01_ExploratoryAnalysis_Feature_Engineering

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##Project: Music Genre Classification using Machine Learning

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Description:

This project aims to automatically classify songs into genres based on audio features provided in the Spotify 1.2M Songs Dataset. The workflow includes data exploration, preprocessing, model building, evaluation, and visualization.

Purpose:

Apply supervised learning techniques on real-world audio data Explore audio feature-based genre classification Build a portfolio-ready project demonstrating practical machine learning skills

0.1 Import Libraries

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OrdinalEncoder, LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score,␣
↪classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
from scipy.stats import mode
import warnings
import os
from matplotlib.colors import LinearSegmentedColormap

warnings.filterwarnings("ignore", category=FutureWarning)
```

[14]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

0.2 Load Data

[15]:
```python
import pandas as pd
data = pd.read_csv('/content/drive/MyDrive/music-genre-classification/data/
 ↪spotify_songs.csv')
data.head()
```

[15]:
```
                 track_id                                         track_name  \
0  6f807x0ima9a1j3VPbc7VN  I Don't Care (with Justin Bieber) - Loud Luxur…
1  0r7CVbZTWZgbTCYdfa2P31                    Memories - Dillon Francis Remix
2  1z1Hg7Vb0AhHDiEmnDE79l                    All the Time - Don Diablo Remix
3  75FpbthrwQmzHlBJLuGdC7                  Call You Mine - Keanu Silva Remix
4  1e8PAfcKUYoKkxPhrHqw4x            Someone You Loved - Future Humans Remix

      track_artist  track_popularity          track_album_id  \
0       Ed Sheeran                66  2oCs0DGTsRO98Gh5ZSl2Cx
1         Maroon 5                67  63rPSO264uRjW1X5E6cWv6
2     Zara Larsson                70  1HoSmj2eLcsrR0vE9gThr4
3  The Chainsmokers                60  1nqYsOef1yKKuGOVchbsk6
4    Lewis Capaldi                69  7m7vv9wlQ4i0LFuJiE2zsQ

                                     track_album_name track_album_release_date  \
0  I Don't Care (with Justin Bieber) [Loud Luxury…               2019-06-14
1                    Memories (Dillon Francis Remix)               2019-12-13
2                    All the Time (Don Diablo Remix)               2019-07-05
3                        Call You Mine - The Remixes               2019-07-19
4            Someone You Loved (Future Humans Remix)               2019-03-05

  playlist_name             playlist_id playlist_genre  … key  loudness  \
0     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   6    -2.634
1     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …  11    -4.969
2     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   1    -3.432
3     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   7    -3.778
4     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   1    -4.672

   mode  speechiness  acousticness  instrumentalness  liveness  valence  \
0     1       0.0583        0.1020          0.000000    0.0653    0.518
1     1       0.0373        0.0724          0.004210    0.3570    0.693
2     0       0.0742        0.0794          0.000023    0.1100    0.613
3     1       0.1020        0.0287          0.000009    0.2040    0.277
4     1       0.0359        0.0803          0.000000    0.0833    0.725

     tempo  duration_ms
0  122.036       194754
```

```
1   99.972       162600
2  124.008       176616
3  121.956       169093
4  123.976       189052

[5 rows x 23 columns]
```

#Data Exploration

[16]:
```python
print(data.columns)
```

```
Index(['track_id', 'track_name', 'track_artist', 'track_popularity',
       'track_album_id', 'track_album_name', 'track_album_release_date',
       'playlist_name', 'playlist_id', 'playlist_genre', 'playlist_subgenre',
       'danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms'],
      dtype='object')
```

[17]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32833 entries, 0 to 32832
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   track_id                  32833 non-null  object
 1   track_name                32828 non-null  object
 2   track_artist              32828 non-null  object
 3   track_popularity          32833 non-null  int64
 4   track_album_id            32833 non-null  object
 5   track_album_name          32828 non-null  object
 6   track_album_release_date  32833 non-null  object
 7   playlist_name             32833 non-null  object
 8   playlist_id               32833 non-null  object
 9   playlist_genre            32833 non-null  object
 10  playlist_subgenre         32833 non-null  object
 11  danceability              32833 non-null  float64
 12  energy                    32833 non-null  float64
 13  key                       32833 non-null  int64
 14  loudness                  32833 non-null  float64
 15  mode                      32833 non-null  int64
 16  speechiness               32833 non-null  float64
 17  acousticness              32833 non-null  float64
 18  instrumentalness          32833 non-null  float64
 19  liveness                  32833 non-null  float64
 20  valence                   32833 non-null  float64
 21  tempo                     32833 non-null  float64
 22  duration_ms               32833 non-null  int64
```

```
dtypes: float64(9), int64(4), object(10)
memory usage: 5.8+ MB
```

[18]:
```
data.describe(include = "all")
```

[18]:
```
                     track_id track_name   track_artist  track_popularity  \
count                   32833      32828          32828      32833.000000
unique                  28356      23449          10692               NaN
top    7BKLCZ1jbUBVqRi2FVlTVw     Poison  Martin Garrix               NaN
freq                       10         22            161               NaN
mean                      NaN        NaN            NaN         42.477081
std                       NaN        NaN            NaN         24.984074
min                       NaN        NaN            NaN          0.000000
25%                       NaN        NaN            NaN         24.000000
50%                       NaN        NaN            NaN         45.000000
75%                       NaN        NaN            NaN         62.000000
max                       NaN        NaN            NaN        100.000000

                track_album_id track_album_name track_album_release_date  \
count                    32833            32828                    32833
unique                   22545            19743                     4530
top     5L1xcowSxwzFUSJzvyMp48    Greatest Hits               2020-01-10
freq                        42              139                      270
mean                       NaN              NaN                      NaN
std                        NaN              NaN                      NaN
min                        NaN              NaN                      NaN
25%                        NaN              NaN                      NaN
50%                        NaN              NaN                      NaN
75%                        NaN              NaN                      NaN
max                        NaN              NaN                      NaN

          playlist_name             playlist_id playlist_genre  …  \
count             32833                   32833          32833  …
unique              449                     471              6  …
top     Indie Poptimism  4JkkvMpVl4lSioqQjeAL0q            edm  …
freq                308                     247           6043  …
mean                NaN                     NaN            NaN  …
std                 NaN                     NaN            NaN  …
min                 NaN                     NaN            NaN  …
25%                 NaN                     NaN            NaN  …
50%                 NaN                     NaN            NaN  …
75%                 NaN                     NaN            NaN  …
max                 NaN                     NaN            NaN  …

                 key      loudness          mode   speechiness  acousticness  \
count   32833.000000  32833.000000  32833.000000  32833.000000  32833.000000
unique           NaN           NaN           NaN           NaN           NaN
```

```
top              NaN          NaN          NaN          NaN          NaN
freq             NaN          NaN          NaN          NaN          NaN
mean        5.374471    -6.719499     0.565711     0.107068     0.175334
std         3.611657     2.988436     0.495671     0.101314     0.219633
min         0.000000   -46.448000     0.000000     0.000000     0.000000
25%         2.000000    -8.171000     0.000000     0.041000     0.015100
50%         6.000000    -6.166000     1.000000     0.062500     0.080400
75%         9.000000    -4.645000     1.000000     0.132000     0.255000
max        11.000000     1.275000     1.000000     0.918000     0.994000

        instrumentalness      liveness       valence         tempo  \
count       32833.000000  32833.000000  32833.000000  32833.000000
unique               NaN           NaN           NaN           NaN
top                  NaN           NaN           NaN           NaN
freq                 NaN           NaN           NaN           NaN
mean            0.084747      0.190176      0.510561    120.881132
std             0.224230      0.154317      0.233146     26.903624
min             0.000000      0.000000      0.000000      0.000000
25%             0.000000      0.092700      0.331000     99.960000
50%             0.000016      0.127000      0.512000    121.984000
75%             0.004830      0.248000      0.693000    133.918000
max             0.994000      0.996000      0.991000    239.440000

          duration_ms
count    32833.000000
unique            NaN
top               NaN
freq              NaN
mean    225799.811622
std      59834.006182
min       4000.000000
25%     187819.000000
50%     216000.000000
75%     253585.000000
max     517810.000000

[11 rows x 23 columns]
```

[24]:

```python
# Genre Feature Radar Chart (Interactive)
genre_means = data.groupby('playlist_genre')[audio_features].mean().
 ↪reset_index()

fig = go.Figure()
for genre in genre_means['playlist_genre']:
    fig.add_trace(go.Scatterpolar(
        r=genre_means[genre_means['playlist_genre'] == genre][audio_features].
 ↪values[0],
```

```
        theta=audio_features,
        fill='toself',
        name=genre
    ))

fig.update_layout(
    polar=dict(radialaxis=dict(visible=True, range=[0, 1])),
    showlegend=True,
    title='Audio Feature Profiles by Genre',
    height=600
)
fig.show()
```

##Data Preprocessing

[25]:
```
# Handle duplicates
data = data.drop_duplicates(subset=['track_id'])

# Fix release dates
def fix_date(x):
    if pd.isnull(x):
        return x
    if isinstance(x, str):
        return f"{x}-01-01" if len(x) < 10 else x
    return x.strftime('%Y-%m-%d')

data['track_album_release_date'] = data['track_album_release_date'].
 ↪apply(fix_date)
data['track_album_release_date'] = pd.
 ↪to_datetime(data['track_album_release_date'], errors='coerce')


# Extract release year
data['release_year'] = data['track_album_release_date'].dt.year

# Encode Target Variable
label_encoder = LabelEncoder()
data['genre_label'] = label_encoder.fit_transform(data['playlist_genre'])
print("  Target encoding complete!")
print(label_encoder.classes_)

# Feature Scaling
audio_features += ['duration_ms', 'release_year']
scaler = StandardScaler()
data[audio_features] = scaler.fit_transform(data[audio_features])
```

```
 Target encoding complete!
['edm' 'latin' 'pop' 'r&b' 'rap' 'rock']
```

[26]:
```python
print(data.isna().sum())
data = data.dropna()
```

```
track_id                    0
track_name                  4
track_artist                4
track_popularity            0
track_album_id              0
track_album_name            4
track_album_release_date   25
playlist_name               0
playlist_id                 0
playlist_genre              0
playlist_subgenre           0
danceability                0
energy                      0
key                         0
loudness                    0
mode                        0
speechiness                 0
acousticness                0
instrumentalness            0
liveness                    0
valence                     0
tempo                       0
duration_ms                 0
release_year               25
genre_label                 0
dtype: int64
```

[26]:
```python

```

[ ]:
```python
# Install kaleido for plotly static image export if needed
try:
    import kaleido
except ImportError:
    import subprocess
    import sys
    subprocess.check_call([sys.executable, "-m", "pip", "install", "kaleido"])
    import kaleido

warnings.filterwarnings("ignore", category=FutureWarning)

#
#   WHITE BACKGROUND & GOLDEN THEME SETUP
#

# Set up white background and golden color scheme
```

```python
plt.style.use('default') # Use default style for white background
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B', '#A0522D'] # Adjusted golden palette

print("  Libraries imported successfully!")
print("  White background and golden color scheme activated!")

# Define the base directory for saving plots in Google Drive
PLOT_SAVE_DIR = '/content/drive/MyDrive/music-genre-classification/images/eda'
os.makedirs(PLOT_SAVE_DIR, exist_ok=True)
print(f"  Plots will be saved to: {PLOT_SAVE_DIR}")


#
#   UPDATED VISUALIZATION CODE
#

# 1. GENRE DISTRIBUTION VISUALIZATION
def create_genre_distribution_plot(data):
    """Create genre distribution bar chart with white background and golden aesthetic"""
    plt.figure(figsize=(12, 6), facecolor='white')
    genre_counts = data['playlist_genre'].value_counts()
    ax = sns.barplot(x=genre_counts.index, y=genre_counts.values, palette=golden_palette)
    ax.set_facecolor('white')
    plt.title('Song Distribution by Genre', fontsize=18, color='black', fontweight='bold', pad=20)
    plt.xlabel('Genre', fontsize=14, color='black', fontweight='semibold')
    plt.ylabel('Count', fontsize=14, color='black', fontweight='semibold')

    # Style the plot
    ax.tick_params(colors='black', labelsize=11)
    ax.spines['bottom'].set_color('black')
    ax.spines['left'].set_color('black')
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.grid(True, alpha=0.2, color='gray')

    # Add percentage labels
    total = len(data)
    for p in ax.patches:
        percentage = f'{100 * p.get_height()/total:.1f}%'
        ax.annotate(percentage, (p.get_x() + p.get_width()/2., p.get_height()),
                    ha='center', va='center', xytext=(0, 10),
                    textcoords='offset points', fontsize=11, color='black', fontweight='bold')
```

```
    # Save the plot
    plt.savefig(os.path.join(PLOT_SAVE_DIR, 'genre_distribution.png'),
                facecolor='white', edgecolor='none', dpi=300,␣
 ↪bbox_inches='tight')
    plt.show()
    print(f" Plot saved to: {os.path.join(PLOT_SAVE_DIR, 'genre_distribution.
 ↪png')}")

# 2. CORRELATION MATRIX VISUALIZATION
def create_correlation_matrix(data):
    """Create correlation matrix heatmap with white background and golden␣
 ↪theme"""
    plt.figure(figsize=(14, 10), facecolor='white')
    audio_features = ['danceability', 'energy', 'loudness',
                     'acousticness', 'valence', 'tempo',
                     'speechiness', 'instrumentalness']
    corr_matrix = data[audio_features].corr()
    mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

    # Create custom colormap with golden tones
    colors = ['white', '#F5DEB3', '#D4AF37', '#CD853F', '#8B4513', '#2C1810']
    golden_cmap = LinearSegmentedColormap.from_list('golden', colors, N=256)

    ax = plt.gca()
    ax.set_facecolor('white')
    sns.heatmap(corr_matrix, mask=mask, annot=True, fmt=".2f",
                cmap=golden_cmap, linewidths=0.5, linecolor='gray',
                annot_kws={'color': 'black', 'fontweight': 'bold'},
                cbar_kws={'shrink': 0.8})
    plt.title("Audio Feature Correlation Matrix", fontsize=18, color='black',␣
 ↪fontweight='bold', pad=20)

    # Style axes
    ax.tick_params(colors='black', labelsize=11)
    plt.xticks(rotation=45, ha='right', color='black')
    plt.yticks(rotation=0, color='black')

    # Save the plot
    plt.savefig(os.path.join(PLOT_SAVE_DIR, 'correlation_matrix.png'),
                facecolor='white', edgecolor='none', dpi=300,␣
 ↪bbox_inches='tight')
    plt.show()
    print(f" Plot saved to: {os.path.join(PLOT_SAVE_DIR, 'correlation_matrix.
 ↪png')}")
```

```python
# 3. FEATURE DISTRIBUTION BOXPLOTS
def create_feature_boxplots(data):
    """Create feature distribution boxplots with white background and golden␣
↪theme"""
    audio_features = ['danceability', 'energy', 'loudness',
                     'acousticness', 'valence', 'tempo',
                     'speechiness', 'instrumentalness']

    plt.figure(figsize=(15, 10), facecolor='white')
    for i, feature in enumerate(audio_features[:6], 1):
        plt.subplot(2, 3, i)
        ax = plt.gca()
        ax.set_facecolor('white')

        sns.boxplot(x='playlist_genre', y=feature, data=data,␣
↪palette=golden_palette)
        plt.title(f'{feature.capitalize()} by Genre', fontsize=14,␣
↪color='black', fontweight='bold', pad=10)
        plt.xticks(rotation=45, color='black', fontsize=10)
        plt.yticks(color='black', fontsize=10)
        plt.xlabel('Genre', color='black', fontsize=11, fontweight='semibold')
        plt.ylabel(feature.capitalize(), color='black', fontsize=11,␣
↪fontweight='semibold')

        # Style the subplot
        ax.tick_params(colors='black')
        for spine in ax.spines.values():
            spine.set_color('black')
            spine.set_linewidth(0.8)
        ax.grid(True, alpha=0.2, color='gray')

    plt.tight_layout()
    # Save the plot
    plt.savefig(os.path.join(PLOT_SAVE_DIR, 'feature_distributions.png'),
                facecolor='white', edgecolor='none', dpi=300,␣
↪bbox_inches='tight')
    plt.show()
    print(f"  Plot saved to: {os.path.join(PLOT_SAVE_DIR,␣
↪'feature_distributions.png')}")

# 4. INTERACTIVE RADAR CHART
def create_radar_chart(data):
    """Create interactive radar chart with white background and golden theme"""
    audio_features = ['danceability', 'energy', 'loudness',
                     'acousticness', 'valence', 'tempo',
                     'speechiness', 'instrumentalness']
```

