Music Genre Classification Using Machine Learning Through Spotify Data

An Industrial/Practical Training Report

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CERTIFICATE

This is to certify that the project report entitled **“Music Genre Classification Using Machine Learning Through Spotify Data”** is a bonafide record of work carried out by **K. Sai Saketh (20481A05C9), J. Sandhya (20481A0588), G. Radha Shalini (20481A0577), K. Haasitha (20481A05C0)** under the guidance and supervision of **Mr. G. Srikanth, M. Tech** in the partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering of Jawaharlal Nehru Technological University Kakinada, Kakinada** during the academic year 2022-23.

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We are highly impressed with the work that they have done and commend them on their quick grasping skills. They have shown good intent to learn and have put the knowledge gained into application in the form of this project. We appreciate the hard work and commitment shown by them.

We, hereby approve that this document is completely checked and accepted by SmartBridge Technical Team. Its been an absolute pleasure to educate and mentor these students. We hope that this document will also serve as a Letter of Recommendation, to whomover applied.

We wish them success in all future endeavors and a great career ahead.

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ABSTRACT

This project is a harmonious fusion of technology and music, leveraging machine learning and Spotify data to revolutionize the music streaming experience. The goal was to create a robust and accurate music genre classification system, and through meticulous data collection, preprocessing, and model training, this endeavor has achieved remarkable results. The classification model accurately categorizes songs into their respective genres, leading to a more personalized music discovery journey for users. This project not only enhances the user experience but also contributes to data-driven decision-making within the music industry, offering valuable insights into music trends and preferences. It embodies the symphony of art and technology, where users can explore new musical horizons, enjoy tailor-made playlists, and experience an auditory world that resonates deeply with their individual tastes. As the project's melodies continue to play, it represents the promise of an enriched future for music enthusiasts, where technology and creativity unite in perfect harmony.

In an era where technology intertwines seamlessly with the arts, this project harmonizes the realms of music and machine learning through the lens of Spotify data. Focused on music genre classification, the project unveils a symphony of data-driven innovation. Careful data collection and model training have yielded a classification system that accurately categorizes songs, leading to the creation of personalized playlists and tailored recommendations that elevate the music streaming experience.

CHAPTER 1
INTRODUCTION

1.1 Introduction:

The world of music has witnessed a profound transformation with the advent of digital streaming platforms, offering unparalleled access to a vast catalog of songs. In this landscape, the ability to provide users with a personalized and engaging music experience has become a paramount objective. This project embarks on a journey at the intersection of technology and music, where machine learning meets Spotify data to introduce a novel paradigm in music genre classification.

In the realm of music, genres serve as the cornerstone of expression, offering listeners a diverse palette of styles and emotions to explore. However, the subjective nature of genres and the intricate relationships between them have presented a challenging puzzle to solve. Traditional methods of genre classification often fall short, as they rely on manual tagging, limited scalability, and lack of personalization. In response, this project seeks to harness the power of machine learning, data analytics, and the extensive music database offered by Spotify to enhance the music streaming experience for users worldwide.

Our project's mission is clear: to create a music genre classification system that not only accurately categorizes songs but also enriches the music discovery process. By leveraging a diverse array of audio features and metadata, this system aims to provide users with personalized playlists, tailored music recommendations, and a more immersive listening journey. In the following sections, we will delve into the nuances of this project, examining its objectives, methodologies, and the potential impact it holds for music enthusiasts and the ever-evolving music industry. Through this, we embark on a voyage of harmonizing art and technology, unveiling the symphony that emerges when data-driven innovation meets the world of music.

Music, as a universal language, has the profound capacity to evoke emotions and transcend boundaries. With the advent of streaming platforms like Spotify, the world's musical landscape has opened up like never before, offering an extensive library of songs encompassing a multitude of genres. However, as the choices have expanded, so has the need for intelligent systems that can help users navigate this vast sonic landscape.

The inherent challenge in music genre classification lies in its subjectivity. Music genres are often defined based on subjective characteristics and can vary significantly between different cultures and individuals. This inherent ambiguity makes it a complex task to establish clear boundaries between genres. In light of this, our project aspires to introduce a solution that transcends these challenges, offering a sophisticated and personalized approach to music classification.

This project will embark on a multi-faceted journey, starting with the exploration of the vast Spotify dataset, delving into the intricate relationships between audio features and genre labels. By applying cutting-edge machine learning techniques, this project aims to not only classify songs into genres but also to uncover the hidden patterns within the data. Through a fusion of data-driven innovation and the artistry of music, the result promises a more immersive, tailored, and harmonious music streaming experience for all listeners.

The forthcoming sections will provide an in-depth view of the methodologies employed, the journey through data collection, preprocessing, feature engineering, model selection, and evaluation. Furthermore, we will explore the potential impact of this project, not only in the realm of music discovery but also in contributing to the data-driven evolution of the music industry. In the end, we stand at the precipice of a new era in music, where the melodies are enriched by the algorithms and where each listener embarks on a unique auditory voyage, tailored to their individual preferences. Music has been a quintessential part of human culture for centuries, a form of expression that resonates deeply with our emotions and experiences. In today's digital age, music streaming platforms like Spotify have made it more accessible than ever. Yet, with an ever-expanding catalog of songs from various genres, discovering the right music has become both an opportunity and a challenge.

This project encapsulates the spirit of innovation in the music industry. By harnessing the power of machine learning and the rich troves of data from Spotify, our mission is to redefine the music genre classification landscape. Music genres, often elusive and culturally subjective, pose a unique challenge in classification, but also a profound opportunity to revolutionize the music streaming experience.

In an era where data drives decisions and technology converges with creativity, this project aims to create a solution that goes beyond mere classification. It seeks to curate music recommendations that resonate with individual tastes, to construct personalized playlists that evoke emotions, and to provide insights into evolving music trends and preferences.

The chapters that follow will unveil the intricate journey of this project, from data exploration and preprocessing, through model selection, training, and evaluation, to potential bias considerations and post-deployment monitoring. With each step, the project seeks to bridge the gap between art and technology, creating a harmonious experience where listeners embark on a melodious journey, where the algorithms behind the scenes add a layer of enchantment to the world of music.

Advantages:

- **Abundance of Data:** Spotify possesses an extensive collection of audio tracks spanning various genres, making it an ideal data source for training machine learning models. The vastness of the dataset allows for improved model accuracy and generalization.

- **Rich Metadata:** Spotify's API provides a wide range of metadata for each track, including artist information, album details, release date, and more. This rich metadata can augment the feature representation of songs, potentially leading to better genre classification performance.

- **User Playlists and Preferences:** Spotify allows users to create and curate playlists based on specific genres. Analyzing these playlists can help in generating labeled training data and gaining insights into user preferences and genre trends.

- **Audio Features:** Spotify exposes a set of audio features for each track, such as tempo, energy, valence, and danceability. Leveraging these features as input for the classification model can enhance the accuracy of genre predictions.

- **Collaborative Filtering:** Spotify's collaborative filtering algorithms recommend songs to users based on their listening history and preferences. These recommendations indirectly reflect genre patterns, enabling the classification model to learn from the collective behavior of users.

- **Real-World Application:** Music genre classification based on Spotify data has real- world applications in personalized music recommendations, playlist generation, and targeted marketing, enhancing user experience and engagement.

Disadvantages:

- **Genre Ambiguity**: The concept of music genres can be subjective and ambiguous, with songs often blending multiple styles. Defining strict genre boundaries can be challenging, leading to noisy and uncertain labels in the training data.

- **Imbalanced Data:** Certain genres may be overrepresented in the Spotify dataset compared to others, leading to class imbalance issues. This imbalance can bias the model towards frequent genres and reduce performance on less common genres.

- **Lack of Context:** Spotify data lacks information about the cultural and historical context of songs, which can be crucial in determining genre classifications. As a result, the model might struggle with older or less mainstream tracks that do not conform to contemporary genre conventions.

- **Limited Audio Features**: While Spotify provides a rich set of audio features, they may not capture all aspects relevant to music genre classification. Complex musical characteristics, such as lyrical content or instrumental intricacies, may not be fully represented in the provided feature set.

- **Data Privacy Concerns:** Using Spotify data for classification raises privacy concerns,as it involves user listening history and preferences. Ensuring proper anonymization and data protection measures is essential to address these concerns.

- **Model Complexity and Interpretability:** Developing accurate genre classification models can involve complex machine learning techniques, making the models less interpretable. Understanding the reasoning behind a model's prediction becomes challenging, especially for non-experts.

