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Introduction

This report describes the details of Python Capstone Project for ST1 (G) unit within the scope of the project requirements provided in the assignment handout [1]. I have decided to work on the project using a Spotify and Youtube dataset available on the Kaggle data repositories [2]. From the dataset, I decided on only work on the Spotify variables and have dropped the Youtube variables for the analysis.

Spotify is a popular music streaming platform that allows users to access a vast library of music, podcasts, and other audio content from around the world. It was founded in 2006 in Sweden and has since expanded to over 170 countries, with a user base of over 517.69 million monthly active users worldwide, as of 2023 out of which 229 million are premium subscribers [3]. Spotify offers both free and premium subscription plans, which allow users to access ad-free listening, higher-quality audio, and offline playback. The platform uses algorithms and personalized recommendations to suggest music and playlists based on users' listening habits and preferences. In addition to music, Spotify also offers a range of original podcasts and other audio content, making it a popular choice for users looking to discover new audio content.

The aim of this project is to have a deeper look into the attributes of the popular songs and identify which type of attributes are most present in these popular songs. Moreover, we will be using data from the dataset to train the machine learning algorithm to be able classify a song by its Album Type based on its various attributes.

This report presents the detailed analysis of the spotify platform, in terms of several Python software tools developed as part of this capstone project, based on a data driven scientific approach, involving exploratory data analysis, predictive analytics and implementation as an online web-based Flask application. The details of the methodology used is presented in the next Section.

Methodology

The methodology used for developing the software platform involves 3 stages as outlined below:

1. Design and development of decision support algorithms based on exploratory data analysis and predictive analytics
2. Identifying the best performing algorithm for predicting the song's album type .
3. Deployment of the tool as a web-based Flask application.

Stage 1: Algorithm Design Stages

This is most important preliminary stage and depending on the complexity of the problem and dataset used, the design of algorithms for exploratory data analysis and predictive analytics algorithms will vary. However, the workflow for algorithm development will be as outlined in the Figure 1 schematic shown below:

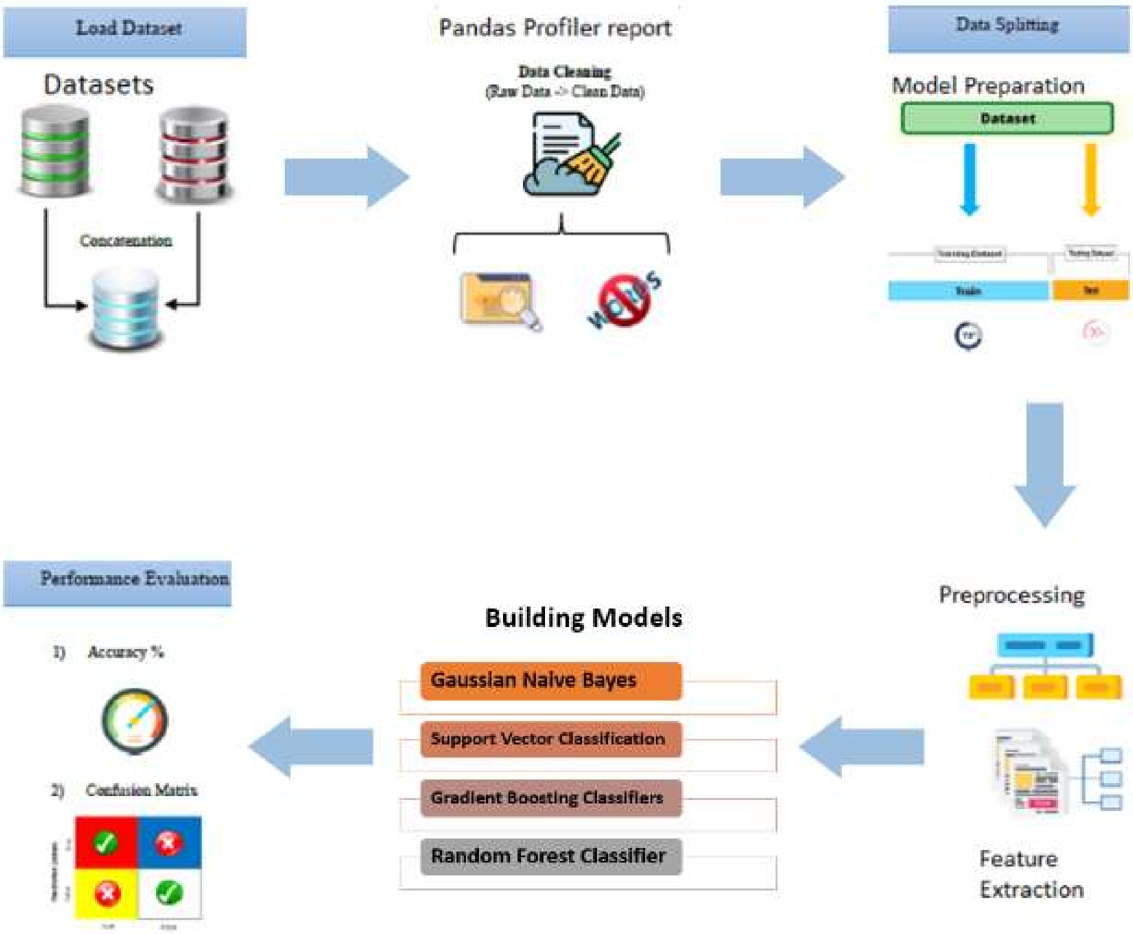


Figure 1: Schematic for Algorithm Design Methodology for Heart Disease Prediction

The details of each building block in Figure 1 schematic for algorithm design is described in the next few sections.

Dataset Description

There is only one dataset used for this project and it is publicly available on Kaggle [2]. The dataset consists of 20,718 datapoints and 28 attributes for both Spotify and Youtube. After dropping the YouTube attributes, the dataset is left with 16 attributes. The YouTube variables were dropped because the focus of this project was on the musical attributes of a track and the YouTube variables did not provide that insight. Moreove, this particular dataset was chosen as this provided the most recent updated Spotify data.

The 16 attributes from Spotify include attrubutes such as Track, Album Type, Danceability, Energy, Key, and more. The Album type and Key are the only two categorical variables from the dataset and the rest are continuous variables. For the Album type variable 0 respresents that the album type of the song is Album, while 1 indicates that the album type is Single and 2 indicates that the album type is Compitation of the song. Therefore, the task at hand is to develop a software tool to predict the the album type of a song based on its attributes.

Exploratory Data Analysis

The first phase of the software development activity involved understanding the data, basic exploratory data analysis and visualisation. Visual Studio (VS) Code was chosen and Anaconda was used to create the experimental environment. The python language was used to create the scripts which ran directly on online Jupyter notebook using VS Code with the Anaconda environment, and by saving all the notebook files locally on the machine. Before the exploratory data analysis can begin, some of the python libraries for EDA need to be imported and dataset acquired, by using the following Python script:

```
#Import Required Packages for EDA

import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import plotly.graph_objects as go
import plotly.express as px
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import numpy as np
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

#Read the dataset/s

df = pd.read_csv(r'D:\Users\DELL\Documents\UC\Sem
3\ST\STCapstone\Spotify_Youtube.csv')

#Cleaning the data by dropping the unwanted variables and missing values
df.drop(['Unnamed:
0','Channel','Url_spotify',"Uri","Url_youtube","Title","Views","Likes","Comments",
"Description","Licensed","official_video"], axis =1, inplace = True)
df.dropna()
```

The EDA starts with understanding the basic description of data as described next:

```
#1. Checking description(first 5 and last 5 rows)
df.head()  #first 5 rows
```