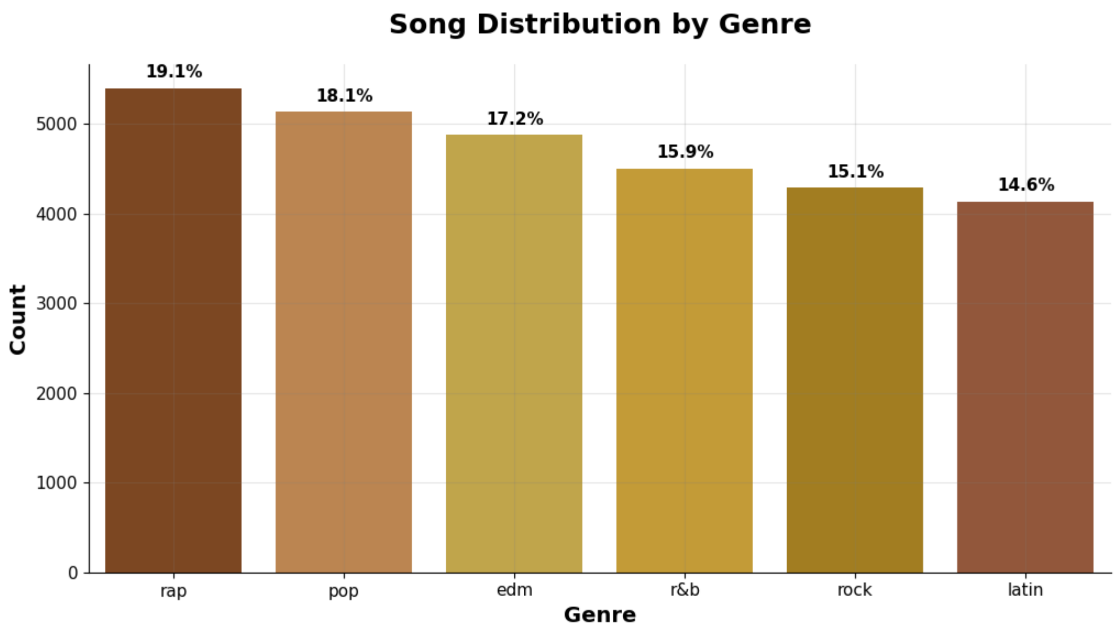
```
    genre_means = data.groupby('playlist_genre')[audio_features].mean().
↪reset_index()

    # Define golden color palette for radar chart
    radar_colors = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
↪'#A0522D'] # Adjusted golden palette

    fig = go.Figure()
    for i, genre in enumerate(genre_means['playlist_genre']):
        fig.add_trace(go.Scatterpolar(
            r=genre_means[genre_means['playlist_genre'] ==␣
↪genre][audio_features].values[0],
            theta=audio_features,
            fill='toself',
            name=genre,
            line=dict(color=radar_colors[i % len(radar_colors)], width=3),
            fillcolor=radar_colors[i % len(radar_colors)],
            opacity=0.6
        ))

    fig.update_layout(
        polar=dict(
            radialaxis=dict(
                visible=True,
                range=[0, 1],
                tickfont=dict(color='black', size=12),
                gridcolor='gray',
                linecolor='gray'
            ),
            angularaxis=dict(
                tickfont=dict(color='black', size=12),
                gridcolor='gray',
                linecolor='gray'
            ),
            bgcolor='white'
        ),
        showlegend=True,
        title=dict(
            text='Audio Feature Profiles by Genre',
            font=dict(color='black', size=18, family='Arial Black'),
            x=0.5
        ),
        height=600,
        paper_bgcolor='white',
        plot_bgcolor='white',
        font=dict(color='black'),
```

```
        legend=dict(
            font=dict(color='black', size=12),
            bgcolor='rgba(255, 255, 255, 0.8)',
            bordercolor='gray',
            borderwidth=1
        )
    )

    # Save the interactive plot as HTML
    fig.write_html(os.path.join(PLOT_SAVE_DIR, 'radar_chart.html'))
    # fig.write_image(os.path.join(PLOT_SAVE_DIR, 'radar_chart.png'),␣
 ↪width=800, height=600) # Still commenting this out due to kaleido issues
    fig.show()
    print(f" Interactive plot saved to: {os.path.join(PLOT_SAVE_DIR,␣
 ↪'radar_chart.html')}")
    # print(f" Static plot saved to: {os.path.join(PLOT_SAVE_DIR, 'radar_chart.
 ↪png')}")

#
#   USAGE INSTRUCTIONS
#

"""
USAGE INSTRUCTIONS:

1. Replace your existing plotting cells in the notebook with the function calls:

   # Instead of the old genre distribution code, use:
   create_genre_distribution_plot(data)

   # Instead of the old correlation matrix code, use:
   create_correlation_matrix(data)

   # Instead of the old boxplot code, use:
   create_feature_boxplots(data)

   # Instead of the old radar chart code, use:
   create_radar_chart(data)

2. All plots will automatically be saved to the directory specified by␣
 ↪PLOT_SAVE_DIR

3. The color scheme matches your presentation slide with:
   - Dark brown background (#2C1810)
   - Golden palette for data visualization
   - Elegant typography and styling
```

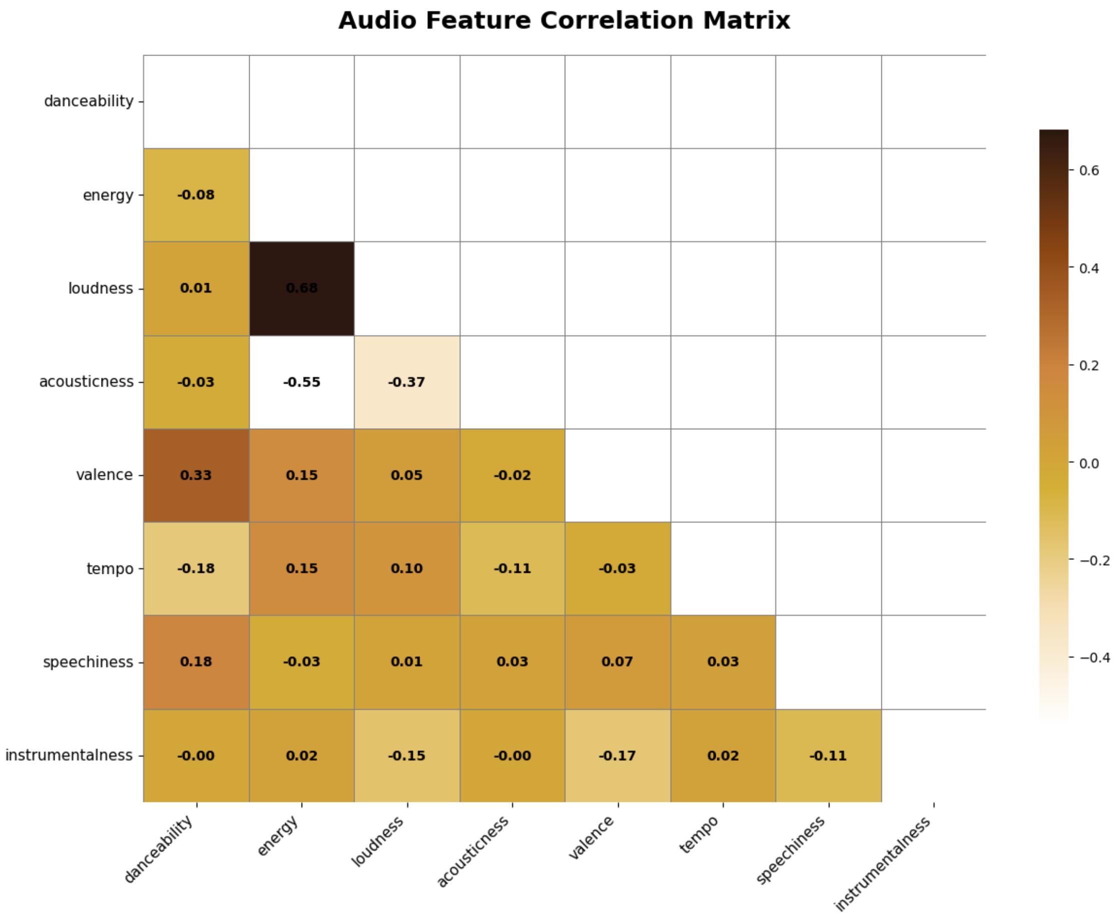
```
4. Make sure your data loading path is correct for your environment:
   - Colab: '/content/spotify_songs.csv'
   - Local: './data/spotify_songs.csv'
   - Current: '/workspace/data/spotify_songs.csv'
"""

print("  Updated Feature Engineering Code Ready!")
print("  Copy the functions above into your notebook cells")
print("  Your visualizations will match the slide aesthetic perfectly!")
```

```
 Libraries imported successfully!
 White background and golden color scheme activated!
 Plots will be saved to: /content/drive/MyDrive/music-genre-
classification/images/eda
 Updated Feature Engineering Code Ready!
 Copy the functions above into your notebook cells
 Your visualizations will match the slide aesthetic perfectly!
```

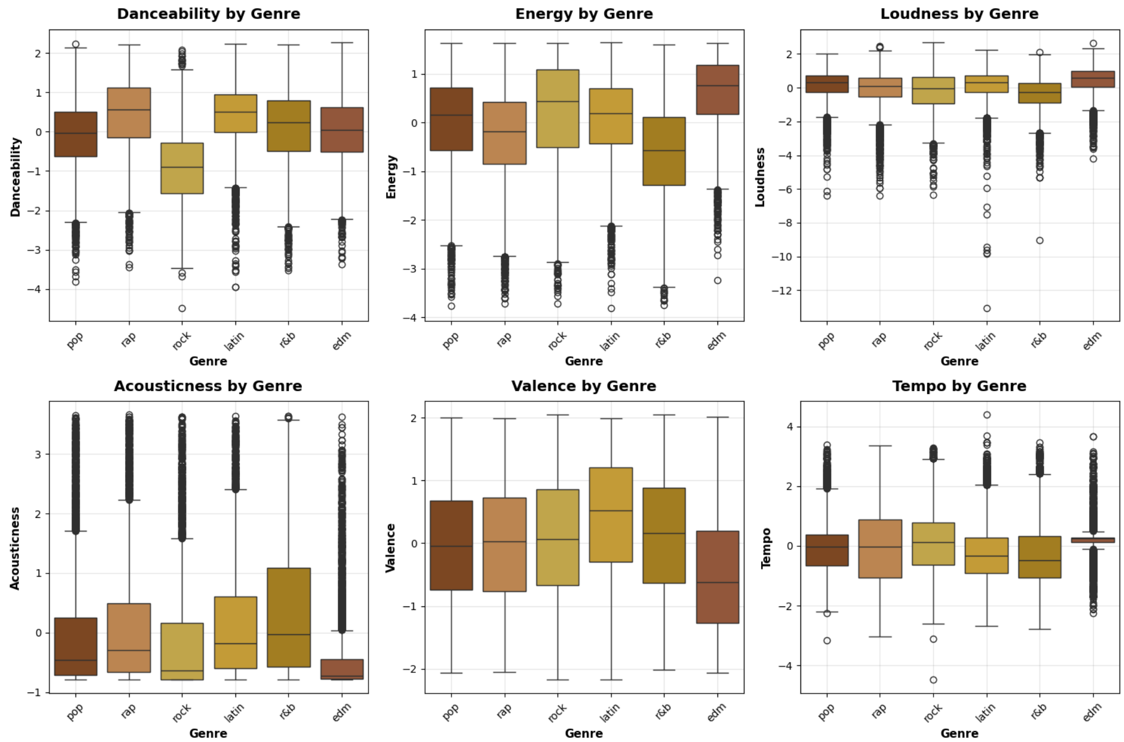
[38]:
```
# Call the plotting functions to generate and save plots
create_genre_distribution_plot(data)
create_correlation_matrix(data)
create_feature_boxplots(data)
create_radar_chart(data)
```




```
 Plot saved to: /content/drive/MyDrive/music-genre-
classification/images/eda/genre_distribution.png
```




```
Plot saved to: /content/drive/MyDrive/music-genre-
classification/images/eda/correlation_matrix.png
```




```
Plot saved to: /content/drive/MyDrive/music-genre-
classification/images/eda/feature_distributions.png

Interactive plot saved to: /content/drive/MyDrive/music-genre-
classification/images/eda/radar_chart.html
```

[31]:

```
%pip install -U kaleido
```

```
Requirement already satisfied: kaleido in /usr/local/lib/python3.11/dist-
packages (1.0.0)
Requirement already satisfied: choreographer>=1.0.5 in
/usr/local/lib/python3.11/dist-packages (from kaleido) (1.0.9)
Requirement already satisfied: logistro>=1.0.8 in
/usr/local/lib/python3.11/dist-packages (from kaleido) (1.1.0)
Requirement already satisfied: orjson>=3.10.15 in
/usr/local/lib/python3.11/dist-packages (from kaleido) (3.11.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-
packages (from kaleido) (25.0)
Requirement already satisfied: simplejson>=3.19.3 in
/usr/local/lib/python3.11/dist-packages (from choreographer>=1.0.5->kaleido)
(3.20.1)
```

02_Modeling

August 10, 2025

##Project: Music Genre Classification using Machine Learning

Niyat Kahsay & Marwah Faraj Summer 2025

Description:

This project aims to automatically classify songs into genres based on audio features provided in the Spotify 1.2M Songs Dataset. The workflow includes data exploration, preprocessing, model building, evaluation, and visualization.

Purpose:

Apply supervised learning techniques on real-world audio data Explore audio feature-based genre classification Build a portfolio-ready project demonstrating practical machine learning skills

#Data Preparation

0.1 Import Libraries

[1]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import confusion_matrix
from imblearn.over_sampling import SMOTE
from xgboost import XGBClassifier
from sklearn.metrics import (accuracy_score, confusion_matrix,
                             classification_report, f1_score)
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import␣
 ↪cross_val_score,GridSearchCV,train_test_split
from sklearn.svm import SVC
```

```python
from sklearn.decomposition import PCA
import numpy as np
import time
import pandas as pd
import plotly.express as px
from scipy.stats import mode
import warnings

warnings.filterwarnings("ignore", category=FutureWarning)
```

0.2 Load Data

[2]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

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

[3]:
```python
import pandas as pd
data = pd.read_csv('/content/drive/MyDrive/music-genre-classification/data/
↪spotify_songs.csv')
data.head()
```

[3]:
```
                 track_id                                          track_name  \
0  6f807x0ima9a1j3VPbc7VN  I Don't Care (with Justin Bieber) - Loud Luxur…
1  0r7CVbZTWZgbTCYdfa2P31                     Memories - Dillon Francis Remix
2  1z1Hg7Vb0AhHDiEmnDE79l                     All the Time - Don Diablo Remix
3  75FpbthrwQmzHlBJLuGdC7                   Call You Mine - Keanu Silva Remix
4  1e8PAfcKUYoKkxPhrHqw4x             Someone You Loved - Future Humans Remix

       track_artist  track_popularity          track_album_id  \
0        Ed Sheeran                66  2oCs0DGTsRO98Gh5ZSl2Cx
1          Maroon 5                67  63rPSO264uRjW1X5E6cWv6
2      Zara Larsson                70  1HoSmj2eLcsrR0vE9gThr4
3  The Chainsmokers                60  1nqYsOef1yKKuGOVchbsk6
4     Lewis Capaldi                69  7m7vv9wlQ4i0LFuJiE2zsQ

                                    track_album_name track_album_release_date  \
0  I Don't Care (with Justin Bieber) [Loud Luxury…               2019-06-14
1                      Memories (Dillon Francis Remix)               2019-12-13
2                      All the Time (Don Diablo Remix)               2019-07-05
3                          Call You Mine - The Remixes               2019-07-19
4              Someone You Loved (Future Humans Remix)               2019-03-05

  playlist_name             playlist_id playlist_genre  … key  loudness  \
0     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   6    -2.634
1     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …  11    -4.969
2     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   1    -3.432
3     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   7    -3.778
```

```
4     Pop Remix  37i9dQZF1DXcZDD7cfEKhW           pop  …   1    -4.672

   mode  speechiness  acousticness  instrumentalness  liveness  valence  \
0     1       0.0583        0.1020          0.000000    0.0653    0.518
1     1       0.0373        0.0724          0.004210    0.3570    0.693
2     0       0.0742        0.0794          0.000023    0.1100    0.613
3     1       0.1020        0.0287          0.000009    0.2040    0.277
4     1       0.0359        0.0803          0.000000    0.0833    0.725

     tempo  duration_ms
0  122.036       194754
1   99.972       162600
2  124.008       176616
3  121.956       169093
4  123.976       189052

[5 rows x 23 columns]
```

#Data Exploration

[4]:
```python
print(data.columns)
```

```
Index(['track_id', 'track_name', 'track_artist', 'track_popularity',
       'track_album_id', 'track_album_name', 'track_album_release_date',
       'playlist_name', 'playlist_id', 'playlist_genre', 'playlist_subgenre',
       'danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms'],
      dtype='object')
```

[5]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32833 entries, 0 to 32832
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   track_id                  32833 non-null  object
 1   track_name                32828 non-null  object
 2   track_artist              32828 non-null  object
 3   track_popularity          32833 non-null  int64
 4   track_album_id            32833 non-null  object
 5   track_album_name          32828 non-null  object
 6   track_album_release_date  32833 non-null  object
 7   playlist_name             32833 non-null  object
 8   playlist_id               32833 non-null  object
 9   playlist_genre            32833 non-null  object
 10  playlist_subgenre         32833 non-null  object
 11  danceability              32833 non-null  float64
```

```
 12  energy                    32833 non-null  float64
 13  key                       32833 non-null  int64
 14  loudness                  32833 non-null  float64
 15  mode                      32833 non-null  int64
 16  speechiness               32833 non-null  float64
 17  acousticness              32833 non-null  float64
 18  instrumentalness          32833 non-null  float64
 19  liveness                  32833 non-null  float64
 20  valence                   32833 non-null  float64
 21  tempo                     32833 non-null  float64
 22  duration_ms               32833 non-null  int64
dtypes: float64(9), int64(4), object(10)
memory usage: 5.8+ MB
```

