Machine Learning Based Music Genre Classification on Spotify Data

A PROJECT REPORT

Submitted by

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TABLE OF CONTENTS

S. NO.	TITLE	PAGE NO.
1	**1. INTRODUCTION** 1.1 Overview 1.2 Purpose	 **3** **3**
2	**2. LITERATURE SURVEY** 2.1 Existing Problem 2.2 Proposed Solution	 **4** **4**
3	**3. THEORITICAL ANALYSIS** 3.1 Block Diagram 3.2 Hardware / Software Designing	 **5** **6**
4	**4. EXPERIMENTAL INVESTIGATIONS**	**7-8**
5	**5. FLOWCHART**	**8**
6	**6. RESULT**	**9-10**
7	**7. ADVANTAGES AND DISADVANTAGES**	**11**
8	**8. APPLICATIONS**	**12**
9	**9. CONCLUSION**	**12-13**
10	**10. FUTURE SCOPE**	**13**
11	**11. BIBILOGRAPHY**	**14**

1. INTRODUCTION

1.1 Overview

Music is like a mirror, and it tells people a lot about who you are and what you care about, whether you like it or not. We love to say “you are what you stream”.

Companies nowadays use music classification, either to be able to place recommendations to their customers (such as Spotify, Soundcloud) or simply as a product (for example Shazam). Determining music genres is the first step in that direction.

Machine Learning techniques have proved to be quite successful in extracting trends and patterns from a large pool of data. The same principles are applied in Music Analysis also.

1.2 Purpose

The purpose of this project is to develop a machine learning model that can accurately classify music genres. This model can be used for a variety of purposes, including music recommendation, music discovery, music research, and music production.

The development of this model can also contribute to the broader field of machine learning. The project aims to identify the most effective approach for music genre classification and provide insights into the strengths and limitations of different algorithms.

This project seeks to contribute to the advancement of music genre classification techniques and facilitate the development of intelligent music recommendation systems that cater to individual preferences and enhance the enjoyment and discovery of music for users worldwide.

2. LITERATURE SURVEY

2.1 Existing Problem

Music genre classification is a challenging task due to the subjective nature of genres and the inherent complexity of music. Different genres often share common elements, making it difficult to accurately categorize music tracks. Additionally, the dynamic nature of music and the emergence of new sub-genres pose further challenges in developing robust classification systems.

Many existing methods rely on extracting a set of audio features from music tracks and using these features as inputs to classification algorithms. Classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests are applied to map the extracted features to genre labels.

Deep learning has gained significant attention in music genre classification. Convolutional Neural Networks (CNNs) have been used to automatically learn hierarchical representations of audio data. Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have been applied to capture temporal dependencies in music sequences.

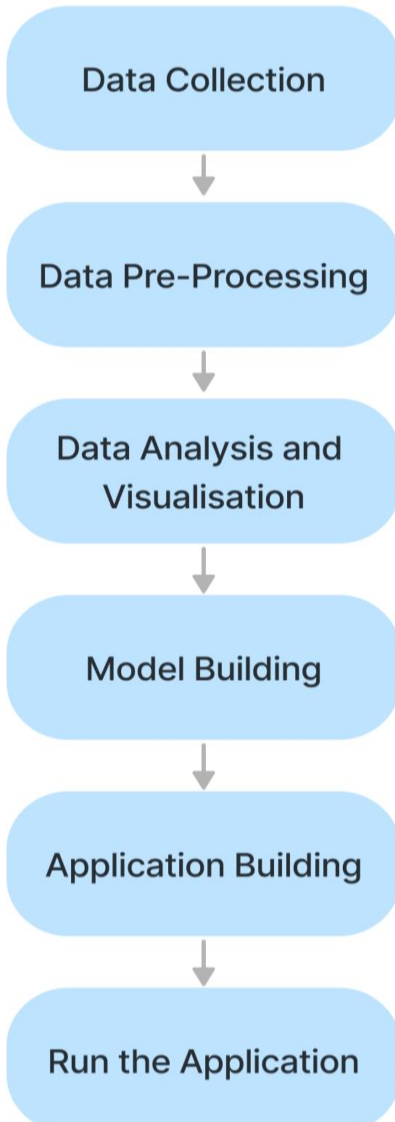
Ensemble Methods: Ensemble methods involve combining multiple classification models to make more accurate predictions. Bagging methods, such as Random Forests, create an ensemble of decision trees trained on different subsets of the data. Boosting methods, such as AdaBoost and Gradient Boosting, iteratively train weak classifiers to improve their collective performance.