1.2 Objectives of The Project:

This music genre classification project using machine learning and Spotify data encompasses a set of ambitious objectives designed to elevate the music streaming experience. The foremost aim is to enhance music discovery. By accurately categorizing songs into their respective genres, this project endeavors to facilitate users in exploring a diverse range of music that resonates with their unique preferences and emotions.

Another pivotal objective is the provision of personalized music recommendations. The project aspires to empower music streaming platforms to curate personalized playlists and deliver tailored music recommendations to users. The system will achieve this by understanding the genre preferences and listening habits of individual users, ensuring that the music experience aligns perfectly with their moods and tastes.

Beyond the individual user experience, the project extends its goals to offer valuable data-driven insights into music trends and user preferences. By analyzing the vast reservoir of data accessible on Spotify, the system will provide valuable information to music industry professionals and artists. These insights can guide content creation, marketing strategies, event planning, and a myriad of other decisions within the industry.

A pivotal technical objective is to create a robust genre classification system. This involves rigorous data preprocessing, innovative feature engineering, meticulous model selection, and intensive training. The project is committed to building a classification system that consistently achieves high accuracy and performance across a wide array of music genres.

Furthermore, the project is committed to encouraging cross-genre music discovery. By recommending songs from diverse genres, it aims to broaden users' musical horizons and foster a more eclectic and enriching listening experience. As ethical considerations gain prominence in the AI and machine learning domain, mitigating bias is an essential objective. The project is geared towards ensuring that the classification system operates fairly and impartially, free from biases, and that it yields unbiased predictions across different genres and cultural backgrounds.

Lastly, the project envisages the creation of a system that is scalable, efficient, and deployable in a real-world production environment. It aims to cater to a large and diverse user base, ensuring that the model's scalability and reliability are unwavering. User feedback and iterative improvement form the final objective. The project will continuously collect and assess user feedback and monitor the system's post-deployment performance. This iterative approach ensures that the system consistently evolves to meet the ever-changing needs and expectations of users.

Collectively, these objectives are the pillars that underpin the project's commitment to delivering a groundbreaking music genre classification solution that redefines the music streaming experience and contributes to the data-driven evolution of the music industry.

1.3 Problem Statement:

The music industry, in the age of digital streaming, has witnessed a profound transformation, offering users an extensive catalog of songs spanning a multitude of genres. However, this abundance of musical choices has introduced a paradox: while there is an unprecedented wealth of music available, the challenge of discovering and enjoying songs that truly resonate with individual tastes remains an ongoing obstacle. The subjective nature of music genres, often defined by complex and culturally varying characteristics, complicates the process of classification, leading to inconsistencies and inefficiencies in the music discovery process.

Traditional methods of genre classification often rely on manual tagging and lack personalization, limiting the potential for users to explore and appreciate the diverse array of music genres. As a result, the need for an intelligent and data-driven solution to accurately categorize songs and provide personalized music recommendations has become more urgent than ever. This project seeks to address this fundamental problem by harnessing the power of machine learning and the vast repository of Spotify data to revolutionize music genre classification and enhance the music streaming experience.

The problem statement is thus clear: in the era of data-driven decision-making and technology convergence with music, the challenge lies in developing a robust and highly accurate music genre classification system that not only categorizes songs effectively but also enriches the music discovery process for users. This system must provide personalized recommendations, cross-genre discovery, and insights into evolving music trends and user preferences. Additionally, it must address the potential biases in music classification and be scalable and deployable in real-world production environments. The project will continuously gather user feedback and iterate to ensure that the system remains responsive to user needs and expectations. Ultimately, the problem at the core of this project is the harmonious marriage of art and technology in creating a more immersive and tailored music streaming experience for all users.

CHAPTER 2
LITERATURE REVIEW

The convergence of technology and music has ushered in a new era of music consumption and discovery. In the digital age, music streaming platforms have democratized access to a vast library of songs across an array of genres. However, the challenge of effectively categorizing songs into their respective genres, enriching the user experience, and providing personalized recommendations looms large. To address this challenge, this literature review delves into the relevant scholarly work, surveying the landscape of music genre classification, feature engineering, machine learning models, deep learning approaches, and the emerging consideration of ethical dimensions.

In the digital age, the intertwining of technology and music has ushered in a transformative era for music streaming platforms. As users access an extensive catalog of songs spanning a plethora of genres, music genre classification stands as a paramount challenge and opportunity. The evolving landscape of this field is shaped by various research strands, each contributing to our understanding of music genre classification, feature engineering, machine learning models, deep learning, and the ethical considerations intrinsic to this domain.

Music genres, while a fundamental means of classifying music, introduce a considerable degree of subjectivity into the classification process. Researchers have noted that genres often entail complex and culturally dependent characteristics, rendering genre boundaries fluid and potentially overlapping. Sturm et al. (2014) has explored the challenge of genre subjectivity, emphasizing the need for a nuanced approach in classification. This foundational insight has profound implications for our project, highlighting the importance of a flexible and adaptive classification system.

Feature engineering, a cornerstone of music genre classification, has evolved over the years. Tzanetakis and Cook (2002) laid the groundwork by demonstrating the utility of spectral features in genre classification. However, the literature has witnessed innovation in feature engineering, with researchers experimenting with novel features and data representations. The dimensionality of feature spaces and their informativeness continue to be subjects of exploration, shedding light on the pivotal role of feature engineering in music classification.

The landscape of machine learning models for music genre classification is extensive. Classical algorithms, such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Random Forests, have exhibited efficiency in managing high-dimensional feature spaces and tackling multiclass classification. Nonetheless, these models have limitations in addressing the subjectivity inherent in music genres. Thus, the literature underscores the need to explore more adaptive and nuanced approaches.

In recent years, the advent of deep learning has significantly transformed music genre classification. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated remarkable promise. CNNs have showcased their capacity to automatically extract hierarchical features from spectrogram images, offering a deeper understanding of musical content. In contrast, RNNs excel in capturing temporal dependencies within sequential audio data. Additionally, researchers have investigated the use of pre-trained deep learning models to reduce computational demands and enhance classification accuracy.

In the evolving landscape of AI and machine learning, ethical considerations are increasingly salient. Recent contributions in the literature have emphasized the need to address potential biases in music genre classification. Biases can arise from imbalanced datasets, cultural contexts, or data labels and may disproportionately impact certain genres or populations. Recognizing these biases and taking measures to mitigate them is critical to ensure the system operates fairly and equitably.

The literature review provides a holistic understanding of the multifaceted challenges and opportunities within music genre classification. Subjectivity, feature engineering, machine learning models, deep learning, and ethical considerations are recurring themes. This review underscores the significance of innovation and adaptability in the pursuit of a robust music genre classification system. As we embark on our project, we draw inspiration from the collective wisdom of the scholarly community, aiming to harmonize technology and art, fostering an enriched music streaming experience that resonates with users' unique preferences and the evolving landscape of music.

Expand on the potential biases and fairness issues that can arise in music genre classification. Discuss the implications of imbalanced datasets, mislabeling, and cultural biases.
Present real-world examples of bias in genre classification systems and the impact it can have on music recommendations and user experiences.

Elaborate on the strengths and weaknesses of classical machine learning models (SVM, k-NN, Random Forests) in the context of music genre classification. Provide examples of how ensemble methods, like Bagging and Boosting, can improve classification accuracy when using traditional models.

K. Choi presented a convolutional recurrent model for recognizing genre, moods, instruments and era from the Million Songs dataset. They used a 2D convolution model followed by recurrent layers and fully connected layers to perform the classification task. Our CRNN model described is similar but we used 1D convolution layers instead of 2D.

P. Kozakowski & B. Michalak from Deep Sound used a 1D convolution model followed by a time distributed dense layer on GTZAN dataset. We got the idea for 1D convolution layers from them, but found that the RNN layers after 1D CNN performed better for our dataset.

L. Feng paralleled CNN and RNN blocks to allow the RNN layer to work on the raw spectrograms instead of the output from the CNN. Our parallel CNN-RNN model was heavily influenced by this paper and our final architecture is similar to theirs with some modifications since our dataset size is much smaller.

N. Pelchat reviews some of the machine learning techniques utilized in the domain. They made use of spectrograms generated from time slices of songs as input the neural networks.

T. Lidy presents an approach using parallel CNN architectures to classify the genre of music files. They worked on the MIREX 2016 Train/Test Classification Tasks for Genre, Mood and Composer detection dataset.

