In [1]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import r2_score
from sklearn.tree import DecisionTreeRegressor
import xgboost as xgb
from sklearn.metrics import roc_curve
from sklearn.metrics import confusion_matrix, classification_report
```

In [2]:

```
# Read the csv file
df=pd.read_csv("/Users/noelm/Downloads/indian_songs_dataset_final_1.csv
df
```

Out[2]:

	Spotify ID	Artist IDs
0	7eQl3Yqv35ioqUfveKHitE	1wRPtKGflJrBx9BmLsSwlU,5GnnSrwNCGyfAU4zuIytiS
1	6aPMWbbdhDhiJHlknZb9Yx	4YRxDV8wJFPHPTeXepOstw,1SyKki7JI1AZNKwgNMkn25
2	6zCQF5tu7HVwU9shhKqiuF	2kkQthS9OLpK4UqNWYqoVl,4YRxDV8wJFPHPTeXepOstw
3	0qxTDueomxqHEUPwlD9y4S	7HCqGPJcQTyGJ2yqntbuyr,3nQ125TJobosBH446Dsvvv,...
4	4iFPsNzNV7V9KJgcOX7TEO	2oSONSC9zQ4UonDKnLqksx,1wRPtKGflJrBx9BmLsSwlU
...	...	...
4217	13MzyV40LsbNrwiVebat88	6pU5oz09VUYtnFTd4P1Mxn
4218	0weDybgloozlzRXAisUYGT	6pU5oz09VUYtnFTd4P1Mxn
4219	7D8CvQ0wlT4mYKwFnEs1B1	182srEbrmnlFxcwkqZ0NR6
4220	42lIM5kcQtIHQK7vcDxcUJ	182srEbrmnlFxcwkqZ0NR6
4221	7ups0PLQ1oiRnkneh3SQSD	6LEG9Ld1aLImEFEVHdWNSB,2SrSdSvpminqmStGELCSNd

4222 rows × 23 columns

In [3]:
```
# Display first 5 records in dataframe
print(df.head())
```

```
               Spotify ID                                        Arti
st IDs  \
0  7eQl3Yqv35ioqUfveKHitE      1wRPtKGflJrBx9BmLsSwlU,5GnnSrwNCGyfAU4z
uIytiS
1  6aPMWbbdhDhiJHlknZb9Yx      4YRxDV8wJFPHPTeXepOstw,1SyKki7JI1AZNKwg
NMkn25
2  6zCQF5tu7HVwU9shhKqiuF      2kkQthS9OLpK4UqNWYqoVl,4YRxDV8wJFPHPTeX
epOstw
3  0qxTDueomxqHEUPwlD9y4S  7HCqGPJcQTyGJ2yqntbuyr,3nQ125TJobosBH446Dsv
vv,...
4  4iFPsNzNV7V9KJgcOX7TEO      2oSONSC9zQ4UonDKnLqksx,1wRPtKGflJrBx9Bm
LsSwlU

                                          Track Name  \
0                                          Tum Se Hi
1  Bekhayali (Arijit Singh Version) [From Kabir S...
2                                         Khamoshiyan
3                           Iktara (From Wake Up Sid)
4                                         Tu Jaane Na

                                          Album Name  \
0                                          Jab We Met
1  Bekhayali (Arijit Singh Version) [From Kabir S...
2   Khamoshiyan (Original Motion Picture Soundtrack)
3                              Perfect 10: Love Story
4  Ajab Prem Ki Ghazab Kahani (Original Motion Pi...

                                  Artist Name(s) Release Date  Duratio
n (ms)  \
0                            Pritam,Mohit Chauhan   21-09-2007
321225
1                  Arijit Singh,Sachet-Parampara   03-06-2019
370444
2                     Jeet Gannguli,Arijit Singh   29-12-2014
335709
3  Amit Trivedi,Kavita Seth,Amitabh Bhattacharya   20-01-2012
251773
4                               Atif Aslam,Pritam   06-11-2009
341933

   Popularity                              Added By              Add
ed At  \
0        77.0  spotify:user:7mq9oy7pfjv07t9yjj4gj2qy9  2019-09-18T16:0
3:30Z
1        56.0  spotify:user:7mq9oy7pfjv07t9yjj4gj2qy9  2019-09-18T16:0
3:47Z
2        69.0  spotify:user:7mq9oy7pfjv07t9yjj4gj2qy9  2019-09-18T16:0
3:57Z
3        30.0  spotify:user:7mq9oy7pfjv07t9yjj4gj2qy9  2020-08-26T13:3
6:59Z
4        71.0  spotify:user:7mq9oy7pfjv07t9yjj4gj2qy9  2020-12-22T21:1
5:41Z

   ... Key  Loudness  Mode  Speechiness  Acousticness  Instrumentalnes
s  \
0  ...   6    -7.842     1       0.0273         0.328           0.00000
0
1  ...   9    -4.767     0       0.0491         0.491           0.00000
0
2  ...   2    -6.837     0       0.0272         0.631           0.00000
0
```

```
3  ...   7   -7.514    1       0.0259        0.429         0.00065
2
4  ...   7   -3.969    1       0.0345        0.361         0.00000
1

   Liveness  Valence    Tempo  Time Signature
0     0.125    0.608  130.015               4
1     0.243    0.345  172.121               3
2     0.158    0.266  143.892               3
3     0.466    0.399   80.013               4
4     0.133    0.829  120.042               4

[5 rows x 23 columns]
```

In [4]:

```
# To get the total number of rows and columns in dataset
df.shape
```

Out[4]:

```
(4222, 23)
```

In [5]:

```
# Check the datatype and non-null count of each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4222 entries, 0 to 4221
Data columns (total 23 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Spotify ID        4222 non-null   object
 1   Artist IDs        4222 non-null   object
 2   Track Name        4070 non-null   object
 3   Album Name        4076 non-null   object
 4   Artist Name(s)    4070 non-null   object
 5   Release Date      4222 non-null   object
 6   Duration (ms)     4222 non-null   int64
 7   Popularity        4221 non-null   float64
 8   Added By          4222 non-null   object
 9   Added At          4222 non-null   object
 10  Genres            3836 non-null   object
 11  Danceability      4222 non-null   float64
 12  Energy            4222 non-null   float64
 13  Key               4222 non-null   int64
 14  Loudness          4222 non-null   float64
 15  Mode              4222 non-null   int64
 16  Speechiness       4222 non-null   float64
 17  Acousticness      4222 non-null   float64
 18  Instrumentalness  4222 non-null   float64
 19  Liveness          4222 non-null   float64
 20  Valence           4222 non-null   float64
 21  Tempo             4222 non-null   float64
 22  Time Signature    4222 non-null   int64
dtypes: float64(10), int64(4), object(9)
memory usage: 758.8+ KB
```

In [6]:
```
# Check missing values
df.isnull().sum()
```

Out[6]:
```
Spotify ID             0
Artist IDs             0
Track Name           152
Album Name           146
Artist Name(s)       152
Release Date           0
Duration (ms)          0
Popularity             1
Added By               0
Added At               0
Genres               386
Danceability           0
Energy                 0
Key                    0
Loudness               0
Mode                   0
Speechiness            0
Acousticness           0
Instrumentalness       0
Liveness               0
Valence                0
Tempo                  0
Time Signature         0
dtype: int64
```

In [7]:
```
# Drop all the rows where we have missing values
data = df.dropna()
data
```

Out[7]:

	Spotify ID	Artist IDs
0	7eQl3Yqv35ioqUfveKHitE	1wRPtKGflJrBx9BmLsSwlU,5GnnSrwNCGyfAU4zuIytiS
1	6aPMWbbdhDhiJHlknZb9Yx	4YRxDV8wJFPHPTeXepOstw,1SyKki7JI1AZNKwgNMkn25
2	6zCQF5tu7HVwU9shhKqiuF	2kkQthS9OLpK4UqNWYqoVl,4YRxDV8wJFPHPTeXepOstw
3	0qxTDueomxqHEUPwlD9y4S	7HCqGPJcQTyGJ2yqntbuyr,3nQ125TJobosBH446Dsvvv,...
4	4iFPsNzNV7V9KJgcOX7TEO	2oSONSC9zQ4UonDKnLqksx,1wRPtKGflJrBx9BmLsSwlU
...	...	...
4217	13MzyV40LsbNrwiVebat88	6pU5oz09VUYtnFTd4P1Mxn
4218	0weDybgloozlzRXAisUYGT	6pU5oz09VUYtnFTd4P1Mxn
4219	7D8CvQ0wlT4mYKwFnEs1B1	182srEbrmnlFxcwkqZ0NR6
4220	42lIM5kcQtIHQK7vcDxcUJ	182srEbrmnlFxcwkqZ0NR6
4221	7ups0PLQ1oiRnkneh3SQSD	6LEG9Ld1aLImEFEVHdWNSB,2SrSdSvpminqmStGELCSNd

3836 rows × 23 columns

In [8]:
```
# Check for missing values again
data.isnull().sum()
```

Out[8]:
```
Spotify ID          0
Artist IDs          0
Track Name          0
Album Name          0
Artist Name(s)      0
Release Date        0
Duration (ms)       0
Popularity          0
Added By            0
Added At            0
Genres              0
Danceability        0
Energy              0
Key                 0
Loudness            0
Mode                0
Speechiness         0
Acousticness        0
Instrumentalness    0
Liveness            0
Valence             0
Tempo               0
Time Signature      0
dtype: int64
```

In [9]:
```
# No. of rows became less in new dataframe
data.shape
```

Out[9]:
```
(3836, 23)
```

In [10]:
```
uni=data['Track Name'].nunique()
print("No of unique songs = ",uni)
```

