#Music Genre Classification

```
#importing all essential libraries
import random
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

#Description of dataset

1.filename: Name of the audio file associated with each observation (e.g., blues.00000.0.wav).

2.length: Duration of the audio sample in milliseconds.

3.chroma_stft_mean and chroma_stft_var: Mean and variance of the chroma short-time Fourier transform (STFT).

4.rms_mean and rms_var: Mean and variance of the Root Mean Square (RMS) energy.

5.spectral_centroid_mean and spectral_centroid_var: Mean and variance of the spectral centroid.

6.spectral_bandwidth_mean and spectral_bandwidth_var: Mean and variance of spectral bandwidth.

7.rolloff_mean and rolloff_var: Mean and variance of spectral roll-off frequency.

8.zero_crossing_rate_mean and zero_crossing_rate_var: Mean and variance of zero-crossing rate.

9.harmony_mean and harmony_var: Mean and variance of harmony.

10.perceptr_mean and perceptr_var: Mean and variance of perceptual spectral contrast.

11.tempo: Estimated tempo of the song in beats per minute (BPM).

12.mfcc1_mean to mfcc20_mean: Mean values of the first 20 Mel-frequency cepstral coefficients (MFCCs).

13.mfcc1_var to mfcc20_var: Variance of the first 20 MFCCs.

14.label: The genre label for each audio sample (e.g., blues, classical, jazz).

```
#import the dataset
dt=pd.read_csv("/content/features_3_sec.csv")
dt
```

{"type":"dataframe","variable_name":"dt"}

```
#Total number of Rows and Colomns
dt.shape
```

```
(9990, 60)
```

```
#Read the first 5 rows of dataset
dt.head()
```

{"type":"dataframe","variable_name":"dt"}

```
#Understanding the central Tendency
dt.describe()
```

{"type":"dataframe"}

```
dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9990 entries, 0 to 9989
Data columns (total 60 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   filename                 9990 non-null   object
 1   length                   9990 non-null   int64
 2   chroma_stft_mean         9990 non-null   float64
 3   chroma_stft_var          9990 non-null   float64
 4   rms_mean                 9990 non-null   float64
 5   rms_var                  9990 non-null   float64
 6   spectral_centroid_mean   9990 non-null   float64
 7   spectral_centroid_var    9990 non-null   float64
 8   spectral_bandwidth_mean  9990 non-null   float64
 9   spectral_bandwidth_var   9990 non-null   float64
 10  rolloff_mean             9990 non-null   float64
 11  rolloff_var              9990 non-null   float64
 12  zero_crossing_rate_mean  9990 non-null   float64
 13  zero_crossing_rate_var   9990 non-null   float64
 14  harmony_mean             9990 non-null   float64
 15  harmony_var              9990 non-null   float64
 16  perceptr_mean            9990 non-null   float64
 17  perceptr_var             9990 non-null   float64
 18  tempo                    9990 non-null   float64
 19  mfcc1_mean               9990 non-null   float64
 20  mfcc1_var                9990 non-null   float64
 21  mfcc2_mean               9990 non-null   float64
 22  mfcc2_var                9990 non-null   float64
 23  mfcc3_mean               9990 non-null   float64
 24  mfcc3_var                9990 non-null   float64
 25  mfcc4_mean               9990 non-null   float64
 26  mfcc4_var                9990 non-null   float64
 27  mfcc5_mean               9990 non-null   float64
 28  mfcc5_var                9990 non-null   float64
 29  mfcc6_mean               9990 non-null   float64
 30  mfcc6_var                9990 non-null   float64
 31  mfcc7_mean               9990 non-null   float64
```

```
 32  mfcc7_var                9990 non-null   float64
 33  mfcc8_mean               9990 non-null   float64
 34  mfcc8_var                9990 non-null   float64
 35  mfcc9_mean               9990 non-null   float64
 36  mfcc9_var                9990 non-null   float64
 37  mfcc10_mean              9990 non-null   float64
 38  mfcc10_var               9990 non-null   float64
 39  mfcc11_mean              9990 non-null   float64
 40  mfcc11_var               9990 non-null   float64
 41  mfcc12_mean              9990 non-null   float64
 42  mfcc12_var               9990 non-null   float64
 43  mfcc13_mean              9990 non-null   float64
 44  mfcc13_var               9990 non-null   float64
 45  mfcc14_mean              9990 non-null   float64
 46  mfcc14_var               9990 non-null   float64
 47  mfcc15_mean              9990 non-null   float64
 48  mfcc15_var               9990 non-null   float64
 49  mfcc16_mean              9990 non-null   float64
 50  mfcc16_var               9990 non-null   float64
 51  mfcc17_mean              9990 non-null   float64
 52  mfcc17_var               9990 non-null   float64
 53  mfcc18_mean              9990 non-null   float64
 54  mfcc18_var               9990 non-null   float64
 55  mfcc19_mean              9990 non-null   float64
 56  mfcc19_var               9990 non-null   float64
 57  mfcc20_mean              9990 non-null   float64
 58  mfcc20_var               9990 non-null   float64
 59  label                    9990 non-null   object
dtypes: float64(57), int64(1), object(2)
memory usage: 4.6+ MB
```

```python
#check if any null values present
dt.isnull()
```

{"type":"dataframe"}

