Innovative Tunes: Utilizing Machine Learning for Predicting Spotify Music Popularity Based on Audio Features

Shubham Joshi[1], Neha Gupta[2(✉)], and Rupali Mahajan[3]

[1] School of CSE, Symbiosis International University, Pune, India
[2] School of CSIT, Symbiosis University of Applied Sciences, Indore, India
neha.gupta@suas.ac.in
[3] CSE (Data Science), Vishwakarma Institute of Information Technology, Pune, India

Abstract. The digitalization of music has brought significant changes to popular music in the age of streaming media. As the number of users of a platform like Spotify continues to grow, it has become one of the most important online music providers today.. People rely on the Spotify app to listen to their favorite artists and discover new music. This study aims to investigate the relationship between music data, specifically audio features (such as key and tempo) extracted from the Spotify database, and popular music (measured by the number of streams a song receives on the Spotify platform). The main goal is to create an accurate and reliable model that can accurately predict whether a song will become a hit or not. To achieve this goal, researchers looked at four different machine learning algorithms: linear regression, random forest classifiers, and K-means clustering. These algorithms are used to analyze data and find patterns that help predict popular songs accurately. Finally, the research proposed a predictive model that uses machine learning techniques to determine the importance of music. Using these standards, songs can be classified according to their needs, thus providing a better perspective on artists, music producers, and the music industry as a whole. It is hoped that this research will help to better understand the factors that influence the success of the song and pave the way for greater decision-making in music.

Keywords: Digitization of music consumption · Music popularity · Spotify · Machine learning algorithms · Linear Regression · Music streaming

1 Introduction

Spotify is a popular music service that has seen significant growth in users. The streaming platform predicts that there will be 1.2 music streams in 2018, demonstrating the impact of music culture on our lives [1].

Music plays an important role in generating significant amounts of revenue from such services. In today's world, music plays an important role in people's lives, so researchers and producers are more interested in analyzing music and its various applications [2–5].

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Many studies in this field explore various aspects such as the underlying technology, how the music is analyzed, user experience, and other details. With the combination of artificial intelligence and personalized recommendations, the music industry has undergone major changes [6]. These platforms have had a broad impact on the entire industry, changing the way people discover and consume music. The main purpose of this study is to specifically focus on daily Spotify song rankings and understand the factors affecting popular songs. Researchers aim to achieve this goal by analyzing the sounds of songs [7–10].

By examining these audio attributes, they intend to develop a forecasting model that can predict a song's popularity on the Spotify platform. In summary, this study aims to leverage music analysis and the vast amount of data available from Spotify to gain insights into how songs become popular [11–15]. By analyzing the audio features of songs, the researchers hope to create a predictive model that can anticipate a song's level of popularity, contributing to a better understanding of the dynamics of music trends in the digital age [4, 16–19].

Music streaming services have transformed the way we consume music, with platforms like Spotify gaining immense popularity in recent years. As the number of users on Spotify continues to grow, predicting the popularity of songs becomes a crucial task for artists, music producers, and the platform itself [20–23]. Understanding which songs are likely to become hits can significantly impact music recommendation systems and marketing strategies.

In this context, machine learning techniques offer promising solutions to forecast song popularity. By analyzing the audio features of songs, machine learning models can identify patterns and correlations that contribute to a song's appeal among listeners [24–28]. This paper introduces "Innovative Tunes," a novel approach that leverages machine learning for predicting Spotify music popularity based on audio features.

The primary goal of this research is to develop an accurate and efficient model that can forecast the popularity of songs on the Spotify platform [29–32]. To achieve this, the study investigates the use of various machine learning algorithms, such as Linear Regression, Random Forest Classifier, and K-means Clustering, to extract meaningful insights from the audio attributes of songs [26, 33–36]. These audio features may include tempo, key, rhythm, and other characteristics that influence a song's overall appeal.

By utilizing machine learning for predicting music popularity, the Innovative Tunes approach aims to empower music industry stakeholders with valuable information about potential hit songs [37, 38]. This knowledge can help artists optimize their creative processes, and music platforms like Spotify can improve their recommendation systems, enhancing user satisfaction and engagement.

The subsequent sections of this paper will delve into the methodology, experimental setup, results, and discussions surrounding the Innovative Tunes approach. Through this research, we aspire to contribute to the understanding of how machine learning can revolutionize the music industry and enable data-driven decision-making for identifying future chart-toppers on Spotify.