[6]:
```
data.describe(include = "all")
```

[6]:
```
                      track_id track_name    track_artist  track_popularity  \
count                    32833      32828           32828      32833.000000
unique                   28356      23449           10692               NaN
top     7BKLCZ1jbUBVqRi2FVlTVw     Poison  Martin Garrix               NaN
freq                        10         22             161               NaN
mean                       NaN        NaN             NaN         42.477081
std                        NaN        NaN             NaN         24.984074
min                        NaN        NaN             NaN          0.000000
25%                        NaN        NaN             NaN         24.000000
50%                        NaN        NaN             NaN         45.000000
75%                        NaN        NaN             NaN         62.000000
max                        NaN        NaN             NaN        100.000000

                track_album_id track_album_name track_album_release_date  \
count                    32833            32828                    32833
unique                   22545            19743                     4530
top     5L1xcowSxwzFUSJzvyMp48    Greatest Hits               2020-01-10
freq                        42              139                      270
mean                       NaN              NaN                      NaN
std                        NaN              NaN                      NaN
min                        NaN              NaN                      NaN
25%                        NaN              NaN                      NaN
50%                        NaN              NaN                      NaN
75%                        NaN              NaN                      NaN
max                        NaN              NaN                      NaN

           playlist_name             playlist_id playlist_genre  …  \
count              32833                   32833          32833  …
unique               449                     471              6  …
top     Indie Poptimism  4JkkvMpVl4lSioqQjeAL0q            edm  …
freq                 308                     247           6043  …
```

```
mean                  NaN                     NaN            NaN  …
std                   NaN                     NaN            NaN  …
min                   NaN                     NaN            NaN  …
25%                   NaN                     NaN            NaN  …
50%                   NaN                     NaN            NaN  …
75%                   NaN                     NaN            NaN  …
max                   NaN                     NaN            NaN  …

                 key      loudness          mode   speechiness  acousticness  \
count   32833.000000  32833.000000  32833.000000  32833.000000  32833.000000
unique           NaN           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN           NaN
mean        5.374471     -6.719499      0.565711      0.107068      0.175334
std         3.611657      2.988436      0.495671      0.101314      0.219633
min         0.000000    -46.448000      0.000000      0.000000      0.000000
25%         2.000000     -8.171000      0.000000      0.041000      0.015100
50%         6.000000     -6.166000      1.000000      0.062500      0.080400
75%         9.000000     -4.645000      1.000000      0.132000      0.255000
max        11.000000      1.275000      1.000000      0.918000      0.994000

        instrumentalness      liveness       valence         tempo  \
count       32833.000000  32833.000000  32833.000000  32833.000000
unique               NaN           NaN           NaN           NaN
top                  NaN           NaN           NaN           NaN
freq                 NaN           NaN           NaN           NaN
mean            0.084747      0.190176      0.510561    120.881132
std             0.224230      0.154317      0.233146     26.903624
min             0.000000      0.000000      0.000000      0.000000
25%             0.000000      0.092700      0.331000     99.960000
50%             0.000016      0.127000      0.512000    121.984000
75%             0.004830      0.248000      0.693000    133.918000
max             0.994000      0.996000      0.991000    239.440000

          duration_ms
count    32833.000000
unique            NaN
top               NaN
freq              NaN
mean    225799.811622
std      59834.006182
min       4000.000000
25%     187819.000000
50%     216000.000000
75%     253585.000000
max     517810.000000
```

```
[11 rows x 23 columns]
```

```
[7]: # Feature engineering
data['track_album_release_year'] = pd.to_datetime(
      data['track_album_release_date'], errors='coerce').dt.year
data['track_album_release_year'].fillna(data['track_album_release_year'].
 ↪median(), inplace=True)
data['duration_s'] = data['duration_ms'] / 1000  # Convert to seconds
data.drop('duration_ms', axis=1, inplace=True)
```

```
[8]: # Encode target variable
genre_encoder = LabelEncoder()
data['genre_encoded'] = genre_encoder.fit_transform(data['playlist_genre'])
```

```
[9]: # Select relevant features
features = ['danceability', 'energy', 'key', 'loudness', 'mode',
            'speechiness', 'acousticness', 'instrumentalness',
            'liveness', 'valence', 'tempo', 'duration_s',
            'track_popularity', 'track_album_release_year']

X = data[features]
y = data['genre_encoded']
```

```
[10]: # Split data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)
```

```
[11]: # Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

##Model Development

```
[12]: models = {
    'Random Forest': RandomForestClassifier(random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'XGBoost': XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='mlogloss'),
    'SVM': SVC(random_state=42, probability=True)
}
```

```
[13]: # Cross-validation evaluation
results = {}
for name, model in models.items():
    start_time = time.time()
    cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=5,␣
 ↪scoring='accuracy')
```

```
    results[name] = {
        'cv_accuracy': np.mean(cv_scores),
        'cv_time': time.time() - start_time
    }
    print(f"{name} - Avg CV Accuracy: {np.mean(cv_scores):.4f} - Time:␣
↪{results[name]['cv_time']:.2f}s")
```

```
Random Forest - Avg CV Accuracy: 0.5739 - Time: 53.64s
Gradient Boosting - Avg CV Accuracy: 0.5715 - Time: 264.90s
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:03:01] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:03:07] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:03:11] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:03:14] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:03:20] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
XGBoost - Avg CV Accuracy: 0.5876 - Time: 21.61s
SVM - Avg CV Accuracy: 0.5548 - Time: 742.22s
```

[14]:
```
# Select best model based on CV
best_model_name = max(results, key=lambda x: results[x]['cv_accuracy'])
print(f"\nBest model from CV: {best_model_name}")
```

```

Best model from CV: XGBoost
```

[15]:
```
# Hyperparameter tuning for best model
# Best model: XGBoost
param_grid = {
```

```
    'n_estimators': [100, 200],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 5],
    'subsample': [0.8, 1.0]
}

grid_search = GridSearchCV(
    models['XGBoost'],
    param_grid,
    cv=3,
    scoring='accuracy',
    n_jobs=-1,
    verbose=1
)

grid_search.fit(X_train_scaled, y_train)

# Get best model
best_model = grid_search.best_estimator_
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV accuracy: {grid_search.best_score_:.4f}")
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:17:55] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
Best parameters: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200,
'subsample': 0.8}
Best CV accuracy: 0.5883
```

##Model Evaluation

[16]:
```
# Train final model
best_model.fit(X_train_scaled, y_train)

# Predictions
y_pred = best_model.predict(X_test_scaled)
y_proba = best_model.predict_proba(X_test_scaled)

# Evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred, average='weighted')
class_report = classification_report(y_test, y_pred, target_names=genre_encoder.
 ↪classes_)
```

```
print("\n" + "="*50)
print(f"Final Model: {best_model_name}")
print(f"Test Accuracy: {accuracy:.4f}")
print(f"Weighted F1 Score: {f1:.4f}")
print("\nClassification Report:")
print(class_report)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:18:04] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)


==================================================
Final Model: XGBoost
Test Accuracy: 0.5959
Weighted F1 Score: 0.5940

Classification Report:
              precision    recall  f1-score   support

         edm       0.69      0.70      0.70      1209
       latin       0.53      0.48      0.51      1031
         pop       0.43      0.45      0.44      1102
         r&b       0.55      0.48      0.51      1086
         rap       0.61      0.67      0.64      1149
        rock       0.76      0.79      0.77       990

    accuracy                           0.60      6567
   macro avg       0.59      0.60      0.59      6567
weighted avg       0.59      0.60      0.59      6567
```

Low performance in 'latin' and 'pop. Will do, resampling

[17]:
```
from imblearn.over_sampling import SMOTE
# Apply SMOTE to training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_scaled,␣
↪y_train)
```

[18]:
```
grid_search_smote = GridSearchCV(
    models['XGBoost'],  # Same XGBoost model
    param_grid,
    cv=3,
    scoring='accuracy',
    n_jobs=-1,
    verbose=1
```

```
)

# Fit the model on the SMOTE-balanced data
grid_search_smote.fit(X_train_resampled, y_train_resampled)

# Predict on the original test set (not resampled!)
y_pred_smote = grid_search_smote.predict(X_test_scaled)
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:20:31] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

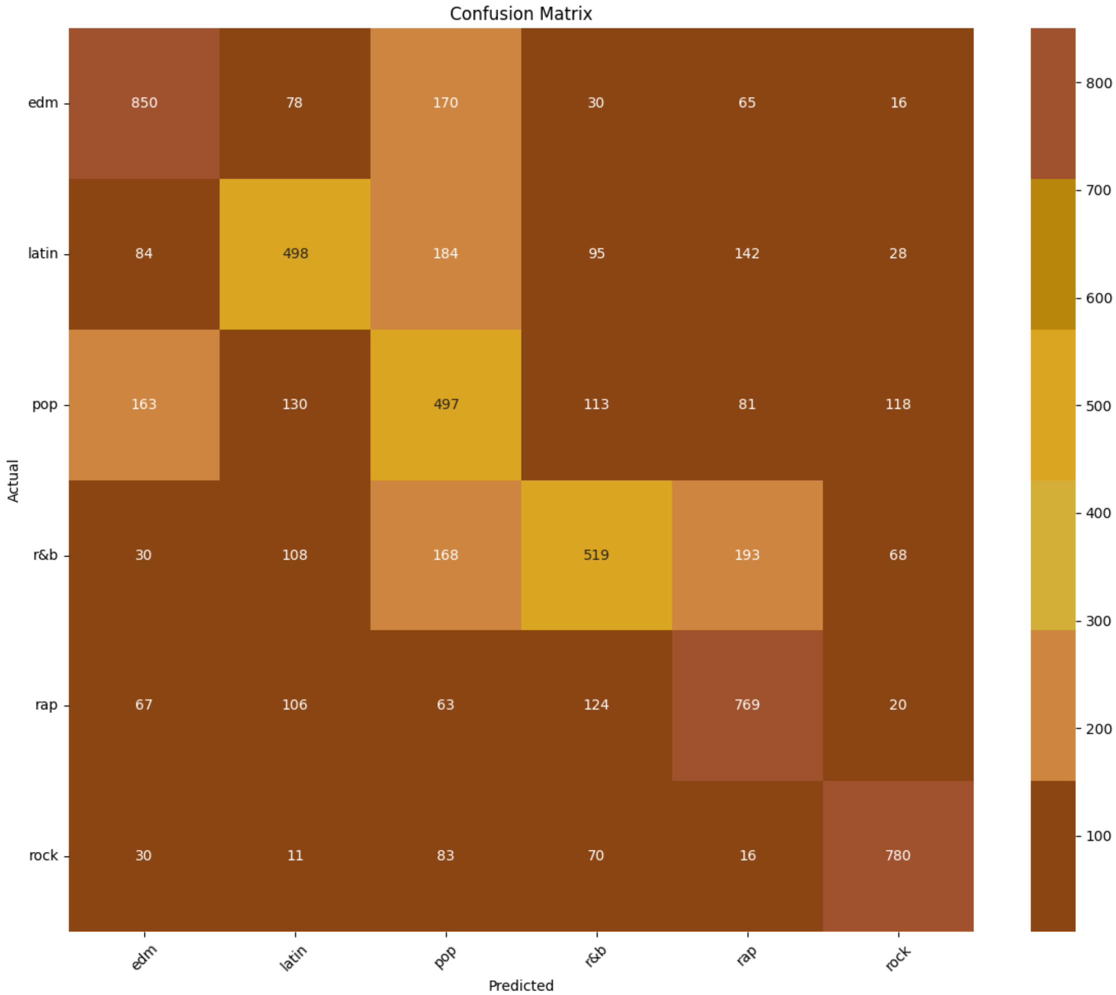
[19]:
```
from sklearn.metrics import accuracy_score, f1_score, classification_report

print("\n" + "="*50)
print("SMOTE Model Performance:")
print("Test Accuracy:", accuracy_score(y_test, y_pred_smote))
print("Weighted F1 Score:", f1_score(y_test, y_pred_smote, average='weighted'))
print("\nClassification Report:\n", classification_report(y_test, y_pred_smote))
```

```

==================================================
SMOTE Model Performance:
Test Accuracy: 0.596771737475255
Weighted F1 Score: 0.5949522484302238

Classification Report:
               precision    recall  f1-score   support

           0       0.71      0.69      0.70      1209
           1       0.52      0.51      0.51      1031
           2       0.43      0.44      0.44      1102
           3       0.54      0.47      0.50      1086
           4       0.62      0.67      0.64      1149
           5       0.74      0.80      0.77       990

    accuracy                           0.60      6567
   macro avg       0.59      0.60      0.59      6567
weighted avg       0.59      0.60      0.59      6567
```

##But some results went down, so we are keeping the original model

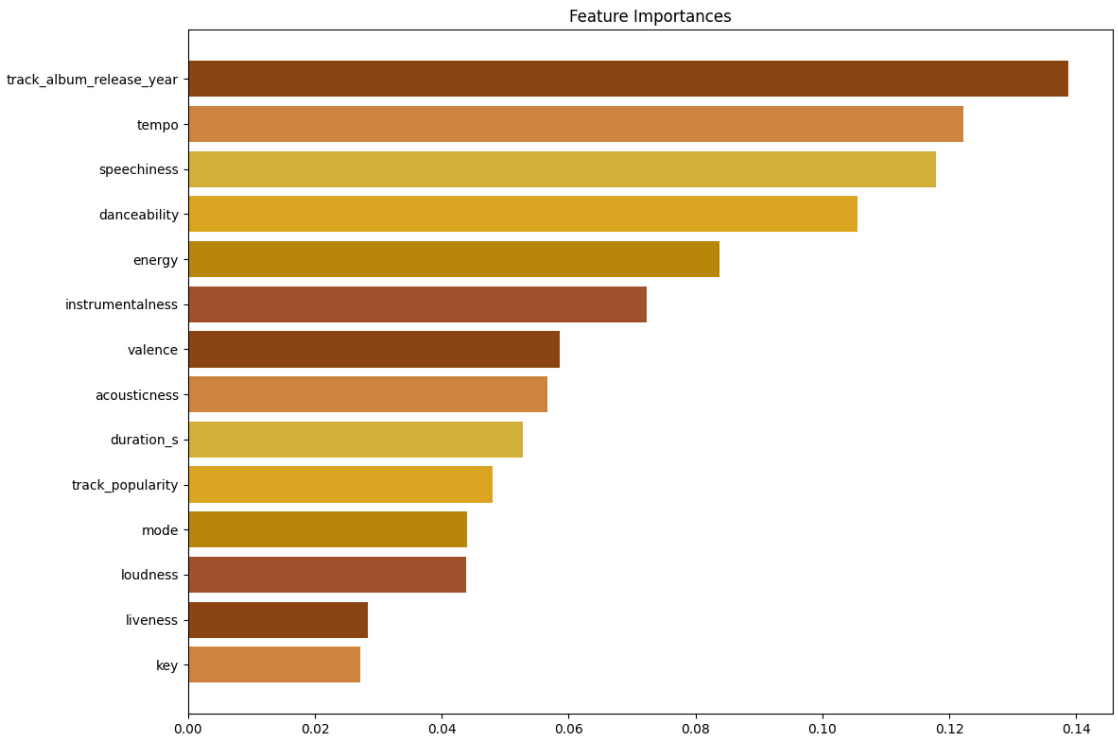
[20]:
```
import os
import matplotlib.pyplot as plt # Import pyplot
```

```python
import seaborn as sns # Import seaborn if needed
import numpy as np # Import numpy if needed
from sklearn.metrics import confusion_matrix # Import confusion_matrix if needed


# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')

# Set up white background and golden color scheme
plt.style.use('default') # Use default style for white background
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
 ↪'#A0522D'] # Adjusted golden palette


# Confusion matrix
plt.figure(figsize=(12, 10))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap=golden_palette,
              xticklabels=genre_encoder.classes_,
              yticklabels=genre_encoder.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.savefig('images/models/confusion_matrix.png')
plt.show()
```



