IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Improving the success of Music on Streaming platforms using Data Science

[1] **Surya Swaminath,** [2] **Jyothi Rao**

[1]Student, [2]Assistant Professor
[1] Computer Engineering,
[1]KJ Somaiya College of Engineering Mumbai, India

Abstract : In recent times streaming platforms such as Spotify, Apple music, etc. have become the go to source of music on the go. The main challenge for a new upcoming artist is to make his music reach a wider audience. The proposed system makes use of a machine learning/ deep learning based model to predict if a music would likely break into the top 50 musics globally on streaming services like Spotify . The proposed system will analyze parameters like acousticness, danceability, , time, signature, mode, tempo, valence, time duration , keys to determine the qualities of the ideal musics which is supported by a dataset of the top musics throughout time. The system will offer suggestions for how to make a music better depending on commercial factors. The proposed framework will predict whether or not a music will hit the top 50 or not based on commercial.

***Keywords*—** **Music, data science, acousticness, danceability, energiness, genre, loudness, liveness, speechness, instrumentalness ,time_signature, mode, tempo, valence.**

INTRODUCTION

Music streaming platforms like Spotify, Amazon music, Apple music are the modern day hubs for music listeners. These apps deliver an on-the-go music listening experience for a user. A song can be termed as successful on the basis of its performance on these music streaming platforms. Predicting the success of a new music and giving some tips to the musician to improve the success of their song on these platforms is the modern day challenge.

MOTIVATION

Being a Musician and data science enthusiast, it is fascinating to see how the two worlds collide. It is very difficult for a new upcoming artist to make his/her music reach a bigger audience and many times good music from an independent artist goes unnoticed. With the help of Data Science a better analysis of a music is possible and can reveal tips and tricks to improve the chances of a music to go viral.

LITERATURE SURVEY

In this research work [1] , author provides a proposed system that uses SpotGenTrack Popularity Dataset (SPD) as an alternative solution to existing datasets. A multimodal end-to-end Deep Learning architecture named as HitMusicNet is presented for predicting popularity in music recordings.Three main modalities to the analysis, such as audio, lyrics and meta-data as well as a preliminary compression stage via autoencoder are used to provide better capability of the model when predicting the popularity.

For the proposed system [2] , it uses published bi-weekly sales data from the Billboard magazine, more specifically, the Top Jazz chart. This system find statistically meaningful patterns within the music data. LMS (least mean square) algorithm is used to see if a new album's position in chart can be predicted on a certain week in the future (such as the 5th week or 12th week), with the first few weeks' sales data. Using both the nearest neighbor algorithm and the LMS algorithm, a prediction was attempted on a new album's life cycle and lifespan.

This paper aims to: (1) give an overview of the shared features of the songs that appeared at Mexico's top 50 during 2019, (2) analyze how these features are related to a track permanence on the top 50; and (3) compare those results with the global top 50 chart. The preliminary results of this research indicate that audio features such as energy, valence, and danceability were relevant for topping songs in 2019.The methods used for this manuscript may be applied to other countries elsewhere in the world. [3]

In this work [4] , authors present results of a user study on the web using two different visualisation techniques (a radar chart and sliders) that allows users to control Spotify recommendations. The Spotify API was employed in order to generate recommendation Evaluations were done for the 14 Spotify musical attributes based on how likely they will be used by participants.To compare the differences between the two interfaces, t-tests for normally distributed data and Wilcoxon signed rank tests for non-normally distributed data were considered.

A dataset is constructed by collecting newly released tracks from May to August 2021. Audio features are acquired from Spotify while social media features are obtained from the official videos on YouTube. Music popularity is defined using five metrics derived from the Spotify Top 200 daily chart performance to measure diverse aspects of the songs' success (Length, Max, Sum, Mean, and Debut). The predicted popularity has three target variables, ranging from Low, Medium to High popularity. During model implementation, four machine learning models were trained on the dataset in two different stages such as purely audio features and both audio and social media features respectively [5]

In this work, the authors proposes a machine learning model that can predict whether a song is likely to crack the top 50 songs globally on music streaming platforms such as Spotify, Apple Music, etc. Backed by the dataset of the top songs across the years it tracks parameters like acousticness, danceability, energiness,genre, etc to identify the characteristics of the ideal songs. The system proposes an SVM based model and a logistic regression based model to predict whether an input song will be popular. Using SVM model, an accuracy of 72.2% has been achieved in predicting whether or not a song will be able to reach the top 50 popularity using the model. [6]

The authors [7] also analyzes the basic parameters of the user profile, which include such parameters as music preferences and movie preferences, personality traits, hobbies and interests, views on life, spending habits, phobias and health habits, and opinions, and demographics. Various models like Linear regression, k-NN. Web profile can be used for music preferences analysis; Random forest and KNN are the best predictors for a chosen dataset; the feature selection is organized based on random forest. It allows to fond the most often preferences to classical music.