	Artist	Track	Album	Album_type	Danceability	Energy	Key	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Duration_ms	Stream
0	Gorillaz	Feel Good Inc.	Demon Days	album	0.818	0.705	6.0	-6.679	0.1770	0.008360	0.002330	0.6130	0.772	138.559	222640.0	1.040235e+09
1	Gorillaz	Rhinestone Eyes	Plastic Beach	album	0.676	0.703	8.0	-5.815	0.0302	0.086900	0.000687	0.0463	0.852	92.761	200173.0	3.100837e+08
2	Gorillaz	New Gold (feat. Tame Impala and Bootie Brown)	New Gold (feat. Tame Impala and Bootie Brown)	single	0.695	0.923	1.0	-3.930	0.0522	0.042500	0.046900	0.1160	0.551	108.014	215150.0	6.306347e+07
3	Gorillaz	On Melancholy Hill	Plastic Beach	album	0.689	0.739	2.0	-5.810	0.0260	0.000015	0.509000	0.0640	0.578	120.423	233867.0	4.346636e+08
4	Gorillaz	Clint Eastwood	Gorillaz	album	0.663	0.694	10.0	-8.627	0.1710	0.025300	0.000000	0.0698	0.525	167.953	340920.0	6.172597e+08

```
df.tail()  #last 5 rows
```

	Artist	Track	Album	Album_type	Danceability	Energy	Key	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Duration_ms	Stream
20713	SICK LEGEND	JUST DANCE HARDSTYLE	JUST DANCE HARDSTYLE	single	0.582	0.926	5.0	-6.344	0.0328	0.44800	0.0000	0.0839	0.6580	90.002	94667.0	9227144.0
20714	SICK LEGEND	SET FIRE TO THE RAIN HARDSTYLE	SET FIRE TO THE RAIN HARDSTYLE	single	0.531	0.936	4.0	-1.786	0.1370	0.02800	0.0000	0.0923	0.6570	174.869	150857.0	10898176.0
20715	SICK LEGEND	OUTSIDE HARDSTYLE SPED UP	OUTSIDE HARDSTYLE SPED UP	single	0.443	0.830	4.0	-4.679	0.0647	0.02430	0.0000	0.1540	0.4190	168.388	136842.0	6226110.0
20716	SICK LEGEND	ONLY GIRL HARDSTYLE	ONLY GIRL HARDSTYLE	single	0.417	0.767	9.0	-4.004	0.4190	0.35600	0.0184	0.1080	0.5390	155.378	108387.0	6873961.0
20717	SICK LEGEND	MISS YOU HARDSTYLE	MISS YOU HARDSTYLE	single	0.498	0.938	6.0	-4.543	0.1070	0.00277	0.9110	0.1360	0.0787	160.067	181500.0	5695584.0

```
#rows and columns-data shape(attributes & samples)
df.shape
```

```
(20718, 16)
```

```
# name of the attributes
df.columns
```

```
Index(['Artist', 'Track', 'Album', 'Album_type', 'Danceability', 'Energy',
       'Key', 'Loudness', 'Speechiness', 'Acousticness', 'Instrumentalness',
       'Liveness', 'Valence', 'Tempo', 'Duration_ms', 'Stream'],
      dtype='object')
```

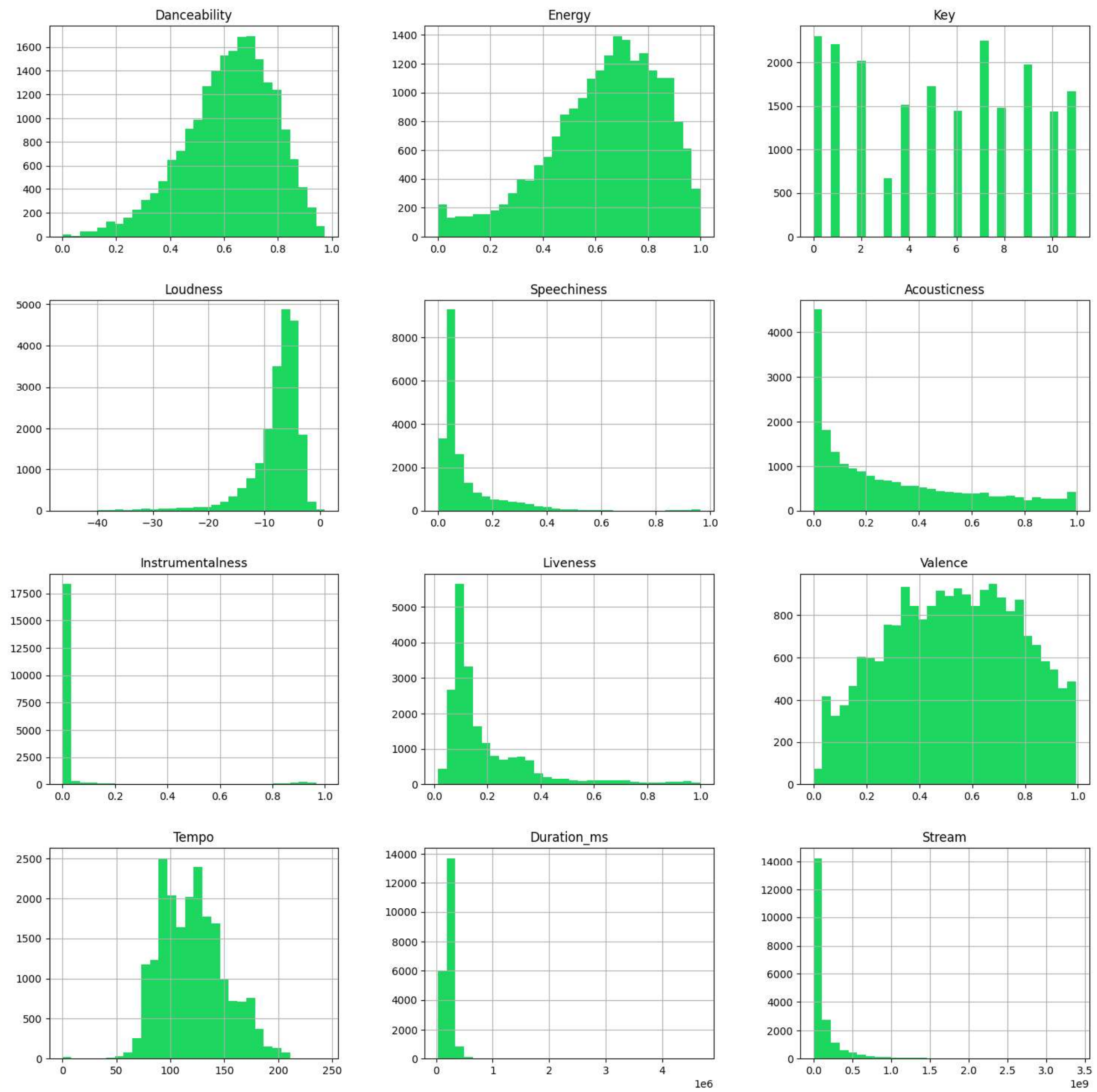
```
#unique values for each attribute
df.nunique()
```

```
Artist               2079
Track               17841
Album               11937
Album_type              3
Danceability          898
Energy               1268
Key                    12
Loudness             9417
Speechiness          1303
Acousticness         3138
Instrumentalness     4012
Liveness             1536
Valence              1293
Tempo               15024
Duration_ms         14690
Stream              18461
dtype: int64
```

```python
#Complete info about data frame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20718 entries, 0 to 20717
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Artist            20718 non-null  object 
 1   Track             20718 non-null  object 
 2   Album             20718 non-null  object 
 3   Album_type        20718 non-null  object 
 4   Danceability      20716 non-null  float64
 5   Energy            20716 non-null  float64
 6   Key               20716 non-null  float64
 7   Loudness          20716 non-null  float64
 8   Speechiness       20716 non-null  float64
 9   Acousticness      20716 non-null  float64
 10  Instrumentalness  20716 non-null  float64
 11  Liveness          20716 non-null  float64
 12  Valence           20716 non-null  float64
 13  Tempo             20716 non-null  float64
 14  Duration_ms       20716 non-null  float64
 15  Stream            20142 non-null  float64
dtypes: float64(12), object(4)
memory usage: 2.5+ MB
```