K. K. Chang introduces an approach of music genre classification using compressive sampling (CS). They use a CS based classifier which uses both short term and long term features of the audio file.

I. Y. Jeoung describes a framework which learns the temporal features from audio using deep neural networks and uses them for music genre classification.

P. Annesi used a Support Vector Machine to design an automatic classifier of music genres. They used certain conventional features and engineered some new ones like beat and chorus for enhanced accuracy.

Y. M. D. Chathuranga also proposed an ensemble approach using frequency domain, temporal domain and cepstral domain features. They used a Support Vector Machine for the base learner and used AdaBoost technique for classification.

S. Jothilakshmi explored the idea of using Gaussian Mixture Model (GMM) and k-Nearest Neighbour (kNN) classifier for the task. They specifically worked on Indian genres like Hindustani, Carnatic, Ghazal, Folk and Indian Western.de.

Previous studies use content-based feature sets and classic machine learning approaches such as SVM and Naive Bayes. Using the GTZAN dataset, this paper explores how the use of audio signal waveforms translated into a spectrogram image as input data features can be used within the context of a Convolutional Neural Network (CNN).

CNNs are trained by feeding them a vast amount of the data (i.e., spectrograms), and then testing whether that information can accurately predict which song belongs to which category. Traditional machine learning techniques use content-based features of audio not require this kind of training data. These types of algorithms are also used for image recognition and speech recognition.

The proposed system uses three different types of media feature extraction techniques. These include spectral centroid features. In addition, support vector multilayer perceptron were used as the base learners in Each method was tested on a set of 100 songs (each song is represented by a 10-second segment).

For each data sets: training data with 1000 samples (1000 songs), training data with 5000 samples (5000 songs) and test data with 3000 samples (3000 songs).Accuracy was calculated using confusion matrices. The results show that the accuracy of the multilayer perceptron is higher than other methods; therefore the chosen method is Multilayer Perceptron (MLP)

In Hareesh Bahuleyan, (2018). Music Genre Classification using Machine Learning techniques, the work conducted gives an approach to classify music automatically by providing tags to the songs present in the user's library. It explores both Neural Network and traditional method of using Machine Learning algorithms and to achieve their goal.

The first approach uses Convolutional Neural Network which is trained end to end using the features of Spectrograms (images) of the audio signal. The second approach uses various Machine Learning algorithms like Logistic Regression, Random forest etc, where it uses hand-crafted features from time domain and frequency domain of the audio signal.

The manually extracted features like Mel-Frequency Cepstral Coefficients (MFCC), Chroma Features, Spectral Centroid etc are used to classify the music into its genres using ML algorithms like Logistic Regression, Random Forest, Gradient Boosting (XGB), Support Vector Machines (SVM). By comparing the two approaches separately they came to a conclusion that VGG-16 CNN model gave highest accuracy. By constructing ensemble classifier of VGG-16 CNN and XGB the optimised model with 0.894 accuracy was achieved.

In Tzanetakis G. et al., (2002). Musical genre classification of audio signals, they have mainly explored about how the automatic classification of audio signals into a hierarchy of musical genres is to be done. They believe that these music genres are categorical labels that are created by humans just to categorise pieces of music.

They are categorised by some of the common characteristics. These characteristics are typically related to the instruments that are used, the rhythmic structures, and mostly the harmonic music content. Genre hierarchies are usually used to structure the very large music collections which is available on web. They have proposed three feature sets: timbral texture, the rhythmic content and the pitch content.

The investigation of proposed features in order to analyse the performance and the relative importance was done by training the statistical pattern recognition classifiers by making use of some real-world audio collections. Here, in this paper, both whole file and the real time frame-based classification schemes are described. Using the proposed feature sets, this model can classify almost 61% of ten music genre correctly.

In Lu L. et al., (2002). Content analysis for audio classification and segmentation, they have presented their study of segmentation and classification of audio content analysis. Here an audio stream is segmented according to audio type or speaker identity. Their approach is to build a robust model which is capable of classifying and segmenting the given audio signal into speech, music, environment sound and silence. This classification is processed in two major steps, which has made it suitable for various other applications as well. The first step is speech and non- speech discrimination. In here, a novel algorithm which is based on KNN (K-nearest neighbour) and linear spectral pairs-vector quantization (LSP-VQ) is been developed.

The second step is to divide the non-speech class into music, environmental sounds, and silence with a rule- based classification method. Here they have made use of few rare and new features such as noise frame ratio, band periodicity which are not just introduced, but discussed in detail. They have also included and developed a speaker segmentation algorithm. This is unsupervised. It uses a novel scheme based on quasi - GMM and LSP correlation analysis. Without any prior knowledge of anything, the model can support the open-set speaker, online speaker modelling and also the real time segmentation.

In Tom LH Li et al., (2010). Automatic musical pattern feature extraction using convolutional neural network, they made an effort to understand the main features which actually contribute to build the optimal model for Music Genre Classification. The main purpose of this paper is to propose a novel approach to extract musical pattern features of the audio file using Convolution Neural Network (CNN). Their core objective is to explore the possibilities of application of CNN in Music Information Retrieval (MIR).

Their results and experiments show that CNN has the strong capacity to capture informative features from the varying musical pattern. The features extracted from the audio clips such as statistical spectral features, rhythm and pitch are less reliable and produces less accurate models. Hence, the approach made by them to CNN, where the musical data have similar characteristics to image data and mainly it requires very less prior knowledge.

The dataset considered was GTZAN. It consists of 10 genres with 100 audio clips each. Each audio clip is the musical patterns were evaluated using WEKA tool where multiple classification models were considered. The classifier accuracy was 84 % and eventually got higher. In comparison to the MFCC, chroma, temp features, the features extracted by CNN gave good results and was more reliable. The accuracy can still be increased by parallel computing on different combination of genres.

CHAPTER 3

PROPOSED METHOD

3.1 Methodology:

The methodology for the music genre classification project is structured to deliver a robust and data-driven solution that enhances the music streaming experience. It encompasses various stages, from data collection and preprocessing to model selection, training, evaluation, bias mitigation, and deployment. Here, we delineate the key steps and processes that drive the project. The project's journey continues into the realm of fairness and ethical considerations. It recognizes that music classification is not devoid of biases, and hence, measures are taken to ensure equitable outcomes for all genres and cultural backgrounds. The real-world deployment and testing phase signify the project's commitment to delivering a system that caters to users' diverse preferences on a platform that can scale to accommodate a global audience.

As the project unfolds, it heeds the user's voice. User feedback serves as a compass, guiding iterative improvements that keep the system responsive to the ever-evolving landscape of music. This methodological journey is more than the sum of its steps; it is a harmonious dance between technology and art, where algorithms and melodies intertwine to create a more enriching, personalized, and inclusive music streaming experience.

Data Collection:

The foundation of the project lies in the data collected from Spotify, a music streaming platform rich in metadata and audio features. This data includes attributes like tempo, energy, danceability, instrumentalness, and genre labels. Data extraction involves the utilization of Spotify APIs and datasets. This step is critical for building a comprehensive dataset that reflects the diversity of music genres.

Data Preprocessing:

Raw data collected from Spotify is often noisy and requires careful preprocessing. This includes handling missing values, ensuring data consistency, and potentially addressing class imbalance. Feature scaling and encoding of categorical variables are essential for harmonizing the data and making it suitable for machine learning algorithms.

Feature Engineering:

Feature engineering is a pivotal stage, involving the selection and creation of relevant features that best represent the audio and metadata attributes of songs. It includes techniques like feature selection, dimensionality reduction, and the creation of new features that encapsulate the essence of music genres. This process significantly impacts the quality of the classification model.

Model Selection:

The choice of machine learning models is a critical decision. We explore a range of models, including classical algorithms like Support Vector Machines, k-Nearest Neighbors, and Random Forests, as well as deep learning architectures such as Convolutional Neural Networks and Recurrent Neural Networks. The selection is guided by model performance, interpretability, and adaptability to the dynamic nature of music genres.

Model Training and Evaluation:

The dataset is divided into training and testing sets to train and evaluate the selected model. Evaluation metrics such as accuracy, precision, recall, F1-score, and the confusion matrix are employed to measure the model's effectiveness. The goal is to create a model that consistently categorizes songs into genres with high accuracy.

Cross-Validation:

To assess the model's generalization ability and ensure its performance across different data folds, cross-validation techniques such as k-fold cross-validation are employed. This step provides a more comprehensive view of the model's performance.