2.2 Proposed Solution

By doing this project we classify if it is a regression or a classification kind of problem and also able to analysis or get insights into data the. In this project, we propose utilizing a bagging classifier as the method for music genre classification based on Spotify data. Bagging, short for bootstrap aggregating, is an ensemble learning technique that combines multiple classifiers to make more accurate predictions. Each base classifier independently makes predictions, and the final prediction is obtained through majority voting or averaging the predictions of all base classifiers. The bagging approach reduces the risk of overfitting and helps handle the complexities and uncertainties inherent in music genre classification.

3. THEORITICAL ANALYSIS

3.1 Block Diagram



3.2 Hardware / Software designing

<u>Hardware Requirements:</u>

Processor	**:** Intel core i3 or above
RAM	**:** Minimum 225MB or more
Hard Disk	**:** Minimum 1 GB of space
CPU	**:** 2 GHz or faster
Architecture	**:** 32-bit or 64-bit
Input Device	**:** Keyboard, mouse
Output Device	**:** Screens of Monitor or a Laptop

<u>Software Requirements:</u>

Operating System	**:** Windows and Linux and macOS
Language	**:** Python , HTML
IDE	**:** VSCode
Software Use	**:** Anaconda navigator

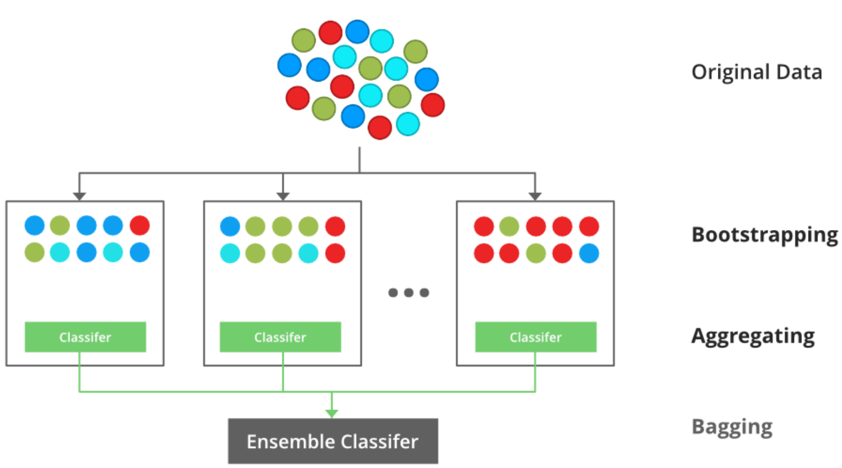
4. EXPERIMENTAL INVESTIGATIONS

The performance of the bagging classifier was compared with other existing approaches for music genre classification, such as feature-based methods, deep learning models, and ensemble techniques. This analysis aimed to evaluate the accuracy, robustness, and efficiency of the bagging classifier in comparison to alternative methods. These analyses and investigations aimed to provide a comprehensive understanding of the proposed solution's performance, limitations, and suitability for music genre classification on Spotify data. The findings helped in refining the solution, optimizing its parameters, and making informed decisions regarding feature selection, hyperparameter tuning, and evaluation metrics.

- Data cleaning and preprocessing are critical processes in preparing data for modeling and can significantly influence model performance.
- Early stopping approaches, such as monitoring validation loss and accuracy, can help to prevent model overfitting.
- We should increase the dataset size, add features, and experiment with alternative methods and hyperparameters to enhance the classification model's performance.