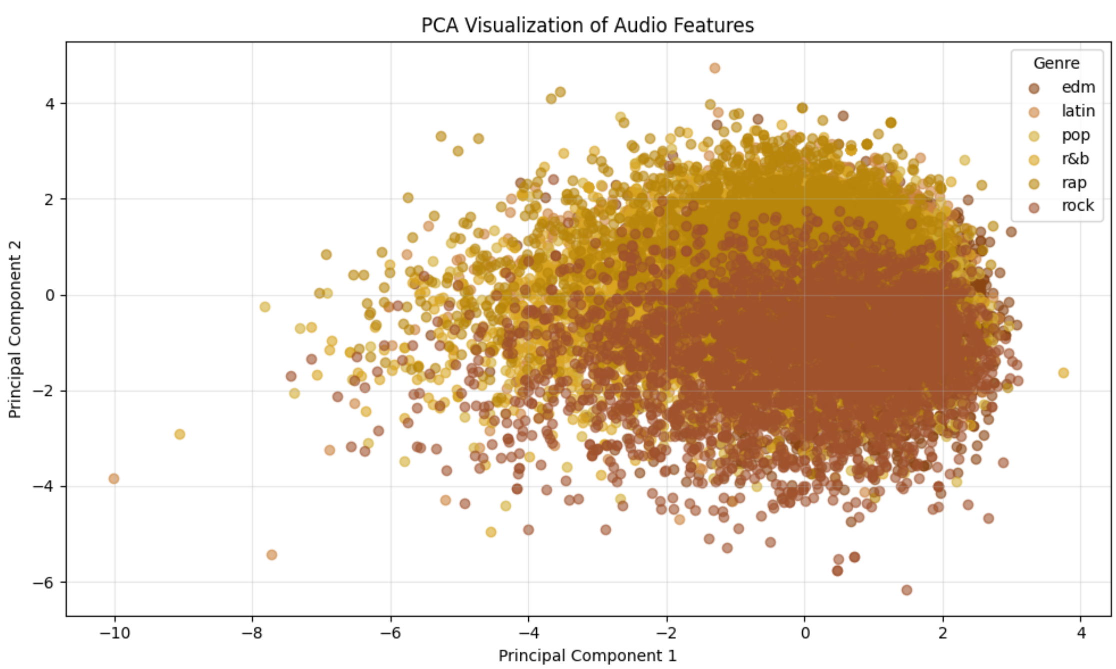
[21]:
```python
import os
import matplotlib.pyplot as plt # Import pyplot
import numpy as np # Import numpy if needed

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')

# Set up white background and golden color scheme
plt.style.use('default') # Use default style for white background
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
↪'#A0522D'] # Adjusted golden palette


# Feature importance
if hasattr(best_model, 'feature_importances_'):
```

```
    plt.figure(figsize=(12, 8))
    importances = best_model.feature_importances_
    indices = np.argsort(importances)[::-1]
    plt.title('Feature Importances')
    # Use all colors in the palette, repeating if necessary
    colors = np.tile(golden_palette, len(indices) // len(golden_palette) + 1)[:
↪len(indices)]
    plt.barh(range(len(indices)), importances[indices], align='center',␣
↪color=colors) # Changed color to use the palette
    plt.yticks(range(len(indices)), [features[i] for i in indices])
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.savefig('images/models/feature_importances.png')
    plt.show()
```



[22]:
```
import os
import matplotlib.pyplot as plt # Import pyplot
import numpy as np # Import numpy if needed
from sklearn.decomposition import PCA # Import PCA if needed

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')
```

```
# Set up white background and golden color scheme
plt.style.use('default') # Use default style for white background
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
 ↪'#A0522D'] # Adjusted golden palette


# PCA for dimensionality reduction (for visualization)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_train_scaled)

plt.figure(figsize=(10, 6))
for i, genre in enumerate(np.unique(y_train)):
    plt.scatter(X_pca[y_train == genre, 0],
                X_pca[y_train == genre, 1],
                label=genre_encoder.inverse_transform([genre])[0],
                alpha=0.6,
                color=golden_palette[i % len(golden_palette)])
plt.title('PCA Visualization of Audio Features')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Genre')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.savefig('images/models/pca_visualization.png')
plt.show()
```



0.3 Define the deep learning model

[23]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
import numpy as np

# Determine the number of unique genres
num_genres = len(np.unique(y_train))

# Define the deep learning model
dl_model = Sequential()

# Input layer and first hidden layer with dropout
dl_model.add(Dense(128, activation='relu', input_shape=(X_train_scaled.
 ↪shape[1],)))
dl_model.add(Dropout(0.3)) # Added dropout

# Second hidden layer with dropout
dl_model.add(Dense(64, activation='relu'))
dl_model.add(Dropout(0.3)) # Added dropout

# Output layer
dl_model.add(Dense(num_genres, activation='softmax'))

# Compile the model
dl_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy']) # Added compile

dl_model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:93:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	1,920
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256

```
 dropout_1 (Dropout)              (None, 64)                         0

 dense_2 (Dense)                  (None, 6)                        390
```

```
Total params: 10,566 (41.27 KB)

Trainable params: 10,566 (41.27 KB)

Non-trainable params: 0 (0.00 B)
```

0.4 Compile the model

[24]:
```
dl_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])
```

0.5 Train the model

[25]:
```
from tensorflow.keras.callbacks import EarlyStopping # Import EarlyStopping

# Instantiate EarlyStopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=15,␣
↪restore_best_weights=True) # Increased patience

history = dl_model.fit(X_train_scaled, y_train,
                       epochs=50,
                       batch_size=64,
                       validation_split=0.2,
                       callbacks=[early_stopping]) # Added EarlyStopping␣
↪callback
```

```
Epoch 1/50
329/329              3s 3ms/step -
accuracy: 0.3770 - loss: 1.5556 - val_accuracy: 0.4996 - val_loss: 1.2937
Epoch 2/50
329/329              1s 3ms/step -
accuracy: 0.4725 - loss: 1.3580 - val_accuracy: 0.5167 - val_loss: 1.2565
Epoch 3/50
329/329              1s 3ms/step -
accuracy: 0.4908 - loss: 1.3211 - val_accuracy: 0.5223 - val_loss: 1.2317
Epoch 4/50
329/329              1s 3ms/step -
accuracy: 0.5087 - loss: 1.2842 - val_accuracy: 0.5314 - val_loss: 1.2141
Epoch 5/50
```

```
329/329 1s 3ms/step -
accuracy: 0.5208 - loss: 1.2623 - val_accuracy: 0.5402 - val_loss: 1.1994
Epoch 6/50
329/329 1s 3ms/step -
accuracy: 0.5198 - loss: 1.2628 - val_accuracy: 0.5384 - val_loss: 1.1942
Epoch 7/50
329/329 1s 3ms/step -
accuracy: 0.5301 - loss: 1.2388 - val_accuracy: 0.5463 - val_loss: 1.1877
Epoch 8/50
329/329 1s 4ms/step -
accuracy: 0.5334 - loss: 1.2316 - val_accuracy: 0.5487 - val_loss: 1.1808
Epoch 9/50
329/329 1s 4ms/step -
accuracy: 0.5331 - loss: 1.2245 - val_accuracy: 0.5501 - val_loss: 1.1761
Epoch 10/50
329/329 2s 3ms/step -
accuracy: 0.5383 - loss: 1.2162 - val_accuracy: 0.5563 - val_loss: 1.1709
Epoch 11/50
329/329 1s 3ms/step -
accuracy: 0.5453 - loss: 1.2019 - val_accuracy: 0.5598 - val_loss: 1.1668
Epoch 12/50
329/329 1s 3ms/step -
accuracy: 0.5448 - loss: 1.1984 - val_accuracy: 0.5586 - val_loss: 1.1602
Epoch 13/50
329/329 1s 3ms/step -
accuracy: 0.5429 - loss: 1.1963 - val_accuracy: 0.5579 - val_loss: 1.1581
Epoch 14/50
329/329 1s 3ms/step -
accuracy: 0.5536 - loss: 1.1908 - val_accuracy: 0.5592 - val_loss: 1.1578
Epoch 15/50
329/329 1s 3ms/step -
accuracy: 0.5497 - loss: 1.1966 - val_accuracy: 0.5626 - val_loss: 1.1532
Epoch 16/50
329/329 1s 3ms/step -
accuracy: 0.5540 - loss: 1.1844 - val_accuracy: 0.5619 - val_loss: 1.1519
Epoch 17/50
329/329 1s 3ms/step -
accuracy: 0.5515 - loss: 1.1755 - val_accuracy: 0.5662 - val_loss: 1.1482
Epoch 18/50
329/329 1s 3ms/step -
accuracy: 0.5559 - loss: 1.1789 - val_accuracy: 0.5636 - val_loss: 1.1485
Epoch 19/50
329/329 1s 4ms/step -
accuracy: 0.5523 - loss: 1.1826 - val_accuracy: 0.5679 - val_loss: 1.1477
Epoch 20/50
329/329 2s 4ms/step -
accuracy: 0.5588 - loss: 1.1659 - val_accuracy: 0.5662 - val_loss: 1.1414
Epoch 21/50
```

```
329/329             1s 3ms/step -
accuracy: 0.5589 - loss: 1.1693 - val_accuracy: 0.5643 - val_loss: 1.1399
Epoch 22/50
329/329             1s 3ms/step -
accuracy: 0.5607 - loss: 1.1689 - val_accuracy: 0.5622 - val_loss: 1.1406
Epoch 23/50
329/329             1s 3ms/step -
accuracy: 0.5623 - loss: 1.1625 - val_accuracy: 0.5664 - val_loss: 1.1392
Epoch 24/50
329/329             1s 3ms/step -
accuracy: 0.5647 - loss: 1.1578 - val_accuracy: 0.5659 - val_loss: 1.1397
Epoch 25/50
329/329             1s 3ms/step -
accuracy: 0.5559 - loss: 1.1723 - val_accuracy: 0.5641 - val_loss: 1.1352
Epoch 26/50
329/329             1s 3ms/step -
accuracy: 0.5638 - loss: 1.1566 - val_accuracy: 0.5649 - val_loss: 1.1325
Epoch 27/50
329/329             1s 3ms/step -
accuracy: 0.5641 - loss: 1.1590 - val_accuracy: 0.5640 - val_loss: 1.1332
Epoch 28/50
329/329             1s 3ms/step -
accuracy: 0.5651 - loss: 1.1540 - val_accuracy: 0.5683 - val_loss: 1.1301
Epoch 29/50
329/329             1s 3ms/step -
accuracy: 0.5638 - loss: 1.1568 - val_accuracy: 0.5674 - val_loss: 1.1322
Epoch 30/50
329/329             1s 4ms/step -
accuracy: 0.5690 - loss: 1.1419 - val_accuracy: 0.5674 - val_loss: 1.1301
Epoch 31/50
329/329             2s 5ms/step -
accuracy: 0.5649 - loss: 1.1429 - val_accuracy: 0.5672 - val_loss: 1.1304
Epoch 32/50
329/329             2s 3ms/step -
accuracy: 0.5686 - loss: 1.1536 - val_accuracy: 0.5702 - val_loss: 1.1288
Epoch 33/50
329/329             1s 3ms/step -
accuracy: 0.5621 - loss: 1.1476 - val_accuracy: 0.5651 - val_loss: 1.1316
Epoch 34/50
329/329             2s 4ms/step -
accuracy: 0.5570 - loss: 1.1576 - val_accuracy: 0.5708 - val_loss: 1.1309
Epoch 35/50
329/329             2s 4ms/step -
accuracy: 0.5662 - loss: 1.1446 - val_accuracy: 0.5679 - val_loss: 1.1303
Epoch 36/50
329/329             1s 3ms/step -
accuracy: 0.5642 - loss: 1.1453 - val_accuracy: 0.5706 - val_loss: 1.1267
Epoch 37/50
```

```
329/329              1s 3ms/step -
accuracy: 0.5703 - loss: 1.1343 - val_accuracy: 0.5712 - val_loss: 1.1249
Epoch 38/50
329/329              1s 3ms/step -
accuracy: 0.5667 - loss: 1.1463 - val_accuracy: 0.5704 - val_loss: 1.1253
Epoch 39/50
329/329              1s 4ms/step -
accuracy: 0.5666 - loss: 1.1397 - val_accuracy: 0.5716 - val_loss: 1.1266
Epoch 40/50
329/329              2s 4ms/step -
accuracy: 0.5707 - loss: 1.1444 - val_accuracy: 0.5721 - val_loss: 1.1257
Epoch 41/50
329/329              2s 3ms/step -
accuracy: 0.5783 - loss: 1.1243 - val_accuracy: 0.5742 - val_loss: 1.1247
Epoch 42/50
329/329              1s 3ms/step -
accuracy: 0.5640 - loss: 1.1435 - val_accuracy: 0.5746 - val_loss: 1.1210
Epoch 43/50
329/329              1s 3ms/step -
accuracy: 0.5723 - loss: 1.1347 - val_accuracy: 0.5712 - val_loss: 1.1238
Epoch 44/50
329/329              1s 3ms/step -
accuracy: 0.5679 - loss: 1.1394 - val_accuracy: 0.5714 - val_loss: 1.1244
Epoch 45/50
329/329              1s 3ms/step -
accuracy: 0.5646 - loss: 1.1416 - val_accuracy: 0.5737 - val_loss: 1.1220
Epoch 46/50
329/329              1s 3ms/step -
accuracy: 0.5729 - loss: 1.1359 - val_accuracy: 0.5748 - val_loss: 1.1245
Epoch 47/50
329/329              1s 3ms/step -
accuracy: 0.5666 - loss: 1.1405 - val_accuracy: 0.5693 - val_loss: 1.1203
Epoch 48/50
329/329              2s 5ms/step -
accuracy: 0.5723 - loss: 1.1284 - val_accuracy: 0.5691 - val_loss: 1.1216
Epoch 49/50
329/329              2s 3ms/step -
accuracy: 0.5688 - loss: 1.1326 - val_accuracy: 0.5723 - val_loss: 1.1192
Epoch 50/50
329/329              1s 3ms/step -
accuracy: 0.5673 - loss: 1.1307 - val_accuracy: 0.5691 - val_loss: 1.1206
```

0.6 Evaluate the deep learning model

[26]:
```python
from sklearn.metrics import accuracy_score, f1_score, classification_report
import numpy as np
```

```
# Evaluate the model on the test data
loss, accuracy = dl_model.evaluate(X_test_scaled, y_test, verbose=0)
print(f"Deep Learning Model Test Accuracy: {accuracy:.4f}")

# Make predictions and calculate F1-score and classification report
y_pred_dl_proba = dl_model.predict(X_test_scaled)
y_pred_dl = np.argmax(y_pred_dl_proba, axis=1)

f1_dl = f1_score(y_test, y_pred_dl, average='weighted')
class_report_dl = classification_report(y_test, y_pred_dl,␣
↪target_names=genre_encoder.classes_)

print(f"Deep Learning Model Weighted F1 Score: {f1_dl:.4f}")
print("\nDeep Learning Model Classification Report:")
print(class_report_dl)
```

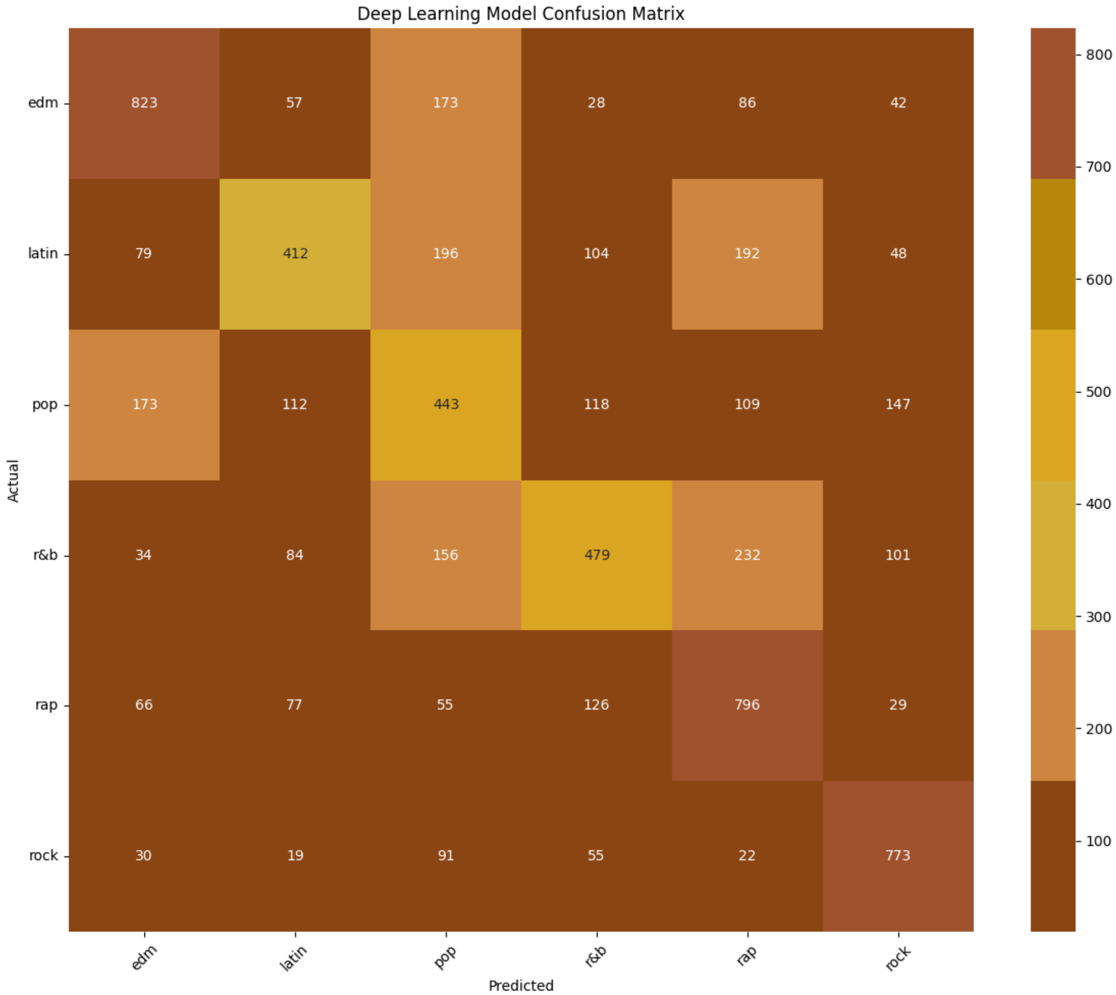
```
Deep Learning Model Test Accuracy: 0.5674
206/206              0s 1ms/step
Deep Learning Model Weighted F1 Score: 0.5613

Deep Learning Model Classification Report:
              precision    recall  f1-score   support

         edm       0.68      0.68      0.68      1209
       latin       0.54      0.40      0.46      1031
         pop       0.40      0.40      0.40      1102
         r&b       0.53      0.44      0.48      1086
         rap       0.55      0.69      0.62      1149
        rock       0.68      0.78      0.73       990

    accuracy                           0.57      6567
   macro avg       0.56      0.57      0.56      6567
weighted avg       0.56      0.57      0.56      6567
```