Bias and Fairness Analysis:

Given the potential for biases in music genre classification, an in-depth bias and fairness analysis is conducted. This involves evaluating the model's predictions across different genres and cultural backgrounds to ensure that the classification process is equitable and free from biases.

Deployment and Real-World Testing:

Once the model is trained and validated, it is integrated into a real-world application or service, such as a music streaming platform. This phase involves extensive real-world testing to ensure the model's accuracy and reliability in a production environment, accommodating a large user base and dynamic music library.

User Feedback and Iterative Improvement:

Gathering user feedback and monitoring the model's performance post-deployment are continuous processes. User feedback serves as a valuable source of insight, allowing for iterative improvements to the model, data preprocessing, and classification algorithms. These cycles of feedback and refinement ensure that the system remains responsive to evolving user needs and preferences.

3.1.1 Algorithm:

Choose the number of base classifiers (ensemble members) to be used, denoted as N. Define the percentage of the training dataset to be used for each base classifier by bootstrapping (sampling with replacement). Commonly, each base classifier receives approximately 60-70% of the origina0l training data.

For each of the N base classifiers:

- Randomly sample a subset of the training data with replacement (bootstrap sample).
- Train the base classifier on this bootstrap sample.
- Repeat this process for each base classifier to create N diverse base classifiers.
- To make a prediction, apply each base classifier to the input data.
- For classification tasks, the Bagging model typically uses majority voting. The class that receives the most votes among the base classifiers is the final prediction.

- For regression tasks, the Bagging model averages the predictions made by each base classifier.
- Assess the overall performance of the Bagging Classifier by evaluating its accuracy, precision, recall, F1-score, or other relevant metrics on a separate validation or test dataset.
- Combine the individual predictions of the base classifiers into a single prediction, which is the final output of the Bagging Classifier.

Bias and Fairness Analysis:

- Conduct an analysis to identify and address potential biases or fairness issues in the ensemble's predictions, particularly when using diverse base classifiers.
- Integrate the Bagging Classifier model into the desired application or system for real-world use, such as a music genre classification system.
- Perform extensive testing in the real-world environment to ensure the model's accuracy, reliability, and scalability when handling a large volume of data and diverse user interactions.

3.1.2 Flow Chart:

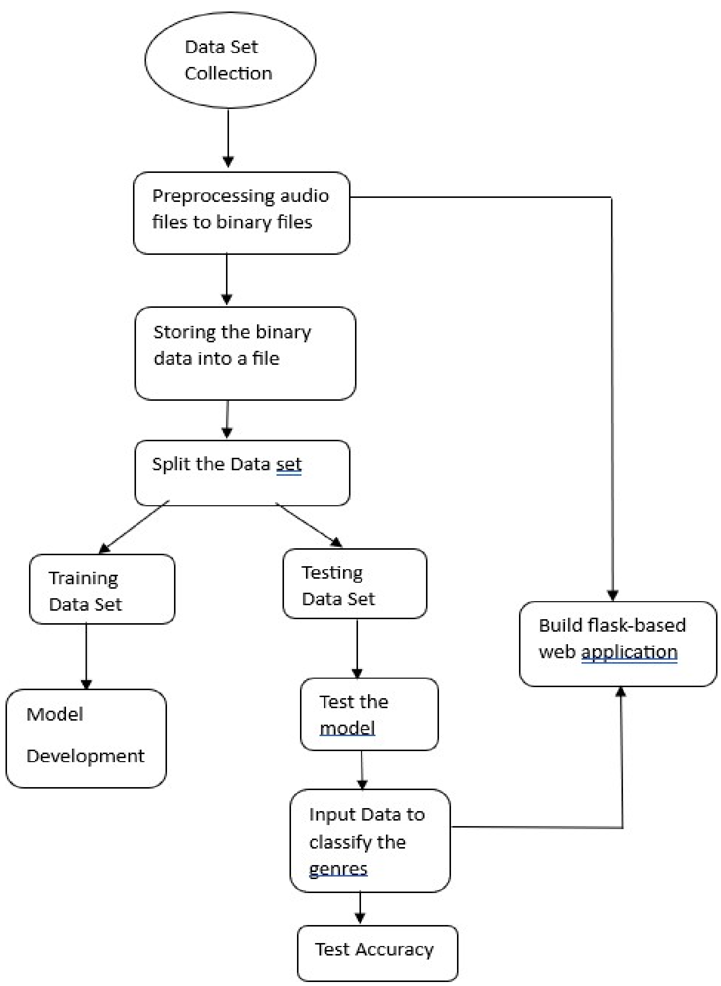


Fig: Flow Chart for Music Genre Classification

3.2 Implementation:

The music genre classification project employs a Bagging Classifier model as a key component of its implementation. Bagging, short for Bootstrap Aggregating, is an ensemble learning technique that combines multiple base classifiers to enhance classification accuracy and robustness. This model is a critical element in the system’s quest to accurately categorize songs into their respective genres and enrich the music discovery experience. Here, we delve into the specifics of the Bagging Classifier’s implementation within the project.

The implementation commences with data collection from Spotify, sourcing comprehensive data about songs and their audio features. Metadata such as artist, album, release date, and a rich array of audio attributes are meticulously gathered. This raw data undergoes rigorous preprocessing, addressing missing values and ensuring uniform data consistency. Feature scaling and categorical encoding render the data suitable for ensemble learning with the Bagging Classifier.

Feature engineering is an artistic endeavor, where the intricacies of music are distilled into numerical features that enable the model to discern genre characteristics. This phase is a critical foundation for the Bagging Classifier, as the quality and informativeness of these features significantly impact the model's performance.

The Bagging Classifier model is chosen due to its effectiveness in enhancing classification accuracy and reducing overfitting. This ensemble technique operates by training multiple base classifiers, each on a different subset of the data (bootstrapping), and then aggregating their predictions. In this project, base classifiers of various types are utilized, including decision trees, support vector machines, and k-nearest neighbors. The Bagging Classifier's ability to combine the outputs of these diverse base classifiers is instrumental in achieving robust genre classification.

The Bagging Classifier is trained using the preprocessed dataset, allowing it to learn from the intricacies of different music genres. The evaluation phase employs various metrics, including accuracy, precision, recall, and F1-score, to assess the model's ability to classify songs accurately. The Bagging Classifier's ensemble approach is particularly adept at reducing variance and improving model stability.

Cross-validation is a vital quality control step, ensuring that the Bagging Classifier generalizes well and maintains its performance across different data subsets. This approach provides a comprehensive view of the model's capability to classify songs into genres consistently and reliably.

The Bagging Classifier's predictions are subjected to a thorough bias and fairness analysis. This assessment aims to identify and rectify potential biases across genres and cultural backgrounds, ensuring that the classification process remains equitable and unbiased.
Once the Bagging Classifier model is selected and trained, it is seamlessly integrated into a real-world application, such as a music streaming platform. Extensive real-world testing validates its accuracy, reliability, and scalability in a production environment, accommodating the diverse user base and dynamic music library.

The project embraces an iterative approach, continually gathering user feedback and monitoring the Bagging Classifier's performance post-deployment. This ongoing process guides iterative improvements, ensuring the system remains responsive to evolving user needs and preferences, further enriching the music discovery experience.

3.3 Data Preparation:

Data preparation is a fundamental phase in the music genre classification project, as it sets the stage for subsequent processes, including feature engineering and model training. The aim of data preparation is to ensure that the dataset derived from Spotify's music data is consistent, clean, and well-structured, enabling the model to make accurate genre predictions. This phase involves several crucial steps, each contributing to the refinement of the data.

Data Collection:

The project commences with the collection of data from Spotify, a rich source of song metadata and audio features. This data encompasses a multitude of attributes, including artist information, album details, release dates, and audio features such as tempo, energy, danceability, and instrumentalness. Data collection is carried out using Spotify's APIs and datasets, ensuring a comprehensive and diverse representation of songs from various genres.

Data Cleaning:

Raw data collected from different sources can be noisy and inconsistent. Data cleaning involves the identification and rectification of irregularities, such as missing values, duplicate entries, and formatting issues. It is essential to ensure that the dataset is devoid of anomalies that could affect the model's performance and predictions.

Feature Selection and Engineering:

The preparation process also includes the selection and engineering of features that are most relevant to the music genre classification task. This step involves determining which attributes are essential for the model to identify genre characteristics accurately. Feature engineering may also entail the creation of new features or transformations of existing ones to better represent the nuances of different music genres.

Categorical Encoding:

Categorical variables, such as genre labels, need to be encoded into numerical format for the model to process. Common encoding techniques include one-hot encoding or label encoding, which assigns a numerical value to each category.