```
No of unique songs =  2494
```

In [11]:
```
# Remove all duplicate songs keeping only the first occurance of that s
duplicate_songs = data[data.duplicated(subset=['Track Name'], keep='fir
print(duplicate_songs)
```

```
                  Spotify ID  \
177   2kRzgmBlmhvFvCEgMHltWz
302   3SHopOL3KEJ8PFl3vJdfmF
338   7ouBSPZKQpm7zQz2leJXta
339   3uL1IBFhg52VcQqOwAG01E
340   3t3wsY5IdLVzB9WidegJSU
...                      ...
4022  595br74XSTX5V9YixYZdXC
4030  23YGhMVq1wJYROCp2kr8yP
4077  0xIuPDzJSnJywALez8dwKR
4083  5XpRKTgWi6skmmQu5sSz8d
4122  5qEFLzru66ilBHP6am3PwA

                                           Artist IDs  \
177                            0oOet2f43PA68X5RxKobEy
302       5bv6NvAYNuvd2Vq13nHdG3,4IKVDbCSBTxBeAsMKjAuTs
338                            4YRxDV8wJFPHPTeXepOstw
339       4YRxDV8wJFPHPTeXepOstw,5UJ2sHO2ELrgW6aXeRLTQQ
340   2oSONSC9zQ4UonDKnLqksx,0oOet2f43PA68X5RxKobEy,...
```

In [12]:
```
# Size of duplicate songs
duplicate_songs.shape
```

Out[12]: (1342, 23)

In [13]:
```
# New dataframe with all unique songs 2484 - 1317 = 1167
df1 = data.drop_duplicates(subset=['Track Name'], keep='first')
df1.shape
```

Out[13]: (2494, 23)

In [14]:
```
# Drop the columns which are not required for the ML model
cols = ['Spotify ID', 'Artist IDs', 'Added By','Added At','Track Name',
       'Duration (ms)']
df1 = df1.drop(columns=cols)
df1.shape
```

Out[14]: (2494, 13)

In [15]:
```
df1.columns
```

Out[15]:
```
Index(['Popularity', 'Danceability', 'Energy', 'Key', 'Loudness', 'Mod
e',
       'Speechiness', 'Acousticness', 'Instrumentalness', 'Liveness',
       'Valence', 'Tempo', 'Time Signature'],
      dtype='object')
```

In [16]:

```
from collections import Counter
def detect_outliers(df,features):
    outlier_indices = []

    for c in features:
        # 1st quartile
        Q1 = np.percentile(df[c],25)
        # 3rd quartile
        Q3 = np.percentile(df[c],75)
        # IQR
        IQR = Q3 - Q1
        # Outlier step
        outlier_step = IQR * 1.5
        # detect outlier and their indeces
        outlier_list_col = df[(df[c] < Q1 - outlier_step) | (df[c] > Q3
        # store indeces
        outlier_indices.extend(outlier_list_col) #The extend() extends

    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list(i for i, v in outlier_indices.items() if v

    return multiple_outliers
```

In [17]:

```
df1.loc[detect_outliers(df1,['Popularity', 'Danceability', 'Energy',
       'Key', 'Loudness', 'Mode', 'Speechiness', 'Acousticness',
       'Instrumentalness', 'Liveness', 'Valence', 'Tempo', 'Time Signat
```

Out[17]:

	Popularity	Danceability	Energy	Key	Loudness	Mode	Speechiness	Acousticn
2725	0.0	0.648	0.88800	1	-5.503	1	0.3220	0.3
42	40.0	0.215	0.14700	10	-14.797	1	0.0379	0.8
1599	39.0	0.207	0.29700	5	-8.845	0	0.0336	0.7
275	52.0	0.620	0.11100	6	-14.142	1	0.0355	0.8
968	50.0	0.472	0.12200	4	-15.837	0	0.0357	0.5
1073	8.0	0.415	0.00865	9	-19.003	1	0.0605	0.9
1418	64.0	0.378	0.14600	6	-15.412	1	0.0403	0.8
307	73.0	0.645	0.32400	1	-13.621	0	0.0545	0.7
1183	70.0	0.556	0.20200	4	-16.397	1	0.0324	0.9
1188	49.0	0.550	0.28900	4	-14.411	1	0.0358	0.8
3080	42.0	0.755	0.73800	7	-7.947	1	0.2090	0.6
3339	33.0	0.636	0.90300	10	-4.791	0	0.2330	0.0
3538	42.0	0.509	0.94900	11	-3.850	1	0.3450	0.4
3549	50.0	0.489	0.95200	5	-3.441	1	0.3320	0.6
3686	25.0	0.554	0.60000	7	-10.621	0	0.3460	0.4
3799	52.0	0.513	0.87100	11	-3.050	0	0.2940	0.3

In [18]:
```
# drop outliers
df1 = df1.drop(detect_outliers(df1,['Popularity', 'Danceability', 'Ener
       'Key', 'Loudness', 'Mode', 'Speechiness', 'Acousticness',
       'Instrumentalness', 'Liveness', 'Valence', 'Tempo', 'Time Signat
```

In [19]:
```
df1.shape
```

Out[19]: (2478, 13)

In [20]:
```
# Seperate into independant and dependant variables
# In Y we keep Popularity as the target variable for predicting and X c
X = df1.iloc[:, np.r_[1:13]]
Y = df1.iloc[:, 0]
print(X.shape, Y.shape)
```

(2478, 12) (2478,)

In [21]:
```
X
```

Out[21]:

	Danceability	Energy	Key	Loudness	Mode	Speechiness	Acousticness	Instrum
0	0.609	0.538	6	-7.842	1	0.0273	0.32800	
1	0.265	0.580	9	-4.767	0	0.0491	0.49100	
2	0.527	0.521	2	-6.837	0	0.0272	0.63100	
3	0.622	0.516	7	-7.514	1	0.0259	0.42900	
4	0.702	0.860	7	-3.969	1	0.0345	0.36100	
...	...	...	...	...	...	...	...	
2473	0.738	0.784	2	-7.172	1	0.3290	0.10500	
2474	0.707	0.632	6	-8.734	0	0.3590	0.00159	
2475	0.724	0.879	10	-8.217	1	0.0863	0.08000	
2476	0.731	0.792	4	-6.560	0	0.1940	0.01210	
2477	0.873	0.455	8	-7.849	0	0.3410	0.50400	

2478 rows × 12 columns

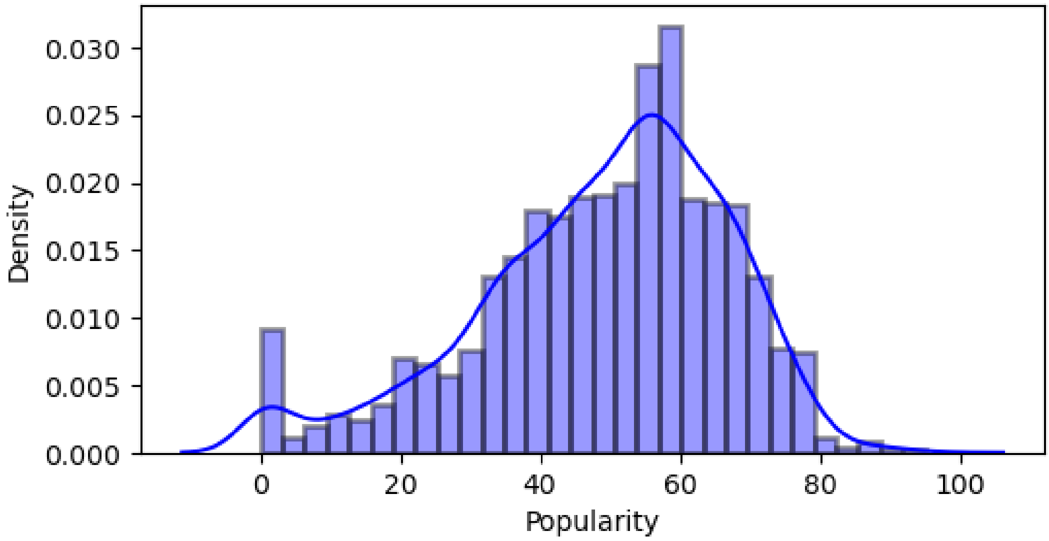
In [22]:
```
Y
```

Out[22]:
```
0       77.0
1       56.0
2       69.0
3       30.0
4       71.0
        ...
2473    22.0
2474    34.0
2475    44.0
2476    35.0
2477    68.0
Name: Popularity, Length: 2478, dtype: float64
```

In [23]:
```
# from sklearn.preprocessing import StandardScaler
# scaler = StandardScaler()
# X = scaler.fit_transform(X)
```

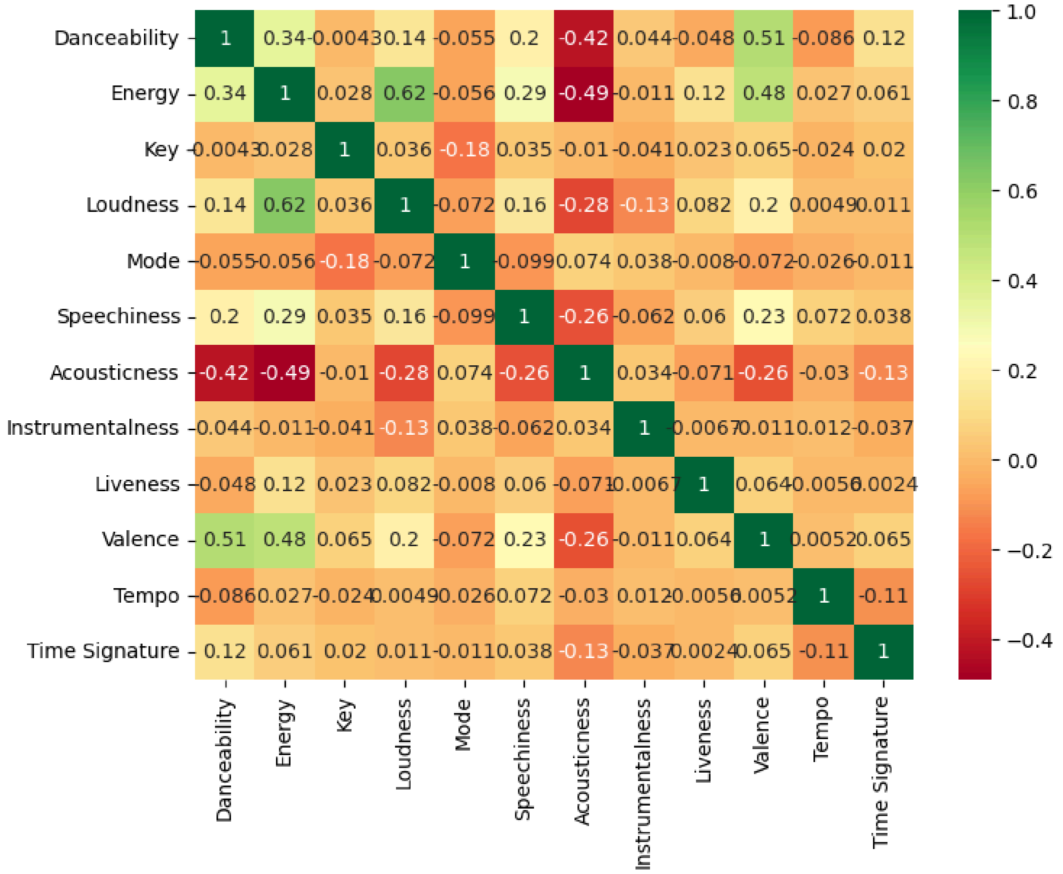
In [24]:
```
# Normal Distribution is observed for popularity showing data near the
plt.figure(figsize=[6,3])
sns.distplot(df1['Popularity'], color='b',hist_kws=dict(edgecolor="blac
plt.show()
```

