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MUSIC GENRE CLASSIFICATION - USING CNN

1.DATA ANALYSIS

[1]:
```
import os
import sys
from tempfile import NamedTemporaryFile
from urllib.request import urlopen
from urllib.parse import unquote, urlparse
from urllib.error import HTTPError
from zipfile import ZipFile
import tarfile
import shutil
```

[4]:
```
# Data Analysis
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
# Data Visualization
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import cm
from mpl_toolkits.mplot3d import Axes3D
import plotly.express as px
# Model Training and Evaluation
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from imblearn.ensemble import BalancedRandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from imblearn.over_sampling import RandomOverSampler, SMOTE
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
# Interactive Prediction Widget
from collections import Counter
import ipywidgets as widgets
from IPython.display import display, clear_output, HTML
# Misc
import warnings
warnings.filterwarnings('ignore')
```

Au421221243044

[5]:
```
data =pd.read_csv('/content/submission.csv')
data =pd.read_csv('/content/test.csv')
data =pd.read_csv('/content/train.csv')
```

[6]:
```
data.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17996 entries, 0 to
17995 Data columns (total 17
columns):
#   Column              Non-Null Count
                        Dtype
--- ------              -------------- ----
                        -
0   Artist Name         17996       non-null
                        object
1   Track Name          17996       non-null
                        object
2   Popularity          17568       non-null
                        float64
3   danceability        17996       non-null
                        float64
4   energy              17996       non-null
                        float64
5   key                 15982       non-null
                        float64
6   loudness            17996       non-null
                        float64
7   mode                17996 non-null
                        int64
8   speechiness         17996       non-null
                        float64
9   acousticness        17996       non-null
                        float64
 10 instrumentalness    13619       non-null
                        float64
 11 liveness            17996       non-null
                        float64
 12 valence             17996       non-null
                        float64
 13 tempo               17996       non-null
                        float64
 14 duration_in min/ms 17996 non-null float64
 15 time_signature     17996 non-null int64
 16 Class   17996 non-null int64
dtypes: float64(12), int64(3),
object(2) memory usage: 4.6 MB
```

Au421221243044

```
[7]: data.describe()
```

```
[7]: Popularity danceability energy key loudness \ count 17568.000000
 17996.000000 17996.000000 15982.000000 17996.000000
 mean      44.512124    0.543433    0.662777    5.952447   -7.910660
 std       17.426928    0.166268    0.235373    3.196854    4.049151
 min        1.000000    0.059600    0.000020    1.000000  -39.952000
 25%       33.000000    0.432000    0.509000    3.000000   -9.538000
 50%       44.000000    0.545000    0.700000    6.000000   -7.016000
 75%       56.000000    0.659000    0.860000    9.000000   -5.189000
 max      100.000000    0.989000    1.000000   11.000000    1.355000

              mode   speechiness acousticness instrumentalness \
 count 17996.000000 17996.000000 17996.000000
 13619.000000 mean      0.636753    0.079707    0.247082
 0.177562 std     0.480949    0.083576    0.310632    0.304048
 min        0.000000     0.022500     0.000000       0.000001
 25%        0.000000     0.034800     0.004300       0.000089
 50%        1.000000     0.047400     0.081400       0.003910
 75%        1.000000     0.083000     0.434000       0.200000
 max        1.000000     0.955000     0.996000       0.996000

           liveness      valence      tempo duration_in min/ms \
 count 17996.000000 17996.000000 17996.000000   1.799600e+04
 mean      0.196170     0.486208   122.623294    2.007445e+05
 std       0.159212     0.240195    29.571527    1.119891e+05
 min       0.011900     0.018300    30.557000    5.016500e-01
 25%       0.097500     0.297000    99.620750    1.663370e+05
 50%       0.129000     0.481000   120.065500    2.091600e+05
 75%       0.258000     0.672000   141.969250    2.524900e+05
 max       1.000000      0.986000  217.416000    1.477187e+06
       time_signature   Class

 count   17996.000000
         17996.000000
 mean       3.924039     6.695821

 std        0.361618     3.206073

 min        1.000000     0.000000

 25%        4.000000     5.000000

 50%        4.000000     8.000000

 75%        4.000000    10.000000

 max        5.000000    10.000000
```

Au421221243044

[8]:
```
data.shape
```

[8]: (17996, 17)

[52]:
```
data.head()
```

[52]:
```
            Artist Name                           Track Name Popularity \
0                 Bruno Mars That's What I Like (feat. Gucci Mane)
                        60.0
1                 Boston     Hitch a Ride     54.0
2                 The Raincoats   No Side to Fall In     35.0
3                 Deno Lingo (feat. J.I & Chunkz) 66.0
4                 Red Hot Chili Peppers      Nobody Weird Like Me -
                  Remastered53.0

  danceability energy key loudness mode speechiness acousticness \
0     0.854 0.564     1.0   -4.964     1     0.0485     0.017100
1     0.382 0.814     3.0   -7.230     1     0.0406     0.001100
2     0.434 0.614     6.0   -8.334     1     0.0525     0.486000
3        0.853 0.597 10.0   -6.528     0     0.0555     0.021200
4        0.167 0.975   2.0   -4.279     1     0.2160     0.000169

  instrumentalness liveness valence tempo duration_in min/ms \
0     0.177562   0.0849     0.8990 134.071   234596.0

1     0.004010   0.1010     0.5690 116.454   251733.0

2     0.000196   0.3940     0.7870 147.681   109667.0

3     0.177562   0.1220 0.5690 107.033 173968.0 4 0.016100   0.1720 0.0918
199.060 229960.0

time_signature Class

0             4  5

1             4  10

2             4  6

3             4  5

4             4  10
```