```python
#total no. of null values in each column
dt.isnull().sum()
```

```
filename                   0
length                     0
chroma_stft_mean           0
chroma_stft_var            0
rms_mean                   0
rms_var                    0
spectral_centroid_mean     0
spectral_centroid_var      0
spectral_bandwidth_mean    0
spectral_bandwidth_var     0
rolloff_mean               0
```

```
rolloff_var                0
zero_crossing_rate_mean    0
zero_crossing_rate_var     0
harmony_mean               0
harmony_var                0
perceptr_mean              0
perceptr_var               0
tempo                      0
mfcc1_mean                 0
mfcc1_var                  0
mfcc2_mean                 0
mfcc2_var                  0
mfcc3_mean                 0
mfcc3_var                  0
mfcc4_mean                 0
mfcc4_var                  0
mfcc5_mean                 0
mfcc5_var                  0
mfcc6_mean                 0
mfcc6_var                  0
mfcc7_mean                 0
mfcc7_var                  0
mfcc8_mean                 0
mfcc8_var                  0
mfcc9_mean                 0
mfcc9_var                  0
mfcc10_mean                0
mfcc10_var                 0
mfcc11_mean                0
mfcc11_var                 0
mfcc12_mean                0
mfcc12_var                 0
mfcc13_mean                0
mfcc13_var                 0
mfcc14_mean                0
mfcc14_var                 0
mfcc15_mean                0
mfcc15_var                 0
mfcc16_mean                0
mfcc16_var                 0
mfcc17_mean                0
mfcc17_var                 0
mfcc18_mean                0
mfcc18_var                 0
mfcc19_mean                0
mfcc19_var                 0
mfcc20_mean                0
mfcc20_var                 0
```

```
label                          0
dtype: int64
```

```
#Getting more info about dataset
dt.info
```

```
<bound method DataFrame.info of                 filename  length  
chroma_stft_mean  chroma_stft_var  rms_mean  \
0     blues.00000.0.wav   66149          0.335406         0.091048  
0.130405   
1     blues.00000.1.wav   66149          0.343065         0.086147  
0.112699   
2     blues.00000.2.wav   66149          0.346815         0.092243  
0.132003   
3     blues.00000.3.wav   66149          0.363639         0.086856  
0.132565   
4     blues.00000.4.wav   66149          0.335579         0.088129  
0.143289   
...                 ...     ...               ...              ...  
...   
9985   rock.00099.5.wav   66149          0.349126         0.080515  
0.050019   
9986   rock.00099.6.wav   66149          0.372564         0.082626  
0.057897   
9987   rock.00099.7.wav   66149          0.347481         0.089019  
0.052403   
9988   rock.00099.8.wav   66149          0.387527         0.084815  
0.066430   
9989   rock.00099.9.wav   66149          0.369293         0.086759  
0.050524   

       rms_var  spectral_centroid_mean  spectral_centroid_var  \
0     0.003521             1773.065032          167541.630869   
1     0.001450             1816.693777           90525.690866   
2     0.004620             1788.539719          111407.437613   
3     0.002448             1655.289045          111952.284517   
4     0.001701             1630.656199           79667.267654   
...        ...                     ...                    ...   
9985  0.000097             1499.083005          164266.886443   
9986  0.000088             1847.965128          281054.935973   
9987  0.000701             1346.157659          662956.246325   
9988  0.000320             2084.515327          203891.039161   
9989  0.000067             1634.330126          411429.169769   

      spectral_bandwidth_mean  spectral_bandwidth_var  ...  mfcc16_var  
\
0                 1972.744388           117335.771563  ...   39.687145   

1                 2010.051501            65671.875673  ...   64.748276   
```

```
2               2084.565132              75124.921716  ...   67.336563
3               1960.039988              82913.639269  ...   47.739452
4               1948.503884              60204.020268  ...   30.336359
...                     ...                       ...  ...         ...
9985            1718.707215              85931.574523  ...   42.485981
9986            1906.468492              99727.037054  ...   32.415203
9987            1561.859087             138762.841945  ...   78.228149
9988            2018.366254              22860.992562  ...   28.323744
9989            1867.422378             119722.211518  ...   38.801735

      mfcc17_mean  mfcc17_var  mfcc18_mean  mfcc18_var  mfcc19_mean  \
0       -3.241280   36.488243     0.722209   38.099152    -5.050335
1       -6.055294   40.677654     0.159015   51.264091    -2.837699
2       -1.768610   28.348579     2.378768   45.717648    -1.938424
3       -3.841155   28.337118     1.218588   34.770935    -3.580352
4        0.664582   45.880913     1.689446   51.363583    -3.392489
...           ...         ...          ...         ...          ...
9985    -9.094270   38.326839    -4.246976   31.049839    -5.625813
9986   -12.375726   66.418587    -3.081278   54.414265   -11.960546
9987    -2.524483   21.778994     4.809936   25.980829     1.775686
9988    -5.363541   17.209942     6.462601   21.442928     2.354765
9989   -11.598399   58.983097    -0.178517   55.761299    -6.903252

      mfcc19_var  mfcc20_mean  mfcc20_var  label
0      33.618073    -0.243027   43.771767  blues
1      97.030830     5.784063   59.943081  blues
2      53.050835     2.517375   33.105122  blues
3      50.836224     3.630866   32.023678  blues
4      26.738789     0.536961   29.146694  blues
...          ...          ...         ...    ...
9985   48.804092     1.818823   38.966969   rock
9986   63.452255     0.428857   18.697033   rock
9987   48.582378    -0.299545   41.586990   rock
9988   24.843613     0.675824   12.787750   rock
9989   39.485901    -3.412534   31.727489   rock