```
C:\Users\noelm\anaconda3\lib\site-packages\seaborn\distributions.py:26
19: FutureWarning: `distplot` is a deprecated function and will be rem
oved in a future version. Please adapt your code to use either `displo
t` (a figure-level function with similar flexibility) or `histplot` (a
n axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



Feature Selection

In [25]:
```
# Using Correlation matrix
corr_matrix = X.corr()
indices = corr_matrix.index
plt.figure(figsize=[8,6])
sns.heatmap(X[indices].corr(), annot=True, cmap="RdYlGn")
plt.show()
```



In [26]:
```
# Getting the columns with highly correlated features
corr_matrix=X.corr().abs() # Convert everything to positive values
upper= corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype
to_drop=[column for column in upper.columns if any(upper[column]>0.6)]
to_drop
```

```
C:\Users\noelm\AppData\Local\Temp\ipykernel_23808\3772953632.py:3: Dep
recationWarning: `np.bool` is a deprecated alias for the builtin `bool
`. To silence this warning, use `bool` by itself. Doing this will not
modify any behavior and is safe. If you specifically wanted the numpy
scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://nump
y.org/devdocs/release/1.20.0-notes.html#deprecations (https://numpy.or
g/devdocs/release/1.20.0-notes.html#deprecations)
  upper= corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).ast
ype(np.bool)) # Consider only the upper triangle values
```

Out[26]: ['Loudness']

In [27]:
```
X=X[['Danceability', 'Energy','Key', 'Mode', 'Speechiness','Acousticnes
X.shape
```

Out[27]:
```
(2478, 11)
```

In [28]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

In [29]:
```
X
```

Out[29]:
```
array([[-0.31500078, -0.66193869,  0.20738069, ...,  0.2067388 ,
         0.50641324,  0.16931883],
       [-2.6914234 , -0.41675422,  1.04752678, ..., -0.99375954,
         1.96342482, -2.96181604],
       [-0.88147361, -0.76118002, -0.91281409, ..., -1.35436551,
         0.98660489, -2.96181604],
       ...,
       [ 0.47944283,  1.32872566,  1.32757547, ...,  1.69937362,
        -0.8763048 ,  0.16931883],
       [ 0.52780027,  0.82084355, -0.3527167 , ...,  0.9233861 ,
         0.85033663,  0.16931883],
       [ 1.50876542, -1.14646989,  0.76747808, ...,  0.179351  ,
         1.02757534,  0.16931883]])
```

Using SelectKBest from scikitlearn to get the best features

In [261]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression
```

In [262]:
```
k=10
X_new=SelectKBest(f_regression,k=k).fit_transform(X,Y)
selected_features = X.columns[SelectKBest(f_regression,k=k).fit(X,Y).ge
```

In [263]:
```
X.columns[SelectKBest(f_regression,k=k).fit(X,Y).get_support()]
```

Out[263]:
```
Index(['Danceability', 'Energy', 'Key', 'Mode', 'Speechiness', 'Acoust
icness',
       'Instrumentalness', 'Liveness', 'Valence', 'Tempo'],
      dtype='object')
```

In [264]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

In [ ]:
```
X
```

Modelling

In [30]:

```
X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size=0.2)
print("X_train:",X_train.shape)
print("X_test:",X_test.shape)
print("y_train",y_train.shape)
print("y_test",y_test.shape)
```

```
X_train: (1982, 11)
X_test: (496, 11)
y_train (1982,)
y_test (496,)
```

1-Linear Regression

In [31]:

```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
lr_predictions = lr_model.predict(X_test)

mae = metrics.mean_absolute_error(y_test, lr_predictions)
rmse = np.sqrt(metrics.mean_squared_error(y_test, lr_predictions))
r2_lr=r2_score(y_test, lr_predictions)

# Mean Absolute Error (MAE) is used to evaluate the accuracy of regress
# It measures the average absolute difference between the predicted val
print('Performance Metrics for Linear Regression:')
print('Mean Absolute Error (MAE) =', mae)
print('Root Mean Squared Error (RMSE) =',rmse)
print('R-squared (R2) =',r2_lr)
```

```
Performance Metrics for Linear Regression:
Mean Absolute Error (MAE) = 13.877628650377329
Root Mean Squared Error (RMSE) = 17.23234131301512
R-squared (R2) = 0.07856822945082553
```

In [32]:
```
# Create a DataFrame to store the predictions and actual values
results_df1 = pd.DataFrame({'Predicted Values': lr_predictions, 'Actual

# Print the DataFrame
print(results_df1)
```

```
      Predicted Values  Actual Values
1112         52.081232           64.0
2398         52.445909           28.0
2445         48.561141           40.0
1240         48.053705           16.0
571          55.466320           48.0
...                ...            ...
1522         45.721257           51.0
1131         51.457009           52.0
132          50.905857           67.0
345          55.257229           61.0
2192         44.643314           27.0