[53]:
```
data.tail()
```

[53]: Artist Name Track Name Popularity danceability energy \ 17991 Green-House Find Home 35.0 0.166 0.109 17992 Micatone All Gone 27.0 0.638 0.223

```
17993         Smash Hit Combo      Peine perdue     34.0  0.558 0.981
17994         Beherit  Salomon's Gate   29.0  0.215 0.805
```

```
17995        The Raconteurs Broken Boy Soldier    43.0  0.400 0.853

       key loudness mode speechiness acousticness instrumentalness \
17991  7.0  -17.100    0     0.0413      0.99300    0.824000
17992  11.0-10.174     0     0.0329      0.85800    0.000016
17993  4.0  -4.683     0     0.0712      0.00003    0.000136
17994  6.0  -12.757    0     0.1340      0.00129    0.916000
17995  4.0  -5.320     0     0.0591      0.00604    0.212000

      liveness valence  tempo duration_in min/ms time_signature Class
17991 0.0984      0.177 171.587    193450.0    3     6 17992    0.0705
                  0.335 73.016     257067.0    4     2
17993   0.6660   0.262 105.000    216222.0    4     8
17994   0.2560   0.355 131.363    219693.0    4     8
17995   0.3340   0.377 138.102    182227.0    4     10
```

2.DATA VISUALIZATION

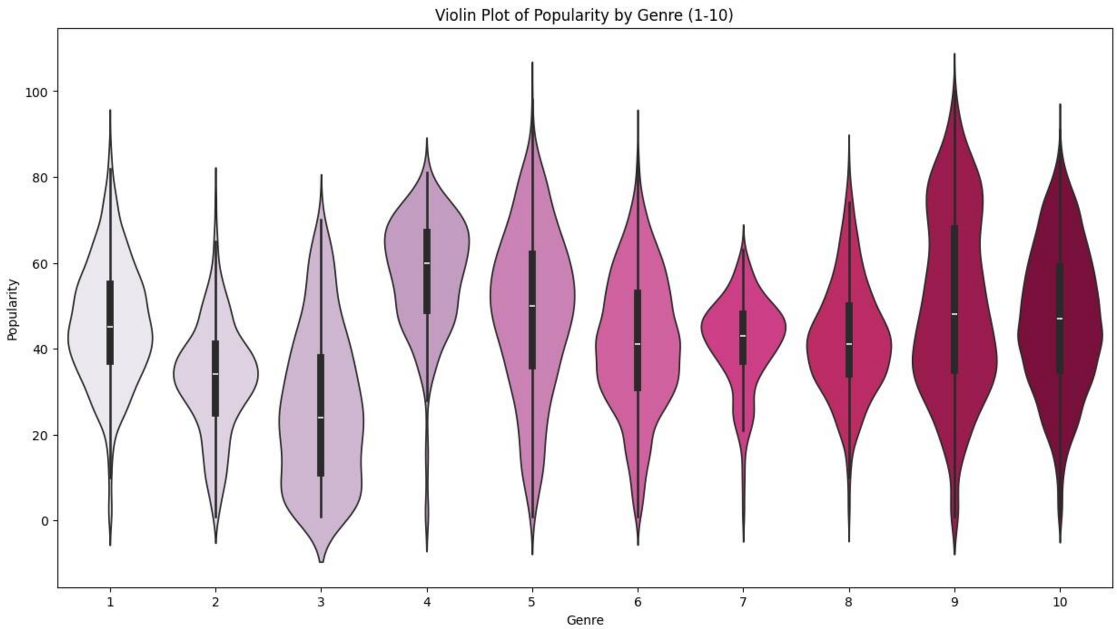
[10]:
```
#2. Data Visualization
# Putting all Numericals columns in one variable.
numerical_columns = ['Popularity', 'danceability', 'energy', 'key',
'loudness', 'mode',
 'speechiness', 'acousticness',
'instrumentalness', 'liveness',
 'valence', 'tempo', 'duration_in min/ms',
'time_signature']
# Figure.1 - Bar Plot.
```

```
plt.figure(figsize=(10, 6))
data['Class'].value_counts().sort_index().plot(kind='bar',
color='#c8a2c8')
plt.title('Distribution of Target Classes')
plt.gca().set_facecolor('lavender')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```

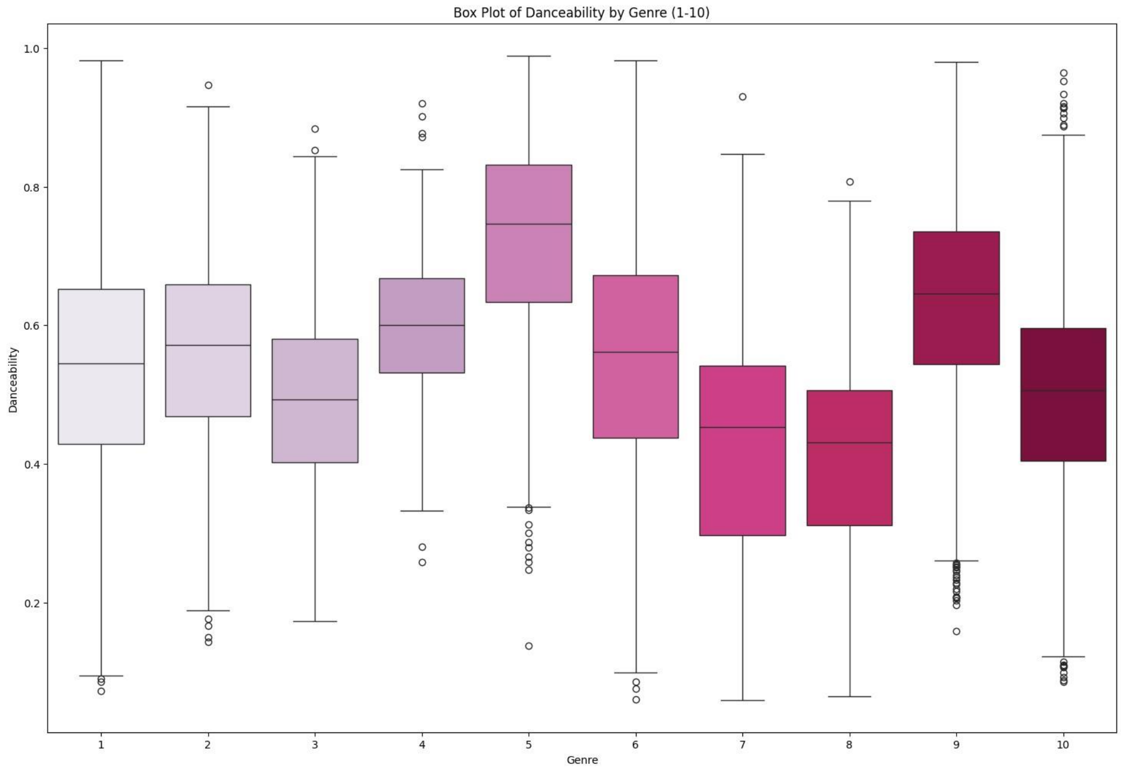
[16]:
```
# Figure.2 - Genre Distribution Pie Chart.
genre_counts =
data['Class'].value_counts().reset_index()
genre_counts.columns = ['Genre', 'Count']
  fig = px.pie(genre_counts, names='Genre', values='Count',
                             title='Genre␣
 ↪Distribution Pie
Chart',color_discrete_sequence=px.colors.sequential.PuRd) fig.show()
# Figure.3 - Correlation Heatmap.
plt.figure(figsize=(12, 8))
sns.heatmap(data[numerical_columns].corr(), annot=True,
cmap='PuRd', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Features')
plt.show
```

[16]: <function matplotlib.pyplot.show(close=None, block=None)>

[17]:
```
# Figure.4 - Violin Plot Graph by Genre.
plt.figure(figsize=(15, 8))
sns.violinplot(x='Class', y='Popularity',
data=data[data['Class'].isin(range(1, 11))],
palette='PuRd') plt.title('Violin Plot of Popularity
by Genre (1-10)')
plt.xlabel('Genre')
plt.ylabel('Popularity')
plt.show()
```




