DS-471 Time Series Analysis

Assignment: PROJECT REPORT

Project Title: "Song **Mood Prediction** and **Clustering Analysis** Using **SPOTIFY DATA."**

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TITLE:

"Song Mood Prediction and Clustering Analysis Using Spotify Data"

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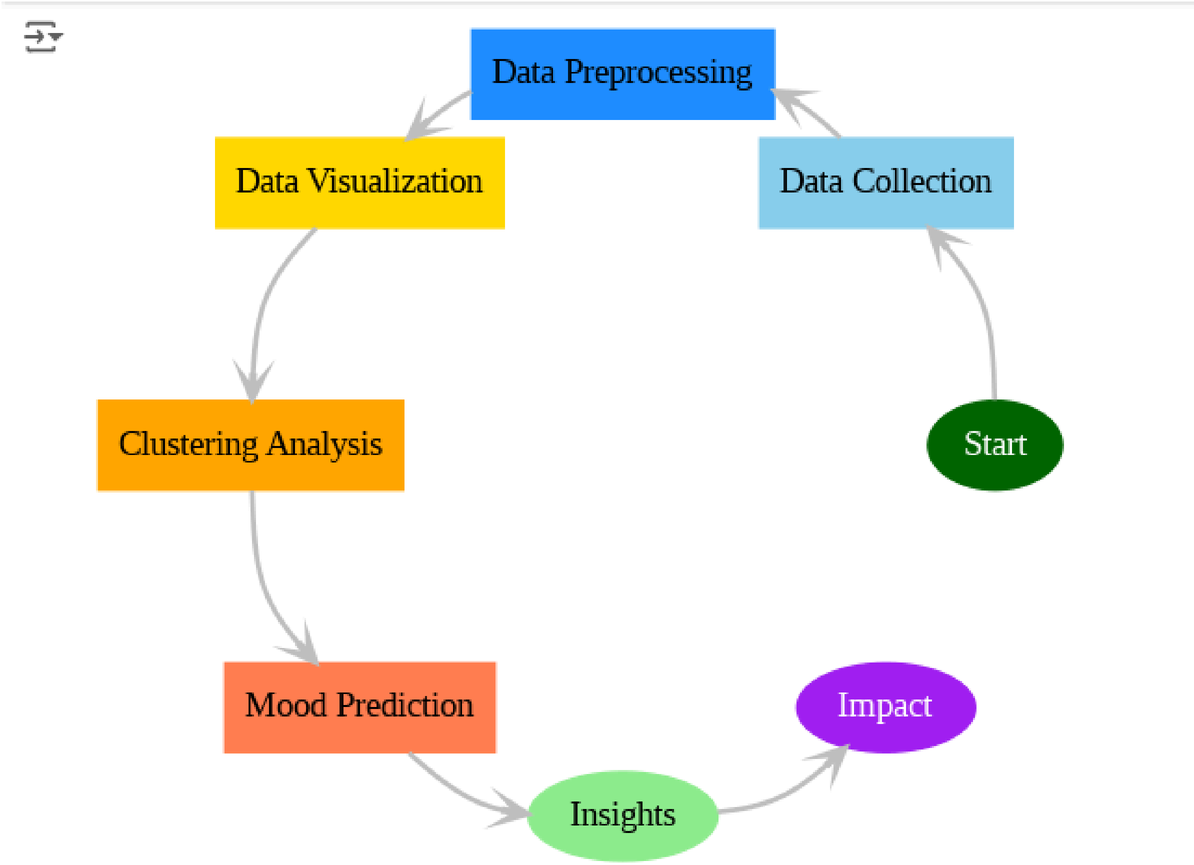
Summary:

For this project, 1,000 artists from **spotify's Web API** are scraped, with an emphasis on the audio features of dancing, energy, loudness, and valence. Data cleaning, analysis and feature extraction is done using python also the mood of the songs are predicted using **K-means clustering and SVC**. The information obtained may be employed for the purpose of creating mood-specific playlists and music for therapeutic uses to partially advance **Sustainable Development Goal 3** through improved knowledge of the effects of music on health.

Introduction:

This work uses Spotify's rich music information dataset to identify and learn song moods based on its audio characteristics. To this end, it employs web scraping, data preprocessing, visualization, clustering, and machine learning to examine the connection between song features such as danceability, energy, loudness, valence, and tempo and the resulting emotions.

Mood responds to music significantly, and this project proposes to measure and model this process scientifically.



Problem Statement:

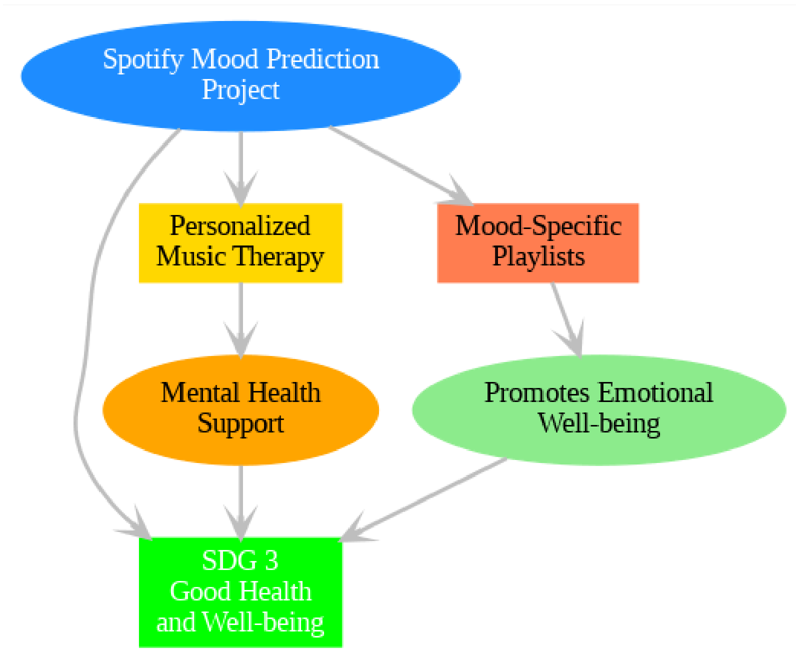
The purpose of this project is to classify song moods and cluster them through data acquired from **Web API** from Spotify. The induction and intensity of emotions elicited by music are well-known facts, and knowledge of how some characteristics of audio data **(for example, danceability, energy, loudness, valence, tempo)** are associated with the reaction of listeners to the song would improve some applications such as **Music Mood Association and Music Therapy.** The provided work is to solve the problem of right classification of songs in terms of the mood and correct clustering taking into account the similarities of audio characteristics. When it comes to the applied analysis, the goal is to explore clustering, visualization, and machine learning approaches to outline trends and patterns in music business; The research is also committed to the UN **Sustainable Development Goal #3**, which deals with strengthening the health of the population.

