Emotion-Based Spotify Song Recommendation System

1. Introduction

Music influences emotions, and this project aims to build an emotion-aware song recommendation system using Spotify's music dataset and machine learning techniques. By leveraging natural language processing (NLP), sentiment analysis, and clustering, the system will analyze song lyrics, metadata, and user preferences to suggest suitable tracks .

2. Objective

•Provide emotion-driven music recommendations for users. •Analyze song lyrics and metadata to categorize songs by sentiment. •Improve playlist curation using audio features, genres, and popularity metrics.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv("S:/project
/light_spotify_dataset.csv")
print(df)print(df.head(20))
```

Out[2]:

	artist	song	emotion	variance	
0	ABBA	She's My Kind Of Girl	joy	0.447619	
1	ABBA	Andante, Andante	love	0.202222	
2	ABBA	As Good As New	sadness	0.300881	
3	ABBA	Bang	joy	0.355000	
4	ABBA	Bang-A-Boomerang	joy	0.355000	
...	...	...	...	...	
236983	(Eri Sasaki)	Gate Of Steiner	sadness	0.833514	Unknown,U
236984	(Elena Tsagrinou)	El Diablo	love	0.833514	Unknown,U
236985	(Dima Bilan)	Believe	joy	0.833514	Unknown,U
236986	(Ani Lorak)	Shady Lady	joy	0.833514	Unknown,U
236987	(Alla Pugacheva) & 50 Cent	Позови меня P.I.M.P	anger	0.833514	Unknown,U

236988 rows × 18 columns

	variance	release_date	tempo	lou
count	236988.000000	236988.000000	236988.000000	236988.0
mean	0.658932	2008.472826	120.609685	-8.0
std	0.320735	14.756158	28.966358	3.8
min	-1.000000	1900.000000	33.000000	-46.7
25%	0.833514	2002.000000	97.000000	-9.8
50%	0.833514	2015.000000	120.000000	-7.1
75%	0.833514	2019.000000	140.000000	-5.3
max	1.000000	2024.000000	200.000000	3.7

```
df1=df.copy()
pd.reset_option("display.max_row")
df1.columns = df1.columns.str.lower().str.replace
(' ', '_').str.replace('-', '_')
```

