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# Music Genre Classification Using Machine Learning

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## ABSTRACT

Navigating the vast realm of digital music in today's world is like searching for a needle in a haystack, especially within music apps. Users of such apps often struggle in categorizing their music into specific genres like jazz, rock, or electronic. This confusion alters the user experience, making it difficult to organize playlists or discover new music of personal preferences. In response to these challenges, our project provides an innovative solution. The project explores an efficient approach to classify music into distinct genres, by leveraging the power of various technologies like Gradio, GNZAN dataset, SciPy, NumPy, Pandas, Python Speech Features, and various ML algorithms. Firstly, the project begins with preprocessing of GNZAN dataset and using SciPy, NumPy for data manipulation. Feature extraction is performed using Python Speech Features, capturing essential characteristics of the audio like tempo, spectral contrast, and various frequency coefficients. These features serve as the input to the ML algorithms, enhancing the model's ability to identify patterns within the data. Gradio, a Python library, is utilized to create a user-friendly interface, allowing users to interact with the model seamlessly. Through this interface, users can upload audio samples, and the model predicts the genre with high accuracy. Pandas help in organizing the results, enhancing the user experience and understanding of the outcomes. The project performs comparative analysis of various ML algorithms for identifying the most suitable approach used in classification of music genres. This project not only serves as a valuable tool for music enthusiasts (or) streaming platforms, but also showcases the potential of ML in solving real-world problems related to audio data analysis.

Keywords: Machine Learning, Gradio, GNZAN dataset, Access portal, Audio Electronics.

## I. INTRODUCTION

Music. A single word that conjures up a kaleidoscope of emotions. The melodious symphony that transcends language, culture, and time. Music is truly the universal language that

speaks directly to our souls. In today's digital era, we have access to a mind-boggling collection of musical masterpieces from every genre, mood, and time period imaginable. Name your favorite artists or songs, and it's just a click away on your smartphone or laptop.

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top. What an amazing time to be alive! However, with the sheer endless selection of songs and artists today, discovering new music that truly resonates with our personal tastes can feel overwhelming. And finding the perfect playlist to match our current mood? That can be an even bigger challenge.

The purpose of embarking on this project lies in addressing the growing need for efficient and accurate music genre classification systems in the digital age. With the vast expansion of digital music platforms and the sheer volume of available songs, users face significant challenges in organizing and exploring their music collections effectively. Traditional methods of genre classification, such as manual tagging or relying solely on artist and album metadata, fall short in capturing the nuanced characteristics of different musical styles. Consequently, there's an pressing demand for intelligent systems capable of automatically analyzing and categorizing music based on its inherent characteristics.



Fig 1.1 Musical instruments in digital era

By delving into the realm of machine learning and data analysis, this project endeavors to develop a sophisticated solution that not only categorizes music accurately but also adapts to evolving musical trends and preferences. The overarching goal is to empower users with a tool that enhances their music listening experience by providing personalized recommendations, curated playlists, and streamlined access to diverse genres. Beyond mere organization, this project aspires to deepen users' engagement with music by facilitating exploration and discovery across a rich spectrum of genres, from mainstream hits to niche underground sounds.

Furthermore, the project seeks to contribute to the broader field of machine learning and artificial intelligence by tackling the unique challenges posed by music data. Unlike structured datasets found in other domains, such as text or images, music data is inherently complex and multi-dimensional, comprising audio waveforms, spectrograms, and metadata. Thus, the development of a robust music genre classification system not only serves practical purposes but also pushes the boundaries of machine learning research, driving innovation in algorithmic techniques and model architectures.

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Fig 1.2 Music apps

In addition to enhancing user experience and advancing scientific knowledge, the project holds potential implications for various industries, including music streaming platforms, radio stations, and advertising agencies. By accurately predicting music genres, these entities can better tailor their content recommendations, targeted advertisements, and curated playlists to suit the diverse tastes and preferences of their audience. Moreover, the insights gleaned from analyzing music consumption patterns can inform strategic decision-making, content curation strategies, and marketing campaigns, thereby driving business growth and fostering a more dynamic music ecosystem.

