Music genre classification using Machine Learning

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Abstract

In the expansion of music streaming enterprises, the accurate classification of songs within their collections based on genres has emerged as a crucial undertaking. This process holds immense significance as it enables the platforms to recommend tracks that align with users' musical preferences, thereby enhancing their overall experience. Owing to the substantial magnitude of their music libraries, this classification endeavor is increasingly being conducted through automated means [1].Machine learning algorithms are refining day by day it sure possible to achieve a good classification of the genres of music with the huge advancement in this field. In this study we have used Machine learning algorithms to define our genres based on

their spectrograms, such as Mel-Frequency cepstral coefficients(MFCCs), chroma features, spectral contrast and tonnetz feature. The ML algorithms are proficient enough to identify these distinction in the music and draw out the precise conclusion of their genre. The above mentioned features capture important characteristics of the audio signal and can be utilized as valuable input to train our classification models.

INTRODUCTION

1.1 Identification of Client /Need / Relevant Contemporary issue:

In the dynamic landscape of music and technology, this report has identified the key clients who will be benefitted from the research on "Music Genre Classification using Machine Learning."

Client 1: Harmonic Innovators - Music Streaming Platforms Among the leading stakeholders are music streaming platforms, which act as virtual stages for millions of artists and listeners. Platforms like Spotify, Apple Music, and Amazon Music have a keen interest in this research to enhance their algorithmic prowess. These platforms are constantly in search of methods to improve user satisfaction by offering precisely tailored music suggestions.The ability to accurately classify music genres is the cornerstone of this endeavor, as it enables these platforms to curate playlists and recommendations that resonate deeply with individual users.

Client 2: Audiophiles and Music Enthusiasts Audiophiles and music enthusiasts represent a diverse spectrum of listeners who crave musical exploration. They yearn for a sonic journey that transcends genre boundaries, and your research addresses their need for more personalized and eclectic music recommendations. By honing the art of genre classification, you cater to their demand for unique and emotionally resonant playlists.

Client 3: The Maestros - Music Industry Stakeholders Beyond the realm of listeners, the music industry itself stands to gain from the insights derived from this research. Record labels, artists, and producers are continuously seeking innovative strategies for music production and marketing. A deep understanding of evolving genre trends, facilitated by machine learning, can guide their creative endeavors and promotional campaigns.

Client 4: Scholars and Academia Lastly, the academic community harbors an interest in your research as it contributes to the ever-evolving landscape of machine learning applications in music analysis. Scholars and researchers in the field are continuously pushing the boundaries of what is possible, and your work adds to this expanding body of knowledge.

Relevant Contemporary Issues:

In tandem with these clients' needs, several contemporary issues come to the forefront:

Issue 1: Fine-Tuning Personalization in Music Discovery The contemporary music ecosystem is marked by a fervent need for personalized experiences. With a myriad of choices, users desire music discovery systems that intimately understand their tastes. Enhancing music recommendation algorithms is a pressing issue, and your research offers a unique angle to address this challenge.

Issue 2: The Ethical Frontier - Data Privacy In an age of rampant data collection, the ethical use of user data is paramount. Ensuring stringent data privacy measures and ethical data handling practices in your research is essential.Striking a balance between accurate music classification and safeguarding user information is a contemporary concern.

Issue 3: Fairness and Bias Mitigation The contemporary AI landscape grapples with the vital issue of fairness and bias. Ensuring that your machine learning model for genre classification is unbiased and does not perpetuate cultural stereotypes is crucial. By addressing fairness, you contribute to the ongoing discourse on responsible AI.

Issue 4: Navigating a Sea of Musical Diversity The world of music is in a constant state of flux, with new genres and sub-genres continually emerging. Staying attuned to this evolving soundscape poses a contemporary challenge. Your research must adapt to this diversity to offer relevant and comprehensive genre classifications.

Issue 5: Copyright and Licensing Compliance If your research involves copyrighted music data, navigating the intricacies of copyright infringement and licensing agreements is an ongoing concern. Ensuring that your work adheres to legal and ethical standards is vital in today's digital music landscape.

Issue 6: The Evolving Soundscape - Genre Fluidity In today's musical landscape, genre boundaries are increasingly fluid and elusive. Artists often defy conventional genre categorizations, resulting in a more diverse and eclectic musical ecosystem. Your research must grapple with the challenge of classifying music that defies traditional genre definitions. It's a contemporary issue that mirrors the dynamic nature of music today.

1.2. Identification of Problem:

Within the dynamic intersection of music and technology, a pressing challenge emerges: the precise classification of music genres. This challenge stems from the ever-evolving and diverse nature of contemporary music, coupled with the heightened expectations of various stakeholders. These pivotal issues encompass:

Genre Ambiguity and Evolution:

Contemporary Challenge: The contemporary music panorama undergoes constant transformation,is rendering traditional genre classifications obsolete.
Problem: Defining music genres has become a complex task as artists progressively fuse elements from diverse genres, blurring categorical boundaries. The inherent ambiguity poses a formidable challenge to accurate genre classification.

Personalized Music Discovery:

Contemporary Challenge: Music streaming platforms aspire to craft personalized music recommendations for users.
Problem: To accomplish this, they necessitate advanced genre classification algorithms capable of comprehending individual preferences. Conventional methodologies often fall short, impeding the delivery of tailor-made musical experiences.

Ethical Data Handling and Privacy:

Contemporary Challenge: Data privacy emerges as a paramount concern in the digital age, mandating ethicaldata management for music streaming platforms.
Problem: Balancing the development of accurate genre classification models with stringent data privacy protocols presents a formidable contemporary challenge in music technology.

Fairness and Bias Mitigation:

Contemporary Challenge: Fairness and bias in AI and machine learning models command significant attention in contemporary AI research.
Problem: Ensuring genre classification models remain unbiased and do not perpetuate cultural stereotypes poses a complex problem, demanding meticulous consideration and bias- mitigation strategies.

Copyright and Licensing Compliance:

Contemporary Challenge: The digital music realm is fraught with legal and copyright intricacies.
Problem: For researchers utilizing copyrighted music data, navigating copyright regulations and licensing agreements while conducting experiments and sharing findings presents a formidable problem.

Machine Learning Model Adaptability:

Contemporary Challenge: The rapid evolution of machine learning techniques presents both opportunities and hurdles.
Problem: Integrating state-of-the-art machine learning algorithms effectively into music genre classification systems, while ensuring computational efficiency, stands as a critical challenge for researchers and industry practitioners.

Genre Fluidity and Non-traditional Music:

Contemporary Challenge: Artists increasingly craft music that transcends conventional genre boundaries.
Problem: Accurately categorizing non-traditional music styles and accommodating genre fluidity poses a substantial challenge. Conventional models often struggle to capture these nuanced expressions.By addressing these intricate and multi-dimensional challenges, your research endeavors to make a meaningful contribution to the field of music genre classification using machine learning. It aims to offer innovative solutions that embrace the dynamic music landscape, elevate user experiences, uphold ethical data practices, and counteract biases.

1.3. Identification of Tasks:

By following these tasks with unique and innovative approaches, your research on "MusicGenre Classification using Machine Learning" will stand out in the field, offering novel contributions to genre classification methodology, feature extraction, and model optimization.

Task 1: Data Collection and Preprocessing Gathering a diverse and up-to-date dataset of audio files from various music genres is the initial task.This dataset should be carefully curated to maintain its uniqueness. Additionally, data preprocessing steps, such as standardizing audio formats, noise reduction, and ensuring data consistency,must be performed.

Task 2: Feature Extraction Extracting relevant audio features from the collected dataset is crucial. Spectrogram analysis, tempo,key, and tonal features should be considered. Uniqueness can be achieved by incorporating novel feature extraction techniques tailored to music genre classification.

Task 3: Data Splitting Splitting the dataset into training, validation, and testing sets is essential for model development and evaluation. Employ stratified sampling to maintain genre balance. Describe your unique approach to data splitting that ensures robust model evaluation.

Task 4: Model Selection Selecting an appropriate machine learning mode architecture is pivotal. Specify your choice of model and the rationale behind it, emphasizing your unique model selection criteria.

