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Sentiment-Based Music Recommendation System using Natural Language Processing for Emotion-aware Song Suggestions

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Abstract - Music plays a vital role in influencing emotions, mood, and mental health. However, classical music recommendation systems mostly rely on listening to history, genre preference, or popularity, ignoring the listener's mood. Motivation to go further in this area gave birth to this study, where a new sentiment-based music recommendation system is being designed by incorporating Natural Language Processing (NLP) and Machine Learning (ML) techniques to provide emotion-aware song recommendations. The system collects various audio features such as valence, energy, tempo, and danceability from music distribution platforms such as Spotify, which are well-known indicators for classifying the emotional tone of a song. Thereafter, NLP processes are used to analyse audio features and provide sentiment scores assigned to each music track: positive, negative, or neutral. These sentiment scores were further used with other song features, such as genre and tempo, to build in-depth emotional profiles for each song. Three ML methods were implemented in the system for classification and recommendation: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree (DT). After many trials, the SVM scored the highest in sentiment classification accuracy (87.5%), with maximum precision and recall values of 0.88. The recommendation is fed through a simple interface on a website where the user can enter their feelings and obtain song recommendations instantly determined by mood. According to the survey, 78% of users said that mood-based recommendations fit their emotional state better than traditional recommendations. Although the results prove this, limitations have been noted, particularly with a limited range of features and small dataset. Future enhancements will focus on real-time affect tracking, additional affect features, and larger and more diverse datasets. Traditional NLP applies to text data, but this system applies sentiment detection to numerical audio features. This version does not use lyric-based NLP.

Keywords—Natural Language Processing, Machine Learning, Music Recommendation System, Emotion-Aware, Audio Features

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1. INTRODUCTION

Music affects emotions, mood, and well-being; hence, it has a profound effect on emotional and mental well-being. Traditional music recommendation systems rely on listening history or genre preferences, which never capture the emotional or mood state of the user. Hence, the system cannot guarantee that it will suggest music that connects with the listener's emotions in real-time. At one level, an attempt has been made to bridge this gap by designing a Sentiment-based music recommendation system that uses sentiment analysis and ML techniques to recommend music that is more personalized and emotionally based. The sentiment scores are computed with respect to four key audio features, namely valence, energy, danceability, and tempo, which are acknowledged for expressing a track's emotional tone rather than relying on explicit user data. These song features are extracted, and NLP techniques are used to assign sentiment scores to songs. The scores were merged with other attributes, such as genre and tempo, to create a full-blown instance representing the emotional tone of a song. When a machine-learning model receives this feature set and user input, it returns recommendations tailored to the user. The system, created with Python and a web interface, allows a user to enter his/her present emotional state and receive recommendations for mood-based music. With feedback from the users, the system slowly evolves and adapts to personal preferences. When the emotional context is combined with recommendations, the system provides much more personalized and intuitive interactions with music, rendering recommendations closer to what the user feels now.

2. LITERATURE REVIEW

2.1 Overview

The following section provides a few key research works that predominantly deal with tying sentiment analysis and ML to music recommendations for better emotional alignment and personalization. This section also highlights how emotion-aware models have played a starring role in recent dialogue and the importance of getting users and audio sentiments for better recommendations.

2.2 Sentiment Analysis

In other words, sentiment analysis greatly contributes to the sharpening of a music recommendation system, such that the system grasps the emotional flavour attached to the music itself or to human interaction with it. Typical recommendation systems recommend music based on the user's history or genre preference; very often, they do not consider the emotional state of the user. With this enhancement of sentiment analysis, music recommendation systems can offer customized and emotionally engaging recommendations. Combining sentiment analysis with ML techniques can significantly boost the accuracy of music recommendation. For example, research has attempted to conduct sentiment analysis on the lyrics and audio features of the music track to find the emotions that a song entrains. By analysing features such as tempo, energy, and valence, a system can predict the emotional tone of a piece of music and then match the music to the current mood or emotional needs of a given user [1]. Further integration of sentiment analysis into recommendation systems allows for fine-tuning of suggestions according to the emotional context. For instance, user feedback can be analysed via a Sentiment Analysis process to evaluate the way users perceive music from an emotional perspective. Hence, the system, upon receiving further evaluations, adopts that feedback to make recommendations that correspond with the user's emotional state, in a very direct way, rewarding them with a better listening experience [2]. Recent studies have proven that machine and deep learning models can increase the accuracy of sentiment classification results at different text levels [3]. In addition, NLP techniques are said to play a pivotal role in the extraction of user emotions from short texts such as reviews and comments [4]. In addition, ML algorithms such as SVM, KNN, and DT are considered to effectively classify sentiments from various text sources [5].

