Spotify_clustering_and_classification

January 20, 2025

[ ]:
```
# prompt: hubungkan google drive

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
!pip install pyspark
```

```
Requirement already satisfied: pyspark in /usr/local/lib/python3.11/dist-
packages (3.5.4)
Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.11/dist-
packages (from pyspark) (0.10.9.7)
```

0.0.1 Importing Libraries

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report
import pickle
from pyspark.ml.classification import GBTClassifier, RandomForestClassifier,␣
↪LogisticRegression
from pyspark.ml.clustering import KMeans, GaussianMixture
from pyspark.ml.feature import VectorAssembler, StringIndexer
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
from pyspark.ml.evaluation import MulticlassClassificationEvaluator,␣
↪ClusteringEvaluator
from pyspark.sql import SparkSession
from pyspark.sql.types import *
from pyspark.ml import Pipeline
```

0.0.2 Loading dataset

[ ]:
```
df=pd.read_csv('/content/drive/MyDrive/BIG DATA LANJUT/dataset.csv',␣
↪index_col=0) #index_col 0 to drop the extra index column
```

0.0.3 Viewing the data

[ ]:
```
df.head()
```

[ ]:
```
                 track_id                 artists  \
0  5SuOikwiRyPMVoIQDJUgSV             Gen Hoshino
1  4qPNDBW1i3p13qLCt0Ki3A            Ben Woodward
2  1iJBSr7s7jYXzM8EGcbK5b  Ingrid Michaelson;ZAYN
3  6lfxq3CG4xtTiEg7opyCyx            Kina Grannis
4  5vjLSffimiIP26QG5WcN2K        Chord Overstreet

                                         album_name  \
0                                            Comedy
1                                  Ghost (Acoustic)
2                                    To Begin Again
3  Crazy Rich Asians (Original Motion Picture Sou…
4                                           Hold On

                   track_name  popularity  duration_ms  explicit  \
0                      Comedy          73       230666     False
1            Ghost - Acoustic          55       149610     False
2              To Begin Again          57       210826     False
3  Can't Help Falling In Love          71       201933     False
4                     Hold On          82       198853     False

   danceability  energy  key  loudness  mode  speechiness  acousticness  \
0         0.676  0.4610    1    -6.746     0       0.1430        0.0322
1         0.420  0.1660    1   -17.235     1       0.0763        0.9240
2         0.438  0.3590    0    -9.734     1       0.0557        0.2100
3         0.266  0.0596    0   -18.515     1       0.0363        0.9050
4         0.618  0.4430    2    -9.681     1       0.0526        0.4690

   instrumentalness  liveness  valence    tempo  time_signature track_genre
0          0.000001    0.3580    0.715   87.917               4    acoustic
1          0.000006    0.1010    0.267   77.489               4    acoustic
2          0.000000    0.1170    0.120   76.332               4    acoustic
3          0.000071    0.1320    0.143  181.740               3    acoustic
4          0.000000    0.0829    0.167  119.949               4    acoustic
```

0.0.4 Checking summary of the data

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 114000 entries, 0 to 113999
Data columns (total 20 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   track_id          114000 non-null  object
 1   artists           113999 non-null  object
 2   album_name        113999 non-null  object
 3   track_name        113999 non-null  object
 4   popularity        114000 non-null  int64
 5   duration_ms       114000 non-null  int64
 6   explicit          114000 non-null  bool
 7   danceability      114000 non-null  float64
 8   energy            114000 non-null  float64
 9   key               114000 non-null  int64
 10  loudness          114000 non-null  float64
 11  mode              114000 non-null  int64
 12  speechiness       114000 non-null  float64
 13  acousticness      114000 non-null  float64
 14  instrumentalness  114000 non-null  float64
 15  liveness          114000 non-null  float64
 16  valence           114000 non-null  float64
 17  tempo             114000 non-null  float64
 18  time_signature    114000 non-null  int64
 19  track_genre       114000 non-null  object
dtypes: bool(1), float64(9), int64(5), object(5)
memory usage: 17.5+ MB
```

[ ]:
```
df.shape #(rows, columns)
```

[ ]:
```
(114000, 20)
```

0.0.5 Looking for null values

[ ]:
```
df[df.isnull().any(axis=1)]
```

[ ]:
```
                     track_id artists album_name track_name  popularity  \
65900  1kR4gIb7nGxHPI3D2ifs59     NaN        NaN        NaN           0

       duration_ms  explicit  danceability  energy  key  loudness  mode  \
65900            0     False         0.501   0.583    7     -9.46     0

       speechiness  acousticness  instrumentalness  liveness  valence  \
```

```
65900       0.0605          0.69            0.00396     0.0747     0.734

         tempo  time_signature track_genre
65900  138.391               4       k-pop
```

- Since there is only one row containing null values, I'll drop this row

[ ]:
```python
df = df.dropna(axis=0)
```

[ ]:
```python
df['track_genre'].nunique() # Checking how many genres are there
```

[ ]:
```
114
```

[ ]:
```python
df["explicit"]=df["explicit"].astype(int) #True=1 and False=0
```

```
<ipython-input-11-4e90e0e4d8e8>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df["explicit"]=df["explicit"].astype(int) #True=1 and False=0
```

[ ]:
```python
df[df.duplicated()] # checking duplicate rows
```

[ ]:
```
                      track_id                 artists  \
1925    0CDucx91KxuCZplLXUz0iX   Buena Onda Reggae Club
2155    2aibwv5hGXSgw7Yru8IYTO    Red Hot Chili Peppers
3738    7mULVp0DJrI2Nd6GesLvxn             Joy Division
4648    6d3RIvHfVkoOtW1WHXmbX3          Little Symphony
5769    481beimUiUnMUzSbOAFcUT             SUPER BEAVER
…                            …                       …
111246  0sSjIvTvd6fUSZZ5rnTPDW  Everything But The Girl
111362  2zg3iJW4fK7KZgHOvJU67z                Faithless
111980  46FPub2Fewe7XrgM0smTYI                Morcheeba
112968  6qVA1MqDrDKfk9144bhoKp              Acil Servis
113345  5WaioelSGekDk3UNQy8zaw              Matt Redman

                                           album_name  \
1925                                          Disco 2
2155                                 Stadium Arcadium
3738                                 Timeless Rock Hits
4648                                           Serenity
5769                                                /
…                                                   …
111246                              Eden (Deluxe Edition)
111362                                     Faithless 2.0
```