[9990 rows x 60 columns]>
```

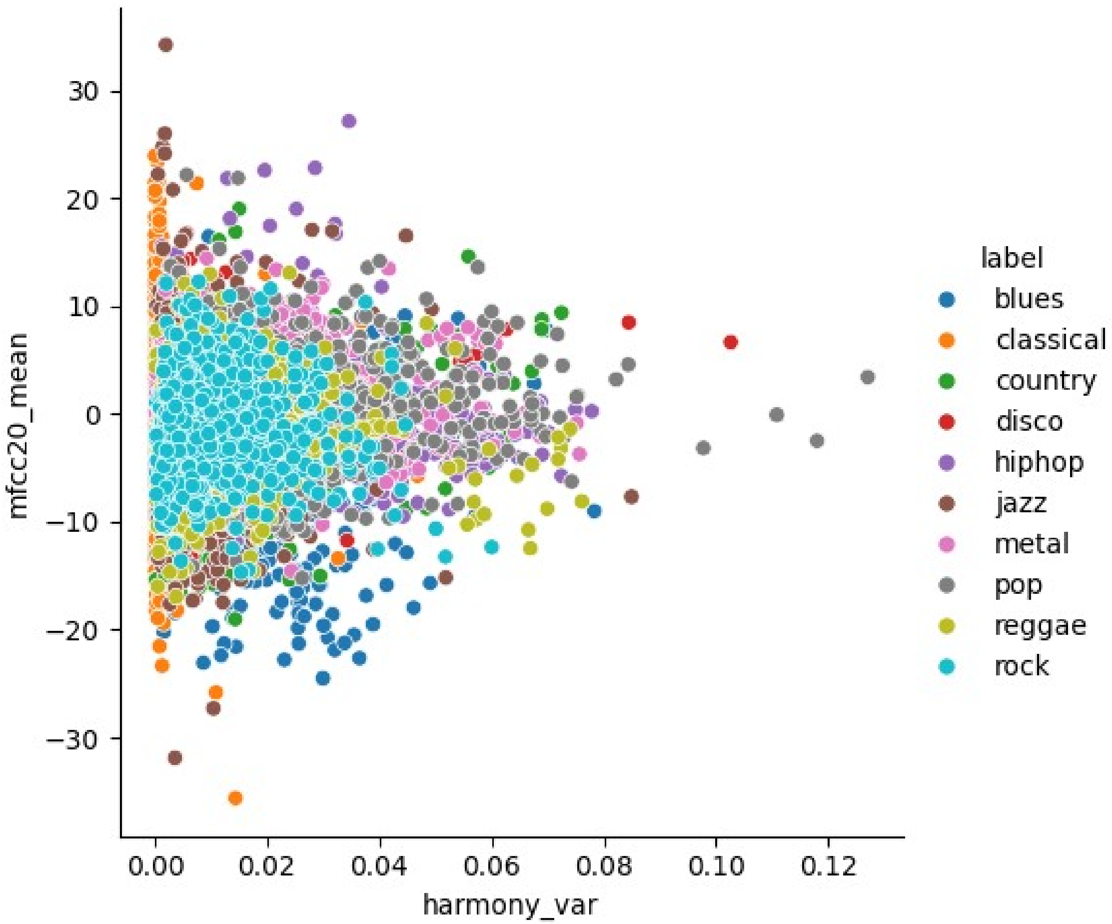
```python
#Getting no of unique values in length column
dt["length"].nunique()
```

```
1
```

```
# Let's visualize all the music genres plotted according to two random features. We use the seaborn library to make a scatterplot of the two random features.
feature_names = dt.keys()[:-1]
x_name = random.choice(feature_names)
y_name = random.choice(feature_names)

while x_name == y_name:
  y_name = random.choice(feature_names)

sns.relplot(x = x_name, y = y_name, hue = "label", data = dt);
```




```
#make a copy of dataset to work on
ndt=dt.copy()

#here we will work on ndt it will be copy dataset .
#here remove all non float values except genre so our length and name id column will get dropped.
non_floats = []
for col in ndt.iloc[:,:-1]:
    if ndt[col].dtypes != "float64":
```

```
        non_floats.append(col)
ndt = ndt.drop(columns=non_floats)

ndt
```

{"type":"dataframe","variable_name":"ndt"}

What are the Most Common Genres in the Dataset?

