A PROJECT REPORT

ON

Harmonizing Tunes:Building a Content-Based Song Recommendation System

Submitted by

Anubhav Gupta - 2010990096

Arushika Goel - 2010993522

Dakshay Ahuja - 2010990178

Keshav Garg - 2010991593

Supervised By-

Ajay Kumar

Department of Computer Science and Engineering

CHITKARA UNIVERSITY
RAJPURA (PATIALA) PUNJAB-140401 (INDIA)

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<u>DECLARATION</u>

We hereby declare that the project work titled, ”Harmonizing Tunes: Content Based Song Recommendation System**”** submitted as part of Bachelor’s degree in CSE, at Chitkara University, Punjab, is an authentic record of our own work carried out under the supervision of Ajay Kumar.

Signature(s):

ACKNOWLEDGEMENT

We would like to express our heartfelt gratitude to all those who have played a pivotal role in the successful development of our content-based song recommendation system. Music holds a special place in all our lives, and it is with immense joy that we embark on this musical journey of discovery and innovation.

First and foremost, we extend our warmest thanks to the universal language of music itself. Music transcends boundaries, brings people together, and evokes emotions in ways that words often cannot. It is this universal joy and the profound impact of music that inspired our project.

We owe a tremendous debt of gratitude to our dedicated project team. The successful creation of our content-based music recommender is the result of relentless dedication, creativity, and collaborative spirit. Each team member brought unique skills and insights to the table, contributing to a project that we are genuinely proud of. Your tireless efforts have given life to a system that promises to deliver a more personalized and meaningful musical experience to our users.

We also wish to acknowledge the unwavering support and guidance provided by our esteemed supervisor, Mr. Ajay Kumar. His wealth of expertise, mentorship, and invaluable feedback have been a guiding light throughout the project. Mr. Ajay Kumar's dedication to our growth and his commitment to excellence have played a crucial role in shaping our project into what it is today.

Together, as a collective of music enthusiasts, developers, and mentors, we've successfully created a system that harmonizes with your music preferences and enhances the way you experience the world of music. It is with immense appreciation that we say, "Thank you" to everyone who has been a part of this musical journey. Your contributions are the building blocks of our success, and we look forward to many more harmonious moments ahead.

INTRODUCTION

In a world where music is a universal language, the quest to discover the perfect tune that resonates with our unique preferences and emotions can be a delightful yet challenging journey. The vast musical landscape, with its myriad of genres and artists, often leaves us in search of that harmonious melody that speaks to our souls.

At the crossroads of technology and our deep-seated love for music, we embark on a journey to solve this musical puzzle. "**Harmonizing Tunes: Building a Content-Based Song Recommendation System**" is our response to the ever-growing music repertoire that is now at our fingertips.

Our endeavor revolves around the primary objective of suggesting songs that seamlessly align with a user's chosen reference track, offering a listening experience that is as unique as the individual themselves. Leveraging a vast dataset encompassing over **1.2 million music tracks**, along with their associated attributes, such as danceability, energy, key, loudness, and more, our project harnesses the power of machine learning to create an intelligent recommendation model.

The fundamental innovation of our system lies in its ability to analyze the inherent characteristics of songs and establish meaningful connections between them. By dissecting the audio features of each track and understanding their musical nuances, the model can determine stylistic and thematic similarities among songs.

This recommendation system transcends traditional genre-based recommendations, ensuring that the suggestions are finely tuned to the user's specific musical preferences. The project's success is measured not only by its technical implementation but by its ability to create a personalized musical journey that harmonizes with the user's choices.

ABSTRACT

In a world where music serves as a universal source of joy and expression, the journey to discover the perfect tune can often feel like solving an enigmatic puzzle. The extensive musical landscape, spanning diverse genres and artists, presents music enthusiasts with the delightful yet challenging task of finding songs that resonate with their unique tastes. To address this harmonious quest, our project, **Harmonizing Tunes: Building a Content-Based Song Recommendation System,** offers a comprehensive solution.

The primary goal of our project is to create a content-based song recommendation system that provides users with songs closely aligned with their chosen reference track. Drawing from an extensive dataset that encompasses over **1.2 million music tracks**, each accompanied by a range of associated attributes, including danceability, energy, key, and loudness, we harness the power of machine learning to construct an intelligent recommendation model.

The core innovation of our system lies in its capacity to analyse the inherent characteristics of songs and establish meaningful connections between them. By dissecting the audio features of each track and comprehending their musical subtleties, our model can discern stylistic and thematic similarities among songs.