```
[18]: # Figure.5 - Box Plot For Danceability.
plt.figure(figsize=(18, 12)) sns.boxplot(x='Class',
y='danceability',
data=data[data['Class'].isin(range(1, 11))],
palette='PuRd') plt.title('Box Plot of Danceability
by Genre (1-10)')
plt.xlabel('Genre')
plt.ylabel('Danceability')
plt.show()
```




```
[19]: # Figure.6 - 3D interactive scatter plot fig =
px.scatter_3d(data, x='danceability', y='energy',
z='loudness', color='Class', size_max=18,labels={'Class':
'Music Genre'})
fig.update_layout(scene=dict(xaxis_title='Danceability',
yaxis_title='Energy', zaxis_title='Loudness')) fig.show()
```

3.DATA PREPROCESSING

```
[22]: # Handling missing values
data['Popularity'].fillna(data['Popularity'].mean(), inplace=True)
data['key'].fillna(data['key'].mean(), inplace=True)
data['instrumentalness'].fillna(data['instrumentalness'].mean(),
inplace=True)
# Encode categorical variables (artist name and track name)
label_encoder = LabelEncoder() data_encoded = data.copy()
data_encoded['Artist Name'] =
label_encoder.fit_transform(data['Artist Name'].
 ↪str.lower()) data_encoded['Track Name'] =
label_encoder.fit_transform(data['Track Name'].str. ↪lower())
# Get feature names after encoding
```

```
encoded_feature_names = list(data_encoded.columns)
encoded_feature_names.remove('Class') # Remove the target variable
# Normalize numerical features
scaler = StandardScaler()
data_encoded[numerical_columns] =
scaler.
 ↪fit_transform(data_encoded[numerical_columns])
```

4.DATA TRAINING AND EVALUATION

```
[24]: # Define features (X) and target variable (y)
X = data_encoded.drop(columns=['Class']) # Dropping Class
Column. y = data_encoded['Class']
```

```
[25]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
 test_size=0.25,␣ ↪random_state=42)
```

```
[26]: # Random Oversampling ros =
RandomOverSampler(random_state=42) X_ros,
y_ros = ros.fit_resample(X_train, y_train)
```

```
# SMOTE on the oversampled data
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_ros, y_ros)
```

```
[27]: # Assign feature names to X_resampled
X_resampled.columns = encoded_feature_names
```

```
[28]: # Split resampled data into training and testing sets
X_train_resampled, X_test_resampled, y_train_resampled,
 y_test_resampled =␣ ↪train_test_split(X_resampled, y_resampled,
 test_size=0.25, random_state=42)
```