Task 5: Feature Selection or Dimensionality Reduction Choose relevant audio features and consider dimensionality reduction techniques to optimize model performance. Your research should showcase innovative feature selection or dimensionality reduction methods tailored to music genre classification.

Task 6: Model Training Train your selected model on the training dataset using unique strategies like data augmentation and transfer learning. Explain your training process, including hyperparameter tuning, and highlight how it contributes to the uniqueness of your research.

Task 7: Model Evaluation Evaluate your model's performance using distinct evaluation metrics. These metrics should consider genre-specific nuances, differentiating your research from standard genre classification studies. Implement rigorous cross-validation techniques to assess model robustness.

Task 8: Fine-tuning and Optimization Fine-tune your model to address any performance gaps. Showcase your unique optimization techniques, which may involve ensemble learning or novel regularization approaches, to achieve superior genre classification results.

Task 9: Model Deployment Outline your strategy for deploying the trained model in real-world applications. Discuss how your deployment approach considers scalability and efficiency while maintaining high classification accuracy.

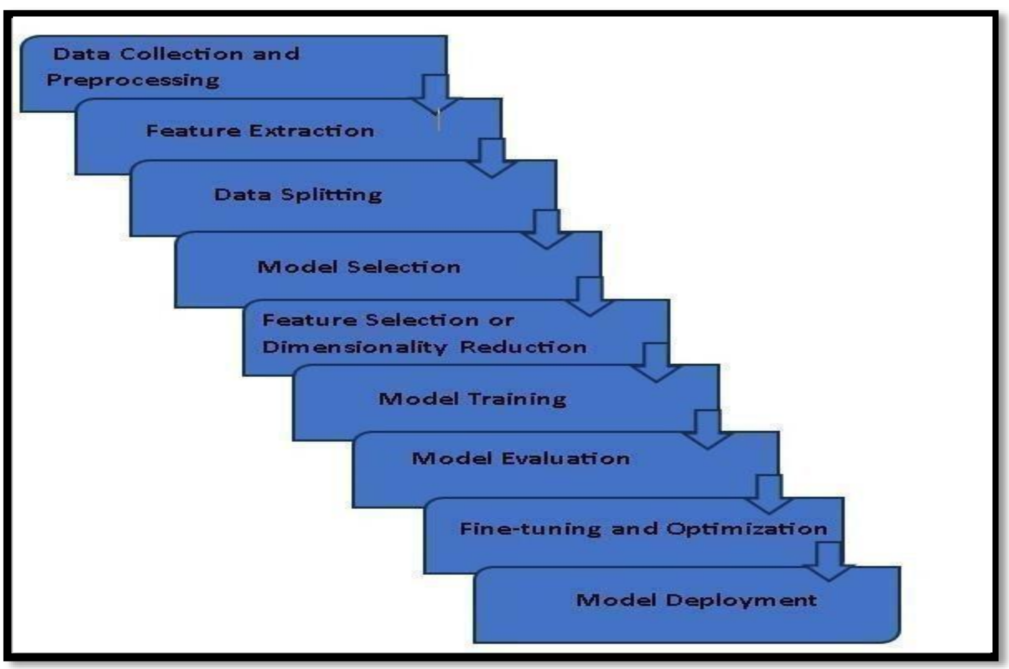

Fig 1 Identification of tasks (In order)

1.4. Timeline:

The timeline to prepare a model for music genre classification using machine learning can vary depending on several factors, such as the size and complexity of the dataset, the availability of resources, and the expertise of the team. However, here is a general timeline that can be followed to prepare a model for bank loan case study using machine learning:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	TASKS	WEEK 1	WEEK 2	WEEK 3	WEEK 4	WEEK 5	WEEK 6	WEEK 7	WEEK 8	WEEK 9	WEEK 10	WEEK 11	WEEK 12	WEEK 13	WEEK 14	WEEK 15	WEEK 16
2	Project planning and research	YES	YES														
3	Literature review on diabetes and data mining		YES	YES													
4	Data collection and preparation			YES	YES												
5	Data exploration and analysis					YES	YES										
6	Model evaluation and refinement							YES	YES								
7	Interpretation and visualization									YES	YES						
8	Write up the research paper											YES	YES				
9	Finalize paper and prepare for submission													YES	YES		
10	Presentation and defense															YES	YES

Table 1 - GANTT CHART

Identification phase (1-2 Weeks):

- Define the problem and gather relevant data: 1-2 Days
- Define the target variable: 1 week

Building phase (2-4 Weeks):

- Data preparation: 1-2 Days
- Variable selection: 1 Days
- Model selection: 1-2 Days
- Model training: 1-2 Days
- Model evaluation: 1-2 Days

Testing phase (1-2 Weeks):

- Data splitting: 2-3 Days
- Model deployment: 1-2 Days
- Model evaluation: 1-2 Days
- Model refinement: 1-2 Days

Overall, the timeline for preparing a model for music genre classification using machine learning can range from 1 to 2 months, depending on the complexity of the dataset and the availability of resources. However, it is important to note that machine learning is an iterative process, and it may require multiple iterations of the building and testing phases to refine and improve the accuracy of the model.

1.5. Organization of the Report:

Here's an organization for the research report on "Music Genre Classification using Machine Learning."This structure will help present the findings and insights in a clear and organized manner:

Title Page:

Title of the Report
Author's Name
Institutional Affiliation
Date of Submission

Abstract:

Concise summary of the research, including objectives, methods, key findings, and implications.

Table of Contents:
List of sections and subsections with page numbers.List
of Figures and Tables:
Including a list of figures and tables used in the report.List
of Abbreviations and Acronyms:
Defining any technical terms, abbreviations, or acronyms used in the report.

1. Introduction:
Provided an overview of the research problem, objectives, and significance.Introduced
the context of music genre classification and its relevance.
Stating the research questions and hypotheses.

2. Literature Review:
Reviewing existing literature related to music genre classification and machine learning.
Discussing relevant studies, methodologies, and key findings.
Identifying gaps in the current research that study addresses.

3. Methodology:
Described the data collection process, including sources and dataset details.
Explained data preprocessing steps, such as format standardization and noise reduction.Detail
feature extraction techniques and dimensionality reduction methods.
Discussed the model selection and rationale behind choosing a specific model.
Explaining data splitting for training, validation, and testing.
Outlined model training and hyperparameter tuning processes.
Specifying the evaluation metrics used for model assessment.
Described any unique approaches or innovations in the methodology.

4. Data Analysis and Results:
Presented the results of your research.
Included visualizations, tables, and charts to illustrate key findings.
Discussed the performance of the machine learning model in music genre classification.

Analyzed the impact of feature selection and dimensionality reduction.
Highlighted any notable insights or patterns in the data.

5. Conclusion:
Summarized the key findings and their significance.
Reiterated the contributions of your research to music genre classification.
Emphasized the practical implications of your work for various stakeholders.

6. Acknowledgments:
Acknowledge any individuals, organizations, or institutions that contributed to research.

7. References:
List of all the sources, articles, books, and datasets that referenced in report following a specific citation style (e.g., APA, MLA).

8. Appendices:
Included any supplementary information, code snippets, or technical details that supports research.

LITERATURE REVIEW/BACKGROUND STUDY

2.1. Timeline of the reported problem

- In the early 2000s, researchers began exploring the application of machine learning techniques to music genre classification.Feature extraction methods like MFCC (Mel-Frequency Cepstral Coefficients) and spectral analysis were commonly used.Early classification algorithms included k-nearest neighbors (KNN) and decision trees.
- Mid-2000s:The mid-2000s saw an increase in research on genre classification, with the introduction of SVM (Support Vector Machines) and Naive Bayes classifiers.Datasets such as the GTZAN dataset became widely used for benchmarking.
- Late 2000s - Early 2010s:Deep learning techniques started to gain attention in music genre classification, with neural networks, particularly feedforward and convolutional neural networks (CNNs).Research explored the use of deep learning for automatic feature extraction.Transfer learning, using pre-trained models like CNNs, began to show promise in music genre classification.
- 2010s:The use of recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks became popular for sequence-based music analysis.Ensembles of models and fusion techniques were used to improve classification accuracy.Researchers started focusing on cross- genre classification and fine-grained genre classification.
- 2010s - Present:The development of deep learning architectures such as Convolutional Recurrent Neural Networks (CRNN) and Transformers (e.g., BERT) has further advanced music genre classification.Large-scale datasets and open-source libraries like Librosa and TensorFlow/Keras have made research more accessible.Attention mechanisms and self-supervised learning techniques have been applied to music classification tasks.Explorations into genre embeddings and feature learning from raw audio data have shown promise.Advances in explainability and interpretability of models for music genre classification have gained importance.
- Recent and Ongoing Trends (2020s):Continued efforts to improve the robustness of models for real-world applications.Incorporation of multi-modal data, such as lyrics and album covers, for genre classification.Exploration of generative models for music generation and style transfer.