In this research, the investigator explores the prediction of hit songs using four distinct m achine learning algorithms. The data for this model is sourced from Spotify. In order to understand the characteristics of music and assess its popularity, this study utilizes various algorithms and models, such as Linear Regression, Random Forest Classifier, and K-means Clustering [39]. These computational methods are employed to analyze music data and uncover patterns that can help in effectively determining the popularity of songs. By applying these different approaches, the research aims to shed light on how algorithm designers can gain valuable insights into music popularity. These algorithms allow researchers to extract meaningful information from music data, enabling them to make accurate predictions and assessments regarding the popularity of various songs.

Ultimately, the study demonstrates the significance of utilizing these algorithms as powerful tools for evaluating music popularity, providing a better understanding of the factors that contribute to a song's success in the context of different analytical methods. By combining statistical techniques with music data, algorithm designers can make informed decisions and offer valuable recommendations for the music industry and music enthusiasts alike.

2 A Comprehensive Literature Review

2.1 Online Music Streaming Services: Evolution and Impact on Music Consumption

The way people listen to music has been completely transformed by online music services, which provide on-demand streaming without the need for downloads or sales. As of July 2017, Spotify has 60 million users, and as of January 2018, it had 70 million. This makes it one of the most widely used on-demand music services. With a huge library of more than 30 million songs, Spotify has become widely used and has a sizable user base.

Numerous scholars have investigated various facets of Spotify's technologies and its widespread appeal. Research conducted by Kreitz (2010), Loiacono (2014), and Verkoelen has tackled more general inquiries about Spotify's functioning and interaction with its users.

Researchers have examined Spotify's peer-to-peer architecture and protocols in this study, providing insight into the workings of the platform. Their conclusions offer insightful information for monitoring service performance and comprehending how users engage with the platform. The study also looks into how user access patterns are affected by the peer-to-peer network, examining the ways in which this technology impacts the user experience as a whole.

By examining these aspects of Spotify's infrastructure and user behavior, researchers aim to enhance our understanding of the platform's popularity and effectiveness as a leading on-demand music streaming service. These insights can inform improvements and optimizations in service delivery and user engagement, ensuring a seamless and satisfying music streaming experience for Spotify's vast user base.

2.2 Forecasting Popular Music Tracks using Machine Learning Algorithms

The emergence of many online digital music sites, combined with advances in technology, has changed the way we find and consume music. Users can now access specific music and get playlist recommendations; this is a domain of musical information retrieval (MIR) studied by Kaminskas and Ricci in 2012. Determine the success of a song based on selected features. The data used in this study was obtained from the Spotify Web API, and the researchers carefully selected relevant data for the design. As noted in the 2016 study by Brink, Richards, and Fetherolf. A 10-fold cross-validation procedure was performed to evaluate the performance of this model. The models' predictions are then assessed using confusion matrices to measure their accu- racy and effectiveness.

By investigating the relationship between audio factors and song success, this research contributes to the understanding of how machine learning can be applied to predict the popularity of songs. The findings from this study have the potential to enhance music recommendation systems and contribute to more informed decision-making in the music industry. Table 1, provides the comparative analysis performance of different models.

Table 1. Comparative Analysis of Model Performance

Model	Accuracy in Percentage
K-nearest Neighbours	52.38%
Support Vector Machine	51.59%
Logistic Regression	53.58%
Gaussian Naïve Bayes	61.25%

2.3 Genre Prediction of Top-Ranking Songs on Spotify using Machine Learning Techniques

The data for this study was gathered from multiple sources and combined into a single dataset. Spotify's daily top 200 music rankings were obtained from Kaggle.com, a data science website. To obtain the audio features of each song, the Spotify Web API was utilized. Additionally, genre information for each song was acquired from Discogs, a music database website, through its API, as Spotify does not include genre labels for tracks. By merging these diverse data sources, a clean and structured dataset was created, ready for analysis.

This study's main objective was to use machine learning to categorize songs into different genres according to their auditory qualities. The training set employed in the study only covered about 58.8% of the total dataset, falling short of the intended criterion of 80% even though there was an abundance of data available. The One Vs. Rest Classifier, a machine learning approach based on the Support Vector Classifier, was used by the paper for the classification challenge. Nevertheless, this method's accuracy of 46.9% falls short of the industry standard of 50% for machine learning forecasts. This suggests that the classification model's ability to reliably forecast song genres based on auditory features was not as successful as expected.