```
[29]: # Defining the classifiers used.
classifiers = {
                     'Gradient Boosting':
          GradientBoostingClassifier(random_state=42),
                       'Random Forest':
        RandomForestClassifier(class_weight='balanced',␣
 ↪random_state=42),
   'Naive Bayes': GaussianNB(),
   'Balanced Random Forest':
BalancedRandomForestClassifier(random_state=42), }
```

Au421221243044

[30]:
```python
# Dictionary to store accuracy values
accuracy_dict = {}
```

[31]:
```python
# Train and evaluate each
classifier for clf_name, clf in
classifiers.items():
    print(f"\nTraining and evaluating {clf_name}...")
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    accuracy_dict[clf_name] = accuracy
    class_report = classification_report(y_test, y_pred)

    print(f"Accuracy ({clf_name}): {accuracy:.4f}")
    print("Classification Report:")
    print(class_report)
```

```
Training and evaluating Gradient Boosting…
Accuracy (Gradient Boosting): 0.5646
Classification Report:
              precision   recall  f1-score  support

           0       0.72      0.80      0.75       172
           1       0.32      0.02      0.03       340
           2       0.55      0.52      0.53       340
           3       0.79      0.69      0.74       104
           4       0.63      0.74      0.68        84
           5       0.72      0.71      0.72       340
           6       0.43      0.34      0.38       626
           7       0.91      0.95      0.93       134
           8       0.63      0.59      0.61       473
           9       0.62      0.59      0.60       663
          10       0.48      0.69      0.57      1223

    accuracy                          0.56      4499
   macro avg       0.62      0.60      0.59      4499
weighted           0.55      0.56      0.54      4499
avg


Training and evaluating Random Forest…
Accuracy (Random Forest): 0.5221
Classification Report:
              precision   recall  f1-score  support
```

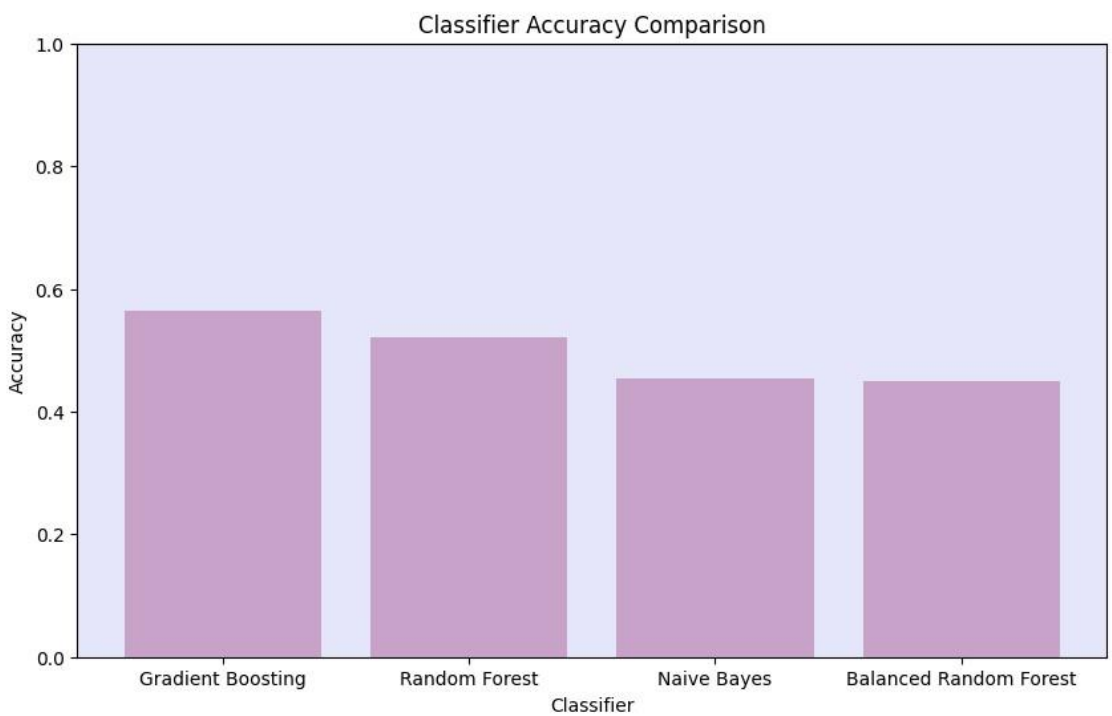
```
           0       0.73      0.82      0.77       172
           1       0.04      0.02      0.03       340
           2       0.55      0.51      0.53       340
           3       0.81      0.70      0.75       104
           4       0.64      0.70      0.67        84
           5       0.67      0.70      0.68       340
           6       0.33      0.26      0.29       626
           7       0.94      0.93      0.94       134
           8       0.62      0.55      0.58       473
           9       0.60      0.54      0.57       663
          10       0.46      0.62      0.53      1223

    accuracy                           0.52      4499
   macro avg       0.58      0.58      0.58      4499
weighted avg       0.51      0.52      0.51      4499
```

```
Training and evaluating Naive Bayes…
Accuracy (Naive Bayes): 0.4548
Classification Report:
              precision    recall  f1-score   support