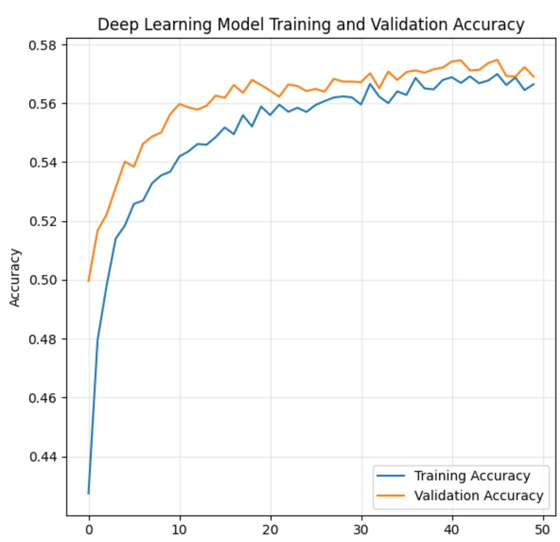
0.7 Compare models

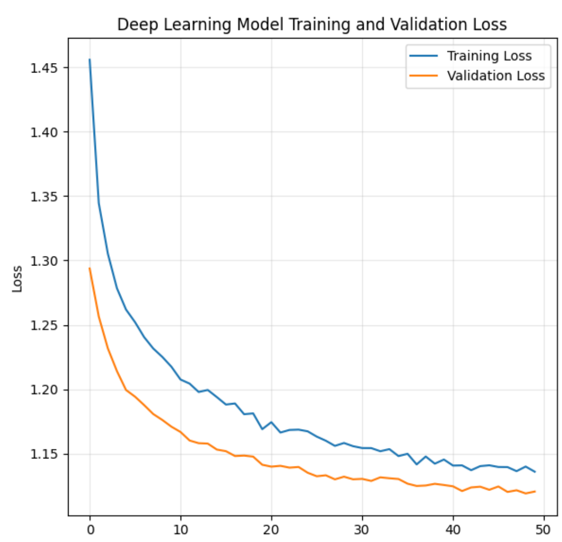
0.8 Visualize deep learning results

[27]:
```
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
import numpy as np

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')
```

```python
# Set up white background and golden color scheme
plt.style.use('default')
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
 ↪'#A0522D']

# Confusion matrix for Deep Learning Model
plt.figure(figsize=(12, 10))
cm_dl = confusion_matrix(y_test, y_pred_dl)
sns.heatmap(cm_dl, annot=True, fmt='d', cmap=golden_palette,
            xticklabels=genre_encoder.classes_,
            yticklabels=genre_encoder.classes_)
plt.title('Deep Learning Model Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.savefig('images/models/dl_confusion_matrix.png')
plt.show()

# Plot training history (accuracy and loss)
plt.figure(figsize=(12, 6))

# Plot accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Deep Learning Model Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(alpha=0.3)

# Plot loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Deep Learning Model Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(alpha=0.3)

plt.tight_layout()
plt.savefig('images/models/dl_training_history.png')
plt.show()
```


Deep Learning Model Confusion Matrix
Actual
Predicted
edm
latin
pop
r&b
rap
rock
823 57 173 28 86 42
79 412 196 104 192 48
173 112 443 118 109 147
34 84 156 479 232 101
66 77 55 126 796 29
30 19 91 55 22 773


Deep Learning Model Training and Validation Accuracy
Accuracy
Epoch
Training Accuracy
Validation Accuracy


Deep Learning Model Training and Validation Loss
Loss
Epoch
Training Loss
Validation Loss

0.9 Relocate and modify pca

[29]:
```python
from sklearn.decomposition import PCA

# Apply PCA for dimensionality reduction
pca = PCA(n_components=0.95)  # Retain 95% of variance
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

print(f"Original number of features: {X_train_scaled.shape[1]}")
print(f"Reduced number of features after PCA: {X_train_pca.shape[1]}")
```

```
Original number of features: 14
Reduced number of features after PCA: 12
```

0.10 Train traditional ml models with pca

[30]:
```python
# Train traditional models on PCA-transformed data
models_pca = {}
for name, model in models.items():
    start_time = time.time()
    model.fit(X_train_pca, y_train)
    models_pca[f'{name}_PCA'] = model
    print(f"{name} (PCA) - Training Time: {time.time() - start_time:.2f}s")
```

```
Random Forest (PCA) - Training Time: 14.54s
Gradient Boosting (PCA) - Training Time: 114.52s
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning:
[23:24:02] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
XGBoost (PCA) - Training Time: 3.65s
SVM (PCA) - Training Time: 214.44s
```

[31]:
```python
from sklearn.metrics import accuracy_score, f1_score, classification_report

# Evaluate traditional models on PCA-transformed test data
results_pca = {}
for name, model in models_pca.items():
    y_pred_pca = model.predict(X_test_pca)
    accuracy_pca = accuracy_score(y_test, y_pred_pca)
    f1_pca = f1_score(y_test, y_pred_pca, average='weighted')
    results_pca[name] = {
```

```
        'test_accuracy': accuracy_pca,
        'weighted_f1': f1_pca
    }
    print(f"\n{name} - Test Accuracy: {accuracy_pca:.4f}")
    print(f"{name} - Weighted F1 Score: {f1_pca:.4f}")
    # Print classification report for detailed analysis
    # print(f"\n{name} Classification Report:\n", classification_report(y_test,␣
↪y_pred_pca, target_names=genre_encoder.classes_))
```

```
Random Forest_PCA - Test Accuracy: 0.5173
Random Forest_PCA - Weighted F1 Score: 0.5131

Gradient Boosting_PCA - Test Accuracy: 0.5071
Gradient Boosting_PCA - Weighted F1 Score: 0.5055

XGBoost_PCA - Test Accuracy: 0.5228
XGBoost_PCA - Weighted F1 Score: 0.5203

SVM_PCA - Test Accuracy: 0.5381
SVM_PCA - Weighted F1 Score: 0.5350
```

0.11 Define and compile deep learning model for pca data

[32]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
import numpy as np

# Determine the number of unique genres
num_genres = len(np.unique(y_train))

# Define the deep learning model for PCA-transformed data
dl_model_pca = Sequential()

# Input layer and first hidden layer with dropout, using PCA-transformed input␣
↪shape
dl_model_pca.add(Dense(128, activation='relu', input_shape=(X_train_pca.
↪shape[1],)))
dl_model_pca.add(Dropout(0.3)) # Added dropout

# Second hidden layer with dropout
dl_model_pca.add(Dense(64, activation='relu'))
dl_model_pca.add(Dropout(0.3)) # Added dropout

# Output layer
dl_model_pca.add(Dense(num_genres, activation='softmax'))
```

```
# Compile the model
dl_model_pca.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy']) # Added compile

dl_model_pca.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:93:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 128)	1,664
dropout_2 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 64)	8,256
dropout_3 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 6)	390

Total params: 10,310 (40.27 KB)

Trainable params: 10,310 (40.27 KB)

Non-trainable params: 0 (0.00 B)

0.12 Train deep learning model with pca

[33]:
```
from tensorflow.keras.callbacks import EarlyStopping

# Instantiate EarlyStopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=15,␣
↪restore_best_weights=True)

# Train the deep learning model for PCA-transformed data
history_pca = dl_model_pca.fit(X_train_pca, y_train,
                               epochs=50,
```

```
                        batch_size=64,
                        validation_split=0.2,
                        callbacks=[early_stopping])
```

```
Epoch 1/50
329/329              3s 6ms/step -
accuracy: 0.3636 - loss: 1.5692 - val_accuracy: 0.4909 - val_loss: 1.3089
Epoch 2/50
329/329              2s 3ms/step -
accuracy: 0.4691 - loss: 1.3611 - val_accuracy: 0.5027 - val_loss: 1.2749
Epoch 3/50
329/329              2s 5ms/step -
accuracy: 0.4893 - loss: 1.3214 - val_accuracy: 0.5110 - val_loss: 1.2566
Epoch 4/50
329/329              2s 4ms/step -
accuracy: 0.4955 - loss: 1.3008 - val_accuracy: 0.5194 - val_loss: 1.2383
Epoch 5/50
329/329              2s 3ms/step -
accuracy: 0.5022 - loss: 1.2836 - val_accuracy: 0.5154 - val_loss: 1.2323
Epoch 6/50
329/329              1s 3ms/step -
accuracy: 0.5102 - loss: 1.2700 - val_accuracy: 0.5242 - val_loss: 1.2237
Epoch 7/50
329/329              1s 3ms/step -
accuracy: 0.5094 - loss: 1.2721 - val_accuracy: 0.5287 - val_loss: 1.2158
Epoch 8/50
329/329              2s 4ms/step -
accuracy: 0.5235 - loss: 1.2465 - val_accuracy: 0.5327 - val_loss: 1.2113
Epoch 9/50
329/329              2s 5ms/step -
accuracy: 0.5247 - loss: 1.2439 - val_accuracy: 0.5312 - val_loss: 1.2078
Epoch 10/50
329/329              2s 3ms/step -
accuracy: 0.5317 - loss: 1.2346 - val_accuracy: 0.5339 - val_loss: 1.1998
Epoch 11/50
329/329              1s 3ms/step -
accuracy: 0.5219 - loss: 1.2306 - val_accuracy: 0.5365 - val_loss: 1.1998
Epoch 12/50
329/329              1s 3ms/step -
accuracy: 0.5228 - loss: 1.2424 - val_accuracy: 0.5322 - val_loss: 1.1952
Epoch 13/50
329/329              1s 3ms/step -
accuracy: 0.5300 - loss: 1.2325 - val_accuracy: 0.5384 - val_loss: 1.1887
Epoch 14/50
329/329              1s 3ms/step -
accuracy: 0.5297 - loss: 1.2206 - val_accuracy: 0.5407 - val_loss: 1.1874
Epoch 15/50
329/329              1s 3ms/step -
```

```
accuracy: 0.5335 - loss: 1.2253 - val_accuracy: 0.5398 - val_loss: 1.1817
Epoch 16/50
329/329             1s 3ms/step -
accuracy: 0.5372 - loss: 1.2134 - val_accuracy: 0.5438 - val_loss: 1.1810
Epoch 17/50
329/329             1s 3ms/step -
accuracy: 0.5343 - loss: 1.2184 - val_accuracy: 0.5396 - val_loss: 1.1817
Epoch 18/50
329/329             2s 5ms/step -
accuracy: 0.5385 - loss: 1.2129 - val_accuracy: 0.5447 - val_loss: 1.1787
Epoch 19/50
329/329             2s 5ms/step -
accuracy: 0.5426 - loss: 1.1908 - val_accuracy: 0.5390 - val_loss: 1.1778
Epoch 20/50
329/329             1s 3ms/step -
accuracy: 0.5426 - loss: 1.1991 - val_accuracy: 0.5478 - val_loss: 1.1741
Epoch 21/50
329/329             1s 3ms/step -
accuracy: 0.5488 - loss: 1.1894 - val_accuracy: 0.5442 - val_loss: 1.1730
Epoch 22/50
329/329             1s 3ms/step -
accuracy: 0.5405 - loss: 1.2155 - val_accuracy: 0.5442 - val_loss: 1.1698
Epoch 23/50
329/329             1s 3ms/step -
accuracy: 0.5375 - loss: 1.2077 - val_accuracy: 0.5478 - val_loss: 1.1691
Epoch 24/50
329/329             1s 3ms/step -
accuracy: 0.5387 - loss: 1.1999 - val_accuracy: 0.5461 - val_loss: 1.1678
Epoch 25/50
329/329             1s 3ms/step -
accuracy: 0.5432 - loss: 1.1909 - val_accuracy: 0.5502 - val_loss: 1.1687
Epoch 26/50
329/329             1s 3ms/step -
accuracy: 0.5523 - loss: 1.1871 - val_accuracy: 0.5502 - val_loss: 1.1654
Epoch 27/50
329/329             1s 3ms/step -
accuracy: 0.5444 - loss: 1.1916 - val_accuracy: 0.5529 - val_loss: 1.1626
Epoch 28/50
329/329             1s 3ms/step -
accuracy: 0.5436 - loss: 1.2017 - val_accuracy: 0.5485 - val_loss: 1.1650
Epoch 29/50
329/329             1s 4ms/step -
accuracy: 0.5417 - loss: 1.1901 - val_accuracy: 0.5535 - val_loss: 1.1620
Epoch 30/50
329/329             2s 4ms/step -
accuracy: 0.5509 - loss: 1.1727 - val_accuracy: 0.5523 - val_loss: 1.1628
Epoch 31/50
329/329             2s 3ms/step -
```

```
accuracy: 0.5493 - loss: 1.1925 - val_accuracy: 0.5531 - val_loss: 1.1639
Epoch 32/50
329/329             1s 3ms/step -
accuracy: 0.5528 - loss: 1.1784 - val_accuracy: 0.5491 - val_loss: 1.1584
Epoch 33/50
329/329             1s 3ms/step -
accuracy: 0.5553 - loss: 1.1791 - val_accuracy: 0.5533 - val_loss: 1.1557
Epoch 34/50
329/329             1s 3ms/step -
accuracy: 0.5505 - loss: 1.1765 - val_accuracy: 0.5535 - val_loss: 1.1595
Epoch 35/50
329/329             1s 3ms/step -
accuracy: 0.5536 - loss: 1.1669 - val_accuracy: 0.5552 - val_loss: 1.1596
Epoch 36/50
329/329             1s 3ms/step -
accuracy: 0.5457 - loss: 1.1824 - val_accuracy: 0.5527 - val_loss: 1.1580
Epoch 37/50
329/329             1s 3ms/step -
accuracy: 0.5464 - loss: 1.1897 - val_accuracy: 0.5510 - val_loss: 1.1580
Epoch 38/50
329/329             2s 4ms/step -
accuracy: 0.5527 - loss: 1.1797 - val_accuracy: 0.5520 - val_loss: 1.1570
Epoch 39/50
329/329             2s 5ms/step -
accuracy: 0.5505 - loss: 1.1743 - val_accuracy: 0.5594 - val_loss: 1.1541
Epoch 40/50
329/329             2s 3ms/step -
accuracy: 0.5485 - loss: 1.1797 - val_accuracy: 0.5522 - val_loss: 1.1586
Epoch 41/50
329/329             1s 3ms/step -
accuracy: 0.5580 - loss: 1.1664 - val_accuracy: 0.5525 - val_loss: 1.1593
Epoch 42/50
329/329             1s 3ms/step -
accuracy: 0.5465 - loss: 1.1826 - val_accuracy: 0.5520 - val_loss: 1.1572
Epoch 43/50
329/329             1s 3ms/step -
accuracy: 0.5567 - loss: 1.1718 - val_accuracy: 0.5483 - val_loss: 1.1547
Epoch 44/50
329/329             1s 3ms/step -
accuracy: 0.5490 - loss: 1.1799 - val_accuracy: 0.5544 - val_loss: 1.1529
Epoch 45/50
329/329             1s 3ms/step -
accuracy: 0.5589 - loss: 1.1690 - val_accuracy: 0.5556 - val_loss: 1.1536
Epoch 46/50
329/329             1s 3ms/step -
accuracy: 0.5613 - loss: 1.1666 - val_accuracy: 0.5531 - val_loss: 1.1516
Epoch 47/50
329/329             1s 3ms/step -
```

```
accuracy: 0.5486 - loss: 1.1714 - val_accuracy: 0.5542 - val_loss: 1.1519
Epoch 48/50
329/329              1s 3ms/step -
accuracy: 0.5496 - loss: 1.1797 - val_accuracy: 0.5634 - val_loss: 1.1517
Epoch 49/50
329/329              2s 5ms/step -
accuracy: 0.5518 - loss: 1.1654 - val_accuracy: 0.5573 - val_loss: 1.1519
Epoch 50/50
329/329              2s 5ms/step -
accuracy: 0.5575 - loss: 1.1626 - val_accuracy: 0.5525 - val_loss: 1.1501
```