Objectives:

1. ***Data Collection and Preprocessing:***
    - Collected song data by making a request to the **Spotify Web API** and utilizing the audio features danceability, energy, loudness, and valence.
2. ***Data Visualization:***
    - Employ Plotly to build near real-time interactive visualizations, analyze charts, and discover new trends. Few examples of what can be questioned are the most frequently followed artist, the release of the songs per year and the number of songs of each artist.
3. ***Clustering Analysis:***
    - Analyse the audial similarity of songs and group them with corresponding patterns concerning moods and music genres.
    - The elbow curve needs to be plotted to decide the correct number of clusters to be formed.
4. ***Mood Prediction (SVC… Support Vector Classifier):***
    - Construct a predictive model on the mood of a song based on features such as **danceability, valence, tempo, loudness, and energy.**
    - Support Vector Classifier **(SVC)** is a supervised machine learning algorithm that is a part of the **Support Vector Machines (SVM)** family. It is designed for classification tasks and works by finding the optimal hyperplane that best separates data points of different classes in a feature space.
    - It handles High Dimensional Feature Spaces, Effective in non-linear classification, Robust to Overfitting, Works well with limited data, High Accuracy for small to Medium datasets. That's why we selected it.

Sustainable Development Goals (SDG) Alignment:

This project relates with the UN sustainable development **goal 3**, **(Good Health and Wellness)** by positing potential uses in music therapy and wellness products. If song moods can be predicted, it can be used to generate moods based on playlists also enhancing mental health and well-being.



Project Scope and Relevance:

The increasing number of people using streaming services makes it essential to use music for mood modulation, and therefore it is essential to recommend a particular type of music. It is especially important for therapeutic use, wellbeing application, or stress management programs, as this project is concentrated on mood prediction. This project to enhance the understanding between musicality aspects and moods help to build data-based mental health intervention, therefore it has connection to **SDG 3.**

Methodology:

Data Collection:

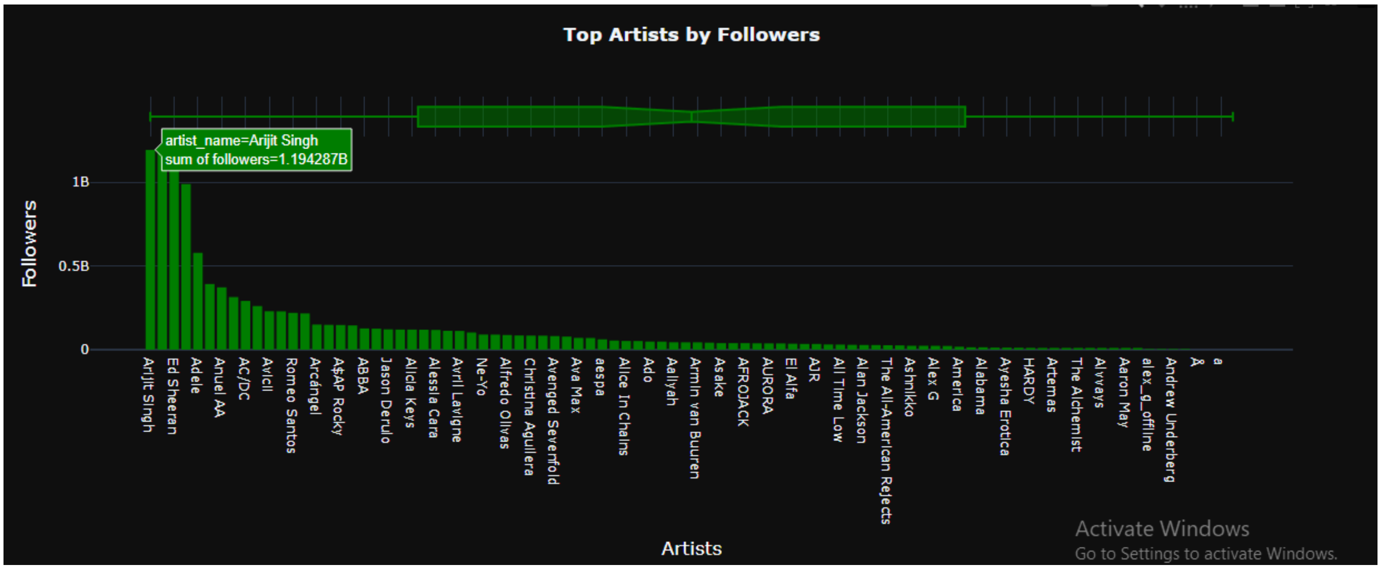
- **Web Scraping**: To that end, song metadata and audio features (for instance tempo, loudness, energy level, danceability) were obtained using the Spotify API.

