Diabetes Detection Using BRFSS Data

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import math
```

+ Code + Text

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.feature_selection import chi2
from sklearn.model_selection import train_test_split  # for splitting dataset
from imblearn.over_sampling import SMOTE  # for oversampling
from imblearn.under_sampling import NearMiss # for undersampling
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from imblearn.under_sampling import NearMiss
from sklearn.metrics import mean_absolute_error , mean_absolute_percentage_error , mean_squared_error , accuracy_score
from sklearn.metrics import confusion_matrix
warnings.simplefilter(action = 'ignore')
```

```
data = upd.read_csv('diabetes_012_health_indicators_BRFSS2015.csv.zip')
data_orginal = pd.read_csv('diabetes_012_health_indicators_BRFSS2015.csv.zip')
```

```
data
```

	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	...	AnyHealthca
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	0.0	0.0	...	
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	1.0	0.0	...	
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	0.0	1.0	...	
3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	1.0	1.0	...	
4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	1.0	1.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
253675	0.0	1.0	1.0	1.0	45.0	0.0	0.0	0.0	0.0	1.0	...	
253676	2.0	1.0	1.0	1.0	18.0	0.0	0.0	0.0	0.0	0.0	...	
253677	0.0	0.0	0.0	1.0	28.0	0.0	0.0	0.0	1.0	1.0	...	
253678	0.0	1.0	0.0	1.0	23.0	0.0	0.0	0.0	0.0	1.0	...	
253679	2.0	1.0	1.0	1.0	25.0	0.0	0.0	1.0	1.0	1.0	...	

253680 rows × 22 columns

```
print('\n=== First 5 rows of data ===')
display(data.head())
```

```
=== First 5 rows of data ===
```

	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	...	AnyHealthcare	N
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	0.0	0.0	...	1.0	
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	1.0	0.0	...	0.0	
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	0.0	1.0	...	1.0	
3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	1.0	1.0	...	1.0	
4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	1.0	1.0	...	1.0	

5 rows × 22 columns

```
print('\n=== Dataset Info ===')
display(data.info())
print('Findings: Need to switch to Int type ')
```

```
=== Dataset Info ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253680 entries, 0 to 253679
Data columns (total 22 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Diabetes_012          253680 non-null  float64
 1   HighBP                253680 non-null  float64
 2   HighChol              253680 non-null  float64
 3   CholCheck             253680 non-null  float64
 4   BMI                   253680 non-null  float64
 5   Smoker                253680 non-null  float64
 6   Stroke                253680 non-null  float64
 7   HeartDiseaseorAttack  253680 non-null  float64
 8   PhysActivity          253680 non-null  float64
 9   Fruits                253680 non-null  float64
 10  Veggies               253680 non-null  float64
 11  HvyAlcoholConsump     253680 non-null  float64
 12  AnyHealthcare         253680 non-null  float64
 13  NoDocbcCost           253680 non-null  float64
 14  GenHlth               253680 non-null  float64
 15  MentHlth              253680 non-null  float64
 16  PhysHlth              253680 non-null  float64
 17  DiffWalk              253680 non-null  float64
 18  Sex                   253680 non-null  float64
 19  Age                   253680 non-null  float64
 20  Education             253680 non-null  float64
 21  Income                253680 non-null  float64
dtypes: float64(22)
memory usage: 42.6 MB
None
```

```
print('\n=== Check Missing Values ===')
display(data.isnull().sum())
print('Findings: No Missing Value ')
```

```
=== Check Missing Values ===
```

	0
Diabetes_012	0
HighBP	0
HighChol	0
CholCheck	0
BMI	0
Smoker	0
Stroke	0
HeartDiseaseorAttack	0
PhysActivity	0
Fruits	0
Veggies	0
HvyAlcoholConsump	0
AnyHealthcare	0
NoDocbcCost	0
GenHlth	0
MentHlth	0
PhysHlth	0
DiffWalk	0
Sex	0
Age	0
Education	0
Income	0

dtype: int64

```
Findings: No Missing Value
```

```
print('\n=== Basic Staistic Describe ===')
display(data.describe())
print('Findings: Inbalance Target Variable')
```

```
=== Basic Staistic Describe ===
```

	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack
count	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000
mean	0.296921	0.429001	0.424121	0.962670	28.382364	0.443169	0.040571	0.094186
std	0.698160	0.494934	0.494210	0.189571	6.608694	0.496761	0.197294	0.292087
min	0.000000	0.000000	0.000000	0.000000	12.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	1.000000	24.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000	27.000000	0.000000	0.000000	0.000000
75%	0.000000	1.000000	1.000000	1.000000	31.000000	1.000000	0.000000	0.000000
max	2.000000	1.000000	1.000000	1.000000	98.000000	1.000000	1.000000	1.000000

8 rows × 22 columns

```
Findings: Inbalance Target Variable
```

```
print('\n=== Duplicated Values ===')
display(data.duplicated().sum())
```

```
=== Duplicated Values ===
```

Pre-Processing

Transform data type to integer

```
for col in data.columns:
    data[col] = data[col].astype(int)

print('\n=== Checking Data Type ===')
display(data.info())
display(data.head())
```

```
=== Checking Data Type ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253680 entries, 0 to 253679
Data columns (total 22 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Diabetes_012          253680 non-null  int64
 1   HighBP                253680 non-null  int64
 2   HighChol              253680 non-null  int64
 3   CholCheck             253680 non-null  int64
 4   BMI                   253680 non-null  int64
 5   Smoker                253680 non-null  int64
 6   Stroke                253680 non-null  int64
 7   HeartDiseaseorAttack  253680 non-null  int64
 8   PhysActivity          253680 non-null  int64
 9   Fruits                253680 non-null  int64
 10  Veggies               253680 non-null  int64
 11  HvyAlcoholConsump     253680 non-null  int64
 12  AnyHealthcare         253680 non-null  int64
 13  NoDocbcCost           253680 non-null  int64
 14  GenHlth               253680 non-null  int64
 15  MentHlth              253680 non-null  int64
 16  PhysHlth              253680 non-null  int64
 17  DiffWalk              253680 non-null  int64
 18  Sex                   253680 non-null  int64
 19  Age                   253680 non-null  int64
 20  Education             253680 non-null  int64
 21  Income                253680 non-null  int64
dtypes: int64(22)
memory usage: 42.6 MB
None
```

	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	...	AnyHealthcare	Nc
0	0	1	1	1	40	1	0	0	0	0	...	1	
1	0	0	0	0	25	1	0	0	1	0	...	0	
2	0	1	1	1	28	0	0	0	0	1	...	1	
3	0	1	0	1	27	0	0	0	1	1	...	1	
4	0	1	1	1	24	0	0	0	1	1	...	1	

5 rows × 22 columns

Checking Unique value

```
print('\n=== Unique Value Overview ===')
unique_values = {}
for col in data.columns:
    unique_values[col] = data[col].value_counts().shape[0]

display(pd.DataFrame(unique_values, index=['Unique Value Count']).transpose())

print('\n=== Unique Value Detailed Overview ===')
for column in data.columns:
    print(f'\n{column}:')
    print(f'Unique Values:{sorted(data[column].unique())}')
```

```
=== Unique Value Overview ===
```