The proposed system [8] assesses and compares the robustness of some commonly used musical and non-musical features on DL models for the MGC task by evaluating the performance of selected models on multiple employed features extracted from various datasets accounting for billions of segmented data samples. In our evaluation, Mel-Scale based features and Swaragram showed high robustness across the datasets over various DL models for the MGC task.

IMPLEMENTATION

3.1 Dataset

,

The Spotify dataset [10] consists of over 600,000 songs, which were extracted from the Spotify Web API. These songs cover a wide range of years from 1920 to 2020. The dataset contains comprehensive song data, including information grouped by the artist's name, year of release, album name, and various audio features. The audio features in the dataset encompass both numerical and categorical attributes. The numerical features include:

1. Acousticness: A numerical value ranging from 0 to 1, indicating the degree of acoustic quality in a song.
2. Danceability: A numerical value ranging from 0 to 1, representing the suitability of a song for dancing.
3. Energy: A numerical value ranging from 0 to 1, indicating the intensity and activity level of a song.
4. Duration_ms: An integer typically ranging from 200,000 to 300,000, representing the duration of a song in milliseconds.
5. Instrumentalness: A numerical value ranging from 0 to 1, indicating the likelihood of a song being instrumental.
6. Valence: A numerical value ranging from 0 to 1, representing the musical positiveness conveyed by a song.
7. Popularity: A numerical value ranging from 0 to 100, indicating the popularity of a song.
8. Tempo: A floating-point value typically ranging from 50 to 150, representing the tempo or speed of a song.
9. Liveness: A numerical value ranging from 0 to 1, indicating the presence of a live audience in a recording.
10. Loudness: A floating-point value typically ranging from -60 to 0, representing the overall loudness of a song.
11. Speechiness: A numerical value ranging from 0 to 1, indicating the presence of spoken words in a song.
12. Year: A numerical value ranging from 1921 to 2020, indicating the year of release.

The categorical features include:

1. Key: Categorical values ranging from 0 to 11, where 0 represents the key of C, 1 represents C#, and so on.
2. Artists: A list of artists associated with a song.
3. Release_date: The date of release, mostly in yyyy-mm-dd format, although the precision of the date may vary.
4. Name: The name or title of the song.