```
print(df1.isnull().sum())df1.describ
e()
```

3. Exploratory Data Analysis (EDA)

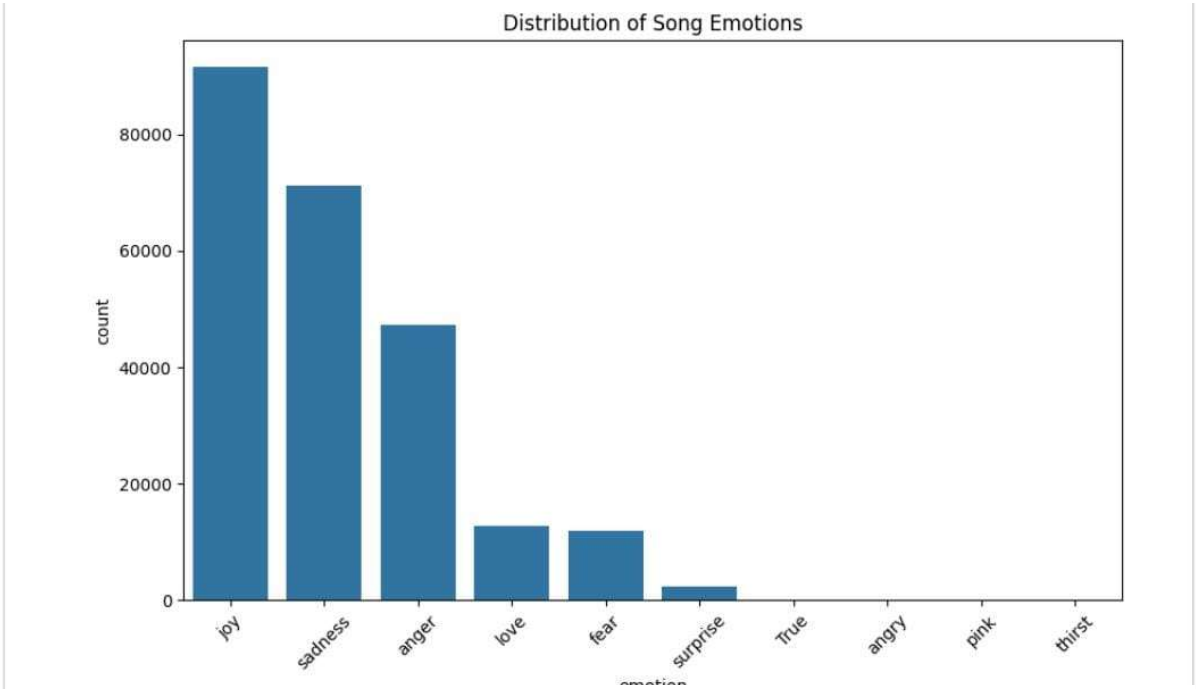
EDA provides insights into the dataset, including:

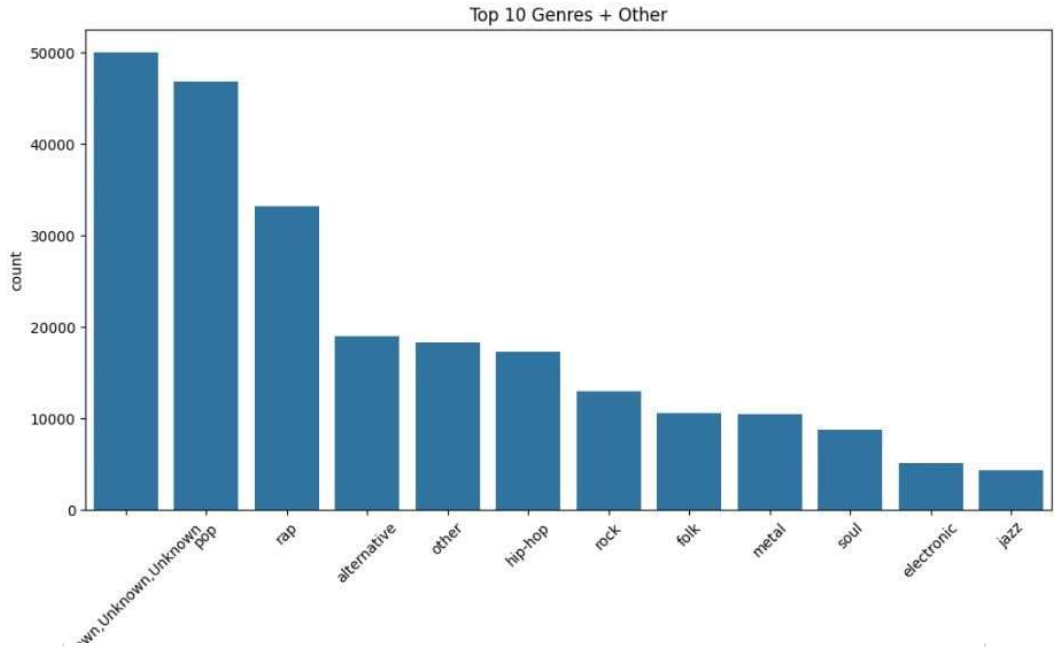
- Emotion Distribution: Understanding sentiment patterns in songs.
- Genre Distribution: Identifying emotional diversity across music genres.
