Enhancing Music Recommendations with Machine Learning Techniques

MSc Research Project
Data Analytics

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Enhancing Music Recommendations with Machine Learning Techniques

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Abstract

The aim of this research is to investigate the development and performance evaluation of a music recommendation classification system that uses various machine learning models. The models under the consideration are Random Forest, Decision Tree, Gradient Boosting, Support Vector Machine (SVM), and Recurrent Neural Network (RNN). The purpose of this study is to evaluate the performance of these models in suggesting music in three distinct scenarios: the explicitness of the song, mode-based preferences, and the popularity of the song. The experiment is based on using extensive large datasets that are customized to recognize and capture the particular aspects of user preferences and behavior. A dataset containing detailed song attributes is used to train the models for explicit song recommendations. In the mode-based scenario, the focus is on understanding user preferences in accordance with the musical mode of the songs. Additionally, popularity is included to assess the models' ability to recommend music according to prevailing trends. A comprehensive overview of the models' performance is provided by the evaluation metrics used, which include accuracy, precision, recall, and F1 score. The results highlight the strengths and weaknesses of each model under different recommendation scenarios. Furthermore, the report describes the findings gained during the experimentation process, shedding light on the factors that influence the effectiveness of machine learning models in the music recommendation field. The research is valuable in providing guidance on selecting appropriate models for specific recommendation contexts in the field of music recommendation systems. The findings demonstrate the value of adjusting machine learning methods to user preferences, and provide a basis for future progress in personalized music recommendation systems.

Keywords: Music Recommendation System, Machine learning Models,

1 Introduction

Music is an integral part of human culture and has evolved significantly over the years. With the advent of digital platforms and streaming services, the sheer volume of music available to users has grown exponentially, presenting a challenge in terms of effective music recommendations. Traditional recommendation systems often fall short when dealing with large-scale datasets and intricate user preferences. This research delves into the area of deep learning based music recommendation system, which is aiming to utilize the huge potential of neural networks to handle with extensive music track datasets efficiently (Chang et al.; 2018; Hoffmann et al.; 2014).

The development of the music recommendation systems became a continual process in which has followed with various improvements in data processing ability and methods. The implementation of the rule-based algorithms in the early models was often limited by their ability to fully represent each and every characteristics of the user preferences (McFee et al.; 2012). The important improvement has been identified in the interactive filtering methods, which utilize the interactions between users and the characteristics to generate predictions with them. But as the large amount of data available got increased, where these approaches experienced the sustainability and the accuracy issues Herlocker et al. (1999).

Recommendation systems experienced from a revolutionary stage, from when the machine learning models are becoming the part of them, which allowing them to learn the models from user behavior and adjust to changing preferences (Quadrana et al.; 2018). The collaborative filtering approaches have been improved another method content-based filtering, which is an approach that takes the user preferences and the item features into consideration Melville et al. (2002). Although these developments, a model get evolved in approach was needed due to the unexpected increasing of the available music data and this requires the need for advanced recommendations to tackle this problem.

Recommendation systems experienced from a revolutionary stage following the introduction of deep learning, which allowed the models to extract large or minor complex patterns and representations from huge amounts of data. Neural networks, where their ability is to capture the complex relationships, have represented the extraordinary to ensure it in various domains, including the natural language processing and the image recognition LeCun et al. (2015); Melville et al. (2002). This research builds on the foundation, while exploring the application of deep learning in the field of music recommendations.

Large-scale music track datasets are going to be prepared and analyzed is the one of objectives of the research process Turrin et al. (2015). First, a variety of data are gathered, such as listening records of users, explicit preferences, and the level of popularity of music track items. Then the data is get preprocessed and cleaned using various machine learning models, while ensuring its accuracy and reliablity for further research Witten et al. (2016).

Our Investigation's important component is the incorporation of machine learning models in the training stage (Adomavicius and Tuzhilin; 2005). By training them to recognize the complex patterns in the data, where the machine learning models are able to produce the results which are able to capture the meaningful representations of user preferences as they train itself with the supervised dataset which we re going to integrate for it to final combined prediction to a by averaging the prediction results of all models to the final model prediction (Ferraro et al.; 2019). Through this procedure, the recommendation system is able to gain the deeper understanding of personal preferences by going beyond the simple relationships.

1.1 Significance of Research

The significance of this research stands in its strength to revolutionize the way music recommendation systems operate. As digital platforms continue to dominate the music consumption landscape, the need for highly accurate and personalized recommendations becomes increasingly crucial (Van den Oord et al.; 2013). The outcomes of this research have implications not only for the field of music recommendation but also for the broader domain of recommendation systems in diverse contexts (Lee and Lee; 2006).

The establishment of an innovative music recommendation system that has the potential to enhance the user satisfaction, increase their engagement, and encourage a deeper understanding and the relationship between users and the huge inventory of musical content (Pu et al.; 2012). Furthermore, the approaches introduced in this research can provide as a blueprint for solving the challenges in recommendation systems across various domains, while contributing it to the advancement of machine learning and deep learning applications (Chang et al.; 2018).

1.2 Objective and Key Questions of the Research

The main objective of this research is to utilise the machine learning model algorithms effectively to create an advanced music recommendation system that can handle the massive amounts of data ((Turrin et al.; 2015); (Witten et al.; 2016)). Because of the huge quantity and variety of music available on the digital platforms, where the recommendation system which crosses traditional limitations, is required. Our goal is to improve the customer's entire music consumption experience by offering the incredibly accurate and personalized recommendations (Quadrana et al.; 2018). To achieve these objectives, we aim to address the following research questions in this study:

- How can machine learning models be effectively integrated to preprocess and clean large-scale music datasets?
- In what ways can Recurrent Neural Networks (RNNs) be employed to capture sequential dependencies and time-dependent factors in user-item interactions?
- What methodologies can be employed to ensure the accuracy and reliability of the data during the preprocessing phase

1.3 Conclusion

This research aims to explore and implement the machine learning approaches to improve the field of music recommendation systems. By addressing the various posed challenges by large-scale dataset (Turrin et al.; 2015) and complicated types user preferences, we aims to develop a system that not only generate the accurate recommendations but also adapts the evolving nature of user preferences as well the them tastes to understand it by recording the history (Schedl et al.; 2015). The integration of diverse machine learning architectures, with a focus, adds a layer of sophistication to the recommendation process, enabling a more nuanced understanding of user-item interactions Witten et al. (2016). As we delve into the complexities of music recommendation, the final objective is to create an innovative system that overcomes from traditional model problems and challenges (Van den Oord et al.; 2013); (LeCun et al.; 2015). Through the customization, personalization, and a deep understanding of user preferences, our research pursues to elevate the user experience in the area of digital music consumption.