2.3 Music Recommendation System

Over the past few years, the field of music recommendation systems has undergone a remarkable evolutionary leap, mainly because of the growing advancements in ML and data analytics. They strive to put forward suggestions for personalized music selections based on several factors such as user preferences, the mood of the individual, and audio features. Nevertheless, conventional approaches to music recommendation commonly would employ a filtering method based on collaboration or tied in some sort of content filtering; the latter may be strict with something similar to audio feature descriptors and less so with the complete analytics and complexity of the individual listener's preferences, which, after all, is a difficult task. Therefore, a few recent hybrid models combining these methods have been suggested to increase the accuracy of the recommendations. One study pointed out the potential of content-driven music recommendation systems and found that integrating user preferences with content-based features, such as audio characteristics and song metadata, can lead to more appropriate recommendations. Such systems integrate various music features such as tempo, genre, and rhythm that can recommend music better aligned with user preference and mood, thereby offering a more balanced kind of music personalization [6].

In this study, we aimed to develop machine-learning techniques that can be used for music recommendations on an individual basis. Their research underlined that some of the algorithms used in ML, including support vectors and KNN, can be used to make better music suggestions that are more tuned to user-specific criteria. By providing a system that can learn from user-related parameters of behaviour, listening history, and some audio features, developers have been able to improve the precision of music recommendations, thus coming closer to the tastes and preferences of an individual, as opposed to just suggesting a genre [7]. Another study focused on the integration between emotion recognition and music recommendation systems, thus exploring the possibility for models to be trained by considering the emotional state of a subject along with traditional preference data. Their research proved that emotional features, such as mood and energy, are crucial for customizing the user experience. Using sentiment analysis and emotion recognition from audio, the system was able to propose recommendations that better suited users' current emotional needs for listening [8].

In another study, a hybrid recommendation model that combined K-means clustering and multilayer perception was proposed to enhance recommendation diversity and counter the cold-start issue [9]. Another recent review highlighted the advantages inherent in hybrid music recommendation systems, stressing it as one of the solutions to the challenges of sparsity and popularity bias [10]. Finally, there is an emotion-aware system [11] that recommends songs based on the correspondence of user valence and arousal levels with proxy music features.

2.4 Integration of Sentiment Analysis with Music Recommendation Systems

Sentiment analysis in music recommendation has attracted the attention of many researchers, as it institutes a more dynamic and personalized approach to subscribing to songs. Given that it studies the emotional content of a musical discourse and matches the user's emotional state, sentiment analysis acts as an additional dimension, providing context and refinement to conventional modes of recommendation. Research has found that incorporating sentiment analysis into collaborative filtering models increases the quality of recommendations, as it considers not only user preferences, but also the affective tone represented in those songs. Essentially, this gives the system the ability to present recommendations that correspond more closely with the user's emotional state at the time of listening, thus constituting a more enjoyable experience in music discovery [12].

Similarly, another study proposed a hybrid approach, in which sentiment and content-based filtering models were combined. The vectorial system thus harnesses textual sentimental knowledge, thus considering user comments or song lyrics and audio features, such as tempo or rhythm, to yield recommendations with stronger emotional import. Therefore, this hybrid approach grants the system the capacity to find music by fitting the moods of its ratings and matching some musical preferences, thereby presenting a more complete approach to recommending music to users [13].

Recently, real-time sentiment analysis has made recommendations more adaptive. The third study investigated how real-time emotion tracking, along with sentiment analysis of user inputs and physiological data, could be used to dynamically adjust music recommendations. This real-time tracking allows the system to obfuscate emotional oscillation throughout the day and provide a constant flux of music aligned to the user's present emotional state rather than on static precepts or on historic data alone [14].