- Popularity Analysis: Evaluating song rankings and user engagement

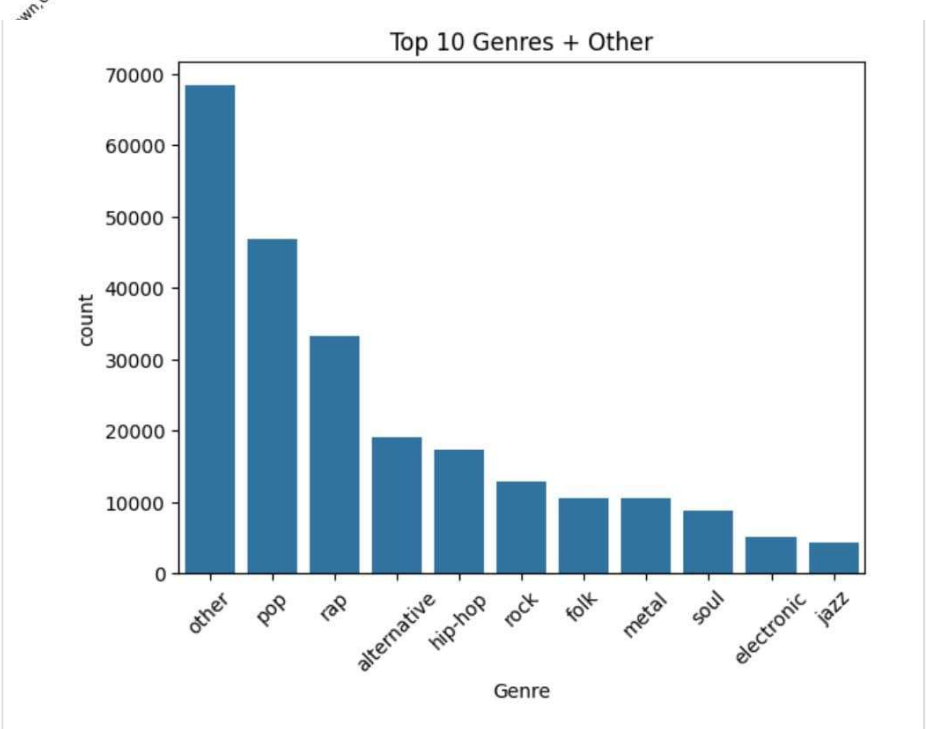
4. Emotion Distribution

- Classifying songs into categories such as joyful, melancholic, energetic, relaxing, etc.
- Using sentiment analysis to extract emotional tones from song lyrics.
- Data visualization aids in understanding emotional trends.