2 Related Work

The use of machine learning techniques has led to significant research and development in the field of music recommendation systems, with a particular emphasis on enhancing the accuracy and personalization of recommendations. The purpose of this section is to examine relevant literature and studies that have examined comparable aspects in music recommendation.

2.1 Traditional Recommendation System

The earliest exercises of rule-based algorithms can be associated with the development of music recommendation systems. Where their the simplicity, these early models frequently had limitations in their ability to accurately present the variety of user preferences (Herlocker et al.; 1999). A considerable development was when the addition of collaborative filtering. By utilizing user preferences and their behaviour, where the collaborative filtering algorithms produce predictions which allow the model to perform more individualized recommendations. However, these approaches overcome into the issues with accuracy and scalability as the volume of data accessible increased over the time (Singhal et al.; 2017).

2.2 Integration of Machine Learning Models

The implementation of various machine learning models into the recommendation systems has resulted in an important development in the existing traditional rule based approach. This evolutionary process which enhanced the ability of systems to acquire knowledge from user behavior as well as their preferences, which allowing them to adjust and adapt the evolving preferences as time passed. The significant improvement of recommendation systems was introduced by (Melville et al.; 2002) with the execution of the content-based filtering techniques. This technique is considered for both user preferences and item features associated in the music track dataset, after delivering the more comprehensive knowledge of user based preferences. These developments have established that the foundation for more advanced recommendation systems that which are capable of successfully handling the various huge amount datasets (Song et al.; 2012).

2.3 Evoluation of Deep Learning in Recommendation Systems

The introduction of deep learning has brought about the significant transformation in the area of recommendation systems. Where the Neural networks have demonstrated their ability to extract the complex patterns as well as the minor patters and representations from large amount datasets, indicating that there is potential in several fields (LeCun et al.; 2015; Zhu et al.; 2006). The integration of deep learning techniques in music recommendation systems signifies an exciting field of research, with the objective of overcome from the capabilities of neural networks to provide enhanced accuracy as well as the personalized recommendations (Park et al.; 2006). The investigation which is focused mainly on the employment of deep learning model techniques in the domain of music recommendation which has demonstrated the positive results. The process of collaborative filtering technique used by neural networks was introduced by (Van den Oord et al.; 2013), here demonstrating the capability of deep learning in recognizing the well defined human behavioral patterns.

2.4 Handling Large-Scale Datasets

The extensive adoption of digital music platforms is now resulted in an enormous increase in the quantity of the available content. The prosperous implementation of the recommendation systems which is largely depends on successfully while dealing with the challenges presented by large-scale datasets (Turrin et al.; 2015). The authors (Witten et al.; 2016; Schedl et al.; 2015) outlined the significance of using the accurate and reliable processes for preparing the data. The utilization of these approaches, which includes the process of cleaning and transforming the raw data, and holds significant im portance in the preparation of many types of datasets, therefore it ensures that they are suitable for the training of machine learning and deep learning models (Kim et al.; 2008).

2.5 Customization and Personalization in Recommendations

Researchers have investigated many approaches to enhance the user satisfaction in recommendation systems, acknowledging the important significance of the customization and personalization. The importance of feedback from the users in recommendation systems was highlighted by (Adomavicius and Tuzhilin; 2005), who highlighted the importance of continuous learning and adaptation to evolve the user preferences and their tastes. The integration of feedback's has been explored in the studies which is conducted by (McFee et al.; 2012) as well as (Quadrana et al.; 2018). In summary, the evolution from the rule-based model algorithms to the integration of machine learning models, represents a continuous improvements to enhance precision and customization in music recommendation systems. This study aims to explore emerging areas in the field of recommendation systems.

2.6 Comparison of Reviewed Techniques in Music Recommendation System

The review of this literature on methods for music recommendation system involves a review of various elements, including the models used and evaluation metrics. Table 1 provides a comprehensive comparative analysis, presenting the discrepancies and achievements observed in various research projects.

Table 1: Comparitive Different Various Studies

Features Extracted	Model	Results	Authors
Machine Learning Model	Support Vector Machine	50.86%	(Herlocker et al.; 1999)
Machine Learning Model	Linear Regression	63.53%	(LeCun et al.; 2015)
Deep Learning Model	Content-Filtering (CNN)	70.98%	(LeCun et al.; 2015)
Deep Learning Model	RNN	85.21%	(Liang et al.; 2018)

Upon reviewing the comparison table, it becomes obvious that the research conducted by (LeCun et al.; 2015) and (Witten et al.; 2016) differentiates itself by focusing on employing machine learning and deep learning techniques to enhance music recommendations. This holds special significance for users and behavior, as they seek to enhance their decision-making skills based on their song preferences.

The results from previous researches play a crucial role in determining the development of an advanced recommendation system. This system not only understands user preferences but also effectively adjusts to the constantly evolving the digital music consumption patterns. The integration of traditional methodologies, machine learning algorithms and deep learning principles demonstrates a dedication to advancing the field while providing customers with personalized music recommendations that match with their own tastes or interests. These research purpose is to maintain the adaptability of recommendation systems by adapting to the evolving nature user preferences according to the period of time. The implementation of these approaches which effectively supports the primary objective is providing personalized and continuously enhanced music recommendations.