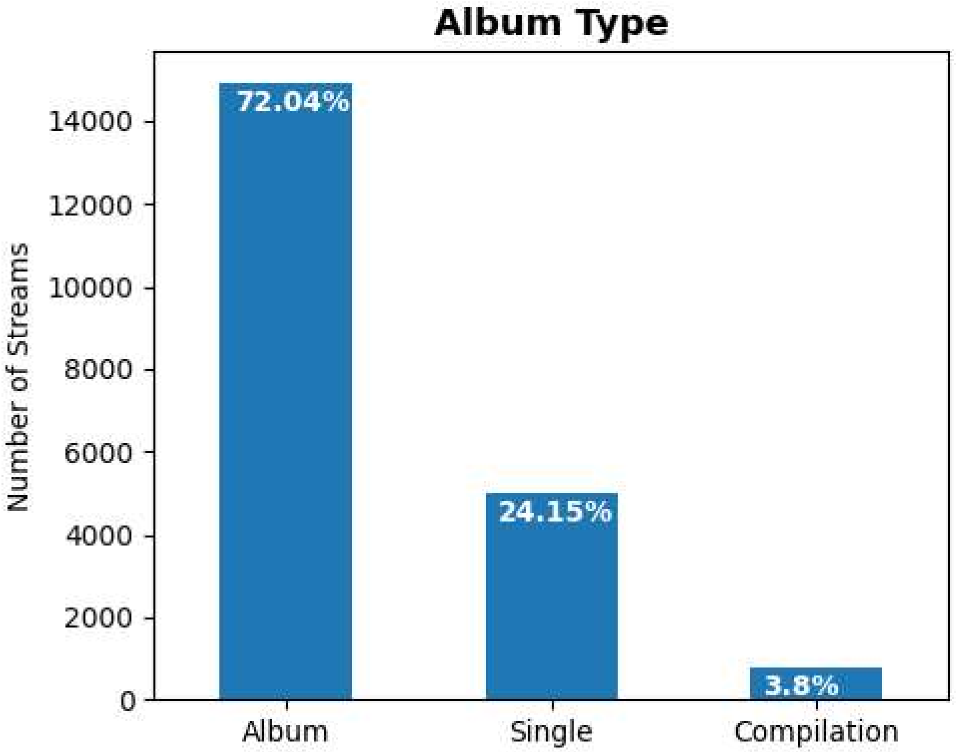
```python
#3. Visualising data  distribution in detail
fig = plt.figure(figsize =(18,18))
ax=fig.gca()
df.hist(ax=ax,bins =30,color='#1ED760')
plt.show()
```




```
#checking target value distribution
print(df.Album_type.value_counts())
fig, ax = plt.subplots(figsize=(5,4))
name = ["Album", "Single", "Compilation"]
ax = df.Album_type.value_counts().plot(kind='bar')
ax.set_title("Album Type", fontsize = 13, weight = 'bold')
ax.set_xticklabels (name, rotation = 0)
plt.ylabel('Number of Streams')

# To calculate the percentage
totals = []
for i in ax.patches:
    totals.append(i.get_height())
total = sum(totals)
for i in ax.patches:
    ax.text(i.get_x()+.09, i.get_height()-50, \
```

```
            str(round((i.get_height()/total)*100, 2))+'%', fontsize=14,
                color='white', weight = 'bold')

plt.tight_layout()
```

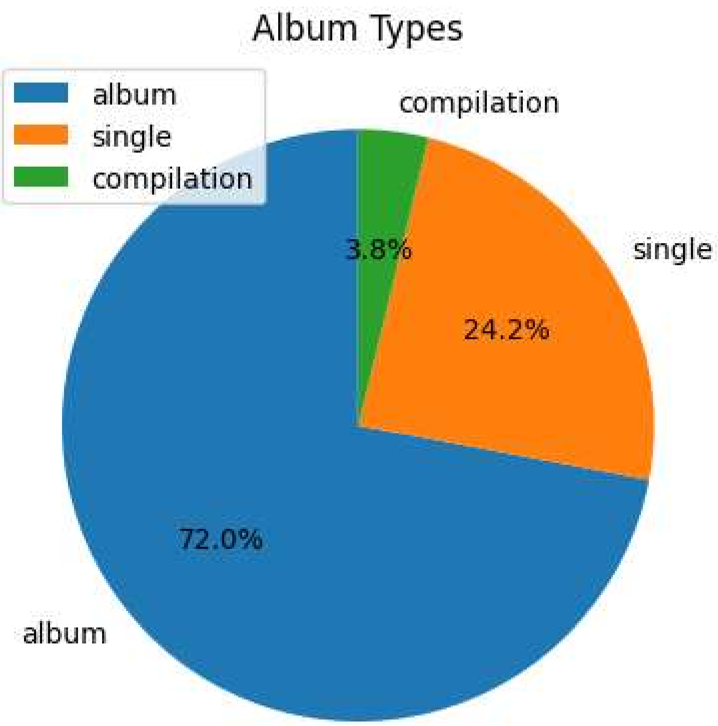
```
album          14926
single          5004
compilation      788
Name: Album_type, dtype: int64
```




```
album_type_count = df['Album_type'].value_counts()
print(album_type_count)
```

```
album          14926
single          5004
compilation      788
Name: Album_type, dtype: int64
```

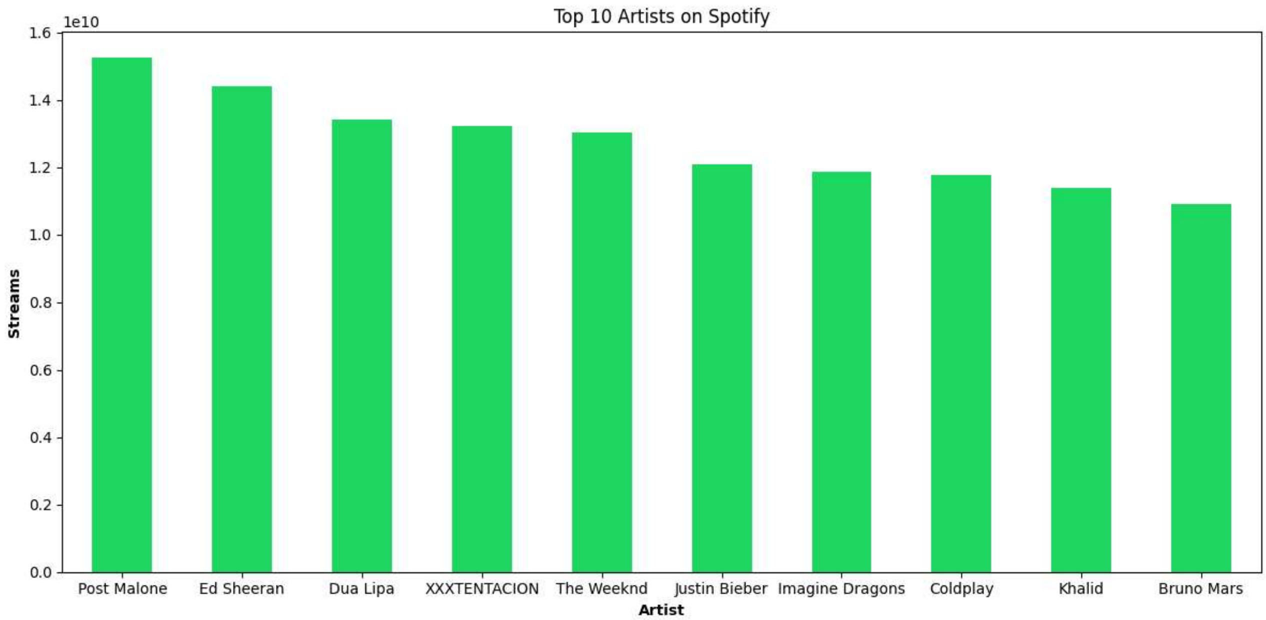
```
labels = album_type_count.index.tolist()
sizes = album_type_count.values.tolist()
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90)

plt.title('Album Types')
plt.legend(labels, loc='best')

plt.show()
```




```python
# Group the songs by artist - stream - spotify
artist_grouped = df.groupby('Artist')[['Stream']].sum()

# Sort the artists by the sum of streams in descending order
artist_sorted = artist_grouped.sort_values(['Stream'], ascending=False)

# Get the top 10 artists with the most number of streams on Spotify
top_10 = artist_sorted.head(10)

top_10
```