Ultimately, the significance of this project extends beyond its immediate application in music genre classification. It serves as a testament to the transformative power of machine learning and data-driven approaches in shaping the future of entertainment, media consumption, and cultural exploration.

By harnessing the vast potential of AI technologies, we aim to revolutionize the way people interact with music, unlocking new avenues for creativity, discovery, and personal expression. In essence, the purpose of this project is to bridge the gap between art and technology, fostering a symbiotic relationship between human creativity and machine intelligence in the realm of music.

The core essence of this project lies in its ability to decipher the intricate nuances of music, transcending mere audio signals to uncover deeper insights into the underlying structures and patterns that define different genres. Through the application of advanced signal processing techniques, feature extraction algorithms, and machine learning models, the system aims to distill the essence of each genre, capturing its unique blend of rhythm, melody, harmony, and timbre. By analyzing audio features such as tempo, spectral characteristics, chord progressions, and rhythmic patterns, the system can discern subtle variations and stylistic markers that distinguish one genre from another.

## II.RELATED WORK

### Music Genre Classification using Machine Learning Techniques

**Author:**Hareesh Bahuleyan

**Description:** Categorizing music files according to their genre is a challenging task

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in the area of music information retrieval (MIR). In this study, we compare the performance of two classes of models. The first is a deep learning approach wherein a CNN model is trained end-to-end, to predict the genre label of an audio signal, solely using its spectrogram. The second approach utilizes hand-crafted features, both from the time domain and frequency domain. We train four traditional machine learning classifiers with these features and compare their performance. The features that contribute the most towards this classification task are identified. The experiments are conducted on the Audio set data set and we report an AUC value of 0.894 for an ensemble classifier which combines the two proposed approaches.

### **Music Genre Classification via Machine Learning Category: Audio and Music[Ref 2]**

**Author:**Li Guo, Zhiwei Gu, Tianchi Liu

**Description:** In the realm of music consumption, playlists curated by genre are a common practice among listeners. This practice has significant implications for applications like playlist recommendation and management. Despite substantial research in music genre classification using machine learning, there remains a substantial opportunity to develop more sophisticated models for addressing Music Information Retrieval (MIR)

problems. This work focuses on enhancing music genre classification accuracy using advanced machine learning techniques applied to the recently published Free Music Archive (FMA) dataset. Music genre classification involves categorizing music tracks into predefined genres based on their audio features. This task is essential for organizing large music libraries, recommending new music to users, and creating genre-specific playlists. Historically, machine learning approaches have been employed to tackle this problem, yet the complexity and subjectivity of musical genres pose significant challenges. The FMA dataset, which contains a diverse collection of music tracks labeled with various genres, provides a robust foundation for developing and testing new classification models

### **III . IMPLEMENTATION**

The system is implemented in web environment using Jupyter notebook software. The server is used as the intelligence server and windows 10 professional is used as the platform. Interface the user interface is based on FLASK provides server system.

**Dataset Acquisition:** Obtain the GNZAN dataset or a similar dataset containing labeled audio samples for music genre classification. This dataset will

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serve as the foundation for training and testing the machine learning models.

**Data Preprocessing:** Clean the dataset to remove duplicates, inconsistencies, and irrelevant information, ensuring data quality and uniformity. This step is crucial for preparing the dataset for feature extraction and model training.

**Library and Dependency Installation:** Install necessary libraries and dependencies such as SciPy, NumPy, Pandas, Gradio, Python Speech Features, and Spotipy for the project implementation. These libraries provide essential functionalities for data manipulation, feature extraction, model training, user interface development, and API integration.

**Data Loading:** Load the GNZAN dataset into memory for further processing and analysis. This step involves reading the dataset files and storing them in a suitable data structure for easy access and manipulation.