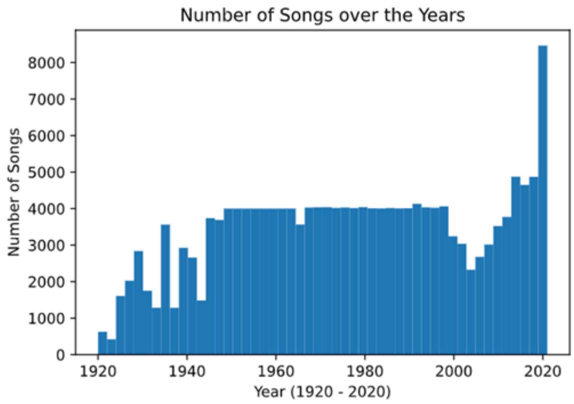


Figure 1. Visualization of Spotify Dataset

3.2 Proposed Architecture

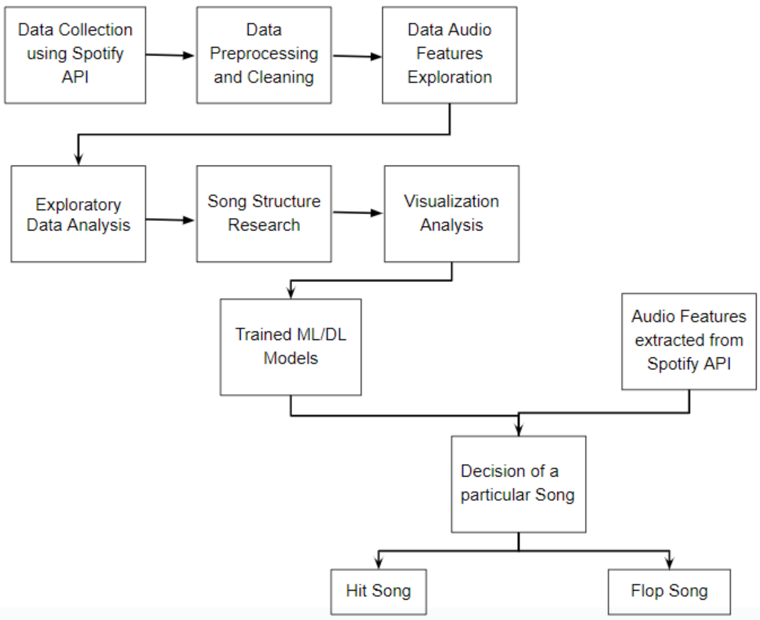


Figure 2. The architecture of the proposed system

1) Data Collection

Dataset is from Kaggle based on the Spotify API. This dataset included all the Spotify songs (175k+ songs) from 1920 to 2020.

2) Data Pre Processing and Cleaning.

The cleaning and preprocessing is done by the Spotify Api itself, which was one of the reason for considering this datatset for the proposed system.

3) Data Audio Features Exploration

The audio features considered for the dataset includes acousticness ,danceability , tempo , speechiness, instrumentalness, energy, key , duration_ms, mode, time_signature, liveness, loudness, popularity.

4) Exploratory Data Analysis

Exploratory Data Analysis (EDA) steps include data visualization techniques to examine and analyse the dataset and find key properties. The aim of exploratory data analysis is to obtain important insights from the dataset. The anlysis of top 50 songs from spotify includes analysis of trends over time by considering how popular a song is with respect to the artist over time and popularity of the song based on attributes like acousticness ,danceability , tempo , speechiness, instrumentalness, energy, key , duration_ms, mode, time_signature, liveness, loudness.

5) Song Structure Research

This step provides the study and analysis of song structures for generating information related to how popular a song is over time.

6) Visualization Analysis

The visualization step provides analysis of various audio features over time, analysis of the popular song features, analysis of top 50 playlist hitting songs with respect to Pop Genre over all the years.

7a) Training various Machine Learning/Deep Learning models

In this step, various machine learning and deep learning models are trained using the preprocessed and cleaned dataset of Spotify songs. The goal is to develop models that can predict the success or popularity of a song based on its audio features for a Pop Genre song.

7b) Audio Features from Spotify API

The new song features are extracted from the Spotify API. The relevant features are considered for making the decision whether a song will be hit/flop. Since python libraries like librosa, mfcc, musicnn,etc can't give the values for mode, key, time signature, Spotify API was used in the proposed system. Other features can be extracted using those libraries. Using Spotify API 15 features were extracted from each song out of which 8 features are considered based on the EDA.

8) Decision of a particular song

By analyzing various attributes's visualization over time and applying the Machine Learning/Deep Learning models, decision can be made whether a particular song can hit the Top 50 playlist .

RESULTS

Table 1. Comaprison of various ML/DL models

Model Name	Precision	Recall	F1-Score	Accuracy
XGBClassifier	0.72	0.86	0.78	0.78
KNN (K-Nearest Neighbors)	0.59	0.78	0.67	0.64
Random Forest	0.73	0.84	0.78	0.78
Particle Swarm Optimization on Random Forest	0.65	0.86	0.74	0.71
Neural Network - Multilayer Perceptron	0.70	0.83	0.76	0.75
Feed-forward Neural Network with Genetic Algorithm	0.71	0.84	0.77	0.75

Based on the evaluation metrics as shown in Table 1, XGBClassifier demonstrated the highest precision (0.72), Random Forest achieved high recall (0.84), and Neural Network - Multilayer Perceptron had a competitive F1-score (0.76) and accuracy

(0.75). However, KNN showed relatively lower precision (0.59) and accuracy (0.64), while Particle Swarm Optimization on Random Forest obtained a lower F1-score (0.74) despite achieving decent recall (0.86). These findings suggest that XGBClassifier, Random Forest, and Neural Network models hold promise in predicting music success on Spotify, while KNN and Particle Swarm Optimization on Random Forest may require further refinement to improve their predictive performance.