```
ndt["label"].value_counts()
```

```
label
blues        1000
jazz         1000
metal        1000
pop          1000
reggae       1000
disco         999
classical     998
hiphop        998
rock          998
country       997
Name: count, dtype: int64
```

```
#Categorisation of data
#feature catergorization
#determine x and y
x=ndt.iloc[:,0:57].values   #:, means all values
y=ndt.iloc[:,57].values

#Label encoding
!pip install --user scikit-learn
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y=le.fit_transform(y)
```

```
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: numpy>=1.19.5 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
```

```
#building machine learning models
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import
```

```
accuracy_score,precision_score,recall_score,f1_score

#model selection
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB

#splittinX
x_train,x_test,y_train,y_test =
train_test_split(x,y,test_size=0.3,random_state=0)
```

Which Machine Learning Model gives the highest accuracy, Precision , F1 Score, Recall?

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using Guassian
Naive Bayes Algorithm
accuracy_list=[]
model_name=[]
gaussian  = GaussianNB()
gaussian.fit(x_train,y_train)
Y_pred = gaussian.predict(x_test)
accuracy_nb=round(accuracy_score(y_test,Y_pred)* 100, 2 )

cm = confusion_matrix(y_test, Y_pred)
accuracy = accuracy_score(y_test,Y_pred)
accuracy_list.append(accuracy)
model_name.append("GNB")
print("accuracy_Naive Bayes: %.3f" %accuracy)

accuracy_Naive Bayes: 0.425

pre_nb=precision_score(y_test,Y_pred,average='weighted')
print("precision_Naive Bayes: %.3f" %pre_nb)
recall_score_nb=recall_score(y_test,Y_pred,average='weighted')
print("recall_Naive Bayes: %.3f" %recall_score_nb)
f1_score_nb=f1_score(y_test,Y_pred,average='weighted')
print("f1_score_Naive Bayes: %.3f" %f1_score_nb)
confusion_matrix_nb=confusion_matrix(y_test,Y_pred)
print("confusion_matrix_Naive Bayes:\n", confusion_matrix_nb)

precision_Naive Bayes: 0.439
recall_Naive Bayes: 0.425
f1_score_Naive Bayes: 0.402
confusion_matrix_Naive Bayes:
 [[ 64  18  39   5   3  30 101   0  21   6]
 [  1 262   3   1   0   7  12   1   3   5]
 [ 19  16 103  47   5  11  71   1  24  16]
 [  9   2  10 120  11   3  92   8  21  14]
 [  7   0  27  57  75   1  55  25  47   7]
 [ 24  63  13  33   0  68  52   8   7  27]
 [  1   2   2  16   8   2 274   1   2   4]
 [  1   2   6  76  11   3  19 140  23   6]
```

```
 [ 32   1  31  36  31   2   8  27 142   8]
 [  3  12  38  42  10   6 134   6  21  27]]
```

```
from sklearn import preprocessing
from sklearn.model_selection import cross_val_score
from sklearn import svm

from sklearn.linear_model import LogisticRegression

#Accuracy, Precision, F1 score,Recall,Confusion Matrix using Logistic
Regression Algorithm
model1=LogisticRegression(max_iter=500,random_state=70)
model1.fit(x_train,y_train)
y_pred=model1.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
accuracy_list.append(accuracy)
model_name.append("LR")
```

```
0.30430430430430433
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/
_logistic.py:469: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
pre_lr=precision_score(y_test,y_pred,average='weighted')
print("precision_Logistic Regression: %.3f" %pre_lr)
recall_score_lr=recall_score(y_test,y_pred,average='weighted')
print("recall_Logistic Regression: %.3f" %recall_score_lr)
f1_score_lr=f1_score(y_test,y_pred,average='weighted')
print("f1_score_Logistic Regression: %.3f" %f1_score_lr)
confusion_matrix_lr=confusion_matrix(y_test,y_pred)
print("confusion_matrix_Logistic Regression:\n", confusion_matrix_lr)
```

```
precision_Logistic Regression: 0.296
recall_Logistic Regression: 0.304
f1_score_Logistic Regression: 0.269
confusion_matrix_Logistic Regression:
 [[ 50  39   4  34   6  38  73  16  26   1]
 [  8 141   4   2   0   8 128   0   4   0]
 [ 23  35  37  47   4  48  42  40  28   9]
```

```
 [ 15   4  14  74  10  16  71  64  21   1]
 [ 11   7  15  55  25   6  47  87  46   2]
 [ 41  48  10  18   2  73  64  32   1   6]
 [  1  11   7  45   1   6 235   4   2   0]
 [  4   5   6  34  13  23  22 152  25   3]
 [ 40  11  19  32  27   9  13  46 118   3]
 [ 14  18  11  62   4  28  83  53  19   7]]
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using
DecisionTree Classifier Algorithm
model2=DecisionTreeClassifier(random_state=42)
model2.fit(x_train,y_train)
y_dpred=model2.predict(x_test)
accuracy1=accuracy_score(y_test,y_dpred)
print(accuracy1)
accuracy_list.append(accuracy1)
model_name.append("DTC")
```

```
0.6489823156489823
```

```
pre_dtc=precision_score(y_test,y_dpred,average='weighted')
print("precision_Decision Tree Classifier: %.3f" %pre_dtc)
recall_score_dtc=recall_score(y_test,y_dpred,average='weighted')
print("recall_Decision Tree Classifier: %.3f" %recall_score_dtc)
f1_score_dtc=f1_score(y_test,y_dpred,average='weighted')
print("f1_score_Decision Tree Classifier: %.3f" %f1_score_dtc)
confusion_matrix_dtc=confusion_matrix(y_test,y_dpred)
print("confusion_matrix_Decision Tree Classifier:\n",
confusion_matrix_dtc)
```

```
precision_Decision Tree Classifier: 0.650
recall_Decision Tree Classifier: 0.649
f1_score_Decision Tree Classifier: 0.649
confusion_matrix_Decision Tree Classifier:
 [[175   1  25  11   5  11  17   1  17  24]
 [  1 263   7   0   1  17   0   0   1   5]
 [ 32   6 164  18   6  21   6   7  13  40]
 [  9   4  10 163  28   5   7  11  24  29]
 [  7   1   7  25 198   1   5  24  25   8]
 [ 14  28  23   4   2 194   3   3   8  16]
 [ 11   0   3   6  14   6 234   1   6  31]
 [  2   2  11  21  17   7   0 198  20   9]
 [ 12   2  14  21  21   7   4  13 214  10]
 [ 18   6  28  32   7  18  27   6  15 142]]
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using
RandomForestClassifier Algorithm
```

```
model3=RandomForestClassifier(n_estimators=100,random_state=1)
model3.fit(x_train,y_train)
y_rpred=model3.predict(x_test)
accuracy2=accuracy_score(y_test,y_rpred)
accuracy_list.append(accuracy2)
model_name.append("RFC")
print(accuracy2)
```

```
0.8638638638638638
```

```
pre_rfc=precision_score(y_test,y_rpred,average='weighted')
print("precision_Random Forest Classifier: %.3f" %pre_rfc)
recall_score_rfc=recall_score(y_test,y_rpred,average='weighted')
print("recall_Random Forest Classifier: %.3f" %recall_score_rfc)
f1_score_rfc=f1_score(y_test,y_rpred,average='weighted')
print("f1_score_Random Forest Classifier: %.3f" %f1_score_rfc)
confusion_matrix_rfc=confusion_matrix(y_test,y_rpred)
print("confusion_matrix_Random Forest Classifier:\n",
confusion_matrix_rfc)
```

```
precision_Random Forest Classifier: 0.864
recall_Random Forest Classifier: 0.864
f1_score_Random Forest Classifier: 0.862
confusion_matrix_Random Forest Classifier:
 [[265   1   3   4   1   7   4   0   2   0]
 [  0 286   3   0   0   6   0   0   0   0]
 [ 16   1 267   3   1  10   3   1   7   4]
 [  4   4   5 248   9   1   3   2   5   9]
 [  1   1   3   9 253   0   5  17   8   4]
 [  5  16  12   3   0 258   0   1   0   0]
 [  2   1   1   2   5   2 286   0   1  12]
 [  0   2   9   9   6   1   0 250   7   3]
 [  5   2  12   5   6   2   0   9 275   2]
 [ 14   3  17  21   5  15  17   2   4 201]]
```

```
from sklearn.ensemble import AdaBoostClassifier
```