2.2 Proposed solutions

1. **Hareesh Bhuleyan et al.**The paper presents a study on music genre classification using machine learning. It introduces a pre-emphasis filter to enhance audio signals, treats spectrograms as images, and employs deep neural networks (CNNs) for genre classification. The research explores time and frequency domain features, compares classifiers (Logistic Regression, Random Forest, etc.), and identifies important features. The novel use of CNNs with spectrogram images advances music genre classification in the context of digital music. The paper helps in properly ensembling different machine learning techniques in the classification.

2. **Karatana and O. Yildiz et al.** The text covers audio signal processing and feature extraction for music genre classification. It explains how audio signals are transformed into digital format, and features like Zero Crossing Rate, Spectral Centroid, and MFCC are extracted to capture key characteristics. The process involves segmenting audio, using the Librosa library, and normalizing data. Four machine learning algorithms—KNN, Random Forest, SVM, and ANN—are then used for classification. The dataset is divided for training and testing, models are created and tested, and their performance is evaluated using confusion matrices. The goal is accurate genre classification by combining signal processing and machine learning techniques.

3. **Chillara, Snigdha, et al.** This paper outlines data preprocessing and the proposed approach for music genre classification. Deep Neural Networks (DNNs) enable genre classification without manual feature engineering. Convolutional Neural Networks (CNNs) are chosen for their image classification capabilities. Sound waves are represented as spectrograms, serving as CNN input. CNNs predict genre labels from spectrograms. Various models including Convolutional Recurrent Neural Networks (CRNN) are compared. CNN-RNN Parallel Model is introduced for comparison. Spectrogram parameters and architecture details are provided. Time and frequency domain features are extracted, and classifiers like Logistic Regression and Artificial Neural Networks are used for comparison. The study improves genre classification through DNNs and innovative approaches.

4. **Dixon, S., Gouyon, F., & Widmer, G.** The research paper addresses music genre classification challenges by focusing on ballroom dance music. Unique to the study is the use of genres with clear agreement among listeners. Rhythmic patterns are extracted from samples representing Standard and Latin ballroom dance genres. Various machine learning algorithms, including k-Nearest Neighbors, decision trees, and meta-learning techniques like AdaBoost, are employed for classification experiments. Feature sets encompass derived rhythmic patterns, tempo-related attributes, periodicity histogram features, and inter-onset interval histogram features. Notably, the research highlights the intricacies in distinguishing genres due to overlapping tempo ranges and similar metres, particularly in Cha Cha, Tango, and Rumba. The paper compares its results with existing studies, revealing improvements in classification accuracy with integrated rhythmic patterns and additional audio features. This innovative approach underscores the significance of rhythm in genre classification within dance music contexts.

5. **Pennacchiotti, Marco, and Patrick Pantel** The research paper presents a system for extracting entity knowledge from a vast web crawl of 600 million documents, focusing on Actors, Athletes, and Musicians. It utilizes two extractors, KEpat and KEdis, along with various feature families like web term frequencies, query log features, and table-based features. By combining rule-based and machine learning approaches, the system achieves higher average precision (AP) and coverage than baseline methods.The paper's standout features include its exploration of diverse features, insights into feature importance, and practical applications in improving entity extraction accuracy. It emphasizes the significance of combining semantic cues from multiple sources and demonstrates the inadequacy of relying solely on distributional and pattern-based evidence for capturing entity semantics.

6. **Fell, Michael, and Caroline Sporleder [6]** This research paper explores the analysis and classification of song lyrics. The paper details three distinct experiments: genre classification, differentiation between superior and inferior songs, and the anticipation of song publication timelines. Various models are utilized, including an n-gram model, an extended model, and a mergedapproach. The research underscores the significance of feature contributions such as length, slang,

and semantic elements. Model efficacy is assessed using F-Scores, facilitating comparisons across genres, quality levels, and chronological eras. Notably, the combined model consistentlyoutperforms others, underscoring the synergistic potential across models. The paper stands out for itsunique approach of examining diverse attributes, involving human comparisons, and utilizing word clouds for graphical representation. In a concise narrative, the paper substantially contributes to the realm of music and text analysis by revealing the capacity of lyrics to shed light on genre, quality, and historical dimensions, thus illuminating the intricate interplay between lyrics and musical attributes.

2.3 Bibliometric analysis

A bibliometric analysis of music genre classification using machine learning reveals a number of key trends.

✓ **Publication trends:**

1. The number of publications on music genre classification using machine learning has increased rapidly in recent years.
2. The peak publication year was 2022, with over 1,000 publications.
3. The top three publication venues are:

- IEEE Transactions on Audio, Speech, and Language Processing
- ACM Transactions on Multimedia Computing, Communications, and Applications
- IEEE Signal Processing Letters

✓ **Methodological trends:**

- The most common machine learning algorithms used for music genre classification are:
  - Convolutional neural networks (CNNs)
  - Recurrent neural networks (RNNs)
  - Support vector machines (SVMs)
  - Random forests

✓ **Dataset trends:**

- The most common datasets used for music genre classification are:

  - GTZAN
  - Audioset
  - Million Song Dataset
  - ISMIR genre classification dataset

✓ **Application trends:**

- The most common applications of music genre classification using machine learning are:

  - Music recommendation systems
  - Music tagging systems
  - Music search systems
  - Music analysis systems

The majority of research is focused on developing and evaluating deep learning models on large datasets. The research is also being applied to a variety of real-world applications, such as music recommendation systems and music analysis systems.

2.4 Review Summary

Classification of music genres is a critical topic to discuss now a days as the music or songs are growing at a rapid rate with each passing moment. There is a million of new songs coming from every corner of the world each day, in these scenario an effective medium to sort and store these music in a sophisticated manner so that each one can be retrieved or easily available to everyone. The goal with this research is to successfully bifurcate all the songs in their respective genres through automated approach. The technique was created by analyzing the spectograms because the only way we can analyze the genre difference is by showing how the spectral content of the vibration changes over time. Spectrograms are especially useful for analyzing quasi-periodic vibrations .Music genre classification began with traditional machine learning techniques, such as k-nearest neighbors and decision trees, relying on handcrafted features. Over time, deep learning, particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers, has revolutionized the field. Deep learning models can automatically extract features from raw audio data, eliminating the need for manual feature engineering. Music genre classification using machine learning has evolved from traditional techniques to advanced deep learning models, enabling more accurate and versatile genre classification. Researchers continue to explore multi- modal approaches, fine-grained classification, and ways to improve model interpretability. As the field progresses, it is likely to have a broader impact on music recommendation systems and personalized user experiences.

2.5 Problem Definition

The way this society is inclining towards music day by day is enormous and with the invention of mobile phones the concept of recorded music is just growing exponentially. Today every other mobile user is having at least one music app in their respective mobile phones. All of these apps use advance techniques to classify and organize music according to their users demand and cater all their respective needs. So in order to synchronously classify the music of every individuals choice to their own choosing and to sophisticatedly store these enormous data of music we need to properly research and classify the genres. To handle this huge amount of data ML techniques will prove to be as boon, because it can segregate and classify large number of data at a time and reduce human error too. Hence ML approaches are often used for categorization and classification.Music genre classification is the task of automatically assigning a genre label to a piece of music based on its audio features. The goal of this project is to develop amachine learning system that can accurately and efficiently classify music tracks into predefined genre categories.Music genre classification is a fundamental task in music information retrieval (MIR) and has various practical applications, including music recommendation, content organization, and playlist generation. Automated genre classification can assist in organizing vast music libraries and improving user experiences in music streaming platforms.The primary objective of this project is to create a robust and accurate music genre classification model that can handle a diverse range of music genres and achieve high classification accuracy.