Column Name	Description
Unnamed: 0	Index column (used for data tracking)
artist_name	The name of the artist
genres	The musical genres associated with the artist
followers	The number of followers the artist has on Spotify (quantitative)
artist_popularity	Popularity score of the artist (quantitative, scale of 0 to 100)
artist_url	URL link to the artist's Spotify page
track_name	Name of the track
album_name	Name of the album the track belongs to
release_date	Date the track was released (qualitative, in the form of a string date)
duration_ms	Duration of the track in milliseconds (quantitative)
explicit	Whether the track contains explicit content (qualitative, boolean)
track_popularity	Popularity score of the track (quantitative, scale of 0 to 100)
danceability	The danceability score of the track (quantitative, scale of 0 to 1)
energy	The energy level of the track (quantitative, scale of 0 to 1)
key	The key of the track (quantitative, musical key represented numerically)
loudness	The overall loudness of the track in decibels (quantitative, scale of dB)
mode	The mode of the track (qualitative, either Major or Minor)
speechiness	The speechiness level of the track (quantitative, scale of 0 to 1)
acousticness	The acoustic nature of the track (quantitative, scale of 0 to 1)
instrumentalness	The level of instrumental nature of the track (quantitative, scale of 0 to 1)
liveness	The liveness score of the track (quantitative, scale of 0 to 1)
valence	The musical positiveness or happiness (quantitative, scale of 0 to 1)
tempo	The tempo (beats per minute) of the track (quantitative)

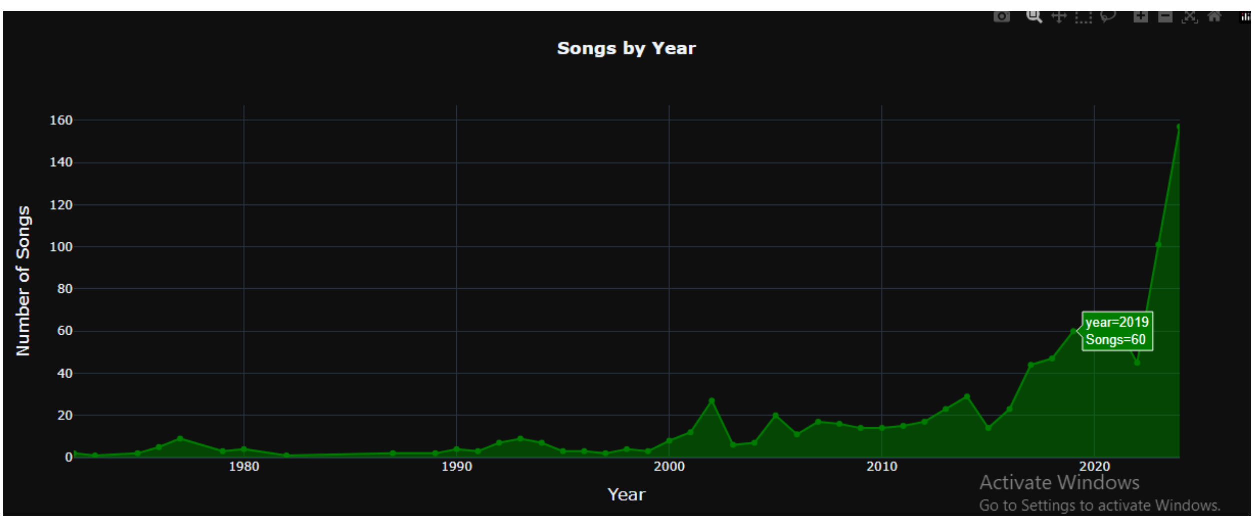
- **Preprocessing**: To make it easy to analyze, the dataset was cleaned and normalized.

Data Visualization:

- Interactive visualizations were created using Plotly to explore patterns in the data, such as:
  - The most-followed artist.

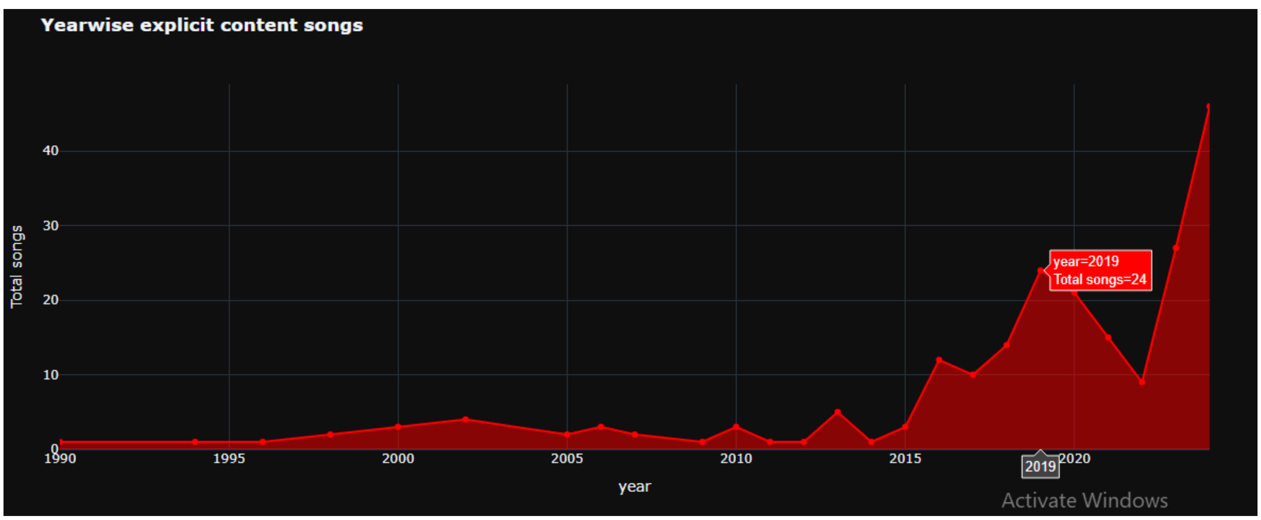


  - The trends recorded in songs over the various years.