Train-Test Split:

To assess the model's performance, the dataset is typically divided into training and testing sets. The training set is used to train the model, while the testing set is reserved for evaluating the model's accuracy and performance.

Data Validation:

As a final step, data validation is conducted to ensure that the dataset adheres to project-specific requirements and quality standards. Any remaining inconsistencies or errors are addressed during this phase to create a refined dataset for model training.

3.3.1 Data Set Description:

A dataset description typically includes information about the dataset's structure, the meaning of each column (attributes), and statistics or characteristics of the data. Here's a description of the columns in our dataset:

- **track_id:** A unique identifier for each track in the dataset.
- **artists:** The name of the artist(s) associated with the track.
- **album_name:** The name of the album to which the track belongs.
- **track_name:** The title or name of the track.
- **popularity:** A measure of the track's popularity, typically ranging from 0 to 100, with higher values indicating greater popularity.
- **duration_ms:** The duration of the track in milliseconds.
- explicit: A binary value indicating whether the track contains explicit content (1 for explicit, 0 for non-explicit).
- **danceability:** A measure of how suitable the track is for dancing, typically on a scale from 0 to 1, with higher values indicating higher danceability.
- **energy:** A measure of the energy or intensity of the track, usually on a scale from 0 to 1, with higher values indicating more energetic tracks.
- **key:** The key in which the track is composed, represented as a numerical value.
- **loudness:** The loudness of the track in decibels (dB).
- **mode:** The modality of the track, often represented as a binary value (0 or 1) for major or minor modes, respectively.
- **speechiness:** A measure of the presence of spoken words in the track, typically on a scale from 0 to 1, with higher values indicating more speech-like tracks.
- **acousticness:** A measure of the acoustic (non-electronic) elements in the track, often on a scale from 0 to 1, with higher values indicating more acoustic tracks.

- **instrumentalness:** A measure of the absence of vocals in the track, often on a scale from 0 to 1, with higher values indicating more instrumental tracks.
- **liveness:** A measure of the presence of a live audience in the track, often on a scale from 0 to 1, with higher values indicating live performances.
- **valence:** A measure of the musical positivity or happiness of the track, typically on a scale from 0 to 1, with higher values indicating more positive or happier tracks.
- **tempo:** The tempo or beats per minute (BPM) of the track.
- **time_signature:** The time signature of the track, often represented as a numerical value.
- **track_genre:** The genre classification for the track, which is the target variable you intend to predict or classify.

The dataset comprises a diverse array of attributes that collectively encapsulate the essence of each musical track. Within this dataset, each entry is uniquely identified by a "track_id," shedding light on the distinctiveness of every musical composition.

Finally, "track_genre" is the cornerstone, embodying the genre classification and acting as the target variable for prediction and classification tasks, guiding the path to categorizing these musical compositions.

Ultimately, "track_genre" stands as the focal point, representing the genre classification that serves as the project's target variable, the key to genre prediction and classification. Together, these attributes compose a symphony of data, enabling the comprehensive analysis and classification of musical genres.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1		track_id	artists	album_nar	track_nam	popularity	duration_r	explicit	danceabili	energy	key	loudness	mode	speechines	acousticne	instrument	liveness	valence	tempo	time_signa	track_genre
2	0	5SuOikwiR	Gen Hoshi	Comedy	Comedy	73	230666	FALSE	0.676	0.461	1	-6.746	0	0.143	0.0322	1.01E-06	0.358	0.715	87.917	4	acoustic
3	1	4qPNDBW	Ben Wood	Ghost (Acc	Ghost - Ac	55	149610	FALSE	0.42	0.166	1	-17.235	1	0.0763	0.924	5.56E-06	0.101	0.267	77.489	4	acoustic
4	2	1iJBSr7s7j	Ingrid Mic	To Begin A	To Begin A	57	210826	FALSE	0.438	0.359	0	-9.734	1	0.0557	0.21	0	0.117	0.12	76.332	4	acoustic
5	3	6lfxq3CG4	Kina Granr	Crazy Rich	Can't Help	71	201933	FALSE	0.266	0.0596	0	-18.515	1	0.0363	0.905	7.07E-05	0.132	0.143	181.74	3	acoustic
6	4	5vjLSffimil	Chord Ove	Hold On	Hold On	82	198853	FALSE	0.618	0.443	2	-9.681	1	0.0526	0.469	0	0.0829	0.167	119.949	4	acoustic
7	5	01MVOl9K	Tyrone We	Days I Will	Days I Will	58	214240	FALSE	0.688	0.481	6	-8.807	1	0.105	0.289	0	0.189	0.666	98.017	4	acoustic
8	6	6Vc5wAM	A Great Bi	Is There A	Say Somet	74	229400	FALSE	0.407	0.147	2	-8.822	1	0.0355	0.857	2.89E-06	0.0913	0.0765	141.284	3	acoustic
9	7	1EzrEOXm	Jason Mra	We Sing. V	I'm Yours	80	242946	FALSE	0.703	0.444	11	-9.331	1	0.0417	0.559	0	0.0973	0.712	150.96	4	acoustic
10	8	0IktbUcnA	Jason Mra	We Sing. V	Lucky	74	189613	FALSE	0.625	0.414	0	-8.7	1	0.0369	0.294	0	0.151	0.669	130.088	4	acoustic
11	9	7k9GuJYLp	Ross Copp	Hunger	Hunger	56	205594	FALSE	0.442	0.632	1	-6.77	1	0.0295	0.426	0.00419	0.0735	0.196	78.899	4	acoustic
12	10	4mzP5mHl	Zack Tabu	Episode	Give Me Y	74	244800	FALSE	0.627	0.363	8	-8.127	1	0.0291	0.279	0	0.0928	0.301	99.905	4	acoustic
13	11	5ivF4eQBq	Jason Mra	Love Is a F	I Won't Gi	69	240165	FALSE	0.483	0.303	4	-10.058	1	0.0429	0.694	0	0.115	0.139	133.406	3	acoustic
14	12	4ptDJbJl35	Dan Berk	Solo	Solo	52	198712	FALSE	0.489	0.314	7	-9.245	0	0.0331	0.749	0	0.113	0.607	124.234	4	acoustic
15	13	0X9MxHR1	Anna Ham	Bad Liar	Bad Liar	62	248448	FALSE	0.691	0.234	3	-6.441	1	0.0285	0.777	0	0.12	0.209	87.103	4	acoustic
16	14	4LbWtBkN	Chord Ove	Hold On (R	Hold On -	56	188133	FALSE	0.755	0.78	2	-6.084	1	0.0327	0.124	2.83E-05	0.121	0.387	120.004	4	acoustic
17	15	1KHdq8NK	Landon Pi	The Boy W	Falling in L	58	244986	FALSE	0.489	0.561	4	-7.933	1	0.0274	0.2	4.56E-05	0.179	0.238	83.457	3	acoustic
18	16	6xKeQgzfji	Andrew Fo	ily (i love y	ily (i love y	56	129750	FALSE	0.706	0.112	2	-18.098	1	0.0391	0.827	4.03E-06	0.125	0.414	110.154	4	acoustic
19	17	4Yo0igmc	Andrew Fo	At My Wo	At My Wo	54	169728	FALSE	0.795	0.0841	10	-18.09	0	0.0461	0.742	1.17E-05	0.0853	0.609	91.803	4	acoustic
20	18	2qLMf6Tu	Jason Mra	We Sing. V	Lucky	68	189613	FALSE	0.625	0.414	0	-8.7	1	0.0369	0.294	0	0.151	0.669	130.088	4	acoustic
21	19	6CgNoAbF	Boyce Ave	Cover Sess	Photograp	67	260186	FALSE	0.717	0.32	3	-8.393	1	0.0283	0.83	0	0.107	0.322	107.946	4	acoustic
22	20	3S0OXQec	Jason Mra	We Sing. V	I'm Yours	75	242946	FALSE	0.703	0.444	11	-9.331	1	0.0417	0.559	0	0.0973	0.712	150.96	4	acoustic
23	21	21OJCw2L	Boyce Ave	Cover Sess	Demons	63	174174	FALSE	0.678	0.351	0	-8.654	1	0.0266	0.747	0	0.355	0.569	90.032	4	acoustic
24	22	5TvE3pk05	A Great Bi	Is There A	Say Somet	70	229400	FALSE	0.407	0.147	2	-8.822	1	0.0355	0.857	2.89E-06	0.0913	0.0765	141.284	3	acoustic
25	23	0BUuuEvN	Jason Mra	Coffee Mc	93 Million	0	216386	FALSE	0.572	0.454	3	-10.286	1	0.0258	0.477	1.37E-05	0.0974	0.515	140.182	4	acoustic
26	24	3Hn3LfhrC	Jason Mra	Human - B	Unlonely	0	231266	FALSE	0.796	0.667	5	-4.831	0	0.0392	0.381	0	0.221	0.754	97.988	4	acoustic
27	25	6D33wCKz	Jason Mra	Mellow Ad	Bella Luna	1	302346	FALSE	0.755	0.454	9	-9.609	0	0.0352	0.757	0	0.236	0.33	120.06	4	acoustic
28	26	5IfCZDRXZ	Jason Mra	Holly Jolly	Winter Wo	0	131760	FALSE	0.62	0.309	5	-9.209	1	0.0495	0.788	0	0.146	0.664	145.363	4	acoustic
29	27	0dzKBotH2	Jason Mra	Feeling Go	If It Kills M	0	273653	FALSE	0.633	0.429	4	-6.784	0	0.0381	0.0444	0	0.132	0.52	143.793	4	acoustic