```
# EmotionDistribution
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='emotion',order=df['emotion'].value_
counts().index)
plt.title('Distribution of Song Emotions’)
plt.xticks(rotation=45)
plt.show()
```


Distribution of Song Emotions
count
80000
60000
40000
20000
0
joy
sadness
anger
love
fear
surprise
True
angry
pink
thirst


Top 10 Genres + Other
count
50000
40000
30000
20000
10000
0
pop
rap
alternative
other
hip-hop
rock
folk
metal
soul
electronic
jazz


Top 10 Genres + Other
count
70000
60000
50000
40000
30000
20000
10000
0
other
pop
rap
alternative
hip-hop
rock
folk
metal
soul
electronic
jazz
Genre

```
df1['emotion'] = df1['emotion'].replace('angry', 'anger')
```

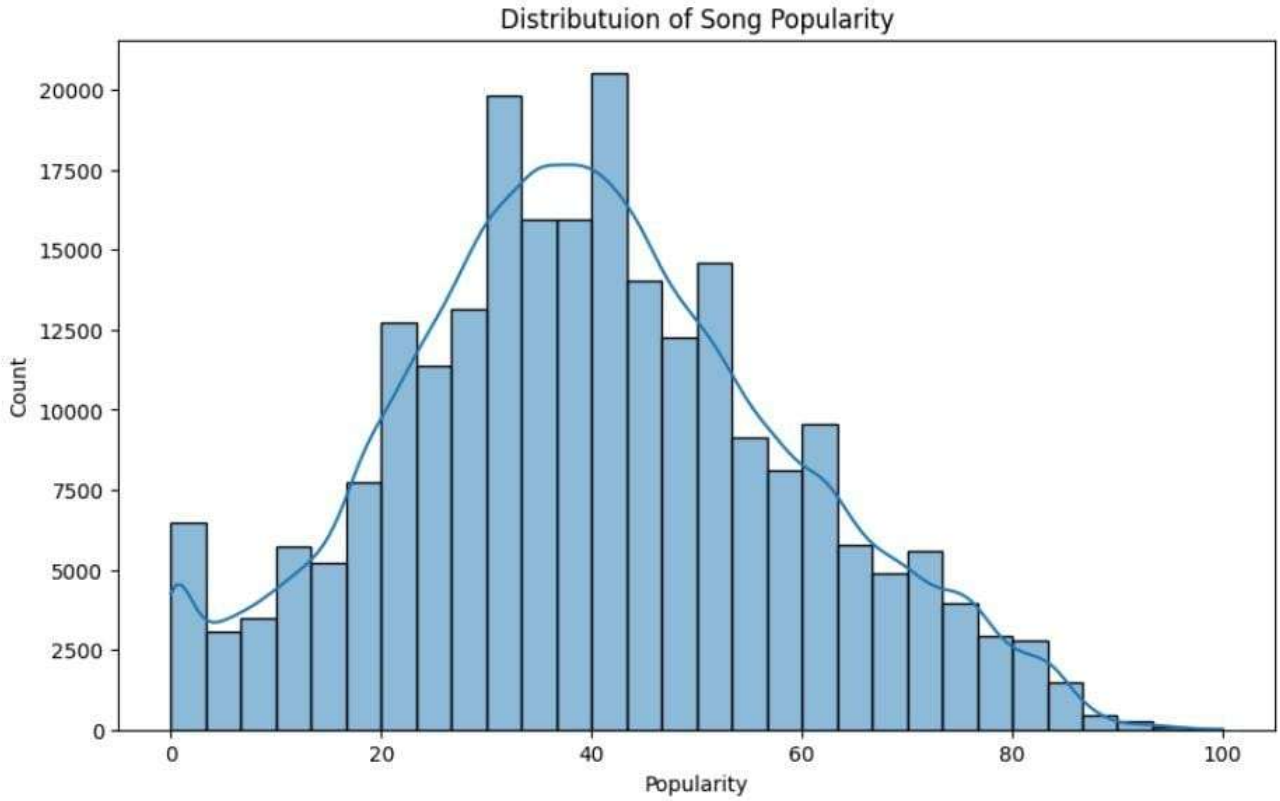
5. Genre Distribution

•Examining how different genres express emotions (e.g., pop for happiness, blues for sorrow)
. •Genre clustering helps improve emotion-based recommendations.
•Mapping musical structures that influence emotional perception

```
# Genre Distribution_
top_Genres=df['Genre'].value_counts().nlargest(11).index
df['Genre']=df['Genre'].apply(lambda x: x if x in top_genres else 'other’)
plt.figure(figsize=(12,6))
sns.countplot(data=df, x='Genre',
order=df['Genre'].value_counts().index)
plt.title('Top 10 Genres + Other’)
plt.xticks(rotation=45)
plt.show()

df['Genre']=df['Genre'].replace('Unknown,Unknown,Unknown','other')
print(df['Genre'].value_counts(normalize=True))
sns.countplot(data=df, x='Genre',
order=df['Genre'].value_counts().index)
plt.title('Top 10 Genres + Other’)
plt.xticks(rotation=45)
plt.show()
```

6. Popularity Distribution


Distributuion of Song Popularity
Count
Popularity
0
2500
5000
7500
10000
12500
15000
17500
20000
0
20
40
60
80
100

•Analyzing the popularity of songs and artists based on emotional resonance.
•Identifying patterns in streaming frequency and user mood preferences.
•Enhancing the recommendation system by integrating trending emotional choices .

 # Popularity of Distribution

```
 Distributionplt.figure(figsize=(10,6))
sns.histplot(df['Popularity'],bins=30, kde=True)
plt.title('Distributuion of Song Popularity’)
plt.show()
```

7. Word Cloud for Song Titles

•A word cloud visualization displays common words in song titles related to emotions.
•Helps in detecting lyrical themes associated with different moods.
•Supports text-based filtering for emotion-driven song selection

#word Cloud of Song Titles

```
from wordcloud import WordCloud
text =''.join(df['song'].dropna())
wordcloud = WordCloud(width=800,height=400,
background_color='black').generate(text)
plt.imshow(wordcloud, interpolation='bilinear’)
plt.title('Word Cloud of Song Titles’)
plt.axis('off’)
plt.show()
```

Word Cloud of Song Titles

8. Emotion-Based Song Recommendation

- Implementing sentiment analysis on song lyrics for emotion classification.
- Creating personalized mood-based playlists using AI-driven techniques.
- Utilizing feedback loops for improving recommendation accuracy .

Emotion-Based Song Recommender