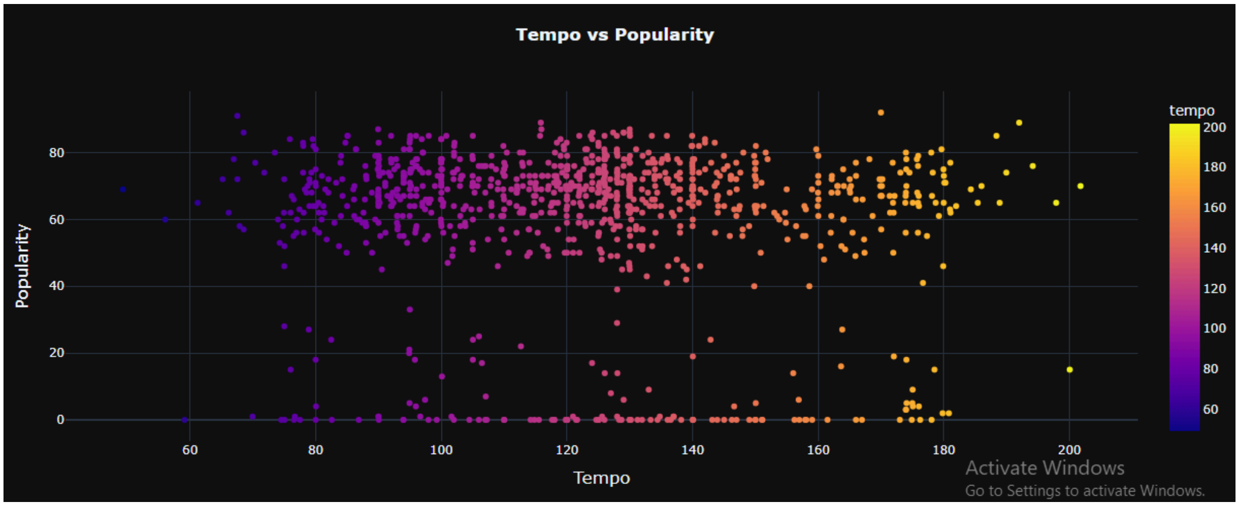


○ Tree map of artists.

○ Explicit Content:



- Audio Features Comparison



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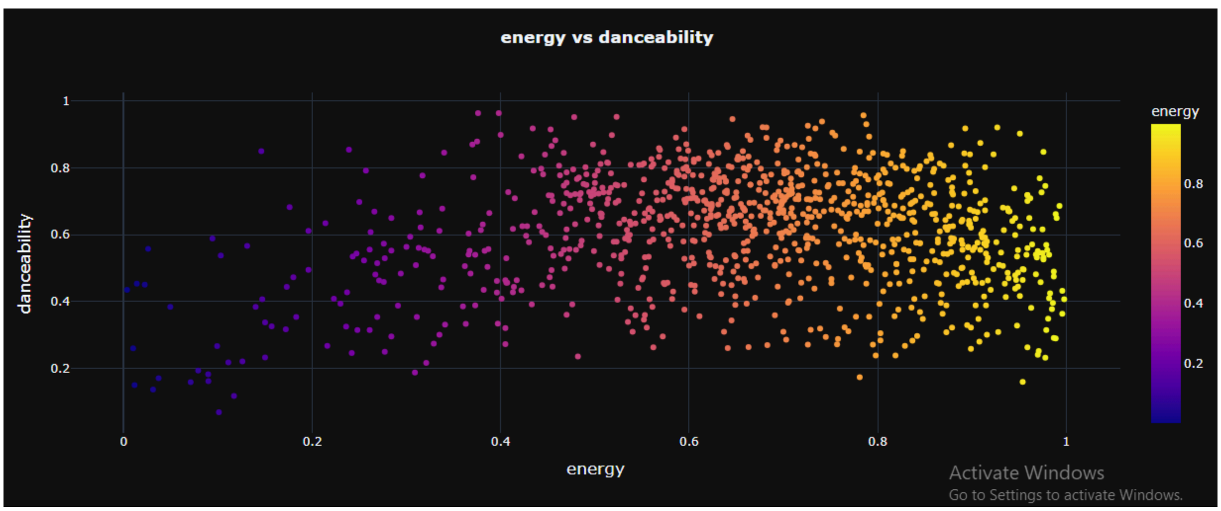
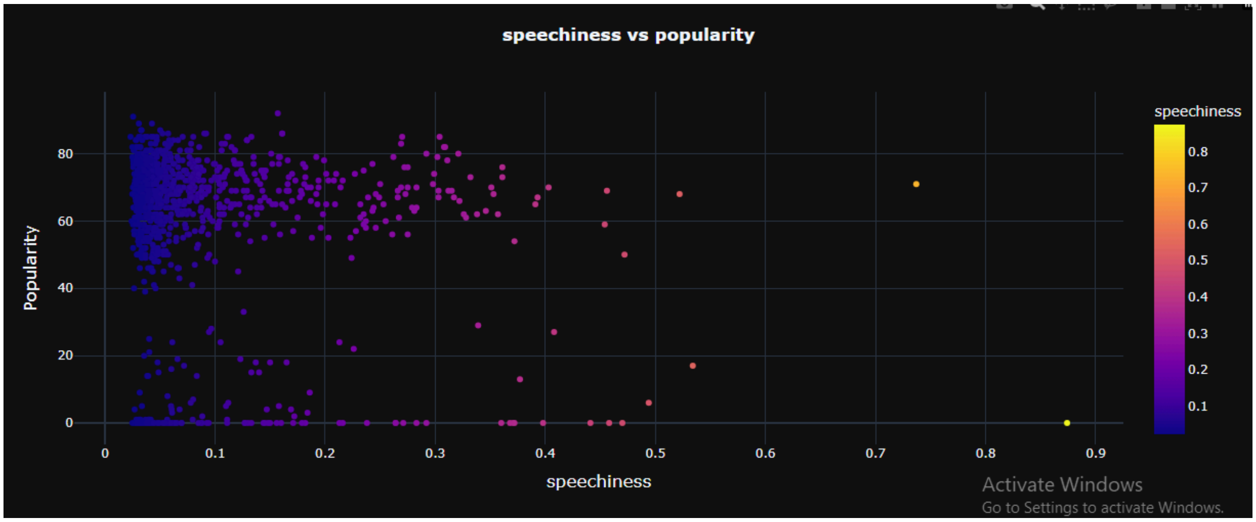
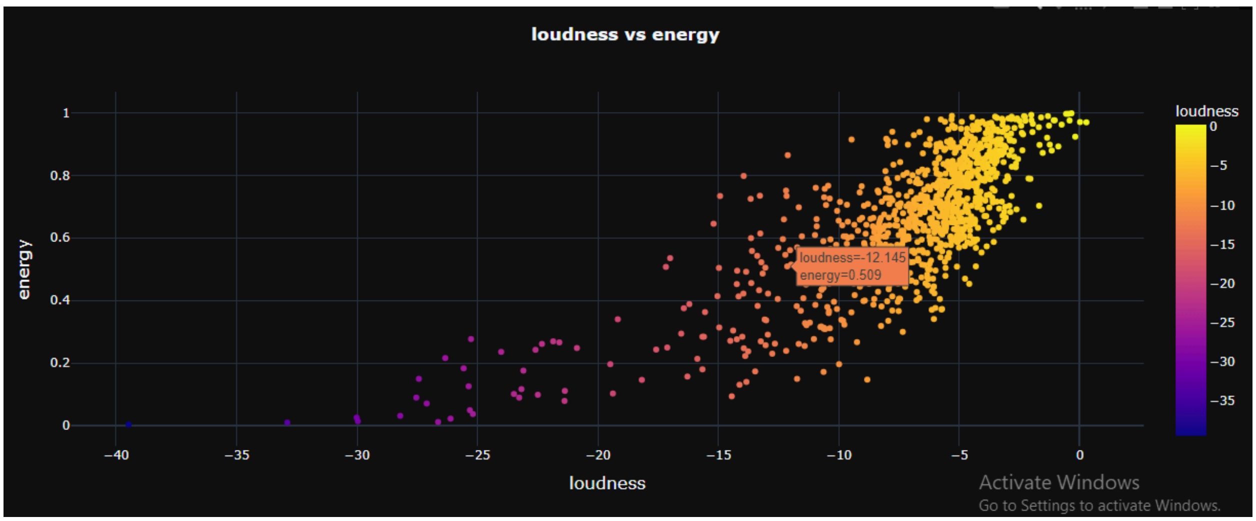
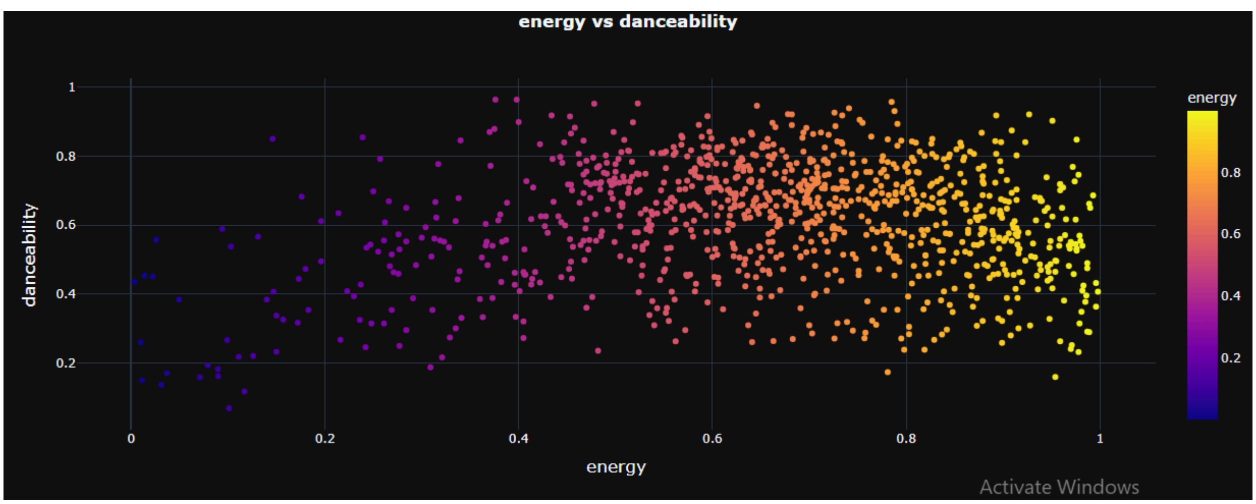


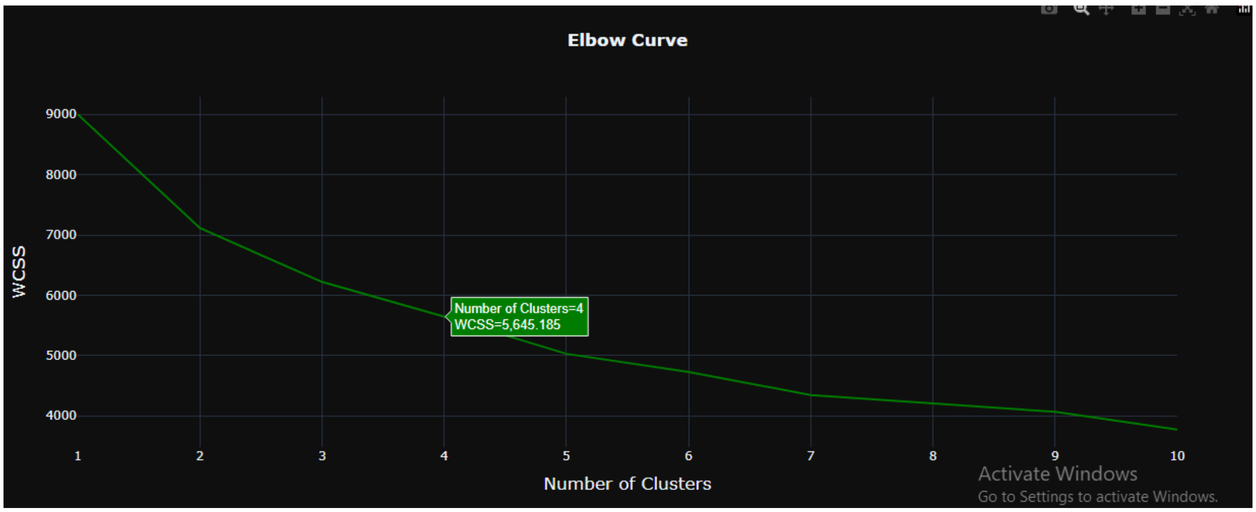

speechiness vs popularity
Popularity
speechiness
speechiness
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
20
40
60
80
0.9
Activate Windows
Go to Settings to activate Windows.