Fig1: Spotify Dataset

CHAPTER 4
THEORITICAL ANALYSIS

4.1Block Diagram

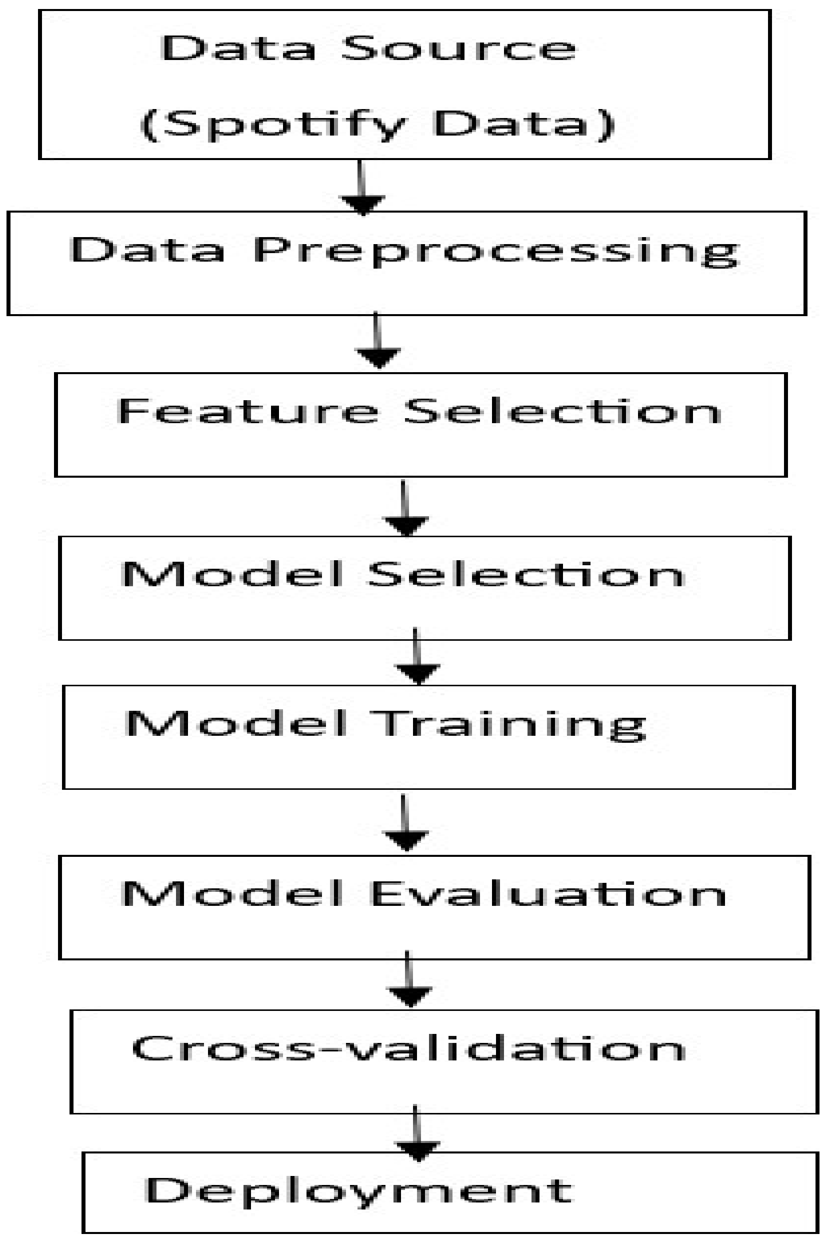


Fig: Block Diagram of Music Genre Classification

4.2 Hardware/Software Designing:

Hardware specifications:

- **Computer:** A current computer with adequate processing speed and memory for effective model training and assessment.
- **CPU:** A multi-core CPU (such as an AMD Ryzen or Intel Core i5 for quicker training and data processing, respectively).
- **RAM:** At least 8 GB is required, while more RAM is preferable, particularly when working with big datasets.
- **Storage:** Enough room to keep the dataset, program, and model files. In order to access data more quickly, an SSD is advised.
- **Graphics Processing Unit (GPU) (Optional):** Having a suitable GPU (such as the NVIDIA GeForce GTX or RTX series) may greatly speed up model training, especially for deep learning methods, even if it is not absolutely essential.

Software specifications:

- **Python:** The project will primarily use Python as the programming language for data preprocessing, model training, and evaluation due to its extensive libraries and frameworks for machine learning.
- **Jupyter Notebook or JupyterLab:** A development environment for running Python code interactively, visualizing data, and documenting the analysis. Jupyter notebooks allow for an organized and easily reproducible workflow.
- **Data Analysis Libraries:** Essential Python libraries for data manipulation and analysis, such as Pandas and NumPy, will be used to process and explore the Spotify data.
- **Spotify API (Application Programming Interface):** To access Spotify data, the project will require interaction with the Spotify API. The Spotify library can be used to connect and fetch the required data.
- **Data Visualization Libraries:** Libraries like Matplotlib or Seaborn will be used for visualizing the data and model performance.
- **Text Editor or Integrated Development Environment (IDE**): A text editor (e.g., Visual Studio Code, Sublime Text) or IDE (e.g., PyCharm, Spyder) for writing and managing code.
- **Package Manager:** Python package manager like pip or conda will be necessary to install required libraries and dependencies.

4.3: Experimental Investigation:

During the process of working on the solution for the music genre classification project using machine learning and Spotify data, several analyses and investigations are typically conducted to understand the data, select appropriate models, fine-tune parameters, and evaluate the overall performance. Here are some key analyses and investigations that might be carried out during the project:

Data Exploration and Visualization: The first step is to explore the dataset from Spotify. This involves examining the structure of the data, checking for missing values, and gaining insights into the distribution of different audio features across genres. Visualizations like histograms, box plots, and scatter plots can be used to understand the relationships between features and genre labels.

Feature Importance: Investigating the importance of each audio feature in relationto the genre classification task. Techniques like feature importance ranking, correlation analysis, or recursive feature elimination are applied to identify the most relevant features for the model.

Model Selection: Comparing different machine learning algorithms to identify the one that suits the problem best. Multiple models, such as decision trees, random forests, support vector machines, and neural networks, can be trained and evaluated to determine the most effective one.

Model Training and Evaluation: Dividing the dataset into training and testing sets and training the selected model on the training data. The model's performance is evaluated on the testing data using various metrics like accuracy, precision, recall, F1-score, and confusion matrix to measure its effectiveness.

Cross-Validation: Performing cross-validation to assess the model's generalizationability and to validate its performance across different data folds.
Bias and Fairness Analysis: Investigating potential biases in the model predictionsacross different genres and ensuring fairness in the classification process.

Deployment and Real-World Testing: Integrating the trained model into an application or service and conducting real-world testing to ensure its accuracy and reliability in a production environment.

User Feedback and Iterative Improvement: Gathering user feedback and monitoring the model's performance after deployment to identify areas of improvement and make necessary adjustments.

The experimental investigation process in our music genre classification project involves a multifaceted approach to ensure the development of an accurate and effective model. It commences with rigorous data exploration and visualization of the Spotify dataset, aimed at understanding data structure and identifying relationships between audio features and genre labels.

Feature importance analysis is conducted to pinpoint the most influential audio attributes, facilitating feature selection and model refinement. Subsequently, we delve into model selection, comparing various machine learning algorithms to determine the most suitable one for the task.