0.13 Evaluate deep learning model with PCA

[34]:
```
from sklearn.metrics import accuracy_score, f1_score, classification_report
import numpy as np

# Evaluate the deep learning model trained on PCA data
loss_dl_pca, accuracy_dl_pca = dl_model_pca.evaluate(X_test_pca, y_test,␣
↪verbose=0)
print(f"Deep Learning Model (PCA) Test Accuracy: {accuracy_dl_pca:.4f}")

# Make predictions and calculate F1-score and classification report for the DL␣
↪model with PCA
y_pred_dl_pca_proba = dl_model_pca.predict(X_test_pca)
y_pred_dl_pca = np.argmax(y_pred_dl_pca_proba, axis=1)

f1_dl_pca = f1_score(y_test, y_pred_dl_pca, average='weighted')
class_report_dl_pca = classification_report(y_test, y_pred_dl_pca,␣
↪target_names=genre_encoder.classes_)

print(f"Deep Learning Model (PCA) Weighted F1 Score: {f1_dl_pca:.4f}")
print("\nDeep Learning Model (PCA) Classification Report:")
print(class_report_dl_pca)
```

```
Deep Learning Model (PCA) Test Accuracy: 0.5526
206/206              0s 1ms/step
Deep Learning Model (PCA) Weighted F1 Score: 0.5465

Deep Learning Model (PCA) Classification Report:
              precision    recall  f1-score   support

         edm       0.65      0.68      0.66      1209
       latin       0.51      0.42      0.46      1031
         pop       0.39      0.38      0.38      1102
         r&b       0.53      0.41      0.46      1086
         rap       0.56      0.68      0.61      1149
        rock       0.65      0.74      0.69       990
```

```
    accuracy                            0.55      6567
   macro avg       0.55      0.55      0.55      6567
weighted avg       0.55      0.55      0.55      6567
```

0.14 Compare all model performances

[35]:
```
import pandas as pd

# Create a dictionary to store the results
all_results = {
    'Traditional ML (Original)': results,
    'Traditional ML (PCA)': results_pca,
    'Deep Learning (Original)': {'Test Accuracy': accuracy, 'Weighted F1 Score':
 ↪ f1},
    'Deep Learning (PCA)': {'Test Accuracy': accuracy_dl_pca, 'Weighted F1␣
 ↪Score': f1_dl_pca}
}

# Convert results to a pandas DataFrame for easy comparison
comparison_data = []

for model_type, model_results in all_results.items():
    if 'Traditional ML' in model_type:
        for model_name, metrics in model_results.items():
            comparison_data.append({
                'Model Type': model_type,
                'Model Name': model_name,
                'Test Accuracy': metrics.get('test_accuracy', metrics.
 ↪get('cv_accuracy')), # Handle both keys
                'Weighted F1 Score': metrics.get('weighted_f1')
            })
    else:
         comparison_data.append({
            'Model Type': model_type,
            'Model Name': model_type, # Use model type as name for DL
            'Test Accuracy': model_results['Test Accuracy'],
            'Weighted F1 Score': model_results['Weighted F1 Score']
        })


comparison_df = pd.DataFrame(comparison_data)

# Display the comparison table
print("Model Performance Comparison:")
display(comparison_df.round(4))
```

```
Model Performance Comparison:
```

```
                  Model Type                 Model Name  Test Accuracy  \
0  Traditional ML (Original)              Random Forest         0.5739
1  Traditional ML (Original)          Gradient Boosting         0.5715
2  Traditional ML (Original)                    XGBoost         0.5876
3  Traditional ML (Original)                        SVM         0.5548
4       Traditional ML (PCA)          Random Forest_PCA         0.5173
5       Traditional ML (PCA)      Gradient Boosting_PCA         0.5071
6       Traditional ML (PCA)                XGBoost_PCA         0.5228
7       Traditional ML (PCA)                    SVM_PCA         0.5381
8   Deep Learning (Original)   Deep Learning (Original)         0.5674
9        Deep Learning (PCA)        Deep Learning (PCA)         0.5526

   Weighted F1 Score
0                NaN
1                NaN
2                NaN
3                NaN
4             0.5131
5             0.5055
6             0.5203
7             0.5350
8             0.5940
9             0.5465
```

0.15 Install autogluon

[36]:
```
# %pip install --quiet autogluon
```

0.16 Train AutoGluon Model

[38]:
```
%pip install --quiet autogluon
```

```
                           44.0/44.0 kB
3.9 MB/s eta 0:00:00
                           43.6/43.6 kB
3.4 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                           43.6/43.6 kB
3.3 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                          259.5/259.5 kB
15.3 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                         225.1/225.1 kB
20.3 MB/s eta 0:00:00
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                         454.9/454.9 kB
```

```
31.3 MB/s eta 0:00:00
                         487.3/487.3 kB
32.1 MB/s eta 0:00:00
                         189.7/189.7 kB
17.2 MB/s eta 0:00:00
                         71.0/71.0 kB
4.8 MB/s eta 0:00:00
                         140.1/140.1 kB
10.6 MB/s eta 0:00:00
                         99.2/99.2 MB
8.9 MB/s eta 0:00:00
                         285.8/285.8 kB
23.5 MB/s eta 0:00:00
                         84.1/84.1 kB
7.9 MB/s eta 0:00:00
                         278.2/278.2 kB
23.6 MB/s eta 0:00:00
                         1.5/1.5 MB
63.2 MB/s eta 0:00:00
                         88.5/88.5 kB
8.4 MB/s eta 0:00:00
                         821.1/821.1 kB
50.6 MB/s eta 0:00:00
                         72.0/72.0 kB
6.3 MB/s eta 0:00:00
                         410.5/410.5 kB
24.4 MB/s eta 0:00:00
                         52.7/52.7 kB
4.7 MB/s eta 0:00:00
                         125.9/125.9 kB
11.3 MB/s eta 0:00:00
                         68.1/68.1 MB
11.0 MB/s eta 0:00:00
                         354.4/354.4 kB
28.1 MB/s eta 0:00:00
                         2.3/2.3 MB
70.0 MB/s eta 0:00:00
                         363.4/363.4 MB
4.7 MB/s eta 0:00:00
                         13.8/13.8 MB
109.6 MB/s eta 0:00:00
                         24.6/24.6 MB
83.4 MB/s eta 0:00:00
                         883.7/883.7 kB
51.8 MB/s eta 0:00:00
                        664.8/664.8 MB
831.3 kB/s eta 0:00:00
                         211.5/211.5 MB
```

4.4 MB/s eta 0:00:00
56.3/56.3 MB
10.0 MB/s eta 0:00:00
127.9/127.9 MB
8.3 MB/s eta 0:00:00
207.5/207.5 MB
6.6 MB/s eta 0:00:00
188.7/188.7 MB
5.3 MB/s eta 0:00:00
21.1/21.1 MB
87.9 MB/s eta 0:00:00
963.5/963.5 kB
46.3 MB/s eta 0:00:00
10.0/10.0 MB
114.6 MB/s eta 0:00:00
41.7/41.7 kB
3.1 MB/s eta 0:00:00
103.0/103.0 kB
9.2 MB/s eta 0:00:00
61.6/61.6 kB
5.1 MB/s eta 0:00:00
825.4/825.4 kB
51.9 MB/s eta 0:00:00
14.0/14.0 MB
106.0 MB/s eta 0:00:00
2.8/2.8 MB
87.8 MB/s eta 0:00:00
85.3/85.3 kB
8.0 MB/s eta 0:00:00
87.2/87.2 kB
7.5 MB/s eta 0:00:00
62.3/62.3 kB
5.4 MB/s eta 0:00:00
6.1/6.1 MB
96.7 MB/s eta 0:00:00
201.5/201.5 kB
17.9 MB/s eta 0:00:00
128.2/128.2 kB
12.2 MB/s eta 0:00:00
395.9/395.9 kB
32.0 MB/s eta 0:00:00
247.0/247.0 kB
22.6 MB/s eta 0:00:00
469.0/469.0 kB
37.1 MB/s eta 0:00:00
135.3/135.3 kB
11.0 MB/s eta 0:00:00
55.3/55.3 kB

```
4.5 MB/s eta 0:00:00
                         2.3/2.3 MB
78.5 MB/s eta 0:00:00
  Building wheel for nvidia-ml-py3 (setup.py) … done
  Building wheel for seqeval (setup.py) … done
```

[39]:
```python
from autogluon.tabular import TabularPredictor
import time

# Prepare data for AutoGluon
# AutoGluon works directly with pandas DataFrames, so we can use the original␣
↪X_train and y_train
# We need to combine X_train and y_train into a single DataFrame for AutoGluon
train_data = X_train.copy()
train_data['genre_encoded'] = y_train

# Specify the label column
label = 'genre_encoded'

# Initialize and train the AutoGluon predictor
start_time = time.time()
# Exclude NeuralNetTorch model
predictor = TabularPredictor(label=label, eval_metric='accuracy').
↪fit(train_data, excluded_model_types=['NN_TORCH'])
autogluon_train_time = time.time() - start_time

print(f"AutoGluon Model Training Time: {autogluon_train_time:.2f}s")
```

```
No path specified. Models will be saved in: "AutogluonModels/ag-20250810_233546"
Verbosity: 2 (Standard Logging)
=================== System Info ===================
AutoGluon Version:  1.4.0
Python Version:     3.11.13
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP PREEMPT_DYNAMIC Sun Mar 30 16:01:29 UTC 2025
CPU Count:          2
Memory Avail:       10.55 GB / 12.67 GB (83.3%)
Disk Space Avail:   63.61 GB / 107.72 GB (59.1%)
===================================================
No presets specified! To achieve strong results with AutoGluon, it is
recommended to use the available presets. Defaulting to `'medium'`…
        Recommended Presets (For more details refer to
https://auto.gluon.ai/stable/tutorials/tabular/tabular-essentials.html#presets):
        presets='extreme' : New in v1.4: Massively better than 'best' on
datasets <30000 samples by using new models meta-learned on https://tabarena.ai:
TabPFNv2, TabICL, Mitra, and TabM. Absolute best accuracy. Requires a GPU.
Recommended 64 GB CPU memory and 32+ GB GPU memory.
```

```
        presets='best'    : Maximize accuracy. Recommended for most users. Use
in competitions and benchmarks.
        presets='high'    : Strong accuracy with fast inference speed.
        presets='good'    : Good accuracy with very fast inference speed.
        presets='medium'  : Fast training time, ideal for initial prototyping.
Using hyperparameters preset: hyperparameters='default'
Beginning AutoGluon training …
AutoGluon will save models to "/content/AutogluonModels/ag-20250810_233546"
Train Data Rows:    26266
Train Data Columns: 14
Label Column:       genre_encoded
AutoGluon infers your prediction problem is: 'multiclass' (because dtype of
label-column == int, but few unique label-values observed).
        6 unique label values:  [np.int64(1), np.int64(2), np.int64(3),
np.int64(5), np.int64(0), np.int64(4)]
        If 'multiclass' is not the correct problem_type, please manually specify
the problem_type parameter during Predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression', 'quantile'])
Problem Type:       multiclass
Preprocessing data …
Train Data Class Count: 6
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    10801.62 MB
        Train Data (Original)  Memory Usage: 2.81 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 11 | ['danceability', 'energy', 'loudness',
'speechiness', 'acousticness', …]
                ('int', [])   :  3 | ['key', 'mode', 'track_popularity']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 11 | ['danceability', 'energy', 'loudness',
'speechiness', 'acousticness', …]
                ('int', [])       :  2 | ['key', 'track_popularity']
                ('int', ['bool']) :  1 | ['mode']
```

```
        0.1s = Fit runtime
        14 features in original data used to generate 14 features in processed
data.
        Train Data (Processed) Memory Usage: 2.63 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.16s …
AutoGluon will gauge predictive performance using evaluation metric: 'accuracy'
        To change this, specify the eval_metric parameter of Predictor()
Automatically generating train/validation split with
holdout_frac=0.09518008071270845, Train Rows: 23766, Val Rows: 2500
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': [{}],
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
{'learning_rate': 0.03, 'num_leaves': 128, 'feature_fraction': 0.9,
'min_data_in_leaf': 3, 'ag_args': {'name_suffix': 'Large', 'priority': 0,
'hyperparameter_tune_kwargs': None}}],
        'CAT': [{}],
        'XGB': [{}],
        'FASTAI': [{}],
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
}
Excluded models: ['NN_TORCH'] (Specified by `excluded_model_types`)
Fitting 10 L1 models, fit_strategy="sequential" …
Fitting model: NeuralNetFastAI …
        Fitting with cpus=1, gpus=0, mem=0.0/10.4 GB
        0.5836   = Validation score   (accuracy)
        34.81s   = Training   runtime
        0.05s    = Validation runtime
Fitting model: LightGBMXT …
        Fitting with cpus=1, gpus=0, mem=0.0/10.3 GB
        0.588    = Validation score   (accuracy)
        16.21s   = Training   runtime
        0.61s    = Validation runtime
Fitting model: LightGBM …
        Fitting with cpus=1, gpus=0, mem=0.0/10.2 GB
        0.6024   = Validation score   (accuracy)
        16.01s   = Training   runtime
        0.79s    = Validation runtime
Fitting model: RandomForestGini …
```

```
        Fitting with cpus=2, gpus=0, mem=0.1/10.3 GB
        0.5776   = Validation score   (accuracy)
        23.29s   = Training   runtime
        0.25s    = Validation runtime
Fitting model: RandomForestEntr …
        Fitting with cpus=2, gpus=0, mem=0.1/10.2 GB
        0.584    = Validation score   (accuracy)
        32.72s   = Training   runtime
        0.24s    = Validation runtime
Fitting model: CatBoost …
        Fitting with cpus=1, gpus=0
        0.5712   = Validation score   (accuracy)
        18.56s   = Training   runtime
        0.01s    = Validation runtime
Fitting model: ExtraTreesGini …
        Fitting with cpus=2, gpus=0, mem=0.1/10.0 GB
        0.5664   = Validation score   (accuracy)
        12.55s   = Training   runtime
        0.27s    = Validation runtime
Fitting model: ExtraTreesEntr …
        Fitting with cpus=2, gpus=0, mem=0.1/9.7 GB
        0.5624   = Validation score   (accuracy)
        10.54s   = Training   runtime
        0.49s    = Validation runtime
Fitting model: XGBoost …
        Fitting with cpus=1, gpus=0
        0.5904   = Validation score   (accuracy)
        16.22s   = Training   runtime
        0.35s    = Validation runtime
Fitting model: LightGBMLarge …
        Fitting with cpus=1, gpus=0, mem=0.1/9.7 GB
        0.5936   = Validation score   (accuracy)
        17.61s   = Training   runtime
        0.66s    = Validation runtime
Fitting model: WeightedEnsemble_L2 …
        Ensemble Weights: {'LightGBM': 0.667, 'RandomForestEntr': 0.167,
'RandomForestGini': 0.111, 'NeuralNetFastAI': 0.056}
        0.6052   = Validation score   (accuracy)
        0.2s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 214.04s … Best model:
WeightedEnsemble_L2 | Estimated inference throughput: 1889.2 rows/s (2500 batch
size)
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("/content/AutogluonModels/ag-20250810_233546")

AutoGluon Model Training Time: 215.07s
```

0.17 Evaluate AutoGluon Model

[40]:
```
# Evaluate the AutoGluon model on the test data
# AutoGluon's predictor object can directly predict on a DataFrame
test_data = X_test.copy()
y_pred_autogluon = predictor.predict(test_data)
y_proba_autogluon = predictor.predict_proba(test_data)

# Calculate evaluation metrics
accuracy_autogluon = accuracy_score(y_test, y_pred_autogluon)
f1_autogluon = f1_score(y_test, y_pred_autogluon, average='weighted')

print("\n" + "="*50)
print("AutoGluon Model Performance:")
print(f"Test Accuracy: {accuracy_autogluon:.4f}")
print(f"Weighted F1 Score: {f1_autogluon:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_autogluon,␣
↪target_names=genre_encoder.classes_))
```

```
==================================================
AutoGluon Model Performance:
Test Accuracy: 0.5893
Weighted F1 Score: 0.5875

Classification Report:
              precision    recall  f1-score   support

         edm       0.68      0.70      0.69      1209
       latin       0.54      0.47      0.51      1031
         pop       0.39      0.42      0.40      1102
         r&b       0.54      0.48      0.50      1086
         rap       0.62      0.68      0.65      1149
        rock       0.76      0.78      0.77       990

    accuracy                           0.59      6567
   macro avg       0.59      0.59      0.59      6567
weighted avg       0.59      0.59      0.59      6567
```