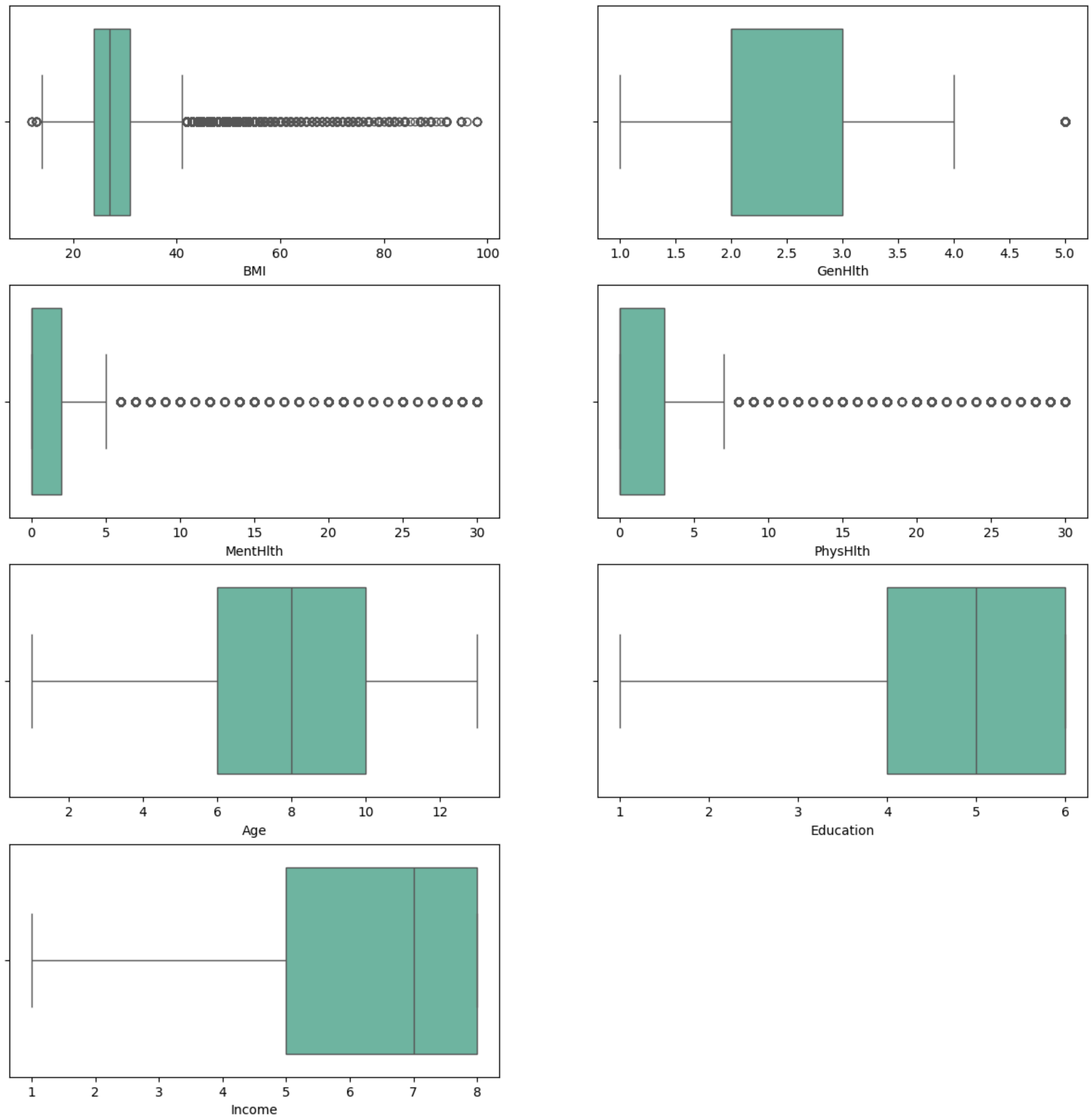
	Unique Value Count
Diabetes_012	3
HighBP	2
HighChol	2
CholCheck	2
BMI	84
Smoker	2
Stroke	2
HeartDiseaseorAttack	2
PhysActivity	2
Fruits	2
Veggies	2
HvyAlcoholConsump	2
AnyHealthcare	2
NoDocbcCost	2
GenHlth	5
MentHlth	31
PhysHlth	31
DiffWalk	2
Sex	2
Age	13
Education	6
Income	8

```
=== Unique Value Detailed Overview ===

Diabetes_012:
Unique Values:[0, 1, 2]

HighBP:
Unique Values:[0, 1]

HighChol:
Unique Values:[0, 1]

CholCheck:
Unique Values:[0, 1]

BMI:
Unique Values:[12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40

Smoker:
Unique Values:[0, 1]

Stroke:
Unique Values:[0, 1]

HeartDiseaseorAttack:
Unique Values:[0, 1]

PhysActivity:
Unique Values:[0, 1]

Fruits:
Unique Values:[0, 1]

Veggies:
Unique Values:[0, 1]

HvyAlcoholConsump:
Unique Values:[0, 1]

AnyHealthcare:
Unique Values:[0, 1]

NoDocbcCost:
Unique Values:[0, 1]

GenHlth:
Unique Values:[1, 2, 3, 4, 5]
```

```
Unique Values:[1, 2, 3, 4, 5]

MentHlth:
Unique Values:[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30]

PhysHlth:
Unique Values:[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30]

DiffWalk:
Unique Values:[0, 1]

Sex:
Unique Values:[0, 1]

Age:
Unique Values:[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13]

Education:
Unique Values:[1, 2, 3, 4, 5, 6]

Income:
Unique Values:[1, 2, 3, 4, 5, 6, 7, 8]
```

Check Outlier

```
plt.figure(figsize = (15,15))
for i, col in enumerate (['BMI', 'GenHlth', 'MentHlth','PhysHlth','Age', 'Education','Income']):
    plt.subplot(4,2,i+1)
    sns.boxplot(x = col, data = data, palette = 'Set2')
plt.show()
```



Check Duplicated Data and Drop

```
data.duplicated().sum()
```

```
23899
```

```
data.drop_duplicates(inplace = True)
```

```
data.duplicated().sum()
```

```
0
```

```
data.shape
```

```
(229781, 22)
```

Better EDA Code

```
data.columns
```

```
Index(['Diabetes_012', 'HighBP', 'HighChol', 'CholCheck', 'BMI', 'Smoker',
       'Stroke', 'HeartDiseaseorAttack', 'PhysActivity', 'Fruits', 'Veggies',
       'HvyAlcoholConsump', 'AnyHealthcare', 'NoDocbcCost', 'GenHlth',
       'MentHlth', 'PhysHlth', 'DiffWalk', 'Sex', 'Age', 'Education',
       'Income'],
      dtype='object')
```

```
# Better show categorical variables
data2 = data.copy()


# That help us to show the relation between features clearly
#### Age
age_maping = {
    1: '18 to 24',
    2: '25 to 29',
    3: '30 to 34',
    4: '35 to 39',
    5: '40 to 44',
    5: '45 to 49',
    6: '50 to 54',
    7: '55 to 59',
    8: '60 to 64',
    9: '65 to 69',
    10: '70 to 74',
    11: '75 to 79',
    12: '80 or Older'
}
data2['Age'] = data2['Age'].replace(age_maping)


education_maping={
    1: 'Never Attended School',
    2: 'Elementary',
    3: 'Junior High School',
    4: 'Senior High School',
    5: 'Undergraduate Degree',
    6: 'Magister'
}
data2['Education']=data2['Education'].replace(education_maping)


income_maping = {
    1: 'Less Than $10,000 ',
    2: 'Less Than $10,000 ',
    3: 'Less Than $10,000 ',
    4: 'Less Than $10,000 ',
    5: 'Less Than $35,000 ',
    6: 'Less Than $35,000 ',
    7: 'Less Than $35,000 ',
    8: '$75,000 or More '
}
data2['Income']=data2['Income'].replace(income_maping)


data2.Diabetes_012[data2['Diabetes_012']==0]='No Diabetes'
data2.Diabetes_012[data2['Diabetes_012']==1]='Diabetes'

data2.HighBP[data2['HighBP']==0]='No High'
data2.HighBP[data2['HighBP']==1]='High BP'

data2.HighChol[data2['HighChol']==0]='No High Cholesterol'
data2.HighChol[data2['HighChol']==1]=' High Cholesterol'

data2.CholCheck[data2['CholCheck']==0]='No Chol Check in 5 Years'
data2.CholCheck[data2['CholCheck']==1]='Chol Check in 5 Years'

data2.Smoker[data2['Smoker']==0]='No'
data2.Smoker[data2['Smoker']==1]='Yes'

data2.Stroke[data2['Stroke']==0]='No'
data2.Stroke[data2['Stroke']==1]='Yes'

data2.HeartDiseaseorAttack[data2['HeartDiseaseorAttack']==0]='No'
data2.HeartDiseaseorAttack[data2['HeartDiseaseorAttack']==1]='Yes'
```

```
data2.PhysActivity[data2['PhysActivity']==0]='No'
data2.PhysActivity[data2['PhysActivity']==1]='Yes'

data2.Fruits[data2['Fruits']==0]='No'
data2.Fruits[data2['Fruits']==1]='Yes'

data2.Veggies[data2['Veggies']==0]='No'
data2.Veggies[data2['Veggies']==1]='Yes'

data2.MentHlth[data2['MentHlth']==0]='No'
data2.MentHlth[data2['MentHlth']==1]='Yes'

data2.PhysHlth[data2['PhysHlth']==0]='No'
data2.PhysHlth[data2['PhysHlth']==1]='Yes'

data2.DiffWalk[data2['DiffWalk']==0]='No'
data2.DiffWalk[data2['DiffWalk']==1]='Yes'

data2.Sex[data2['Sex']==0]='Female'
data2.Sex[data2['Sex']==1]='Male'

data2.AnyHealthcare[data2['AnyHealthcare']==0]='No'
data2.AnyHealthcare[data2['AnyHealthcare']==1]='Yes'

data2.NoDocbcCost[data2['NoDocbcCost']==0]='No'
data2.NoDocbcCost[data2['NoDocbcCost']==1]='Yes'


data2.head(20)
```