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using
AdaboostClassifier Algorithm
model_ada=AdaBoostClassifier(model2,learning_rate=1.0,random_state=42)
model_ada.fit(x_train,y_train)
y_apred=model_ada.predict(x_test)
accu=accuracy_score(y_test,y_apred)
accuracy_list.append(accu)
model_name.append("ABC")
print(accu)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/
_weight_boosting.py:527: FutureWarning: The SAMME.R algorithm (the
default) is deprecated and will be removed in 1.6. Use the SAMME
```

```
algorithm to circumvent this warning.
  warnings.warn(
```

```
0.6866866866866866
```

```python
pre_dtc=precision_score(y_test,y_apred,average='weighted')
print("precision_AdaBoost Classifier: %.3f" %pre_dtc)
recall_score_dtc=recall_score(y_test,y_apred,average='weighted')
print("recall_AdaBoost Classifier: %.3f" %recall_score_dtc)
f1_score_dtc=f1_score(y_test,y_apred,average='weighted')
print("f1_score_AdaBoost Classifier: %.3f" %f1_score_dtc)
confusion_matrix_dtc=confusion_matrix(y_test,y_apred)
print("confusion_matrix_AdaBoost Classifier:\n", confusion_matrix_dtc)
```

```
precision_AdaBoost Classifier: 0.688
recall_AdaBoost Classifier: 0.687
f1_score_AdaBoost Classifier: 0.687
confusion_matrix_AdaBoost Classifier:
 [[190   0  27   7  10  17   8   2  13  13]
 [  0 256   8   0   0  23   2   0   1   5]
 [ 24   3 185  18   7  26   5   6  14  25]
 [ 16   3  12 172  16   5  10  10  21  25]
 [  8   0   9  14 197   2  10  30  22   9]
 [  8  15  27   5   5 216   1   7   2   9]
 [  7   0   2   9   7   2 256   0   1  28]
 [  1   5  14  12  10   7   0 213  14  11]
 [ 13   2  17  15  26   3   5   9 211  17]
 [ 21   3  31  20   7  16  22   8   9 162]]
```

```python
from sklearn.ensemble import GradientBoostingClassifier
```

```python
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using Gradient
BoostingClassifier Algorithm
model_gra=GradientBoostingClassifier(n_estimators=100,max_depth=3,rand
om_state=42)
model_gra.fit(x_train,y_train)
y_gpred=model_gra.predict(x_test)
accu_g=accuracy_score(y_test,y_gpred)
print(accu_g)
accuracy_list.append(accu_g)
model_name.append("GBC")
```

```
0.8218218218218218
```

```python
pre_gbc=precision_score(y_test,y_gpred,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %pre_gbc)
recall_score_gbc=recall_score(y_test,y_apred,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %recall_score_gbc)
f1_score_gbc=f1_score(y_test,y_apred,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %f1_score_gbc)
confusion_matrix_gbc=confusion_matrix(y_test,y_gpred)
```