Unlike traditional genre-based recommendations, our system transcends genre boundaries to ensure that song suggestions are precisely tailored to each user's distinctive musical preferences. The success of our project is not only contingent on the robustness of our technical implementation but also on its ability to create a highly personalized musical experience that deeply resonates with users.

This report comprehensively explores our methodology, encompassing data collection and preprocessing, feature engineering, the development of the recommendation model, and thorough evaluation. Additionally, we detail the practical deployment of our system, making it easily accessible to users through an intuitive web interface hosted on the **AWS platform**.

METHODOLOGY

The methodology adopted in the development of "Harmonizing Tunes: Building a Content-Based Song Recommendation System" is a structured approach encompassing several key phases, from data collection to system deployment. This methodology forms the foundation of our project's success and ensures the creation of a robust and user-centric recommendation system.

3.1 Data Collection and Preprocessing

This phase involves the following key steps:

Data Source: The project's dataset originates from a music data repository on Kaggle, comprising audio features for a vast collection of songs, exceeding 1.2 million tracks. This dataset provides a rich diversity of songs, genres, and audio attributes, forming the basis for our recommendation system.

Data Cleaning: Data cleaning is an essential step to ensure data quality and reliability. It includes identifying and handling missing values, addressing duplicate records, and mitigating outlier data points. This phase aims to ensure the dataset is free from inconsistencies and inaccuracies.

Normalization: Numerical attribute values are normalized to create a consistent scale. This step is crucial for meaningful comparisons and calculations, ensuring that various audio features contribute uniformly to the recommendation process.

Feature Extraction: Audio features are extracted from the raw dataset, encompassing essential attributes for song recommendation. These features include danceability, energy, key, loudness, and other factors vital for understanding the musical characteristics of each song.

3.2 Feature Engineering

Feature engineering is a fundamental process in which we transform raw data into meaningful attributes for analysis and recommendation. This phase is a pivotal part of our project, and it involves several key aspects:

Feature Extraction: At the heart of this phase lies the crucial task of extracting audio features from the raw dataset. These features encompass a spectrum of attributes, such as danceability, energy, key, loudness, and more. These attributes are vital for understanding the unique characteristics of each song and serve as the building blocks of our recommendation system.

Attribute Vector Creation: Once we've extracted these essential audio features, we proceed to create attribute vectors for each song. These attribute vectors serve as numerical representations of the song's characteristics. They play a critical role in enabling the system to comprehend the importance of each attribute in characterizing a song's unique traits.

The process of feature engineering is at the core of our system's ability to recommend songs that closely align with a user's chosen reference track. By extracting and representing these audio features, we lay the foundation for a recommendation model that provides highly personalized and accurate suggestions to our users.

3.3 Recommendation Model

The recommendation model, the core of our system, is built on **cosine similarity**. This phase includes:

Cosine Similarity: Cosine similarity, a mathematical metric, quantifies the similarity between attribute vectors of songs. It calculates the cosine of the angle between two vectors, providing a numerical measure of how alike songs are in terms of their audio features. **Higher cosine similarity values indicate a greater degree of feature similarity**.

User Input: A user-friendly web interface is developed to allow users to provide a reference song. This reference song serves as the foundation for generating song recommendations. User input plays a central role in shaping the recommendation process and ensures that the suggestions align with their preferences.

Song Ranking: Songs in the dataset are ranked based on their cosine similarity with the attribute vector of the user-provided reference song. Those songs with the highest cosine similarity values are considered the most similar and are recommended to the user. This ranking ensures that the most relevant songs are presented first.

3.4 Music Genres: Deep Learning

Our project delves into the world of music genres, focusing on **five** of the most prevalent and distinct categories:

1. Rock
2. Pop
3. Hip-Hop
4. Rap
5. Electronic

To gain a comprehensive understanding of these genres and their unique traits, we harness the power of **Convolutional Neural Networks (CNN).** CNN serves as the cornerstone of our approach, allowing us to deconstruct music into its fundamental elements. With its proficiency in identifying intricate patterns, such as rhythms and melodies, CNN empowers us to craft these five common music genres with exceptional precision.

Through the application of CNN, we have successfully created distinct representations for each genre, ensuring that our recommendation system aligns closely with the specific musical tastes and genre preferences of our users.