111980	Parts of the Process
112968	Küçük Adam
113345	Sing Like Never Before: The Essential Collection

	track_name	popularity	duration_ms	explicit \
1925	Song for Rollins	16	219346	0
2155	Snow (Hey Oh)	80	334666	0
3738	Love Will Tear Us Apart	0	204621	0
4648	Margot	27	45714	0
5769		54	255080	0
…	…	…	…	…
111246	Another Bridge - 2012 Remaster	26	132826	0
111362	Tarantula	21	398152	0
111980	Undress Me Now	17	203773	0
112968	Bebek	38	319933	0
113345	Our God - New Recording	34	265373	0

	danceability	energy	key	loudness	mode	speechiness	acousticness \
1925	0.841	0.577	0	-7.544	1	0.0438	0.238000
2155	0.427	0.900	11	-3.674	1	0.0499	0.116000
3738	0.524	0.902	2	-8.662	1	0.0368	0.000989
4648	0.269	0.142	0	-23.695	1	0.0509	0.866000
5769	0.472	0.994	8	-1.786	1	0.1140	0.025900
…	…	…	…	…	…	…	…
111246	0.480	0.853	0	-6.276	1	0.0734	0.030600
111362	0.622	0.816	6	-11.095	0	0.0483	0.009590
111980	0.576	0.352	7	-10.773	0	0.0268	0.700000
112968	0.486	0.485	5	-12.391	0	0.0331	0.004460
113345	0.487	0.895	11	-5.061	1	0.0413	0.000183

	instrumentalness	liveness	valence	tempo	time_signature \
1925	0.860000	0.0571	0.843	90.522	4
2155	0.000017	0.1190	0.599	104.655	4
3738	0.695000	0.1370	0.907	146.833	4
4648	0.904000	0.1140	0.321	67.872	3
5769	0.000000	0.0535	0.262	103.512	4
…	…	…	…	…	…
111246	0.000001	0.3200	0.775	85.181	4
111362	0.578000	0.0991	0.427	136.007	4
111980	0.270000	0.1600	0.360	95.484	4
112968	0.000017	0.3690	0.353	120.095	4
113345	0.000000	0.3590	0.384	105.021	4

	track_genre
1925	afrobeat
2155	alt-rock
3738	alternative

```
4648        ambient
5769          anime
…               …
111246     trip-hop
111362     trip-hop
111980     trip-hop
112968      turkish
113345  world-music

[450 rows x 20 columns]
```

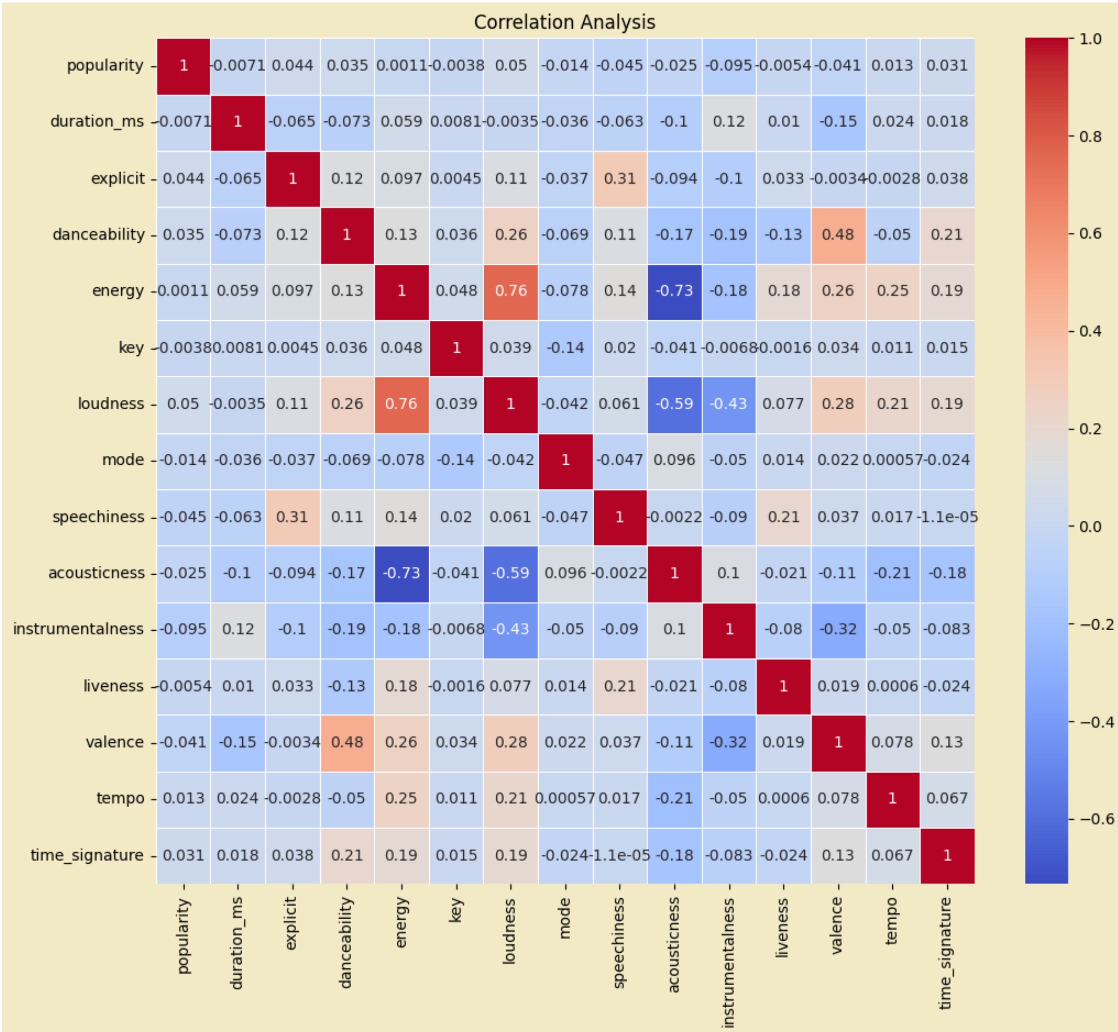
0.0.6 Descriptive Statistics

[ ]:
```
df.describe().style.background_gradient(cmap="Accent") # Dark boxes denote very␣
↪high values
```