	Stream
Artist	
Post Malone	1.525126e+10
Ed Sheeran	1.439488e+10
Dua Lipa	1.340808e+10
XXXTENTACION	1.322435e+10
The Weeknd	1.303197e+10
Justin Bieber	1.209777e+10
Imagine Dragons	1.185831e+10
Coldplay	1.177848e+10
Khalid	1.138684e+10
Bruno Mars	1.089786e+10

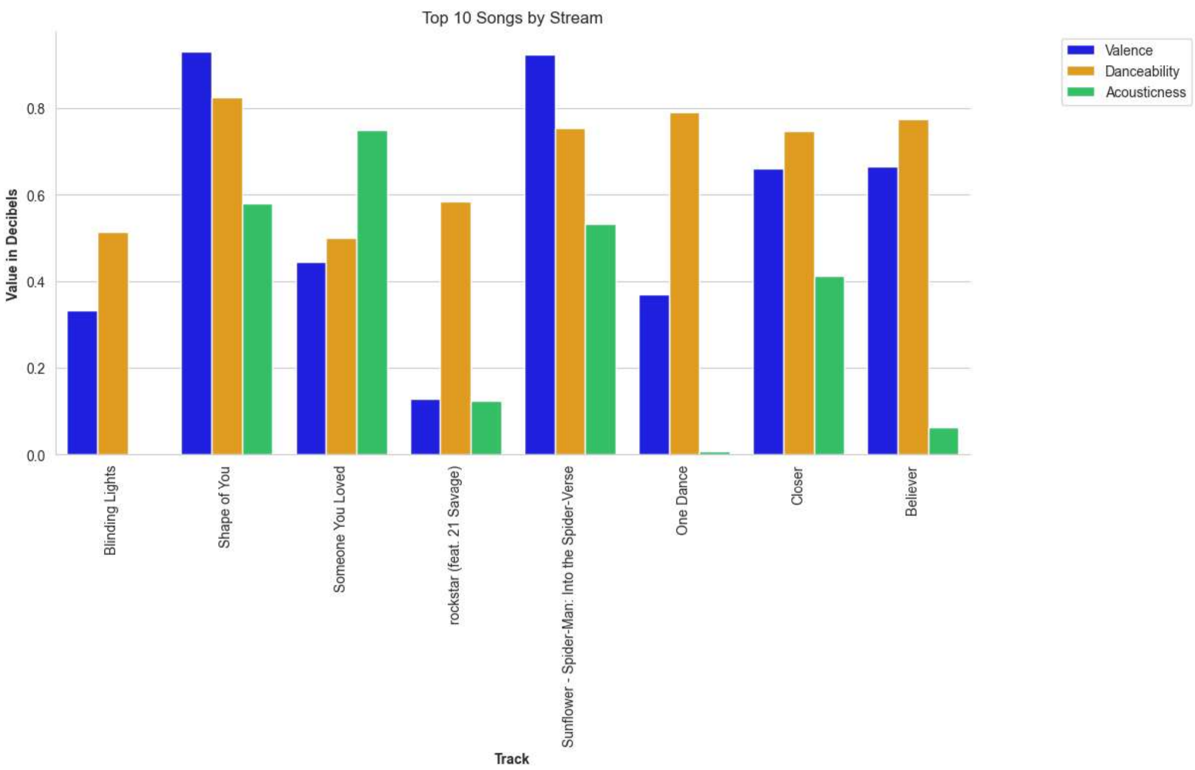
```python
# Create two separate DataFrames for views and streams
df_streams =
df.groupby('Artist')['Stream'].sum().sort_values(ascending=False)[:10]

fig, (ax1) = plt.subplots(1, figsize=(12,6))

# top 10 spotofy
ax1.set_title('Top 10 Artists on Spotify')
df_streams.plot(kind='bar', ax=ax1, color='#1ED760', rot=0)

ax1.set_xlabel('Artist', weight='bold')
ax1.set_ylabel('Streams', weight='bold')

fig.tight_layout()
plt.show()
```



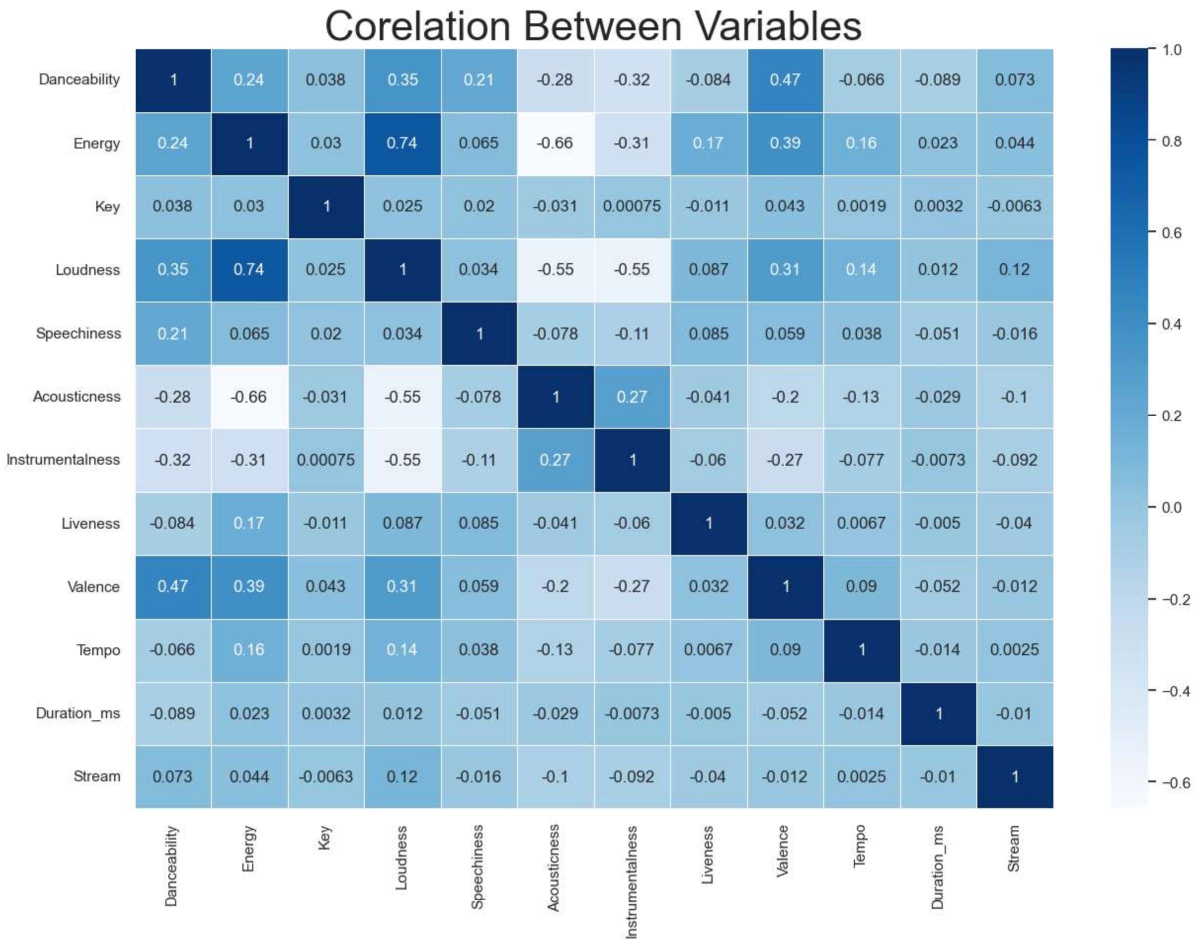

```python
top_songs = df.sort_values('Stream', ascending=False).head(10)
top_songs[['Track', 'Valence', 'Danceability', 'Acousticness']]
```