3 Methodology

This study aims to develop a novel Music Recommendation System by employing an extensive methodology where the process depicts in Figure 1. The primary objective of our study is to develop a system that not only offers highly accurate and customized music recommendations, but also investigates several machine learning methods to assess their efficacy in this particular domain.

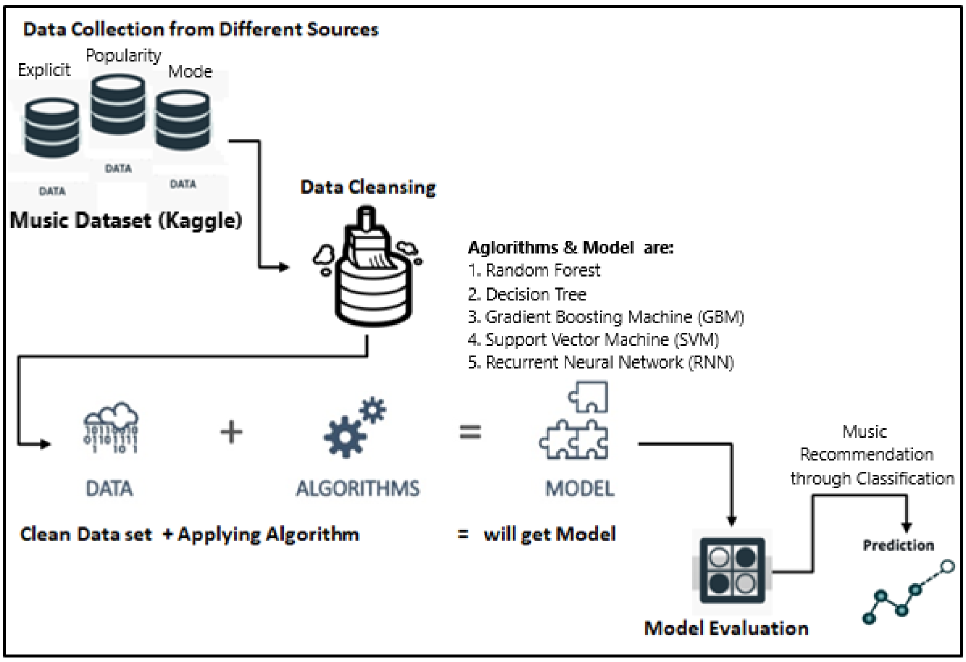


Figure 1: Implementation Workflow of Machine Learning & Deep Learning (Schedl et al.; 2021)

The methods that were chosen are Random Forest, Decision Tree, Gradient Boosting, Support Vector Machine (SVM) and Recurrent Neural Network (RNN), respectively. Naive Bayes was also an option. These algorithms have been shown to be useful in a range of contexts, which is one of the reasons why they are a popular choice for use in music recommendation. The objective in this project is focused on the creation of specific recommendations for individual users, based on their explicit, mode, and popularity of thier preferences.

3.1 Data Acquisition

In this research, we aim to use music dataset that was obtained via Kaggle, a popular platform for data science competitions and datasets. It is presented in the form of a CSV file, including a wide range of parameters that are linked to songs. The Pandas library is employed to effectively manage and manipulate the given dataset.
Dataset Link: `https://www.kaggle.com/datasets/vatsalmavani/spotify-dataset`

In order to facilitate analysis and music recommendation, the dataset contains representations of multiple features associated with songs. The dataset consists of a variety of essential properties, including the following Table 2:

Table 2: Description of Parameters in the Music Track Dataset

Column Name	**Description**
`valence`	Positivity or happiness of the track (0.0 to 1.0)
`year`	Release year of the music track
`acousticness`	Level of acoustic sound in the track (0.0 to 1.0)
`artists`	Names of the artists who performed or contributed to the track
`danceability`	Suitability of the track for dancing (0.0 to 1.0)
`duration_ms`	Duration of the track in milliseconds
`energy`	Energy level of the track (0.0 to 1.0)
`explicit`	Indication of explicit or mature content (0 or 1)
`id`	Unique identifier for the track
`instrumentalness`	Proportion of instrumental music in the track (0.0 to 1.0)
`key`	Musical key of the track
`liveness`	Indicates if the track was recorded with a live audience (0.0 to 1.0)
`loudness`	Overall loudness of the track in decibels (dB)
`mode`	Modality of the track (major or minor)
`name`	Name or title of the music track
`popularity`	Popularity of the track (numerical value)
`release_date`	Date on which the track was released
`speechiness`	Presence of spoken words or speech in the track (0.0 to 1.0)
`tempo`	Tempo of the track in beats per minute (BPM)

3.2 Data Preprocessing

The process of data preparation holds significant importance in the analysis stage, as it includes the essential tasks of cleaning and transforming the dataset in order to improve its ability to be used for the purpose of modeling. This section provides a in depth exploration and understanding for each step undertaken to assuse the quality and dependability of the data to be utilize in the music recommendation system.

Key Steps in Data Preprocessing:

- Data cleaning is the process of detecting and eliminating the inaccuracies or inconsistencies within the dataset, including but not limited to the presence of missing values, duplicate entries, and incorrect data points where the missing values are going to be checked by "data.isna().sum()" function to get the sum of missing values and then if any missing values and the duplicated row get also dropped by the "data.dropna(axis=1, how='all') & data.drop_duplicates()" function.
- Data transformation is known to be the process of transforming the dataset into a format that is suitable for analysis or modelling approaches. This may include the music data points to preprocessing techniques such as adding the new feature attributes through the ".groupby()" function and the numerical values to transform them and encoding of categorical variables with the "LabelEncoder()" comes in feature engineering one of the popular used technique.

3.3 Exploratory Data Analysis (EDA)

The method of Exploratory Data Analysis (EDA) upholds the importance within their field of statistical analysis. It involves a comprehensive review and brief overview of data sets, with the objective of obtaining useful insights, identifying patterns, and revealing hidden relationships to understand the dataset very clearly. The main objective is to collect the a comprehensive understanding of the properties, trends, and distributions of the music track track before integrate it or using in modeling or hypothesis testing.