[496 rows x 2 columns]
```

2-Random Forest

In [33]:
```
rfmodel = RandomForestRegressor()
```

In [34]:
```
n_estimators = [int(x) for x in np.linspace(start=100, stop=1000,num=12
max_features=['auto','sqrt']
max_depth=[int(x) for x in np.linspace(5,30,num=6)]
min_samples_split=[2,5,10,15,100]
min_samples_leaf=[1,2,5,10]
```

In [35]:
```
hyperparameter_grid={'n_estimators':n_estimators,'max_features':max_fea
print(hyperparameter_grid)
```

```
{'n_estimators': [100, 181, 263, 345, 427, 509, 590, 672, 754, 836, 91
8, 1000], 'max_features': ['auto', 'sqrt'], 'max_depth': [5, 10, 15, 2
0, 25, 30], 'min_samples_split': [2, 5, 10, 15, 100], 'min_samples_lea
f': [1, 2, 5, 10]}
```

In [36]:
```
model=RandomizedSearchCV(estimator=rfmodel,param_distributions=hyperpar
model
```

Out[36]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_iter=5,
                   param_distributions={'max_depth': [5, 10, 15, 20, 2
5, 30],
                                        'max_features': ['auto', 'sqr
t'],
                                        'min_samples_leaf': [1, 2, 5,
10],
                                        'min_samples_split': [2, 5, 1
0, 15,
                                                              100],
                                        'n_estimators': [100, 181, 26
3, 345,
                                                         427, 509, 59
0, 672,
                                                         754, 836, 91
8, 1000]},
                   random_state=8, scoring='neg_mean_squared_error', v
erbose=2)
```

In [37]:
```
model.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samp
les_split=10, n_estimators=672; total time=   3.2s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samp
les_split=10, n_estimators=672; total time=   3.3s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samp
les_split=10, n_estimators=672; total time=   3.3s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samp
les_split=10, n_estimators=672; total time=   3.3s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samp
les_split=10, n_estimators=672; total time=   3.3s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=5, min_samp
les_split=15, n_estimators=754; total time=   5.3s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=5, min_samp
les_split=15, n_estimators=754; total time=   5.2s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=5, min_samp
les_split=15, n_estimators=754; total time=   5.2s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=5, min_samp
les_split=15, n_estimators=754; total time=   5.5s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=5, min_samp
les_split=15, n_estimators=754; total time=   5.1s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samp
les_split=100, n_estimators=509; total time=   6.4s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samp
les_split=100, n_estimators=509; total time=   7.3s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samp
les_split=100, n_estimators=509; total time=   5.9s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samp
les_split=100, n_estimators=509; total time=   7.6s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samp
les_split=100, n_estimators=509; total time=   6.9s
[CV] END max_depth=30, max_features=auto, min_samples_leaf=1, min_samp
les_split=2, n_estimators=836; total time=  21.7s
[CV] END max_depth=30, max_features=auto, min_samples_leaf=1, min_samp
les_split=2, n_estimators=836; total time=  22.3s
[CV] END max_depth=30, max_features=auto, min_samples_leaf=1, min_samp
les_split=2, n_estimators=836; total time=  20.9s
[CV] END max_depth=30, max_features=auto, min_samples_leaf=1, min_samp
les_split=2, n_estimators=836; total time=  21.9s
[CV] END max_depth=30, max_features=auto, min_samples_leaf=1, min_samp
les_split=2, n_estimators=836; total time=  21.0s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=5, n_estimators=836; total time=   7.7s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=5, n_estimators=836; total time=   7.8s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=5, n_estimators=836; total time=   7.6s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=5, n_estimators=836; total time=   7.9s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=5, n_estimators=836; total time=   7.7s
```

Out[37]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_iter=5,
                   param_distributions={'max_depth': [5, 10, 15, 20, 2
5, 30],
                                        'max_features': ['auto', 'sqr
t'],
                                        'min_samples_leaf': [1, 2, 5,
10],
                                        'min_samples_split': [2, 5, 1
0, 15,
                                                              100],
                                        'n_estimators': [100, 181, 26
3, 345,
                                                         427, 509, 59
0, 672,
                                                         754, 836, 91
8, 1000]},
                   random_state=8, scoring='neg_mean_squared_error', v
erbose=2)
```

In [38]:
```
model.best_params_
```

Out[38]:
```
{'n_estimators': 754,
 'min_samples_split': 15,
 'min_samples_leaf': 5,
 'max_features': 'sqrt',
 'max_depth': 15}
```

In [39]:

```
rf_predictions = model.predict(X_test)
print(rf_predictions)
```

```
[55.81127659 51.945716   50.58947829 50.15689558 55.06442696 52.777994
3
 52.66167292 47.72347281 45.68335977 52.27730727 44.91916602 51.228498
88
 46.3628544  47.07859826 48.92709991 44.72689663 45.66429468 49.704780
2
 39.12038475 50.33471801 46.73733996 47.90591895 47.40509164 40.913301
01
 57.76726181 55.24281189 53.79648186 50.36150153 44.49476937 44.391625
11
 44.73683819 46.0244701  42.73416756 47.26318835 52.19848589 49.932467
07
 48.28203262 50.24554359 48.89822167 42.18010586 47.20870572 43.698395
18
 56.58234964 47.72631333 45.0551989  61.22050699 49.90452267 53.430990
32
 55.867331   50.1499132  48.80739432 52.82621755 45.05518195 51.466578
2
 53.11326986 44.30401848 54.45119255 46.40110877 59.68693392 47.448179
68
 43.15724287 48.05853355 45.09127422 55.29610978 56.66335053 45.540473
32
 54.2176948  46.48246665 45.97179198 54.41983168 53.7464889  42.463816
82
 53.20000371 49.97919498 54.34029419 44.83525668 55.78587794 49.114722
89
 47.15930845 40.3829295  45.24011732 50.63567703 56.3655255  51.816250
01
 48.54659316 44.43162172 44.46147579 50.16579289 47.46654643 61.760375
36
 45.74081619 48.05538762 42.74319612 55.51880159 46.97114314 50.121349
85
 48.01622683 46.00931962 41.87964298 52.30066794 45.24812017 42.729174
5
 51.49788156 50.21210573 56.30223623 45.13089789 44.68816186 42.212639
97
 41.85554941 48.7790576  45.05944303 59.15056629 48.56806833 46.065634
87
 52.85429105 47.7051745  53.41753564 43.34480287 53.35205419 53.581055
9
 53.10208641 55.28138328 42.57411281 48.97023095 55.91948844 47.064097
53
 42.62524373 42.32727901 52.13705911 46.87176771 45.87041442 60.004112
53
 49.74207661 46.80523777 44.05110355 55.10264342 50.5309853  55.878335
52
 44.98430436 48.83953223 56.48111473 51.99212894 51.82236861 58.079894
25
 59.06260105 55.5611799  41.15786641 45.8099356  46.77172313 57.088217
33
 49.34824415 46.35960167 53.96384364 44.06750484 49.18421493 55.798954
02
 58.01681184 49.64281548 49.02683597 54.14494574 49.56704072 44.378108
 49.76335111 46.65277485 44.18911028 51.02764684 51.49197814 48.132361
52
 47.78763683 43.71137189 45.85183047 46.50450841 44.31848539 50.029612
34
 50.83326556 49.41250491 46.42664861 53.66293612 58.28833079 43.735081
96
 49.70986616 46.0367801  42.77576189 44.53015161 52.05678938 48.547367
54
```