loudness vs energy
energy
loudness
loudness
loudness=-12.145
energy=0.509
−40
−35
−30
−25
−20
−15
−10
−5
0
1
Activate Windows
Go to Settings to activate Windows.


energy vs danceability
danceability
energy
energy
0
0.2
0.4
0.6
0.8
1
Activate Windows

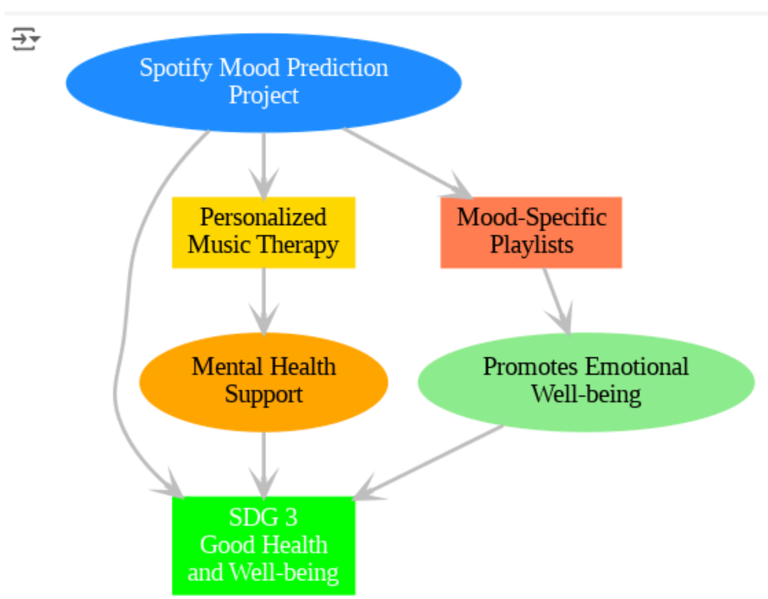
Clustering Analysis:

- As an instance, by using the K-means clustering, the set of songs was divided into several clusters according to some characteristics of their audio.
- The elbow curve was plotted to decide the number of clusters we are going to use in the analysis.



Mood Prediction (Machine Learning):

- Support vector classifiers (SVC) is used for the purpose of classifying song moods despite their statistical nature and complex structures by considering features such as danceability, valence, tempo loudness, and energy.



Key measures such as accuracy, precision and recall were used to assess the model's performance.

- **Cross-Validation Accuracy Scores:**

  The accuracy scores range between **83.75%** and **93.75%**, indicating the model performs consistently well across splits.

- **Mean CV Accuracy:**

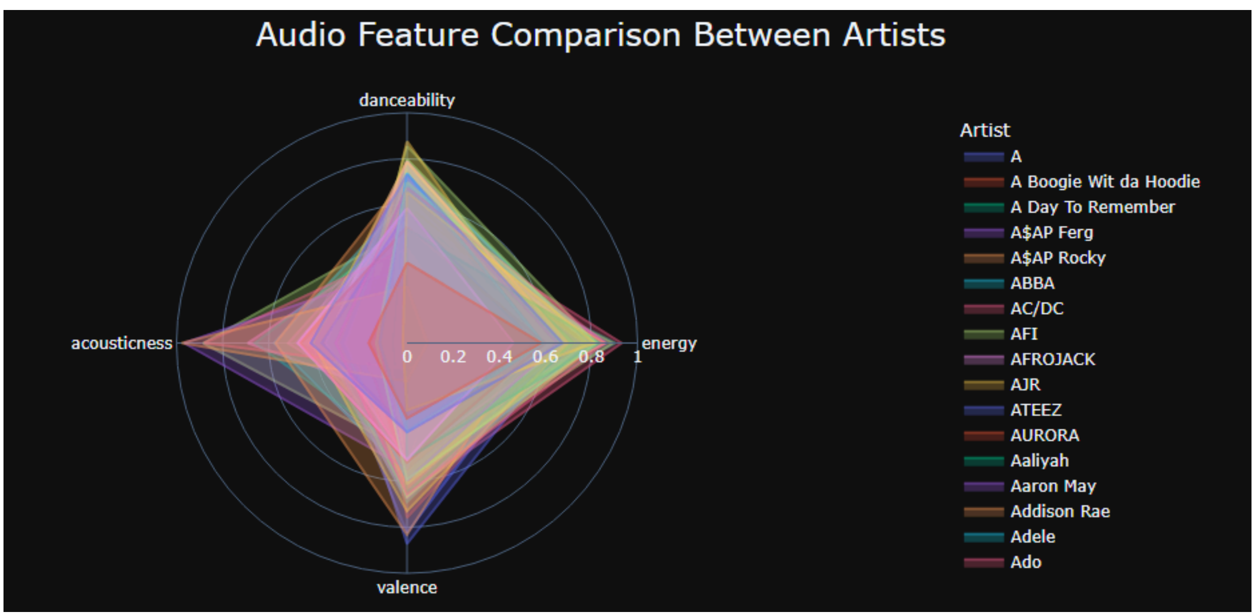
  The average cross-validation accuracy is **89%**, showing the model performs well on unseen data.