[ ]:
```
<pandas.io.formats.style.Styler at 0x7b01b32611d0>
```

0.0.7 Correlation Analysis

[ ]:
```
# Including numerical colmumns
corr_mat = df.select_dtypes(include=["int", "float"]).corr()

# Adjusting figure visuals
plt.figure(figsize=(12, 10), facecolor='#F2EAC5', edgecolor='black')
ax = plt.axes()
ax.set_facecolor('#F2EAC5')
sns.heatmap(corr_mat, annot=True, cmap='coolwarm', linewidths=0.5,␣
↪annot_kws={"size": 10})
plt.title('Correlation Analysis')
plt.show()
```



0.0.8 Selecting Numerical columns for further analysis

[ ]:
```
num_cols = df[df.columns[(df.dtypes == 'float64') | (df.dtypes == 'int64')]]
num_cols.shape
```

[ ]:
```
(113999, 15)
```

[ ]:
```
num_cols.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 113999 entries, 0 to 113999
Data columns (total 15 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   popularity        113999 non-null  int64
```

```
 1   duration_ms       113999 non-null  int64
 2   explicit          113999 non-null  int64
 3   danceability      113999 non-null  float64
 4   energy            113999 non-null  float64
 5   key               113999 non-null  int64
 6   loudness          113999 non-null  float64
 7   mode              113999 non-null  int64
 8   speechiness       113999 non-null  float64
 9   acousticness      113999 non-null  float64
 10  instrumentalness  113999 non-null  float64
 11  liveness          113999 non-null  float64
 12  valence           113999 non-null  float64
 13  tempo             113999 non-null  float64
 14  time_signature    113999 non-null  int64
dtypes: float64(9), int64(6)
memory usage: 13.9 MB
```

0.0.9 Checking distribution of numerical columns

[ ]:
```
sns.set_style('darkgrid')
sns.set(rc={"axes.facecolor":"#F2EAC5","figure.facecolor":"#F2EAC5"})
num_cols.hist(figsize=(20,15), bins=30, xlabelsize=8, ylabelsize=8)
plt.tight_layout()
plt.show()
```


```
[ ]: # Select and scale the relevant features
     features = df[['danceability','energy', 'loudness', 'valence', 'tempo']] #␣
      ↪features selected by refering correlation matrix
     scaler = StandardScaler()
     scaled_features = scaler.fit_transform(features)
```

```
[ ]: df['track_genre'].unique()
```

```
[ ]: array(['acoustic', 'afrobeat', 'alt-rock', 'alternative', 'ambient',
            'anime', 'black-metal', 'bluegrass', 'blues', 'brazil',
            'breakbeat', 'british', 'cantopop', 'chicago-house', 'children',
            'chill', 'classical', 'club', 'comedy', 'country', 'dance',
            'dancehall', 'death-metal', 'deep-house', 'detroit-techno',
            'disco', 'disney', 'drum-and-bass', 'dub', 'dubstep', 'edm',
            'electro', 'electronic', 'emo', 'folk', 'forro', 'french', 'funk',
            'garage', 'german', 'gospel', 'goth', 'grindcore', 'groove',
            'grunge', 'guitar', 'happy', 'hard-rock', 'hardcore', 'hardstyle',
            'heavy-metal', 'hip-hop', 'honky-tonk', 'house', 'idm', 'indian',
            'indie-pop', 'indie', 'industrial', 'iranian', 'j-dance', 'j-idol',
            'j-pop', 'j-rock', 'jazz', 'k-pop', 'kids', 'latin', 'latino',
            'malay', 'mandopop', 'metal', 'metalcore', 'minimal-techno', 'mpb',
```

```
 'new-age', 'opera', 'pagode', 'party', 'piano', 'pop-film', 'pop',
 'power-pop', 'progressive-house', 'psych-rock', 'punk-rock',
 'punk', 'r-n-b', 'reggae', 'reggaeton', 'rock-n-roll', 'rock',
 'rockabilly', 'romance', 'sad', 'salsa', 'samba', 'sertanejo',
 'show-tunes', 'singer-songwriter', 'ska', 'sleep', 'songwriter',
 'soul', 'spanish', 'study', 'swedish', 'synth-pop', 'tango',
 'techno', 'trance', 'trip-hop', 'turkish', 'world-music'],
dtype=object)
```

[ ]:
```
# Genre to category mapping for playlist creation
genre_to_category = {
    # EDM
    'edm': 'Electronic Dance Music',
    'house': 'Electronic Dance Music',
    'electro': 'Electronic Dance Music',
    'trance': 'Electronic Dance Music',
    'techno': 'Electronic Dance Music',
    'dubstep': 'Electronic Dance Music',
    'drum-and-bass': 'Electronic Dance Music',
    'deep-house': 'Electronic Dance Music',
    'detroit-techno': 'Electronic Dance Music',
    'minimal-techno': 'Electronic Dance Music',
    'progressive-house': 'Electronic Dance Music',
    'breakbeat': 'Electronic Dance Music',

    # Rock
    'alt-rock': 'Rock',
    'rock': 'Rock',
    'indie': 'Rock',
    'indie-pop': 'Rock',
    'punk': 'Rock',
    'punk-rock': 'Rock',
    'hard-rock': 'Rock',
    'metal': 'Rock',
    'heavy-metal': 'Rock',
    'black-metal': 'Rock',
    'death-metal': 'Rock',
    'grunge': 'Rock',

    # Hip-Hop and R&B
    'hip-hop': 'Hip-Hop and R&B',
    'r-n-b': 'Hip-Hop and R&B',
    'trap': 'Hip-Hop and R&B',

    # Pop
    'pop': 'Pop',
    'electro-pop': 'Pop',
```

```
    'synth-pop': 'Pop',
    'k-pop': 'Pop',
    'pop-film': 'Pop',
    'power-pop': 'Pop',

    # Latin & Reggae/Dancehall
    'latin': 'Latin & Reggae/Dancehall',
    'reggaeton': 'Latin & Reggae/Dancehall',
    'salsa': 'Latin & Reggae/Dancehall',
    'samba': 'Latin & Reggae/Dancehall',
    'reggae': 'Latin & Reggae/Dancehall',
    'dancehall': 'Latin & Reggae/Dancehall',

    # Funk and Disco
    'funk': 'Funk and Disco',
    'disco': 'Funk and Disco',
    'groove': 'Funk and Disco',
}

# Map each track to a category
df['music_category'] = df['track_genre'].apply(lambda x: genre_to_category.
 ↪get(x, 'Other'))
```

[ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 113999 entries, 0 to 113999
Data columns (total 21 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   track_id          113999 non-null  object
 1   artists           113999 non-null  object
 2   album_name        113999 non-null  object
 3   track_name        113999 non-null  object
 4   popularity        113999 non-null  int64
 5   duration_ms       113999 non-null  int64
 6   explicit          113999 non-null  int64
 7   danceability      113999 non-null  float64
 8   energy            113999 non-null  float64
 9   key               113999 non-null  int64
 10  loudness          113999 non-null  float64
 11  mode              113999 non-null  int64
 12  speechiness       113999 non-null  float64
 13  acousticness      113999 non-null  float64
 14  instrumentalness  113999 non-null  float64
 15  liveness          113999 non-null  float64
 16  valence           113999 non-null  float64
```

```
 17  tempo             113999 non-null  float64
 18  time_signature    113999 non-null  int64
 19  track_genre       113999 non-null  object
 20  music_category    113999 non-null  object
dtypes: float64(9), int64(6), object(6)
memory usage: 19.1+ MB
```

[ ]:
```python
df.sample(5)
```

[ ]:
```
                      track_id                                 artists  \
55379   52B3XCIgDUwQLj2ZdmykRF  Pritam;Mohan Kannan;Amitabh Bhattacharya
39817   7kDSAQQkmuqECgUBWcozrm                            FFRAGEZEICHEN
113781  7GyF1KwnX5YBxPw2gjbf0d                            Shane & Shane
91185   2AjLI6h9DZrFw0XVtTYwdT                                blink-182
5956    47ltbGJTejvcljxYfzAlUZ                                    JUNNA

                album_name                    track_name  popularity  \
55379   Laal Singh Chaddha                        Kahani          52
39817             FR EP 2                     Passed Out          38
113781            Vintage  Lord I Lift Your Name on High          42
91185    Rock Workout 2023          All The Small Things           1
5956                                                          49

        duration_ms  explicit  danceability  energy  key  …  mode  \
55379        208539         0         0.406   0.336    1  …     1
39817        125000         1         0.900   0.573    1  …     1
113781       196022         0         0.549   0.466    2  …     1
91185        171066         0         0.442   0.900    0  …     1
5956         299200         0         0.472   0.924    7  …     0

        speechiness  acousticness  instrumentalness  liveness  valence  \
55379        0.0345        0.8150          0.000005    0.0888    0.327
39817        0.3530        0.1180          0.000000    0.0869    0.236
113781       0.0379        0.2000          0.000001    0.1210    0.258
91185        0.0529        0.0109          0.000000    0.3950    0.609
5956         0.2180        0.0225          0.000000    0.1110    0.441

          tempo  time_signature  track_genre music_category
55379   149.354               3       indian          Other
39817   100.015               4       german          Other
113781  149.870               4  world-music          Other
91185   148.620               4         rock           Rock
5956    144.812               4        anime          Other

[5 rows x 21 columns]
```

```
[ ]: #music categories for different playlists
df['music_category'].unique()
```

```
[ ]: array(['Other', 'Rock', 'Electronic Dance Music',
           'Latin & Reggae/Dancehall', 'Funk and Disco', 'Hip-Hop and R&B',
           'Pop'], dtype=object)
```

```
[ ]: #Clustering songs in different playlists
from sklearn.cluster import KMeans # Ensure you're using sklearn's KMeans

kmeans = KMeans(n_clusters=7, random_state=48) # This will now use the correct␣
 ↪KMeans
df['cluster'] = kmeans.fit_predict(scaled_features)
```

```
[ ]: #PCA for visualisation
pca = PCA(n_components=2)
reduced_features = pca.fit_transform(scaled_features)
```

```
[ ]: from pyspark.sql import SparkSession

# Create a SparkSession
spark = SparkSession.builder.appName("MusicRecommendation").getOrCreate()

# Convert the Pandas DataFrame to a PySpark DataFrame
spark_df = spark.createDataFrame(df)

# Now you can use randomSplit on the spark_df
train_data, test_data = spark_df.randomSplit([0.6, 0.4], seed=0)


# Prepare features using VectorAssembler
assembler = VectorAssembler(inputCols=num_cols.columns.tolist(),␣
 ↪outputCol="features")
train_data = assembler.transform(train_data)
test_data = assembler.transform(test_data)

# Index the target column (for classification models)
indexer = StringIndexer(inputCol="music_category",␣
 ↪outputCol="indexed_music_category")
train_data = indexer.fit(train_data).transform(train_data)
test_data = indexer.fit(test_data).transform(test_data)
```

```
[ ]: # Pilih kolom yang ingin disimpan
final_data = train_data.select("features", "indexed_music_category")

# Konversi ke Pandas DataFrame
final_pandas_data = final_data.toPandas()
```

```python
# Ekstrak kolom `features` menjadi beberapa kolom numerik
features_df = pd.DataFrame(
    final_pandas_data['features'].apply(lambda x: x.toArray()).tolist(),
    columns=[f'feature_{i}' for i in range(len(final_pandas_data['features'][0]))]
)

# Gabungkan dengan kolom target
final_pandas_data = pd.concat([features_df, final_pandas_data['indexed_music_category']], axis=1)

# Simpan ke Google Drive
output_path = '/content/drive/MyDrive/preprocessed_train_data.csv'
final_pandas_data.to_csv(output_path, index=False)

print(f"Dataset yang sudah diproses disimpan di: {output_path}")
```

```
Dataset yang sudah diproses disimpan di:
/content/drive/MyDrive/preprocessed_train_data.csv
```

[ ]:

```python
# Classification models
models_classification = {
    'Gradient Boosting Tree': GBTClassifier(labelCol='indexed_music_category', featuresCol='features'),
    'Random Forest': RandomForestClassifier(labelCol='indexed_music_category', featuresCol='features'),
    'Logistic Regression': LogisticRegression(labelCol='indexed_music_category', featuresCol='features')
}

# Clustering models
from pyspark.ml.clustering import KMeans # This line ensures you are using the PySpark KMeans
models_clustering = {
    'K-Means': KMeans(featuresCol='features', predictionCol='prediction', k=3, seed=0), # Changed 'k' to 'n_clusters'
    'Gaussian Mixture': GaussianMixture(k=3, seed=0, featuresCol='features', predictionCol='prediction')
}
```

[ ]:

```python
if "features" in train_data.columns:
    train_data = train_data.drop("features")

if "features" in test_data.columns:
    test_data = test_data.drop("features")
```

[ ]:
```
from pyspark.ml.feature import VectorAssembler

# Pastikan semua kolom numerik dipilih dengan benar
num_cols = ['danceability', 'energy', 'loudness', 'valence', 'tempo']

assembler = VectorAssembler(inputCols=num_cols, outputCol="features")

# Transform train_data dan test_data
train_data = assembler.transform(train_data)
test_data = assembler.transform(test_data)
```

[ ]:
```
print(train_data.columns)
print(train_data.schema['features'].dataType)
# Periksa distribusi nilai pada kolom label
train_data.select("indexed_music_category").distinct().show()
```

```
['track_id', 'artists', 'album_name', 'track_name', 'popularity', 'duration_ms',
'explicit', 'danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
'time_signature', 'track_genre', 'music_category', 'cluster',
'indexed_music_category', 'features']
VectorUDT()
+----------------------+
|indexed_music_category|
+----------------------+
|                   0.0|
|                   1.0|
|                   3.0|
|                   2.0|
|                   6.0|
|                   5.0|
|                   4.0|
+----------------------+
```

[ ]:
```
from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(labelCol="indexed_music_category",␣
 ↪featuresCol="features", numTrees=10)
rf_model = rf.fit(train_data)
predictions = rf_model.transform(test_data)
```

[ ]:
```
# Mapping nilai label menjadi 0 atau 1
from pyspark.sql.functions import when

train_data = train_data.withColumn(
    "indexed_music_category",
```

```
    when(train_data["indexed_music_category"] == 0, 0).otherwise(1)
)

test_data = test_data.withColumn(
    "indexed_music_category",
    when(test_data["indexed_music_category"] == 0, 0).otherwise(1)
)
```

[ ]:
```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator,␣
↪BinaryClassificationEvaluator

# Evaluator
evaluator_accuracy = MulticlassClassificationEvaluator(
    labelCol='indexed_music_category',
    predictionCol='prediction',
    metricName='accuracy'
)
evaluator_f1 = MulticlassClassificationEvaluator(
    labelCol='indexed_music_category',
    predictionCol='prediction',
    metricName='f1'
)
evaluator_precision = MulticlassClassificationEvaluator(
    labelCol='indexed_music_category',
    predictionCol='prediction',
    metricName='weightedPrecision'
)
evaluator_recall = MulticlassClassificationEvaluator(
    labelCol='indexed_music_category',
    predictionCol='prediction',
    metricName='weightedRecall'
)
evaluator_auc = BinaryClassificationEvaluator(
    labelCol='indexed_music_category',
    rawPredictionCol='prediction',
    metricName='areaUnderROC'
)

# Training and evaluating classification models
for model_name, model in models_classification.items():
    print(f"\n--- {model_name} ---")
    # Train the model
    model_trained = model.fit(train_data)

    # Make predictions
    predictions = model_trained.transform(test_data)
```

```
    # Calculate metrics
    accuracy = evaluator_accuracy.evaluate(predictions)
    f1 = evaluator_f1.evaluate(predictions)
    precision = evaluator_precision.evaluate(predictions)
    recall = evaluator_recall.evaluate(predictions)
    auc = evaluator_auc.evaluate(predictions)

    # Display metrics
    print(f"Accuracy: {accuracy:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"AUC (ROC Curve): {auc:.4f}")
```

```
--- Gradient Boosting Tree ---
Accuracy: 0.6864
F1 Score: 0.6562
Precision: 0.6686
Recall: 0.6864
AUC (ROC Curve): 0.6017

--- Random Forest ---
Accuracy: 0.6682
F1 Score: 0.5933
Precision: 0.6521
Recall: 0.6682
AUC (ROC Curve): 0.5469

--- Logistic Regression ---
Accuracy: 0.6537
F1 Score: 0.6192
Precision: 0.6244
Recall: 0.6537
AUC (ROC Curve): 0.5645
```

[ ]:
```
from pyspark.ml.evaluation import ClusteringEvaluator

# Clustering evaluator
evaluator_clustering = ClusteringEvaluator(featuresCol='features',
 ↪predictionCol='prediction', metricName='silhouette')

# Training and evaluating clustering models
for model_name, model in models_clustering.items():
    print(f"\n--- {model_name} ---")
    # Train the model
    model_trained = model.fit(train_data)
```

```
    # Make predictions
    predictions = model_trained.transform(test_data)

    # Calculate Silhouette Score
    silhouette_score = evaluator_clustering.evaluate(predictions)
    print(f"Silhouette Score: {silhouette_score:.4f}")
```

```
--- K-Means ---
Silhouette Score: 0.7110

--- Gaussian Mixture ---
Silhouette Score: 0.0415
```

[ ]:
```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Param grid for Gradient Boosting Tree
paramGrid_gbt = ParamGridBuilder() \
    .addGrid(models_classification['Gradient Boosting Tree'].maxDepth, [5, 10])␣
 ↪\
    .addGrid(models_classification['Gradient Boosting Tree'].maxIter, [10, 20])␣
 ↪\
    .build()

# CrossValidator
crossval_gbt = CrossValidator(
    estimator=models_classification['Gradient Boosting Tree'],
    estimatorParamMaps=paramGrid_gbt,
    evaluator=evaluator_accuracy,
    numFolds=3
)

# Perform cross-validation
cv_model_gbt = crossval_gbt.fit(train_data)
best_model_gbt = cv_model_gbt.bestModel

# Evaluate best model on test data
best_predictions_gbt = best_model_gbt.transform(test_data)
best_accuracy_gbt = evaluator_accuracy.evaluate(best_predictions_gbt)
print(f"Best GBT Accuracy after tuning: {best_accuracy_gbt:.4f}")
```

```
Best GBT Accuracy after tuning: 0.6886
```

[ ]:
```
from pyspark.ml.classification import RandomForestClassifier, LogisticRegression
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
```

```
# ---------------------------------------------
# Param grid for Random Forest
paramGrid_rf = ParamGridBuilder() \
    .addGrid(models_classification['Random Forest'].maxDepth, [5, 10]) \
    .addGrid(models_classification['Random Forest'].numTrees, [50, 100]) \
    .build()