	Track	Valence	Danceability	Acousticness
15250	Blinding Lights	0.334	0.514	0.00146
12452	Shape of You	0.931	0.825	0.58100
19186	Someone You Loved	0.446	0.501	0.75100
17937	rockstar (feat. 21 Savage)	0.129	0.585	0.12400
17445	Sunflower - Spider-Man: Into the Spider-Verse	0.925	0.755	0.53300
17938	Sunflower - Spider-Man: Into the Spider-Verse	0.925	0.755	0.53300
13503	One Dance	0.370	0.792	0.00776
16099	Closer	0.661	0.748	0.41400
16028	Closer	0.661	0.748	0.41400
14030	Believer	0.666	0.776	0.06220

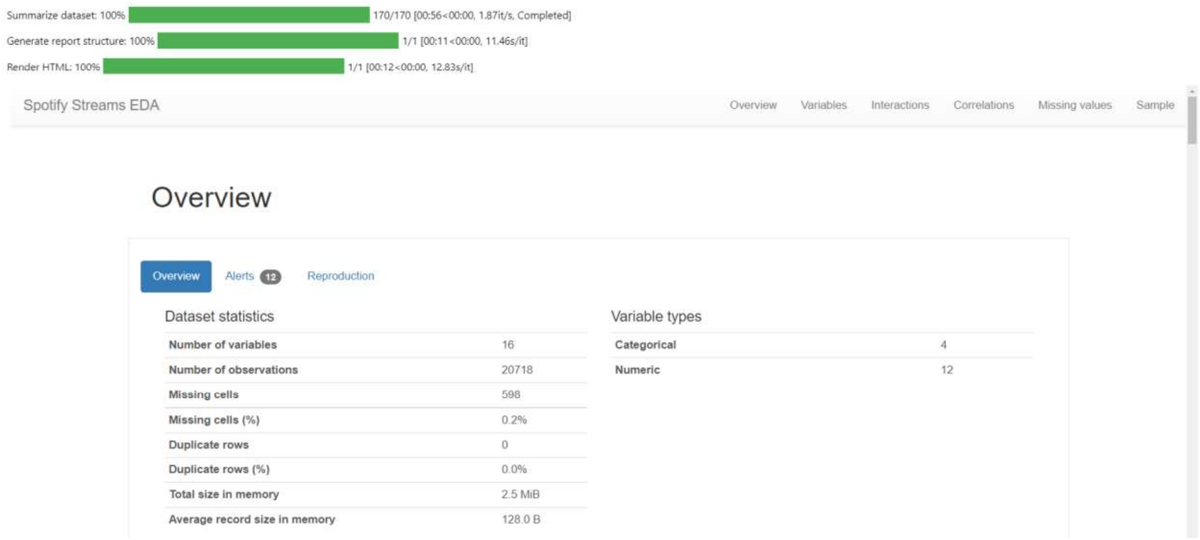
```
top_songs_melt = top_songs.melt(id_vars=['Track'], value_vars=['Valence',
'Danceability', 'Acousticness'],
                                var_name='Attribute', value_name='Value')

sns.set_style('whitegrid')
sns.catplot(x='Track', y='Value', hue='Attribute', data=top_songs_melt,
kind='bar',
            palette={'Valence': 'blue', 'Danceability': 'orange', 'Acousticness':
'#1ed760'},
            aspect=2, legend=False)

plt.legend(loc='upper right', bbox_to_anchor=(1.25, 1))
plt.title('Top 10 Songs by Stream')
plt.xlabel('Track', weight='bold')
plt.ylabel('Value in Decibels', weight='bold')

plt.xticks(rotation=90)
plt.show()
```




```
#check correlation between variables
sns.set(style="white")
plt.rcParams['figure.figsize'] = (15, 10)
sns.heatmap(df.corr(), annot = True, linewidths=.5, cmap="Blues")
plt.title('Corelation Between Variables', fontsize = 30)
plt.show()
```




```
!pip install ydata-profiling

#obtain full profiler report
#restart kernel

#re-run import libraries and data
from ydata_profiling import ProfileReport
profile = ProfileReport(df,title="Spotify Streams EDA",
                        html={'style':{'full_width':True}})
profile.to_notebook_iframe()

#Exporting the profiler report as an HTML

profile.to_file(output_file="Spotify EDA report.html")
```



To view the entire profiler report, please open the Spotify EDA report html file from the project folder.

Predictive Data Analytics

The process of predictive data analytics involves several steps. These steps include pre-processing, comparing classifiers to determine the best machine learning classifier, and evaluating performance using various objective metrics like accuracy, classification report, confusion matrix, and prediction report. These steps were implemented using the Python scikit-learn package. Each of the steps is explained below in detail.

1. Pre-processing: As the dataset contains both continuous and categorical attributes/variables, it requires pre-processing with attribute transformation, standardization, and normalization. To perform attribute transformation, we utilized the OrdinalEncoder() function provided by scikit-learn.
2. Normalization of the independent variables in the dataframe was done by excluding the target variable from the dataframe, performing normalization on it, and then reattaching the target variable to the dataframe:

```
#pre-processing
from sklearn.exceptions import DataDimensionalityWarning
#encode object columns to integers
from sklearn import preprocessing
from sklearn.preprocessing import OrdinalEncoder

for col in df:
  if df[col].dtype =='object':
    df[col]=OrdinalEncoder().fit_transform(df[col].values.reshape(-1,1))
df
```

	Artist	Track	Album	Album_type	Danceability	Energy	Key	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Duration_ms	Stream
0	687.0	4982.0	2638.0	0.0	0.818	0.705	6.0	-6.679	0.1770	0.008360	0.002330	0.6130	0.7720	138.559	222640.0	1.040235e+09
1	687.0	12385.0	7760.0	0.0	0.676	0.703	8.0	-5.815	0.0302	0.086900	0.000687	0.0463	0.8520	92.761	200173.0	3.100837e+08
2	687.0	10330.0	6941.0	2.0	0.695	0.923	1.0	-3.930	0.0522	0.042500	0.046900	0.1160	0.5510	108.014	215150.0	6.306347e+07
3	687.0	10895.0	7760.0	0.0	0.689	0.739	2.0	-5.810	0.0260	0.000015	0.509000	0.0640	0.5780	120.423	233867.0	4.346636e+08
4	687.0	2898.0	4140.0	0.0	0.663	0.694	10.0	-8.627	0.1710	0.025300	0.000000	0.0698	0.5250	167.953	340920.0	6.172597e+08
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
20713	1616.0	7413.0	5073.0	2.0	0.582	0.926	5.0	-6.344	0.0328	0.448000	0.000000	0.0839	0.6580	90.002	94667.0	9.227144e+06
20714	1616.0	12661.0	8505.0	2.0	0.531	0.936	4.0	-1.786	0.1370	0.028000	0.000000	0.0923	0.6570	174.869	150857.0	1.089818e+07
20715	1616.0	10776.0	7206.0	2.0	0.443	0.830	4.0	-4.679	0.0647	0.024300	0.000000	0.1540	0.4190	168.388	136842.0	6.226110e+06
20716	1616.0	10765.0	7195.0	2.0	0.417	0.767	9.0	-4.004	0.4190	0.356000	0.018400	0.1080	0.5390	155.378	108387.0	6.873961e+06
20717	1616.0	9051.0	6117.0	2.0	0.498	0.938	6.0	-4.543	0.1070	0.002770	0.911000	0.1360	0.0787	160.067	181500.0	5.695584e+06

20718 rows × 16 columns

```
class_label =df['Album_type']
df = df.drop(['Album_type'], axis =1)
df = (df-df.min())/(df.max()-df.min())
df['Album_type']=class_label
df
```