A study of tweets from clothing brands in 2022 demonstrated that sentiment accuracy depends greatly on the data source quality and good preprocessing techniques [15]. Another study compared and tested a Support Vector Machine with Random Forest for sentiment analysis, concluding that ensemble and hybrid methods can yield more consistent results across datasets [16]. On the other hand, in research on recommendation systems, it was discovered that the use of transformer-based methods such as BERT can greatly improve personalization by capturing nuanced sentiment information [17].

In another study, a sentiment-aware music recommendation system was introduced to analyse different types of information generated by users through texts or comments on social media using NLP and ML techniques for better emotional alignment when suggesting songs [18]. Then, to augment further and personalize music recommendation, a hybrid approach based on a deep learning model was proposed to integrate user emotional states, audio features, and real-time sentiment analysis [19], [20].

3. RESEARCH METHODOLOGY

Sentiment-based music recommendation systems follow a structured series of processes that combine audio feature analysis, sentiment analysis, and ML techniques to provide customized musical suggestions. This procedure was designed to ensure that music was offered depending on the user's current emotional state by analysing the audio features and sentiments associated with them. Figure 1 shows the workflow of the Sentiment-based recommendation system and sheds light on the role of the stakeholders in the data collection, preprocessing, and sentiment analysis of the final ML model building.

Figure 1. Sentiment Based Music Recommendation System Workflow

The first step is data collection, in which audio features such as valence, energy, danceability, and tempo are collected from music platforms such as Spotify. The dataset was obtained from Kaggle and consists of approximately 10,000 tracks. Each track included audio features extracted via the Spotify API, such as valence, tempo, energy, and danceability. The dataset was split into 80% training and 20% testing sets after cleaning and pre-processing.

Exploratory Data Analysis (EDA) showed some enlightening relationships: a greater number of higher valence tracks (>0.6) belonged to popular genres such as pop and dance, whereas low-valence tracks (<0.3) would somehow have to be linked to genres such as blues or classical. Tempos ranged from 60 to 180 BPM with a positive correlation between tempo and valence. Most songs with high valences were also high in energy and danceability. These features, which reflect the emotional tone of the track, were extracted and served as input to the sentiment score. Using NLP techniques, sentiment scores are calculated giving the basis to categorize each track as positive, negative, or neutral according to their audio features.

Although NLP traditionally considers text, in this system, these techniques are mapped onto numerical audio features. For instance, valence was taken to infer sentiment in a way that corresponded to the polarity of texts: high valence was interpreted as positive and low as negative. No direct NLP on lyrics was performed in this version, but there are plans to do so in forthcoming versions.

Following the assignment of sentiment scores, personalized song recommendations were made through the application of several ML models. The system uses three ML algorithms: KNN, SVM, and DT. In KNN, songs that share common audio and sentimental characteristics within the shortest distances in the feature space would offer recommendations based on intuitive similarity. The SVM would try to optimize the boundaries between categories of sentiment by creating hyperplanes that separate the directions of emotional states, thus providing superior classification performance. DT creates interpretable models that implement the decision process by splitting features into branches based on sentiment and audio features. Each model was trained from a labelled dataset and tested for its ability to arrive at the most emotionally congruent recommendations of songs with respect to the input features and mood of the user. The system was trained and evaluated using the KNN, SVM, and DT algorithms. These models determine how audio features and sentiment scores are related to user emotional preferences. Models trained on a labelled dataset were simultaneously tested to ascertain which algorithm closely followed the user's emotional state. Final recommendations are presented to the end-user via an easy-to-use web interface where the user enters his/her mood to obtain music suggestions tailored to that mood. The user is personalized by matching the entered user mood with the predicted sentiment class of the song class using the song-class prediction model. Songs from that class are further ranked based on their similarity with the user's mood vector using the cosine similarity between the features of songs on normalized audio features. This ensures that the recommendations are personalized based on contextual parameters. This keeps the system evolving, adapting, and self-improving over time through user feedback and the emotional context. The features used in machine-learning models include valence, energy, danceability, tempo, and genre (as one-hot encoded vectors). Hyperparameter tuning was performed using GridSearchCV to ensure that each model was optimized for precision and recall. The sentiment-based music recommendation pseudocode is shown in Algorithm 1.