Descriptive Statistics: Measures of dataframe, including the mean, median, and mode, as well as the measures of dispersion, including variance and standard deviation, for the numerical variables throughout the dataset is get find out by "data.describe()" function technique. Use frequency tables and cross-tabulations to analyze categorical data.

Data Visualization : Histograms, box plots, and density plots are commonly employed in order to gain insights into the distribution patterns of numerical data. Scatter plots, correlation matrices, and parallel coordinate plots are commonly employed in data visualization to illustrate relationships between variables.

3.4 Model Selection

Our Music Recommendation System incorporates a range of machine learning models into its architecture: Random Forest, Gradient Boosting, Support Vector Machine (SVM), and Recurrent Neural Network (RNN).

3.4.1 Random Forest

The Random Forest (Hoffmann et al.; 2014) method is an ensemble learning approach that involves the construction of many decision trees during the training phase. The final output of the Random Forest model is determined by either selecting the class that appears most frequently among the individual trees (in the case of classification tasks) or calculating the aver- age prediction of the individual trees (in the case of regression tasks). The constructed "forest" consists of decision trees, with each tree being trained on a randomly selected subset of the training data.

3.4.2 Decision Tree

Decision trees (Van den Oord et al.; 2013) is the popular machine learning algorithm which is also used for both classification and regression tasks. The main idea behind the decision tree is that it recursively split the data based on the features, creating a tree-like structure where each internal node represents a decision based on a features, each branch represents it the possible results of that decision, and each leaf node demonstrate the final prediction or class.

3.4.3 Gradient Boosting

Gradient Boosting (Witten et al.; 2016) is an ensemble learning technique which the strong predictive model by combining the predictions of multiple weak models, like decision trees. It's an Iteration type algorithm which reduces a loss function by adding weak learners in a phase wise manner. The main process is to train the new model from the residual errors of the current ensemble.

3.4.4 Support Vector Machine (SVM)

Support Vector Machines (SVM) (Schedl et al.; 2021) is a supervised machine learning model algorithm which is used for classification as well as for the regression. The main objective of SVM is to find the hyperplane whom are best separates the data into different classes.

3.4.5 Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) (LeCun et al.; 2015) is a type of artificial neural network which is designed for sequential data processing task. This neural network is particularly well-suited for the tasks such as time series prediction, language modeling, and sequence-to-sequence tasks. RNNs have relationships that form the directed cycles, and allowing them to preserve the hidden state which gains the information about the previous inputs in the sequence. Here we applies the Hyperparameter tunning process, to enhance the model by get differnt differnt configurations here we have two main types of hyperparameter tunning are Gridsearch and RandomSearch, where both are used to find the appropriate configurations where the models are performing good. In general, this is a good effective approaches to identify the best configurations which impacts the accuracy for the predictive models.

3.5 Feature Selection/Data Splitting

Feature selection and data splitting are the important and essential components in the machine learning process. Therefore they have the separate processes, where they are interconnected to each other and have the important roles while building the models that are both effective and generalizable.

3.6 Model Training

The process of model training is providing the machine learning algorithm with labeled data, enabling it to acquire knowledge of the fundamental patterns and relationships present in the data. The method performs an iterative process to optimize its parameters by minimizing a loss function. This loss function quantifies the difference between the model's predictions and the actual target values.

3.7 Model Evaluation

The evaluation of a model includes an evaluation of its performance on data that it has not been previously exposed to, so providing an indication of its ability to apply trained model to real-world situations. The process involves multiple sequential sections:

- The evaluation criteria is of greatest significance when evaluating the performance of the model. Commonly employed measures in several domains encompass accuracy, precision, recall, F1-score, and confusion matrix.

Table 3: Description of Classification Metrics and Confusion Matrix

Metric	Description
Accuracy	The accuracy metric measures the overall correctness of a model by calculating the ratio of the number of correct predictions to the total number of predictions. It is given by: $Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$
Precision	Precision is a metric that evaluates the accuracy of positive predictions made by a model. It is calculated as the ratio of true positives to the sum of true positives and false positives: $Precision = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$
Recall	Recall, also known as sensitivity or true positive rate, measures the ability of a model to capture all relevant instances. It is defined as the ratio of true positives to the sum of true positives and false negatives: $Recall = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$
F1 Score	The F1 Score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is calculated using the formula: $F1\ Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}$
Confusion Matrix	The confusion matrix is a table that summarizes the performance of a classification algorithm. It includes four values: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

- The test set, which is a subset of data that is not utilized during the training process, is used to assess the ability of the model to extrapolate. The performance of the model on the test set provides an impartial evaluation of its performance in real-world scenarios.

3.8 Model Comparison

In addition, the investigation of ensemble approaches involves the combination of multiple models in order to utilize the distinctive strengths of every single model. This methodology frequently results in enhanced overall performance and adaptability, therefore offsetting the constraints of individual models.

The continuous process of the model comparison stage enables the inclusion of changes and modifications based on the findings. The goal is not just to determine the extremely proposed effective model, but it also provide an in-depth understanding of the particular situations and the contexts in which each model demonstrates outstanding results or overcome from the limitations. The in-depth investigation of this analysis provides the foundation for making well-informed decisions when selecting the music recommendation model which is to be utilized.

The final phase of our research attempt which would be resulted in the development of the final music recommendation model. During this stage, we utilize the combined and the average the all predictive capabilities of multiple models, such as Random Forest, Decision Tree, Gradient Boosting, Support Vector Machine (SVM), and Recurrent Neural Network (RNN). The methodology involves the combining the individual predictions generated by each model to make the system model more robust and comprehensive proposal.