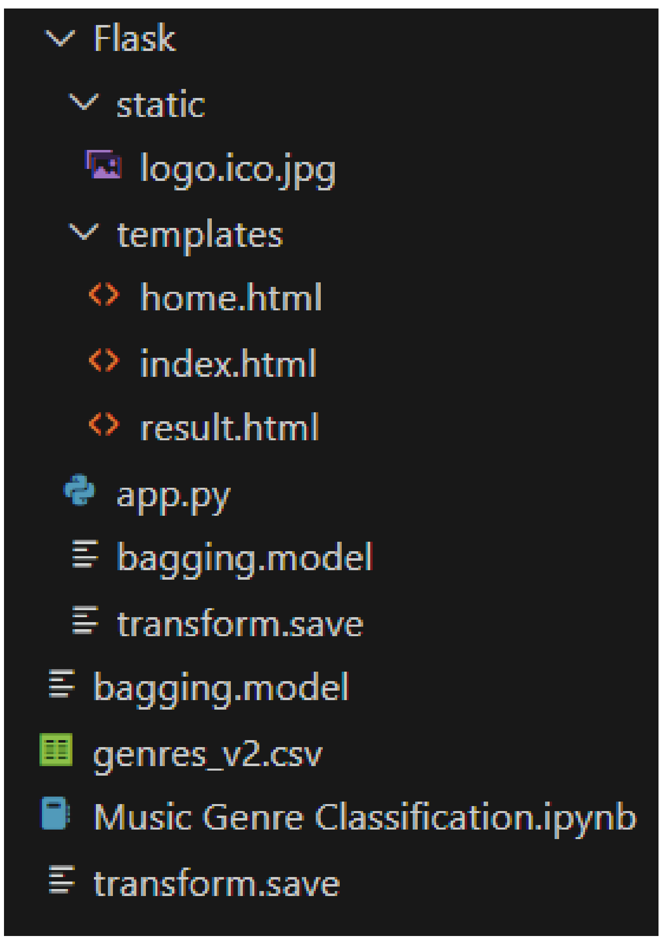
Bagging Classifier:

Bagging, also known as Bootstrap aggregating, is an ensemble learning technique that helps to improve the performance and accuracy of machine learning algorithms. It is used to deal with bias-variance trade-offs and reduces the variance of a prediction model.



- Consider there are n observations and m features in the training set. You need to select a random sample from the training dataset without replacement
- A subset of m features is chosen randomly to create a model using sample observations
- The feature offering the best split out of the lot is used to split the nodes
- The tree is grown, so you have the best root nodes