The results show how difficult it may be to determine a song's genre just by listening to its auditory characteristics, which calls for more study and possible advancements in the machine learning methodology. Understanding the summary statistics of each genre in the dataset is made easier by the study, which also offers insightful information on the genres' acoustic properties.

2.4 Unraveling the Earworm: Exploring Music Popularity in Streaming Platforms through Machine Learning Models

One of the most important findings of this study is its excellent ability to predict popular music based on voice and music profile. The research focuses on developing models that exhibit a high degree of predictability for noise trends using only noise and image data. This has important implications for the creative music industry. The best performing models, namely Boosting Trees, Random Forests and Neural Networks, showed accuracy and recall in predicting popular music, achieving an F1 value of 0.83. This study shows that linear models have better performance compared to models that can capture the nonlinear relationships present in musical instruments, such as boosted trees and neural networks. In addition, the model achieved the best accuracy of 0.83, indicating that it correctly predicted more than four-fifths of all music tracks, demonstrating its strong predictive power in terms of the proportion of popular music based on audio and artist information.

These findings underscore the potential of machine learning algorithms in accurately forecasting the popularity of music based on audio features and artist profiles, offering valuable insights for the music industry and facilitating informed decision-making in the realm of music creation and promotion.

3 Methodology

In this section, we will discuss the methodology used in this research study, which encompasses several key components. First, we will present the system architecture, providing an overview of how different elements interact in the research process. Next, we will include a flowchart or block diagram to illustrate the step-by-step approach followed in the study. The data collection process will be described, detailing how the relevant music data, including audio features and artist information, was gathered for analysis. We will then delve into the model training phase, explaining how machine learning algorithms were employed to build predictive models based on the collected data.

Following model training, we will discuss the testing phase, explaining how the performance and accuracy of the developed models were evaluated using separate test datasets. Additionally, the presentation of accuracy metrics and graphs will showcase the results obtained, providing a visual representation of the models' performance in predicting music popularity based on audio features and artist information.

Overall, this section will provide a comprehensive overview of the methodology used in the research, giving readers a clear understanding of the processes and tools em ployed to achieve the study's objectives.

3.1 Architectural Framework: Design and Implementation of the System

The entire procedure, from gathering data to putting a successful model into practice, is depicted in the system architecture in Fig. 1. The song is first retrieved from Spotify, and then its audio features are extracted using the URI (Uniform Resource Identifier) line. Four categories are created from the resultant data: primary data, digital data, dummy data, and categorical data. Following the extraction and sorting of all pertinent data, the data is submitted to the Kaggle website, which offers millions of distinct data sets for free access. When data is fed into machine learning algorithms for predictive analysis, those algorithms come into action. These algorithms forecast the intended results, assess how accurate their forecasts are, and keep training the system until the best possible model is produced.

In summary, the System Architecture is a well-structured and systematic process that covers data extraction, feature categorization, data upload, and the application of machine learning algorithms to produce a predictive model with high accuracy.