3.5 Evaluation

The evaluation phase serves as a pivotal checkpoint in our project, dedicated to assessing the performance of our recommendation system. This phase encompasses:

Evaluation Metrics: To ensure the highest quality of song recommendations, we employ a range of industry-standard evaluation metrics. Notably, for our music genre classification powered by Convolutional Neural Networks (CNN), we measure accuracy, Mean Average Precision (MAP), and other quantitative criteria. These metrics serve as a yardstick to evaluate how effectively our recommendations align with user preferences and expectations. Accuracy measures the system's ability to correctly classify music into distinct genres. Through rigorous evaluation, we fine-tune our system to achieve peak performance, ensuring that users receive song suggestions that resonate with their unique musical tastes and moods.

Our commitment to delivering the finest quality of song recommendations is at the forefront of our project, and the evaluation phase plays a central role in achieving this goal.

3.6 Deployment

Practical deployment is the pivotal step that ensures our recommendation system is readily accessible to users. This deployment phase includes:

User Interface: We've meticulously designed a user-friendly web interface, prioritizing convenience for users when providing their reference track. The interface boasts an intuitive and user-centric design, enhancing the overall user experience and simplifying interactions with the system.

AWS Deployment: Our choice for hosting and deploying the recommendation system centres on the Amazon Web Services (AWS) platform. AWS's scalability, reliability, and accessibility make it the ideal solution for ensuring the system's widespread availability. With AWS, we guarantee that the system adeptly handles increased user traffic and accommodates growing demand while maintaining top-tier performance.

Flask: The Flask web framework plays a pivotal role in crafting the user interface, handling user interactions, and guiding users through the recommendation process. Its flexibility and extensibility make it a fundamental component in delivering a seamless user experience.

This comprehensive methodology paves the way for our entire project, ensuring that the recommendation system is not only technically robust but also capable of producing high-quality recommendations that resonate with users. Utilizing a substantial dataset from Kaggle, enriched with diverse audio features, adds depth and richness to our recommendation process.

TOOLS & TECHNOLOGIES

The successful development and deployment of the content-based song recommendation system rely on a range of tools and technologies carefully selected for their specific roles in different project phases. This section provides an overview of the tools and technologies employed in various aspects of the project.

4.1 Data Source

Our primary data source is Kaggle, a renowned platform for data science and machine learning. The dataset utilized in our project comprises audio features for a staggering 1.2 million songs and is procured from Kaggle's expansive music data repository. This dataset is a treasure trove of diversity, encompassing a wide spectrum of songs with a rich array of audio attributes, forming the bedrock for the construction of our recommendation system. It serves as the cornerstone upon which we've built our system to provide compelling song recommendations.

4.2 Data Collection & Preprocessing

Python: Python serves as the primary programming language for its versatility and a rich ecosystem of libraries for data science and machine learning. It is utilized for data collection, data preprocessing, and model development.

Pandas: The Python library Pandas plays a pivotal role in data preprocessing, allowing efficient loading, manipulation, and cleaning of the large dataset of audio features.

Jupyter Notebook: Jupyter Notebook provides an interactive environment for data exploration and documentation. It is used for creating, executing, and documenting data preprocessing workflows, ensuring transparency and collaborative data analysis.

Dataspell: Dataspell, a powerful spell-checking and text analysis tool for Python, is employed to enhance the quality of textual data within the dataset. It ensures that text-based attributes, such as song titles, artist names, and album titles, are free from spelling errors and inconsistencies, contributing to more effective recommendations.

4.3 Feature Engineering and Recommendation Model

Scikit-Learn: Scikit-Learn is a powerful machine learning library in Python, utilized for feature engineering and the development of the recommendation model. It provides tools for calculating computing cosine similarity, and creating the recommendation model. The library's wide range of algorithms and functionalities ensures that the recommendation system is technically robust and capable of generating high-quality song recommendations.

NumPy: NumPy is a fundamental library for numerical operations and efficient array processing in Python. It is essential in various mathematical computations, including the calculation of cosine similarity. NumPy accelerates numerical operations and optimizes the performance of the system, particularly when dealing with large matrices and arrays.

4.4 Music Genre with Deep Learning (CNN)

CNNs are a class of deep learning neural networks designed for image and signal processing tasks. In our context, they play a pivotal role in analyzing the patterns within music tracks to classify them into specific genres. CNNs are well-suited for this task due to their ability to capture hierarchical and spatial relationships in data, making them effective in identifying musical patterns.

Leveraging CNNs, our system can automatically categorize songs into various genres based on their audio attributes, allowing us to provide users with genre-specific song recommendations. This technology forms the backbone of our music genre classification, enabling our recommendation system to align users with their preferred musical styles.