5. FLOWCHART

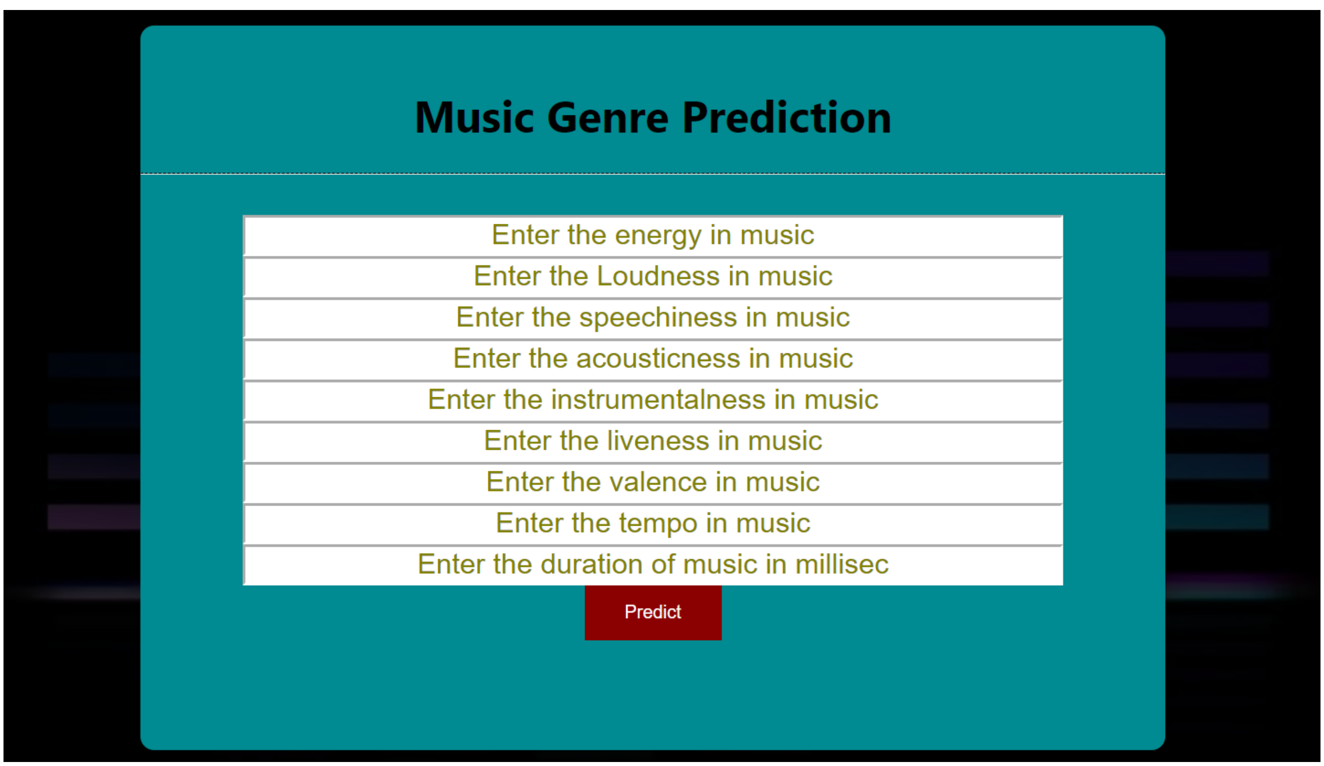


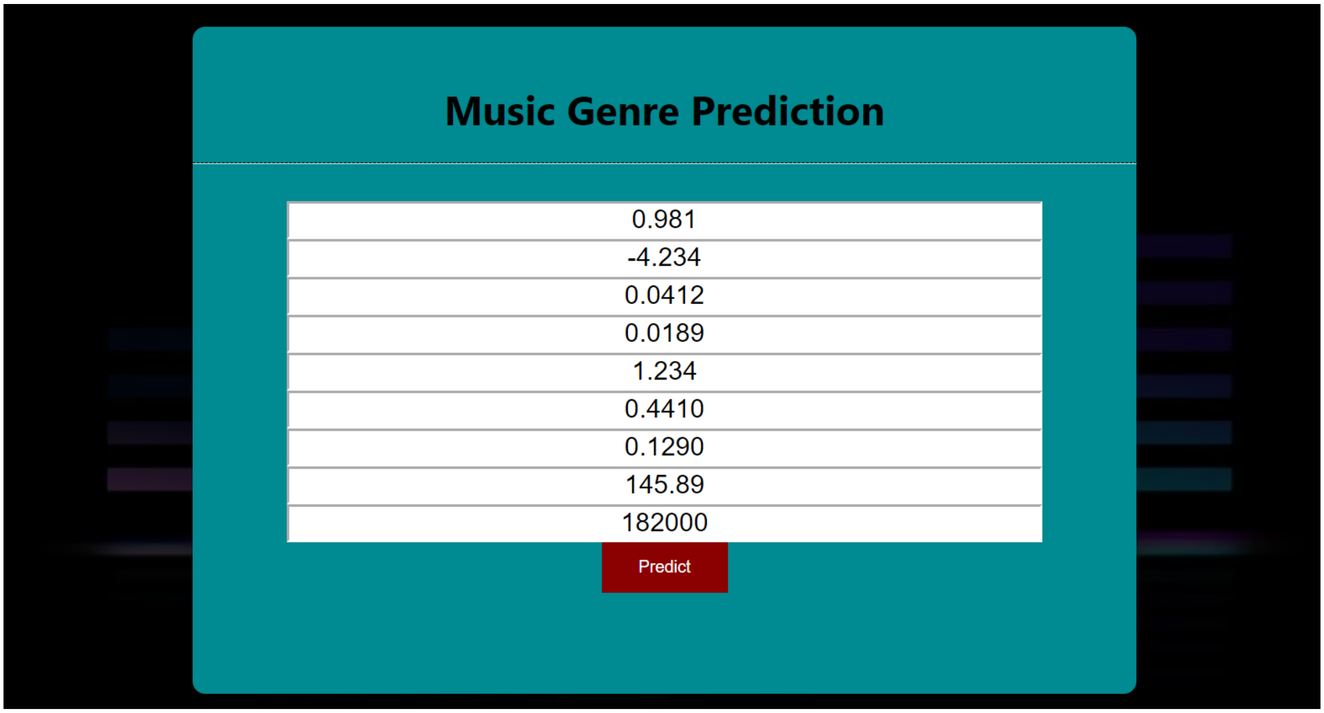
6. RESULT

For Getting Music Genre prediction for Spotify the user will click on Prediction.