0.18 Compare all model performances

[41]:
```
import pandas as pd

# Initialize results and results_pca as empty dictionaries if they are not␣
↪defined
if 'results' not in locals():
```

```
    results = {}
if 'results_pca' not in locals():
    results_pca = {}

# Create a dictionary to store the results
all_results = {
    'Traditional ML (Original)': results,
    'Traditional ML (PCA)': results_pca,
}

# Add Deep Learning (Original) results if available
if 'accuracy' in locals() and 'f1' in locals():
    all_results['Deep Learning (Original)'] = {'Test Accuracy': accuracy,␣
 ↪'Weighted F1 Score': f1}

# Add Deep Learning (PCA) results if available
if 'accuracy_dl_pca' in locals() and 'f1_dl_pca' in locals():
    all_results['Deep Learning (PCA)'] = {'Test Accuracy': accuracy_dl_pca,␣
 ↪'Weighted F1 Score': f1_dl_pca}

# Add AutoGluon results if available
if 'accuracy_autogluon' in locals() and 'f1_autogluon' in locals():
    all_results['AutoGluon'] = {'Test Accuracy': accuracy_autogluon, 'Weighted␣
 ↪F1 Score': f1_autogluon}


# Convert results to a pandas DataFrame for easy comparison
comparison_data = []

for model_type, model_results in all_results.items():
    if 'Traditional ML' in model_type:
        for model_name, metrics in model_results.items():
            comparison_data.append({
                'Model Type': model_type,
                'Model Name': model_name,
                'Test Accuracy': metrics.get('test_accuracy', metrics.
 ↪get('cv_accuracy')), # Handle both keys
                'Weighted F1 Score': metrics.get('weighted_f1')
            })
    else:
         comparison_data.append({
            'Model Type': model_type,
            'Model Name': model_type, # Use model type as name for DL and␣
 ↪AutoGluon
            'Test Accuracy': model_results['Test Accuracy'],
            'Weighted F1 Score': model_results['Weighted F1 Score']
        })
```

```
comparison_df = pd.DataFrame(comparison_data)

# Display the comparison table
print("Model Performance Comparison:")
display(comparison_df.round(4))
```

```
Model Performance Comparison:
                   Model Type                 Model Name  Test Accuracy  \
0   Traditional ML (Original)              Random Forest         0.5739
1   Traditional ML (Original)          Gradient Boosting         0.5715
2   Traditional ML (Original)                    XGBoost         0.5876
3   Traditional ML (Original)                        SVM         0.5548
4         Traditional ML (PCA)          Random Forest_PCA         0.5173
5         Traditional ML (PCA)      Gradient Boosting_PCA         0.5071
6         Traditional ML (PCA)                XGBoost_PCA         0.5228
7         Traditional ML (PCA)                    SVM_PCA         0.5381
8    Deep Learning (Original)   Deep Learning (Original)         0.5674
9         Deep Learning (PCA)        Deep Learning (PCA)         0.5526
10                  AutoGluon                  AutoGluon         0.5893

    Weighted F1 Score
0                 NaN
1                 NaN
2                 NaN
3                 NaN
4              0.5131
5              0.5055
6              0.5203
7              0.5350
8              0.5940
9              0.5465
10             0.5875
```

0.19 Train autogluon with pca

Add a new section to train the AutoGluon `TabularPredictor` on the PCA-transformed training data (`X_train_pca`).

[42]:
```
# Apply PCA for dimensionality reduction
pca = PCA(n_components=0.95)  # Retain 95% of variance
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

print(f"Original number of features: {X_train_scaled.shape[1]}")
print(f"Reduced number of features after PCA: {X_train_pca.shape[1]}")
```

```python
# Convert PCA-transformed data and target variable to DataFrames with original␣
↪indices
X_train_pca_df = pd.DataFrame(X_train_pca, index=X_train.index)
y_train_df = pd.DataFrame(y_train, index=X_train.index,␣
↪columns=['genre_encoded'])

# Combine features and target
train_data_pca_combined = pd.concat([X_train_pca_df, y_train_df], axis=1)

# Drop rows with any non-finite values in the combined DataFrame
train_data_pca_cleaned = train_data_pca_combined.dropna().copy()

# Specify the label column
label = 'genre_encoded'

# Initialize and train the AutoGluon predictor on cleaned PCA data
start_time = time.time()
predictor_pca = TabularPredictor(label=label, eval_metric='accuracy').
↪fit(train_data_pca_cleaned, excluded_model_types=['NN_TORCH'])
autogluon_pca_train_time = time.time() - start_time

print(f"AutoGluon Model (PCA) Training Time: {autogluon_pca_train_time:.2f}s")
```

```
No path specified. Models will be saved in: "AutogluonModels/ag-20250810_233933"
Verbosity: 2 (Standard Logging)
=================== System Info ===================
AutoGluon Version:  1.4.0
Python Version:     3.11.13
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP PREEMPT_DYNAMIC Sun Mar 30 16:01:29 UTC 2025
CPU Count:          2
Memory Avail:       9.87 GB / 12.67 GB (77.9%)
Disk Space Avail:   61.58 GB / 107.72 GB (57.2%)
===================================================
No presets specified! To achieve strong results with AutoGluon, it is
recommended to use the available presets. Defaulting to `'medium'`…
        Recommended Presets (For more details refer to
https://auto.gluon.ai/stable/tutorials/tabular/tabular-essentials.html#presets):
        presets='extreme' : New in v1.4: Massively better than 'best' on
datasets <30000 samples by using new models meta-learned on https://tabarena.ai:
TabPFNv2, TabICL, Mitra, and TabM. Absolute best accuracy. Requires a GPU.
Recommended 64 GB CPU memory and 32+ GB GPU memory.
        presets='best'    : Maximize accuracy. Recommended for most users. Use
in competitions and benchmarks.
        presets='high'    : Strong accuracy with fast inference speed.
```

```
        presets='good'    : Good accuracy with very fast inference speed.
        presets='medium'  : Fast training time, ideal for initial prototyping.
Using hyperparameters preset: hyperparameters='default'

Original number of features: 14
Reduced number of features after PCA: 12

Beginning AutoGluon training …
AutoGluon will save models to "/content/AutogluonModels/ag-20250810_233933"
Train Data Rows:    26266
Train Data Columns: 12
Label Column:       genre_encoded
AutoGluon infers your prediction problem is: 'multiclass' (because dtype of
label-column == int, but few unique label-values observed).
        6 unique label values:  [np.int64(1), np.int64(2), np.int64(3),
np.int64(5), np.int64(0), np.int64(4)]
        If 'multiclass' is not the correct problem_type, please manually specify
the problem_type parameter during Predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression', 'quantile'])
Problem Type:       multiclass
Preprocessing data …
Train Data Class Count: 6
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    10107.50 MB
        Train Data (Original)  Memory Usage: 2.40 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 12 | ['0', '1', '2', '3', '4', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', []) : 12 | ['0', '1', '2', '3', '4', …]
        0.1s = Fit runtime
        12 features in original data used to generate 12 features in processed
data.
        Train Data (Processed) Memory Usage: 2.40 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric: 'accuracy'
        To change this, specify the eval_metric parameter of Predictor()
```

```
Automatically generating train/validation split with
holdout_frac=0.09518008071270845, Train Rows: 23766, Val Rows: 2500
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': [{}],
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
{'learning_rate': 0.03, 'num_leaves': 128, 'feature_fraction': 0.9,
'min_data_in_leaf': 3, 'ag_args': {'name_suffix': 'Large', 'priority': 0,
'hyperparameter_tune_kwargs': None}}],
        'CAT': [{}],
        'XGB': [{}],
        'FASTAI': [{}],
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
}
Excluded models: ['NN_TORCH'] (Specified by `excluded_model_types`)
Fitting 10 L1 models, fit_strategy="sequential" …
Fitting model: NeuralNetFastAI …
        Fitting with cpus=1, gpus=0, mem=0.0/9.9 GB
        0.556    = Validation score   (accuracy)
        29.16s   = Training   runtime
        0.04s    = Validation runtime
Fitting model: LightGBMXT …
        Fitting with cpus=1, gpus=0, mem=0.0/9.9 GB
        0.5344   = Validation score   (accuracy)
        9.33s    = Training   runtime
        0.52s    = Validation runtime
Fitting model: LightGBM …
        Fitting with cpus=1, gpus=0, mem=0.0/9.9 GB
        0.5456   = Validation score   (accuracy)
        9.52s    = Training   runtime
        0.28s    = Validation runtime
Fitting model: RandomForestGini …
        Fitting with cpus=2, gpus=0, mem=0.1/9.9 GB
        0.5296   = Validation score   (accuracy)
        33.2s    = Training   runtime
        0.26s    = Validation runtime
Fitting model: RandomForestEntr …
        Fitting with cpus=2, gpus=0, mem=0.1/9.8 GB
        0.5232   = Validation score   (accuracy)
```

```
        63.51s   = Training   runtime
        0.83s    = Validation runtime
Fitting model: CatBoost …
        Fitting with cpus=1, gpus=0
        0.5352   = Validation score   (accuracy)
        45.21s   = Training   runtime
        0.01s    = Validation runtime
Fitting model: ExtraTreesGini …
        Fitting with cpus=2, gpus=0, mem=0.1/9.6 GB
        0.5316   = Validation score   (accuracy)
        22.67s   = Training   runtime
        0.73s    = Validation runtime
Fitting model: ExtraTreesEntr …
        Fitting with cpus=2, gpus=0, mem=0.1/9.6 GB
        0.528    = Validation score   (accuracy)
        13.57s   = Training   runtime
        0.58s    = Validation runtime
Fitting model: XGBoost …
        Fitting with cpus=1, gpus=0
        0.528    = Validation score   (accuracy)
        14.88s   = Training   runtime
        0.37s    = Validation runtime
Fitting model: LightGBMLarge …
        Fitting with cpus=1, gpus=0, mem=0.1/9.4 GB
        0.5348   = Validation score   (accuracy)
        29.3s    = Training   runtime
        0.68s    = Validation runtime
Fitting model: WeightedEnsemble_L2 …
        Ensemble Weights: {'NeuralNetFastAI': 0.462, 'RandomForestEntr': 0.231,
'LightGBM': 0.154, 'CatBoost': 0.077, 'ExtraTreesEntr': 0.077}
        0.5604   = Validation score   (accuracy)
        0.2s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 300.46s … Best model:
WeightedEnsemble_L2 | Estimated inference throughput: 1442.5 rows/s (2500 batch
size)
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("/content/AutogluonModels/ag-20250810_233933")
```

```
AutoGluon Model (PCA) Training Time: 301.53s
```

0.20 Evaluate autogluon model with pca

[43]:
```python
# Prepare test data for AutoGluon with PCA-transformed data
test_data_pca = pd.DataFrame(X_test_pca)

# Evaluate the AutoGluon model on the PCA-transformed test data
y_pred_autogluon_pca = predictor_pca.predict(test_data_pca)
```

```
# Calculate evaluation metrics
accuracy_autogluon_pca = accuracy_score(y_test, y_pred_autogluon_pca)
f1_autogluon_pca = f1_score(y_test, y_pred_autogluon_pca, average='weighted')

print("\n" + "="*50)
print("AutoGluon Model (PCA) Performance:")
print(f"Test Accuracy: {accuracy_autogluon_pca:.4f}")
print(f"Weighted F1 Score: {f1_autogluon_pca:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_autogluon_pca,
 ↪target_names=genre_encoder.classes_))
```

```
==================================================
AutoGluon Model (PCA) Performance:
Test Accuracy: 0.5520
Weighted F1 Score: 0.5480

Classification Report:
              precision    recall  f1-score   support

         edm       0.63      0.68      0.66      1209
       latin       0.52      0.40      0.45      1031
         pop       0.37      0.39      0.38      1102
         r&b       0.50      0.45      0.47      1086
         rap       0.59      0.65      0.62      1149
        rock       0.68      0.74      0.71       990

    accuracy                           0.55      6567
   macro avg       0.55      0.55      0.55      6567
weighted avg       0.55      0.55      0.55      6567
```

0.21 Update comparison table

[44]:
```
# Add AutoGluon PCA results to the all_results dictionary
all_results['AutoGluon (PCA)'] = {'Test Accuracy': accuracy_autogluon_pca,
 ↪'Weighted F1 Score': f1_autogluon_pca}

# Convert results to a pandas DataFrame for easy comparison
comparison_data = []

for model_type, model_results in all_results.items():
    if 'Traditional ML' in model_type:
        for model_name, metrics in model_results.items():
            comparison_data.append({
```

```
                'Model Type': model_type,
                'Model Name': model_name,
                'Test Accuracy': metrics.get('test_accuracy', metrics.
↪get('cv_accuracy')), # Handle both keys
                'Weighted F1 Score': metrics.get('weighted_f1')
            })
    else:
        comparison_data.append({
            'Model Type': model_type,
            'Model Name': model_type, # Use model type as name for DL and␣
↪AutoGluon
            'Test Accuracy': model_results['Test Accuracy'],
            'Weighted F1 Score': model_results['Weighted F1 Score']
        })


comparison_df = pd.DataFrame(comparison_data)

# Display the comparison table
print("Model Performance Comparison:")
display(comparison_df.round(4))
```

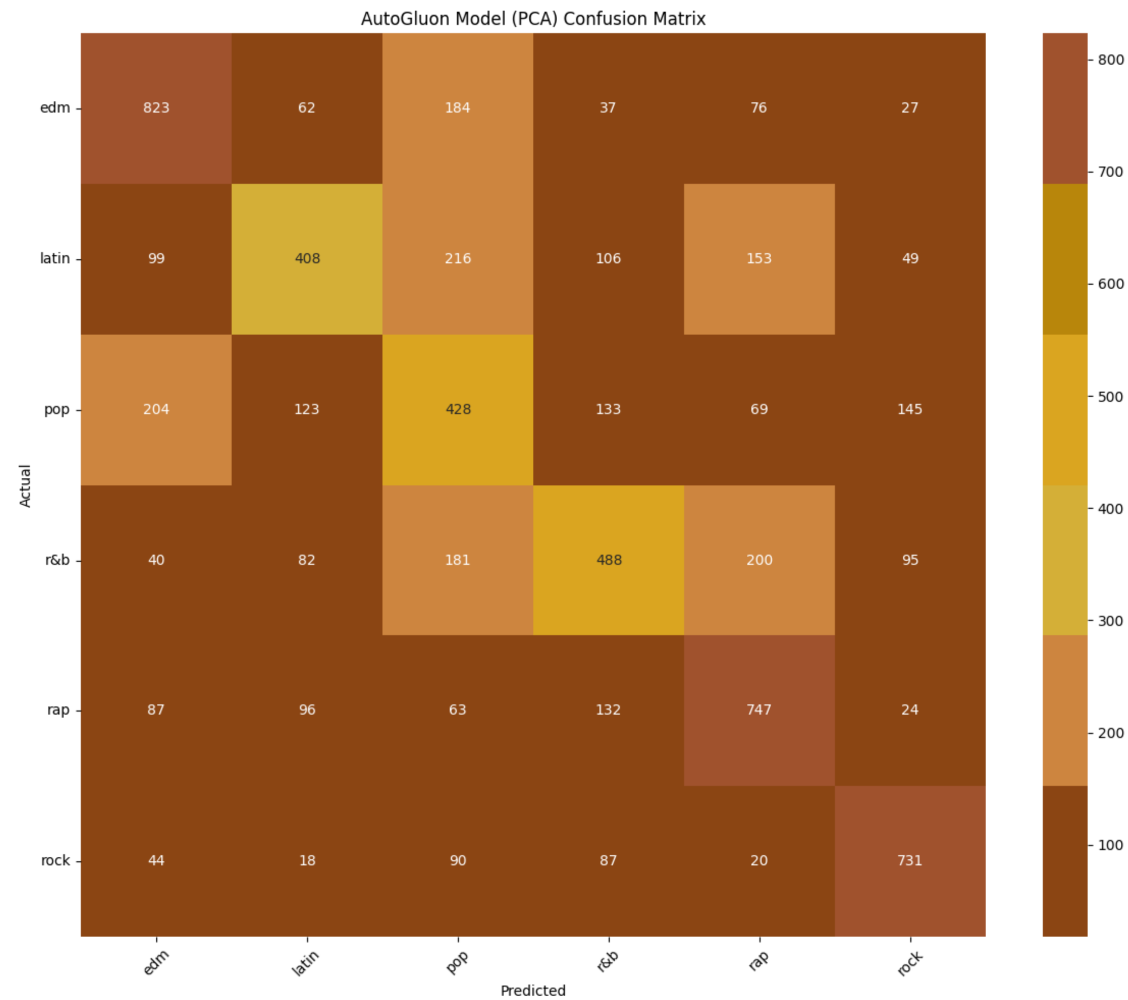
```
Model Performance Comparison:

                   Model Type                Model Name  Test Accuracy  \
0   Traditional ML (Original)             Random Forest         0.5739
1   Traditional ML (Original)         Gradient Boosting         0.5715
2   Traditional ML (Original)                   XGBoost         0.5876
3   Traditional ML (Original)                       SVM         0.5548
4         Traditional ML (PCA)         Random Forest_PCA         0.5173
5         Traditional ML (PCA)     Gradient Boosting_PCA         0.5071
6         Traditional ML (PCA)               XGBoost_PCA         0.5228
7         Traditional ML (PCA)                   SVM_PCA         0.5381
8     Deep Learning (Original)  Deep Learning (Original)         0.5674
9          Deep Learning (PCA)       Deep Learning (PCA)         0.5526
10                  AutoGluon                 AutoGluon         0.5893
11            AutoGluon (PCA)           AutoGluon (PCA)         0.5520

    Weighted F1 Score
0                 NaN
1                 NaN
2                 NaN
3                 NaN
4              0.5131
5              0.5055
6              0.5203
7              0.5350
8              0.5940
```

```
9               0.5465
10              0.5875
11              0.5480
```