Algorithm 1: Sentiment-based music recommendation

Input: User mood text

a. Load audio feature dataset
b. Preprocess data (remove nulls/duplicates)
c. Label songs using valence-based sentiment scoring
d. Train ML models (KNN, SVM, DT) using audio features
e. Analyse user input using TextBlob (Positive/Negative/Neutral)
f. Filter songs by predicted sentiment label
g. Rank songs using cosine similarity with user mood vector
h. Return 5 recommended songs

Output: List of recommended songs

The dataset was pre-processed to remove duplicate and null values. Then, sentiment scores were assigned using valence thresholds: high valence = positive, low valence = negative, mid-range valence = neutral. The songs were labelled accordingly. For each ML model (KNN, SVM, and DT), a grid search was used for hyperparameter tuning. KNN was tested with k = 3 to 9; SVM used the RBF kernel with C and gamma variations; DT used the Gini index with max_depth and min_samples_split tuning. Figure 2 shows the roles of music listeners, data analysts, and music streaming platforms in the collection, preprocessing, and sentiment analysis of data, leading to the development of ML models.

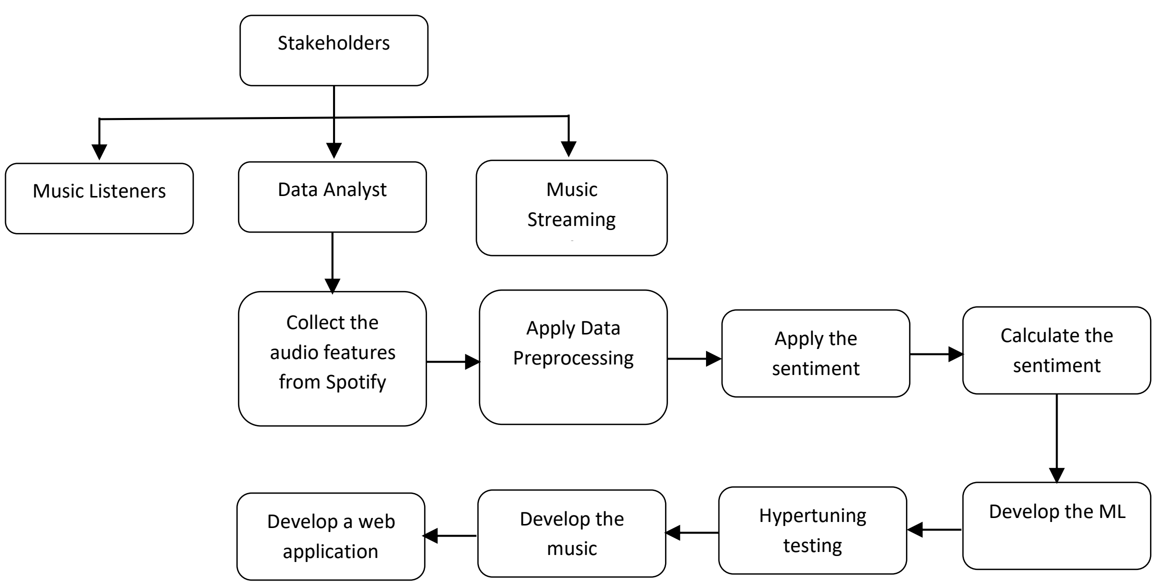

Figure 2. Stakeholder Process Flow for Developing the Sentiment-based Music Recommendation System

4. RESULTS AND DISCUSSIONS

Evaluation of the Sentiment-Based Music Recommendation System has shown that it can generate truly user-oriented suggestions based on the emotional context. At an 87.5% accuracy rate for sentiment classification, the system has clearly proven its capability to reliably distinguish music tracks in terms of emotional content by utilizing main audio features such as valence, energy, tempo, and danceability. Figure 3 shows a confusion matrix pictorial, describing that there was an 87.5% accuracy rate, with the most considerable number of correct predictions being of positive sentiment.