           0       0.61      0.61      0.61       172
           1       0.00      0.00      0.00       340
           2       0.39      0.36      0.37       340
           3       0.69      0.51      0.59       104
           4       0.34      0.71      0.46        84
           5       0.65      0.64      0.65       340
           6       0.39      0.20      0.27       626
           7       0.84      0.93      0.89       134
           8       0.42      0.70      0.53       473
           9       0.41      0.45      0.43       663
          10       0.42      0.49      0.46      1223

    accuracy                           0.45      4499
   macro avg       0.47      0.51      0.48      4499
weighted       0.42      0.45      0.43      4499
avg
Training and evaluating Balanced Random Forest…
Accuracy (Balanced Random Forest): 0.4488
Classification Report:
              precision    recall  f1-score   support

           0       0.65      0.73      0.69       172
           1       0.14      0.21      0.16       340
           2       0.38      0.76      0.51       340
```

```
          3       0.73     0.80     0.76      104
          4       0.36     0.80     0.49       84
          5       0.59     0.75     0.66      340
          6       0.32     0.20     0.24      626
          7       0.92     0.92     0.92      134
          8       0.46     0.79     0.58      473
          9       0.52     0.44     0.47      663
          10      0.51     0.20     0.29     1223
    accuracy0.45  4499 macro avg   0.51  0.60  0.53
 4499 weighted avg     0.47  0.45  0.43  4499
```

5. Classifier Visualizations

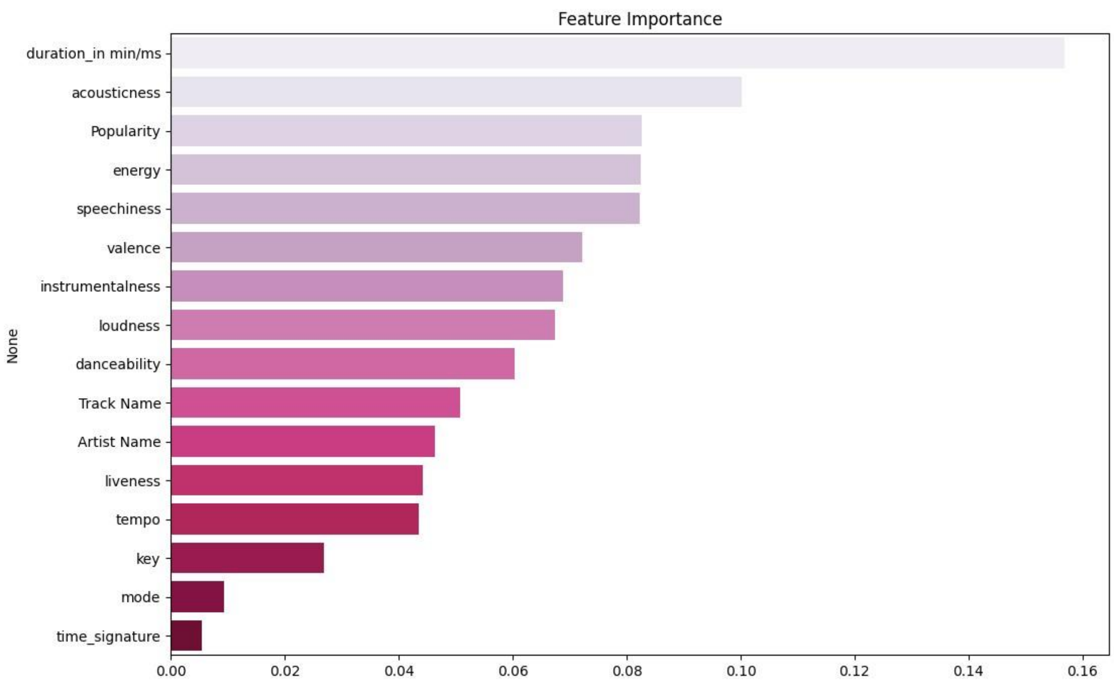
[32]:
```
# Figure.7 - Accuracy bar plot.
plt.figure(figsize=(10, 6))
# Set a custom background color for the entire bar chart
plt.gca().set_facecolor('lavender')
plt.bar(accuracy_dict.keys(), accuracy_dict.values(), color='#c8a2c8')
plt.title('Classifier Accuracy Comparison')
plt.xlabel('Classifier')
plt.ylabel('Accuracy')
plt.ylim(0, 1) # Set y-axis limit to ensure proper scale (0 to 1)
plt.show()
```



[34]:
```
# Figure.8 - Feature Importance Plot.
```

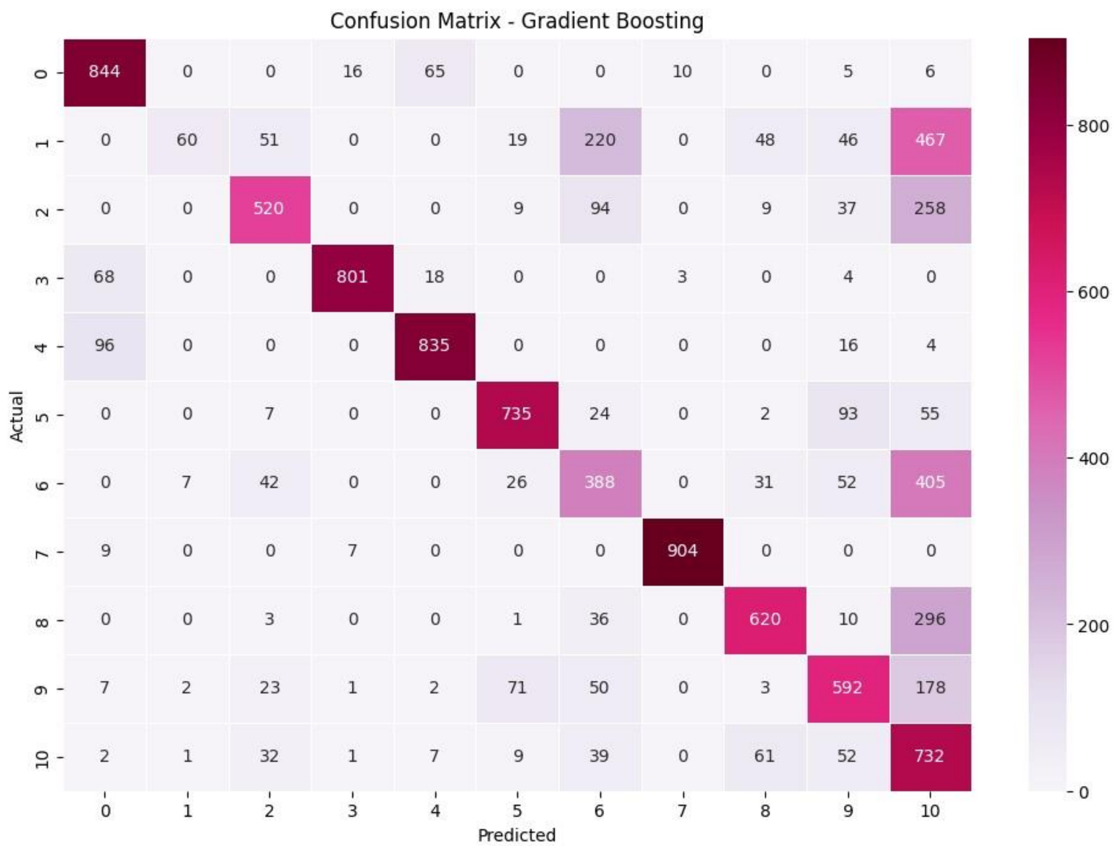
```
feature_importance = clf.feature_importances_ sorted_idx =
feature_importance.argsort()[::-1] plt.figure(figsize=(12,
8)) sns.barplot(x=feature_importance[sorted_idx],
y=X.columns[sorted_idx],␣
↪palette='PuRd')
plt.title("Feature
Importance")
```