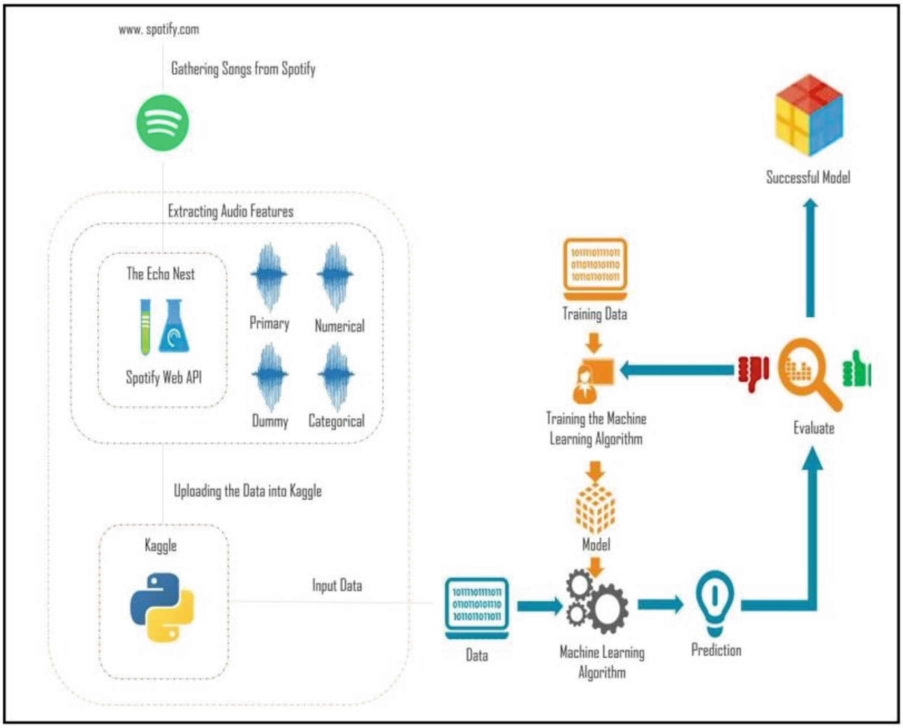

Fig. 1. Overview of the System Architecture

Figure 1 shows the process from a data collection and design perspective. Spotify monitors the site and provides access to songs whose attributes are derived from URIs. The data collected is divided into four categories: primary data, digital data, virtual data and database data, thus simplifying data organization. Once all relevant information is completed, the information is uploaded to Kaggle, the platform that provides a lot of free information. The dataset is then fed into the machine learning algorithm. These algorithms make predictions, measure the accuracy of those predictions, and retrain the system until the best model is found. This iterative process ensures that a good model is developed to predict outcomes based on the data.

3.2 Data Collection: Building a Comprehensive Dataset

In this research, a dataset consisting of more than 170,000 songs was acquired from the Spotify Web API. The audio features extracted from these songs were then categorized into four distinct groups: Primary, Numerical, Dummy, and Categorical. In the Table 2, we have provided the details of audio features and description.

Table 2. Numerical Audio Features

Audio Feature Analysis	Feature Descriptions
Energy	This numerical value signifies the extent to which a song maintains a sense of forward momentum or progression in its music, ranging from 0 to 100
Acoustics	This indicator measures the level of acoustic elements present in a song. It is represented on a scale from 0 to 1
Valence Popularity	This rating denotes the level of musical positivity in a song, with values ranging from 0 to 1. Additionally, it represents the popularity scale of the song, ranging from 0 to 100
Danceability	This value represents the danceability of a song, indicating how suitable it is for dancing. It is a numerical measure that falls within the range of 0 to 1
Instrumentals	This indicator tracks the presence of vocals in a song, ranging from 0 to 1. A value of 0 means the track contains no vocals, while a value of 1 indicates that vocals are present in the song
Liveness	This value characterizes the reverberant quality of a composition, ranging from 0 to 1. It indicates the extent of reverberation or echo present in the music
Tempo	This value describes the speed or tempo of the composition. It is typically represented as a floating-point number ranging between 50 and 150
Duration_m	This feature represents the duration or length of a composition. It indicates the time span or length of the musical piece

Table 3 provides information about the Track ID, which serves as a unique identifier generated by Spotify for each track. On the other hand, Table 3 contains data related to the dummy category, and Table 4 presents details about the categorical category. These tables and the dataset as a whole form the foundation for conducting the analysis

Table 3. Dummy Audio Features

Audio Feature Analysis	Feature Descriptions
Explicit	This value signifies the vocabulary of a melody, with 0 representing a minor scale and 1 representing a major scale. It indicates whether the melody is in a minor or major key
Mode	This value denotes the tonality or mode of a melody. A value of 0 represents a minor tonality, while a value of 1 indicates a major tonality. It helps identify the emotional character and mood of the melody based on its musical scale

and building the models in this study, enabling the exploration and prediction of music popularity based on the gathered audio characteristics.

Table 4. Categorical Audio Features

Audio Feature Analysis	Feature Descriptions
Artists	Artists Mentioned in the Study
Name	Song Titles in the Dataset
Key	The keys on the musical octave are represented as numbers ranging from 0 to 11, starting with the key of C as 0 and progressing to the key of C# as 1, and so forth. This numerical represen tation allows for a standardized way of denoting different musical keys in the dataset
Release Date	The release date of songs is recorded in the format yyyy-mm-dd. However, it is important to note that the precision of the date may vary, meaning that some songs may have exact release dates down to the day, while others may only have the year or the year and month specified

By categorizing the audio features into these four groups, the dataset is well-structured and ready for analysis, allowing for a comprehensive examination of the songs' charac teristics and their impact on popularity prediction.