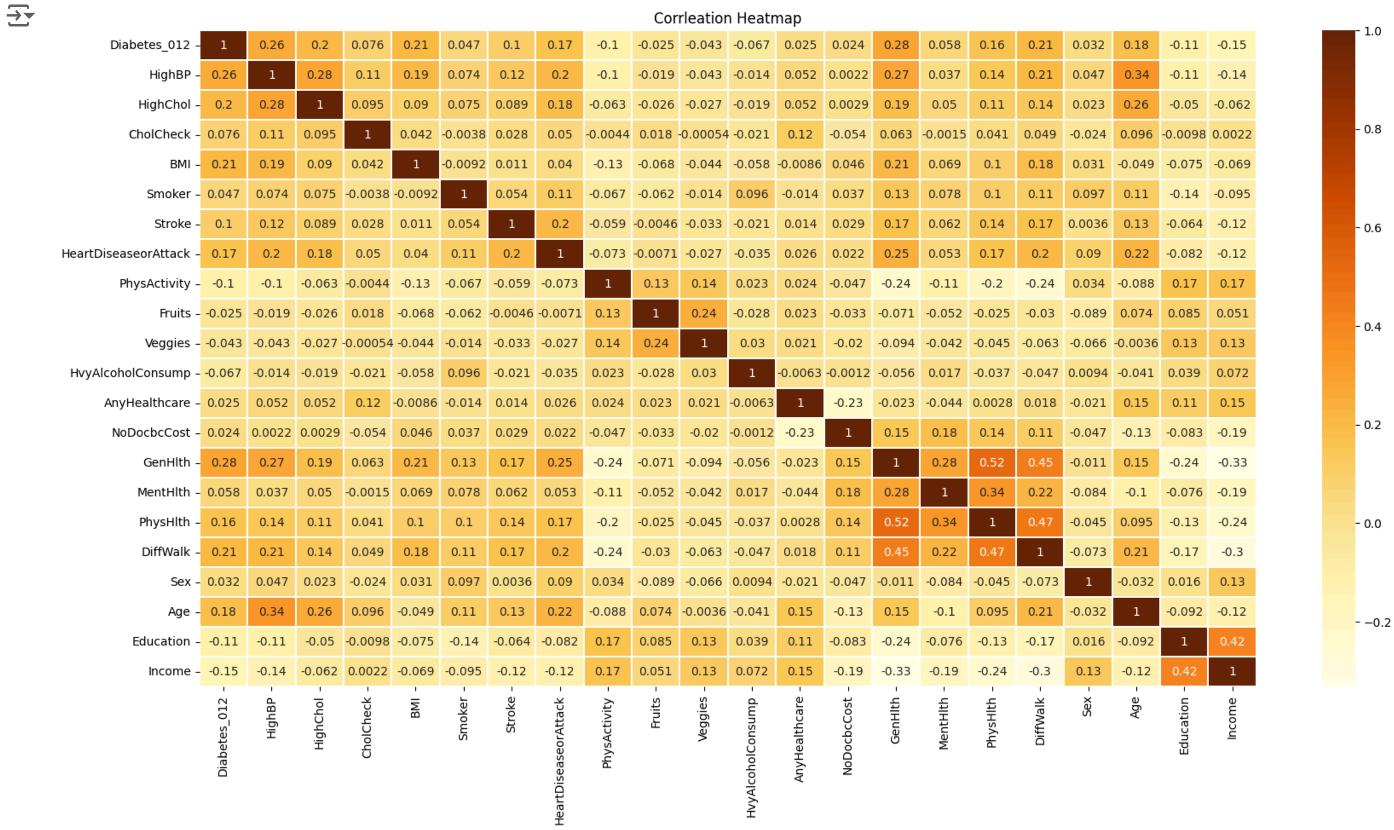
	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	...	AnyHealthcar
0	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	40	Yes	No	No	No	No	...	Ye
1	No Diabetes	No High	No High Cholesterol	No Chol Check in 5 Years	25	Yes	No	No	Yes	No	...	N
2	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	28	No	No	No	No	Yes	...	Ye
3	No Diabetes	High BP	No High Cholesterol	Chol Check in 5 Years	27	No	No	No	Yes	Yes	...	Ye
4	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	24	No	No	No	Yes	Yes	...	Ye
5	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	25	Yes	No	No	Yes	Yes	...	Ye
6	No Diabetes	High BP	No High Cholesterol	Chol Check in 5 Years	30	Yes	No	No	No	No	...	Ye
7	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	25	Yes	No	No	Yes	No	...	Ye
8	2	High BP	High Cholesterol	Chol Check in 5 Years	30	Yes	No	Yes	No	Yes	...	Ye
9	No Diabetes	No High	No High Cholesterol	Chol Check in 5 Years	24	No	No	No	No	No	...	Ye
10	2	No High	No High Cholesterol	Chol Check in 5 Years	25	Yes	No	No	Yes	Yes	...	Ye
11	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	34	Yes	No	No	No	Yes	...	Ye
12	No Diabetes	No High	No High Cholesterol	Chol Check in 5 Years	26	Yes	No	No	No	No	...	Ye
13	2	High BP	High Cholesterol	Chol Check in 5 Years	28	No	No	No	No	No	...	Ye
14	No Diabetes	No High	High Cholesterol	Chol Check in 5 Years	33	Yes	Yes	No	Yes	No	...	Ye
15	No Diabetes	High BP	No High Cholesterol	Chol Check in 5 Years	33	No	No	No	Yes	No	...	Ye
16	No Diabetes	High BP	High Cholesterol	Chol Check in 5 Years	21	No	No	No	Yes	Yes	...	Ye
17	2	No High	No High Cholesterol	Chol Check in 5 Years	23	Yes	No	No	Yes	No	...	Ye
18	No Diabetes	No High	No High Cholesterol	No Chol Check in 5 Years	23	No	No	No	No	No	...	Ye
19	No Diabetes	No High	High Cholesterol	Chol Check in 5 Years	28	No	No	No	No	No	...	Ye

20 rows × 22 columns

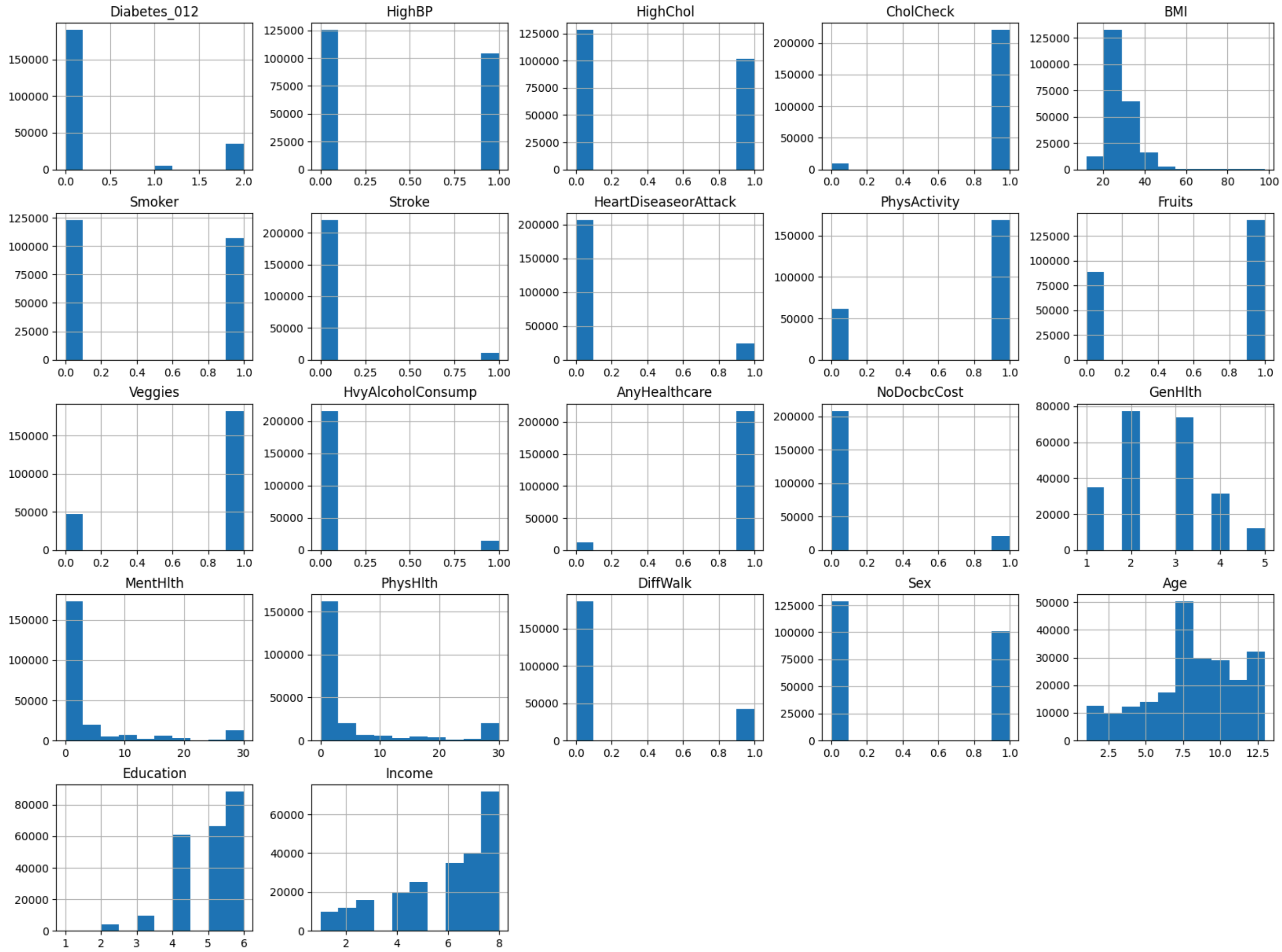
EDA

Correlation Heatmap

```
plt.figure(figsize = (20,10))
sns.heatmap(data.corr(), annot = True, cmap = 'YlOrBr', linewidths = 0.3)
plt.title('Corrleation Heatmap')
plt.show()
```