```
plt.show()
```

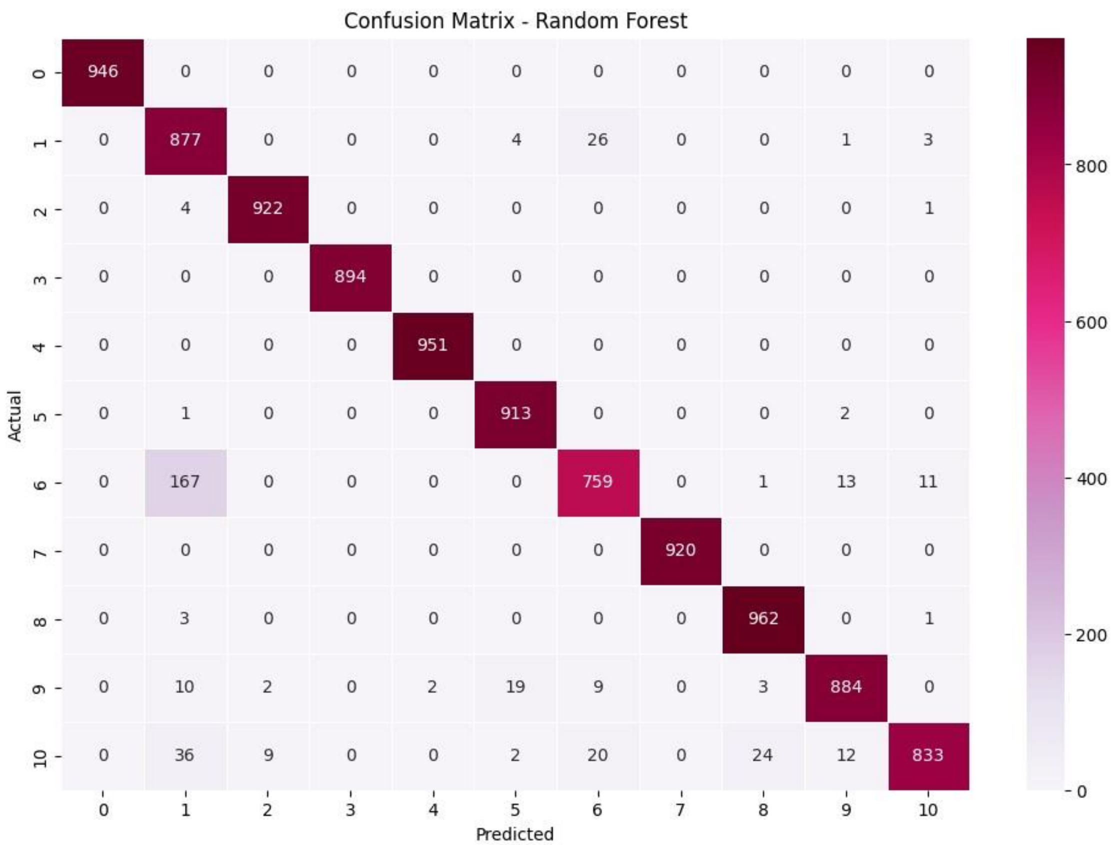


[36]:
```
# Figure.9 - Confusion matrices for each classifier.

