ML Project - Pima Indians Diabetes Detection 💉

Description:

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage.

The datasets consists of several medical predictor variables and one target variable, Outcome. Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and so on. Can you build a machine learning model to accurately predict whether or not the patients in the dataset have diabetes or not?

Objective:

- Understand the Dataset & cleanup (if required).
- Build classification models to predict whether or not the patients have diabetes.
- Compare the evaluation metrics of vaious classification algorithms.

1. Data Exploration

In [298]:

```
#Importing the basic librarires

import numpy as np
import pandas as pd
import seaborn as sns
from IPython.display import display

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10,6]

import warnings
warnings.filterwarnings('ignore')
```

In [299]:

```
#Importing the dataset

df = pd.read_csv('pima-indians-diabetes.csv')
df.reset_index(drop=True, inplace=True)
original_dataset = df.copy(deep=True)
display(df.head())

print('\n\033[1mInference:\033[0m The Datset consists of {} features & {} samples.'.format(
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

Inference: The Datset consists of 9 features & 768 samples.

In [300]:

```
#Checking the dtypes of all the columns

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [301]:

```
#Checking the stats of all the columns

display(df.describe())
print('\n \033[1mInference:\033[0m The stats seem to be unrealistic for few samples, \
let us visualize the dataset to gain better understanding...')
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabete
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

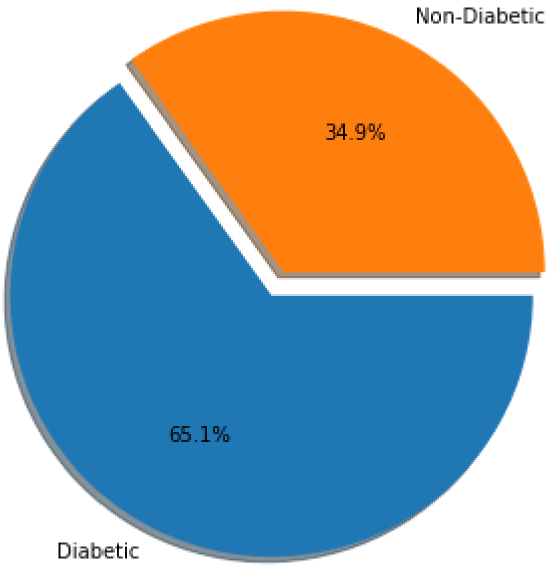
```
 Inference: The stats seem to be unrealistic for few samples, let us visuali
ze the dataset to gain better understanding...
```

2. Exploratory Data Analysis (EDA)

In [302]:

```
#Let us first analyze the distribution of the target variable

print('\033[1mTarget Variable Distribution'.center(55))
plt.pie(df.Outcome.value_counts(), labels=['Diabetic','Non-Diabetic'], counterclock=False,
        explode=[0,0.1], autopct='%1.1f%%', radius=1)
plt.show()

print('\n\033[1mInference:\033[0m The Target Variable seems to be slightly imbalanced! We c
```

Target Variable Distribution

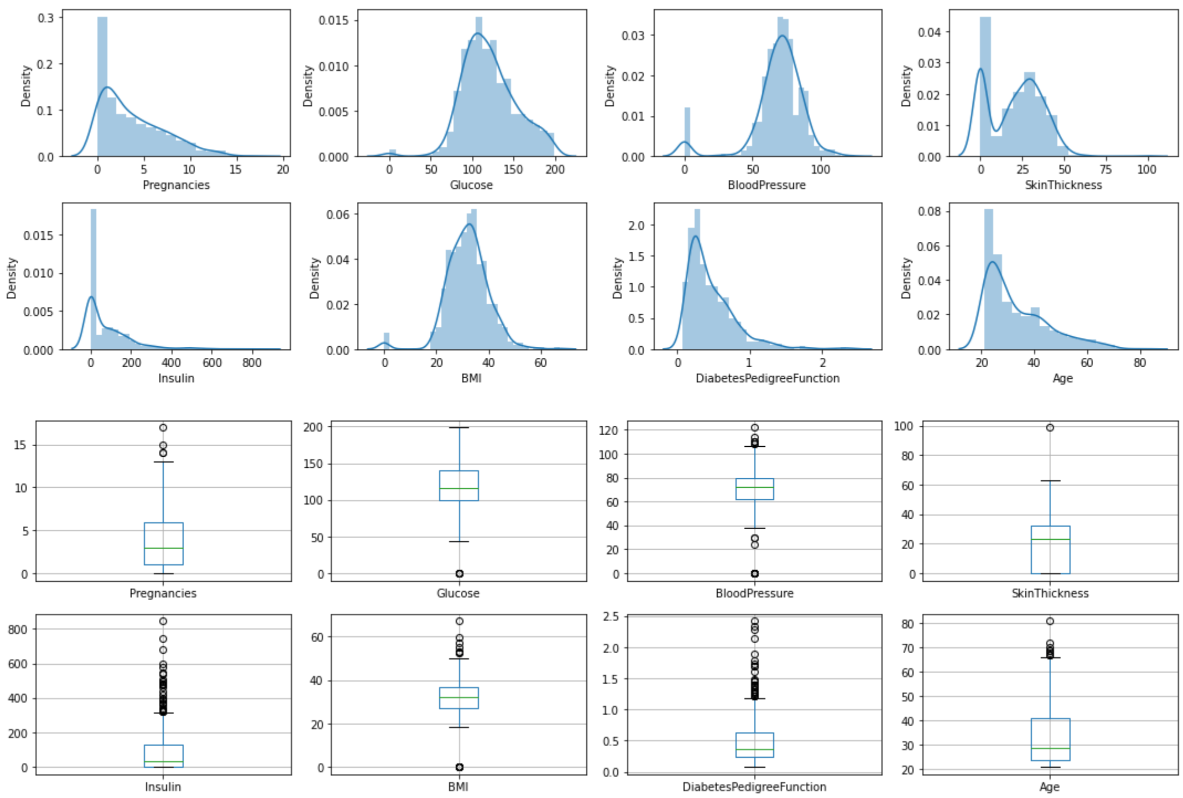


Inference: The Target Variable seems to be slightly imbalanced! We can try t
o fix this later on...

In [303]:

```
#Understanding the feature set

print('\033[1mFeatures Distribution'.center(130))

plt.figure(figsize=[15,5])
for c in range(8):
    plt.subplot(2,4,c+1)
    sns.distplot(df[df.columns[c]])
plt.tight_layout()
plt.show()

plt.figure(figsize=[15,5])
for c in range(8):
    plt.subplot(2,4,c+1)
    df.boxplot(df.columns[c])
plt.tight_layout()
plt.show()

print('\n\033[1mInference:\033[0m The data distribution revealed the multiple samples are i
bloodpressure, BMI, which are not supposed to be zero. We shall try to fix these in the upc
```

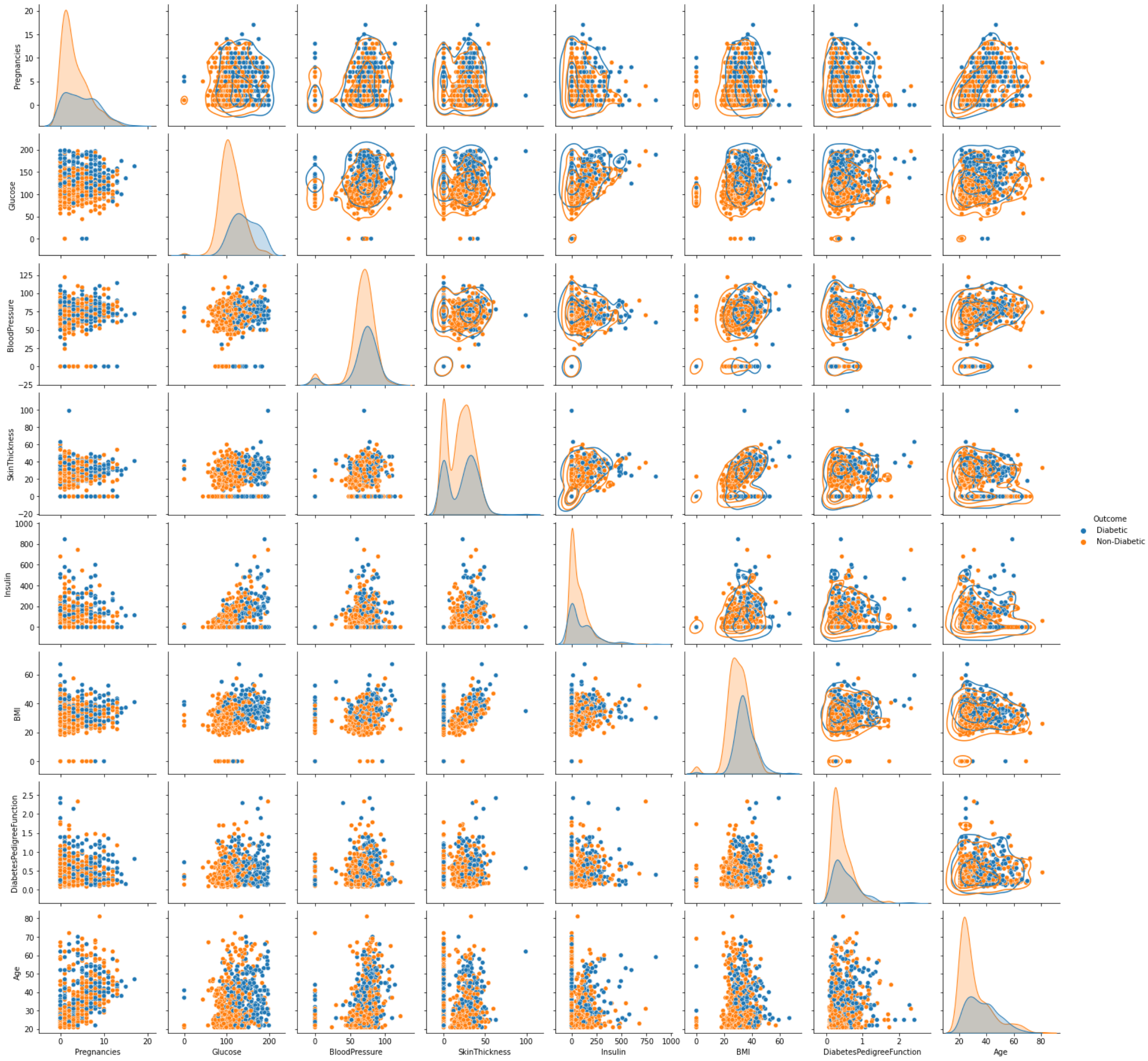
Features Distribution



Inference: The data distribution revealed the multiple samples are inaccurat
e, like glucose, bloodpressure, BMI, which are not supposed to be zero. We s
hall try to fix these in the upcoming cleanup stage...

In [73]:

```
#Understanding the relationship between all the features

df1 = df.copy()
df1.Outcome = df.Outcome.map({0:'Non-Diabetic',1:'Diabetic'})

g=sns.pairplot(df1, hue="Outcome")
g.map_upper(sns.kdeplot, levels=4, color=".2")
plt.show()

print('\n\033[1mInference:\033[0m The data samples of most of the features don\'t show an e
to have lot of overlap for the outcome classes, making it difficult to be distingusihable.'
```



Inference: The data samples of most of the features don't show an exact patt
ern. Also they seemto have lot of overlap for the outcome classes, making it
difficult to be distingusihable.

3. Data Preprocessing

In [304]:

```
#Check for empty elements

print(df.isnull().sum())
print('\n\033[1mInference:\033[0m The dataset doesn\'t have any null elements')
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

Inference: The dataset doesn't have any null elements

In [305]:

```
#Removal of any Duplicate rows (if any)

counter = 0
r,c = df1.shape

df.drop_duplicates(inplace=True)

if df.shape==(r,c):
    print('\n\033[1mInference:\033[0m The dataset doesn\'t have any duplicates')
else:
    print(f'\n\033[1mInference:\033[0m Number of duplicates dropped/fixed ---> {r-df.shape[
```

Inference: The dataset doesn't have any duplicates

In [306]:

```
xf = df.columns.to_list()
xf.remove('Outcome')
xf
```

Out[306]:

```
['Pregnancies',
 'Glucose',
 'BloodPressure',
 'SkinThickness',
 'Insulin',
 'BMI',
 'DiabetesPedigreeFunction',
 'Age']
```

In [307]:

```
#Removal of outlier:

for i in df.columns:
    Q1 = df[i].quantile(0.25)
    Q3 = df[i].quantile(0.75)
    IQR = Q3 - Q1
    df = df[df[i] <= (Q3+(1.5*IQR))]
    df = df[df[i] >= (Q1-(1.5*IQR))]
    df = df.reset_index(drop=True)
display(df)
df2 = df.copy()
print('\n\033[1mInference:\033[0m After removal of outliers, The dataset now has {} feature
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
0	6	148	72	35	0	33.6	0.
1	1	85	66	29	0	26.6	0.
2	8	183	64	0	0	23.3	0.
3	1	89	66	23	94	28.1	0.
4	5	116	74	0	0	25.6	0.
...	...	...	...	...	...	...	
631	10	101	76	48	180	32.9	0.
632	2	122	70	27	0	36.8	0.
633	5	121	72	23	112	26.2	0.
634	1	126	60	0	0	30.1	0.
635	1	93	70	31	0	30.4	0.

636 rows × 9 columns