# CrossValidator for Random Forest
crossval_rf = CrossValidator(
    estimator=models_classification['Random Forest'],
    estimatorParamMaps=paramGrid_rf,
    evaluator=evaluator_accuracy,
    numFolds=3
)

# Perform cross-validation for Random Forest
cv_model_rf = crossval_rf.fit(train_data)
best_model_rf = cv_model_rf.bestModel

# Evaluate best model for Random Forest on test data
best_predictions_rf = best_model_rf.transform(test_data)
best_accuracy_rf = evaluator_accuracy.evaluate(best_predictions_rf)
print(f"Best RF Accuracy after tuning: {best_accuracy_rf:.4f}")


# ---------------------------------------------
# Param grid for Logistic Regression
paramGrid_lr = ParamGridBuilder() \
    .addGrid(models_classification['Logistic Regression'].regParam, [0.01, 0.1]) \
    .addGrid(models_classification['Logistic Regression'].elasticNetParam, [0.0, 0.5]) \
    .build()

# CrossValidator for Logistic Regression
crossval_lr = CrossValidator(
    estimator=models_classification['Logistic Regression'],
    estimatorParamMaps=paramGrid_lr,
    evaluator=evaluator_accuracy,
    numFolds=3
)

# Perform cross-validation for Logistic Regression
cv_model_lr = crossval_lr.fit(train_data)
best_model_lr = cv_model_lr.bestModel

# Evaluate best model for Logistic Regression on test data
```

```
best_predictions_lr = best_model_lr.transform(test_data)
best_accuracy_lr = evaluator_accuracy.evaluate(best_predictions_lr)
print(f"Best Logistic Regression Accuracy after tuning: {best_accuracy_lr:.4f}")
```

```
Best RF Accuracy after tuning: 0.6953
Best Logistic Regression Accuracy after tuning: 0.6533
```

[ ]:
```
paramGrid_kmeans = ParamGridBuilder() \
    .addGrid(models_clustering['K-Means'].k, [3, 5, 7]) \
    .build()

# CrossValidator for K-Means (manual iteration since CrossValidator isn't␣
↪directly compatible with clustering)
best_silhouette_score = -1
best_kmeans_model = None

for params in paramGrid_kmeans:
    model = models_clustering['K-Means'].copy(params)
    trained_model = model.fit(train_data)
    predictions = trained_model.transform(test_data)
    silhouette_score = evaluator_clustering.evaluate(predictions)
    if silhouette_score > best_silhouette_score:
        best_silhouette_score = silhouette_score
        best_kmeans_model = trained_model

print(f"Best Silhouette Score after tuning: {best_silhouette_score:.4f}")
```

```
Best Silhouette Score after tuning: 0.7110
```

[ ]:
```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator,␣
↪BinaryClassificationEvaluator

# ---- 1. Evaluator Setup ----
# Evaluator untuk klasifikasi biner (AUC, precision, recall)
binary_evaluator =␣
↪BinaryClassificationEvaluator(labelCol="indexed_music_category",␣
↪rawPredictionCol="rawPrediction", metricName="areaUnderROC")

# Evaluator untuk multiklas (akurasi, F1-score, precision, recall)
multiclass_evaluator =␣
↪MulticlassClassificationEvaluator(labelCol="indexed_music_category",␣
↪predictionCol="prediction")

# ---- 2. Latih dan Evaluasi Model ----
# Daftar model
models = {
```

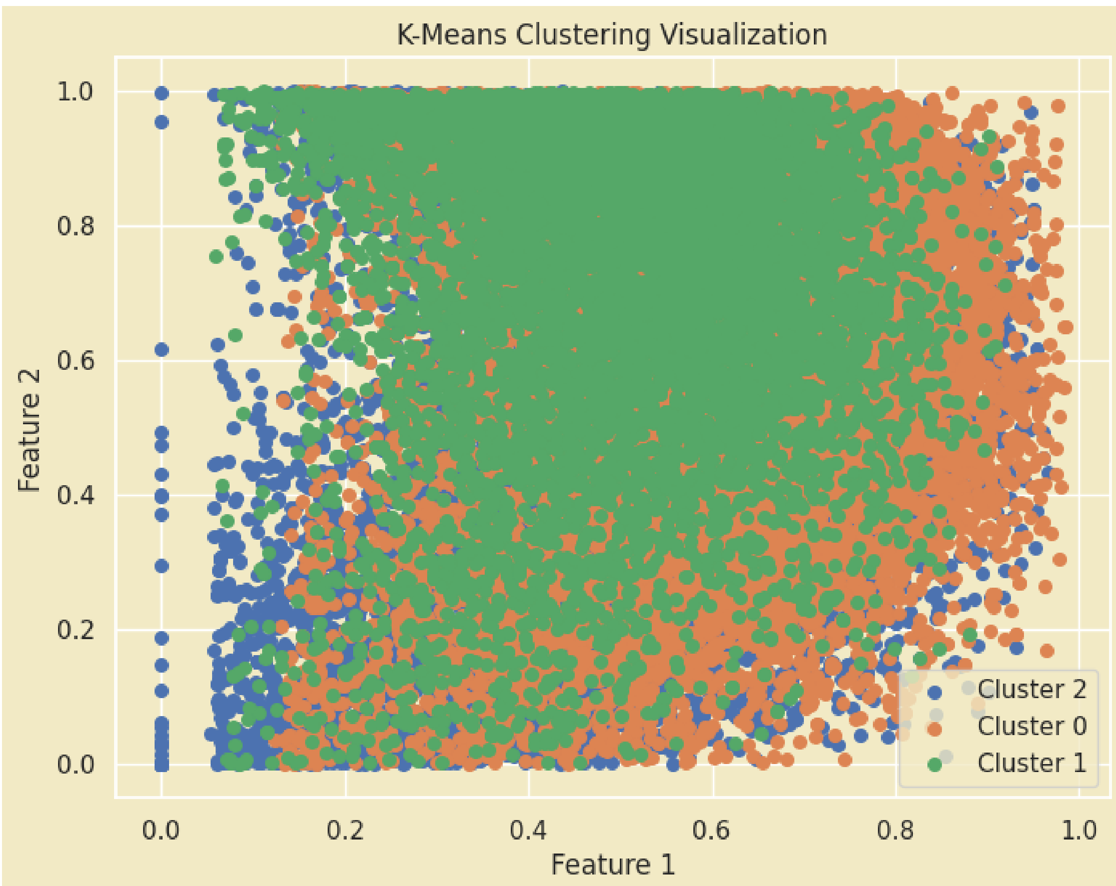
```python
    "Gradient Boosted Tree": GBTClassifier(labelCol="indexed_music_category",␣
↪featuresCol="features", maxIter=10),
    "Random Forest": RandomForestClassifier(labelCol="indexed_music_category",␣
↪featuresCol="features", numTrees=10)
}