```
 48.03728176 56.51904927 50.59427824 51.27409647 40.9115229  51.425830
77
 49.18691216 41.45304221 51.83991836 56.86902934 58.63631112 55.314437
48
 50.32004116 46.11924434 53.13482457 44.14100561 43.60979638 47.664438
16
 48.05259662 49.12316128 49.57810168 42.8412692  48.98760075 53.637198
78
 50.383681   46.47788467 49.59419835 50.83052141 40.55379461 60.933443
3
 49.87327869 50.24379808 60.98649748 52.50654518 39.96151017 45.747925
48
 45.60553508 46.62276942 45.79932446 46.15044213 53.51594035 58.576454
16
 46.30101757 54.78261194 47.21304049 48.00553823 57.93338679 45.577888
65
 56.23718121 50.39217457 42.16581174 55.78007226 52.90048353 52.200256
67
 47.21146387 55.23851585 47.59258427 41.46536161 53.62041943 45.142330
55
 44.1884359  52.41220792 43.73418442 51.99858128 37.18484338 56.771066
8
 46.65493408 45.34680069 55.78396423 44.62641702 52.93737972 51.023328
87
 55.22480026 49.6946697  47.96570048 52.67525258 52.17290543 44.522527
35
 45.03830261 43.02836144 54.69002585 54.21949805 53.13538731 50.449364
9
 47.28427603 49.87988156 50.42829652 53.67839197 44.65525873 49.096417
71
 52.10155473 46.03272835 43.80524733 40.90511358 52.50861152 43.890095
84
 57.06519326 44.34337595 45.67758357 50.95123568 40.16125346 47.039903
09
 39.12217144 41.15405845 43.44957199 45.79612501 41.00516092 48.440313
53
 46.42141312 54.37550783 56.25479722 46.33498888 41.95742209 55.870500
26
 42.11291893 50.34900399 48.6513502  51.58645758 46.60342749 45.323389
97
 40.68760398 52.02933885 58.96947078 55.04975937 44.06322959 41.633818
09
 49.18474898 57.82548605 47.63801017 55.65982187 46.25353239 42.788526
96
 44.65882983 52.74056519 58.26194194 50.97551144 43.52233755 48.646231
31
 41.59678326 40.40625921 55.24036504 44.4184708  55.17629688 50.491887
96
 44.23910926 43.6762449  45.39485503 43.88098183 49.82924763 54.745884
92
 54.73921102 44.34727613 54.62926977 51.812272   48.55536782 42.483345
02
 59.15315926 44.20333233 44.83110004 56.22163442 49.49713095 44.959649
16
 45.69529799 41.83740064 53.91728712 57.1954671  55.95133603 53.105106
81
 44.65111981 52.61622872 57.73780965 48.17361977 44.02462003 47.461188
54
 46.49452582 47.64483598 46.88980981 49.07278551 47.16691826 51.125348
43
 51.85647687 54.98284245 48.52023866 48.74392041 42.90135078 52.825286
```

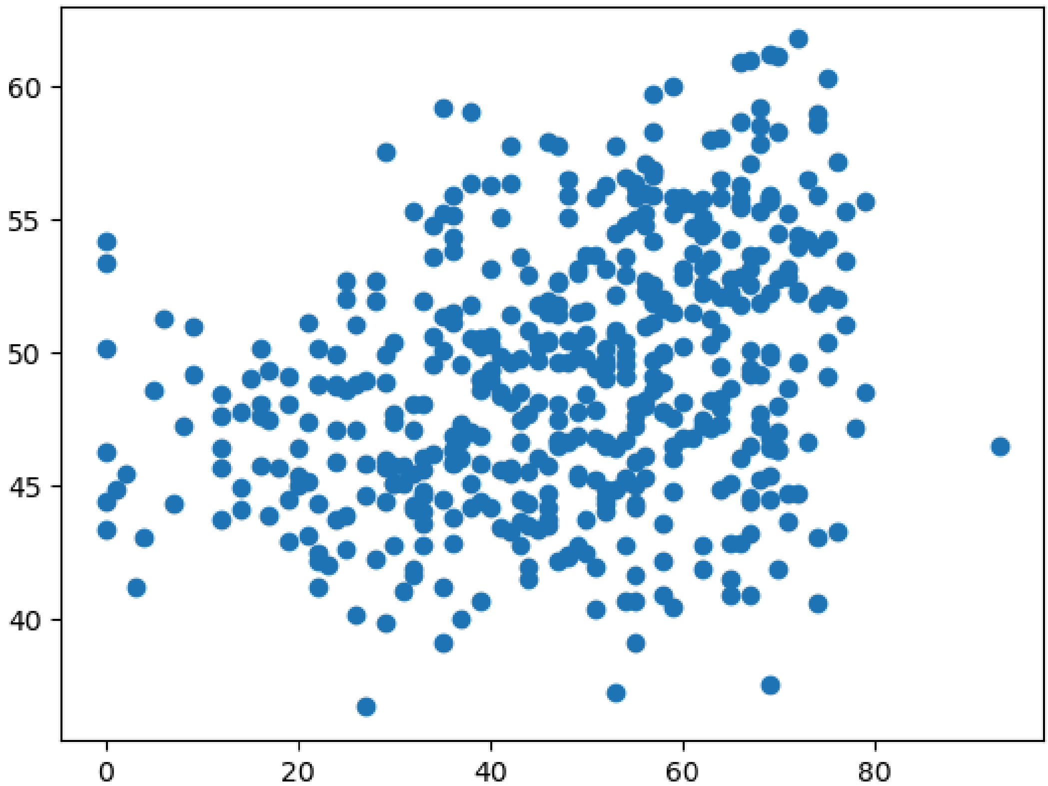
```
05
 49.04193899 50.74332386 37.4954315  43.04853568 48.19617148 42.781102
57
 45.40364482 41.95846608 51.91327195 51.9584819  46.39490031 45.760887
58
 54.18555613 46.82793614 55.82816967 47.33856208 46.70197371 54.247737
44
 45.40637665 43.30127324 45.9020617  47.38517072 50.37773658 55.912089
74
 57.78550126 48.53511114 39.80365776 55.66975633 58.47576995 44.820788
66
 47.53856068 51.60448551 56.3177721  47.76202778 53.60036674 42.355392
18
 47.18415672 49.85313058 44.36361208 51.10997752 43.18172829 46.751763
06
 57.53630045 51.52427911 55.79610861 45.3038785  46.60621721 52.705223
 61.1230396  54.48367446 60.27049961 51.45389878 47.57851499 49.343924
07
 50.32591257 48.15174891 47.46594289 42.80265984 51.34379068 48.477826
86
 48.41712417 51.41810424 52.97330783 44.84757156 55.68114064 56.522257
07
 42.71332302 49.9003238  48.12746191 40.63868492 53.55473853 45.103052
27
 56.31474118 55.78396423 47.84670842 49.6543847  55.44811542 50.671547
41
 45.60076982 50.06585325 36.66076226 49.63780487 48.81191334 43.249554
57
 48.78533494 43.58884424 46.72701095 49.31510162 45.43632193 49.944727
18
 51.08459255 45.75094989 49.57622385 49.47462271 52.21702812 44.483804
89
 48.03072354 51.88644541 46.44923746 42.00570907 46.76947935 49.089545
58
 43.46114344 47.08610429 50.60224576 45.31424423 43.5529413  43.340908
11
 40.6754108  41.16854859 48.33931664 51.77825735 44.35288703 52.198485
89
 52.66527877 55.7173745  50.45393186 45.42634154 52.52913841 49.392314
98
 53.09980803 50.068346   55.57846443 48.91913636]
```

In [40]:
```
# Create a DataFrame to store the predictions and actual values
results_df = pd.DataFrame({'Predicted Values': rf_predictions, 'Actual

# Print the DataFrame
print(results_df)
```

```
      Predicted Values  Actual Values
1112         55.811277           64.0
2398         51.945716           28.0
2445         50.589478           40.0
1240         50.156896           16.0
571          55.064427           48.0
...                ...            ...
1522         49.392315           51.0
1131         53.099808           52.0
132          50.068346           67.0
345          55.578464           61.0
2192         48.919136           27.0

[496 rows x 2 columns]
```

In [41]:
```
plt.scatter(y_test, rf_predictions)
```

Out[41]: <matplotlib.collections.PathCollection at 0x2468d2d6160>



In [42]:
```
mae_rf=metrics.mean_absolute_error(y_test, rf_predictions)
rmse_rf=np.sqrt(metrics.mean_squared_error(y_test, rf_predictions))
r2_rf=r2_score(y_test, rf_predictions)

print('Performance Metrics for Random Forest Regressor:')
print('Mean Absolute Error (MAE) =',mae_rf)
print('Root Mean Squared Error (RMSE) =',rmse_rf)
print('r2 square test =',r2_rf)
```

```
Performance Metrics for Random Forest Regressor:
Mean Absolute Error (MAE) = 13.641418746830162
Root Mean Squared Error (RMSE) = 17.088330402878135
r2 square test = 0.09390471256907651
```

3-Decision Tree

In [43]:
```
dt_model = DecisionTreeRegressor(random_state=0)
```

In [44]:
```
hyperparameter_grid = {
    'max_depth': [None] + [int(x) for x in np.linspace(5, 30, num=6)],
    'min_samples_split': [2, 5, 10, 15, 100],
    'min_samples_leaf': [1, 2, 5, 10]
}
```

In [45]:
```
# Instantiate the GridSearchCV object
grid_search = GridSearchCV(estimator=dt_model, param_grid=hyperparamete

# Perform grid search
grid_search.fit(X_train, y_train)

# Best parameters found
print("Best parameters found: ", grid_search.best_params_)

# Re-train the model with the best parameters
best_dt_model = grid_search.best_estimator_
best_dt_model.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 140 candidates, totalling 700 fits
Best parameters found:  {'max_depth': 5, 'min_samples_leaf': 10, 'min_
samples_split': 100}
```

Out[45]:
```
DecisionTreeRegressor(max_depth=5, min_samples_leaf=10, min_samples_sp
lit=100,
                      random_state=0)
```

In [46]:
```
# Make predictions
dt_predictions = best_dt_model.predict(X_test)
```

In [47]:
```
# Evaluate the model
mae_dt = metrics.mean_absolute_error(y_test, dt_predictions)
rmse_dt = np.sqrt(metrics.mean_squared_error(y_test, dt_predictions))
r2_dt = r2_score(y_test, dt_predictions)
print('Performance Metrics for Decision Tree Regressor:')
print('Mean Absolute Error:', mae_dt)
print('Root Mean Squared Error:', rmse_dt)
print('R-squared (R2) test:', r2_dt)
```