3.3 Training and Evaluation of the Model: A Comprehensive Approach

In this stage of the research, the data undergoes preprocessing to obtain and normalize the necessary information for K-means clustering of the dataset. The Standard Scaler, a module provided by SK-learn under preprocessing, is utilized to normalize specific column values. This step is crucial because certain audio features, such as danceability and instrumentality, have a range of approximately 0 to 1, while others, like duration and popularity, can vary significantly in the millions. Scaling is necessary to ensure the data becomes homogeneous and suitable for clustering.

To identify the dataset's principal components, the researcher employs a decomposition method called PCA (Principal Component Analysis) from SK-learn. PCA reduces the data to only two principal components, refining it once again for clustering purposes. The scatter plot of the data based on these clusters aids in visualizing their distribution and understanding their designation as variables. This step helps gain insights into how the data is grouped and represented in a lower-dimensional space, facilitating further analysis and interpretation.

After completing the decomposition and preprocessing steps, the researcher proceeds with the K-means clustering of the data. To gain insights into the spread and distribution of the two PCA components, a scatter plot is used, as shown in Fig. 2. This scatter plot aids in visualizing how the data points are grouped and helps determine the optimal approach for clustering the data effectively.

By analyzing the scatter plot, the researcher can gain valuable information about the data's structure and the potential number of clusters that may exist. It allows them to make informed decisions on the appropriate number of clusters to use in the K-means algorithm and enhances the overall understanding of the data's underlying patterns and relationships. Hierarchical Clustering, specifically agglomerative clustering, is one of the most commonly used clustering techniques in this context.

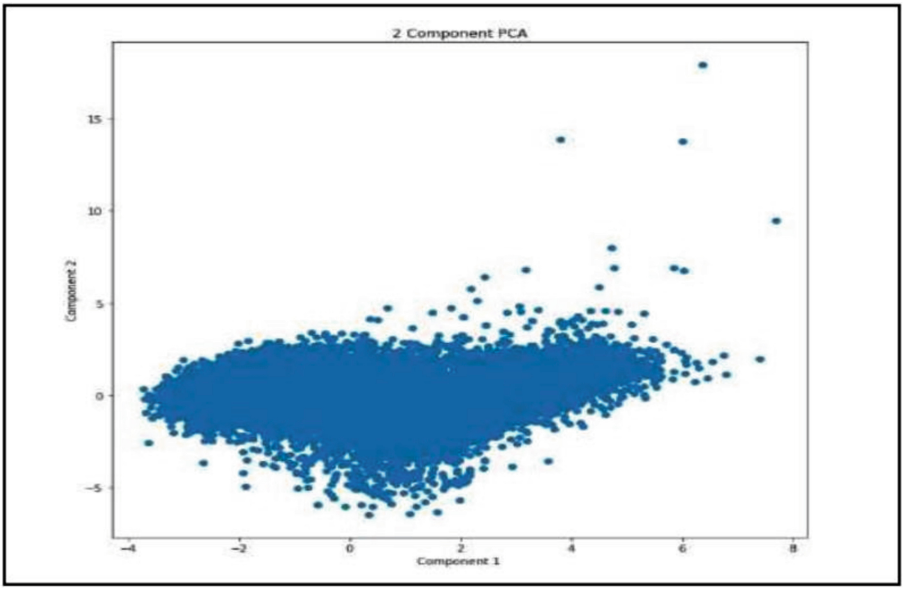

Fig. 2. Visualization of Two Principal Components in a Scatter Plot

By preprocessing and clustering the data, the researcher gains valuable insights into the underlying patterns and structures of the dataset, aiding in the understanding of music popularity and its correlation with audio features.