	Artist	Track	Album	Danceability	Energy	Key	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Duration_ms	Stream	Album_type
0	0.330606	0.279260	0.221012	0.838974	0.704994	0.545455	0.838905	0.183610	0.008392	0.002330	0.607306	0.777442	0.569330	0.041260	0.307168	0.0
1	0.330606	0.694226	0.650134	0.693333	0.702994	0.727273	0.857222	0.031328	0.087248	0.000687	0.032268	0.858006	0.381149	0.036423	0.091562	0.0
2	0.330606	0.579036	0.581518	0.712821	0.922998	0.090909	0.897183	0.054149	0.042670	0.046900	0.102993	0.554884	0.443823	0.039647	0.018620	2.0
3	0.330606	0.610706	0.650134	0.706667	0.738995	0.181818	0.857328	0.026971	0.000014	0.509000	0.050228	0.582075	0.494810	0.043677	0.128349	0.0
4	0.330606	0.162444	0.346850	0.680000	0.693994	0.909091	0.797609	0.177386	0.025401	0.000000	0.056114	0.528701	0.690108	0.066723	0.182268	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
20713	0.777671	0.415527	0.425017	0.596923	0.925998	0.454545	0.846007	0.034025	0.449799	0.000000	0.070421	0.662638	0.369812	0.013710	0.002723	2.0
20714	0.777671	0.709697	0.712550	0.544615	0.935999	0.363636	0.942634	0.142116	0.028111	0.000000	0.078945	0.661631	0.718526	0.025806	0.003216	2.0
20715	0.777671	0.604036	0.603720	0.454359	0.829997	0.363636	0.881304	0.067116	0.024397	0.000000	0.141553	0.421954	0.691896	0.022789	0.001837	2.0
20716	0.777671	0.603419	0.602798	0.427692	0.766995	0.818182	0.895614	0.434647	0.357429	0.018400	0.094876	0.542800	0.638438	0.016663	0.002028	2.0
20717	0.777671	0.507343	0.512483	0.510769	0.937999	0.545455	0.884187	0.110996	0.002780	0.911000	0.123288	0.079255	0.657705	0.032403	0.001680	2.0

20718 rows × 16 columns

```
#pre-processing
spotify_data = df.copy()
le = preprocessing.LabelEncoder()
album_type = le.fit_transform((list(spotify_data["Album_type"])))
danceability = le.fit_transform((list(spotify_data["Danceability"])) )
energy = le.fit_transform((list(spotify_data["Energy"])) )
key = le.fit_transform((list(spotify_data["Key"])) )
loudness = le.fit_transform((list(spotify_data["Loudness"])) )
speechiness = le.fit_transform((list(spotify_data["Speechiness"])) )
acousticness = le.fit_transform((list(spotify_data["Acousticness"]))   )
instrumentalness = le.fit_transform((list(spotify_data["Instrumentalness"])) )
liveness = le.fit_transform((list(spotify_data["Liveness"])))
valence = le.fit_transform((list(spotify_data["Valence"])))
tempo = le.fit_transform(list(spotify_data["Tempo"]))
duration_ms = le.fit_transform((list(spotify_data["Duration_ms"])))
stream = le.fit_transform(list(spotify_data["Stream"]))
artist = le.fit_transform((list(spotify_data["Artist"])))
```

Model Preparation and Development

Steps used for machine learning model preparation are described below:

- Convert the dataframe to training and validation/test subsets by taking a random sample of 80% of the data and defining it as train subset. This leaves 20% of the data for validation/testing

- Create the validation/test set by dropping all of the rows that comprise the training set from the dataframe.
- Create y_train by using using the last column of train (target class).
- Create x_train by using all of the columns in train except the last one.
- The validation set of y_val and x_val or (y_test and x_test), can be created using the same methodology that used to create y_train and x_train

```
#Predictive analytics model development by comparing different Scikit-learn
classification algorithms

import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier

x = list(zip( danceability, energy, key , loudness, speechiness,acousticness,
instrumentalness, liveness,valence, tempo))
y = list(album_type)
# Test options and evaluation metric
num_folds = 5
seed = 7
scoring = 'accuracy'

# Model Test/Train
# Splitting what we are trying to predict into 4 different arrays -
# X train is a section of the x array(attributes) and vise versa for Y(features)
# The test data will test the accuracy of the model created
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x, y,
test_size = 0.20, random_state=seed)
#splitting 20% of our data into test samples. If we train the model with higher
data it already has seen that information and knows

#size of train and test subsets after splitting
np.shape(x_train), np.shape(x_test)
```

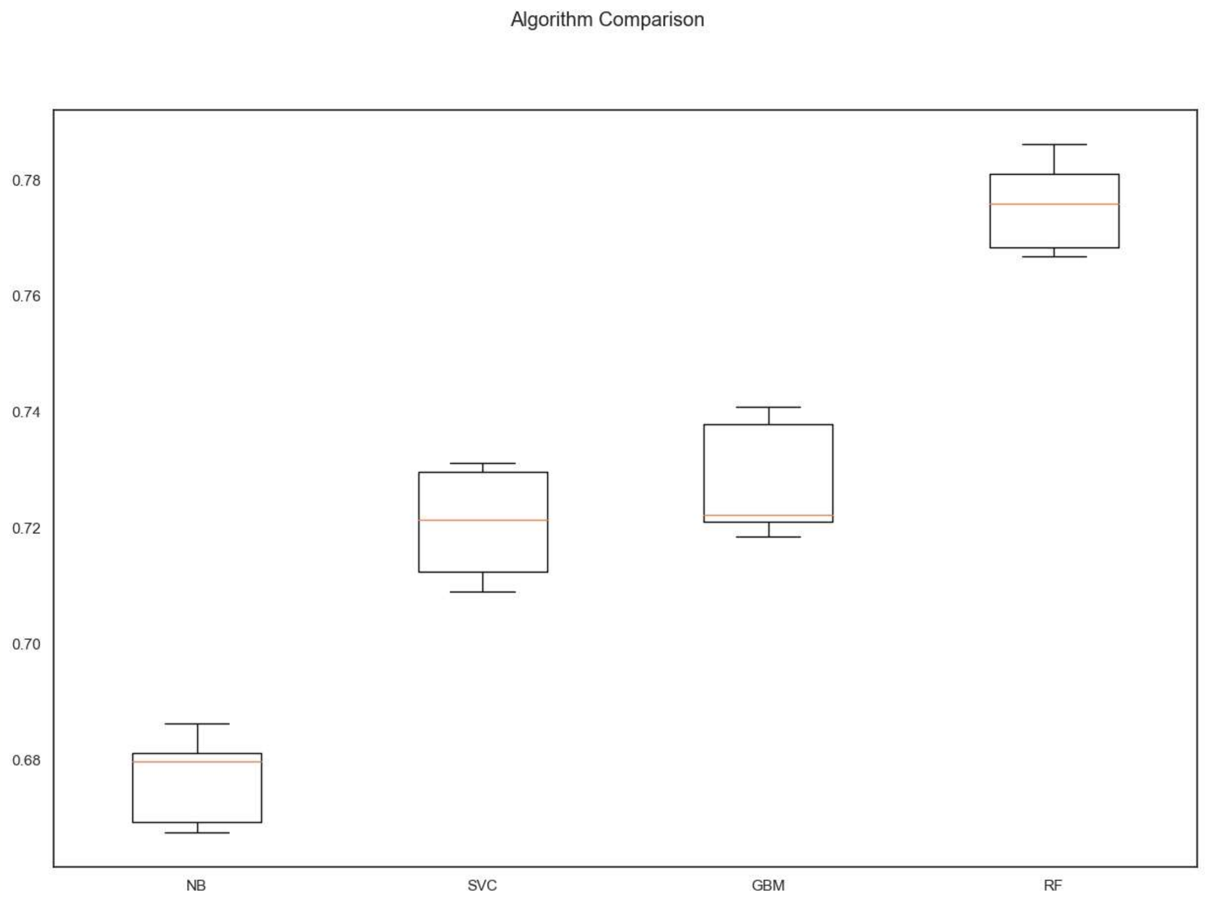
```
((16574, 10), (4144, 10))
```

```
models = []
models.append(('NB', GaussianNB()))
models.append(('SVC', SVC()))
models.append(('GBM', GradientBoostingClassifier()))
models.append(('RF', RandomForestClassifier()))
# evaluate each model in turn
results = []
names = []
print("Performance on Training set")
for name, model in models:
  kfold = KFold(n_splits=num_folds,shuffle=True,random_state=seed)
  cv_results = cross_val_score(model, x_train, y_train, cv=kfold,
scoring='accuracy')
  results.append(cv_results)
  names.append(name)
  msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
  msg += '\n'
  print(msg)
```

```
Performance on Training set
NB: 0.676782 (0.007194)

SVC: 0.720707 (0.008943)

GBM: 0.728067 (0.009351)

RF: 0.775612 (0.007362)
```