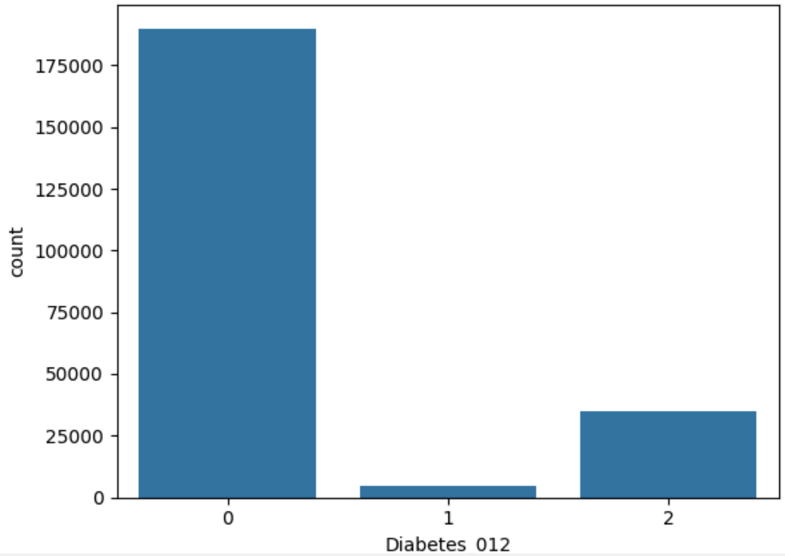



```
data.hist(figsize = (20,15));
```




```
sns.countplot(x = 'Diabetes_012', data = data)
```

```
<Axes: xlabel='Diabetes_012', ylabel='count'>
```



VIF Test

```
def calc_VIF(x):
    vif=pd.DataFrame()
    vif['variables'] = x.columns
    vif['VIF'] = [variance_inflation_factor(x.values, i)for i in range(x.shape[1])]
    retrun(vif)

X=add_constant(data)
ds = pd.Series([variance_inflation_factor(X.values,i)
              for i in range(X.shape[1])],
               index = X.columns)
print(ds)
```

```
const                 109.547733
Diabetes_012            1.196142
HighBP                  1.315868
HighChol                1.167606
CholCheck               1.036087
BMI                     1.143747
Smoker                  1.076218
Stroke                  1.077925
HeartDiseaseorAttack    1.170203
PhysActivity            1.130800
Fruits                  1.098139
Veggies                 1.098315
HvyAlcoholConsump       1.027818
AnyHealthcare           1.110036
NoDocbcCost             1.135822
GenHlth                 1.742978
MentHlth                1.221952
PhysHlth                1.594631
DiffWalk                1.514183
Sex                     1.076794
Age                     1.359986
Education               1.272637
Income                  1.432763
dtype: float64
```

```
data.shape
```

```
(229781, 22)
```

ANOVA Feature Select

```
X = data_orginal.iloc[:,1:]
Y = data_orginal.iloc[:,0]


fs = SelectKBest(score_func = f_classif, k =10)
X_selected = fs.fit_transform(X,Y)
print(X_selected.shape)

pd.DataFrame(X_selected).head(3)
```

```
(253680, 10)
```

	0	1	2	3	4	5	6	7	8	9
0	1.0	1.0	40.0	0.0	5.0	15.0	1.0	9.0	4.0	3.0
1	0.0	0.0	25.0	0.0	3.0	0.0	0.0	7.0	6.0	1.0
2	1.0	1.0	28.0	0.0	5.0	30.0	1.0	9.0	4.0	8.0

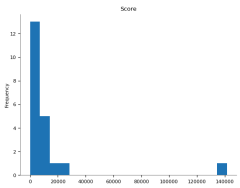
Best Feature

```
BestFeatures = SelectKBest(score_func=chi2, k=10)
fit = BestFeatures.fit(X,Y)

df_scores = pd.DataFrame(fit.scores_)
df_columns = pd.DataFrame(X.columns)

#concatenating two dataframes for better visualization
f_Scores = pd.concat([df_columns,df_scores], axis=1)
f_Scores.columns = ['Feature','Score']

# Sort values from highest to lowest
f_Scores_sorted = f_Scores.sort_values(by='Score', ascending=False)
display(f_Scores_sorted)

print(f_Scores_sorted.nlargest(16,'Score'))
```

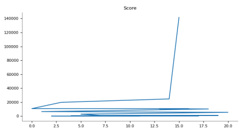
	Feature	Score
15	PhysHlth	141598.783225
14	MentHlth	24607.463010
3	BMI	19775.252090
0	HighBP	10731.721009
16	DiffWalk	10627.556856
13	GenHlth	10595.234173
18	Age	10225.159975
6	HeartDiseaseorAttack	7468.339377
1	HighChol	6483.776499
20	Income	5380.434934
5	Stroke	2798.417025
7	PhysActivity	922.529401
19	Education	849.169260
10	HvyAlcoholConsump	802.538572
4	Smoker	562.684715
12	NoDocbcCost	362.740875
9	Veggies	168.560797
8	Fruits	166.174822
17	Sex	140.390490
2	CholCheck	43.816645
11	AnyHealthcare	3.381194

```
                 Feature          Score
15              PhysHlth  141598.783225
14              MentHlth   24607.463010
3                    BMI   19775.252090
0                 HighBP   10731.721009
16              DiffWalk   10627.556856
13               GenHlth   10595.234173
18                   Age   10225.159975
6   HeartDiseaseorAttack    7468.339377
1               HighChol    6483.776499
20                Income    5380.434934
5                 Stroke    2798.417025
7           PhysActivity     922.529401
19             Education     849.169260
10     HvyAlcoholConsump     802.538572
4                 Smoker     562.684715
12           NoDocbcCost     362.740875
```

Distributions



Values



```
data.columns
```

```
Index(['Diabetes_012', 'HighBP', 'HighChol', 'CholCheck', 'BMI', 'Smoker',
       'Stroke', 'HeartDiseaseorAttack', 'PhysActivity', 'Fruits', 'Veggies',
       'HvyAlcoholConsump', 'AnyHealthcare', 'NoDocbcCost', 'GenHlth',
       'MentHlth', 'PhysHlth', 'DiffWalk', 'Sex', 'Age', 'Education',
       'Income'],
      dtype='object')
```

```
columns =["Fruits" , "Veggies" , "Sex" , "CholCheck" , "AnyHealthcare"]
data.drop(columns, axis = 1, inplace = True)
```

Data Splitting

```
X = data.drop('Diabetes_012', axis = 1)
y = data['Diabetes_012']
```

```
X_train, X_test,Y_train, y_test = train_test_split(
X,y, test_size = 0.2, random_state = 42)
```

Dealing with Imbalance

SMOTE

```
data['Diabetes_012'].value_counts()
```

```
smote = SMOTE(random_state = 42)
X_train_smote,Y_train_smote = smote.fit_resample(X_train, Y_train)
print('Training set Distribution after SMOTE')
print(pd.DataFrame(Y_train_smote).value_counts())
print('\nTest set Distribution')
print(pd.DataFrame(y_test).value_counts())
```

```
Training set Distribution after SMOTE
Diabetes_012
0               151939
1               151939
2               151939
Name: count, dtype: int64

Test set Distribution
Diabetes_012
0               38116
2                6935
1                 906
Name: count, dtype: int64
```

Near Miss

```
nm = NearMiss(version = 1, n_neighbors = 10)
x_sm, y_sm = nm.fit_resample(X,y)
```

```
display(data.shape)
x_sm.shape
# 250k droped to 70k
```

```
(229781, 17)
```

```
X_train, X_test,Y_train,y_test = train_test_split(x_sm,y_sm, test_size = 0.3, random_state = 42)
```

Data Scalling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

Modeling

Logistic Regression

```
lg = LogisticRegression(random_state = 42, max_iter = 1500)
lg.fit(X_train,Y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=1500, random_state=42)
```

```
y_pred_lg=lg.predict(X_test)
```

```
print('Training set score:{:4f}'.format(lg.score(X_train,Y_train)))
print('test set score {:4f}'.format(lg.score(X_test,y_test)))
```

```
Training set score:0.708848
test set score 0.708183
```

Logistic Regression MSE and RMSE

```
# MSE and RMSE
mse_lg = mean_squared_error(y_test,y_pred_lg)
print('MSE_lg:'+str(mse_lg))
rmse_lg = math.sqrt(mean_squared_error(y_test,y_pred_lg))
print('RMSE_lg:'+str(rmse_lg))
```