```
Performance Metrics for Decision Tree Regressor:
Mean Absolute Error: 14.094667307202734
Root Mean Squared Error: 17.64992056440947
R-squared (R2) test: 0.03337033993221494
```

4-XGBoost

In [182]:
```
pip install xgboost
```

```
Collecting xgboost
  Downloading xgboost-2.0.3-py3-none-win_amd64.whl (99.8 MB)
     ---------------------------------------- 99.8/99.8 MB 2.8 MB/s et
a 0:00:00
Requirement already satisfied: scipy in c:\users\noelm\anaconda3\lib\s
ite-packages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\noelm\anaconda3\lib\s
ite-packages (from xgboost) (1.21.5)
Installing collected packages: xgboost
Successfully installed xgboost-2.0.3
Note: you may need to restart the kernel to use updated packages.
```

In [48]:
```
# Define the parameter grid to search
param_grid = {
    'learning_rate': [0.05, 0.1, 0.15],
    'max_depth': [3, 4, 5],
    'min_child_weight': [1, 3, 5],
    'gamma': [0.0, 0.1, 0.2],
    'colsample_bytree': [0.6, 0.8, 1.0]
}

# Create the XGBRegressor model
xgmodel = xgb.XGBRegressor()

# Instantiate the GridSearchCV object
grid_search = GridSearchCV(estimator=xgmodel, param_grid=param_grid, cv

# Perform the grid search
grid_search.fit(X_train, y_train)

# Best parameters found
print("Best parameters found: ", grid_search.best_params_)
```

```
Fitting 5 folds for each of 243 candidates, totalling 1215 fits
Best parameters found:  {'colsample_bytree': 0.6, 'gamma': 0.0, 'learn
ing_rate': 0.05, 'max_depth': 3, 'min_child_weight': 5}
```

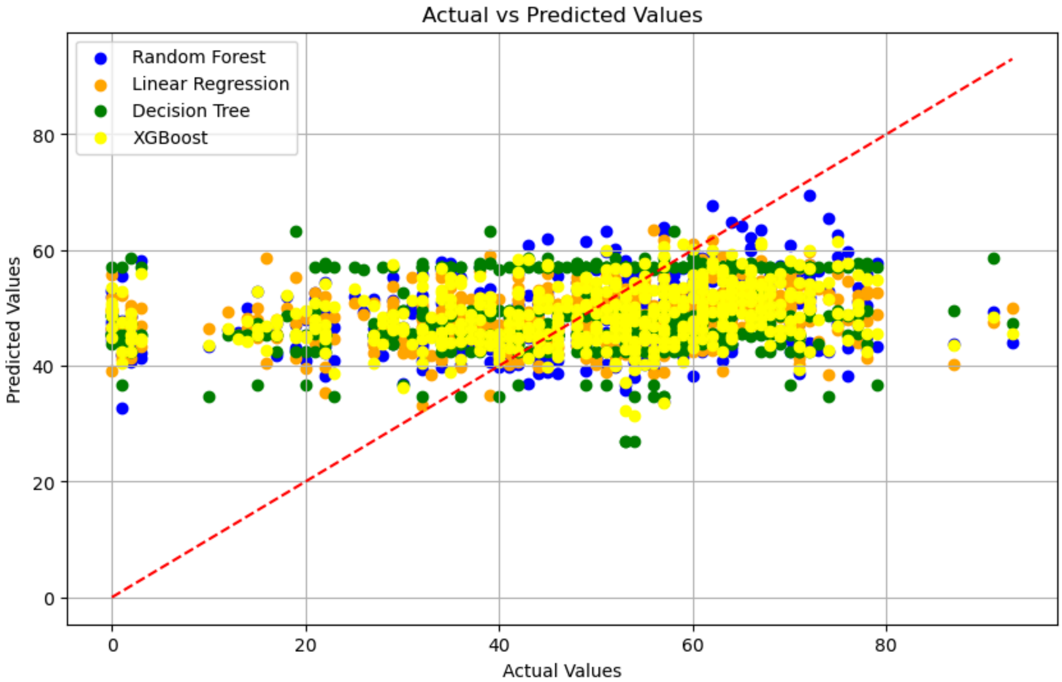
In [49]:
```
# Re-train the model with the best parameters
best_xgmodel = grid_search.best_estimator_
best_xgmodel.fit(X_train, y_train)

# Make predictions
xg_predictions = best_xgmodel.predict(X_test)

# Evaluate the model
xgmae = metrics.mean_absolute_error(y_test, xg_predictions)
xgrmse = np.sqrt(metrics.mean_squared_error(y_test, xg_predictions))
r2_xgb = r2_score(y_test, xg_predictions)

print('Mean Absolute Error:', xgmae)
print('Root Mean Squared Error (RMSE) =', xgrmse)
print('r2 square test =', r2_xgb)
```

```
Mean Absolute Error: 13.733958275087419
Root Mean Squared Error (RMSE) = 17.257893062407266
r2 square test = 0.0758336446756046
```

In [51]:
```
from tabulate import tabulate

results = [
    ['Random Forest', mae_rf, rmse_rf, r2_rf],
    ['XGBoost', xgmae, xgrmse, r2_xgb],
    ['Linear Regression', mae, rmse, r2_lr],
    ['Decision Tree', mae_dt, rmse_dt, r2_dt],
]

print(tabulate(results, headers=['Model', 'Mean Absolute Error', 'Root
```

```
+-------------------+-----------------------+------------------------
--+-------------------+
| Model             |   Mean Absolute Error |   Root Mean Squared Erro
r |   R-squared (R2) |
+===================+=======================+========================
==+===================+
| Random Forest     |               13.6414 |                   17.088
3 |         0.0939047 |
+-------------------+-----------------------+------------------------
--+-------------------+
| XGBoost           |               13.734  |                   17.257
9 |         0.0758336 |
+-------------------+-----------------------+------------------------
--+-------------------+
| Linear Regression |               13.8776 |                   17.232
3 |         0.0785682 |
+-------------------+-----------------------+------------------------
--+-------------------+
| Decision Tree     |               14.0947 |                   17.649
9 |         0.0333703 |
+-------------------+-----------------------+------------------------
--+-------------------+
```

In [287]:
```
# scatter plots will show how well each model's predictions align with
# The diagonal dashed line represents perfect predictions, where actual
# Points closer to this line indicate better model performance.
plt.figure(figsize=(10, 6))
plt.scatter(y_test, rf_predictions, color='blue', label='Random Forest'
plt.scatter(y_test, lr_predictions, color='orange', label='Linear Regre
plt.scatter(y_test, dt_predictions, color='green', label='Decision Tree
plt.scatter(y_test, xg_predictions, color='yellow', label='XGBoost')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color=
plt.title('Actual vs Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.legend()
plt.grid(True)
plt.show()
```



Classification Analysis

In [452]:
```
df2 = df1.copy()

# Create a new column 'Popularity_binary' based on the condition
df2['Popularity_binary'] = df2['Popularity'].apply(lambda x: 1 if x > 3

# Drop the original 'Popularity' column if you want
df2.drop('Popularity', axis=1, inplace=True)

# Display the new DataFrame
df2
```

Out[452]:

	Danceability	Energy	Key	Loudness	Mode	Speechiness	Acousticness	Instrum
0	0.609	0.538	6	-7.842	1	0.0273	0.32800	
1	0.265	0.580	9	-4.767	0	0.0491	0.49100	
2	0.527	0.521	2	-6.837	0	0.0272	0.63100	
3	0.622	0.516	7	-7.514	1	0.0259	0.42900	
4	0.702	0.860	7	-3.969	1	0.0345	0.36100	
...	...	...	...	...	...	...	...	
2473	0.738	0.784	2	-7.172	1	0.3290	0.10500	
2474	0.707	0.632	6	-8.734	0	0.3590	0.00159	
2475	0.724	0.879	10	-8.217	1	0.0863	0.08000	
2476	0.731	0.792	4	-6.560	0	0.1940	0.01210	
2477	0.873	0.455	8	-7.849	0	0.3410	0.50400	

2478 rows × 13 columns

In [453]:
```
# Count the number of popular (1) and unpopular (0) songs
popularity_counts = df2['Popularity_binary'].value_counts()

# Display the counts
print("Number of popular songs (1):", popularity_counts[1])
print("Number of unpopular songs (0):", popularity_counts[0])
```

```
Number of popular songs (1): 1965
Number of unpopular songs (0): 513
```

In [454]:
```
df2.columns
```

Out[454]:
```
Index(['Danceability', 'Energy', 'Key', 'Loudness', 'Mode', 'Speechine
ss',
       'Acousticness', 'Instrumentalness', 'Liveness', 'Valence', 'Tem
po',
       'Time Signature', 'Popularity_binary'],
      dtype='object')
```

In [455]:
```
X1 = df2.iloc[:, np.r_[0:12]]
Y1 = df2.iloc[:, 12]
print(X1.shape, Y1.shape)
```