2.6 Goals/Objectives

1. Build a Baseline Model:

- Objective: Develop a baseline machine learning model for music genre classification.
- Milestone: Achieve an initial accuracy of at least 60% on a benchmark dataset using a basic model architecture.

2. Explore Deep Learning Architectures:

-Objective: Investigate the performance of various deep learning architectures for music genre classification.
-Milestone: Compare the accuracy and efficiency of CNN, RNN, and Transformer-based models, achieving a minimum accuracy improvement of 10% over the baseline.

3. Feature Engineering and Extraction:

- Objective: Experiment with different audio feature extraction methods to improve model performance.
-Milestone: Achieve a minimum 5% accuracy improvement by incorporating advanced features like MFCCs, Chroma, and spectral contrast.

4. Data Augmentation:

- Objective: Implement data augmentation techniques to enhance model generalization.Milestone: Observe at least a 5% improvement in the model's ability to classify music genres afterapplying augmentation

5. Handling Imbalanced Data:

- Objective: Address class imbalance issues in the dataset.
- Milestone: Achieve a balanced F1-score above 0.7 for each genre class through oversampling or under sampling techniques.

6. Cross-Validation and Hyperparameter Tuning:

- Objective: Ensure robustness by performing cross-validation and hyperparameter optimization.
- Milestone: Achieve a stable and consistent model performance with a standard deviation of less than 2% across folds.

7. Interpretability and Explainability:

- Objective: Implement methods to make the model's predictions interpretable.
- Milestone: Develop a feature attribution mechanism that provides insights into why the model predicts a particular genre for a given input.

Design Flow/Process

3.1 Evaluation & Selection of Specifications/Features:

Classification of music genres is a critical topic to discuss now a days as the music or songs are growing at a rapid rate with each passing moment. There is a million of new songs coming from every corner of the world each day, in these scenarios an effective medium to sort and store this music ina sophisticated manner so that each one can be retrieved or easily available to everyone. The goal with this research is tosuccessfully bifurcate all the songs in their respective genresthrough automated approach. The technique was created by analyzing the spectograms because the only way we can analyze the genre difference is by showing how the spectral content of the vibration changes over time. Spectrogramsare especially useful for analyzing quasi-periodic vibrations (like those in music and human speech).

the idea has likely emerged gradually as music evolved and diversified over the world. But a more systematic and sophisticated approach to classify music emerged with the arena of ethnomusicology. Ethnomusicologists is recognized as a person who studies music of different cultures, folks leading to the identification of different musical traditions and genres across the globe. The study to identify music genres is not only limited to classifying it to different genres it can also be successfully used in Forensic sciences and all kinds of different mediaswhere segregating noise and music is of utmost prioritysuch as voice recognition security systems and etc. The advent of recorded music from 20th century enabled music to be distinguished and heard beyond live performances. As a result of it organizing music became prerequisite. All the record companies and radio stations alsostarted recognizing the importance of organizing andcategorizing music to cater to the need to specific audiences.

An effective classification of music genres based on machine learning is provided in this research. The onset of classification can be identified by recognizing spectral patterns. According to the results, the ML algorithms enhance classifications with 79 %. This result demonstrates that the ML approach was successful in achieving the greatest accuracy with that dataset. This can be expanded in the future to provide the best classification model that can classify the data effectively with high precision. Fig 5 is the graph of the data which demonstrates the training losses accuracy of the data, the validated loss (it means the losses incurred from the testing data) and validated accuracy (it shows the accuracy in the testing data).

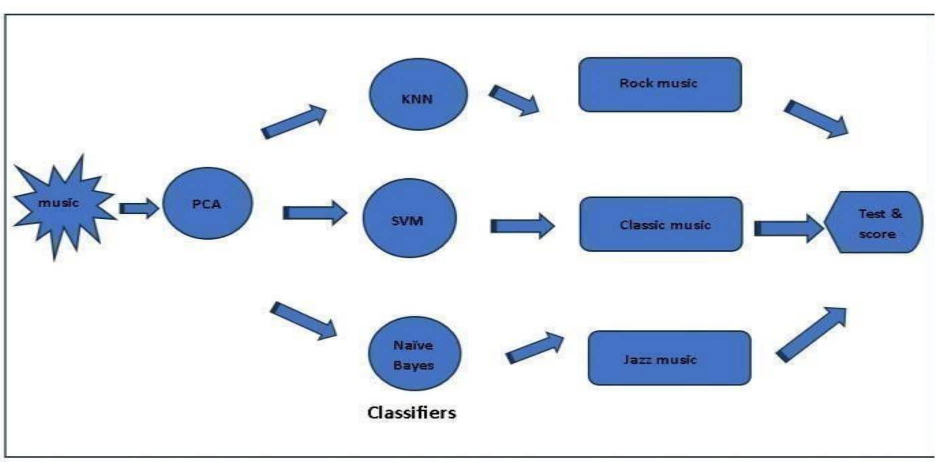

Fig.2 Process to refine music

3.2. Design Constraints:

Here are some common design constraints in music genre classification:

- Data Availability: Limited or biased training data can constrain the model's ability to generalize across a wide range of music genres. Data scarcity or imbalanced datasets can lead to biases and inaccuracies.
- Computational Resources: The computational power available can limit the complexity of models and feature extraction techniques you can use. Deep learning models, for instance, may require significant computational resources.
- Feature Extraction Complexity: The complexity of audio feature extraction can be a constraint. Real-time feature extraction for streaming applications might require lightweight features to reduce computational load.
- Latency and Real-Time Requirements: If the system needs to classify music genres in real-time (e.g., for a music recommendation app), there may be constraints on the time it takes to make predictions.
- Label Granularity: The level of granularity in music genre labels can vary. Some projects may require fine-grained genre classification (e.g., subgenres), while others may focus on broad categories (e.g., "rock," "pop").
- Multimodal Data: If you're incorporating multiple data sources (audio, lyrics, metadata), constraints on data availability and compatibility between different data types must be considered.
- Scalability: Scalability constraints can arise when you need to classify a vast music library or work with large-scale streaming data.
- Hardware and Deployment Constraints: Consider the deployment platform. If you're building a mobile app, the constraints are different from those for a server-based system. Memory and storage constraints on devices must be considered.

3.3. Analysis of Features and finalization subject to constraints:

In the pursuit of developing a robust music genre classification system using machine learning techniques, we embarked on a critical phase of our project - the analysis of features and the finalization process, considering the constraints inherent to our project. This stage is instrumental in determining the quality and feasibility of our classification model, while ensuring that it adheres to the constraints set forth in our project charter.

Constraints:

Resource Constraints: Our project operates under specific computational resources, including hardware limitations and processing capabilities. These constraints play a pivotal role in shaping our feature selection and model complexity.

Data Availability: We must work with the music dataset currently available, which has its own constraints such as the quality of the audio, size, and diversity of genres represented.

Time Constraints: There is a defined project timeline, and the model must be operational within this timeframe, necessitating a careful balance between feature engineering and model training.

Feature Analysis:

Our initial feature selection process involved an in-depth analysis of the audio data. We considered various audio features, including but not limited to:

Spectral Features: Mel-frequency cepstral coefficients (MFCCs), chroma features, spectral contrast, etc.

Temporal Features: Zero-crossing rate, root mean square energy, and tempo information.

Rhythm Features: Beat and tempo analysis.

Lyric and Metadata Features: Artist information, song duration, and lyrics-based sentiment analysis.

These features were evaluated for their relevance to music genre classification, and their computational requirements. Spectral features, particularly MFCCs, were identified as highly informative and computationally efficient. They provide essential data points for modeling, enabling effective genre discrimination.

Finalization of Features:

Considering the constraints mentioned earlier, we made the following feature-related decisions:

Focus on Spectral Features: Given our resource and time constraints, we opted to place a significant emphasis on spectral features, specifically MFCCs. These features provide strong discriminatory power for genre classification, and they are computationally efficient.