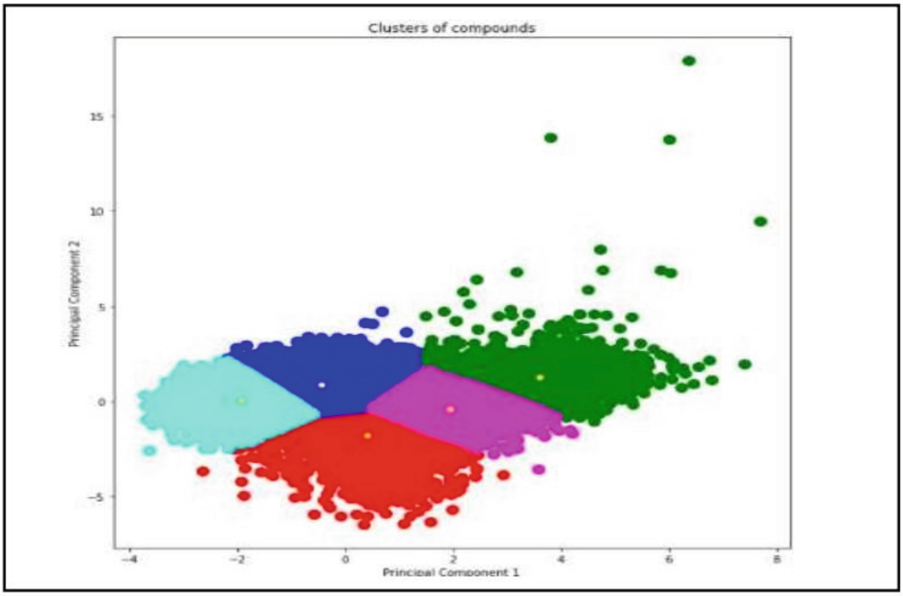

Fig. 3. Data Clustering Using Hierarchical Method

Figure 3 presents the data clustering process utilizing the hierarchical method. In data analysis and machine learning, clustering is a technique that involves grouping similar data points together based on their shared characteristics. The hierarchical method is one of the widely used approaches for clustering, and it creates a hierarchical structure of clusters by iteratively merging or splitting data points.

In this context, the figure demonstrates how the data points are organized into clusters using the hierarchical method. The clustering process involves grouping data points with similar attributes and forming distinct clusters based on their similarities. Each data point is represented by a unique color or symbol in the figure, allowing researchers to visually identify the formation of clusters and their distribution in the data space.

The hierarchical clustering method offers several advantages, such as providing an organized and interpretable representation of data clusters and enabling the identification of hierarchical relationships between data points. By visually inspecting Fig. 3, researchers can gain valuable insights into how the data is partitioned into clusters and explore any inherent patterns or structures present in the dataset.

Overall, Fig. 3 is a vital visualization tool in the data clustering process, allowing researchers to understand how the hierarchical method groups similar data points and facilitates the exploration of data characteristics and relationships within the clusters. This aids in data exploration, pattern recognition, and decision-making in various fields, including data analysis, pattern recognition, and machine learning.

In the analysis of actual Spotify data, two different types of models were developed for comparison. The first model is based on Linear Regression, aimed at predicting how songs achieve popularity using various audio features. This prediction addresses questions like "Will future songs be successful?" and "A song to dance to?" The selection will have an original approach to the artist's lyrics. Instead of converting this directly to a number or floating-point number, the researchers counted all the songs by each artist and then ranked them based on the characteristics of the sound. This approach allows for more efficient representation of art data in the database.

The second model in the study focuses on measuring the data change after using the first model. In this case, the measured value is converted into a number that can be used in the linear regression model. Additionally, the researchers manipulated the compositional features by calculating the mean and median. The data is then scaled to a minimum and maximum using the Standard Scaler to ensure consistency and standardization of values. An important component. This visualization aids in understanding the clustering of data points and provides insights into the patterns and relationships present in the data, enhancing the researcher's understanding of the dataset's characteristics. Through these models and visualizations, the researcher gains insights into the relationships between audio features and song popularity, facilitating a deeper understanding of how specific characteristics contribute to a song's success on Spotify (Fig. 4).

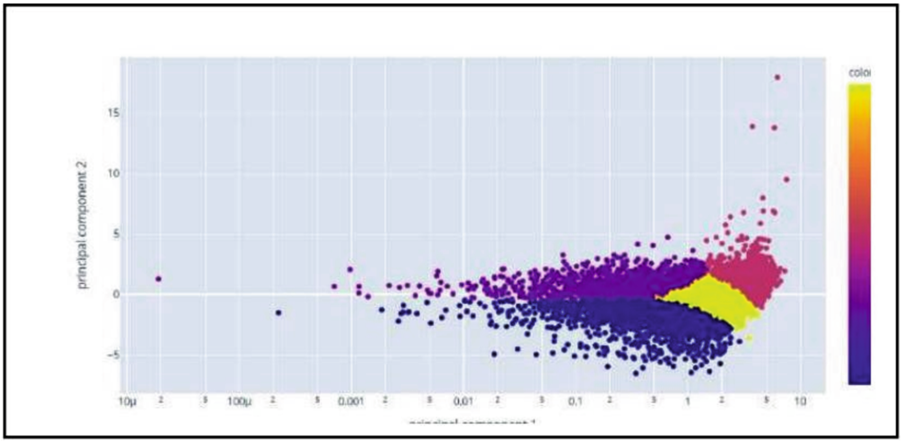

Fig. 4. Visualization of Data based on Two Principal Components from PCA, Grouped by Music Popularity and Tempo