```
(2478, 12) (2478,)
```

In [456]:
```
X1
```

Out[456]:

	Danceability	Energy	Key	Loudness	Mode	Speechiness	Acousticness	Instrum
0	0.609	0.538	6	-7.842	1	0.0273	0.32800	
1	0.265	0.580	9	-4.767	0	0.0491	0.49100	
2	0.527	0.521	2	-6.837	0	0.0272	0.63100	
3	0.622	0.516	7	-7.514	1	0.0259	0.42900	
4	0.702	0.860	7	-3.969	1	0.0345	0.36100	
...	...	...	...	...	...	...	...	
2473	0.738	0.784	2	-7.172	1	0.3290	0.10500	
2474	0.707	0.632	6	-8.734	0	0.3590	0.00159	
2475	0.724	0.879	10	-8.217	1	0.0863	0.08000	
2476	0.731	0.792	4	-6.560	0	0.1940	0.01210	
2477	0.873	0.455	8	-7.849	0	0.3410	0.50400	

2478 rows × 12 columns

In [457]:
```
Y1
```

Out[457]:
```
0       1
1       1
2       1
3       0
4       1
       ..
2473    0
2474    0
2475    1
2476    0
2477    1
Name: Popularity_binary, Length: 2478, dtype: int64
```

In [458]:

```
from sklearn.model_selection import train_test_split
X1_train, X1_test, y1_train, y1_test = train_test_split(X1,Y1,test_size
print("X1_train:",X1_train.shape)
print("X1_test:",X1_test.shape)
print("y1_train",y1_train.shape)
print("y1_test",y1_test.shape)
```

```
X1_train: (1982, 12)
X1_test: (496, 12)
y1_train (1982,)
y1_test (496,)
```

Decision Tree Classifier

In [459]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import export_graphviz
from sklearn import tree
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, classification_report
```

In [460]:

```
dt= DecisionTreeClassifier()
dt.fit(X1_train,y1_train)
y_pred=dt.predict(X1_test)
DecisionTree_score=dt.score(X1_test,y1_test)
print("Train accuracy of decision tree:",dt.score(X1_train,y1_train))
print("Test accuracy of decision tree:",dt.score(X1_test,y1_test))
```

```
Train accuracy of decision tree: 0.9984863773965691
Test accuracy of decision tree: 0.6411290322580645
```

In [461]:

```
max_depth = [8,10,12]
min_samples_split = [8,10,12]
min_samples_leaf=[1,2,3,4]
parameters = dict(max_depth=max_depth, min_samples_split=min_samples_sp
```

In [462]:

```
tree_clf = DecisionTreeClassifier()
tree_clf_gs = GridSearchCV(tree_clf, parameters)
tree_clf_gs.fit(X1_train,y1_train)
```

Out[462]:

```
GridSearchCV(estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [8, 10, 12],
                         'min_samples_leaf': [1, 2, 3, 4],
                         'min_samples_split': [8, 10, 12]})
```

In [463]:

```
print('Best max_depth:', tree_clf_gs.best_estimator_.get_params()['max_
print('Best min_samples_split:', tree_clf_gs.best_estimator_.get_params
print('Best min_samples_leaf:', tree_clf_gs.best_estimator_.get_params(
```

```
Best max_depth: 8
Best min_samples_split: 12
Best min_samples_leaf: 1
```

In [464]:
```
from sklearn.tree import plot_tree
tree_clf = DecisionTreeClassifier(max_depth=10, max_features='auto', cr
tree_clf.fit(X1_train,y1_train)
```

Out[464]:
```
DecisionTreeClassifier(max_depth=10, max_features='auto', min_samples_
split=12)
```

In [465]:
```
from sklearn.tree import export_graphviz
import graphviz

# Generate DOT data
dot_data = export_graphviz(tree_clf, filled=True, feature_names=X1_trai

# Convert DOT data to a graph
graph = graphviz.Source(dot_data)

# Save the graph as a pdf file
graph.render("decision_tree_visualization", format='pdf')
```

Out[465]:
```
'decision_tree_visualization.pdf'
```

In [466]:
```
print(tree_clf.tree_.max_depth)
```

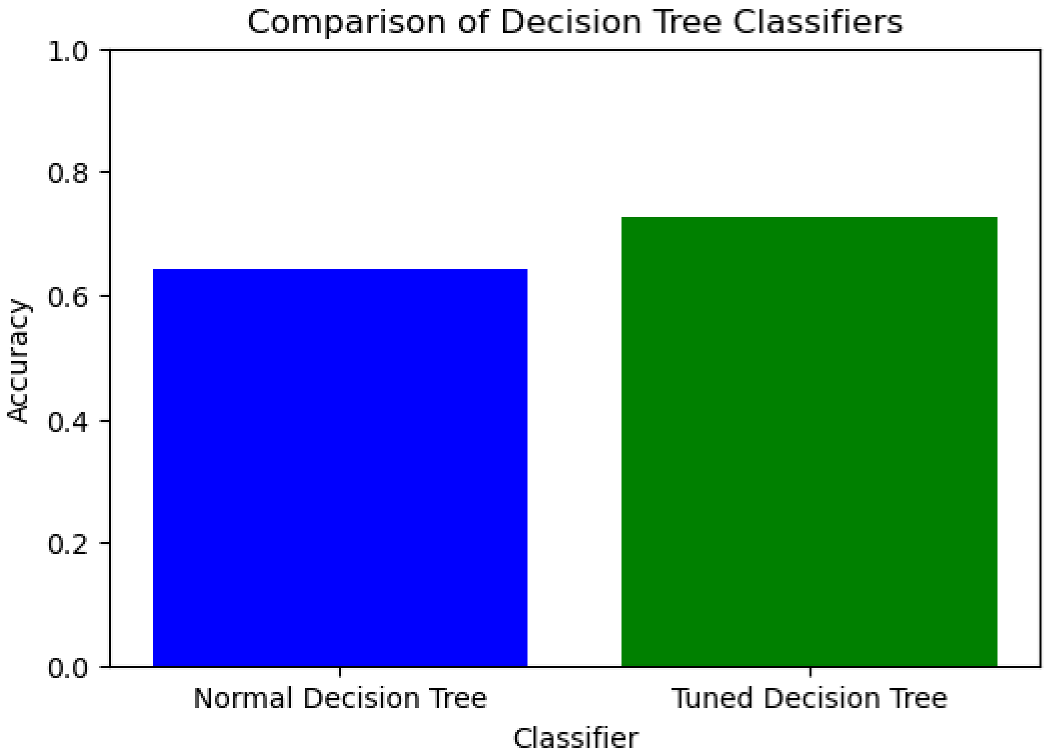
```
10
```

In [467]:
```
y_pred = tree_clf.predict(X1_test)
print("Tuned Decision Tree Testing Accuracy=",accuracy_score(y1_test, y
```

```
Tuned Decision Tree Testing Accuracy= 0.7258064516129032
```

In [472]:

```
import matplotlib.pyplot as plt

# Define labels and scores
labels = ['Normal Decision Tree', 'Tuned Decision Tree']
scores = [DecisionTree_score, accuracy_score(y1_test, y_pred)]

# Plot the bar plot
plt.figure(figsize=(6, 4))
plt.bar(labels, scores, color=['blue', 'green'])
plt.xlabel('Classifier')
plt.ylabel('Accuracy')
plt.title('Comparison of Decision Tree Classifiers')
plt.ylim(0.0, 1.0)
plt.show()
```



In [479]:

```
print(confusion_matrix(y1_test, y_pred))
print("Classification report\n")
print(classification_report(y1_test, y_pred))
```

```
[[ 11 106]
 [ 30 349]]
Classification report

              precision    recall  f1-score   support

           0       0.27      0.09      0.14       117
           1       0.77      0.92      0.84       379

    accuracy                           0.73       496
   macro avg       0.52      0.51      0.49       496
weighted avg       0.65      0.73      0.67       496
```

Naive Bayes Classifier

In [434]:
```
from sklearn.naive_bayes import GaussianNB
nb= GaussianNB()
nb.fit(X1_train,y1_train)
print("Train accuracy of naive bayes:",nb.score(X1_train,y1_train))
print("Test accuracy of naive bayes:",nb.score(X1_test,y1_test))
NaiveBayes_score=nb.score(X1_test,y1_test)
```

```
Train accuracy of naive bayes: 0.784561049445005
Test accuracy of naive bayes: 0.7762096774193549
```

In [484]:
```
nb_y_pred = nb.predict(X1_test)
report = classification_report(y1_test, nb_y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.42      0.09      0.14       117
           1       0.77      0.96      0.86       379

    accuracy                           0.76       496
   macro avg       0.59      0.52      0.50       496
weighted avg       0.69      0.76      0.69       496
```