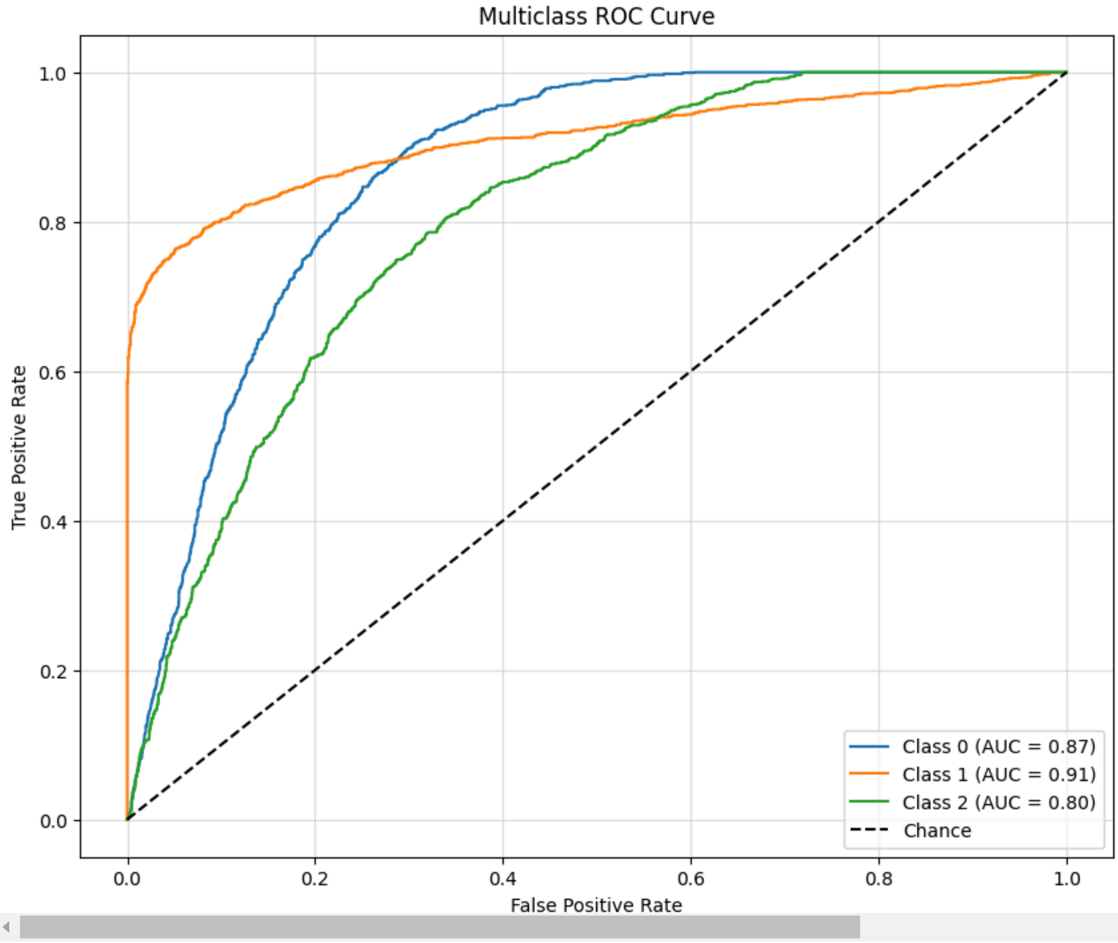
```
MSE_lg:0.839692824574034
RMSE_lg:0.9163475457347141
```

Logistic Regression Classification Report

```
cm_lg = classification_report(y_test,y_pred_lg)

print('Logistic Regression Model1:')
print(cm_lg)
print('MSE_lg:'+str(mse_lg))
print('RMSE_lg:'+str(rmse_lg))
```

```
Logistic Regression Model1:
              precision    recall  f1-score   support

           0       0.64      0.79      0.71      1389
           1       0.93      0.73      0.82      1410
           2       0.61      0.61      0.61      1368

    accuracy                           0.71      4167
   macro avg       0.73      0.71      0.71      4167
weighted avg       0.73      0.71      0.71      4167

MSE_lg:0.839692824574034
RMSE_lg:0.9163475457347141
```

```
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Binarize the target labels
classes = np.unique(y_test)
y_test_binarized = label_binarize(y_test, classes=classes)

# Predicted probabilities
y_pred_proba = lg.predict_proba(X_test)

# Number of classes
n_classes = y_test_binarized.shape[1]

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_pred_proba[:, i])
    auc = roc_auc_score(y_test_binarized[:, i], y_pred_proba[:, i])
    plt.plot(fpr, tpr, label=f'Class {classes[i]} (AUC = {auc:.2f})')

# Plot baseline
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.title('Multiclass ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(alpha=0.4)
plt.show()
```

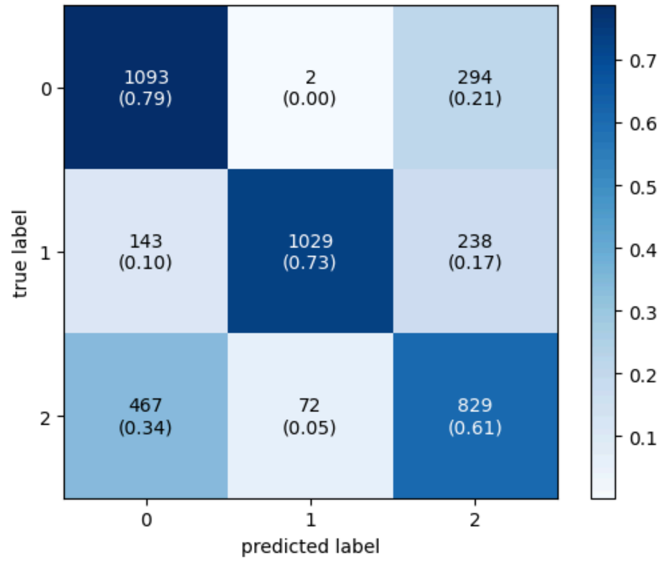


Logistic Regression Confusion Matrix

```
pip install mlxtend
```

```
Requirement already satisfied: mlxtend in /usr/local/lib/python3.10/dist-packages (0.23.3)
Requirement already satisfied: scipy>=1.2.1 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (1.13.1)
Requirement already satisfied: numpy>=1.16.2 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (1.26.4)
Requirement already satisfied: pandas>=0.24.2 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (2.2.2)
Requirement already satisfied: scikit-learn>=1.3.1 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (1.5.2)
Requirement already satisfied: matplotlib>=3.0.0 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (3.8.0)
Requirement already satisfied: joblib>=0.13.2 in /usr/local/lib/python3.10/dist-packages (from mlxtend) (1.4.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (1.3.1
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (4.55
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (1.4.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (3.2.0
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0.0->mlxtend) (2
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.2->mlxtend) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.2->mlxtend) (2024.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.3.1->mlxtend)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=3.0.0->ml
```

```
from sklearn.metrics import confusion_matrix, mean_squared_error
from mlxtend.plotting import plot_confusion_matrix

cm_lg = confusion_matrix(y_test,y_pred_lg)
plot_confusion_matrix(conf_mat=cm_lg, show_absolute = True,
                      show_normed = True,
                      colorbar = True)
plt.show()
print('MSE_lg:'+str(mse_lg))
print('RMSE_lg:'+str(rmse_lg))
```