Stage 2: Identifying the best model

```
# Compare Algorithms' Performance
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```




```
#Model Evaluation by testing with independent/external test data set.
# Make predictions on validation/test dataset

svc = SVC()
gb = GradientBoostingClassifier()
rf = RandomForestClassifier()
nb = GaussianNB()

best_model = rf

best_model.fit(x_train, y_train)
y_pred = best_model.predict(x_test)
print("Best Model Accuracy Score on Test Set:", accuracy_score(y_test, y_pred))
```

```
Best Model Accuracy Score on Test Set: 0.7898166023166023
```

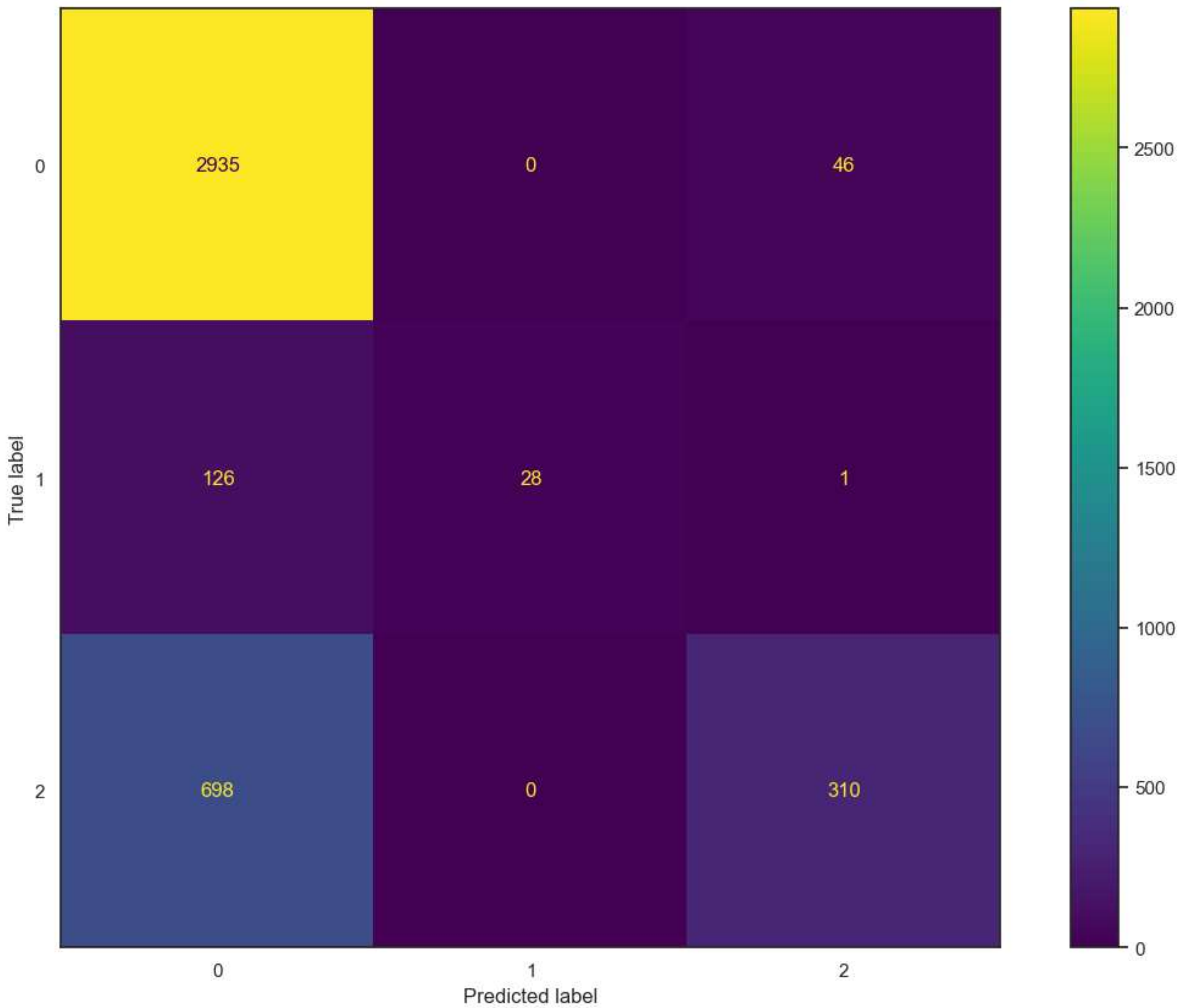
Through this, we can tell that Random Forest Classifier (RF) is the best performing model as its Accuracy Score is 0.7898… which is 78.98%. Moreover, it has the lowest standard deviation rate from the rest of the models as we can see in the table below:

Model	Mean	Standard Deviation
Gaussian NB	0.676782	0.007194
Support Vector Machine	0.720707	0.008943
Gradient Boosting Classifier	0.728128	0.009415
Random Forest Classifier	**0.773017**	**0.008295**

```
#Model Performance Evaluation Metric 1 - Classification Report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.98      0.87      2981
           1       1.00      0.18      0.31       155
           2       0.87      0.31      0.45      1008

    accuracy                           0.79      4144
   macro avg       0.88      0.49      0.54      4144
weighted avg       0.81      0.79      0.75      4144
```

```
#Model Performance Evaluation Metric 2
#Confusion matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.show()
```




```
import sys

#Model Evaluation Metric 3-prediction report
for x in range(len(y_pred)):
  print("Predicted: ", y_pred[x], "Actual: ", y_test[x], "Data: ", x_test[x],)

# Define the filename
filename = "prediction_report.txt"

# Open the file in write mode
with open(filename, "w") as file_object:
  # Redirect the standard output to the file
  sys.stdout = file_object

  # Print the prediction report
  for x in range(len(y_pred)):
    print("Predicted: ", y_pred[x], "Actual: ", y_test[x], "Data: ", x_test[x])

