Vibe Flow: Enhancing Music Discovery with Mood-Based Classification

Abstract
"Vibe Flow" is a pioneering project aimed at enhancing the user experience on Spotify by implementing a mood-based music classification system. Utilizing Spotify's rich dataset of audio features, this project employs machine learning techniques to accurately classify tracks into distinct mood categories, initially focusing on "Happy" and "Sad." This report outlines the project's comprehensive methodology, from data collection and preprocessing to model training and evaluation, concluding with a discussion on potential applications within Spotify's ecosystem and adherence to best practices for data security and privacy.

1. Introduction

Music streaming services like Spotify have transformed the way we discover, listen to, and interact with music. Personalization and contextual recommendations stand at the forefront of this transformation, significantly enhancing user engagement and satisfaction. "Vibe Flow" introduces a machine-learning approach to mood classification, aiming to further personalize music recommendations by aligning them with the listener's current emotional state.

2. Data Collection

2.1 Spotify Web API

The dataset was compiled using Spotify's Web API, focusing on extracting relevant audio features that influence the mood of a track, such as **danceability**, **energy**, **valence**, **tempo**, and **acousticness**.

2.2 Handling Credentials

To ensure the security of Spotify API credentials (**client_id** and **client_secret**), environment variables were utilized, following best practices for sensitive data management:

2.3 Adherence to Spotify's Guidelines

The data collection process strictly adhered to Spotify's Developer Terms of Service, ensuring respect for user privacy and copyright restrictions. The dataset comprises publicly available information, devoid of personal user data, and is used solely for academic and research purposes.

3. Exploratory Data Analysis (EDA)

The EDA phase provided several key insights:

Valence and Energy Relationship: A positive correlation between valence and energy indicated that tracks perceived as happier tend to be more energetic.
Mood Distribution: The dataset was balanced with respect to mood categories, mitigating the risk of model bias towards a particular mood.
Correlation: Correlation analysis highlighted relationships between features, such as valence and energy, suggesting potential predictors for mood classification.

4. Feature Engineering and Preprocessing
Label encoding was applied to convert mood categories into a numerical format suitable for machine learning algorithms. The primary focus was on utilizing raw audio features without extensive preprocessing, given the decision tree-based nature of the chosen model, which is inherently robust to feature scale differences.

5. Model Building
A Random Forest classifier was selected for its ability to handle non-linear relationships and its robustness against overfitting. The model was trained on 80% of the data, with the remaining 20% used for testing. Hyperparameters were set to default values initially, with n_estimators=100 and random_state=42 to ensure reproducibility.

Results
The Random Forest classifier achieved an accuracy of 86.47% on the test set, demonstrating strong performance in mood classification. Further metrics include:
- Precision for "Happy": 89%
- Recall for "Happy": 87%
- F1-Score for "Happy": 88%
- Precision for "Sad": 82%
- Recall for "Sad": 85%
- F1-Score for "Sad": 84%

The confusion matrix and classification report provided deeper insights into model performance, confirming its effectiveness in distinguishing between "Happy" and "Sad" tracks.

6. Model Optimization and Evaluation
To further refine "Vibe Flow". I explored.
- **Feature Importance Analysis**: Conducted an analysis to determine the **"ENERGY"** feature most significantly impacts mood prediction, offering insights into the musical elements that contribute to emotional perception.

7. Recommendation to Spotify
- **Personalized Playlist Creation:**
  Spotify could use the model to automatically generate and suggest playlists to users based on their current mood, detected through their recent listening history or explicitly selected by the user.
- **Dynamic Mood-based Recommendations:**
  During different times of the day or week, Spotify could offer dynamic recommendations that match the general mood of the user base or individual listener preferences, enhancing the listening experience with appropriately timed mood-based music suggestions.
- **Music Discovery and Exploration:**
  Enhance Spotify's "Discover Weekly" or "Daily Mix" features with mood-based tracks discovery, encouraging users to explore new music that fits their emotional preferences.

8. Future Directions:

- Deep Learning: Explore neural networks, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for potentially improved mood classification.
- User Feedback Loop: Implement a mechanism to incorporate user feedback into the model, allowing for dynamic learning and adaptation based on user interactions.
- Expanded Mood Categories: Broaden the scope of mood classifications to include a wider range of emotional states, facilitating more nuanced recommendations.

Conclusion:

"Vibe Flow" represents a significant step forward in the application of machine learning to music classification and recommendation. By accurately identifying the mood of music tracks, it lays the groundwork for more personalized and emotionally attuned music discovery experiences on Spotify. Future enhancements and integrations promise to further solidify Spotify's position as a leader in personalized music streaming services.