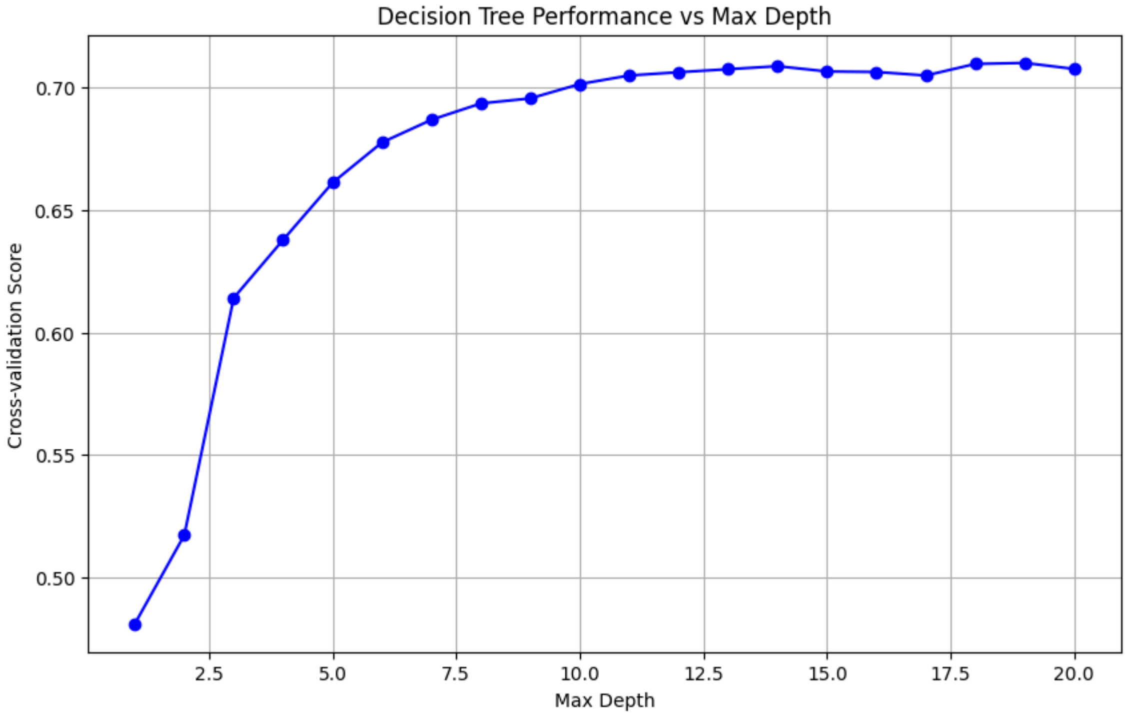



```
MSE_lg:0.839692824574034
```

Decision Trees

Find the optimal depth

```
max_depths = range(1, 21)
scores = []

for depth in max_depths:
    dt = DecisionTreeClassifier(max_depth=depth, random_state=42)
    score = cross_val_score(dt, X_train, Y_train, cv=5).mean()
    scores.append(score)

# Plot results
plt.figure(figsize=(10, 6))
plt.plot(max_depths, scores, 'bo-')
plt.xlabel('Max Depth')
plt.ylabel('Cross-validation Score')
plt.title('Decision Tree Performance vs Max Depth')
plt.grid(True)
plt.show()

# Find best depth
best_depth = max_depths[np.argmax(scores)]
print(f"Best depth: {best_depth}")
print(f"Best score: {max(scores):.4f}")
```




```
Best depth: 19
```

```
dt = DecisionTreeClassifier(max_depth = 14)
dt.fit(X_train,Y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=14)
```

```
y_pred_dt = dt.predict(X_test)
```

Decision Tree MSE and RMSE

```
mse_dt = mean_squared_error(y_test, y_pred_dt)
rmse_dt = math.sqrt(mean_squared_error(y_test,y_pred_dt))
print("MSE_dt:"+str(mse_dt))
print('RMSE_dt:'+str(rmse_dt))
```

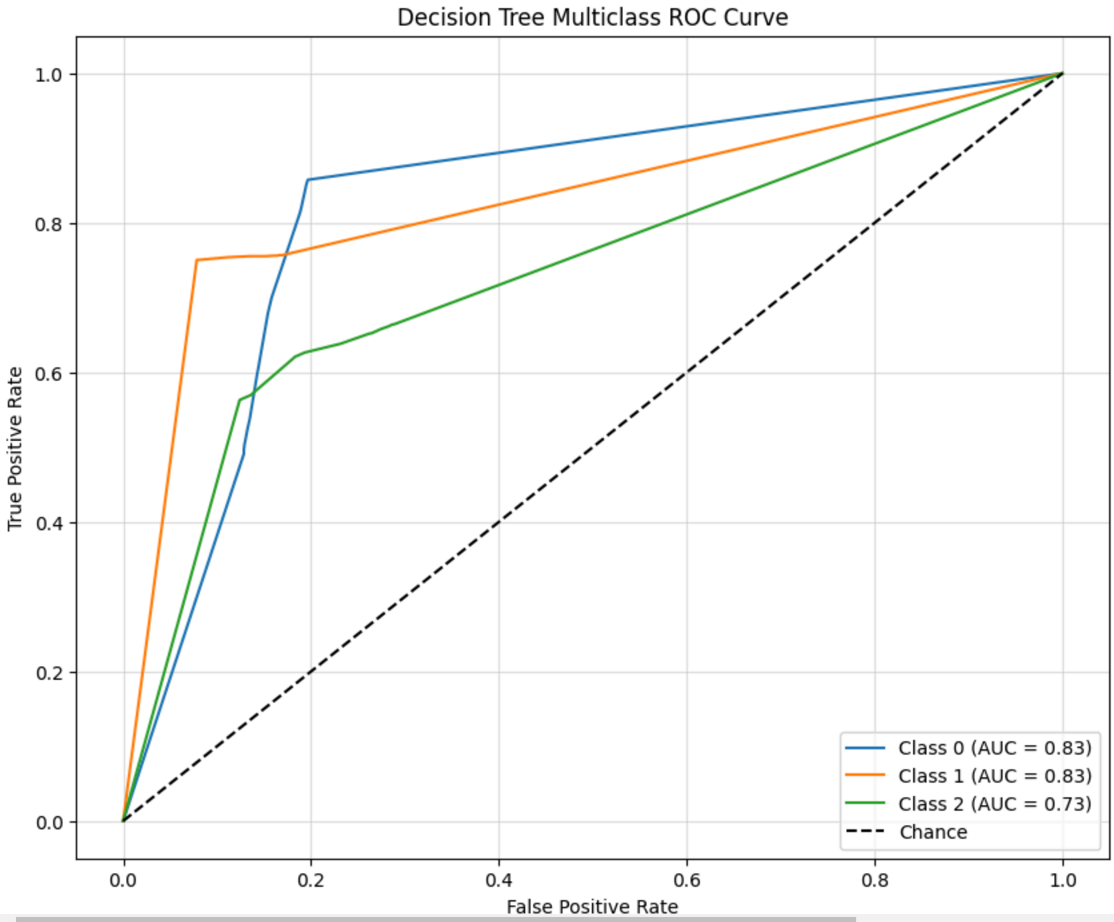
```
MSE_dt:0.7890568754499641
RMSE_dt:0.8882887342806752
```

```
cm_dt_report = classification_report(y_test,y_pred_dt)
print(cm_dt_report)
print("MSE_dt:"+str(mse_dt))
print('RMSE_dt:'+str(rmse_dt))
```

```
              precision    recall  f1-score   support

           0       0.67      0.80      0.73      1389
           1       0.90      0.74      0.81      1410
           2       0.61      0.61      0.61      1368

    accuracy                           0.72      4167
   macro avg       0.73      0.72      0.72      4167
weighted avg       0.73      0.72      0.72      4167

MSE_dt:0.7890568754499641
RMSE_dt:0.8882887342806752
```

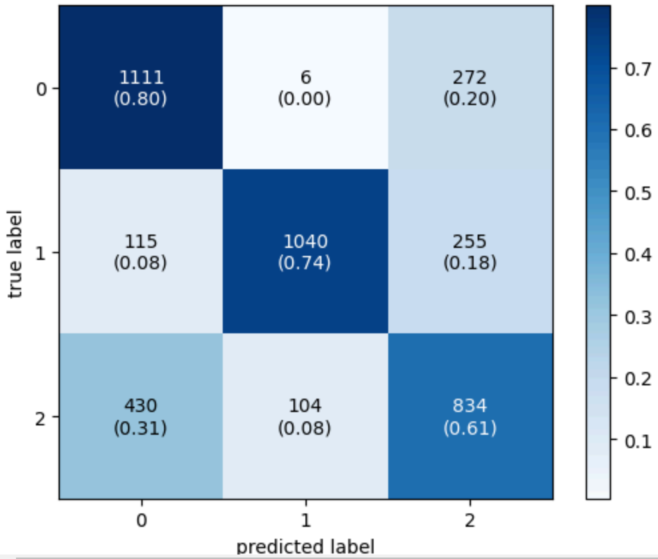
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Train Decision Tree
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, Y_train)
```

```
# Predicted probabilities
y_pred_proba = dt.predict_proba(X_test)

# Binarize the target labels for multiclass ROC
classes = np.unique(y_test)
y_test_binarized = label_binarize(y_test, classes=classes)

# Number of classes
n_classes = y_test_binarized.shape[1]

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_pred_proba[:, i])
    auc = roc_auc_score(y_test_binarized[:, i], y_pred_proba[:, i])
    plt.plot(fpr, tpr, label=f'Class {classes[i]} (AUC = {auc:.2f})')

# Plot baseline
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.title('Decision Tree Multiclass ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(alpha=0.4)
plt.show()
```



Decision Tree Confusion Matrix