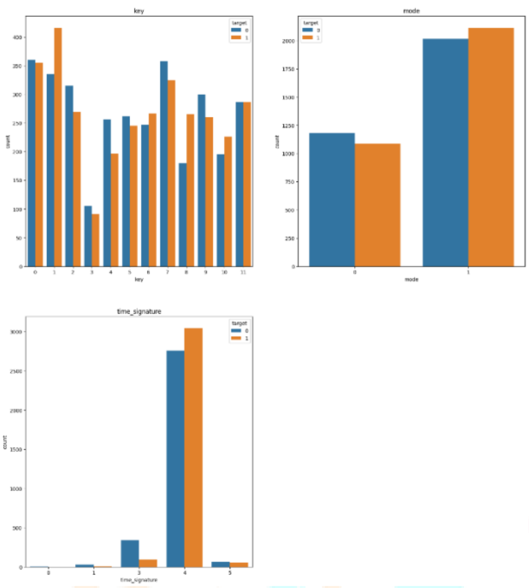
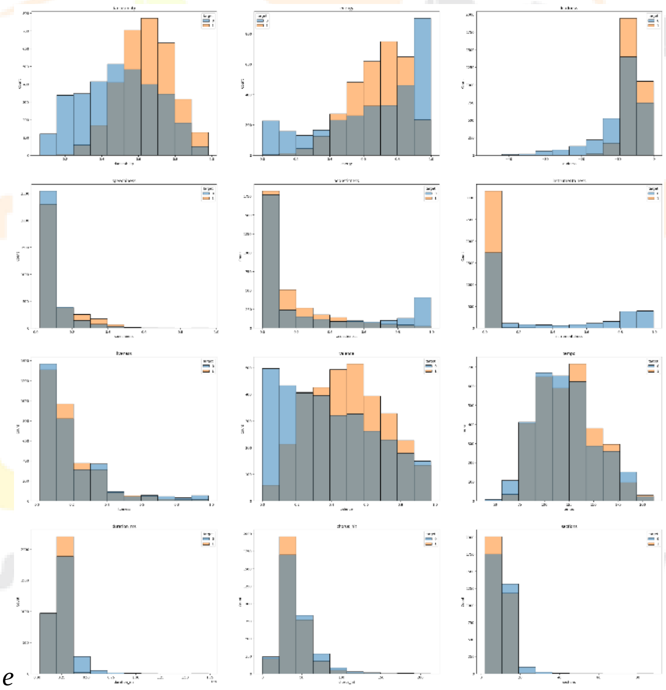


Figure 3. Visualization of Numeric Features

Based on the above visualization as shown in Figure 3, it can be observed that songs composed in the keys of C#, F#, G#, Bb/A#, and B (corresponding to key numbers 1, 6, 8, 10, and 11) have a higher frequency of appearing in the top 50. The visualization of the mode indicates that songs in major keys (mode 1) have a better chance of reaching the top 50. Furthermore, the visualization of the time signature suggests that songs with a time signature of 4 are more likely to achieve top 50 rankings, particularly for songs in the Pop genre.



e

Figure 4. Visualization of categorical Features

Based on the visualization as shown in Figure 4, it can be observed that a danceability score ranging from 0.5 to 1 is generally considered favorable, with the best performance seen in the range of 0.6 to 0.7. An acousticness score below 0.5 is considered ideal, and particularly good performance was observed in songs with an acousticness score below 0.2. A valence score between 0.3 and 0.9 is regarded as positive, while the range of 0.4 to 0.6 exhibited exceptionally good performance. Songs with tempos ranging from 125 to 175 bpm and 195 to 250 bpm have a higher likelihood of becoming popular. For optimal popularity, a song's duration of around 0.21ms (approximately 3.5 minutes) is most preferred, while a duration within the range of 0.18 to 0.30 ms (3 to 5 minutes) is considered suitable for achieving popularity

```
Danceability: 0.807
Key: 11
Mode: 0
Acousticness: 0.045
Valence: 0.537
Tempo: 126.011
Duration (ms): 230746
Time Signature: 4
Predicted Hit: 1
```

Figure 5. Success predictor UI for a Hit song

Based on the previous comparisons and analysis, a music success predictor in Figure 5 has been developed using the Random Forest algorithm. When predicting a hit song, the predictor will correctly identify it as a hit.

```
Danceability: 0.4
Key: 5
Mode: 1
Acousticness: 0.61
Valence: 0.2
Tempo: 115
Duration (ms): 0.15
Time Signature: 4
The song is predicted to be a flop.
You can improve the success of your song by tweaking the below parameters. Here are the differences:
Danceability Difference: 0.1
Acousticness Difference: 0.11
Valence Difference: 0.1
Tempo Difference: 10.0
Duration Difference: 0.03
```

Figure 6. Success predictor UI for a Flop song with a Time signature other than 4

However, in the case of a flop song as seen in Figure 6, the predictor will also provide insights into the audio feature differences that, if corrected, could potentially improve the song's performance. These feature differences are based on the ranges of audio features obtained from the detailed visualizations.