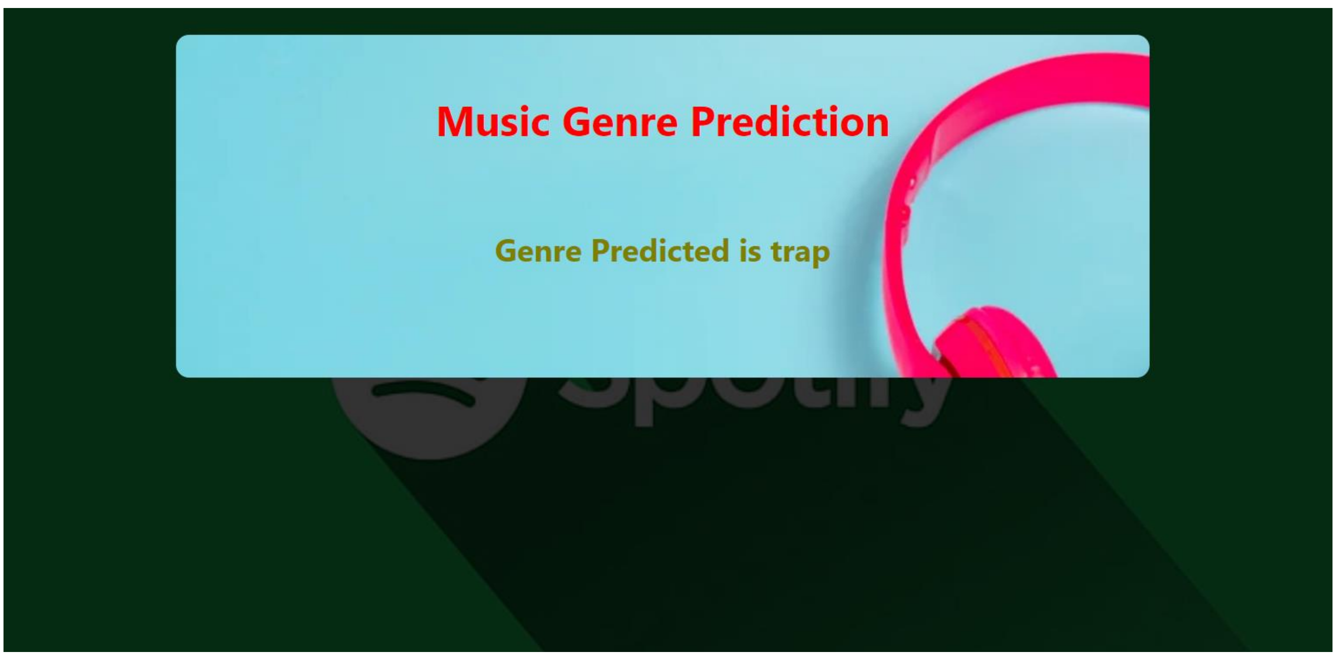
- If the user click on the Home button, it will refresh the home page.
- If the user click on the prediction button, it will redirect to new web page.