```
cm_dt = confusion_matrix(y_test,y_pred_dt)
plot_confusion_matrix(conf_mat = cm_dt, show_absolute = True,
                      show_normed = True,
                      colorbar = True)
plt.show()
```

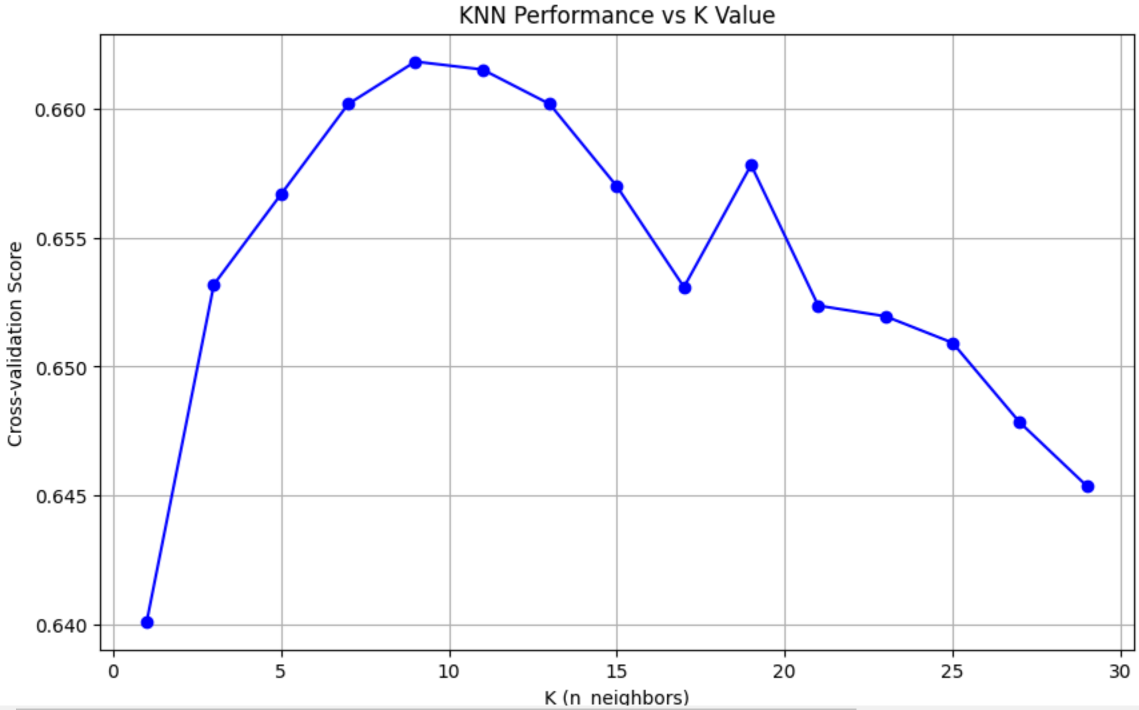


KNN

Find the Optimal k-value

```
param_grid = {
    'n_neighbors': range(1, 31, 2)
}

# Create and fit GridSearchCV
knn = KNeighborsClassifier()
grid_search = GridSearchCV(knn, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, Y_train)

# Print results
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)

# Plot scores
plt.figure(figsize=(10, 6))
plt.plot(range(1, 31, 2), grid_search.cv_results_['mean_test_score'], 'bo-')
plt.xlabel('K (n_neighbors)')
plt.ylabel('Cross-validation Score')
plt.title('KNN Performance vs K Value')
plt.grid(True)
plt.show()
```

```
Best parameters: {'n_neighbors': 9}
Best score: 0.6618312757201646
```




```
knn = KNeighborsClassifier(n_neighbors = 13)
knn.fit(X_train,Y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=13)
```

```
y_pred_knn = knn.predict(X_test)
mse_knn = mean_squared_error(y_test,y_pred_knn)
print('MSE_knn:'+str(mse_knn))
rmse_knn = math.sqrt(mean_squared_error(y_test,y_pred_knn))
print('RMSE_knn:'+str(rmse_knn))
```

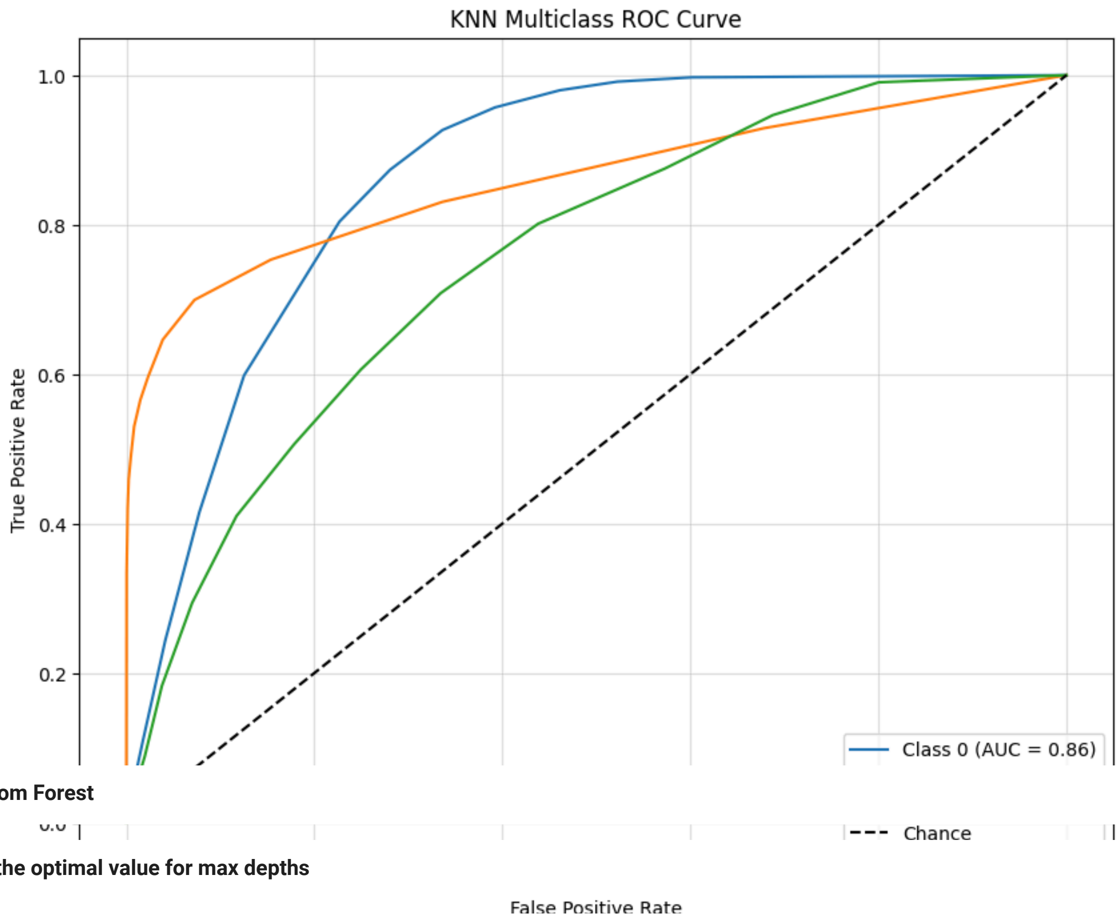
```
MSE_knn:0.8761699064074874
RMSE_knn:0.9360394790859451
```

```
cf_knn_report = classification_report(y_test,y_pred_knn)
print(cf_knn_report)
print('MSE_knn:'+str(mse_knn))
print('RMSE_knn:'+str(rmse_knn))
```

```
              precision    recall  f1-score   support

           0       0.61      0.87      0.71      1389
           1       0.93      0.58      0.72      1410
           2       0.57      0.54      0.56      1368

    accuracy                           0.66      4167
   macro avg       0.70      0.66      0.66      4167
weighted avg       0.70      0.66      0.66      4167

MSE_knn:0.8761699064074874
RMSE_knn:0.9360394790859451
```

```
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Assuming KNN is already trained as `knn`
# Predict probabilities
y_pred_proba = knn.predict_proba(X_test)

# Binarize the target labels for multiclass ROC
classes = np.unique(y_test)
y_test_binarized = label_binarize(y_test, classes=classes)

# Number of classes
```

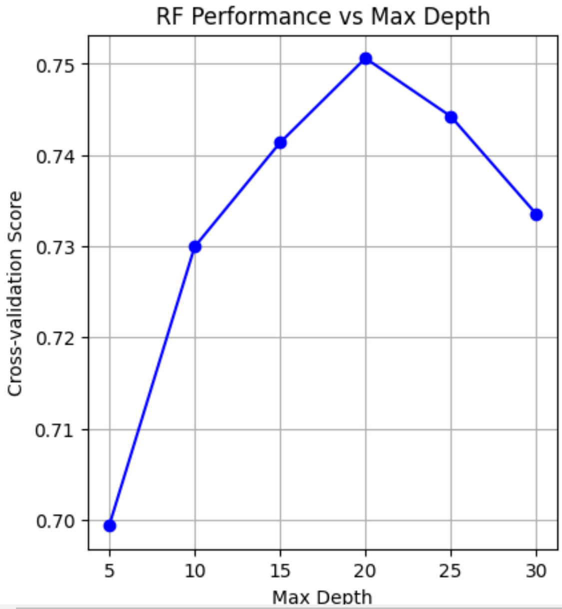
```
n_classes = y_test_binarized.shape[1]

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_pred_proba[:, i])
    auc = roc_auc_score(y_test_binarized[:, i], y_pred_proba[:, i])
    plt.plot(fpr, tpr, label=f'Class {classes[i]} (AUC = {auc:.2f})')