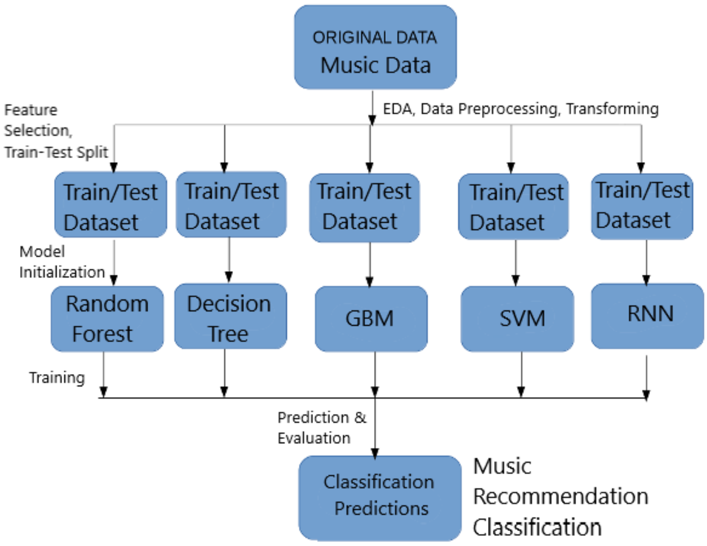


Figure 2: Music Recommendation Process for all Model Predictions (Liang et al.; 2018)

In conclusion, the development of the final model which includes the integration of predictions generated using multiple machine learning algorithms, which are Random Forest, Decision Tree, Gradient Boosting, Support Vector Machines (SVM), and Recurrent Neural Networks (RNN), via an averaging the all models generated prediction method. The combination of various predictive abilities results in an in-depth and adaptable music recommendation system classification, which is capable of providing customers customized and captivating music selections to best preferences.

4 Design Specification

The Research for music recommendation system where the project Design Process, demonstrated in Figure 3, relates to the classification of a Music Recommendation System using a integration of Machine Learning and Deep Neural Networks models. It includes two tiers: Tier 1, indicating the Presentation Layer that how the results is going to be used, and Tier 2, representing the Business Logic Tier how the task is performed. This process involves that the analysis of data collection, the selection of suitable models, the training of selected models, and the evaluation of results. The results are then conveyed in the Presentation Tier through the means of visualization and the distribution of the insights to make it accessible to the users preferences.

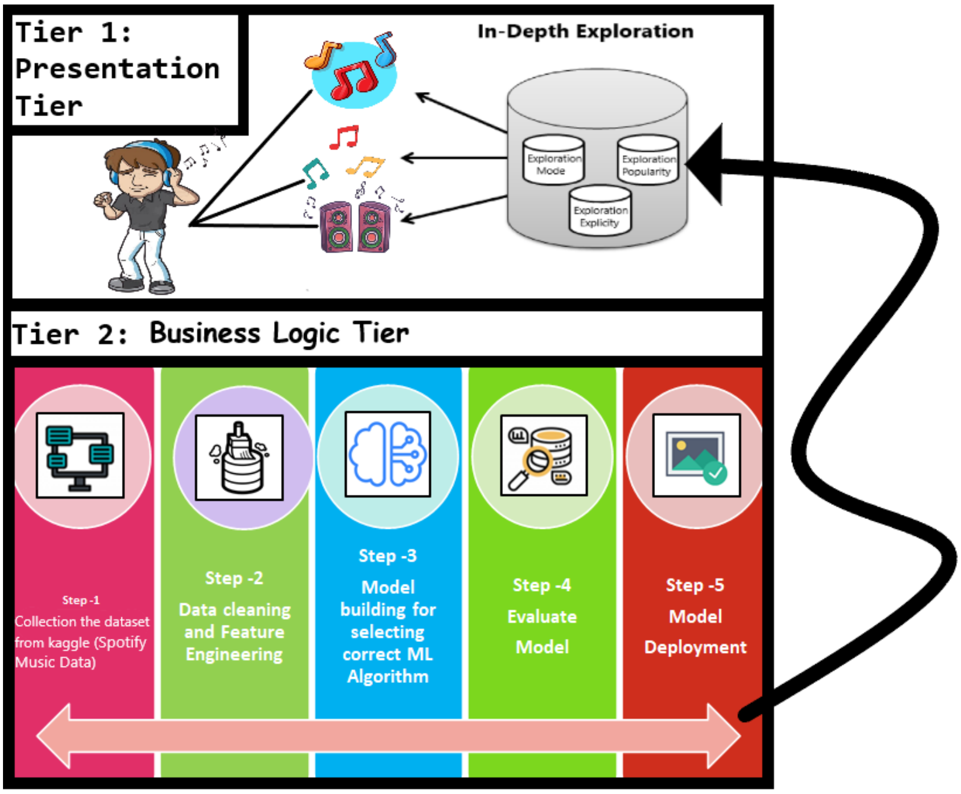


Figure 3: Project Design process of Music Recommendation Classification System

5 Implementation

The aim of this implementation reveal is to present a comprehensive overview of the procedures accompanied in the development and evaluation of models for music recommendation classification. The primary emphasis of these models is on considering the explicitness, mode, and popularity of songs as key factors in the recommendation process. The report will outline the specific steps taken to achieve this objective, without introducing any additional information beyond what was provided. In this analysis, we will provide a comprehensive breakdown of each section:

5.1 Data Pre-Processing Music Recommendation:

The implementation process was initiated by loading the music dataset from the kaggle through the dataset source link. The utilization of the Pandas library played a crucial role in this particular phase of the research, as it facilitated the creation of a comprehensive DataFrame where it is preprocessed by removing any missing values, eliminating the duplicated rows and creating a new feature attribute with the name of artists which contains only the details of the artist music tracks are depicted in Figure 4.

```
# Remove columns with all NaN values if any lefted
song_dataFrame = song_dataFrame.dropna(axis=1, how='all')
```

```
# Remove any duplicate rows
song_dataFrame = song_dataFrame.drop_duplicates()
```