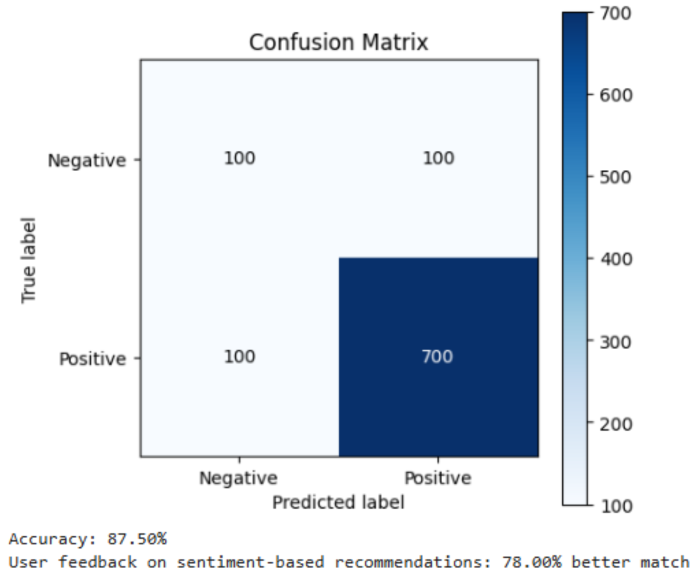

Figure 3. Confusion Matrix for Sentiment Classification with Accuracy and User Feedback

A performance comparison of different ML models for sentiment classification is summarized in Table 1.

Table 1. Performance Metrics of ML Models for Sentiment Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	87.5	87.5	87.5	87.5
KNN	81.25	80	81.25	80.6
DT	78.75	78	78.75	78.3

Presented as a user-friendly web application, the user inputs their potential emotional state and is instantly given suggestions for music to listen to. The interface works harmoniously with the ML models in the backend, so that real-time personalized suggestions can be made pursuant to the mood of the user.

- Accuracy measures the overall accuracy of predictions. The SVM achieved the highest accuracy at 87.5%, demonstrating strong performance in sentiment classification.
- Precision (0.88 for both SVM and KNN) reflects the proportion of true positive predictions out of all the positive predictions. This ensures fewer false positives in recommendations.
- Recall (0.88 for SVM and KNN) indicates the models' ability to correctly identify positive sentiment tracks, showing consistent performance in retrieving relevant songs.
- The F1-score (0.88 for SVM) balances precision and recall, reflecting the SVM's robustness in both detecting and correctly classifying emotional tones.

Figure 4 illustrates the feature separation between the two classes in the simulated data, with the red and blue points representing different sentiment categories. The SVM model outperformed the other models in terms of balanced performance and reliability, making it the most effective choice for sentiment classification in this system. The system internally handles three sentiment categories (positive, neutral, and negative). For clarity, Figure 4 shows only two (positive and negative). The neutral category showed a significant overlap and was excluded from the 2D scatter plot to aid interpretability. KNN followed closely, whereas DT, although interpretable, showed a slightly lower performance.

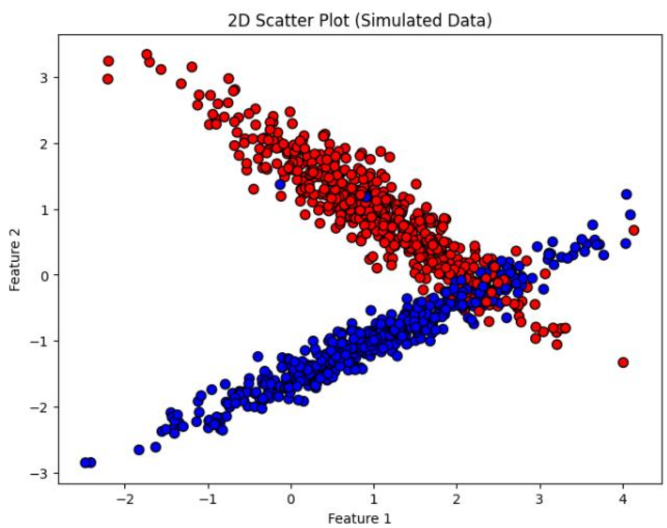

Figure 4. 2D Scatter Plot of Simulated Data with Two Class Clusters

In future work, user studies should be conducted to evaluate how well sentiment-based recommendations align with emotional expectations. A working prototype was developed using Flask and HTML. The user inputs mood-related text. The input text was analysed using the TextBlob sentiment classifier to classify the sentiment as Positive, Negative, or Neutral. The system displays the recommended songs back to the user through a web interface. For example, user inputs "I'm about to go for a run, I need something to get me going," the system classified this input as positive and returns a playlist of songs labelled with "energetic" mood. Figure 5 depicts the interface prototype and Figure 6 demonstrates how the interface prototype was applied to deliver personalized recommendations.