```
import difflib
# A fuzzy matching function
  def fuzzy_match_emotion(user_input,
valid_emotions):
closest = difflib.get_close_matches(user_input,
valid_emotions, n=1, cutoff=0.5)

    return closest[0] if closest else None
# Alias conversion, fuzzy matching, and fallback
mechanism
def recommend_by_emotion_fuzzy(emotion_label,
top_n=10):
   #  Alias mapping table

 emotion_aliases =
 {       'happy': 'joy',       'cheerful': 'joy',       'romance':
'love',       'romantic': 'love',       'depressed': 'sadness',
'mad': 'anger',       'rage': 'anger',       'relax': 'joy',
'chill': 'joy',       'cry': 'sadness'    }
```

```
recommend_by_emotion_fuzzy('happy')
```

```
Showing songs for emotion: 'joy'
Out[37]:
```

	song	artist	Genre	Popularity
219931	Lifetime	Ben&Ben	other	100
219937	Doors	Ben&Ben	other	100
219936	War	Ben&Ben	other	100
219939	Limasawa Street	Ben&Ben	other	100
219932	Make It With You	Ben&Ben	other	100
219933	Fall	Ben&Ben	other	100
219928	Maybe The Night	Ben&Ben	other	100
223443	Never Gonna Regret U	BEAUZ & SIIGHTS	other	99
181895	Stripes Like Burberry	Future & Lil Uzi Vert	other	96
181887	Mink Flow	Future & Young Thug	other	96

```
valid_emotions = df['emotion'].unique().tolist()
# Alias conversion
  if emotion_label in emotion_aliases:
emotion_label = emotion_aliases[emotion_label]

 # Handling null values
  if not emotion_label:       print("No emotion specified. Showing
random recommendations.")       return df.sample(n=top_n)[['song',
'artist', 'Genre', 'Popularity']]

 # Fuzzy matching: Find the closest valid emotion.
matched_emotion = fuzzy_match_emotion(emotion_label,
valid_emotions)    if not matched_emotion:       print(f"No
close match for emotion: '{emotion_label}'. Showing random
recommendations.")       return df.sample(n=top_n)[['song',
'artist', 'Genre', 'Popularity']]

  # Normally recommend the most popular songs
 under that emotion.
   filtered = df[df['emotion'] == matched_emotion]

 if filtered.empty:
   print(f"No songs found for emotion: '{matched_emotion}'.
 Showing random recommendations.")       return
 df.sample(n=top_n)[['song', 'artist', 'Genre', 'Popularity']]


  print(f"Showing songs for emotion: '{matched_emotion}'")
 top_songs = filtered.sort_values(by='Popularity',
 ascending=False).head(top_n)
 return top_songs[['song', 'artist', 'Genre', 'Popularity']]

 # Enter your Mood Now

     recommend_by_emotion_fuzzy('love')
```

9. Feature-Based Similarity Recommendation

- Extracting audio features (tempo, pitch, loudness, spectral contrast) for song comparison.
- Machine learning methods such as Cosine Similarity, KNN (K-Nearest Neighbors), and PCA ensure precise matching.
- Enhancing user experience by providing emotion aware song suggestions.

```
# Feature-Based Similarity Recommender
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import StandardScaler
import numpy as np
feature_cols = ['Energy', 'Danceability', 'Positiveness', 'Tempo',
'Acousticness', 'Instrumentalness’]
scaler = StandardScaler()X_scaled = scaler.fit_transform
(df[feature_cols])
# index
song_to_index = pd.Series(df.index, index=df['song']).dropna()

def recommend_similar_songs(song_name, top_n=10):
If song_name not in song_to_index:
print(f"Song '{song_name}' not found in dataset. Try another one.")
return df.sample(n=top_n)[['song','artist','Genre','Popularity']]

 idx = song_to_index[song_name]
target_vector = X_scaled[idx].reshape(1, -1)
sim_scores = cosine_similarity(target_vector, X_scaled)[0]

top_indices = np.argsort(sim_scores)[::-1]
top_indices = top_indices[top_indices != idx][:top_n]
return df.iloc[top_indices][['song', 'artist', 'Genre', 'Popularity']]