Figure 4: Remove the Missing Values and Duplicate Rows

5.2 Data Exploration:

Performing a thorough examination of the dataset was important to acquire an in-depth understanding of its fundamental characteristics and features. The initial phase involved the first five rows of the dataset, offering an overview of its contents. Moreover, a comprehensive investigation was carried out to look into the form, fundamental attributes, and statistical aspects of the dataset, thus creating a solid foundation for subsequent analyses.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 170653 entries, 0 to 170652
Data columns (total 19 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   valence           170653 non-null  float64
 1   year              170653 non-null  int64
 2   acousticness      170653 non-null  float64
 3   artists           170653 non-null  object
 4   danceability      170653 non-null  float64
 5   duration_ms       170653 non-null  int64
 6   energy            170653 non-null  float64
 7   explicit          170653 non-null  int64
 8   id                170653 non-null  object
 9   instrumentalness  170653 non-null  float64
 10  key               170653 non-null  int64
 11  liveness          170653 non-null  float64
 12  loudness          170653 non-null  float64
 13  mode              170653 non-null  int64
 14  name              170653 non-null  object
 15  popularity        170653 non-null  int64
 16  release_date      170653 non-null  object
 17  speechiness       170653 non-null  float64
 18  tempo             170653 non-null  float64
dtypes: float64(9), int64(6), object(4)
memory usage: 24.7+ MB
```

Figure 5: Basic Information About the Dataframe

In Figure 5, in-depth overview of the dataset Basic Information and statistical characteristics associated with the music dataset.

Table 4: Descriptive statistics of Music Track Dataset (PART 1)

	Valence	Year	Acousticness	Danceability	Duration (ms)	Energy	Explicit
Count	170653.000	170653.000	170653.000	170653.000	1.70653e+05	170653.000	170653.000
Mean	0.528587	1976.787241	0.502115	0.537396	2.30948e+05	0.482389	0.084575
Std	0.263171	25.917853	0.376032	0.176138	1.26118e+05	0.267646	0.278249
(ms)	0.000000	1921.000000	0.000000	0.000000	5.108e+03	0.000000	0.000000
25%	0.317000	1956.000000	0.102000	0.415000	1.69827e+05	0.255000	0.000000
50%	0.540000	1977.000000	0.516000	0.548000	2.07467e+05	0.471000	0.000000
75%	0.747000	1999.000000	0.893000	0.668000	2.624e+05	0.703000	0.000000
Max	1.000000	2020.000000	0.996000	0.988000	5.4035e+06	1.000000	1.000000

Table 5: Descriptive statistics of Music Track Dataset (PART 2)

	Instrumentalness	Key	Liveness	Loudness	Mode	Popularity	Speechiness	Tempo
Count	170653.000	170653.000	170653.000	170653.000	170653.000	170653.000	170653.000	170653.000
Mean	0.167010	5.199844	0.205839	-11.467990	0.706902	31.431794	0.098393	116.861590
Std	0.313475	3.515094	0.174805	5.697943	0.455184	21.826615	0.162740	30.708533
Min	0.000000	0.000000	0.000000	-60.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	0.098800	-14.615000	0.000000	11.000000	0.034900	93.421000
50%	0.000216	5.000000	0.136000	-10.580000	1.000000	33.000000	0.045000	114.729000
75%	0.102000	8.000000	0.261000	-7.183000	1.000000	48.000000	0.075600	135.537000
Max	1.000000	11.000000	1.000000	3.855000	1.000000	100.000000	0.970000	243.507000

The statistical aspects of the dataset offer valuable information on the average, range, and spread of the different musical features. They aid in summarizing and comprehending the attributes of the music data else follow the Table 4 & 5 for other major descriptive statistics for numerical variables.

5.3 Exploratory Data Analysis (EDA):

Exploratory data analysis (EDA) was utilized to represent the patterns and relationships within the data in the form of visualization. The analysis involves several types of visualizations to explore the dataset. These included, the distribution of release years music which was analyses using mean and median lines. A pie chart was used to represent the explicit and non-explicit songs which is demonstrated in Figure 6.

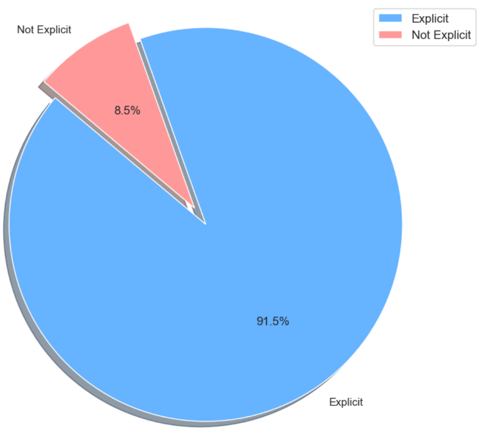


Figure 6: Distribution of Explicit/Non-Explicity Songs

This above figure tells us about that the dataset contains the songs which are related to explicit are around 91.5% percent and for non-explicit types of songs are represented to 8.5%. Where the below image repsents the top 10 artists where there music tracks are most listened songs is represented in Figure 7.

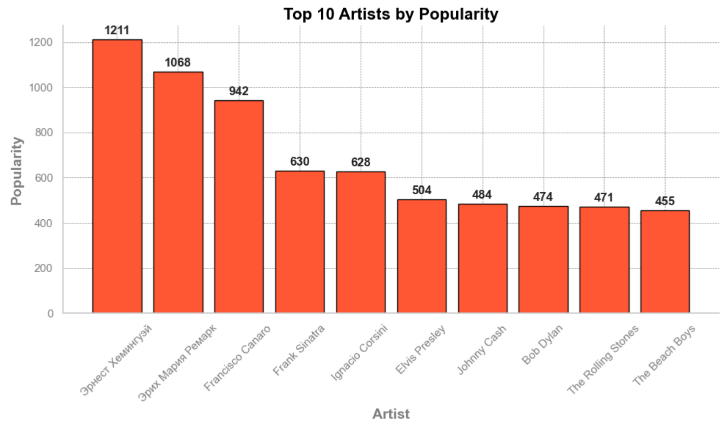


Figure 7: Distribution of Top 10 Artists by their Popularity

5.4 Initialize & Train the Models:

The main component of the implementation process revolved around the creation of various models three perspective role by Explicit, Mode and Popularity of Music:

- Random Forest Classifier
- Decision Tree Classifier
- Gradient Boosting Classifier
- Support Vector Machine (SVM)
- Recurrent Neural Network (RNN)

After the establishment of the training data, I proceeded to conduct training for all the models for all three roles includes for Explicity, Mode and Popularity. The implementation of a new class within the RNN model allowed for the calculation of feature importances during training using the Gradient times Input (GradInput) method.

5.5 Evaluate the Models:

The performance of each model was assessed by utilizing the test data and computing accuracy scores. According to the research findings, the Recurrent Neural Network, Gradient Boosting and Random Forest model, demonstrated the highest accuracy rate. For major role these techniques and methods are performing outstanding for classifying the music features. The implemented models in this research study offer a wide range of approaches for music recommendation, focusing on the explicitness, Mode and Popularity of music. In the study conducted, it was observed that the Recurrent Neural Network, Random Forest and Gradient Boosting models exhibited superior performance in terms of accuracy compared to the other models evaluated. The potential for enhancing the performance of these models lies in further fine-tuning and optimization of hyperparameters. The inclusion of feature importance analysis in the RNN model enhances the interpretability of the recommendations by providing an additional layer of insight.

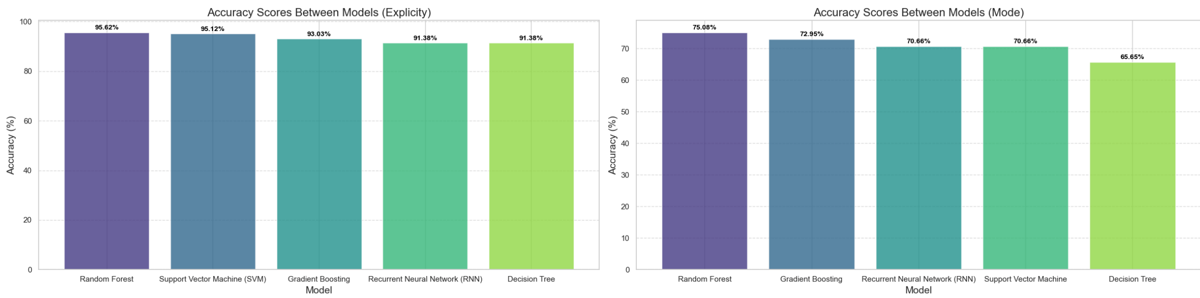
6 Evaluation

The evaluation of the music recommendation classification system provides valuable insights into the performance of different models across various target variables includes by Explicit, Mode and Popularity of Music. The following are key observations and considerations:

6.1 Model Performance by Target Variable:

6.1.1 Explicitness:

- Random Forest and Gradient Boosting models have higher accuracy rates compared to SVM, Decision Tree, and RNN, with accuracy rates of 95.62% and 95.12%, respectively which is depicted in Figure 8a.
- The Decision algorithm faces difficulties in accurately forecasting explicitness, potentially because of the imbalance distribution of classes or the inherent complexity of the problem.
- The RNN model, although it attains similar levels of accuracy, exhibits limitations in terms of precision and recall for class 0.



(a) Accuracy Scores for Explicity

(b) Accuracy Scores for Mode

Figure 8: Comparison of Accuracy Scores Between Models

6.1.2 Mode:

- Mode prediction has comparable patterns, whereas Random Forest and Gradient Boosting demonstrate superior accuracy rates of 75.08% and 72.95%, respectively where it is represented in Figure 8b.
- Decision Tree continues to encounter challenges, which indicate a persistent difficulty in specific classification scenarios.

6.1.3 Popularity:

- Random Forest and Gradient Boosting models demonstrate outstanding results in predicting popularity, attaining impressive accuracy rates of 82.73% and 82.55% respectively. The illustration of these accuracies is demonstrated in Figure 9
- SVM & RNN, exhibits limitations in predicting minority classes, indicating the presence of potential bias in its predictions.

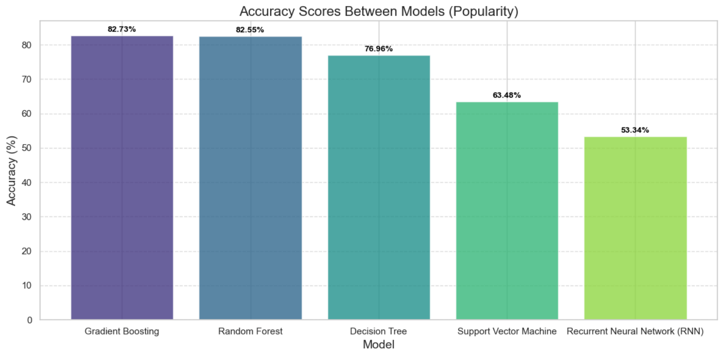


Figure 9: Differentiate the Accuracy Scores Between Models for Popularity

6.2 Average Model Performance:

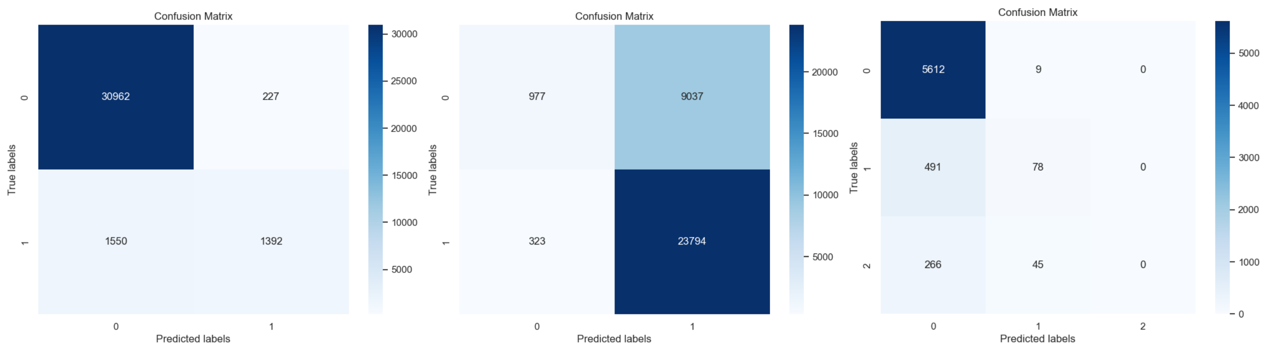
Table 6: Comparative Different Accuracies

Preferences	Accuracies
Explicitness	94.79%
Mode	72.58%
Popularity	87.52%

- The average accuracy across all target variables is 94.79% for the explicitness of the song, on addition the investigation for mode preferences the accuracy depicted at 72.58% and for the last popularity of the song preferences is emphasised at 87.52%, which demonstrates the resilience of the models.
- The precision, recall, and F1-score for class 1 (positive class) are very high, indicating the accuracy in predicting the majority class.

6.3 Discussion:

The evaluation of the music recommendation classification system after the evaluation which provides the valuable insights into the effectiveness of different models for different target variables. The Random Forest and Gradient Boosting models regularly displays the higher accuracy, where they are solid potential options for music classification recommendation. The actuality is that they can accurately classify the level of explicitness, mode, and popularity which indicates that they can easily adjust to the different user preferences to their accuracy's are depicted in Table 6. The Support Vector Machine



(a) Explicity (b) Mode (c) Popularity

Figure 10: Confusion Matrix of Average Models

(SVM) encounters with difficulties, especially when dealing with the imbalanced classes. This suggests that it may have limitations in its adaptability for specific classification tasks. This highlighted the importance of introducing the additional step to the hyper-parameters of SVM and which considers the potential tweaks to class weights in order to enhance its projections capabilities.

The Recurrent Neural Network (RNN) model, while it achieves the high accuracy for the user preference of explicitness of the songs to around 91.38% , but it poses difficulties while performing the predictions for minority classes of other preference for popularity of songs to 53.4%. To enhance the overall performance and interpretability of RNN architecture, it is possible to perform the future investigations into the feature engineering. The actual characteristics of the target variable provide the insight into the small variations in the models' performance. Random Forest and Gradient Boosting outperform SVM in predicting explicitness, especially when users' preferences for non-explicit content are important. In the task of forecasting the musical modes based on users' preferences for major or minor mains, Random Forest and Gradient Boosting models provide outstanding performance when compared to other models. When it comes to forecasting the popularity, Random Forest and Gradient Boosting are successful in gathering the user preferences. However, SVM has faced the difficulties in predicting less popular songs.