The user will enter here all the desired values that it wants in each field accordingly and then, check the genre prediction by clicking on Predict.





The user will get the 'Genre Predicted' as the result.



7. ADVANTAGES & DISADVANTAGES

Advantages:

- The main thing to identify and divide the audio into different features is amplitude and frequency that changes within a short span of time.
- The use of a bagging classifier can enhance the accuracy of music genre classification by combining multiple base classifiers and aggregating their predictions.
- The ensemble approach reduces the risk of overfitting and leverages the collective decision-making capabilities of the classifiers.
- The bagging classifier can effectively handle complex and non-linear relationships between audio features and music genres.
- The bagging classifier is flexible and can accommodate various base classifiers, allowing for experimentation with different algorithms and techniques. This flexibility enables the adaptation of the solution to different datasets and genre classification scenarios.

Disadvantages:

- Need for more diversity in our Dataset, primarily rap and hip-hop music on Spotify. This influenced our research and modelling in favour of specific genres. We must incorporate a wider variety of music genres into the Dataset to improve our model.
- Likelihood of human mistakes in classifying the data, which might have resulted in genre categorization discrepancies. We may utilize more sophisticated approaches, such as deep learning models, to automatically label music based on auditory attributes to address this.

8. APPLICATIONS

- **Music recommendation:** Music streaming services such as Spotify and Apple Music use music genre classification to recommend new music to users. By understanding the genres of music that a user likes, these services can suggest other songs that the user might enjoy.
- **Music discovery:** Music genre classification can also be used to help users discover new music. By identifying the genres of music that are popular in a particular region or time period, music discovery platforms can recommend songs that users might not have otherwise found.
- **Music analysis:** Music genre classification can also be used to analyze the evolution of music over time. By tracking the popularity of different genres, researchers can gain insights into the changing tastes of music listeners.
- **Music copyright:** Music genre classification can also be used to help enforce music copyrights. By identifying the genres of music that are used in a particular video or commercial, copyright holders can ensure that they are properly compensated for the use of their music.

9. CONCLUSION

In conclusion, we could categorize Spotify music genres with an accuracy of 76.55% using the bagging classifier. Given the complexity and subjectivity in defining music genres, this is a reasonable level of accuracy. Yet, there is always an opportunity for improvement, and our analysis has a few limitations.

In this project, we have presented a solution for music genre classification based on Spotify data using a bagging classifier. The aim was to improve the accuracy and robustness of genre classification by combining the predictions of multiple base classifiers in an ensemble.

Automatic genre classification is a difficult and problematic task that none the less has important value in terms of both pure research and commercial application. Continuing research in automatic genre classification has much to offer, as does parallel research involving other aspects of musical similarity.

Automatic genre classification performance appears to have fallen into a local maximum recently, and serious modifications to the approaches used are needed in order to realize further improvements.

The project findings contribute to the understanding of effective methods for genre classification and highlight areas for further research and development in this field. By incorporating the identified enhancements, the proposed solution can be refined and extended to achieve even higher accuracy and adaptability in classifying music genres.

10. FUTURE SCOPE

The model can be made more flexible and scalable in the future. Music genres and sub-genres are constantly evolving. To adapt to emerging genres and ensure the model's relevancy over time, incremental learning approaches or online learning techniques can be employed. This allows the model to continuously learn from new data and update its classification capabilities. By increasing the dataset size, add features, and experiment with alternative methods and hyperparameters we can enhance the classification model’s performance. Our analysis and modelling give a solid foundation for categorizing Spotify music genres, but more study and improvements are required to increase the model’s accuracy and resilience.

11. BIBILOGRAPHY

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