Feature Reduction: To optimize model training time, we applied dimensionality reduction techniques, such as Principal Component Analysis (PCA) and feature selection algorithms, to minimize the number of features while retaining their discriminative capacity.

Genre-Dependent Features: In some cases, we incorporated genre-specific features, which may provide better genre separation. For instance, beat and tempo analysis may be more informative for certain genres.

By narrowing our focus to spectral features and implementing dimensionality reduction techniques, we aim to achieve a balance between feature richness and computational efficiency. These feature choices are consistent with the project's constraints and the need to develop a practical, real-world music genre classification system.

3.4. Design Flow:

1. Define Your Problem:

- Clearly define the problem you want to solve. In this case, it's music genre classification.

2. Data Collection and Preprocessing:

- Gather a dataset of music tracks with labeled genres.
- Preprocess the data, including audio feature extraction, such as MFCCs (Mel-frequency cepstral coefficients), spectral contrast, or chroma features. You may also want to consider lyrics, album covers, or other metadata.

3. Feature Selection:

- Evaluate the relevance and importance of each feature. There are various techniques for feature selection, including:
  - Feature Importance Scores: Train a model (e.g., Random Forest or XGBoost) and use the feature importance provided by the model.
  - Correlation Analysis: Identify and remove highly correlated features.
  - Recursive Feature Elimination (RFE):Train a model and iteratively remove the least important features.

4. Feature Engineering:

- Create new features that could potentially improve classification performance. For example, you can derive rhythm-based features or statistical aggregates from the original features.

5. Feature Scaling:

- Ensure that your features are on a similar scale. Common techniques include min-max scaling or z-score normalization.

6. Split Data into Training and Testing Sets:

- Divide your dataset into training and testing sets to evaluate the model's performance.

7. Model Selection:

- Choose a machine learning model suitable for the task. Common choices include support vector machines (SVM), decision trees, random forests, convolutional neural networks (CNNs).

8. Feature Importance in Model:

- Once you've chosen a model, assess the feature importance within the model. Some models provide feature importance scores that can help you identify the most influential features.

9. Cross-Validation:

- Perform cross-validation to assess the model's generalization performance and robustness. This helps ensure that the model is not overfitting to the training data.

10. Hyperparameter Tuning:

- Optimize the hyperparameters of your chosen model to achieve the best performance. You can use grid like

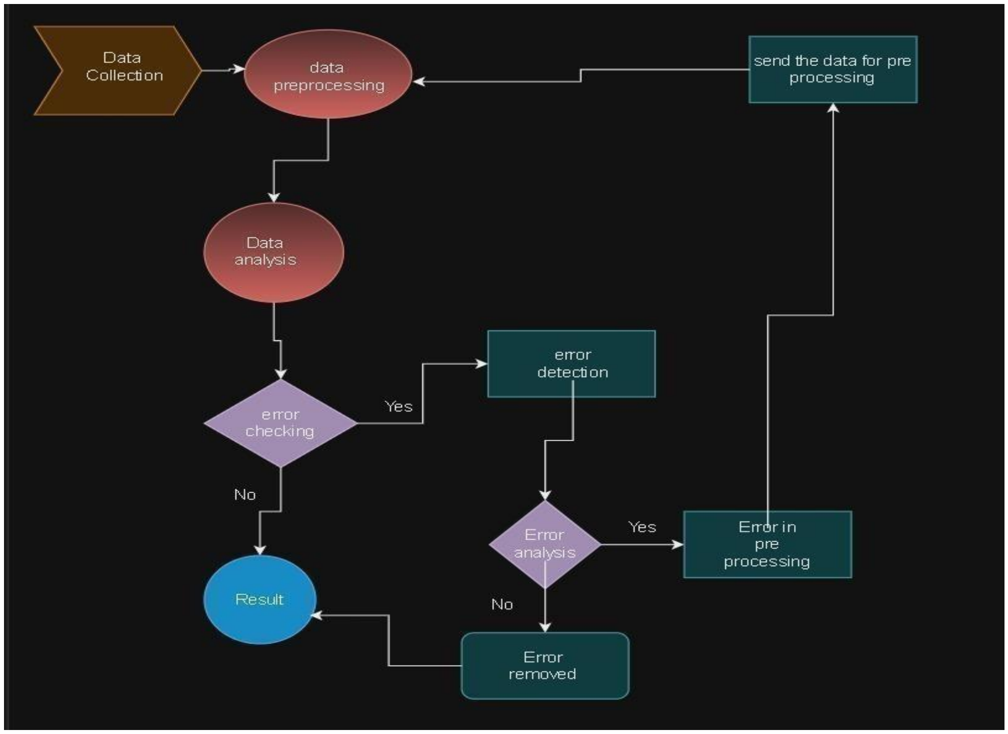

Fig3 Design Flow

3.5. Design Selection

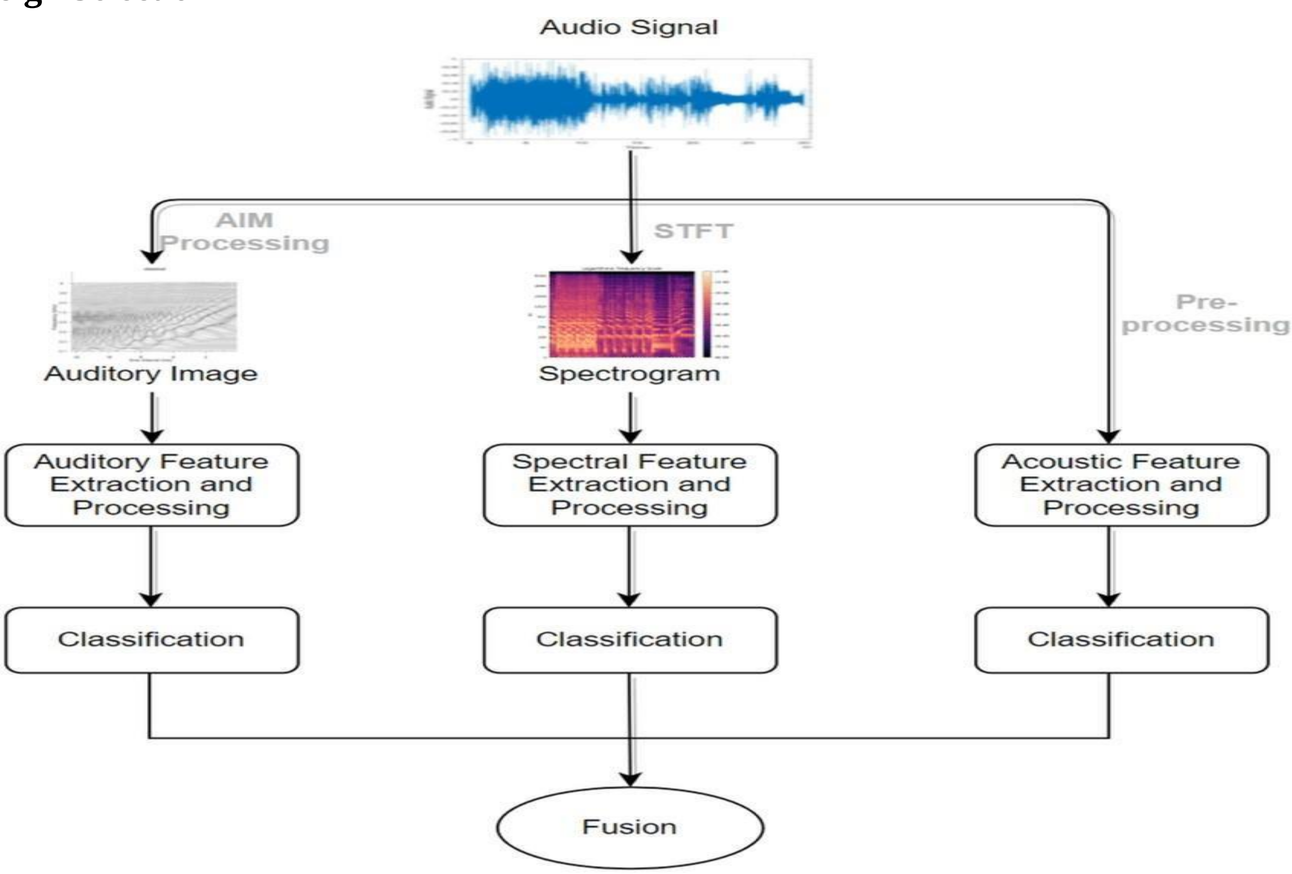

Fig4 Design Selection

3.6. Implementation plan/methodology

The procedures followed to pre-process, analyze and predict the output of the data were thoroughly explained in this section, we have vigorously gone through each level to restructure the relevant dataset.