# Simpan hasil evaluasi
evaluation_results = []

for model_name, model in models.items():
    print(f"\n--- Evaluating {model_name} ---")

    # Latih model
    trained_model = model.fit(train_data)

    # Prediksi
    predictions = trained_model.transform(test_data)

    # Evaluasi biner (AUC-ROC)
    auc = binary_evaluator.evaluate(predictions)

    # Evaluasi multiklas (akurasi, F1, dll.)
    accuracy = multiclass_evaluator.evaluate(predictions, {multiclass_evaluator.
↪metricName: "accuracy"})
    f1 = multiclass_evaluator.evaluate(predictions, {multiclass_evaluator.
↪metricName: "f1"})
    precision = multiclass_evaluator.evaluate(predictions,␣
↪{multiclass_evaluator.metricName: "weightedPrecision"})
    recall = multiclass_evaluator.evaluate(predictions, {multiclass_evaluator.
↪metricName: "weightedRecall"})

    # Simpan hasil
    evaluation_results.append({
        "Model": model_name,
        "AUC": auc,
        "Accuracy": accuracy,
        "F1-Score": f1,
        "Precision": precision,
        "Recall": recall
    })

    print(f"AUC: {auc:.4f}, Accuracy: {accuracy:.4f}, F1-Score: {f1:.4f},␣
↪Precision: {precision:.4f}, Recall: {recall:.4f}")

# ---- 3. Tampilkan Hasil Evaluasi ----
print("\n--- Summary of Model Evaluation ---")
```

```
for result in evaluation_results:
    print(f"{result['Model']} -> AUC: {result['AUC']:.4f}, Accuracy:␣
 ↪{result['Accuracy']:.4f}, F1: {result['F1-Score']:.4f}, Precision:␣
 ↪{result['Precision']:.4f}, Recall: {result['Recall']:.4f}")

# ---- 4. Pilih Model Terbaik ----
best_model = max(evaluation_results, key=lambda x: x["AUC"])
print(f"\nBest Model: {best_model['Model']} with AUC: {best_model['AUC']:.4f}")
```

```
--- Evaluating Gradient Boosted Tree ---
AUC: 0.7128, Accuracy: 0.6800, F1-Score: 0.6440, Precision: 0.6602, Recall:
0.6800

--- Evaluating Random Forest ---
AUC: 0.6916, Accuracy: 0.6661, F1-Score: 0.5991, Precision: 0.6430, Recall:
0.6661

--- Summary of Model Evaluation ---
Gradient Boosted Tree -> AUC: 0.7128, Accuracy: 0.6800, F1: 0.6440, Precision:
0.6602, Recall: 0.6800
Random Forest -> AUC: 0.6916, Accuracy: 0.6661, F1: 0.5991, Precision: 0.6430,
Recall: 0.6661

Best Model: Gradient Boosted Tree with AUC: 0.7128
```

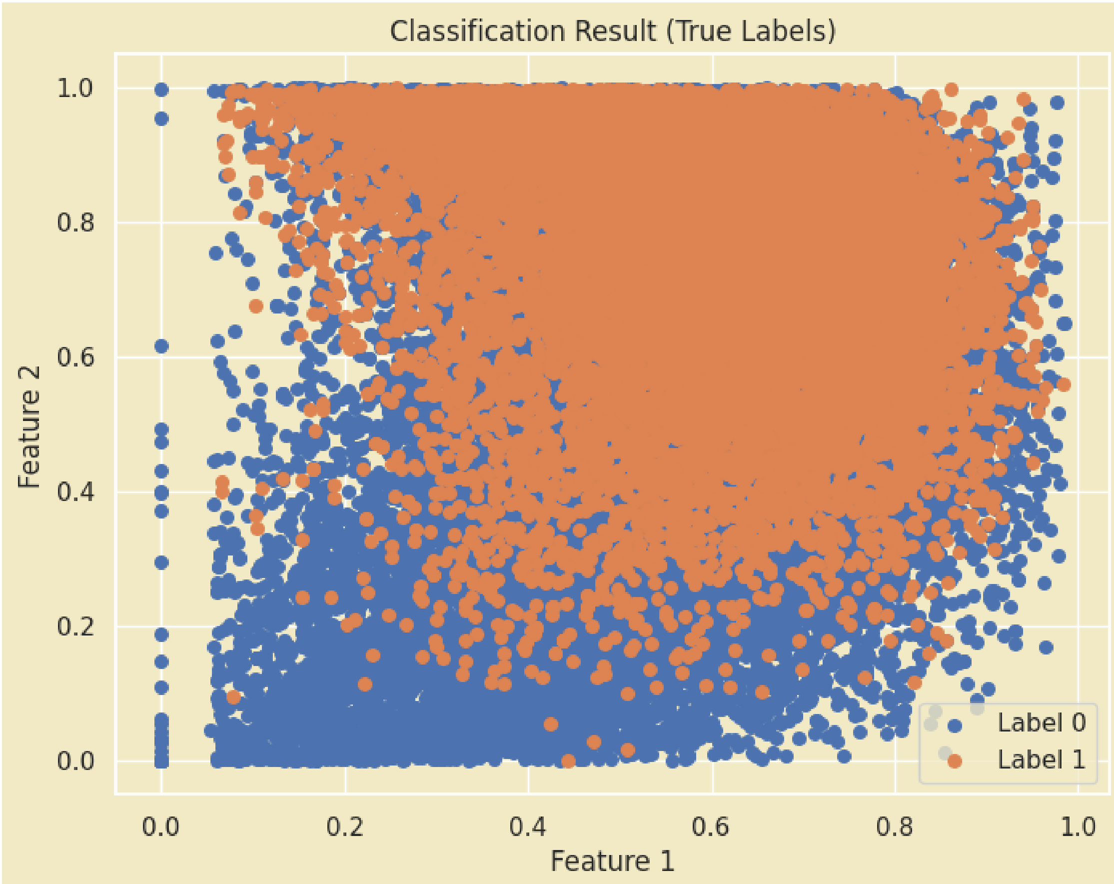
[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Convert predictions to Pandas DataFrame
from pyspark.ml.clustering import KMeans
from pyspark.ml.evaluation import ClusteringEvaluator

# Konfigurasi model K-Means
kmeans = KMeans(k=3, seed=1, featuresCol="features")  # 'k' adalah jumlah␣
 ↪kluster
model_kmeans = kmeans.fit(train_data)  # Pastikan train_data terdefinisi

# Prediksi cluster untuk data test
predictions_kmeans = model_kmeans.transform(test_data)

pandas_kmeans = predictions_kmeans.select("features", "prediction").toPandas()
pandas_kmeans["x"] = pandas_kmeans["features"].apply(lambda x: x[0])  # Ambil␣
 ↪fitur pertama
pandas_kmeans["y"] = pandas_kmeans["features"].apply(lambda x: x[1])  # Ambil␣
 ↪fitur kedua
```

```
# Scatter plot untuk clustering
plt.figure(figsize=(8, 6))
for cluster in pandas_kmeans["prediction"].unique():
    cluster_data = pandas_kmeans[pandas_kmeans["prediction"] == cluster]
    plt.scatter(cluster_data["x"], cluster_data["y"], label=f"Cluster␣
 ↪{cluster}", s=30)

plt.title("K-Means Clustering Visualization")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.legend()
plt.show()
```