# Plot baseline
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.title('KNN Multiclass ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(alpha=0.4)
plt.show()
```



Random Forest

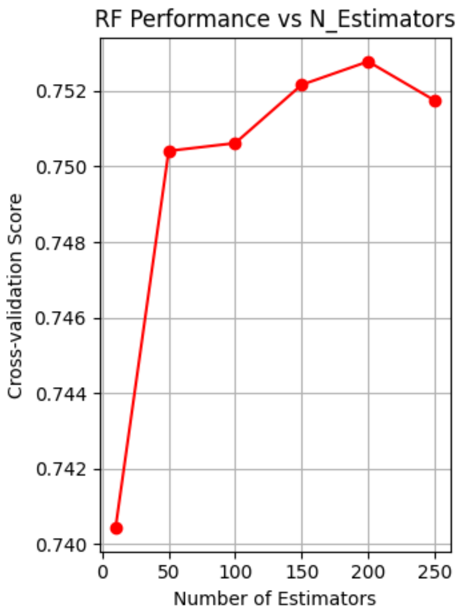
Find the optimal value for max depths

```
# Test different depths
max_depths = [5, 10, 15, 20, 25, 30]
n_estimators = [10,50, 100, 150, 200,250]

depth_scores = []
estimator_scores = []

# Test max_depths (keeping n_estimators fixed at 100)
for depth in max_depths:
    rf = RandomForestClassifier(max_depth=depth,
                                n_estimators=100,
                                random_state=42)
    scores = cross_val_score(rf, X_train, Y_train, cv=5)
    depth_scores.append(scores.mean())

# Plot depth results
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(max_depths, depth_scores, 'bo-')
plt.xlabel('Max Depth')
plt.ylabel('Cross-validation Score')
plt.title('RF Performance vs Max Depth')
plt.grid(True)
```



Find the optimal value for n_estimators

```
# Test n_estimators (using best depth)
best_depth = max_depths[np.argmax(depth_scores)]
for n_est in n_estimators:
    rf = RandomForestClassifier(max_depth=best_depth,
                                n_estimators=n_est,
                                random_state=42)
    scores = cross_val_score(rf, X_train, Y_train, cv=5)
    estimator_scores.append(scores.mean())

# Plot n_estimators results
plt.subplot(1, 2, 2)
plt.plot(n_estimators, estimator_scores, 'ro-')
plt.xlabel('Number of Estimators')
plt.ylabel('Cross-validation Score')
plt.title('RF Performance vs N_Estimators')
plt.grid(True)
plt.tight_layout()
plt.show()

# Print best parameters
print(f"Best max_depth: {best_depth}")
print(f"Best n_estimators: {n_estimators[np.argmax(estimator_scores)]}")
```




```
Best max_depth: 20
Best n_estimators: 200
```

```
rf = RandomForestClassifier(max_depth = 15, n_estimators = 50, random_state = 42)
rf.fit(X_train,Y_train)
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=15, n_estimators=50, random_state=42)
```

```
y_pred_rf = rf.predict(X_test)
```

Check RF MSE and RMSE

```
mse_rf = mean_squared_error(y_test,y_pred_rf)
rmse_rf = math.sqrt(mean_squared_error(y_test,y_pred_rf))
print('MSE_RF:'+str(mse_rf))
print('RMSE_RF'+str(rmse_rf))
```

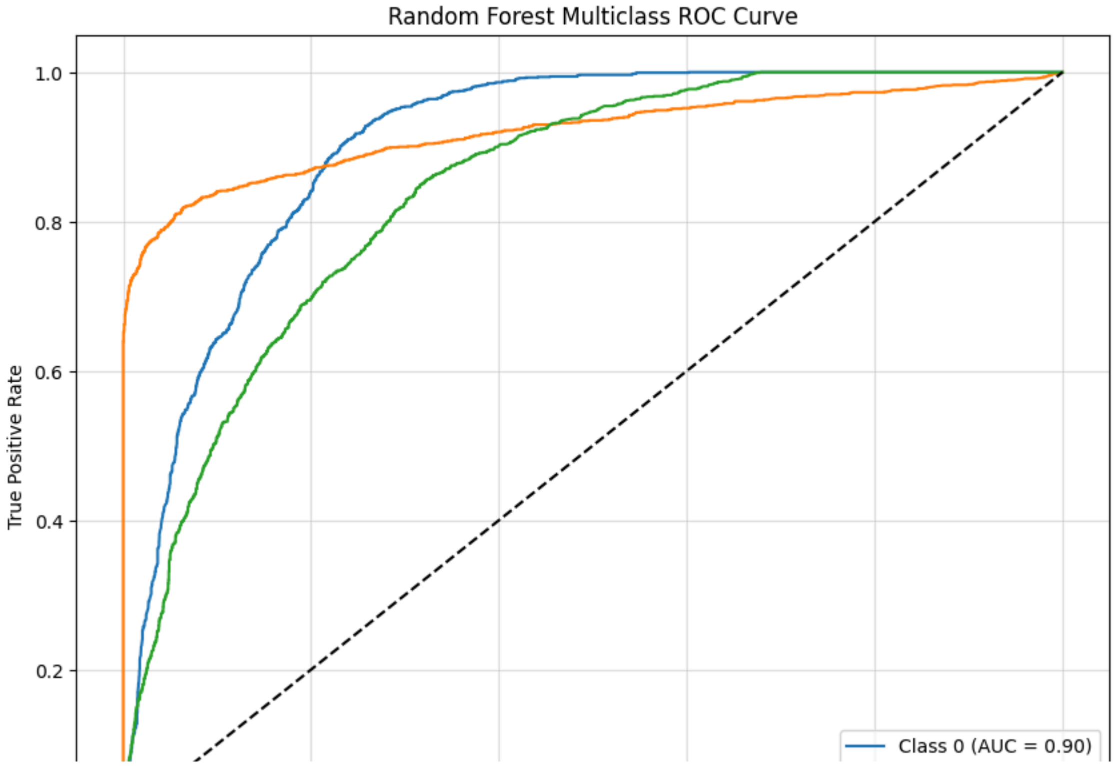
```
MSE_RF:0.7314614830813535
RMSE_RF0.8552552151734321
```

RF Classification Report

```
rf_matrix = classification_report(y_test,y_pred_rf)
print(rf_matrix)
print('MSE_RF:'+str(mse_rf))
print('RMSE_RF'+str(rmse_rf))
```

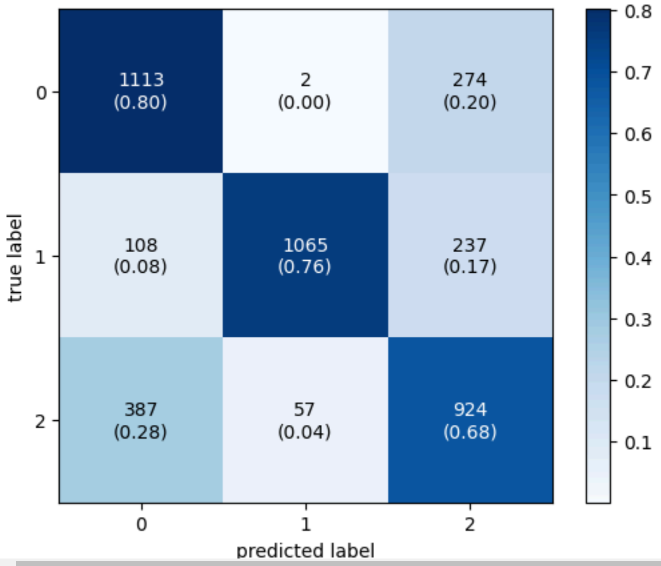
```
              precision    recall  f1-score   support

           0       0.69      0.80      0.74      1389
           1       0.95      0.76      0.84      1410
           2       0.64      0.68      0.66      1368

    accuracy                           0.74      4167
   macro avg       0.76      0.74      0.75      4167
weighted avg       0.76      0.74      0.75      4167

MSE_RF:0.7314614830813535
RMSE_RF0.8552552151734321
```

```
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Assuming RandomForestClassifier is already trained as `rf`
# Predicted probabilities
y_pred_proba = rf.predict_proba(X_test)

# Binarize the target labels for multiclass ROC
classes = np.unique(y_test)
y_test_binarized = label_binarize(y_test, classes=classes)

# Number of classes
n_classes = y_test_binarized.shape[1]

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_pred_proba[:, i])
    auc = roc_auc_score(y_test_binarized[:, i], y_pred_proba[:, i])
    plt.plot(fpr, tpr, label=f'Class {classes[i]} (AUC = {auc:.2f})')

# Plot baseline
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.title('Random Forest Multiclass ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(alpha=0.4)
plt.show()
```



RF Confusion Matrix


```
cm_rf = confusion_matrix(y_test,y_pred_rf)
plot_confusion_matrix(conf_mat = cm_rf, show_absolute = True,
                      show_normed = True,
                      colorbar = True)
plt.show()

# The best model so far
```



RF Secondary Test with 250 n_estimators

```
rf_2 = RandomForestClassifier(max_depth = 15, n_estimators = 250, random_state = 42)
rf_2.fit(X_train,Y_train)
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=15, n_estimators=250, random_state=42)
```

```
y_pred_rf_2 = rf_2.predict(X_test)
```