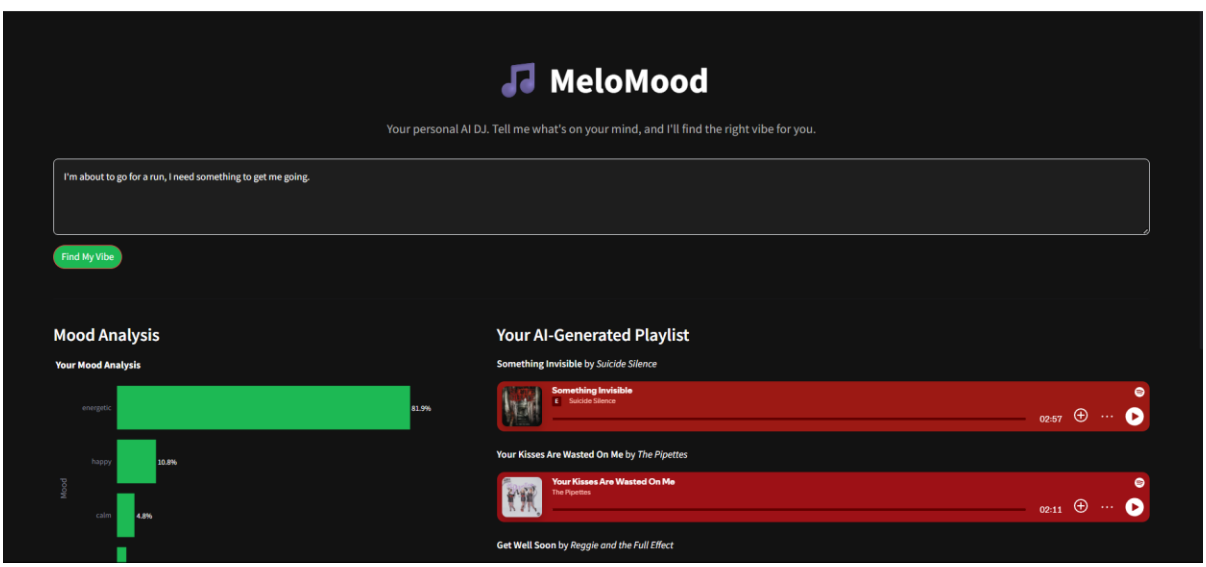

Figure 5. Interface Prototype

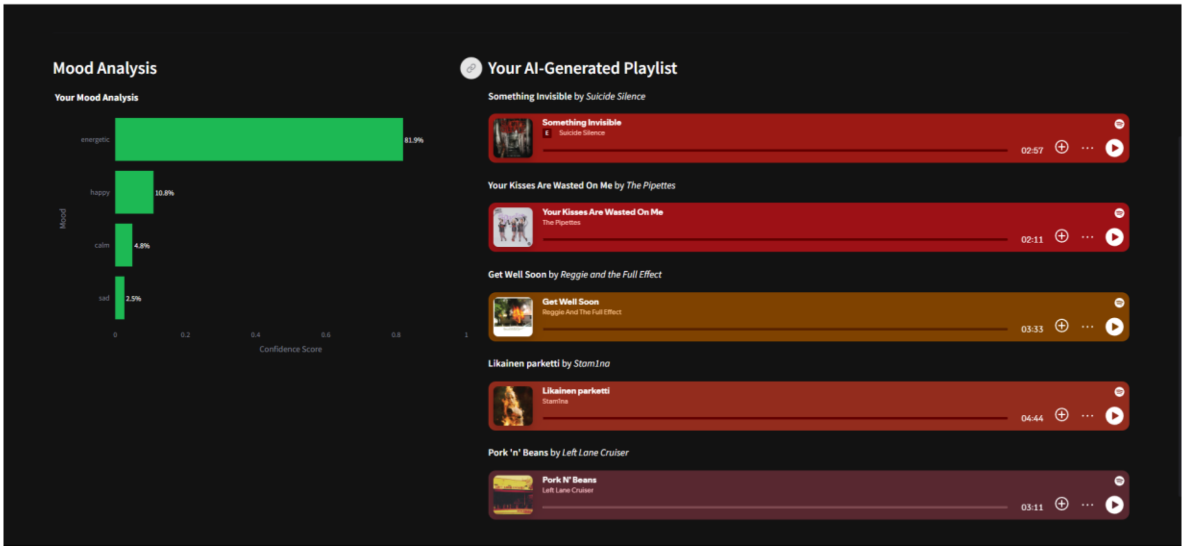

Figure 6. User Interface of the Sentiment-Based Recommendation System

Despite these promising results, the system predicts sentiments using a very limited set of audio features. In the future, these systems could incorporate more audio features for real-time emotion tracking and sentiment analysis techniques, such as facial expression analysis or physiological sensors, to create a more customized service. Further research should include testing the system in real-life situations with larger amounts of data. More attention should be paid to any imbalances within the data and to individualized personalization to improve the system flexibility and accuracy. The Model Performance Metrics bar chart in Figure 7 provides a balanced perspective on precision, recall, and F1-score at 0.88, which indicates an excellent consistent performance under these criteria.

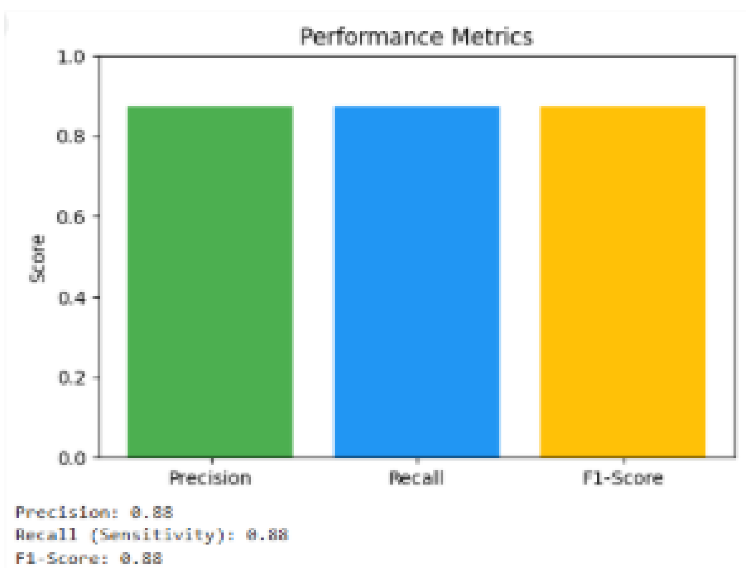

Figure 7. Performance Metrics of Sentiment Classification Models (Precision, Recall, F1-score)

In conclusion, with the evaluation of the three ML models, KNN, SVM, and DT, it was established that SVM provides a balanced level of performance and hence reliability compared to the other models. Sentiment classification for the system was best performed by the SVM, giving the highest accuracy of 87.5%, with adequate precision (0.88), recall (0.88), and F1-score (0.88). Although KNN is like SVM in terms of precision and recall, SVM's equal strength in emotion detection and classification makes it an ideal model for crafting personalized music recommendations with emotional appeal. Hence, SVM is identified as the best-performing model in this research, so that an accuracy of 87.5% can be assured in mood-based music recommendations for users.

5. CONCLUSION