for clf_name, clf in classifiers.items():
    print(f"\nTraining and evaluating {clf_name}...")
    # Make predictions
    y_pred = clf.predict(X_test_resampled)
    # Create confusion matrix cm =
    confusion_matrix(y_test_resampled, y_pred) fig, ax =
    plt.subplots(figsize=(12, 8)) sns.heatmap(cm, annot=True,
    fmt='d',linewidths=0.5, cmap='PuRd', )
    plt.title(f"Confusion Matrix - {clf_name}"),
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```

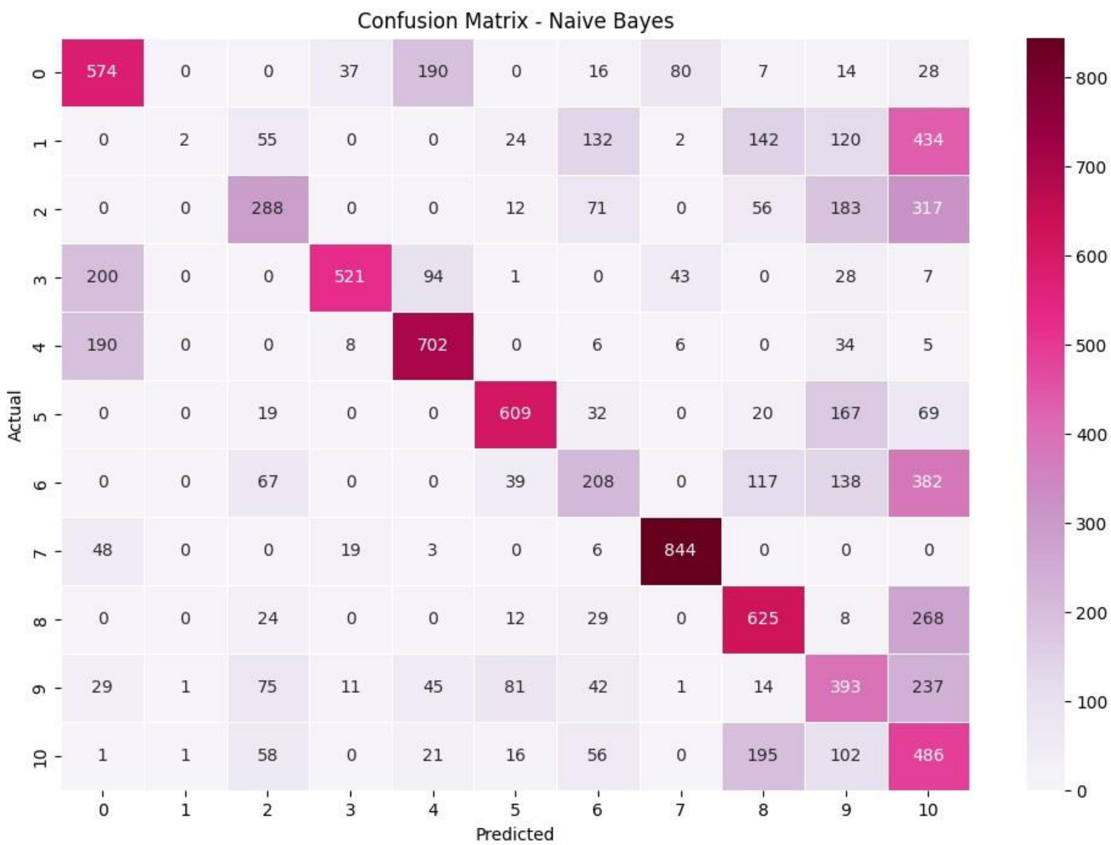
Training and evaluating Gradient Boosting…