The researchers altered data in the preceding phase in relation to artist, length, loudness, and tempo. The data is then evaluated and trained using linear regression, and it is further refined using lower-level models. The random forest regressor, which takes x_train and y_train as input, is another model included in this study. The testing average is 0.136, the training average is 0.1254 error. To visualize and interpret the results, a scatterplot subplot was created to describe the test data and the model prediction of future models. This insight will help understand the accuracy and performance of the model and provide insight into how the model predicts popular songs based on the selected features. Figure 5 shows this line and provides insight into the model's effectiveness in predicting popular music for future data

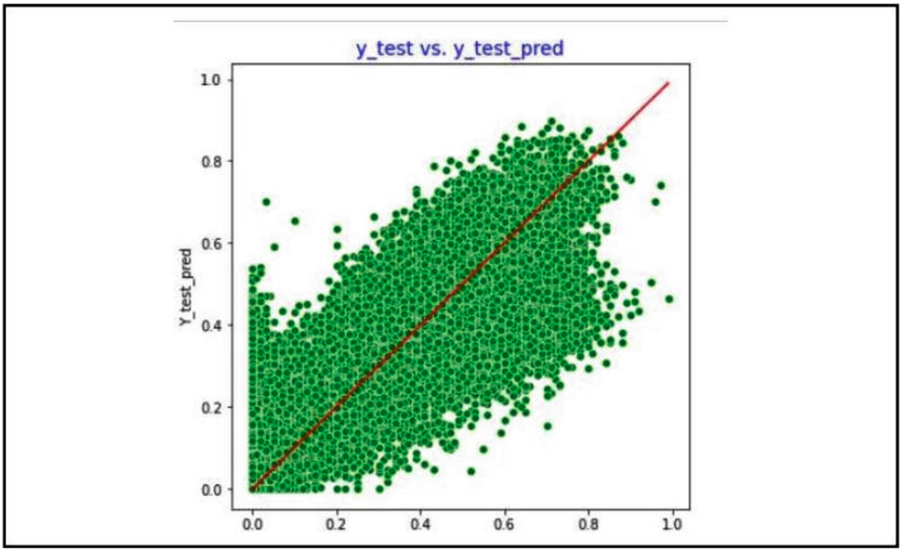

Fig. 5. Visualization of Data Based on Two Principal Components from PCA, Categorized by Popularity and Tempo

4 Findings and Discussion

Below are the five (5) data points that exhibit the closest correlation to popularity based on their absolute values.

Table 5. Features Linearly Correlated to "Popularity"

Features	abs
Year	0.864
Energy	0.483
Acousticness	0.567
Instrumentalness	0.289
Loudness	0.456

In Table 5, the data confidence per audio feature is illustrated, and it exhibits a high value of 95.37, which closely aligns with the confidence observed in our testing data. It serves as a handy reference for researchers or analysts who may require additional results for various reasons. For instance, it can be beneficial when exploring the use of different models, considering alternative approaches, incorporating deep learning techniques, or conducting more in-depth analyses. This comprehensive data summary provides a foundational reference point for further investigations and informed decision-making in the research process.