```
Inference: After removal of outliers, The dataset now has 9 features & 636 s
amples.
```

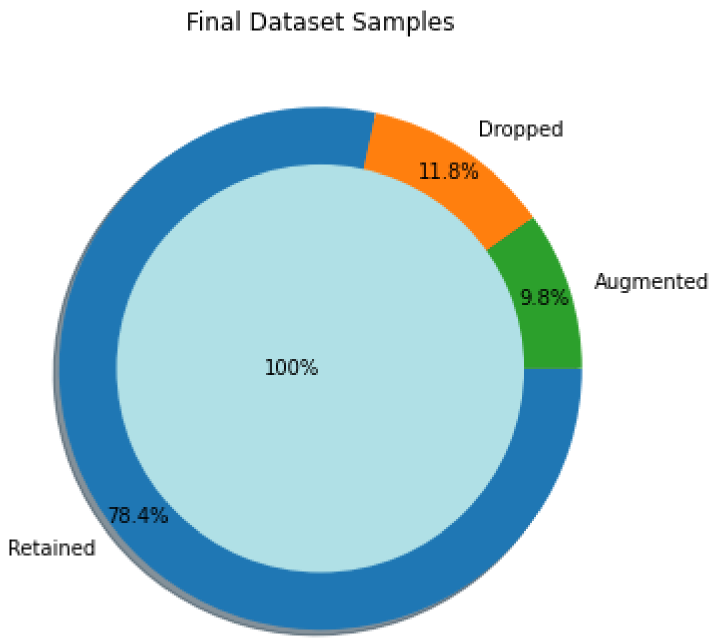
In [308]:

```python
#Fixing the imbalance using SMOTE Technique
from imblearn.over_sampling import SMOTE

print('Original class distribution:')
print(df.Outcome.value_counts())

X = df.drop(['Outcome'],axis=1)
Y = df.Outcome

smote = SMOTE()
X, Y = smote.fit_resample(X, Y)

df3 = pd.DataFrame(X, columns=xf)
df3['Outcome'] = Y
df = df3.copy()

print('\nClass distribution after applying SMOTE Technique:',)
print(Y.value_counts())
```

```
Original class distribution:
0    439
1    197
Name: Outcome, dtype: int64

Class distribution after applying SMOTE Technique:
1    439
0    439
Name: Outcome, dtype: int64
```

In [309]:

```
#Final Dataset size after performing Preprocessing

plt.title('Final Dataset Samples')
plt.pie([df.shape[0], df1.shape[0]-df2.shape[0], df.shape[0]-df1.shape[0]], radius = 1, sha
        labels=['Retained','Dropped','Augmented'], counterclock=False, autopct='%1.1f%%', p
plt.pie([df.shape[0]], labels=['100%'], labeldistance=-0, radius=0.78, shadow=True, colors=
plt.show()

print('\n\033[1mInference:\033[0mThe final dataset after cleanup has {} samples & {} rows.'
```



Inference: The final dataset after cleanup has 9 samples & 878 rows.

---

4. Feature Selection/Extraction

In [310]:

```
#Checking the correlation

plt.figure(figsize=[12,10])
sns.heatmap(df.corr(), annot=True, cmap='BuGn')#, vmin=-1, vmax=1)
plt.show()

print('\n\033[1mInference:\033[0m\nCorrelation plt between the variables convey lot of info
betweem them. \nSome of them are obvious like realtionship between number of pregrenencies
It is fine to drop any one one of the variable either age, or pregnancies. But for our prob
features and the correlation is also not too strong, we can proceed without dropping any fe
the results with dropping any feature...')
```

Inference:
Correlation plt between the variables convey lot of information about the re alationshipbetweem them.
Some of them are obvious like realtionship between number of pregrenencies & age, glucose & diabtes, etc.It is fine to drop any one one of the variable either age, or pregnancies. But for our problem since we are having lessfeatures and the correlation is also not too strong, we can proceed without dropping any feature. Feel free to comparethe results with dropping any feature...

---

5. Feature Scaling

In [311]:

```
#Splitting the data intro training & testing sets

from sklearn.model_selection import train_test_split

X = df.drop(['Outcome'],axis=1)
Y = df.Outcome
Train_X, Test_X, Train_Y, Test_Y = train_test_split(X, Y, train_size=0.8, test_size=0.2, ra

print('Original set  ---> ',X.shape,Y.shape,'\nTraining set  ---> ',Train_X.shape,Train_Y.s
```

```
Original set  --->  (878, 8) (878,)
Training set  --->  (702, 8) (702,)
Testing set   --->  (176, 8)  (176,)
```

In [312]:

```
#Feature Scaling (Standardization)

from sklearn.preprocessing import StandardScaler

std = StandardScaler()

Train_X_std = std.fit_transform(Train_X)
Test_X_std = std.transform(Test_X)
```

---

6. Predictive Modeling

In [313]:

```
#Let us create first create a table to store the results of various models

Evaluation_Results = pd.DataFrame(np.zeros((8,5)), columns=['Accuracy', 'Precision','Recall
Evaluation_Results.index=['Logistic Regression (LR)','Decision Tree Classifier (DT)','Rando
                         'Support Vector Machine (SV)','K Nearest Neighbours (KNN)', 'Gradi
Evaluation_Results
```

Out[313]:

	Accuracy	Precision	Recall	F1-score	AUC-ROC score
Logistic Regression (LR)	0.0	0.0	0.0	0.0	0.0
Decision Tree Classifier (DT)	0.0	0.0	0.0	0.0	0.0
Random Forest Classifier (RF)	0.0	0.0	0.0	0.0	0.0
Naïve Bayes Classifier (NB)	0.0	0.0	0.0	0.0	0.0
Support Vector Machine (SV)	0.0	0.0	0.0	0.0	0.0
K Nearest Neighbours (KNN)	0.0	0.0	0.0	0.0	0.0
Gradient Boosting (GB)	0.0	0.0	0.0	0.0	0.0
Extreme Gradient Boosting (XGB)	0.0	0.0	0.0	0.0	0.0

In [314]:

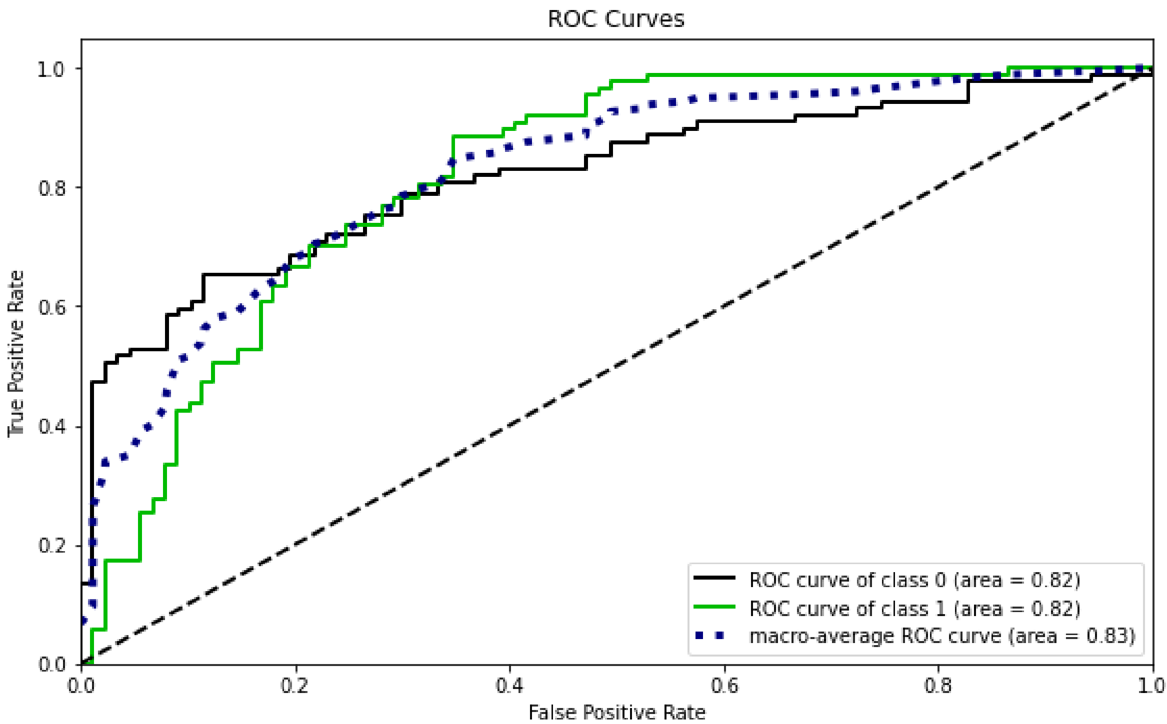
```
#Let us define functions to summarise the Prediction's scores .

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, f1_sco

#Classification Summary Function
def Classification_Summary(pred,i):
    Evaluation_Results.iloc[i]['Accuracy']=round(accuracy_score(Test_Y, pred),3)*100
    Evaluation_Results.iloc[i]['Precision']=round(precision_score(Test_Y, pred, average='we
    Evaluation_Results.iloc[i]['Recall']=round(recall_score(Test_Y, pred, average='weighted
    Evaluation_Results.iloc[i]['F1-score']=round(f1_score(Test_Y, pred, average='weighted')
    Evaluation_Results.iloc[i]['AUC-ROC score']=round(roc_auc_score(Test_Y, pred, average='
    print('{}{}\033[1m{}\033[0m{}{}\n'.format('<'*3,'-'*35,Evaluation_Results.index[i], '-'
    print('Accuracy = {}%'.format(round(accuracy_score(Test_Y, pred),3)*100))
    print('F1 Score = {}%'.format(round(f1_score(Test_Y, pred, average='weighted'),3)*100))
    print('\n \033[1mConfusiton Matrix:\033[0m\n',confusion_matrix(Test_Y, pred))
    print('\n\033[1mClassification Report:\033[0m\n',classification_report(Test_Y, pred))

#Visualising Function
def AUC_ROC_plot(Test_Y, pred):
    ref = [0 for _ in range(len(Test_Y))]
    ref_auc = roc_auc_score(Test_Y, ref)
    lr_auc = roc_auc_score(Test_Y, pred)

    ns_fpr, ns_tpr, _ = roc_curve(Test_Y, ref)
    lr_fpr, lr_tpr, _ = roc_curve(Test_Y, pred)

    plt.plot(ns_fpr, ns_tpr, linestyle='--')
    plt.plot(lr_fpr, lr_tpr, marker='.', label='AUC = {}'.format(round(roc_auc_score(Test_Y
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.legend()
    plt.show()
```

1. Logistic Regression:

In [315]:

```
#Logistic Regression

from sklearn.linear_model import LogisticRegression

LR = LogisticRegression().fit(Train_X_std, Train_Y)
pred = LR.predict(Test_X_std)
Classification_Summary(pred,0)

pred_prob = LR.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Logistic Regression (LR)--------------
---------------------->>>

Accuracy = 71.6%
F1 Score = 71.3%

 Confusiton Matrix:
 [[73 16]
 [34 53]]

Classification Report:
               precision    recall  f1-score   support

           0       0.68      0.82      0.74        89
           1       0.77      0.61      0.68        87

    accuracy                           0.72       176
   macro avg       0.73      0.71      0.71       176
weighted avg       0.72      0.72      0.71       176
```

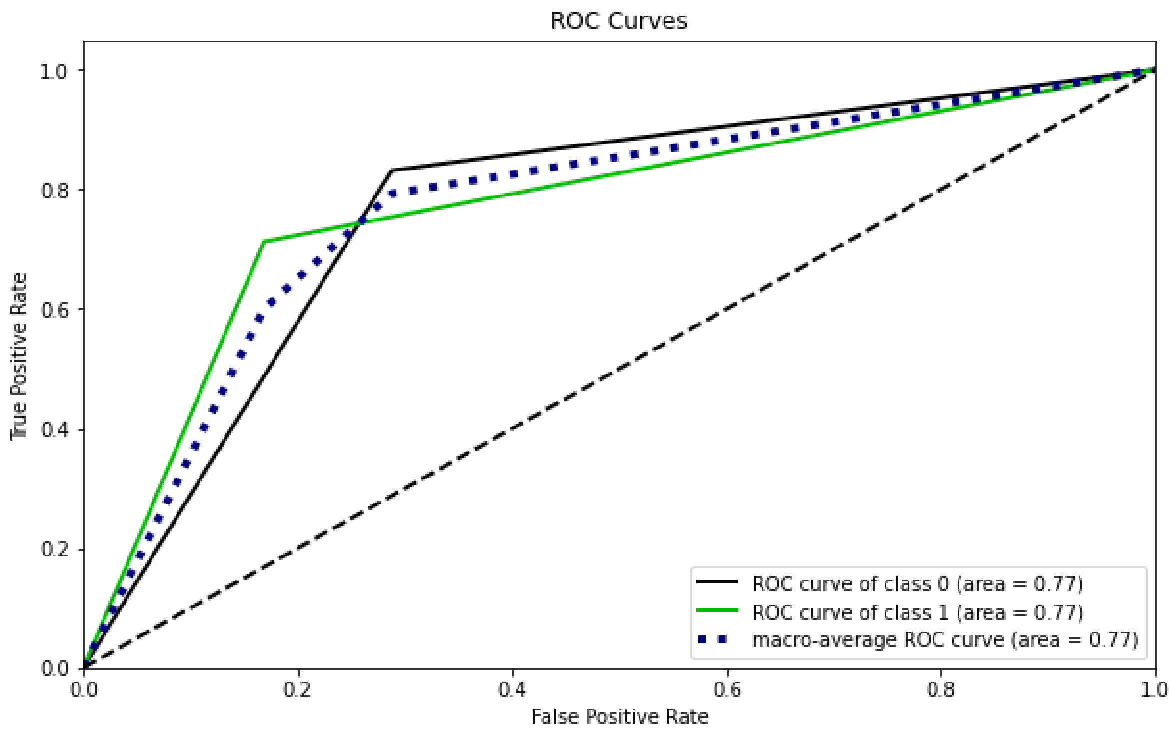


2. Decisoin Tree Classfier:

In [316]:

```
from sklearn.tree import DecisionTreeClassifier

DT = DecisionTreeClassifier().fit(Train_X_std, Train_Y)
pred = DT.predict(Test_X_std)
Classification_Summary(pred,1)

pred_prob = DT.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Decision Tree Classifier (DT)---------
-------------------------->>>

Accuracy = 77.3%
F1 Score = 77.2%

 Confusiton Matrix:
 [[74 15]
 [25 62]]

Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.83      0.79        89
           1       0.81      0.71      0.76        87

    accuracy                           0.77       176
   macro avg       0.78      0.77      0.77       176
weighted avg       0.78      0.77      0.77       176
```

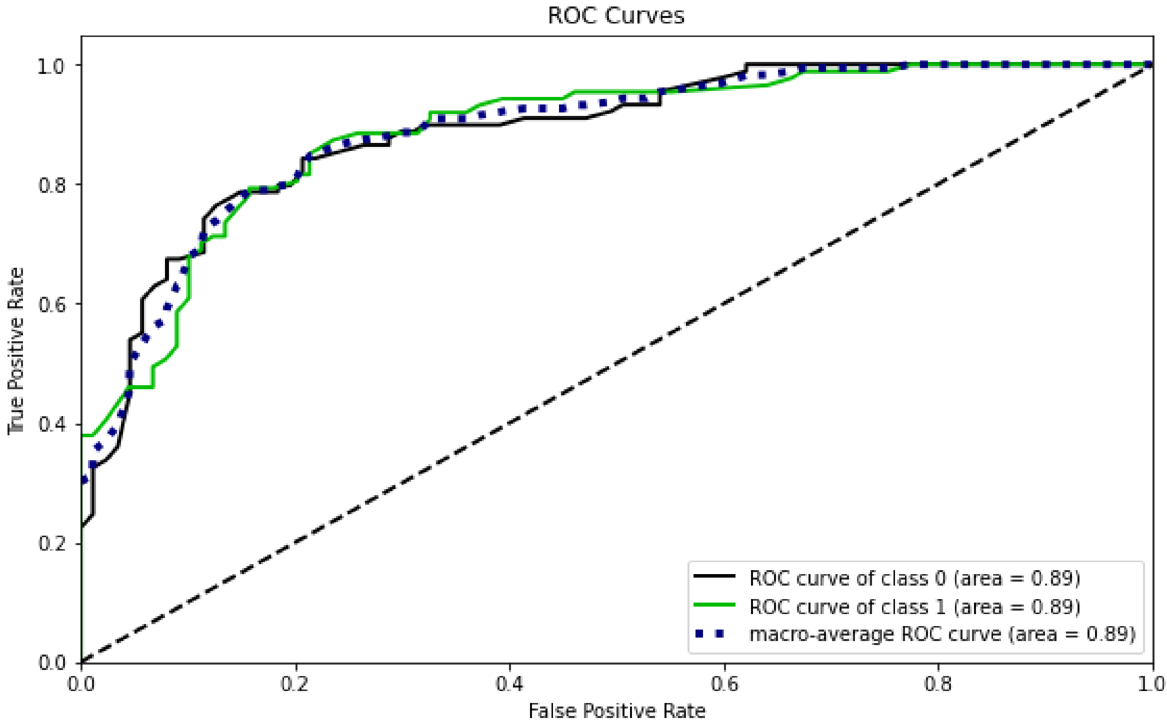


3. Random Forest Classfier:

In [317]:

```
from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier().fit(Train_X_std, Train_Y)
pred = RF.predict(Test_X_std)
Classification_Summary(pred,2)

pred_prob = RF.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Random Forest Classifier (RF)---------
-------------------------->>>

Accuracy = 80.10000000000001%
F1 Score = 80.0%

 Confusiton Matrix:
 [[77 12]
 [23 64]]

Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.87      0.81        89
           1       0.84      0.74      0.79        87

    accuracy                           0.80       176
   macro avg       0.81      0.80      0.80       176
weighted avg       0.81      0.80      0.80       176
```

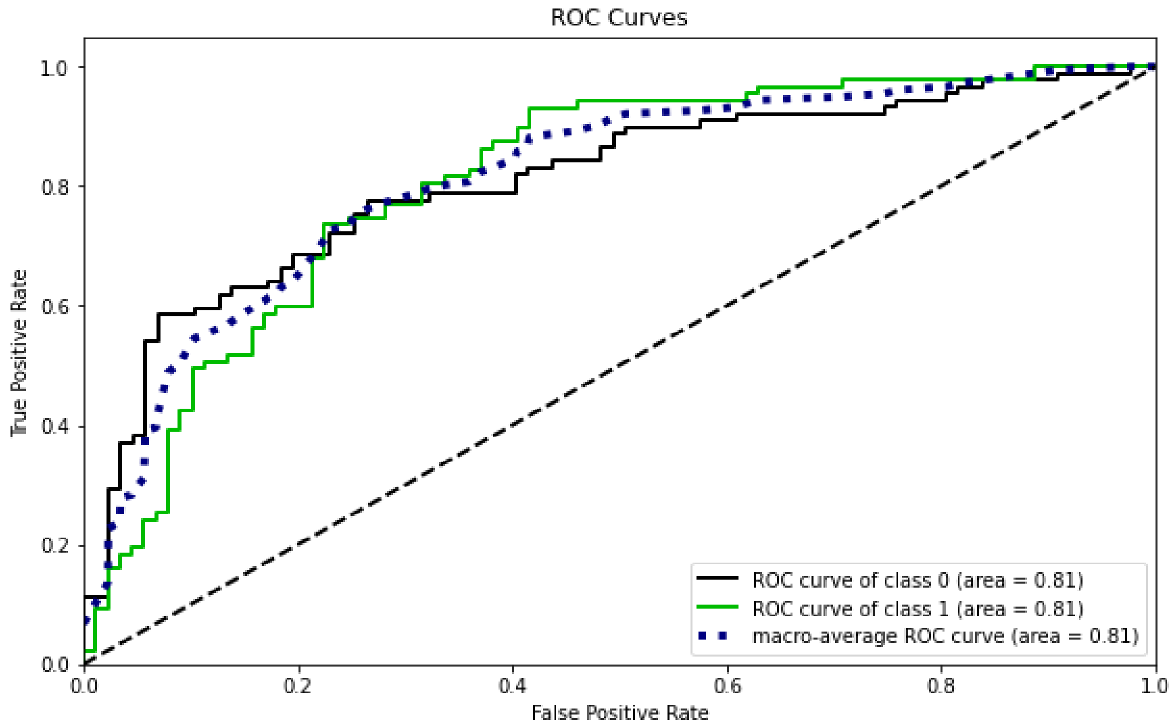


4. Naive Bayes Classfier:

In [318]:

```
from sklearn.naive_bayes import GaussianNB

NB = GaussianNB().fit(Train_X_std, Train_Y)
pred = NB.predict(Test_X_std)
Classification_Summary(pred,3)

pred_prob = NB.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Naïve Bayes Classifier (NB)-----------
------------------------>>>

Accuracy = 71.0%
F1 Score = 70.6%

 Confusiton Matrix:
 [[73 16]
 [35 52]]

Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.82      0.74        89
           1       0.76      0.60      0.67        87

    accuracy                           0.71       176
   macro avg       0.72      0.71      0.71       176
weighted avg       0.72      0.71      0.71       176
```

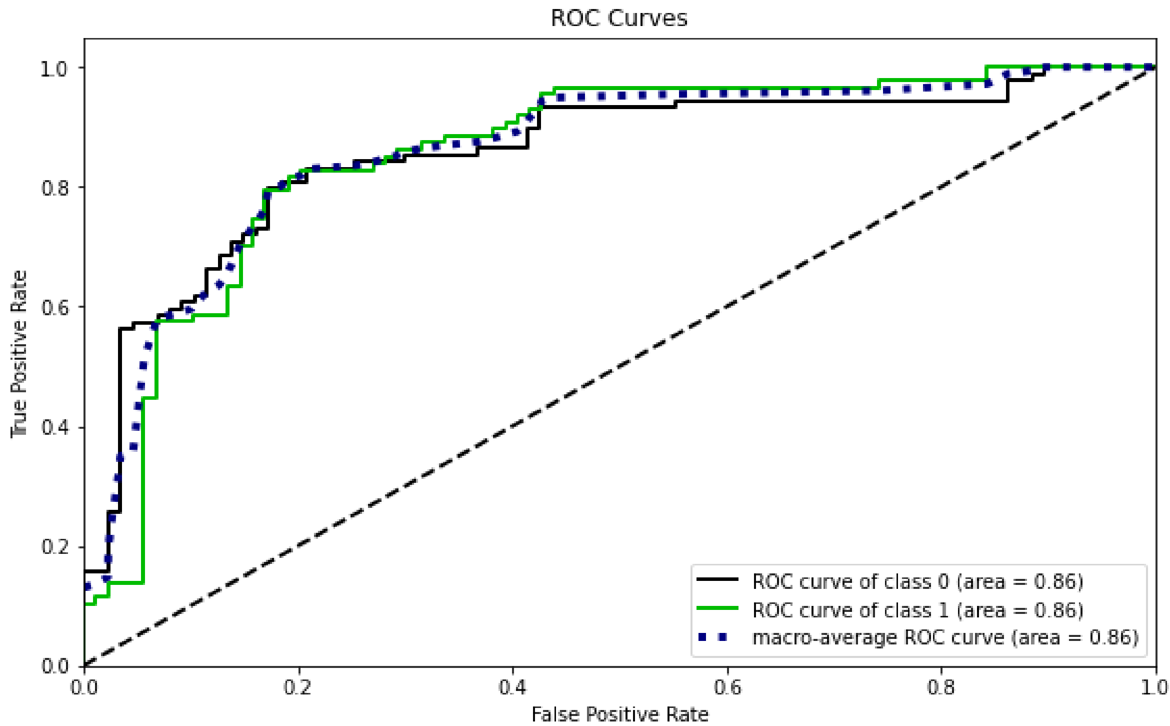


5. Support Vector Machine Classfier:

In [319]:

```
from sklearn.svm import SVC

SV = SVC(probability=True).fit(Train_X_std, Train_Y)
pred = SV.predict(Test_X_std)
Classification_Summary(pred,4)

pred_prob = SV.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Support Vector Machine (SV)-----------
------------------------>>>

Accuracy = 79.5%
F1 Score = 79.5%

 Confusiton Matrix:
 [[75 14]
 [22 65]]

Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.84      0.81        89
           1       0.82      0.75      0.78        87

    accuracy                           0.80       176
   macro avg       0.80      0.79      0.79       176
weighted avg       0.80      0.80      0.79       176
```

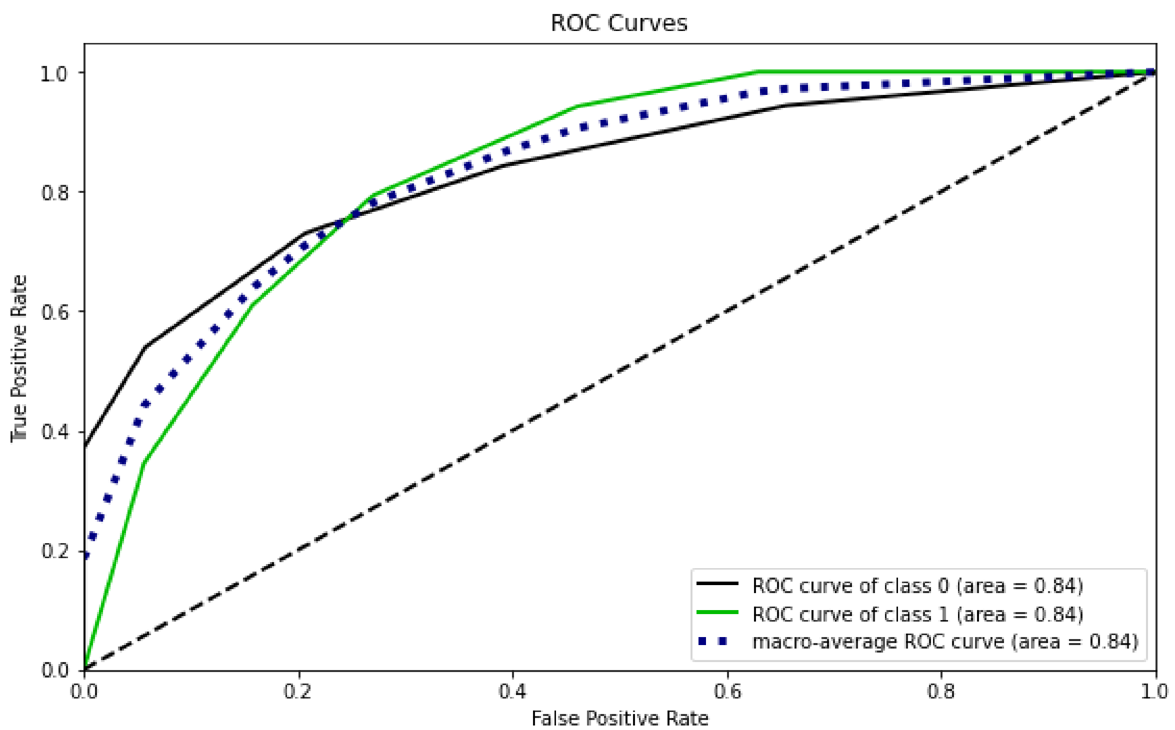


6. K-Nearest Neighbours Classfier:

In [320]:

```
from sklearn.neighbors import KNeighborsClassifier

KNN = KNeighborsClassifier().fit(Train_X_std, Train_Y)
pred = KNN.predict(Test_X_std)
Classification_Summary(pred,5)

pred_prob = KNN.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------K Nearest Neighbours (KNN)------------
----------------------->>>

Accuracy = 76.1%
F1 Score = 76.1%

 Confusiton Matrix:
 [[65 24]
 [18 69]]

Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.73      0.76        89
           1       0.74      0.79      0.77        87

    accuracy                           0.76       176
   macro avg       0.76      0.76      0.76       176
weighted avg       0.76      0.76      0.76       176
```

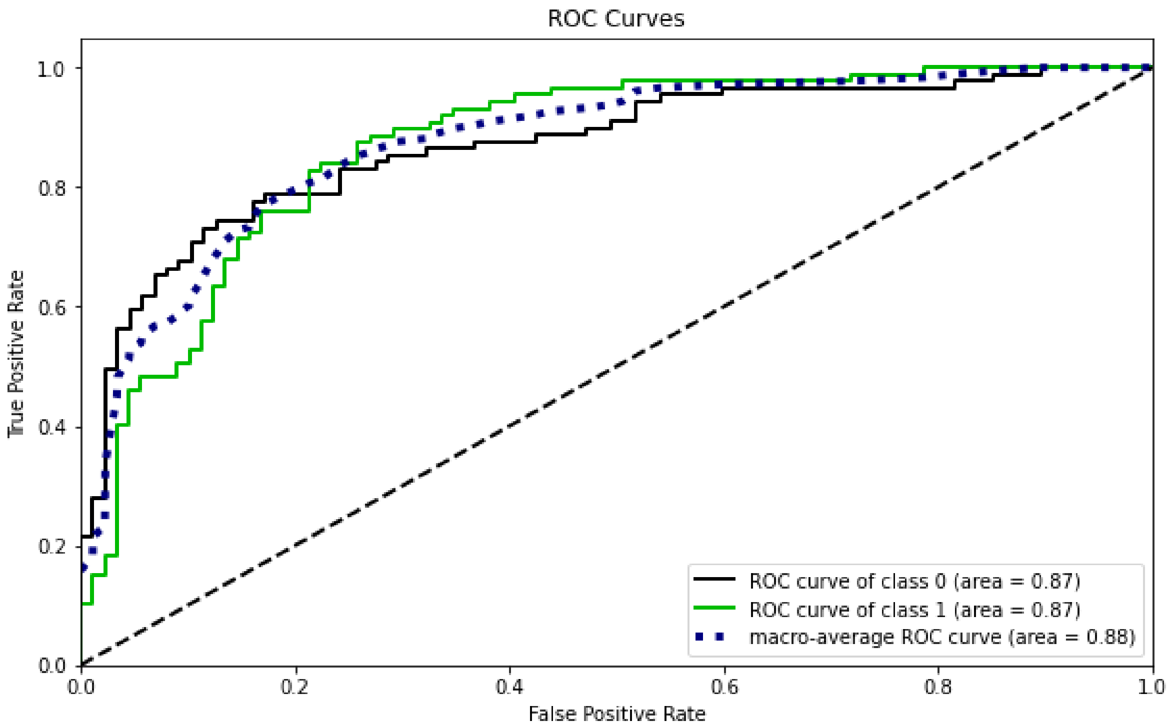


7. Gradient Boosting Classfier:

In [321]:

```
from sklearn.ensemble import GradientBoostingClassifier

GB = GradientBoostingClassifier().fit(Train_X_std, Train_Y)
pred = GB.predict(Test_X_std)
Classification_Summary(pred,6)

pred_prob = GB.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
<<<-----------------------------------Gradient Boosting (GB)----------------
------------------->>>

Accuracy = 79.0%
F1 Score = 79.0%

 Confusiton Matrix:
 [[73 16]
 [21 66]]

Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.82      0.80        89
           1       0.80      0.76      0.78        87