CONCLUSION

From the EDA analysis, the most popular songs today tend to be louder, more energetic, and have a higher tempo. Songs with more acousticness did well to reach the top charts.The visualizations suggested that more popular songs are constructed on white major keys, with the most popular being C# major, A# major, and B major. In addition, most songs end at around 3.5 minutes.

Further indepth analysis suggested that 8 features for a pop song were most important which are danceability, key, mode, acousticness, valence, tempo, duration_ms and time signature. With the correlation matrix and detailed visualizations further suggested that these features are interconnected and are of at most importance for a pop genre song.

On detailed comparison of various Machine learning and Deep learning models, Random Forest, and Neural Network models hold promise in predicting music success on Spotify, these models exhibited higher precision, recall, F1-scores, and accuracy compared to KNN and Particle Swarm Optimization on Random Forest. A Feed-forward Neural Network with Genetic Algorithm showed a decent performance and also banked a good f1 score, recall and precision score and while testing with various inputs this model was predicting the songs very proficiently. For the songs which did not hit the Top 50 in the prediction model, the model displays the necessary changes the user can make on the audio features so that the song will have a better chance at hitting the top50 and thereby havibg a great chance of being successful.

REFERENCES

[1] D. Martín-Gutiérrez, G. Hernández Peñaloza, A. Belmonte-Hernández and F. Álvarez García, "A Multimodal End-to-End Deep Learning Architecture for Music Popularity Prediction," in IEEE Access, vol. 8, pp. 39361-39374, 2020

[2] Song Hui Chon, Malcolm Slaney, and Jonathan Berger. 2006. Predicting success from music sales data: a statistical and adaptive approach. In Proceedings of the 1st ACM workshop on Audio and music computing multimedia (AMCMM '06). Association for Computing Machinery, New York, NY, USA

[3] Pérez-Verdejo, J.M., Piña-García, C.A., Ojeda, M.M. et al. The rhythm of Mexico: an exploratory data analysis of Spotify's top 50. J Comput Soc Sc 4, 147–161 (2021)R. Sigit, E. Triyana and M. Rochmad, "Cataract Detection Using Single Layer Perceptron Based on Smartphone," 2019 3rd International Conference on Informatics and Computational Sciences (ICICoS), Semarang, Indonesia, 2019
[4] Martijn Millecamp, Nyi Nyi Htun, Yucheng Jin, and Katrien Verbert. 2018. Controlling Spotify Recommendations: Effects of Personal Characteristics on Music Recommender User Interfaces. In Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization (UMAP '18). Association for Computing Machinery, New York, NY, USAXiaoling Luo, Quang H. Nguyen, Ramasamy Muthuraman, Laxman Singh, Gopa Sen, Anh Cuong Tran, Binh P. Nguyen, and Matthew Chua. "Diabetic Retinopathy Detection using Deep Learning". In Proceedings of the 4th International Conference on Machine Learning and Soft Computing (ICMLSC 2020). Association for Computing Machinery, New York, NY, USA, 2023
[5] Yee YK, Raheem M (2022)Predicting Music Popularity Using Spotify and YouTube Features. Indian Journal of Science and Technology
[6] A. Prabhu, N. Balasubramanian, C. Tiwari and A. Nerurkar, "Improving the commercial success of music on streaming platforms using data science," 2021 International Conference on Advances in Computing, Communication, and Control (ICAC3), Mumbai,
[7] Nataliya Shakhovska, Solomiia Fedushko, Data analysis of music preferences of web users based on social and demographic factors, Procedia Computer Science, Volume 198, 2022
[8] Yeshwant Singh, Anupam Biswas, "Robustness of musical features on deep learning models for music genre classification," Expert Systems with Applications, Volume 199, 2022
[9] Dataset :- https://www.kaggle.com/general/153757