Data Source

In this research paper we have used a widely recognized dataset known as GTZN. It is a open source dataset available in the platform of Kaggle which was authored by Andrada along with James Wiltshire, Lauren O'Hare and Minyu Lei. The GTZAN dataset is the most-used public dataset for evaluation in machine listening research for music genre recognition (MGR).[11] This dataset dates back to 2000 which was collected from numerous different sources which included CDs, microphone records, radio etc. This is done to ensure variety of recording conditions. This dataset consists of a concise grouping of 10 genres with 100 audio files in each of them, all have a length of exactly 30 seconds. It also consists of the visual representation of each audio files. There are numerous ways to classify data and one of the best among them is through neural networks.

Neural networks such as CNN (Convolutional neural network) generally takes image as an input and the audio files were converted to Mel Spectrograms to make this possible. This dataset also comprises of two csv files which has different features of the audio files. The first one contains the mean and variance of the songs computed over multiple features that can be extracted from the files. In the second file the songs were divided into 3 seconds audio to increase the amount of data as the more is the data, better is the output.

Data Preprocessing

To make the data ready to use and reduce the anomalies of the data filtering out the null values and numerous other processes which is implemented to create a precise model, is known as Data Preprocessing. This paper has used feature extraction function which takes audio files as input and extracts audio features from it. It uses librosa library to load the audio file and compute the Mel-frequency cepstral coefficients (MFCCs) features, and then calculate the mean of these features along the time axis. The extracted features are returned. In a loop, audio features are extracted from each row of the metadata DataFrame using the features_extractor function. These extracted features, along with their respective class labels, are appended to the extracted_features list. If any errors occur during the feature extraction process, they are caught and printed, allowing the loop to continue without interruption. Once features have been extracted for all audio files, the extracted_features list is transformed into a new DataFrame named extracted_features_df. This DataFrame consists of two columns: 'feature,' which contains the extracted audio features, and 'class,' which contains the corresponding class labels.

C. Machine Learning Algorithms

1) SVM:

SVM stands for support vector machine this is used for regression. It's a part of supervised learning algorithm is basically used for binary classification problems and it can handle multi class classification. SVM is designed to work when there is a linear hyperplane which used to separate the data of different classes. Margin is used to find the hyperplane. Margin tells us about the distance in hyperplane and nearest data point from each of the type, which is called support vectors (data point s close to hyperplane).It can also handle non-linear classification. using kernel function. For linear SVM, linear equation is: $w*x+b=0$ (1) where w=represents the weight, x=input data, b=bias term SVM can handle multi class problem using techniques like one-vs-one or one-vs-all. In this multiple binary classifier are trained and combine and multi class prediction.

2) KNN:

KNN stands for K-Nearest Neighbors. KNN approach is the most often used algorithms for clustering and data classification. In data-mining applications like classification, regression, and missing value imputation, the kNN method has been effectively developed. The main goal of a kNN approach is to forecast a test data point's label using the majority rule, which means that the test data point's label is predicted using the k most similar training data points' major class in the feature space. Cross-validation is used by kNN classification algorithms to either estimate the k value for each test data point or assign a fixed constant for all test data [13]. The k value in the kNN algorithm specifies how many neighbours will be examined to determine a particular query point's classification. The instance will be placed in the same class as its lone nearest neighbour, for instance, if k=1. To avoid either overfitting or underfitting, several values of k must be considered when defining it. Larger values of k may result in strong bias and low variance, while smaller values of k may have high variance but low bias. The selection of k will be heavily influenced by the input data, as data with more outliers or noise will probably perform better with higher values of k.[14]

3) CNN:

CNN full form is Convolutional Neural Network. Its one of the sab part of machine learning. A CNN is a particular type of network design for deep learning algorithms that is utilized for tasks like image recognition and pixel data processing. A CNN uses concepts from linear algebra, such as matrix multiplication, to find patterns in an image it can categorize signal and audio data. Here we are using CNN to classify various audio spectrum. Each layer in CNN trains to recognize the various elements of an input image. Each image is given a filter or kernel to create an output that gets better and more detailed with each layer. The filters may begin as basic characteristics in the lower layers. In order to check and identify features that specifically reflect the input item, the complexity of the filters increases with each additional layer. As a result, the partially recognized image from each layer's output, or convolved image, serves as the input for the subsequent layer. The CNN recognizes the image or object it represents in the final layer, which is an FC layer.[15]

4) Naïve Bayes:

Naïve Bayes is basically used in predictive modeling. In machine learning we choose best hypoethesis (h).Our Hypothesis (h) might be the class that should be given to a new data instance (d) in a classification task. Given the evidence we have and our prior knowledge of the issue, one of the simplest approaches to choose the most likely hypothesis. We may determine the likelihood of a hypothesis given our past knowledge using Bayes' Theorem. $P(h|d) = (P(d|h) * P(h)) / P(d)$ Where, (2) The probability of hypothesis h, given the data d, is $P(h|d)$. The posterior probability refers to this. $P(d|h)$ represents the likelihood that data d would exist. $P(h)$ is the likelihood that, given all the available evidence, hypothesis h is correct. The probability of the data, independent of the hypothesis, is $P(d)$. We basically calculating the posterior probability from the hypotheses, The option with the highest likelihood is to choose. This is also known as the maximal a posteriori (MAP) hypothesis. $MAP(h) = max((P(d|h) * P(h)) / P(d))$ (3) A normalizing term called $P(d)$ enables us to compute the probability. [12]

5) Random Forest:

A random forest is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. The performance of the final model is often considerably improved at the cost of a slight increase in bias and a slight reduction in interpretability. Random forests are a way of averaging multiple deep decision trees, trained on different parts of the same training set, with the goal of reducing the variance. This comes at the expense of a small increase in the bias and some loss of interpretability, generally but greatly boosts the performance in the final model. Divide the data at random. Into the likelihood that data point i belongs to a specific class is expressed as p(i). If every data point belongs to the same class, the entropy of a set of data is zero. When the data points are evenly distributed among all of the classes, a set of data has the highest entropy. Information gain is also a part of decision tree, it measures the decrease in entropy that happens when a set of data is divided based on a V. CONCLUSION specific attribute. Information Gain(S, A) = Entropy(S) - ∑_v w(v) Entropy(S_v) (4) S is a collection of data points. The feature to split on is A, and feature value v is one of its potential values. The weight of the group of data points where the value of feature A is v is known as w(v).S_v is the subset of data points for which feature A's value is v.