```
print("confusion_matrix_Gradient_Boosting Classifier:\n",
confusion_matrix_gbc)
```

```
Gradient_Boosting Classifier: 0.822
Gradient_Boosting Classifier: 0.687
Gradient_Boosting Classifier: 0.687
confusion_matrix_Gradient_Boosting Classifier:
 [[243   1  10   8   5   7   4   0   4   5]
 [  0 275   4   0   0  10   0   0   1   5]
 [ 19   2 244   6   0  13   5   3   9  12]
 [  3   3   8 232  16   3   3   7   8   7]
 [  4   1   5   5 242   1   5  17  15   6]
 [  2  17  19   1   0 254   0   0   0   2]
 [  5   1   1   8   6   1 269   0   0  21]
 [  0   2   8  15   8   4   0 238   8   4]
 [  6   1  12   7   9   0   0   9 262  12]
 [ 16   4  20  18   5  11  13   4   4 204]]
```

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using SVC
Algorithm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
svm = SVC(kernel='rbf')

# Hyperparameter tuning
param_grid = {'C': [0.5,1,10], 'gamma': ['scale', 'auto']}
grid_search = GridSearchCV(svm, param_grid, cv=5)
grid_search.fit(x_train, y_train)

# Evaluate model
best_model = grid_search.best_estimator_
y_predsvm = best_model.predict(x_test)
accuracy = accuracy_score(y_test, y_predsvm)
acc_svm=accuracy_score(y_test,y_predsvm)
print("Accuracy:",acc_svm)
model_name.append("SVM")
accuracy_list.append(acc_svm)
```

```
Accuracy: 0.314647981314648
```

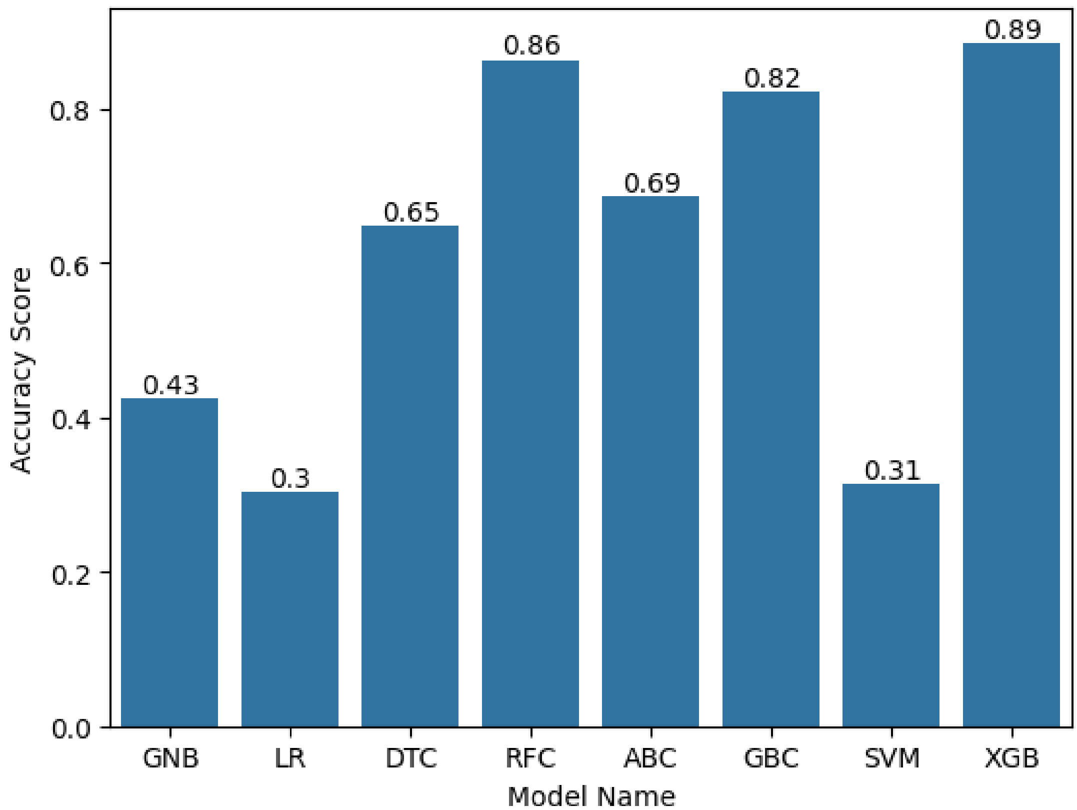
```
pre_svm=precision_score(y_test,y_predsvm,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %pre_svm)
recall_score_svm=recall_score(y_test,y_predsvm,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %recall_score_svm)
f1_score_svm=f1_score(y_test,y_predsvm,average='weighted')
print("Gradient_Boosting Classifier: %.3f" %f1_score_svm)
confusion_matrix_svm=confusion_matrix(y_test,y_predsvm)
print("confusion_matrix_Gradient_Boosting Classifier:\n",
confusion_matrix_svm)
```

```
#Accuracy, Precision, F1 score,Recall,Confusion Matrix using xgboost Algorithm
import xgboost as xgb
xgb_model=xgb.XGBClassifier()
xgb_model.fit(x_train,y_train)
y_predxgb=xgb_model.predict(x_test)
acc_xgb=accuracy_score(y_test,y_predxgb)
print("Accuracy:",acc_xgb)
model_name.append("XGB")
accuracy_list.append(acc_xgb)

pre_xgb=precision_score(y_test,y_predxgb,average='weighted')
print("xgboost Classifier: %.3f" %pre_xgb)
recall_score_xgb=recall_score(y_test,y_predxgb,average='weighted')
print("xgboost Classifier: %.3f" %recall_score_xgb)
f1_score_xgb=f1_score(y_test,y_predxgb,average='weighted')
print("xgboost Classifier: %.3f" %f1_score_xgb)
confusion_matrix_xgb=confusion_matrix(y_test,y_predxgb)
print("confusion_matrix_xgboost Classifier:\n", confusion_matrix_xgb)
```

```
xgboost Classifier: 0.887
xgboost Classifier: 0.886
xgboost Classifier: 0.886
confusion_matrix_xgboost Classifier:
 [[263   1   5   5   2   5   3   0   0   3]
 [  0 280   2   0   0   8   0   0   0   5]
 [ 11   2 275   2   1   8   0   0   4  10]
 [  6   4   6 248   7   1   1   4   6   7]
 [  2   1   4   4 269   1   3   8   7   2]
 [  1  11  12   1   0 268   1   0   0   1]
 [  4   1   1   2   6   1 287   0   0  10]
 [  0   1   6   5   6   2   0 256   6   5]
 [  6   2   6   4  10   1   0   8 277   4]
 [ 10   5  13   9   4   8  10   3   4 233]]
```

```
#Comparing the accuracy of all the models and determining the model with greatest accuracy
new_df=pd.DataFrame({
    "Model Name":model_name,"Accuracy Score":accuracy_list
})
bar_plot=sns.barplot(new_df,x="Model Name",y="Accuracy Score")
for index,row in new_df.iterrows():
  bar_plot.text(index,row["Accuracy Score"],round(row["Accuracy Score"],2),color="black",ha="center",va="bottom")
plt.show()
```