- **Accuracy:**

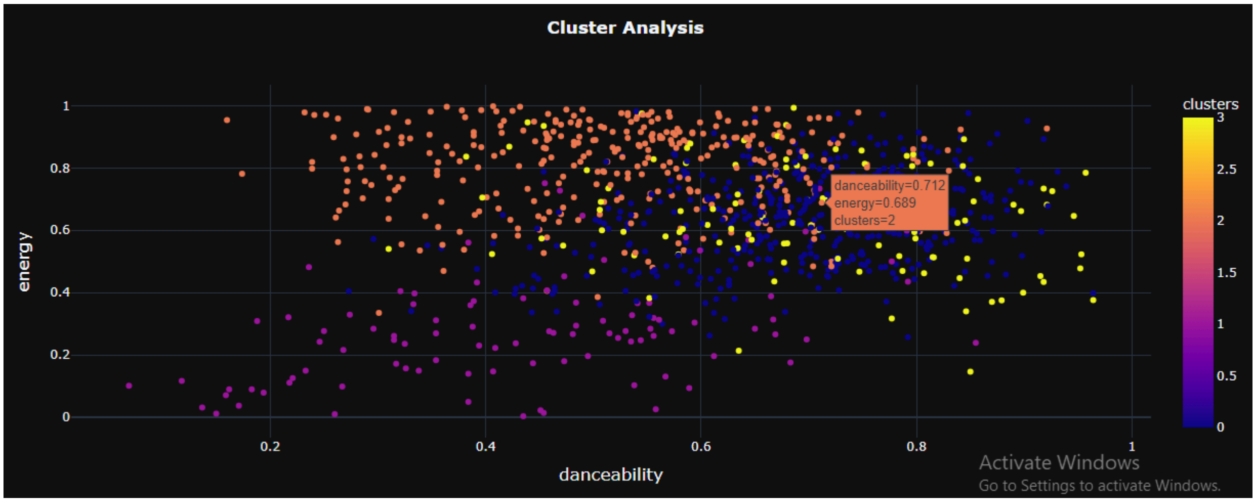
```
Accuracy: 0.86
```

Outcomes:

1. ***Insightful Visualizations:***
   - An infographic with needling and plotted points showing some of the features and their relativity to mood and type of music.

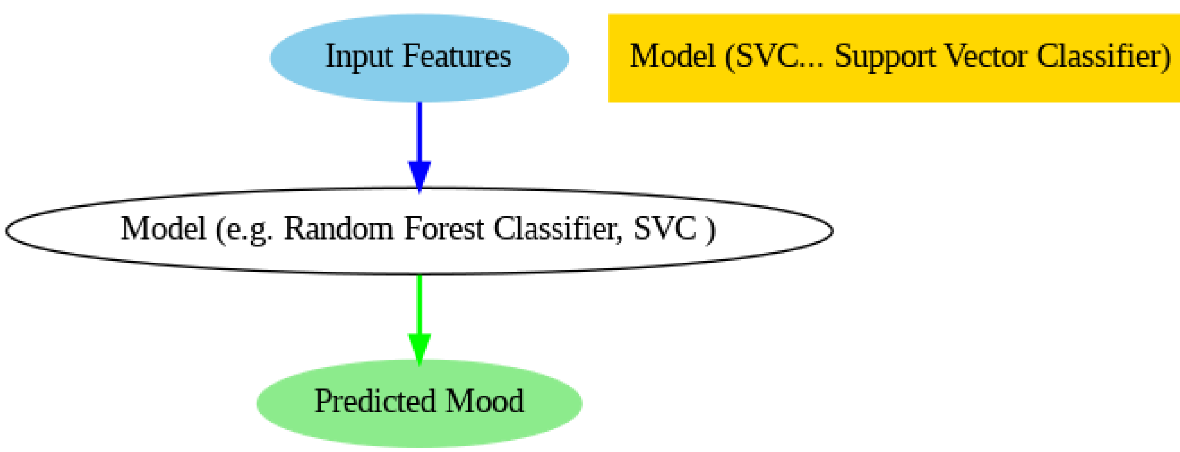


2. ***Clustering Analysis Results:***
    - Groups of related songs that have different patterns in terms of the audio characteristics necessary to assess the mood specific to a genre.



3. ***Predictive Model:***
    - An ML model that will enable the decision-making process on what song moods could be linked to a given set of audio features, and signal the first step toward personalization of music playing and creation of mood-based playlists. We used the SVC Model.

Show code



- **Classification Report:**

```
Classification Report:
              precision    recall  f1-score   support

        calm       0.73      0.71      0.72        31
   energetic       0.84      0.90      0.87        52
       happy       0.89      0.93      0.91        91
         sad       1.00      0.73      0.84        26

    accuracy                           0.86       200
   macro avg       0.87      0.82      0.84       200
weighted avg       0.87      0.86      0.86       200
```

Accuracy: 86%

- Overall, the model correctly predicts **86%** of moods across all test samples.