Logistic regression

In [443]:
```
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X1_train, y1_train)
train_accuracy_log_reg = log_reg.score(X1_train, y1_train)
test_accuracy_log_reg = log_reg.score(X1_test, y1_test)
print("Train accuracy of Logistic Regression:", train_accuracy_log_reg)
print("Test accuracy of Logistic Regression:", test_accuracy_log_reg)
LogisticRegression_score=log_reg.score(X1_test,y1_test)
```

```
Train accuracy of Logistic Regression: 0.7926337033299697
Test accuracy of Logistic Regression: 0.7883064516129032
```

In [485]:
```
lr_y_pred = log_reg.predict(X1_test)
report = classification_report(y1_test, lr_y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       117
           1       0.76      0.99      0.86       379

    accuracy                           0.76       496
   macro avg       0.38      0.50      0.43       496
weighted avg       0.58      0.76      0.66       496
```

KNN

In [448]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X1_train, y1_train)
train_accuracy_knn = knn.score(X1_train, y1_train)
test_accuracy_knn = knn.score(X1_test, y1_test)
print("Train accuracy of KNN:", train_accuracy_knn)
print("Test accuracy of KNN:", test_accuracy_knn)
KNN_score=knn.score(X1_test,y1_test)
```

```
Train accuracy of KNN: 0.806760847628658
Test accuracy of KNN: 0.7681451612903226

C:\Users\noelm\anaconda3\lib\site-packages\sklearn\neighbors\_classifi
cation.py:228: FutureWarning: Unlike other reduction functions (e.g. `
skew`, `kurtosis`), the default behavior of `mode` typically preserves
the axis it acts along. In SciPy 1.11.0, this behavior will change: th
e default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no
longer be accepted. Set `keepdims` to True or False to avoid this warn
ing.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\noelm\anaconda3\lib\site-packages\sklearn\neighbors\_classifi
cation.py:228: FutureWarning: Unlike other reduction functions (e.g. `
skew`, `kurtosis`), the default behavior of `mode` typically preserves
the axis it acts along. In SciPy 1.11.0, this behavior will change: th
e default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no
longer be accepted. Set `keepdims` to True or False to avoid this warn
ing.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\noelm\anaconda3\lib\site-packages\sklearn\neighbors\_classifi
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skew`, `kurtosis`), the default behavior of `mode` typically preserves
the axis it acts along. In SciPy 1.11.0, this behavior will change: th
e default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no
longer be accepted. Set `keepdims` to True or False to avoid this warn
ing.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [486]:
```
knn_y_pred = knn.predict(X1_test)
report = classification_report(y1_test, knn_y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.58      0.13      0.21       117
           1       0.78      0.97      0.87       379

    accuracy                           0.77       496
   macro avg       0.68      0.55      0.54       496
weighted avg       0.73      0.77      0.71       496


C:\Users\noelm\anaconda3\lib\site-packages\sklearn\neighbors\_classifi
cation.py:228: FutureWarning: Unlike other reduction functions (e.g. `
skew`, `kurtosis`), the default behavior of `mode` typically preserves
the axis it acts along. In SciPy 1.11.0, this behavior will change: th
e default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no
longer be accepted. Set `keepdims` to True or False to avoid this warn
ing.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Random Forest Classifier

In [435]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=150,random_state = 3)
rf.fit(X1_train,y1_train)
print("Train accuracy of random forest",rf.score(X1_train,y1_train))
print("Test accuracy of random forest",rf.score(X1_test,y1_test))
RandomForestClassifier_score=rf.score(X1_test,y1_test)
rf_y_pred=rf.predict(X1_test)
t_true=y_test
```

```
Train accuracy of random forest 0.9984863773965691
Test accuracy of random forest 0.7903225806451613
```

In [470]:

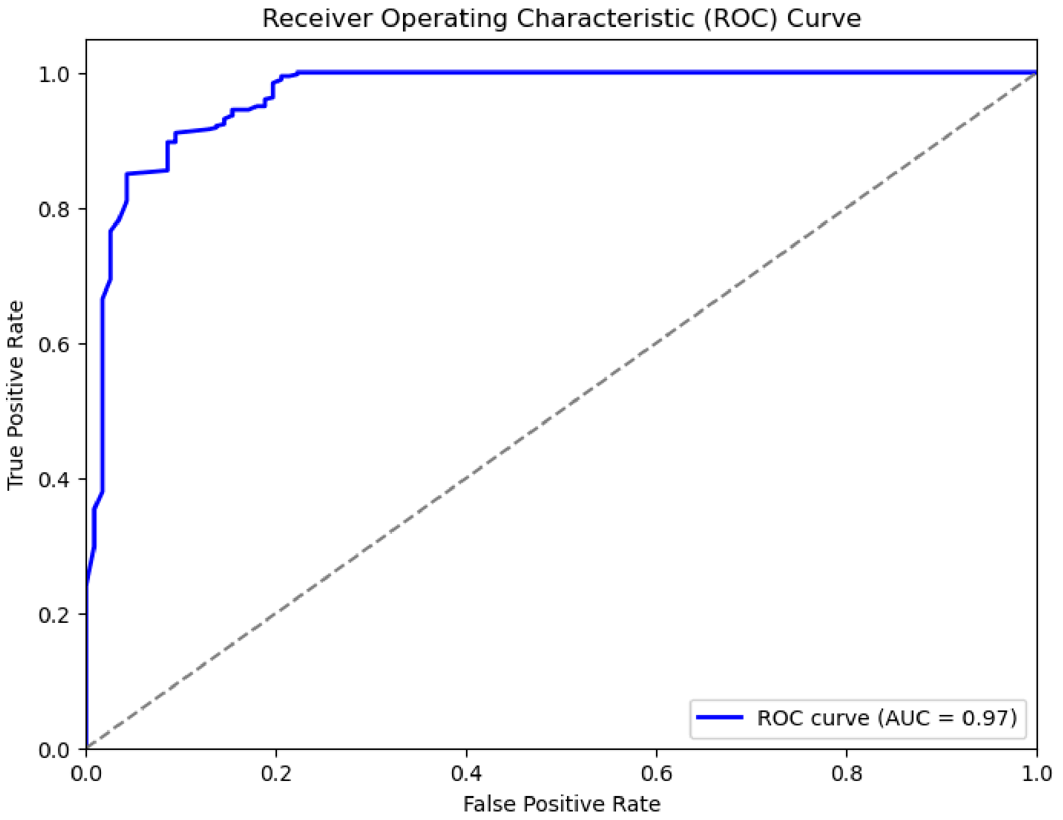
```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Get the predicted probabilities for the positive class
rf_probs = rf.predict_proba(X1_test)[:, 1]

# Calculate the ROC curve
fpr, tpr, thresholds = roc_curve(y1_test, rf_probs)

# Calculate the AUC score
auc = roc_auc_score(y1_test, rf_probs)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)'
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
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')
plt.legend(loc="lower right")
plt.show()
```



In [473]:

```
print(confusion_matrix(y1_test, rf_y_pred))
print("Classification report\n")
print(classification_report(y1_test, rf_y_pred))
```

```
[[  1 116]
 [  6 373]]
Classification report

              precision    recall  f1-score   support

           0       0.14      0.01      0.02       117
           1       0.76      0.98      0.86       379

    accuracy                           0.75       496
   macro avg       0.45      0.50      0.44       496
weighted avg       0.62      0.75      0.66       496
```

Ensemble Model

In [450]:

```
#Voting Classifier
from sklearn.ensemble import VotingClassifier
ensemble=VotingClassifier(estimators=[('Random Forest', rf), ('Logistic
                          voting='soft', weights=[2,1]).fit(X1_train,y1
print('The train accuracy for Random Forest and Logistic Regression is:
print('The test accuracy for Random Forest and Logistic Regression is:'
ensemble_score=ensemble.score(X1_test,y1_test)
```

```
The train accuracy for Random Forest and Logistic Regression is: 0.977
2956609485368
The test accuracy for Random Forest and Logistic Regression is: 0.7923
387096774194
```

In [451]:

```
model_performances=pd.DataFrame({'Model':['Random Forest Classifier','D
                                 'Accuracy':[RandomForestClassifier_sc
model_performances.sort_values(by="Accuracy",ascending=False)
```

Out[451]:

	Model	Accuracy
5	Ensemble Model	0.792339
0	Random Forest Classifier	0.790323
3	Logistic Regression	0.788306
2	Naive Bayes	0.776210
4	KNN	0.768145
1	Desicion Tree Classifier	0.687500

Conclusion

We tried to predict popular songs using audio features by regressional analysis. Then we converted the target variable to a binary column, 1 representing all popular songs and 0 representing all unpopular songs. Although accusticness is the most important of these features did not lead us to a strong result. We had around 4000 songs available in our initial dataset. Decision Tree algorithms mainly give better results when we don’t have so much data but we got the best result with Random Forest. There were no strong linear correlations in our data, so linear methods like linear regression did not fit well.