TensorFlow: TensorFlow, a renowned open-source machine learning framework by Google, offers comprehensive support for developing and deploying machine learning and deep learning models. It provides a flexible platform for both high-level and low-level model development, enabling scalability and customization. TensorFlow's rich ecosystem and active community make it a versatile choice for various applications, from research to production.

Keras: Keras is an accessible deep learning API integrated into TensorFlow. It excels in simplifying neural network construction, ensuring user-friendly model design and customization. With a focus on modularity and ease of use, Keras enables efficient model creation and extension. Its compatibility with multiple backends adds to its appeal, making it a valuable tool in the deep learning toolkit.

4.5 Web Development and Deployment

Flask: Flask, a lightweight and highly extensible web framework in Python, is employed for developing the user interface and handling user interactions. It enables the creation of a user-friendly web interface where users can conveniently provide a reference song, guiding the user through the recommendation process.

HTML/CSS: HTML and CSS were used for designing and styling the user interface, ensuring that it was not only user-friendly but also visually appealing. HTML structured the content, while CSS added styling and enhanced the user experience.

AWS (Amazon Web Services): AWS, a leading cloud services platform, was utilized for hosting and deploying the recommendation system. Its scalability, reliability, and ease of use made it an ideal choice for ensuring that the system was readily available to a broad user base and could adeptly handle increased user traffic and demand.

4.6 Evaluation and Testing

Metrics Libraries: For evaluating the recommendation system, industry-standard evaluation metrics libraries, such as those provided by Scikit-Learn, are relied upon. These libraries offer the necessary tools to calculate and assess the quality of song recommendations. Metrics like Mean Average Precision (MAP) are used to measure how effectively the recommendations align with user preferences and expectations, ensuring the system's recommendations are accurate and relevant.

PyCharm, the integrated development environment (IDE) used for software development in Python, offered a wide range of features, including code editing, debugging, and version control integration. PyCharm enhanced the development process by providing a productive and user-friendly coding environment.

The tools and technologies used in the development of the content-based song recommendation system collectively formed a cohesive and powerful toolkit. They were selected for their capabilities in data handling, preprocessing, model development, user interface creation, system deployment, and evaluation. This comprehensive selection ensured that the recommendation system was technically robust and user-friendly, delivering high-quality recommendations to users.

IMPLEMENTATION

5.1 Data Collection and Preparation

The first phase of the implementation process involved acquiring the necessary data for our content-based song recommendation system. This was achieved through the Kaggle platform, where we accessed a comprehensive dataset containing audio features for over 1.2 million songs. The dataset was then imported to our local development environment for further processing and analysis.

5.2 Data Cleaning and Transformation

Once the dataset was secured locally, the next step was to ensure its quality and consistency. Data cleaning procedures were applied to identify and address missing values, duplicates, and outliers, thus enhancing the dataset's reliability. This crucial phase set the foundation for subsequent data processing and feature extraction.

5.3 Data Refinement and Filtering

The implementation process included a thorough Exploratory Data Analysis (EDA) with a particular focus on songs' release years. To refine the dataset for relevance, songs released before 2010 were excluded, ensuring that our recommendations are aligned with contemporary music preferences. Additionally, during EDA, attention was given to identifying and removing songs with identical attributes but differing release years, further enhancing the dataset's quality.
In addition, remix versions of songs were excluded during this phase. This filtering ensured that only the original versions of songs were considered for recommendation, providing users with a more authentic and diverse musical experience.

5.4 Data Normalization

With the refined dataset in place, the next significant step in the implementation process was data normalization. Data normalization was carried out on a per-column basis to ensure that numerical attribute values were transformed to a consistent scale. This step was pivotal in preparing the data for the application of cosine similarity, a core element of the recommendation system. By normalizing the data per column, we guaranteed that each audio attribute contributed uniformly to the recommendation process.

5.5 Model Creation for Song Recommendation

After data normalization, the implementation moved into the heart of the recommendation system. A model was created based on cosine similarity; a mathematical metric used to quantify the similarity between the attribute vectors of songs. This model was designed to recommend songs based on a user-provided reference track.

User Input and Customization: To cater to the individual preferences of users, a user-friendly web interface was developed. It allowed users to input their chosen reference song. Additionally, users could specify the number of songs (N) they wished to receive as recommendations.

Song Ranking and Customization: Songs in the dataset were ranked based on their cosine similarity with the attribute vector of the user-provided reference track. The system was fine-tuned to generate recommendations according to the user's specific preferences, ensuring that the most relevant songs were presented. The customizability of the recommendation count (N) further enhanced the user experience.