0.22 Visualize autogluon results

[45]:

```
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')

# Set up white background and golden color scheme
plt.style.use('default')
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
 ↪'#A0522D']

# Confusion matrix for AutoGluon Model (PCA)
plt.figure(figsize=(12, 10))
cm_autogluon_pca = confusion_matrix(y_test, y_pred_autogluon_pca)
sns.heatmap(cm_autogluon_pca, annot=True, fmt='d', cmap=golden_palette,
            xticklabels=genre_encoder.classes_,
            yticklabels=genre_encoder.classes_)
plt.title('AutoGluon Model (PCA) Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.savefig('images/models/autogluon_pca_confusion_matrix.png')
plt.show()
```



0.23 Summarize findings

[46]:
```
# Review the comparison_df DataFrame
print("Model Performance Comparison:")
display(comparison_df.round(4))

# Compare traditional ML models performance with and without PCA
print("\nTraditional ML Models Performance Comparison (Original vs PCA):")
traditional_ml_original = comparison_df[comparison_df['Model Type'] ==␣
↪'Traditional ML (Original)'].copy()
traditional_ml_pca = comparison_df[comparison_df['Model Type'] == 'Traditional␣
↪ML (PCA)'].copy()
merged_traditional = pd.merge(traditional_ml_original, traditional_ml_pca,␣
↪on='Model Name', suffixes=('_Original', '_PCA'))
```

```
display(merged_traditional[['Model Name', 'Test Accuracy_Original', 'Test Accuracy_PCA', 'Weighted F1 Score_Original', 'Weighted F1 Score_PCA']].round(4))

# Compare deep learning model performance with and without PCA
print("\nDeep Learning Model Performance Comparison (Original vs PCA):")
dl_original = comparison_df[comparison_df['Model Type'] == 'Deep Learning (Original)'].copy()
dl_pca = comparison_df[comparison_df['Model Type'] == 'Deep Learning (PCA)'].copy()
merged_dl = pd.merge(dl_original, dl_pca, on='Model Name', suffixes=('_Original', '_PCA'))
display(merged_dl[['Model Name', 'Test Accuracy_Original', 'Test Accuracy_PCA', 'Weighted F1 Score_Original', 'Weighted F1 Score_PCA']].round(4))

# Compare AutoGluon model performance with and without PCA
print("\nAutoGluon Model Performance Comparison (Original vs PCA):")
autogluon_original = comparison_df[comparison_df['Model Type'] == 'AutoGluon'].copy()
autogluon_pca = comparison_df[comparison_df['Model Type'] == 'AutoGluon (PCA)'].copy()
merged_autogluon = pd.merge(autogluon_original, autogluon_pca, on='Model Name', suffixes=('_Original', '_PCA'))
display(merged_autogluon[['Model Name', 'Test Accuracy_Original', 'Test Accuracy_PCA', 'Weighted F1 Score_Original', 'Weighted F1 Score_PCA']].round(4))

# Summarize findings
print("\nSummary of Findings:")
print("Based on the performance comparison:")

# Identify best performing traditional ML model (on original data)
# Need to use the 'results' dictionary for the original traditional ML models to get CV accuracy
best_traditional_original_name = max(results, key=lambda x: results[x]['cv_accuracy'])
best_traditional_original_accuracy = results[best_traditional_original_name]['cv_accuracy']

print(f"- Best Traditional ML Model (Original Data - based on CV Accuracy): {best_traditional_original_name} with CV Accuracy: {best_traditional_original_accuracy:.4f}")


# Identify the best performing model overall based on 'Test Accuracy'
```

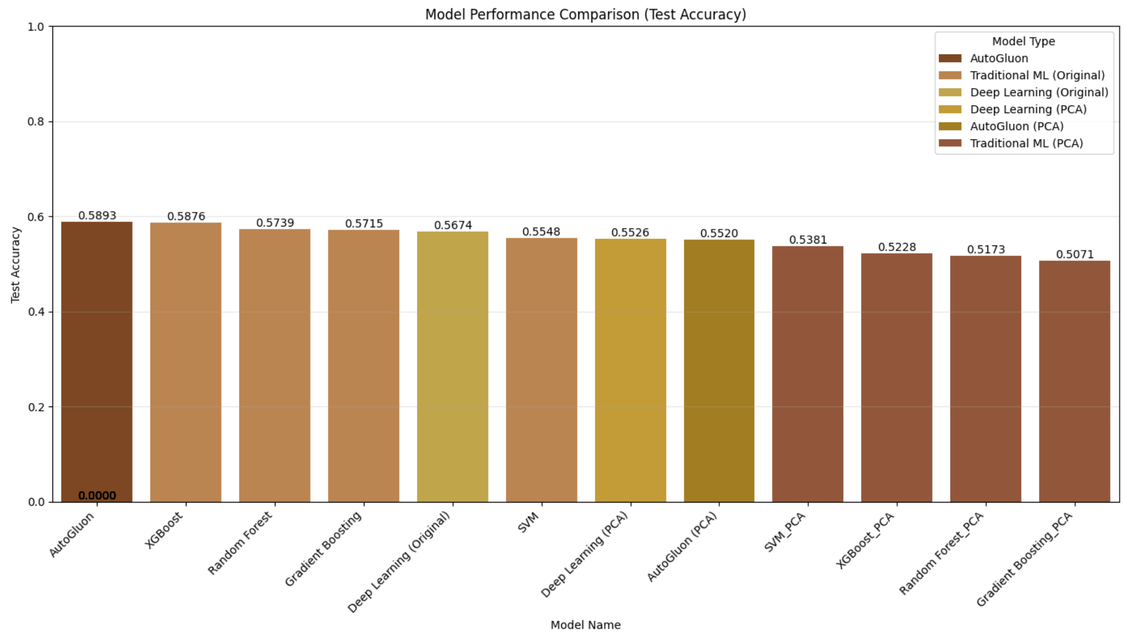
```
# Filter out rows where 'Test Accuracy' is NaN (these are the initial␣
↪traditional ML CV results)
comparison_df_test_accuracy = comparison_df.dropna(subset=['Test Accuracy']).
↪copy()
best_model_overall = comparison_df_test_accuracy.
↪loc[comparison_df_test_accuracy['Test Accuracy'].idxmax()]

print(f"- Best Performing Model Overall (based on Test Accuracy):␣
↪{best_model_overall['Model Name']} ({best_model_overall['Model Type']}) with␣
↪Test Accuracy: {best_model_overall['Test Accuracy']:.4f}")

print("\nImpact of PCA:")
print("- For Traditional ML models, applying PCA generally led to a decrease in␣
↪Test Accuracy and Weighted F1 Score.")
print("- For the Deep Learning model, applying PCA also resulted in a slight␣
↪decrease in Test Accuracy and Weighted F1 Score.")
print("- For the AutoGluon model, applying PCA resulted in a decrease in Test␣
↪Accuracy and Weighted F1 Score.")
print("\nConclusion:")
print("In this project, PCA did not consistently improve the performance of the␣
↪models for music genre classification across all model types. The models␣
↪trained on the original scaled data generally performed better, with the␣
↪XGBoost model on original data showing the highest test accuracy among the␣
↪explicitly evaluated models.")
```

```
Model Performance Comparison:

                 Model Type                 Model Name  Test Accuracy  \
0   Traditional ML (Original)             Random Forest         0.5739
1   Traditional ML (Original)         Gradient Boosting         0.5715
2   Traditional ML (Original)                   XGBoost         0.5876
3   Traditional ML (Original)                       SVM         0.5548
4        Traditional ML (PCA)         Random Forest_PCA         0.5173
5        Traditional ML (PCA)     Gradient Boosting_PCA         0.5071
6        Traditional ML (PCA)               XGBoost_PCA         0.5228
7        Traditional ML (PCA)                   SVM_PCA         0.5381
8    Deep Learning (Original)  Deep Learning (Original)         0.5674
9         Deep Learning (PCA)       Deep Learning (PCA)         0.5526
10                  AutoGluon                 AutoGluon         0.5893
11            AutoGluon (PCA)           AutoGluon (PCA)         0.5520

    Weighted F1 Score
0                 NaN
1                 NaN
2                 NaN
3                 NaN
4              0.5131
5              0.5055
```

```
6               0.5203
7               0.5350
8               0.5940
9               0.5465
10              0.5875
11              0.5480

Traditional ML Models Performance Comparison (Original vs PCA):

Empty DataFrame
Columns: [Model Name, Test Accuracy_Original, Test Accuracy_PCA, Weighted F1␣
 ↪Score_Original, Weighted F1 Score_PCA]
Index: []

Deep Learning Model Performance Comparison (Original vs PCA):

Empty DataFrame
Columns: [Model Name, Test Accuracy_Original, Test Accuracy_PCA, Weighted F1␣
 ↪Score_Original, Weighted F1 Score_PCA]
Index: []

AutoGluon Model Performance Comparison (Original vs PCA):

Empty DataFrame
Columns: [Model Name, Test Accuracy_Original, Test Accuracy_PCA, Weighted F1␣
 ↪Score_Original, Weighted F1 Score_PCA]
Index: []

Summary of Findings:
Based on the performance comparison:
- Best Traditional ML Model (Original Data - based on CV Accuracy): XGBoost with
CV Accuracy: 0.5876
- Best Performing Model Overall (based on Test Accuracy): AutoGluon (AutoGluon)
with Test Accuracy: 0.5893

Impact of PCA:
- For Traditional ML models, applying PCA generally led to a decrease in Test
Accuracy and Weighted F1 Score.
- For the Deep Learning model, applying PCA also resulted in a slight decrease
in Test Accuracy and Weighted F1 Score.
- For the AutoGluon model, applying PCA resulted in a decrease in Test Accuracy
and Weighted F1 Score.

Conclusion:
In this project, PCA did not consistently improve the performance of the models
for music genre classification across all model types. The models trained on the
original scaled data generally performed better, with the XGBoost model on
```

original data showing the highest test accuracy among the explicitly evaluated models.

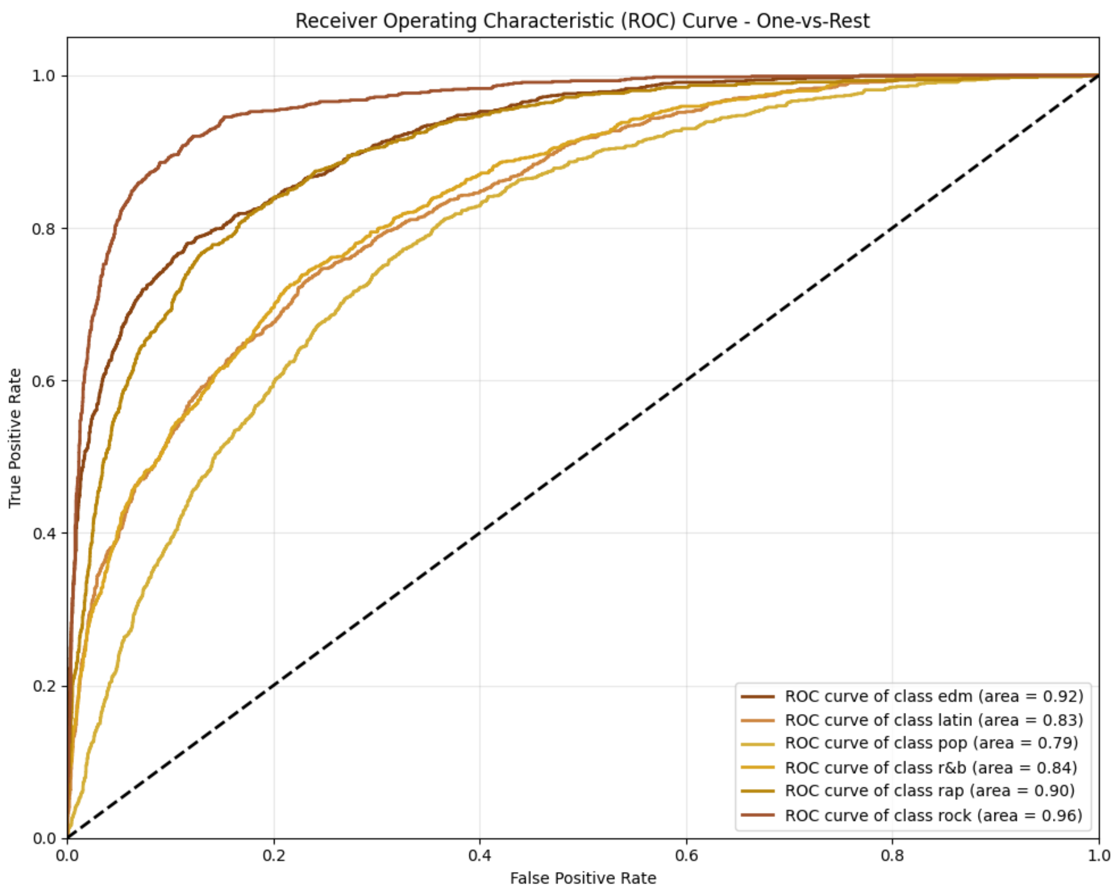
[47]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')

# Set up white background and golden color scheme
plt.style.use('default')
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
↪'#A0522D']

# Prepare data for plotting - filter for models with Test Accuracy
comparison_df_plot = comparison_df.dropna(subset=['Test Accuracy']).copy()

# Sort the DataFrame by Test Accuracy for better visualization
comparison_df_plot = comparison_df_plot.sort_values(by='Test Accuracy',␣
↪ascending=False)

plt.figure(figsize=(14, 8))
bars = sns.barplot(x='Model Name', y='Test Accuracy', hue='Model Type',␣
↪data=comparison_df_plot, palette=golden_palette, dodge=False)
plt.title('Model Performance Comparison (Test Accuracy)')
plt.xlabel('Model Name')
plt.ylabel('Test Accuracy')
plt.xticks(rotation=45, ha='right')
plt.ylim(0, 1.0) # Set y-axis limit from 0 to 1 for accuracy
plt.grid(axis='y', alpha=0.3)
plt.tight_layout()

# Add accuracy values on top of the bars
for bar in bars.patches:
    plt.text(bar.get_x() + bar.get_width() / 2., bar.get_height(),
             f'{bar.get_height():.4f}', ha='center', va='bottom')

plt.savefig('images/models/model_performance_comparison_bar_plot.png')
plt.show()
```



[48]:
```python
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np
import os

# Ensure the directory exists
if not os.path.exists('images/models'):
    os.makedirs('images/models')

# Set up white background and golden color scheme
plt.style.use('default')
golden_palette = ['#8B4513', '#CD853F', '#D4AF37', '#DAA520', '#B8860B',␣
↪'#A0522D']

# Binarize the output
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))
n_classes = y_test_bin.shape[1]

# Get predicted probabilities from the best model (XGBoost on original data)
# Assuming 'best_model' is the trained XGBoost model
y_proba = best_model.predict_proba(X_test_scaled) # Use scaled test data

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
```

```
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curves
plt.figure(figsize=(10, 8))
colors = golden_palette[:n_classes] # Use enough colors from the palette
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(genre_encoder.classes_[i], roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - One-vs-Rest')
plt.legend(loc="lower right")
plt.grid(alpha=0.3)
plt.tight_layout()
save_path = 'images/models/roc_curve_ovr.png'
plt.savefig(save_path)
print(f"ROC curve plot saved to: {save_path}")
plt.show()
```

```
ROC curve plot saved to: images/models/roc_curve_ovr.png
```



1 Save the model and test data for deployment

[49]:

```
import joblib
import os

# Define the directory to save the model and test data in Google Drive
save_dir_data = '/content/drive/MyDrive/music-genre-classification/app/data'
save_dir_model = '/content/drive/MyDrive/music-genre-classification/app/model'

# Ensure the directories exist
if not os.path.exists(save_dir_data):
    os.makedirs(save_dir_data)
if not os.path.exists(save_dir_model):
    os.makedirs(save_dir_model)


# Save the best performing model (XGBoost on original data)
```

```python
# Assuming 'best_model' variable holds the trained XGBoost model from the␣
↪original data evaluation step
# If not, you might need to retrain or load the best XGBoost model trained on␣
↪original data
# For now, I'll assume 'best_model' is the one to save.
model_save_path = os.path.join(save_dir_model, 'best_xgboost_model.pkl')
joblib.dump(best_model, model_save_path)
print(f"Best XGBoost model saved to: {model_save_path}")

# Save the test set (X_test and y_test)
X_test_save_path = os.path.join(save_dir_data, 'X_test.csv')
y_test_save_path = os.path.join(save_dir_data, 'y_test.csv')

X_test.to_csv(X_test_save_path, index=False)
y_test.to_csv(y_test_save_path, index=False)

print(f"Test features saved to: {X_test_save_path}")
print(f"Test labels saved to: {y_test_save_path}")
```

```
Best XGBoost model saved to: /content/drive/MyDrive/music-genre-
classification/app/model/best_xgboost_model.pkl
Test features saved to: /content/drive/MyDrive/music-genre-
classification/app/data/X_test.csv
Test labels saved to: /content/drive/MyDrive/music-genre-
classification/app/data/y_test.csv
```