**Dataset Exploration:** Explore the dataset to understand its structure, characteristics, and distribution of genres. This exploration helps in gaining insights into the dataset and identifying potential patterns or biases that may influence the model's performance.

**Data Splitting:** Split the dataset into training and testing sets to facilitate model training and evaluation. This step ensures that the model is trained on a portion of the data and evaluated on a separate portion to assess its generalization ability.

**Feature Extraction:** Utilize Python Speech Features library to extract relevant audio features such as tempo, spectral contrast, and frequency coefficients from the audio samples. These features capture essential characteristics of the audio signals and serve as input to the machine learning models.

**Feature Normalization:** Normalize the extracted features to ensure uniformity and compatibility for machine learning algorithms. Normalization helps in scaling the features to a similar range, preventing certain features from dominating others during model training.

**Algorithm Selection:** Choose suitable machine learning algorithms such as SVM, Random Forest, or neural networks for music genre classification. The selection of algorithms depends on factors such as dataset size, complexity, and performance requirements.

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**Model Training:** Train the selected machine learning algorithms using the training dataset to learn patterns and relationships between audio features and genre labels. This step involves optimizing model parameters to minimize prediction errors and maximize accuracy.

**Performance Evaluation:** Evaluate the performance of trained models using metrics like accuracy, precision, recall, and F1-score on the testing dataset. Performance evaluation helps in assessing the model's effectiveness in correctly predicting music genres.

**Comparative Analysis:** Compare the performance of different machine learning algorithms to identify the most effective approach for genre classification. This analysis helps in selecting the best-performing model for deployment.

**User Interface Design:** Design a user-friendly interface using Gradio library to enable users to interact with the model seamlessly. The interface should be intuitive, visually appealing, and accessible across different devices and screen sizes.

**Interface Implementation:** Implement functionalities for users to upload audio samples and receive genre predictions from the model. This involves integrating the model with the user interface to enable real-time interaction and feedback.

**Result Organization:** Utilize Pandas to organize and present the classification results in a structured format for better user understanding. The organized results can include predicted genres, confidence scores, and additional metadata for each audio sample.

**Spotify API Integration:** Integrate Spotify API to access Spotify's music catalog and retrieve information about songs similar to the detected genre. This integration enhances the user experience by providing relevant recommendations and suggestions based on the predicted genres.

**API Result Processing:** Process the Spotify API results to generate a list of similar songs based on the detected genre. This involves parsing the API response, extracting relevant information, and presenting it to the user in a meaningful way.

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**System Testing:** Conduct comprehensive testing of the entire system to ensure functionality, accuracy, and robustness. This includes unit tests, integration tests, and user acceptance tests to validate the system's behavior under various conditions.

**Debugging and Issue Resolution:** Address any issues or errors encountered during testing, debugging code as necessary to ensure smooth operation. This may involve troubleshooting errors, fixing bugs, and optimizing performance for better user experience.

**Documentation:** Document the codebase, including comments and explanations, to facilitate future maintenance and understanding. The documentation should cover code structure, functionality, usage instructions, and troubleshooting tips.

**User Guide Creation:** Write user guides and documentation explaining how to access and use the application effectively. The user guide should provide step-by-step instructions, screenshots, and examples to help users navigate the application.

**Deployment:** Deploy the application on a suitable platform such as a web server or cloud

service to make it accessible to users. This involves configuring servers, setting up databases, and deploying code changes in a production environment.

**Performance Monitoring:** Monitor the deployed application for performance metrics and user feedback, addressing any issues that arise. This includes tracking server uptime, response times, and user engagement metrics to ensure optimal performance and user satisfaction.

**Feedback Collection:** Collect feedback from users to identify areas for improvement and prioritize future enhancements. This can be done through surveys, feedback forms, user interviews, and analytics tools to gather insights and suggestions for the application.