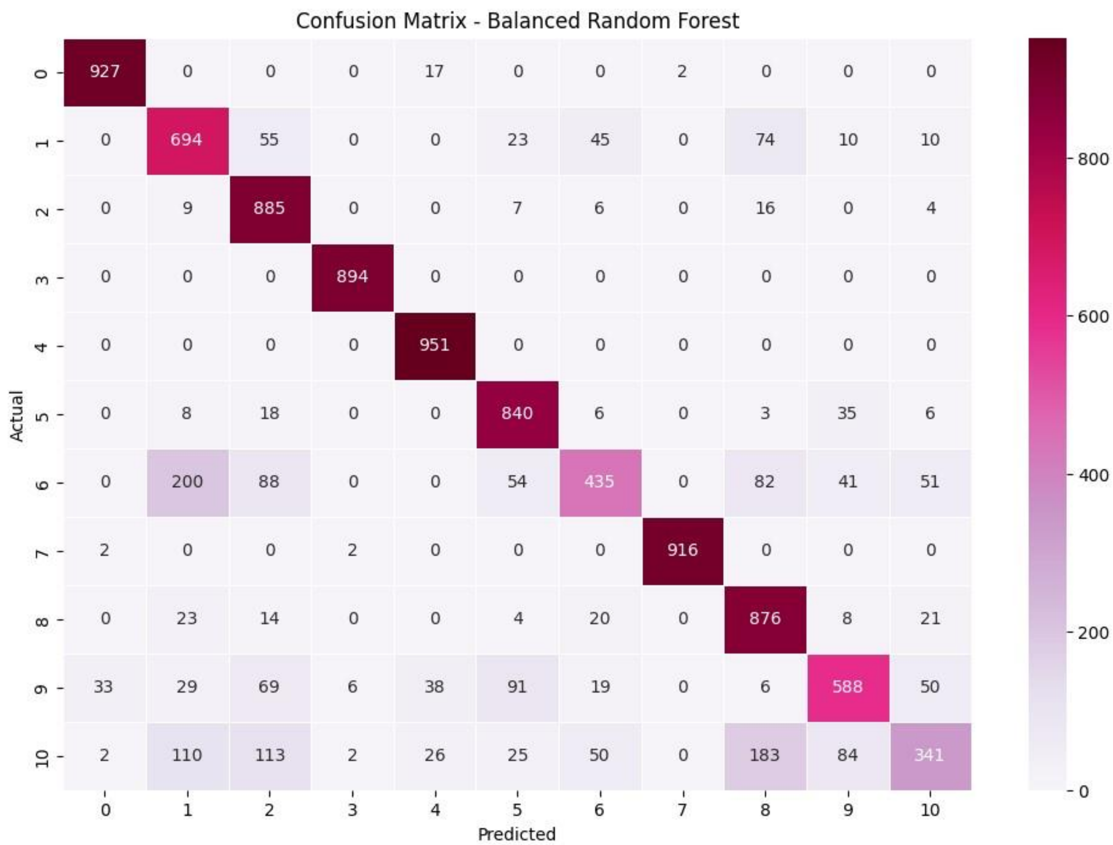
Training and evaluating Random Forest…



Training and evaluating Naive Bayes…



Training and evaluating Balanced Random Forest…



6.INTERACTIVE PREDICTION WIDGET

[37]:
```
# Create mapping between actual track names and encoded values
track_name_to_encoded = dict(zip(data['Track Name'], data_encoded['Track␣
↪Name']))
```

[38]:
```
# Create dropdown for track selection using actual track names
track_dropdown = widgets.Dropdown(
    options=data['Track Name'].unique(),
    value=data['Track Name'].unique()[0],
    description='Select Track:'
)
```

[39]:
```
# Button to predict the genre
predict_button = widgets.Button(description='Predict Genre')

# Output area for displaying the predicted genre
output_area = widgets.Output()
```

[47]:
```
# Function to perform majority voting
def majority_vote(predictions):
    vote_counter = Counter(predictions)
    majority_class = vote_counter.most_common(1)[0][0]
    return majority_class
```

[48]:
```
# Function to handle button click event
def on_button_click(b):
    with output_area:
        clear_output(wait=True)
        # Fetch values from the selected track details
        selected_track_name = track_dropdown.value
        encoded_value = track_name_to_encoded[selected_track_name]
        selected_track_data = data_encoded[data_encoded['Track Name'] == encoded_value].iloc[0]

        # Prepare the input data for prediction
        input_data = [selected_track_data.drop('Class').values]

        # List to store predictions from all classifiers
        all_predictions = []

        # HTML content for all predictions
        predictions_html = ''

        # Iterate over all classifiers and make predictions
        for clf_name, clf in classifiers.items():
            predicted_class = clf.predict(input_data)[0]
            all_predictions.append(predicted_class)

            # Map the predicted class to the actual genre
            genre_mapping = {
                0: 'Acoustic/Folk', 1: 'Alt_Music', 2: 'Blues', 3: 'Bollywood', 4: 'Country',
                5: 'HipHop', 6: 'Indie Alt', 7: 'Instrumental', 8: 'Metal', 9: 'Pop', 10: 'Rock'
            }
            predicted_genre = genre_mapping.get(predicted_class, 'Unknown')

            # Concatenate HTML content for each prediction
            predictions_html += f'<p style="color: #f4f3f3; font-size: 14px;">{clf_name}: {predicted_genre}</p>'

        # Perform majority voting to get the final prediction
        final_prediction = majority_vote(all_predictions)

        # Map the final predicted class to the actual genre
```

```
        final_predicted_genre = genre_mapping.get(final_prediction, 'Unknown')

        # Display all predictions in the same styled window
        display(HTML(f'''
            <div style="background-color: #ccb1ce; border: 3px solid #6e0f34; ␣
↪padding: 10px; border-radius: 10px; width: 450px; ">
                <p style="color: #f4f3f3; font-size: 16px; font-weight: bold; ␣
↪text-align: center;">Final Predicted Genre (Majority Voting):␣
↪{final_predicted_genre}</p>
                <p style="color: #6e0f34; font-size: 14px; font-weight: bold; ␣
↪text-align: center;">Individual Predictions:</p>
                {predictions_html}
            </div>
        '''))

# Attach the button click event
predict_button.on_click(on_button_click)
```

[49]:
```
# Apply styling to the dropdown
track_dropdown.add_class('custom-dropdown-style')

# Create a custom CSS style for the dropdown
custom_dropdown_style = """
    .custom-dropdown-style {
        width: 475px;
        font-weight: bold;
        background-color: #ccb1ce;
        border-radius: 15px;
        padding-left: 15px;
        padding-right: 20px;
    }
"""
display(HTML(f'<style>{custom_dropdown_style}</style>'))

predict_button.style.button_color = '#ccb1ce'
predict_button.style.font_weight = 'bold'
predict_button.layout.width = '475px'
```

```
<IPython.core.display.HTML object>
```

[51]:
```
# Display widgets
display(track_dropdown, predict_button, output_area)
```

```
Dropdown(_dom_classes=('custom-dropdown-style',), description='Select
 Track:',␣ ↪index=25, options=("That's What…

Button(description='Predict Genre', layout=Layout(width='475px'),␣
```

```
↪style=ButtonStyle(button_color='#ccb1ce', fo…
Output()
```