  # Reset the standard output
  sys.stdout = sys.__stdout__
```

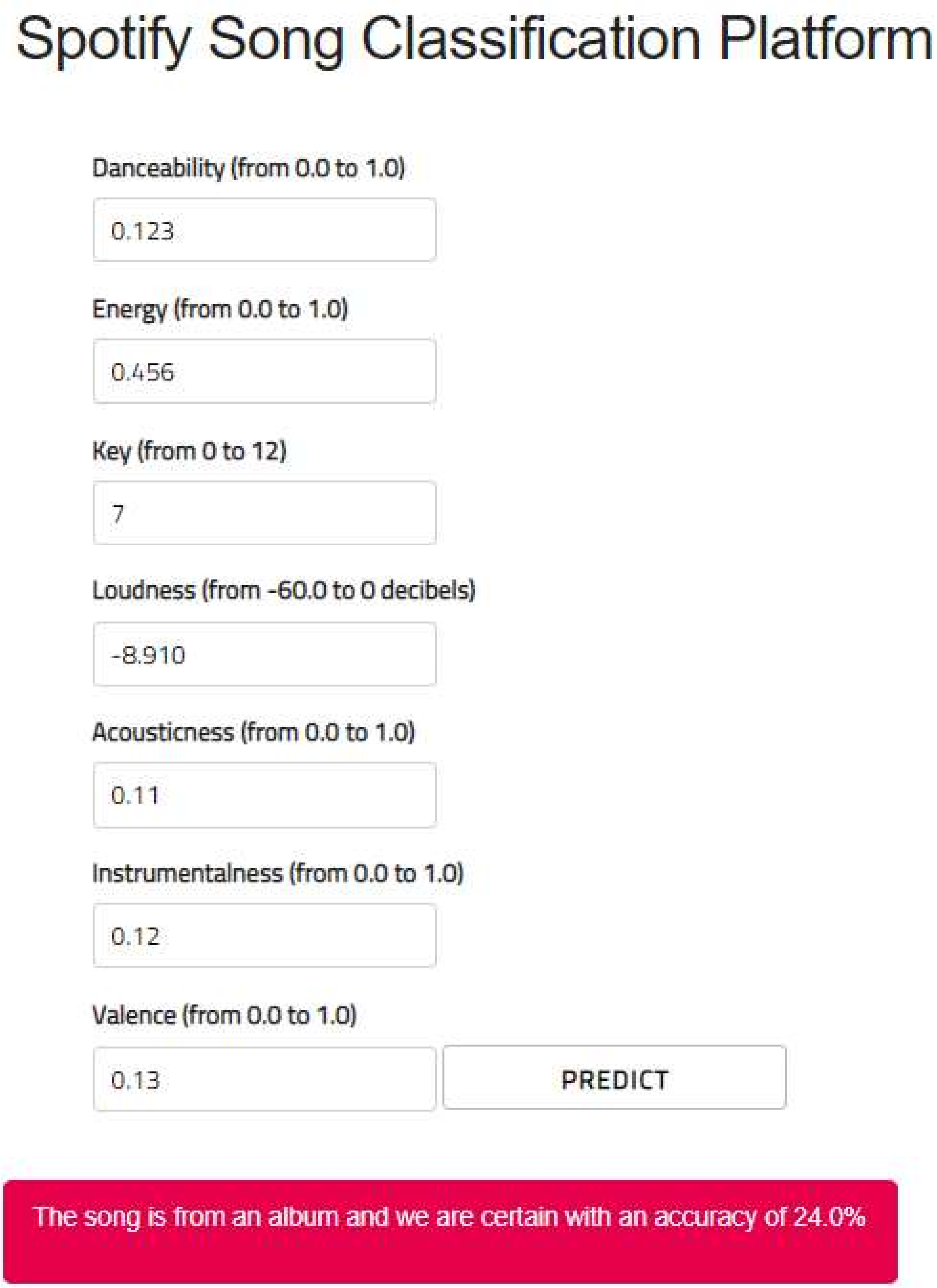
```
Predicted:  0 Actual:  0 Data:  (492, 1095, 8, 7515, 162, 2776, 0, 368, 972, 12193)
Predicted:  0 Actual:  1 Data:  (492, 1015, 8, 5705, 79, 1897, 392, 643, 917, 3781)
Predicted:  0 Actual:  0 Data:  (339, 992, 3, 6429, 102, 2510, 862, 623, 743, 8400)
Predicted:  0 Actual:  2 Data:  (523, 1107, 7, 5322, 155, 172, 3859, 1164, 504, 5789)
Predicted:  0 Actual:  2 Data:  (447, 1100, 8, 5297, 91, 2150, 211, 365, 884, 11196)
Predicted:  0 Actual:  0 Data:  (422, 626, 10, 3746, 134, 2590, 1229, 767, 433, 8587)
Predicted:  0 Actual:  2 Data:  (529, 958, 5, 6411, 150, 1505, 0, 1196, 880, 11903)
Predicted:  0 Actual:  0 Data:  (224, 594, 6, 814, 88, 1236, 3888, 442, 757, 14201)
Predicted:  0 Actual:  0 Data:  (218, 1090, 7, 5503, 185, 1374, 1329, 773, 547, 2379)
Predicted:  0 Actual:  0 Data:  (715, 808, 2, 5802, 511, 2175, 2925, 755, 1035, 12106)
Predicted:  0 Actual:  0 Data:  (289, 869, 0, 3628, 71, 2512, 0, 723, 1113, 14649)
Predicted:  0 Actual:  0 Data:  (305, 875, 0, 5279, 812, 821, 1924, 866, 544, 1340)
Predicted:  0 Actual:  0 Data:  (614, 990, 6, 5580, 799, 1673, 1567, 920, 921, 10945)
Predicted:  0 Actual:  2 Data:  (232, 598, 8, 1645, 426, 3086, 2911, 977, 879, 13779)
Predicted:  2 Actual:  2 Data:  (571, 1088, 11, 8373, 891, 1749, 0, 811, 1147, 14483)
Predicted:  0 Actual:  0 Data:  (320, 928, 4, 3858, 870, 1355, 0, 961, 638, 12140)
Predicted:  0 Actual:  0 Data:  (113, 588, 10, 3999, 116, 2962, 255, 733, 126, 1353)
Predicted:  0 Actual:  0 Data:  (534, 419, 7, 443, 850, 2977, 0, 800, 775, 7690)
Predicted:  0 Actual:  0 Data:  (399, 1153, 8, 5437, 806, 320, 0, 724, 708, 8757)
Predicted:  0 Actual:  2 Data:  (718, 965, 1, 5887, 850, 2630, 3222, 745, 1054, 9420)
Predicted:  0 Actual:  0 Data:  (820, 671, 9, 6308, 808, 2594, 57, 519, 1062, 4714)
Predicted:  0 Actual:  0 Data:  (610, 805, 10, 4252, 158, 2493, 1511, 812, 1091, 11480)
Predicted:  0 Actual:  0 Data:  (363, 994, 2, 6762, 71, 1789, 0, 721, 536, 343)
Predicted:  0 Actual:  0 Data:  (556, 767, 1, 3809, 389, 2752, 1043, 732, 618, 11589)
Predicted:  2 Actual:  2 Data:  (538, 707, 0, 6326, 118, 2903, 156, 576, 986, 9996)
...
Predicted:  0 Actual:  0 Data:  (603, 508, 8, 2375, 185, 2988, 0, 241, 1266, 13939)
Predicted:  2 Actual:  2 Data:  (511, 1179, 10, 7353, 667, 773, 0, 726, 1131, 13320)
Predicted:  0 Actual:  2 Data:  (690, 978, 11, 7709, 356, 1484, 28, 746, 612, 7598)
Predicted:  0 Actual:  2 Data:  (719, 575, 0, 2738, 244, 2754, 814, 671, 763, 10256)
```
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

To see the full prediction report, please see the exported text file prediction_report in the project folder.

Stage 3: Software Deployment Stage

Once the best performing algorithm and machine learning model for the album type prediction has been identified from stage 1, the deployment of the algorithm as a desktop software tool using Flask API. It is a widely used micro web framework for creating APIs in Python. Flask is a simple yet powerful web framework in Python, with an the ability to scale up to complex applications. The Flask project deployment for the Spotify Album Type prediction is available in the sub-folder Spotify Classifier Flask in the project folder.

Through the Flask took, users will be able to input the Danceability, Energy, Loudness, Key, Acousticness, Instrumentalness and Valence of a song and the tool will predict which type of Album type the song will have. Below are the screenshots from the test run:



Conclusions

This report presents the work done towards the ST1 (G) capstone project for design, development, implementation and deployment of data driven Spotify album type prediction software platform using Python. As can be seen from the outcomes of this project, we can train models that can predict album type of a track with substantial accuracy. The availability of predictive analytics tools as a web based tool, allows the wider application of this project.

References

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[4] https://towardsdatascience.com/creating-restful-apis-using-flask-and-python-655bad51b24

[5] ST_Capstone_Project_Report_Template.docx

[6] penguin_classifier.ipynb

[7] Penguin_Classifier_Project