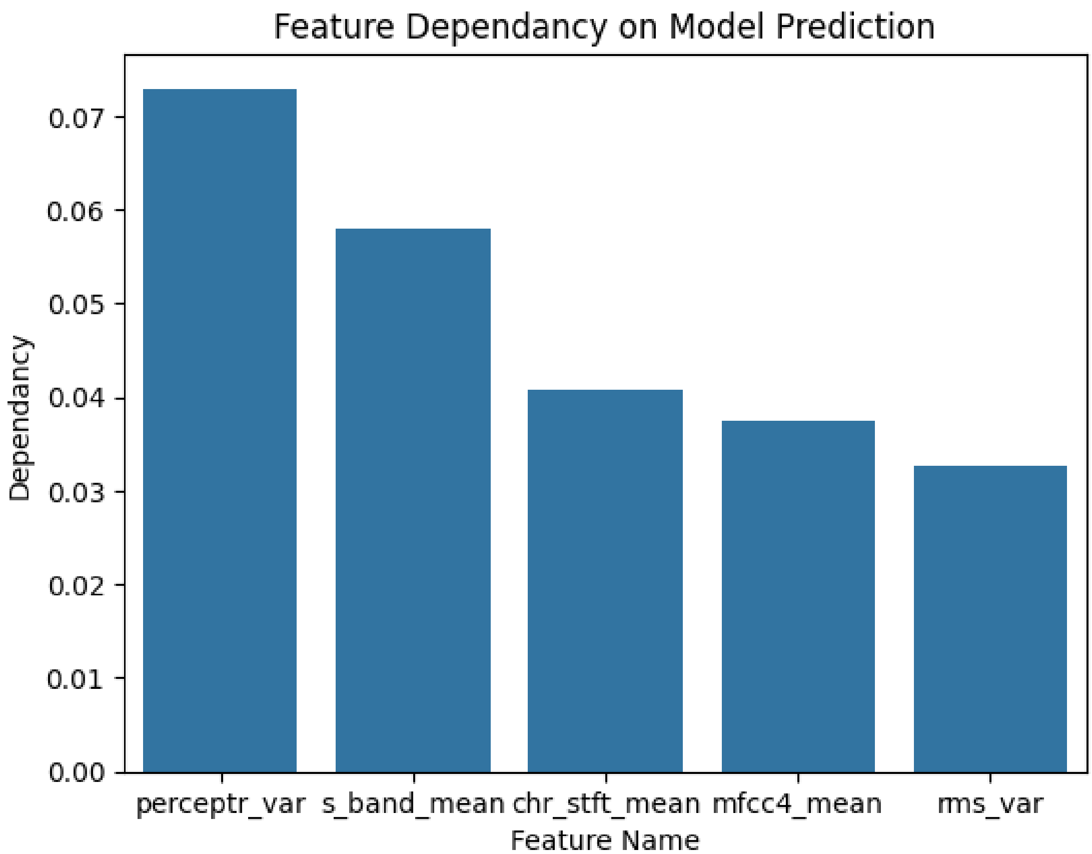
On which top 5 features accuracy is highly dependent?

```
imp_list=xgb_model.feature_importances_
model_imp=pd.Series(imp_list,ndt.columns[:-1])
top_5=model_imp.nlargest(5)
print(top_5)

perceptr_var              0.072947
spectral_bandwidth_mean   0.057957
chroma_stft_mean          0.040678
mfcc4_mean                0.037323
rms_var                   0.032699
dtype: float32

#Comparing the above top 5 feature dependency
feat_name=["perceptr_var","s_band_mean","chr_stft_mean","mfcc4_mean","
rms_var"]
new_df2=pd.DataFrame({
    "feat_name":feat_name,"top_5":top_5
})
bar_plot2=sns.barplot(x=feat_name,y=top_5)
plt.xlabel("Feature Name")
plt.ylabel("Dependancy")
plt.title("Feature Dependancy on Model Prediction")
#for index,row in new_df2.iterrows():
```

```
#
bar_plot2.text(index,row["top_5"],round(row["top_5"],2),color="black",
ha=",va="top")
plt.show()
```



