SpotiFinder - A Music Recommendation app built using Machine Learning

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***Abstract*— In a world where digital content is abundant, providing users with personalized recommendations is essential to enhance their entertainment experience. This project focuses on developing a recommendation system that delivers customized music suggestions based on user-defined preferences. Leveraging the Spotify API for music data , the app extracts relevant features from the dataset of Spotify tracks . By employing Content-Based Filtering techniques, the system matches user inputs with the available content, identifying the most relevant movies . The recommendation engine is built using Python, while Streamlit is utilized to create an interactive user interface. This approach allows users to receive recommendations that closely align with their tastes, making the content discovery process efficient and enjoyable**

***Keywords— Music Recommendation System, Personalized Music, Machine Learning, Content-Based Filtering, Fuzzy C means clustering, Nearest Neighbors, Streamlit, Spotify, , Audio Features, Interactive User Interface***

1. INTRODUCTION

The digital transformation of the music industry, particularly through streaming platforms like Spotify, has fundamentally changed how people discover and consume music. With over 100 million tracks available on major streaming platforms, users face a paradox of choice - an overwhelming number of options that can actually hinder the discovery of new music they might enjoy. This challenge has made sophisticated music recommendation systems not just beneficial but essential for both user experience and platform engagement.Traditional recommendation approaches often rely heavily on collaborative filtering, which can suffer from the "cold start" problem and may not capture the nuanced characteristics that make songs musically similar.This project addresses these challenges through a novel hybrid approach that combines fuzzy clustering for flexible genre classification with a content-based recommendation system. The system analyzes audio features from Spotify's dataset to create a more nuanced understanding of musical similarities while giving users substantial control over their discovery experience.

1. DATASET

The dataset used in this project is a collection of Spotify tracks ,available on Kaggle. The dataset has varied features like the song id,name,name of the artists,release date of the particular song,release year,duration of the song ,along with different musical attributes. The key attributes in the data include :

* track\_id: The Spotify ID for the track
* artists: The artists' names who performed the track. If there is more than one artist, they are separated by a ;
* album\_name: The album name in which the track appears
* track\_name: Name of the track
* popularity: The popularity of a track is a value between 0 and 100, with 100 being the most popular.
* duration\_ms: The track length in milliseconds
* explicit: Whether or not the track has explicit lyrics (true = yes it does; false = no it does not OR unknown)
* danceability: It describes how suitable a track is for dancing based on a combination of musical elements. A value of 0.0 is least danceable and 1.0 is most danceable
* energy: Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity.
* key: The key the track is in. Integers map to pitches using standard Pitch Class notation. If no key was detected, the value is -1
* loudness: The overall loudness of a track in decibels (dB)
* mode: Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
* speechiness: Speechiness detects the presence of spoken words in a track. It has value between 0 and 1.
* acousticness: A value of 1.0 represents high confidence the track is acoustic while 0 indicates low confidence.
* instrumentalness: Predicts whether a track contains no vocals. A value near to 1.0 means greater likelihood of the track to contain no vocal content.
* liveness: Detects the presence of an audience in the recording
* valence: A measure from 0.0 to 1.0 , tracks with high valence sound more positive while tracks with low valence sound more negative
* Tempo : The estimated tempo of the track in beats per minuter(BPM)

1. METHODOLOGY

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