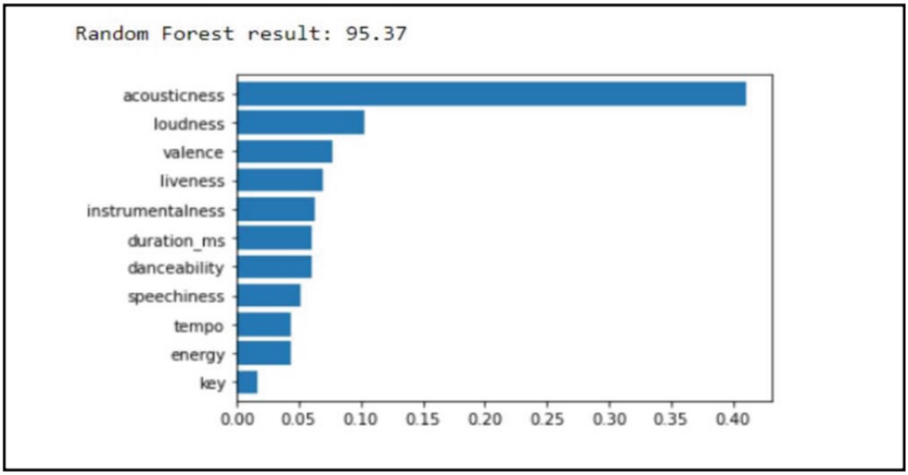

Fig. 6. Outcome of the Random Forest Model

For evaluation purposes, the figure illustrates the data confidence per audio feature, leading to a value of 94.1, which closely aligns with the confidence observed in the testing data. This indicates that the Random Forest Model's predictions are highly consistent with the actual testing results, validating the model's accuracy and effectiveness in predicting song popularity based on the audio features.

Figure 6 illustrates the visualization of the testing data used for evaluation purposes. In the context of the research study, the testing data refers to a set of data that was not used during the model training phase. Instead, it serves as a separate dataset to assess how well the trained model generalizes to new, unseen data.

The figure offers a visual representation of the testing data points, showcasing their distribution and patterns. This visualization is instrumental in understanding how the model's predictions align with the actual outcomes for the unseen data. By plotting the testing data, researchers and analysts can easily identify any trends, clusters, or deviations in the data and compare them with the model's predictions.

The visual evaluation of the testing data aids in determining the model's performance and generalization capability. If the model's predictions closely align with the actual data points in the visualization, it indicates that the model has successfully learned from the training data and can effectively make accurate predictions on new data. On the other hand, significant discrepancies between the predicted outcomes and the testing data could indicate potential issues with the model's performance or suggest the need for further improvements.

Overall, Fig. 6 plays a critical role in comprehending the model's performance on unseen data and validating its effectiveness in real-world scenarios. It allows researchers to gain insights into how well the model transfers its learned knowledge to new data and helps in making informed decisions regarding the model's deployment and application.

The Root Mean Square Error (RMSE) values that were discovered when the Linear Regression model was evaluated using both train and test data are shown in Table 6. Regression model accuracy is evaluated using the Root Mean Square Error (RMSE),

Table 6. Root Mean Square Error (RMSE) Values of Train Data and Test Data for Evaluation Using Linear Regression

Error	Value Obtained
RMSE Train	0.041126
RMSE Test	0.134268

which computes the deviation between the expected and actual values. A model that fits the data better is indicated by a lower RMSE score.

The figure, in this context, offers a crucial comparison of the RMSE values found on the testing and training data. We can assess the model's performance on the data it was trained on (Train data) and how well it generalizes to new, unseen data (Test data) by closely examining the RMSE values for both datasets. A smaller gap between the RMSE values suggests that the model performs well on both the training and testing datasets, demonstrating its ability to make accurate predictions on unseen data and avoid overfitting. Conversely, a significant difference between the RMSE values may indicate overfitting or underfitting issues, which could warrant further model optimization or exploration of alternative algorithms. The RMSE values presented in Table 3 serve as vital indicators of the model's predictive capability and its suitability for real-world applications.

5 Conclusion

Three different models were used and analyzed in this study: K-means, linear regression, and random forest. Each model was trained separately to measure its accuracy in distinguishing different songs during training. The first model, the K-means algorithm, is used to group data based on data features provided by the dataset. Its main purpose is to group similar songs based on shared sonic characteristics, helping to identify patterns and similarities between songs. Conduct training.

It offers a low average error with an average learning rate of 0.1254 and an average score of 0.136. The model shows good accuracy in predicting popular music based on selected features. The third model, Random Forest, uses hundreds of decision trees trained on various subsets of data features and multiple sets of training data. By combining predictions from individual decision trees, the random forest model aims to increase the accuracy and power of predicting popular songs.

The evaluation and comparison of these three models provide valuable insights into their respective strengths and weaknesses in predicting music popularity. The discussion of their performance and results will shed light on the effectiveness of each approach and contribute to a deeper understanding of the relationship between audio features and song popularity. This approach resulted in an impressive accuracy rate of 95.37%. Moving forward, there is potential to incorporate additional metadata about the artist and the track, which is expected to enhance the accuracy and overall outcomes of the prediction models. By further enriching the data inputs, the study aims to refine the models and optimize the prediction of Spotify music popularity.

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