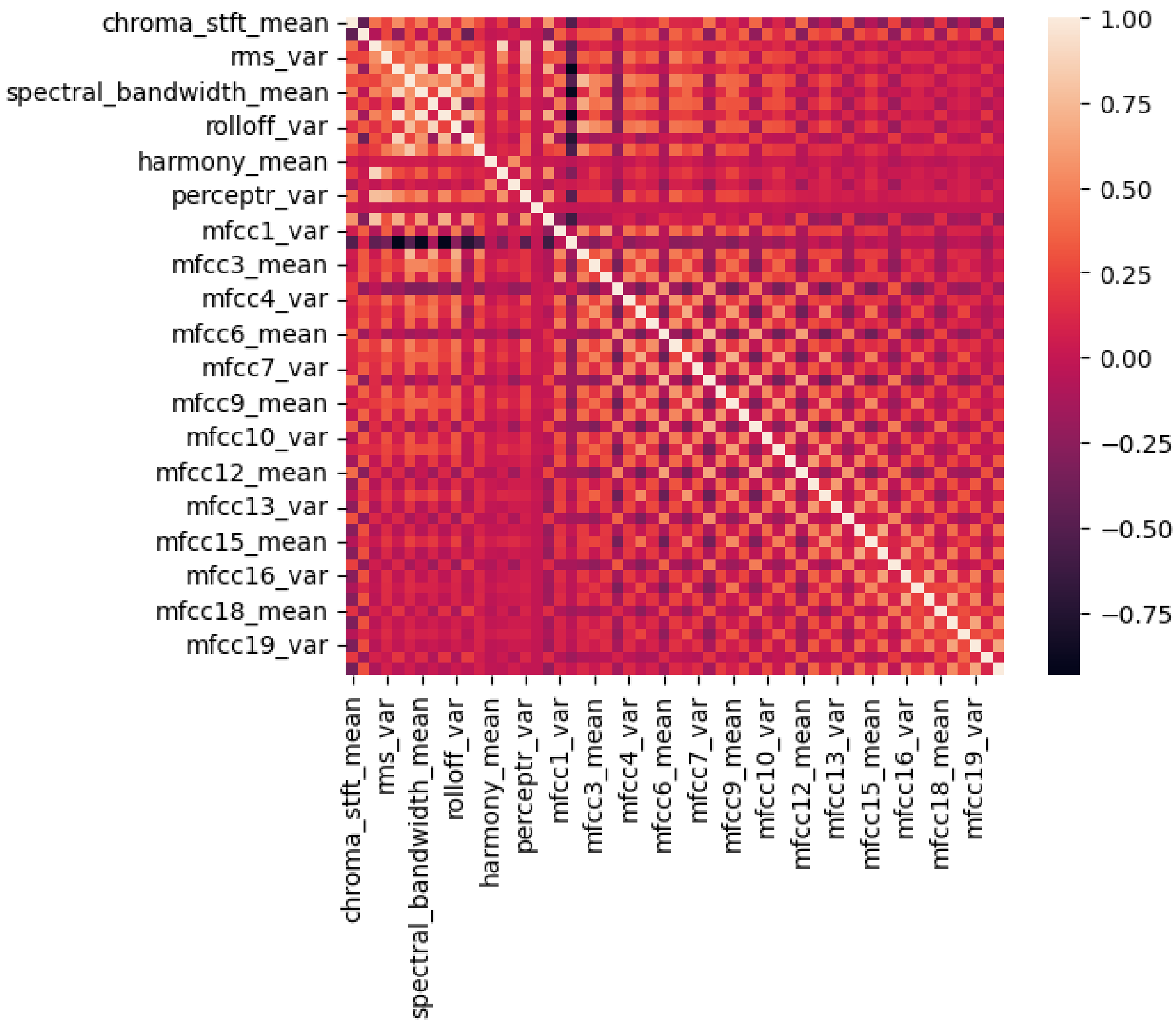
Are There Any Correlations Between Features?

```
correlation = ndt.iloc[:,0:57].corr()
correlation
```

{"type":"dataframe","variable_name":"correlation"}

```
sns.heatmap(correlation,square=True)
```

```
<Axes: >
```



CONCLUSION:

```
#In this project,we have build a model which predicts genre of the
music based on some features of the music.
#from above analysis we concluded that among naive bais,logistic
regression, decision tree classifier,
 #random forest classifier, adaboost classifier, xgboost classifier
#,gradient boosting classifier the most accurate model is xgboost
classifier with accuracy of almost 89% .
#Using the model we analysed the top five features on which the
accuracy of this model are most dependent.
#Among these the topmost was perceptr_var followed by
ms_var,chroma_stft_mean,rms_mean,mfcc4_mean.
```