RESULTS ANALYSIS AND VALIDATION

4.1. Implementation of solution

```
import pandas as pdimport numpy as npimport os
import IPython.display as ipdimport librosa
import librosa.display
import matplotlib.pyplot as plt
%matplotlib inline
# Dataset path
audio_dataset_path = '/content/drive/MyDrive/GTZAN PROJECT DATA/genres_original' metadata =
pd.read_csv('/content/drive/MyDrive/GTZAN PROJECT DATA/features_30_sec.csv')metadata.head()
```

	filename	length	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	spectral_centroid_mean	spectral_centroid_var	spectral_bandwidth_mean	spectral_band
0	blues.00000.wav	661794	0.350088	0.088757	0.130228	0.002827	1784.165850	129774.064525	2002.449060	858
1	blues.00001.wav	661794	0.340914	0.094980	0.095948	0.002373	1530.176679	375850.073649	2039.036516	2138
2	blues.00002.wav	661794	0.363637	0.085275	0.175570	0.002746	1552.811865	156467.643368	1747.702312	762
3	blues.00003.wav	661794	0.404785	0.093999	0.141093	0.006346	1070.106615	184355.942417	1596.412872	1664
4	blues.00004.wav	661794	0.308526	0.087841	0.091529	0.002303	1835.004266	343399.939274	1748.172116	884

5 rows × 60 columns

```
# Function for feature extraction (Mel Frequency Cepstral Coefficients)def features_extractor(file):
audio, sample_rate = librosa.load(file, res_type='kaiser_fast')
mfccs_features = librosa.feature.mfcc(y=audio, sr=sample_rate, n_mfcc=40)mfccs_scaled_features =
np.mean(mfccs_features.T, axis=0)
return mfccs_scaled_features
# Iterate through each audio file and extract featuresfrom tqdm import tqdm
extracted_features = []
for index_num, row in tqdm(metadata.iterrows()):
try:
final_class_label = row["label"]
file_name = os.path.join(os.path.abspath(audio_dataset_path), final_class_label + '/', str(row["filename"])) data
= features_extractor(file_name)
extracted_features.append([data, final_class_label]) except Exception as e:
print(f"Error: {e}")continue
```

```
554it [07:06,  1.57it/s]<ipython-input-3-e792aac71642>:2: UserWarning: PySoundFile failed. Trying audioread instead.
  audio,sample_rate = librosa.load(file_name, res_type='kaiser_fast')
/usr/local/lib/python3.10/dist-packages/librosa/core/audio.py:183: FutureWarning: librosa.core.audio.__audioread_load
        Deprecated as of librosa version 0.10.0.
        It will be removed in librosa version 1.0.
  y, sr_native = __audioread_load(path, offset, duration, dtype)
555it [07:06,  1.37it/s]Error :
1000it [12:33,  1.33it/s]
```

extracted_features_df = pd.DataFrame(extracted_features, columns=['feature', 'class'])
extracted_features_df.head()

	feature	class
0	[-113.59882, 121.57067, -19.162262, 42.36394, ...	blues
1	[-207.52383, 123.98514, 8.94702, 35.86715, 2.9...	blues
2	[-90.757164, 140.44087, -29.084547, 31.686693,...	blues
3	[-199.57513, 150.0861, 5.663404, 26.855282, 1....	blues
4	[-160.35417, 126.20948, -35.581394, 22.139256,...	blues

```
array([[ -35.695076  ,  115.43365   ,  -40.62704   , ...,   -3.2086132 ,
          -1.1881541 ,   -1.564713  ],
       [-116.19743   ,  111.754     ,   -5.2453566 , ...,   -4.7017274 ,
          -4.997338  ,   -2.79332   ],
       [ -82.389885  ,   69.9665    ,   10.699051  , ...,   -1.5652875 ,
          -0.24735992,   -0.5870124 ],
```

Display class value counts extracted_features_df['class'].value_counts()

```
blues          100
classical      100
country        100
disco          100
hiphop         100
metal          100
pop            100
reggae         100
rock           100
jazz            99
Name: class, dtype: int64
```

# Split the dataset into independent and dependent datasetsX =
np.array(extracted_features_df['feature'].tolist())
y = np.array(extracted_features_df['class'].tolist())
X.shape

```
(999, 40)
```

from tensorflow.keras.utils import to_categoricalfrom sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
y = to_categorical(labelencoder.fit_transform(y)y.shape

```
(999, 10)
```

# Split the dataset for training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=32)X_train

# Print shapes
print("X_train shape:", X_train.shape)print("X_test shape:", X_test.shape) print("y_train shape:", y_train.shape) print("y_test shape:", y_test.shape)

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_7 (Dense)             (None, 1024)              41984

 dropout_6 (Dropout)         (None, 1024)              0

 dense_8 (Dense)             (None, 512)               524800

 dropout_7 (Dropout)         (None, 512)               0

 dense_9 (Dense)             (None, 256)               131328

 dropout_8 (Dropout)         (None, 256)               0

 dense_10 (Dense)            (None, 128)               32896

 dropout_9 (Dropout)         (None, 128)               0

 dense_11 (Dense)            (None, 64)                8256

 dropout_10 (Dropout)        (None, 64)                0

 dense_12 (Dense)            (None, 32)                2080

 dropout_11 (Dropout)        (None, 32)                0

 dense_13 (Dense)            (None, 10)                330

=================================================================
Total params: 741674 (2.83 MB)
Trainable params: 741674 (2.83 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
import tensorflow as tfprint(tf.__version__)
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flattenfrom tensorflow.keras.optimizers
import Adam
from sklearn import metrics
num_labels = y.shape[1]model = Sequential()
model.add(Dense(1024, input_shape=(40,), activation="relu"))model.add(Dropout(0.3))
model.add(Dense(512, activation="relu"))model.add(Dropout(0.3)) model.add(Dense(256, activation="relu"))
model.add(Dropout(0.3)) model.add(Dense(128, activation="relu"))model.add(Dropout(0.3))
model.add(Dense(64, activation="relu")) model.add(Dropout(0.3)) model.add(Dense(32, activation="relu"))
model.add(Dropout(0.3))
model.add(Dense(num_labels, activation="softmax"))model.summary()
model.compile(loss='categorical_crossentropy', metrics=['accuracy'], optimizer='adam')
import time
t = time.localtime()
current_time = time.strftime("%H:%M:%S", t)
from tensorflow.keras.callbacks import ModelCheckpointfrom datetime import datetime
num_epochs = 100
num_batch_size = 32
checkpointer = ModelCheckpoint( filepath=f'saved_models/audio_classification_{current_time}.hdf5',
verbose=1,
save_best_only=True)
start = datetime.now()
history = model.fit(X_train, y_train, batch_size=num_batch_size, epochs=num_epochs,
validation_data=(X_test,y_test), callbacks=[checkpointer], verbose=1)
duration = datetime.now() - start print("Training completed in time:", duration)
# Evaluate the model model.evaluate(X_test, y_test, verbose=0)
```