recommend_similar_songs('Bang-A-Boomerang')
```

```
recommend_similar_songs('Bang-A-Boomerang')
```

Out[33]:

	song	artist	Genre	Popularity
3	Bang	ABBA	pop	52
18784	Let Me Love You Baby	Stevie Ray Vaughan	rock	46
178135	You	George Harrison	rock	38
14868	The Boy From The Chemist Is Here To See You	Omd	pop	16
79937	Fun House	The Stooges	other	32
51658	There Is A Light That Never Goes Out	Smiths	alternative	83
80053	There Is a Light That Never Goes Out	The Smiths	alternative	82
4200	Twistin' The Night Away	Divine	pop	11
14593	Mechanical Wonder	Ocean Colour Scene	pop	32
221534	One Little Slip	Barenaked Ladies	alternative	46

10. User Profile Clustering Recommendation

- Grouping users based on listening behavior and emotional music preferences.
- Using K-Means and hierarchical clustering to improve recommendation accuracy.
- Enabling playlist personalization for specific user moods

```
# User Profile Clustering Recommender
from sklearn.cluster import KMeans\
# Still use the previous feature columns
feature_cols = ['Energy', 'Danceability', 'Positiveness',
'Tempo', 'Acousticness', 'Instrumentalness’]
# The data has already been standardized, so we'll directly
use X_scaled.
kmeans = KMeans(n_clusters=5,
random_state=42)cluster_labels =
kmeans.fit_predict(X_scaled)
# Add the clustering results to the DataFrame
df['cluster'] = cluster_labels
```

```
#"Simulate a user preference vector with a preference for high
energy and danceability
user_profile =
{ 'Energy': 80, 'Danceability': 85, 'Positiveness': 70, 'Tempo':
120, 'Acousticness': 10, 'Instrumentalness': 5}
```

```
# Convert to a DataFrame and
standardize it
```

Out[39]:

	song	artist	Genre	Popularity
88927	working	Tate McRae & Khalid	other	97
88928	lie to me	Tate McRae & Ali Gatie	other	97
88931	3am	Tate McRae	other	97
170424	I See Dead People	Iam GreedyBoy	other	97
123017	Hurt Somebody	Noah Kahan & Julia Michaels	other	95
13037	Que Sera!	Miley Cyrus	pop	94
13034	Old Blue Jeans	Miley Cyrus	pop	94
43990	This Is The Life	Miley Cyrus	pop	94
43899	All The Time	Miley Cyrus	pop	94
54372	Sound Siren	Unwritten Law	alternative	94

```
user_df =
pd.DataFrame([user_profile])
user_scaled =
scaler.transform(user_df)

user_cluster =
kmeans.predict(user_scaled)[0]

def recommend_from_cluster(user_cluster, top_n=10):
 subset = df[df['cluster'] == user_cluster]
 return subset.sort_values(by='Popularity',
ascending=False).head(top_n)[['song', 'artist', 'Genre',
'Popularity']]


recommend_from_cluster(user_cluster)
```

11. Logistic Regression for Emotion Classification

Based on emotional sentiment.
•Training the model using lyrics sentiment, audio metadata, and user feedback. •Improving prediction accuracy by detecting instrumental and lyrical emotional cues.

```
# Logistic Regression
from sklearn.model_selection import
train_test_split
from sklearn.linear_model import
LogisticRegression
from sklearn.metrics import classification_report,
confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
```

```
# Create binary labels
df['is_joy'] = df['emotion'].apply(lambda x: 1 if x == 'joy'
else 0)

# Feature columnsfeature
_cols = ['Energy', 'Danceability', 'Positiveness', 'Tempo',
'Acousticness', 'Instrumentalness']

# feature labels
X = df[feature_cols]y = df['is_joy']

# Standardize features
scaler = StandardScaler()X_scaled =
scaler.fit_transform(X)

# Split into training and testing sets
X_train, X_test, y_train, y_test =
train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

# Build and train the model
Logreg=LogisticRegression()
logreg.fit(X_train, y_train)

# Make predictions" or "Predict
y_pred = logreg.predict(X_test)

# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test,
y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