The music recommendation system that is being analyzed performs well in different preference categories where as approach represents that its has the overall effectiveness by the average all the model's performance. The accuracy for explicit user preferences is 94.79%, demonstrating the system's ability to meet precisely stated musical preferences. Mode-based recommendations have a moderate accuracy of 72.58%, but popularity-based recommendations perform exceptionally well with an accuracy of 87.52%. The feature-extracted models further contribute to the system's effectiveness. The accuracy rate of Support Vector Machine (SVM) was found to be lower with 50.86%, while linear regression and content-filtering (CNN) models offer moderate accuracy rates of 63.53% and 70.98%, respectively, as shown in earlier studies results. The Recurrent Neural Network (RNN) is the most accurate model with an impressive accuracy of 85.21%, especially when it comes to recognizing the sequential patterns for music recommendations (Liang et al.; 2018). The precision, recall, and F1-score measures for the majority class (class 1) represents a significant level of accuracy in forecasting the most common events. Class imbalance requires the diligent preprocessing and the model training. Resampling the approaches or adjusting the class weights can be used to handle those imbalances, specifically in terms of explicitness and mode forecasting predictions. To further optimize the performance of the model, it is recommended to look on fine-tune the hyper- parameters, studying on advanced feature engineering approaches, and exploring the alternate deep learning architectures. The objective of these attempts is to augment their interpretability of the model and enhance the overall performance of the system.

These findings demonstrate the system's scalability to diverse recommendation scenarios and highlight the advantages and disadvantages of different feature extraction approaches, providing valuable insights for future improvements.

In conclusion, the evaluation provides us with a comprehensive analysis of the model's potential strength and opportunities for modification as well as the enhancements in the music recommendation classification system. The identified insights provides as a roadmap for future research and the development, aiming to create a music recommendation experience that is both personalized and beneficial for users.

7 Conclusion and Future Work

7.1 Conclusion:

The research has been conducted a in-depth investigation for the classification of music recommendations, assessing the effectiveness for several models which has implemented in predicting the explicitness, mode, and popularity of songs which is based on the user preferences. The results highlight the strength of Random Forest and Gradient Boosting models in providing precise recommendations for accuracy around 95.62% and 95.12% for the preference of explicitness of the song, which boards to a wide range of user preferences. Therefore, the challenges faced by the Support Vector Machine (SVM) and the problems related to interpretability of the Recurrent Neural Network (RNN) model require the additional research and the improvement because it lacks the understanding of the parameters sequentially. The research has provided the useful insights into the potential strength and boundary limitations of several models, and discovered that possibilities for improvements in the music classification recommendation system. The successful predictions after averaging all the model's prediction performance for the task of music recommendation system of different preferences to the explicitness of the song at 94.79%, mode of the song at 72.58%, and popularity of that particular music track at 87.52% provide a foundation and robust models investigation for enhancing the user experience.

7.2 Future Work:

Expanding on the current study, where there are several possibilities for future investigations become obvious. First is the enhancing the hyperparameters across the models, investigation required feature engineering approaches, and handling of the class imbalance through the resampling methods which all are essential measures to enhance the model performance. Examining the optimization of SVM parameters is important too to address the difficulties in accurately predicting particular classes. The RNN model's interpretability is continues to be the crucial phase that requires the enhancement. Future research should be focused on while conducting further extensive investigations into the architecture of Recurrent Neural Networks (RNNs) and then the process of feature engineering. This will leads to improving the interpretability and prediction abilities of RNNs, particularly when dealing with minor types of classes. Demonstrating the different machine learning and deep learning architectures and combined approaches has the strength to provide the further insights and improvements to the music classification recommendation system. Therefore, the integration of user feedback and their preferences during the model training process, where the recommendations can be further customized to individual needs.

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