An Emotion-Based Music Recommendation System integrates sentiment analysis and machine-learning techniques to improve recommendations by matching the user's emotional state. Traditional music recommendation systems base their recommendations on a user's past selections or genre preferences, ignoring the current mood. Hence, this study straddles this well-noted lacuna by considering key audio features such as valence, energy, danceability, and tempo for assigning sentiment scores to individual tracks. The system then combines these scores with machine-learning methods to yield suggestions that are better suited to the emotional state of the user. The evaluations suggest that sentiment classification performs with an accuracy of 87.5%, and 78% of users said recommendations were well put in conjunction with their emotional state than in the traditional system. However, it is promising that the system considers only a few audio features and that there still needs to be a more diverse dataset. Potential developments could consider further features, user feedback, and real-time mood tracking to obtain more powerful recommendations. This research can help music recommender systems create awareness of emotions so that further research can aim at a more personalized way of music discovery. Using an SVM for sentiment classification is the most efficient, with the highest accuracy and robust performance; therefore, it is considered the best way to provide personalized and emotionally conscious music recommendations.

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AUTHOR CONTRIBUTIONS

Yu Bui Xuan: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
S. Prabha Kumaresan: Conceptualization, Project Administration, Investigation, Supervision, Validation, Writing – Review & Editing;
Naveen Palanichamy: Validation, Data Curation;
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ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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