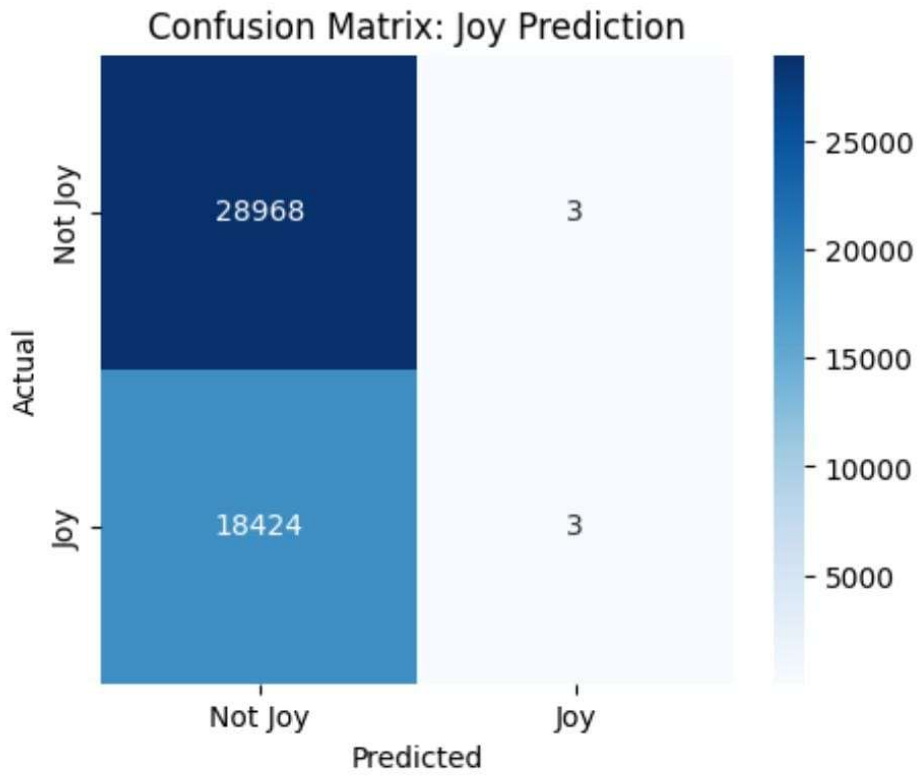
```
Accuracy: 0.6112283218701211

Confusion Matrix:
 [[28968     3]
 [18424     3]]

Classification Report:
              precision    recall  f1-score   suppor
t

           0       0.61      1.00      0.76     28971
           1       0.50      0.00      0.00     18427

    accuracy                           0.61     47398
   macro avg       0.56      0.50      0.38     47398
weighted avg       0.57      0.61      0.46     47398
```



```
import seaborn as snsimport
matplotlib.pyplot as plt
cm = confusion_matrix(y_test,
y_pred)
plt.figure(figsize=(5,4))

sns.heatmap(cm, annot=True,
fmt='d', cmap='Blues',
xticklabels=['Not Joy', 'Joy'],
yticklabels=['Not Joy', 'Joy'])

plt.xlabel('Predicted’)
plt.ylabel('Actual’)
plt.title('Confusion Matrix: Joy Prediction’)
plt.show()
```

12. Implementation Strategy

1.Data Collection– Gathering song metadata, lyrics, and listening history.

2.EDA & Preprocessing– Cleaning dataset and identifying emotional trends.

3.Emotion Classification– Using NLP and sentiment analysis models for emotion detection.

4.Feature Engineering– Extracting relevant song attributes for similarity analysis.

5.Model Training– Training clustering and classification models.

6.Recommendation Deployment– Integrating the model into a user-friendly interface.

7.User Feedback Optimization– Refining recommendations based on user interactions.

13. Challenges & Limitations

- Mapping subjective emotions accurately to songs.
- Addressing data sparsity in music metadata for effective predictions.
- Handling real-time recommendation processing for seamless user experience.

14. Future Enhancements

- Implementing real-time emotion detection via facial recognition or biometric signals.
- Integrating multi-modal emotion recognition, including voice analysis.
- Expanding recommendations with cross-platform integration (Spotify, YouTube, etc.)

15. Conclusion

The Emotion-Based Spotify Song Recommendation System introduces a data-driven approach to enhancing user experiences. By combining machine learning, NLP, clustering, and sentiment analysis, this system creates highly personalized playlists that align with users' emotions. Future developments aim to expand real-time emotion tracking and cross platform music recommendations for a seamless listening experience.