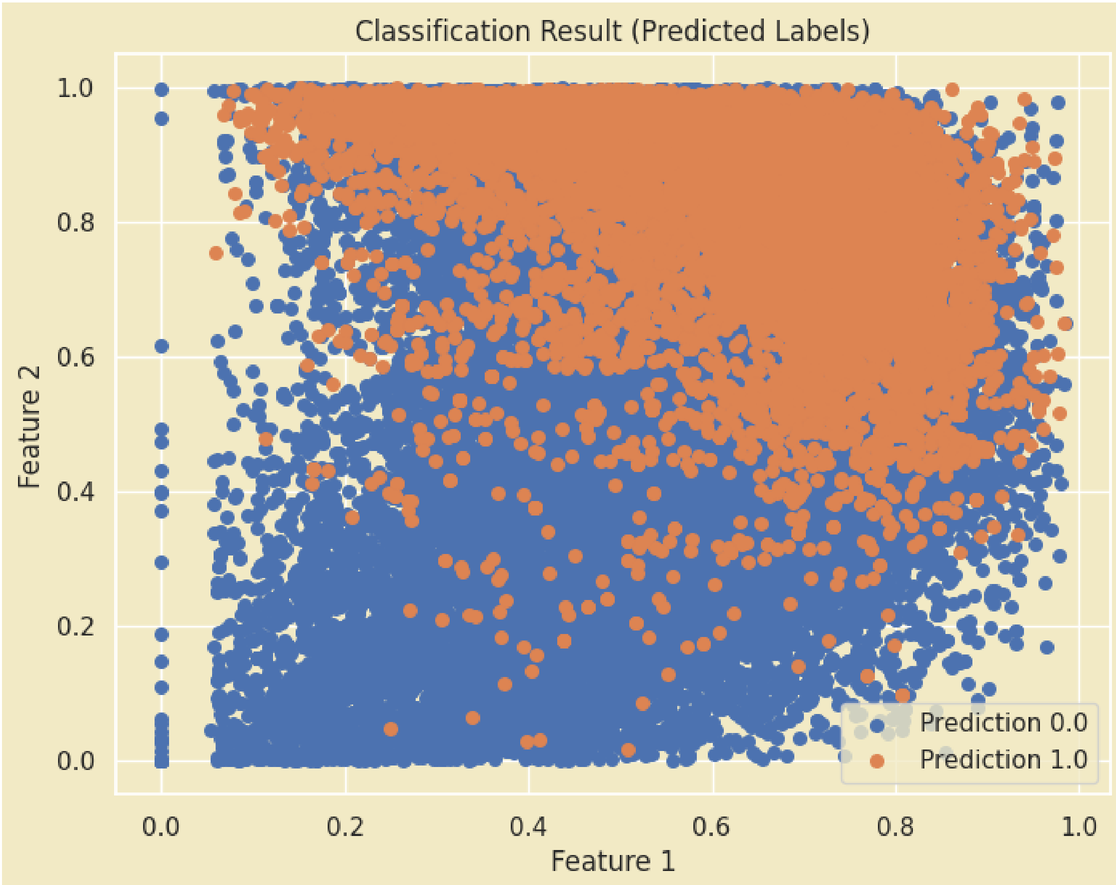


[ ]:
```
# Convert predictions to Pandas DataFrame
pandas_classification = best_predictions_gbt.select("features",␣
 ↪"indexed_music_category", "prediction").toPandas()
pandas_classification["x"] = pandas_classification["features"].apply(lambda x:␣
 ↪x[0])  # Ambil fitur pertama
```

```
pandas_classification["y"] = pandas_classification["features"].apply(lambda x:␣
↪x[1])  # Ambil fitur kedua

# Scatter plot untuk classification
plt.figure(figsize=(8, 6))
for label in pandas_classification["indexed_music_category"].unique():
    label_data =␣
↪pandas_classification[pandas_classification["indexed_music_category"] ==␣
↪label]
    plt.scatter(label_data["x"], label_data["y"], label=f"Label {label}", s=30)

plt.title("Classification Result (True Labels)")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.legend()
plt.show()

# Scatter plot untuk predicted labels
plt.figure(figsize=(8, 6))
for pred in pandas_classification["prediction"].unique():
    pred_data = pandas_classification[pandas_classification["prediction"] ==␣
↪pred]
    plt.scatter(pred_data["x"], pred_data["y"], label=f"Prediction {pred}",␣
↪s=30)

plt.title("Classification Result (Predicted Labels)")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.legend()
plt.show()
```



Classification Result (True Labels)
1.0
0.8
0.6
0.4
0.2
0.0
Feature 2
0.0
0.2
0.4
0.6
0.8
1.0
Feature 1
Label 0
Label 1


Classification Result (Predicted Labels)
Feature 2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Feature 1
Prediction 0.0
Prediction 1.0