- **Prediction Of Mood:**

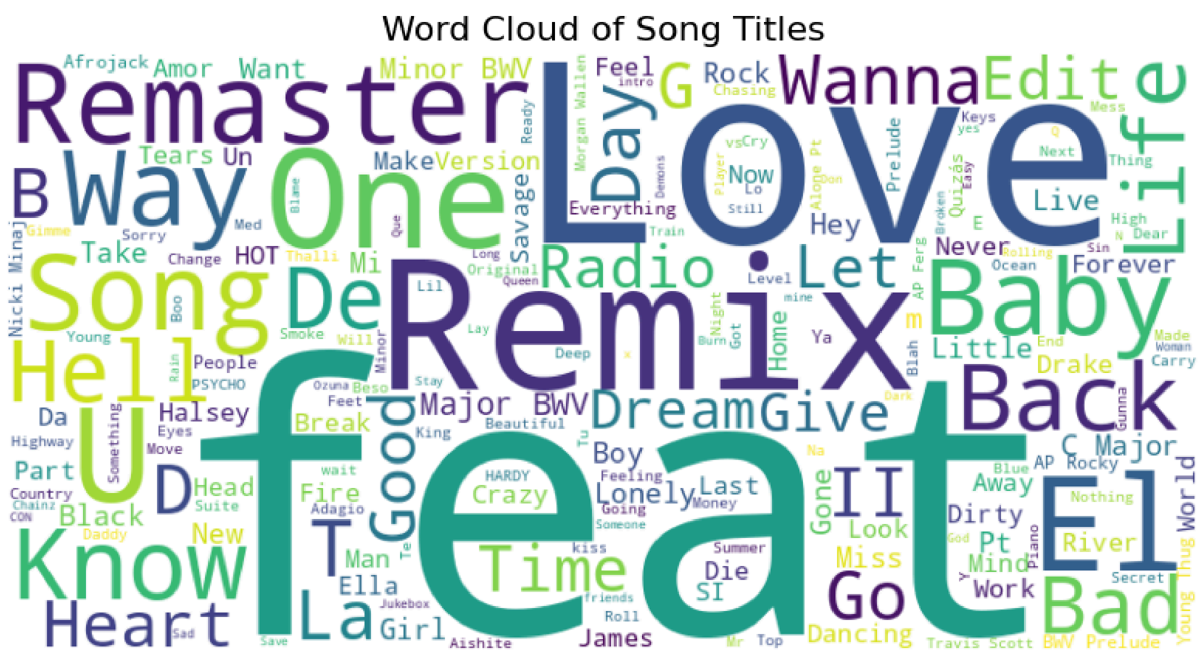
```
new_song_features = {
    "danceability": 0.506,
    "energy": 0.362,
    "loudness": -9.480,
    "speechiness": 0.0416,
    "acousticness": 0.6700,
    "instrumentalness": 0.00000,
    "liveness": 0.17,
    "valence": 0.385,
    "tempo": 84.726
}
```

OUTPUT:

```
Predicted Mood: sad
```

Impact and Uniqueness:

- ***Sustainable Development Goals (SDG 3):***
  - ➔ Focusing on Good Health and Well-being, this project seeks to improve understanding of the correlation between the music played and the consequent mood.
  - ➔ Examples in mental health and wellness apps are using Spotify to provide a playlist based on the user's mood as a way of improving mood and decreasing stress.
- ***Uniqueness:***
  - ➔ Elementary prediction of mood helps to partially distinguish this project from the music analysis ones that are typically prescriptive by genre.
  - ➔ In this way, the integration of visualization, clustering and predictive modeling entails value to data science and the mental health field.



STATE OF THE ART WORK:

PART 01:

Music Mood classification is relatively new research field which integrates the use of machine algorithms with peoples feelings. A number of emerging methods have been proposed to forecast and infer the emotional characteristics of music tracks with help of using machine learning and deep learning approaches and tools from audio signal processing. We briefly review the existing work related to this research area below.

1. Machine Learning Approaches

Most machine learning techniques have been used in the past for music mood prediction specifically with music mood prediction. Implementations of the current model used the Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), or Decision Trees to classify mood by using sound frequency features including tempo, loudness, and pitch. For example, Panda et al showed that three Spotify audio features-energy, valence, and acousticness —are most important in using those algorithms to classify music moods[6]. Although these models serve a purpose, their inability to incorporate so many features automatically through the computational model might hamper their ability to be consistent across different datasets.

specific attribute or callable. Then, the minor key features are pruned from the current features. The procedure is repeated on the pruned set until the desired number of selected features is eventually reached.

TABLE II
FEATURE RANKING

Ranking	Audio Features
1	Energy
2	Acousticness
3	Valence
4	Instrumentalness
5	Speechiness
6	Danceability
7	Liveness
8	Mode
9	Loudness
10	Time Signature
11	Key
12	Tempo

4) Evaluating the Model: To assess the model's accuracy, a heatmap confusion matrix is displayed using the Seaborn Library and Matplotlib. The data is shown in two dimensions on the heatmap. The Seaborn library offers a high-level data visualization interface that allows us to create our matrix while the data values are represented in the graph by colors.

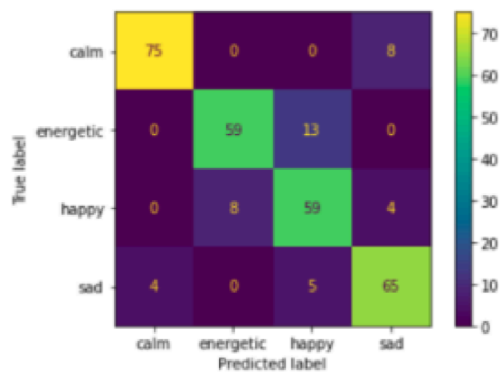


Fig. 1. The confusion matrix shows the number of correct and incorrect classification, per mood.

TABLE III
PERFORMANCE EVALUATION

Mood	accuracy	precision	recall	f1 score
Calm	0.9866	0.9494	0.9036	0.9259
Energetic	0.9733	0.8806	0.8194	0.8489
Happy	0.9400	0.7662	0.8310	0.7973
Sad	0.9600	0.8442	0.8784	0.8610
AVERAGE	0.9600	0.8442	0.8784	0.8610

$$F1 = 2 * \frac{precision * recall}{precission + recall} \quad (4)$$

Conclusion:

This project combines data science and mental health as MUSIC matches the spotify data with the mood of the individual. It uses visualization techniques, clustering, and machine learning to identify how music changes people's moods. Besides, the study advances knowledge in the data science domain and mental health support action, which also corresponds to SDGs 3 by using a digital approach to enhance people's well-being. Future uses include creating individualised music therapy and improving music recommendations, illustrating the practical value of the project.

References:

- **https://www.researchgate.net/publication/370450676_Music_Mood_Prediction_Based_on_Spotify's_Audio_Features_Using_Logistic_Regression**
- **https://research.atspotify.com/2022/07/the-contribution-of-lyrics-and-acoustics-to-collaborative-understanding-of-mood/**