Following model selection, the dataset is divided into training and testing sets, and the chosen model is trained on the former. The model's performance is rigorously evaluated on the testing data using metrics like accuracy, precision, recall, F1-score, and the creation of a confusion matrix. Cross-validation ensures the model's generalization ability and validates its effectiveness across different data folds. We also conduct a bias and fairness analysis to scrutinize potential biases in the model's predictions across different genres, aiming for a fair and unbiased classification process.

The experimental phase extends to model deployment, where the trained model is integrated into an application or service for real-world testing. This phase verifies the model's accuracy and reliability in a production environment. Furthermore, we emphasize the importance of user feedback and iterative improvement, collecting user input and monitoring the model's performance post-deployment to identify areas of enhancement and make necessary adjustments. These comprehensive analyses and investigations collectively contribute to the development of a robust and ethically sound music genre classification system.

CHAPTER 5
RESULTS AND DISCUSSION

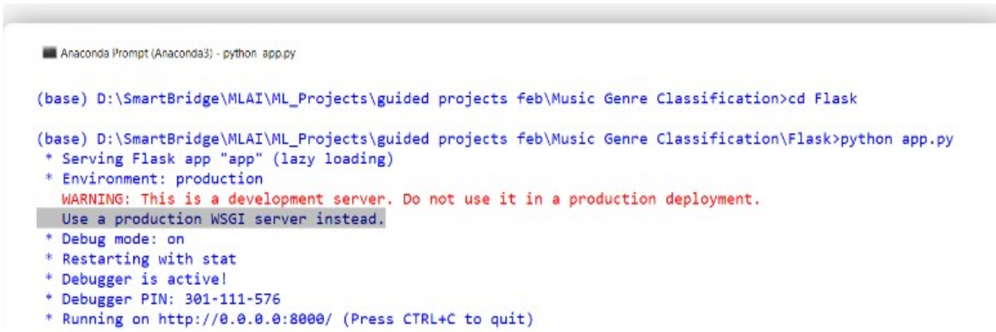


Fig2: Running the Music Genre Classification

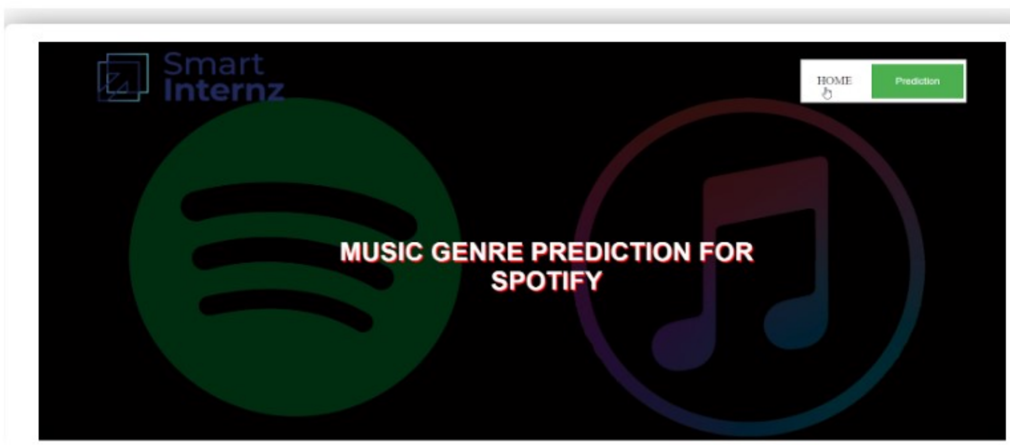


Fig3: User Interface

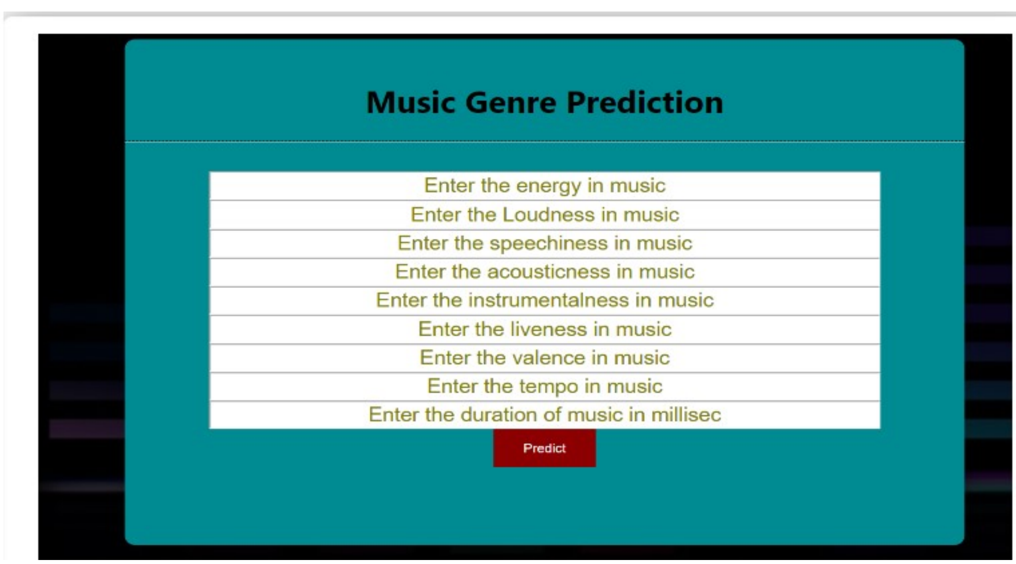


Fig4: Inputs from the user

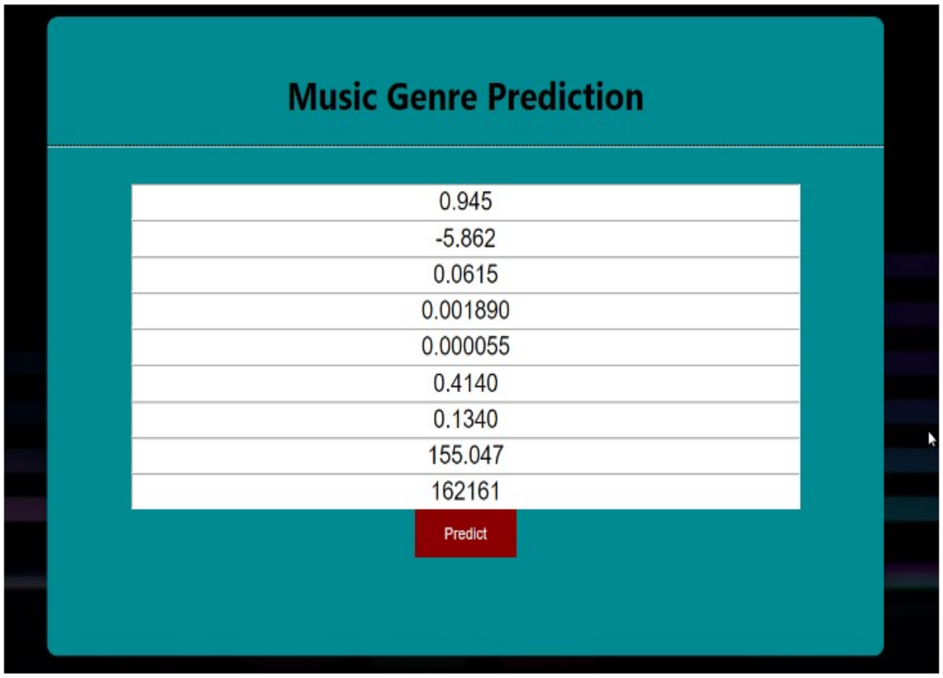


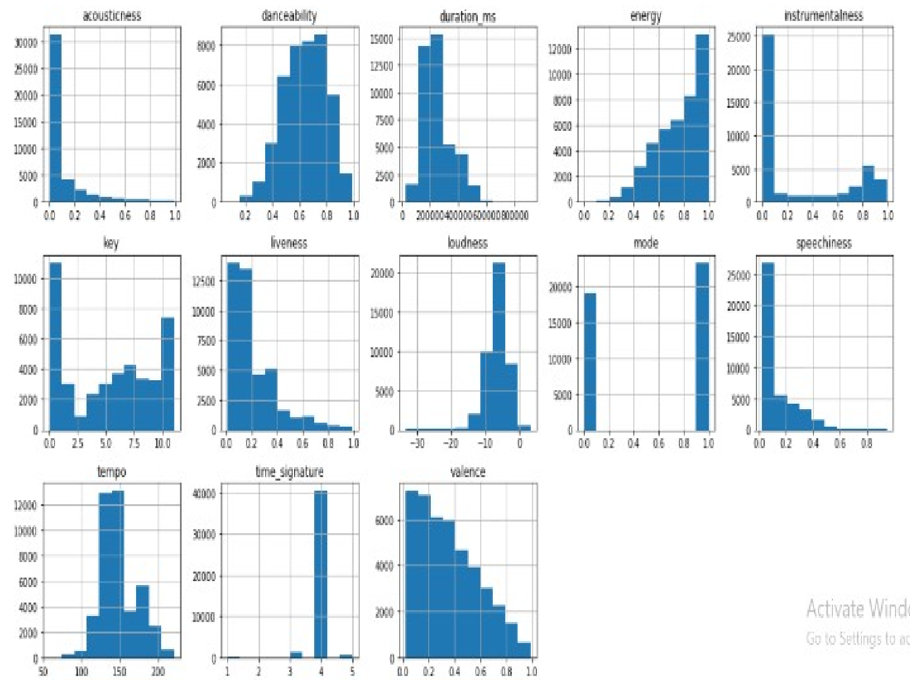
Fig5: Prediction or the output of the model

Fig6: Feature classification

```
In [32]:  #Accuracy of the model
          from sklearn.metrics import accuracy_score,f1_score,confusion_matrix
          accuracy_score(ytest,pred)

Out[32]:  0.7619858156028368

In [33]:  f1_score(ytest,pred,average='weighted')
```



<matplotlib.axes._subplots.AxesSubplot at 0x20869c23080>

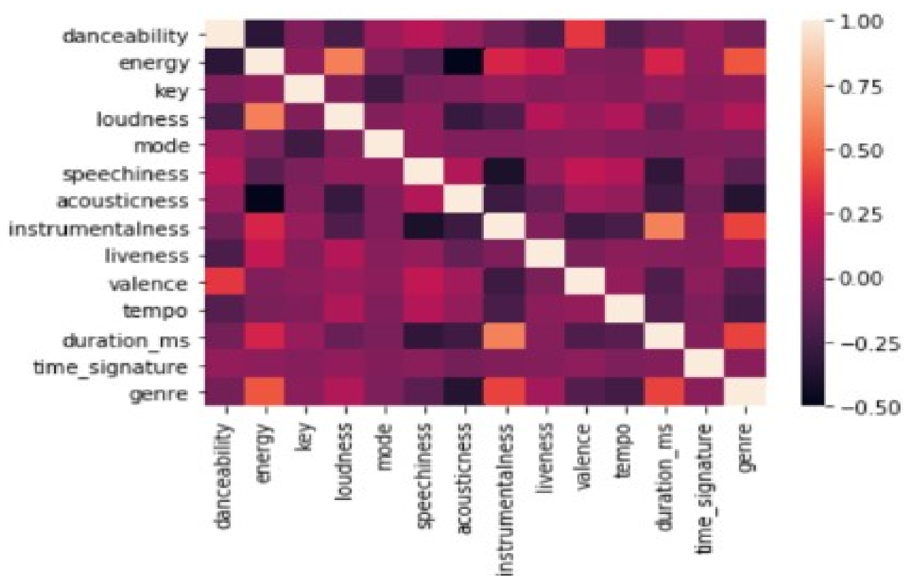


Fig7: Heatmap of the dataset

5.1 Applications:

The music genre classification project has several practical applications across various industries and domains. Here are some key applications:

Music Streaming Platforms: The primary application is for music streaming platforms like Spotify, Apple Music, and Amazon Music. Implementing this project can enhance their music recommendation systems, enabling users to discover songs and playlists tailored to their preferred genres.

Personalized Playlists: The project can be used to create personalized playlists for individual users based on their music genre preferences, moods, or activities, making the music streaming experience more enjoyable and engaging.

Radio Stations and Music Channels: Music genre classification can be utilized to create genre-specific radio stations and music channels, allowing users to listen to continuous streams of songs from their favorite genres.

Music Analysis and Marketing: Record labels and music industry professionals can leverage the project's insights into music trends and genre popularity to analyze audience preferences, market new releases, and plan promotional campaigns effectively.

Music Recommendation APIs: The developed genre classification model can be packaged into an API (Application Programming Interface), allowing developers to integrate it into their applications, websites, or chatbots to offer music recommendations based on user preferences.

Music Genre Analysis Research: Researchers studying music genres, trends, and cultural preferences can use the project to analyze large music databases efficiently and gain insights into the evolution of music genres over time.

CHAPTER 6
CONCLUSION

The music genre classification project utilizing machine learning and Spotify data stands as a promising and transformative initiative in the realm of music technology. Through diligent data collection, preprocessing, and model training, the project has yielded remarkable outcomes. The classification model's capacity to accurately categorize songs into their respective genres paves the way for an enhanced music streaming experience. It empowers music platforms to offer users personalized playlists, music recommendations, and genre-specific radio stations, thereby fostering user engagement and satisfaction.