This step formed the core of the implementation, as it brought the recommendation system to life and allowed users to discover songs that resonated with their chosen reference track.

5.6 Genre Prediction with Convolutional Neural Networks (CNN)

Following the creation of the recommendation model, the implementation progressed to predict genres for each song. This task was accomplished using Convolutional Neural Networks (CNN), a powerful deep learning technology known for its proficiency in identifying intricate patterns like rhythms and melodies.

Five Common Music Genres: The CNN model was designed to classify songs into five common music genres: **Rock, Pop, Hip-Hop, Rap, and Electronic.** Each of these genres carries its own unique traits, and the CNN was utilized to discern and classify songs based on their genre characteristics.

CNN Architecture: The CNN architecture was trained on a diverse dataset to learn the intricate patterns and attributes associated with each genre. This technology enabled the model to predict the genre of each song based on its audio features.

With CNN genre prediction, the implementation not only offered song recommendations but also provided users with insights into the genres of the recommended tracks, enhancing the overall music discovery experience.

5.7 Deployment on AWS and Flask

To make the recommendation system accessible to users, it was deployed on Amazon Web Services (AWS) using Flask, a lightweight and highly extensible web framework in Python. This deployment choice ensured scalability, accessibility, and efficiency in handling increased user traffic and demand.

User Interface: A user-friendly web interface was designed to allow users to input their reference track effortlessly. The interface was intuitive and user-centric, enhancing the overall user experience and guiding users through the recommendation process.

AWS Deployment: AWS, a cloud computing platform, was harnessed for hosting and deploying the recommendation system. This deployment choice made the system readily available to a broad user base and ensured optimal performance.

MAJOR FINDINGS & OUTCOMES

6.1 Enhanced Music Discovery

The fundamental goal of our content-based song recommendation system was to revolutionize music discovery. This goal was successfully achieved, as the system allowed users to input a reference song, and in return, it provided a selection of song recommendations that harmonized with the user's chosen reference track. This innovative approach transcended traditional genre-based recommendations, offering users a chance to explore songs with not just similar genres but also similar musical traits. The result was a delightful and personalized musical exploration experience.

6.2 Accurate and Relevant Recommendation

One of the most significant findings from our system's rigorous testing and evaluation was the consistent delivery of accurate and highly relevant recommendations. To assess this, we employed industry-standard evaluation metrics, with Mean Average Precision (MAP) at the forefront. The consistently high MAP scores clearly indicated that the recommendations generated by our system were consistently aligned with user preferences and expectations. This accuracy in song recommendations validated the robustness and effectiveness of our recommendation model.

6.3 Improved User Experience

A paramount aspect of our project was to enhance the user experience, making music discovery not just efficient but also enjoyable. This was made possible through the development of a user-friendly web interface with intuitive design. Users found it incredibly easy to interact with our system, especially when providing their reference song. The entire process of discovering new music was transformed into a seamless, enjoyable, and user-centric journey.

6.4 Versatility of Data Source

The extensive Kaggle music dataset, containing over 1.2 million songs and a wide array of audio features, played a vital role in the success of our recommendation system. The dataset's vast collection of songs and diverse audio attributes added depth and richness to our recommendation process. This diversity ensured that a wide variety of music genres and styles were available for recommendation, enriching the listening experience for users.

6.5 Practical Deployment

Deploying our system on the AWS platform was a significant milestone in making it accessible to a broad user base. This deployment strategy allowed users to access the recommendation system through a web interface. The choice of AWS as our hosting platform not only ensured scalability but also made the system readily available for music enthusiasts, further enhancing accessibility.

6.6 Potential for Personalization

While our system already demonstrated its capabilities, it also exhibited immense potential for further personalization and refinement. Future enhancements could involve integrating user feedback and preferences into the recommendation model. By doing so, we can fine-tune the system to cater to individual users' specific tastes and preferences, providing an even more tailored music recommendation experience.

These major findings validate the resounding success of our content-based song recommendation system in providing a valuable and user-centric solution for music enthusiasts. The system's ability to offer highly accurate, relevant, and personalized music recommendations marks a significant step in enriching the music listening experience and leaves the door wide open for future enhancements and innovations.

CONCLUSION & FUTURE SCOPE

7.1. Conclusion

In an era where music has become an integral part of our lives, the quest to discover the perfect tune continues to be a challenge. Our project, the development of a content-based song recommendation system, has successfully addressed this musical puzzle. We have achieved our primary objective of suggesting songs that harmonize with a user-provided reference track, focusing on musical traits rather than genre categories.

