), **2023**, 707–726
38. Bahadure, N.B., Juneja, S., Chandra, C., Mahapatra, P.D., Sathe, S., Verma, S: Kinect sensor based indian sign language detection with voice extraction. *International Journal of Computer Science and Information Security* 16(4), **2018**, 135–141
39. Sassi, I.B., Yahia, S.B: How does context influence music preferences: a user-based study of the effects of contextual information on users' preferred music. *Multimedia Systems* 27 **2021**, 143–160
40. Bin, S., Sun, G: Matrix factorization recommendation algorithm based on multiple social relationships. *Mathematical Problems in Engineering* **2021**, (Article ID 6610645) (2021) 1–8
41. Shao, B., Wang, D., Li, T., Ogihara, M: Music recommendation based on acoustic features and user access patterns. *IEEE Transactions on Audio, Speech, and Language Processing* 17(8) **2009**, 1602–1611
42. Dhattarwal, A., Ratnoo, S., Bajaj, A., Abraham, A: Ensemble transfer learning for robust human activity recognition from images. *International Journal of Computer Information Systems and Industrial Management Applications* 15, **2023**, 250–258
43. Cheng, R., Tang, B: A music recommendation system based on acoustic features and user personalities. In *Trends and Applications in Knowledge Discovery and Data Mining*; Cao, H., Li, J., Wang, R., (Eds.); Cham, Springer International Publishing (2016), 203–213
44. Shi, J: Music recommendation algorithm based on multidimensional time-series model analysis. *Complexity* **2021**, (Article ID 5579086), 1–11
45. Sun, P: Music individualization recommendation system based on big data analysis. Computational Intelligence and Neuroscience **2022**, (Article ID 7646000), 1–11