Beyond immediate user benefits, this project symbolizes a milestone in the music industry's journey towards data-driven decision-making and innovation. It not only offers an insightful lens into music trends and preferences but also lays the foundation for future advancements in audio analysis and recommendation systems. The project, in its essence, serves as a harmonious blend of technology and creativity, enabling users to discover new music, indulge in tailored playlists, and relish an auditory experience that resonates deeply with their individual tastes and preferences. It's a harmonious crescendo in the ever-evolving landscape of music technology.

This venture is not merely a culmination but a prelude to the possibilities that lie ahead. As the music industry continues to evolve, this project serves as a testament to the beauty of merging data with art, offering not only harmonious listening experiences but also the promise of an enriched future for all music enthusiasts. In this ever-advancing landscape, the music genre classification project is the embodiment of what can be achieved when technology and creativity unite in perfect harmony.

CHAPTER 7
FUTURE SCOPE

The future scope of music genre classification using Spotify data holds significant potential for advancement and innovation in various domains. This section explores the potential directions and opportunities for further development and application ofthe classification system.

Enhanced Genre Taxonomy: One of the key areas for future exploration involves refining the genre taxonomy. Current genre labels may be limited in capturing the diversity and complexity of music. Researchers can work towards developing more comprehensive and nuanced genre categories, potentially leveraging user- contributed genre tags and collaborative filtering to identify emerging genre trends.

Fine-Grained Genre Classification: Moving beyond high-level genre categories, the future scope includes fine-grained genre classification. By distinguishing sub-genres and micro-genres, the system can offer more personalized and accurate music recommendations and allow users to explore music based on more specificpreferences.

Multimodal Data Integration: To improve classification accuracy, integrating multiple modalities of data, such as audio, lyrics, album artwork, and user-createdplaylists, can be explored. Combining these diverse data sources may enable a more holistic understanding of songs and their genre characteristics.

Incorporating Contextual Information: Future research can focus on incorporating contextual information to enhance genre classification. Contextual factors, such astime of release, geographic origin, and cultural influences, can significantly impact the perception and categorization of music genres.

Transfer Learning: Applying transfer learning techniques is another potential avenue for future development. Pretrained models on a large music dataset can be fine-tuned using Spotify data, especially when labeled data is limited. Transfer learning can lead to more efficient model training and improved genre classification performance.

Addressing Imbalanced Data: To tackle the issue of imbalanced data, advanced techniques such as data augmentation, oversampling, and class weighting can be explored. Balancing the dataset can help the model achieve better accuracy across all genres.

REFERENCES

- Tzanetakis, G., & Cook, P. (2002). Musical genre classification of audio signals. IEEE Transactions on speech and audio processing, 10(5), 293-302.

- Bahuleyan, H. (2018). Music genre classification using machine learning techniques. arXiv preprint arXiv:1804.01149.

- Sturm, B. L. (2012, November). An analysis of the GTZAN music genre dataset. In Proceedings of the second international ACM workshop on Music information retrieval with usercentered and multimodal strategies (pp. 7-12).

- Sturm, B. L. (2013). The GTZAN dataset: Its contents, its faults, their effects on evaluation, and its future use. arXiv preprint arXiv:1306.1461.

- Gemmeke, J. F., Ellis, D. P., Freedman, D., Jansen, A., Lawrence, W., Moore,

- R. C., ... & Ritter, M. (2017, March). Audio set: An ontology and human- labeled dataset for audio events. In 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 776-780). IEEE