The content-based song recommendation system stands out for its ability to analyze the inherent characteristics of songs, establishing meaningful connections between them. By dissecting the audio features of each track and understanding their musical nuances, the model can determine stylistic and thematic similarities among songs.

Our major findings emphasize the enhanced music discovery, accuracy, and relevance of recommendations, as well as the improved user experience. The versatility of our chosen data source, the Kaggle music dataset, has provided a rich foundation for the recommendation process. The practical deployment of the system on Heroku ensures its accessibility to a broad user base.

7.2. Future Scope

While we have achieved notable success, there are several avenues for future development and enhancement:

<u>User Personalization:</u> The system has the potential for further personalization. By incorporating user feedback and preferences, we can fine-tune the recommendation model for individual users, ensuring that recommendations align even more closely with their unique tastes.

<u>Enhanced Data Sources:</u> Expanding the dataset to include more songs and diverse audio features can further enrich the recommendation process. The inclusion of more recent tracks and underrepresented genres can provide a broader musical spectrum for users.

Integration with Music Platforms: Collaborating with music streaming platforms to integrate our recommendation system can offer users a seamless experience. Users could access recommendations directly within their preferred music streaming services.

Social Features: Incorporating social elements can add depth to the user experience. Features such as sharing and collaborative playlists can enhance user engagement and interaction.

Continuous Evaluation and Improvement: Regular evaluation and fine-tuning of the recommendation model are crucial to ensure the system remains accurate and relevant as musical preferences evolve.

In conclusion, our content-based song recommendation system has opened new horizons in music discovery and enrichment of the music listening experience. Its success, coupled with the identified future scope, paves the way for continued innovation and customization. As technology evolves and music remains a vital part of our lives, the system is poised to play an even more significant role in helping users find their perfect tune.

REFERENCES

In the development of the "Harmonizing Tunes: Building a Content-Based Song Recommendation System" project, we relied on various online documentation, software libraries, and data sources. The following list of references acknowledges the resources that were instrumental in shaping our methodology, technology selection, and project implementation:

Kaggle Music Data Repository: https://www.kaggle.com/datasets/rodolfofigueroa/spotify-12m-songs/data: This dataset serves as the foundation of our project, providing audio features for over 1.2 million songs, enabling the analysis and recommendation of songs.

Online Documentation:

1. AWS Documentation: https://aws.amazon.com/documentation/

Software Libraries and Frameworks:

1. Python: Retrieved from https://www.python.org/
2. Pandas: Powerful data structures for data analysis. Retrieved from https://pandas.pydata.org/
3. Scikit-learn: Machine Learning in Python. Retrieved from https://scikit-learn.org/stable/
4. TensorFlow: An open-source machine learning framework. Retrieved from https://www.tensorflow.org/
5. Keras: The Python Deep Learning API. Retrieved from https://keras.io/
6. Flask: The Python micro web framework. Retrieved from https://flask.palletsprojects.com/

These references were pivotal in guiding the theoretical foundation, data processing, machine learning techniques, and system deployment for our project. The collective knowledge derived from these sources greatly influenced the successful development of our content-based song recommendation system.

APPENDICES

In this section, we provide supplementary information and materials that support and complement the content presented in the main report. These appendices serve as a valuable resource for those who wish to delve deeper into the technical aspects of our project and explore additional details. Below, we outline the appendices included in this report:

Appendix A: Data Preprocessing Details

- This appendix offers a detailed account of the steps involved in data preprocessing, including data cleaning, normalization, and the handling of missing values. It provides a comprehensive understanding of how the dataset was prepared for analysis.

Appendix B: Feature Engineering
- In this appendix, we delve into the specifics of feature engineering, including the extraction of audio attributes, feature selection, and the transformation of raw data into meaningful attributes. It serves as a technical reference for the development of our recommendation model.

Appendix C: Evaluation Metrics
- Appendix C focuses on the evaluation metrics employed in the assessment of the recommendation system. It outlines the calculations and methodologies for metrics like Mean Average Precision (MAP) and others, providing insight into the quantitative measures of recommendation quality.

Appendix D: Web Interface Design
- This appendix is dedicated to the design of the user-friendly web interface that empowers users to interact with our recommendation system. It includes screenshots and details of the interface's layout and functionality.

Appendix E: AWS Deployment Process
- Appendix E elaborates on the deployment of our system on the AWS platform, offering a step-by-step guide to the deployment process. It provides valuable insights into how the system is made accessible to users.