**Maintenance:** Conduct regular maintenance to keep the application up-to-date, addressing any updates or changes in dependencies. This involves applying security patches, fixing bugs, and adding new features to meet evolving user needs.

**Compliance Check:** Ensure compliance with relevant regulations and standards regarding data privacy and security. This may include



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implementing encryption, access controls, and data anonymization techniques to protect user data.

**Backup:** Implement regular backups of data and codebase to prevent loss in case of unforeseen events. This ensures that critical data and code are securely stored and can be restored in case of emergencies or system failures.

**Continuous Learning:** Stay updated on advancements in machine learning and audio analysis to incorporate new techniques and approaches. This involves reading research papers, attending conferences, and participating in online courses to expand knowledge and skills.

**Community Engagement:** Engage with relevant communities and forums for knowledge sharing and collaboration, seeking input and feedback from other developers. This fosters a supportive environment for learning, sharing ideas, and solving challenges together.

**Experimentation:** Experiment with different feature extraction techniques and machine learning algorithms to improve classification accuracy and performance. This involves

trying out new approaches, tweaking parameters, and analyzing results to iteratively refine the model.

**Optimization:** Optimize the performance of the application by identifying and addressing bottlenecks, improving efficiency and scalability. This may involve optimizing code, tuning server configurations, and leveraging caching mechanisms to reduce latency and improve responsiveness.

**Collaboration:** Collaborate with music enthusiasts and streaming platforms to gather insights and feedback for further enhancements. This can involve partnering with industry experts, participating in hackathons, and contributing to open-source projects to drive innovation and collaboration.

**Sharing:** Share the project and its outcomes with the broader community through presentations, articles, or conferences to inspire others in the field. This includes sharing code repositories, research findings, and lessons learned to contribute to the collective knowledge.

**Celebration:** Celebrate milestones and achievements reached during the

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implementation process, acknowledging the efforts of the team and collaborators. This fosters a sense of accomplishment and motivation to continue pushing boundaries and striving for excellence.

**Reflection:** Reflect on lessons learned and challenges overcome throughout the project journey, identifying areas for personal and professional growth. This involves self-assessment, feedback solicitation, and continuous improvement to become better at what we do.

**Recognition:** Recognize and appreciate the contributions of team members and collaborators who contributed to the project's success. This can be done through public acknowledgments, awards, or rewards to express gratitude and build a positive team culture.

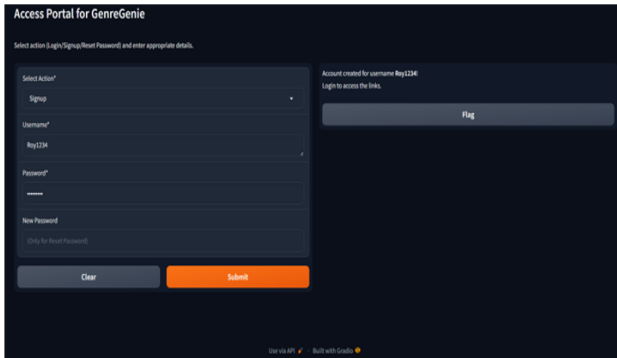
**Innovation:** Foster innovation and creativity in solving real-world problems through machine learning and data analysis, pushing the boundaries of what is possible. This involves thinking outside the box, challenging assumptions, and exploring new ideas to drive meaningful impact.

**Inspiration:** Inspire others in the field of machine learning and audio analysis by sharing the project's impact and outcomes, encouraging further exploration and experimentation. This involves storytelling, thought leadership, and mentorship to inspire others to pursue their passions and make a difference.