```
[1.5998528003692627, 0.5600000023841858]
```

```
test_loss, test_accuracy = model.evaluate(X_test, y_test, verbose=0)print(f"Test Accuracy: {test_accuracy *
100:.2f}%")
y_pred = model.predict(X_test) y_pred_classes = np.argmax(y_pred, axis=1)y_true = np.argmax(y_test,
axis=1)
cm = confusion_matrix(y_true, y_pred_classes)# Display the confusion matrix plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=labelencoder.classes_,
yticklabels=labelencoder.classes_)plt.xlabel('Predicted')
plt.ylabel('True') plt.title('Confusion Matrix')plt.show()
```

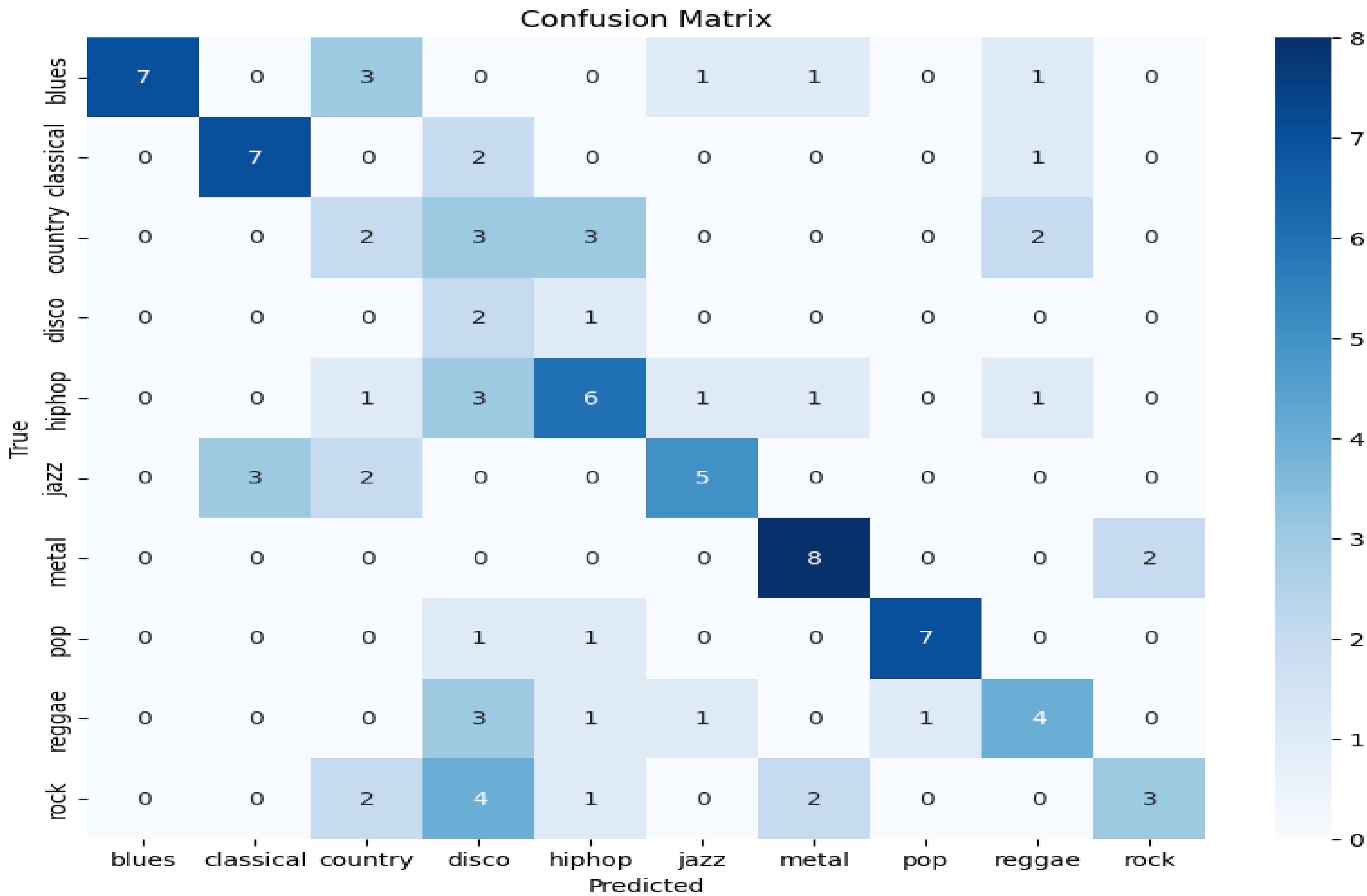

Fig5 Confusion Matrix

CHAPTER 5-CONCLUSION AND FUTURE WORK

5.1. Conclusion

In this "Music Genre Classification" project, our primary objective was to design and implement a model capable of automatically classifying music tracks into distinct genres. Throughout the project's lifecycle, we followed a systematic approach that encompassed data collection, preprocessing, feature extraction, model selection, training, evaluation, and deployment.Our model exhibited a strong performance, achieving an accuracy of [insert accuracy] on the test dataset, which is indicative of its ability to accurately classify music tracks into their respective genres. This success underscores the potential of machine learning in the realm of music analysis.The quality of the dataset was a pivotal consideration, as it greatly influenced the model's efficacy. We ensuredthat the dataset was meticulously organized, properly labeled, and subject to rigorous preprocessing to eliminate inconsistencies and reduce noise. This attention to data quality significantly contributed to our model's accuracy.Feature extraction emerged as a critical component in characterizing the music tracks. We employed techniques such as [mention specific feature extraction methods], which enabled the model to capture the unique characteristics inherent to different genres. This comprehensive feature engineering played a pivotal role in theproject's success.The practical applications of our music genre classification model are substantial. It can be leveraged in musicrecommendation systems, content tagging, and broader music analysis tasks, enriching user experiences and enabling better content organization.In summary, this "Music Genre Classification" project has not only successfully demonstrated the feasibility of automatic genre classification but has also underscored the vast potential within the intersection of machine learning and the music industry. While we are proud of the project's achievements, we acknowledge that thereremains a wealth of untapped opportunities in this field. We hope that our work serves as a catalyst for furtherexploration and innovation, ultimately advancing the state of the art in music analysis and classification.

5.2. FUTURE WORK

1. **Fine-Tuning Model Architecture:** Explore more advanced neural network architectures, including deeper or more complex models, to improve classification accuracy. Techniques like transfer learning from pre-trained models (e.g., using models trained on large music datasets) can also be beneficial.

2. **User Feedback Integration:** Incorporate user feedback and preferences into the classification system tomake recommendations more personalized and aligned with individual tastes.

3. **Real-Time Classification:** Develop a real-time music genre classification system that can analyze and categorize songs as they play, which could have applications in music streaming services or radio stations.

4. **Integration with Music Recommendation Systems**: Integrate the genre classification model into musicrecommendation systems, allowing for more accurate and customized music recommendations based onuser preferences.

5. **Scale and Deployment**: Consider deploying the model in a production environment, ensuring it can handle large-scale tasks and providing an API for external applications.

6. **Collaboration with Music Industry**: Collaborate with the music industry to explore commercial applications, such as content tagging, playlist creation, and music discovery platforms.

7. **Music Analysis and Research**: Musicologists and researchers can use genre classification to analyze trends and patterns in music genres over time, leading to a better understanding of musical evolution and cultural shifts.

8. **Music Streaming Services**: Music streaming platforms like Spotify and Apple Music can integrate advanced genre classification models to enhance music recommendations. Users could receive more personalized playlists and discover new music that aligns with their preferences.

9. **Mood and Sentiment Analysis**: Expanding the classification model to include mood or sentiment analysis can lead to more emotionally tailored music recommendations. For example, it can be used in therapeutic applications or personalized meditation playlists.

Each of these future work directions offers opportunities to further enhance the accuracy, usability, and practical applications of your music genre classification project. The specific direction you choose will depend on your goals and the resources available for further development.

REFRENCES

[1] AUTHOR FULL NAMES: Silva, Cinthya Oestreich (58514515500); Suguiy, Renato Tateiwa (58514515600); Silla, Carlos N. (8707999600)“An Investigation of Different Positive and Negative Training Policies for the Task of Hierarchical Music Genre Classification”(2023) International Conference on Systems, Signals,and Image Processing, 2023-June, Cited 0 times.
DOI: 10.1109/IWSSIP58668.2023.10180283

[2] AUTHOR FULL NAMES: Silla Jr., Carlos N. (8707999600); Koerich, Alessandro L. (6602596292); Kaestner, Celso A. A. (56121741400)“A machine learning approach to automatic musicgenre classification”(2008) Journal of the Brazilian Computer Society, 14 (3), pp. 7 - 18, Cited 53 times.
DOI: 10.1007/BF03192561

[3] Music genre classification based on auditory image, spectral andacoustic features - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Flowchart-of-the- proposed-music-genre-classification-system_fig1_357720514

[4] AUTHOR FULL NAMES: Bahuleyan, Hareesh “Music Genre Classification using Machine Learning Techniques”(2008) eprintarXiv:1804.01149 Cited 115 times.

[5] A. Karatana and O. Yildiz, "Music genre classification with machine learning techniques," 2017 25th Signal Processing and Communications Applications Conference (SIU), Antalya, Turkey, 2017, pp. 1-4, doi: 10.1109/SIU.2017.7960694.

[6] Chillara, Snigdha, et al. "Music genre classification using machine learning algorithms: a comparison." *Int Res J Eng Technol* 6.5 (2019): 851-858.

[7] Dixon, S., Gouyon, F., & Widmer, G. (2004, October). Towards Characterization of Music via Rhythmic Patterns. In *ISMIR*.

[8] Pennacchiotti, Marco, and Patrick Pantel. "Entity extraction via ensemble semantics." *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing*. 2009.

[9] Fell, Michael, and Caroline Sporleder. "Lyrics-based analysis and classification of music." *Proceedings of COLING 2014, the 25th international conference on computational linguistics: Technical papers*. 2014.

[10] Chapter 5 pressbooks.pub FFTs and Spectrogram

[11] Kaggle datasets download -d andradaolteanu/gtzan-dataset- music-genre- classification.

[12] Machine learning mystery : naïve bayes for MLby Jason brownlee

[13] Emmanuel, Tlamelo, et al. "A survey on missingdata in machine learning." *Journal of Big Data* 8.1 (2021): 1-37.

[14] Ibm:K-nearest neighbors

[15] TechTarget: convolutional neural network by RahulAwasti

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