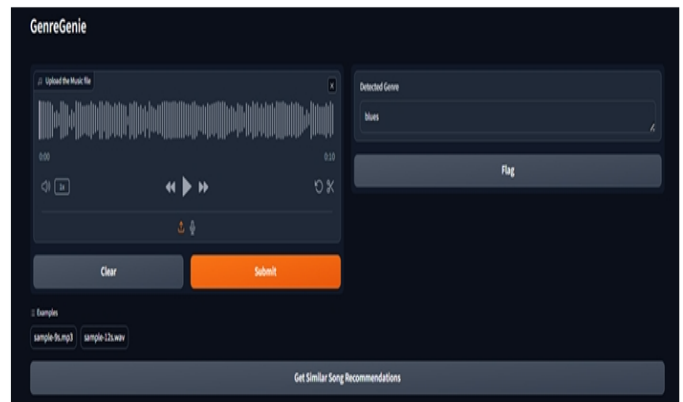
**Support:** Provide support and guidance to other developers interested in similar projects, fostering a supportive and collaborative environment within the community. This involves sharing knowledge, offering assistance, and building relationships to support each other's growth and success.

**Iteration:** Iterate and improve the project based on user feedback, changing requirements, and advancements in technology to ensure its continued relevance and effectiveness. This involves continuous learning, adaptation, and evolution to meet the evolving needs of users and stakeholders.

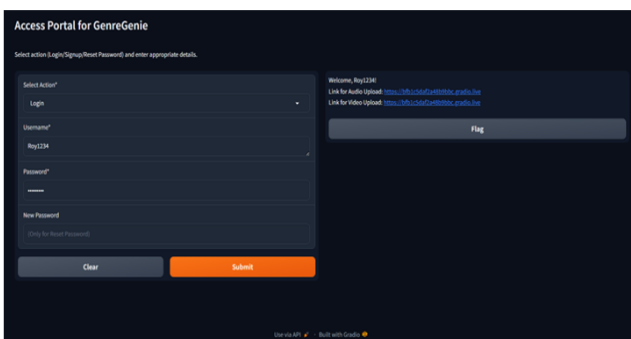
## RESULTS



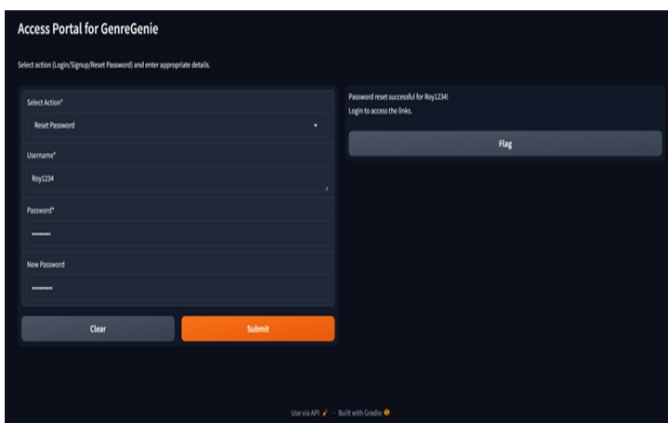
**Fig 1 Access Portal (Signup Page)**



**Fig 4 Uploading an Audio File**



**Fig .2 Access Portal (Login Page)**



**Fig .3 Access Portal (Reset Password Page)**

## CONCLUSION

Inculmination, the project on Music Genre Classification utilizing Machine Learning algorithms and integrating with the Spotify API presents a comprehensive solution to the complex task of categorizing music into distinct genres. Through meticulous goal-setting, strategic technical implementation, and a user-centric methodology, the project aims to revolutionize the way listeners interact with and discover music.

The core objectives of the Music Genre Classification project can be distilled as follows:

Develop a robust machine learning model capable of accurately categorizing music tracks into an extensive array of genres, spanning from mainstream to niche categories.

Forge a seamless integration with the Spotify API, leveraging its vast music library

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and rich metadata to enhance model training and recommendation accuracy.

Craft an intuitive and immersive user interface, empowering listeners to effortlessly navigate through personalized genre recommendations and curated playlists.

Foster user engagement and community interaction, fostering a collaborative environment where users can share musical discoveries and explore new genres together.

Implement advanced user preference modeling techniques to tailor genre recommendations based on individual listening habits, mood preferences, and contextual factors.

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