    accuracy                           0.79       176
   macro avg       0.79      0.79      0.79       176
weighted avg       0.79      0.79      0.79       176
```

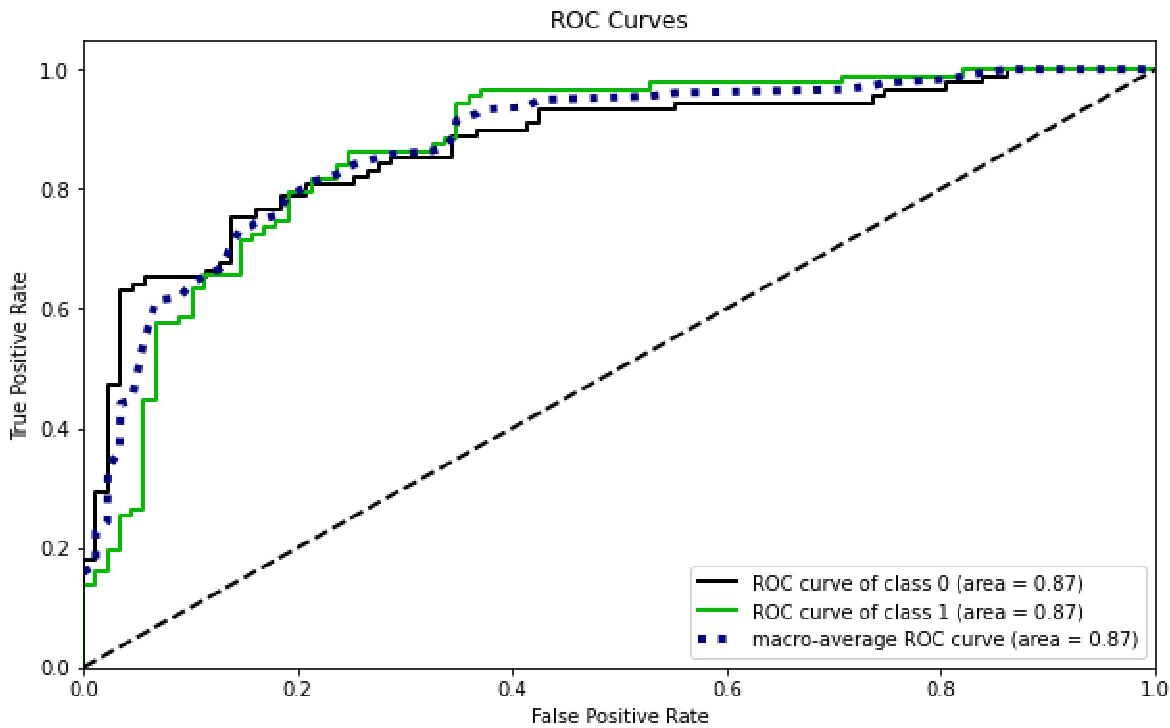


8. Extreme Gradient Boosting Classfier:

In [322]:

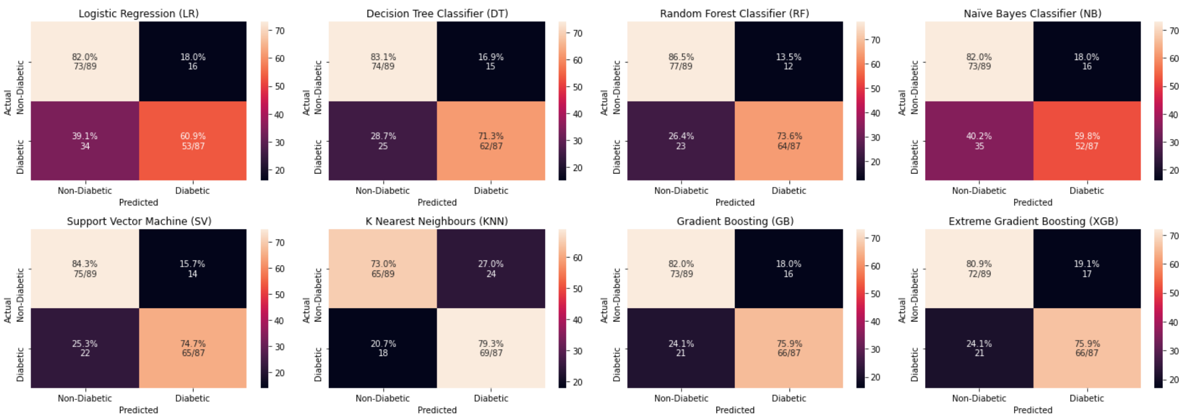
```
from xgboost import XGBClassifier

XGB = XGBClassifier().fit(Train_X_std, Train_Y)
pred = XGB.predict(Test_X_std)
Classification_Summary(pred,7)

pred_prob = XGB.predict_proba(Test_X_std)
auc(Test_Y, pred_prob, curves=['macro','each_class'])
plt.show()
```

```
[22:00:45] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_
1.4.0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation
metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behav
ior.
<<<-----------------------------------Extreme Gradient Boosting (XGB)-------
---------------------------->>>

Accuracy = 78.4%
F1 Score = 78.4%

 Confusiton Matrix:
 [[72 17]
 [21 66]]

Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.81      0.79        89
           1       0.80      0.76      0.78        87

    accuracy                           0.78       176
   macro avg       0.78      0.78      0.78       176
weighted avg       0.78      0.78      0.78       176
```



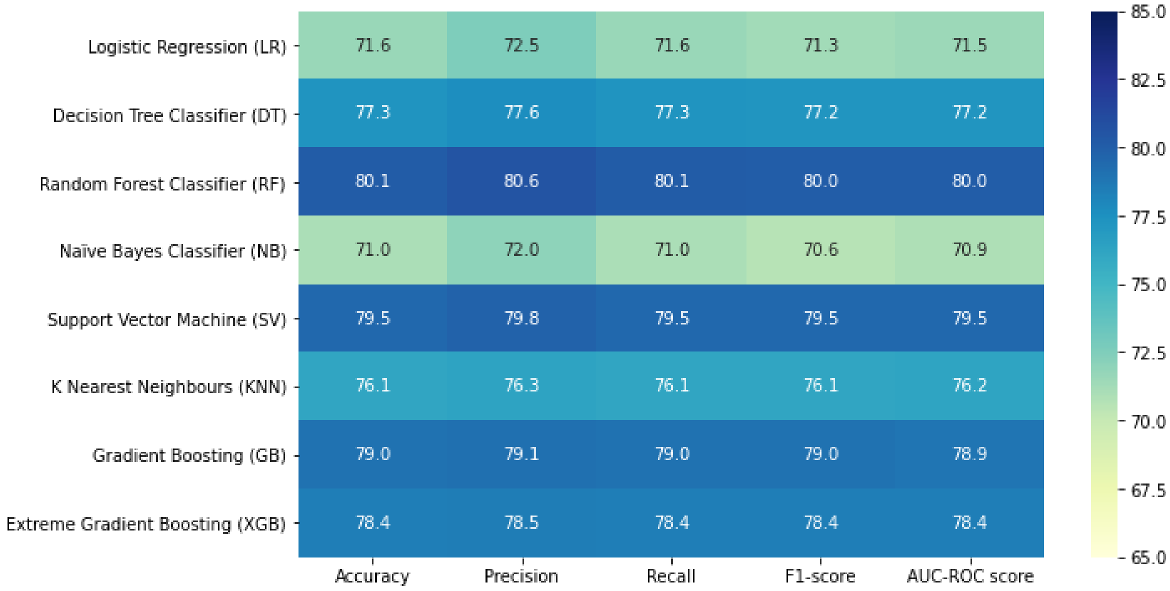
In [323]:

```python
#Plotting Confusion-Matrix of all the predictive Models

labels=['Non-Diabetic','Diabetic']

def plot_cm(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_true))
    cm.columns=labels
    cm.index=labels
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    #fig, ax = plt.subplots()
    sns.heatmap(cm, annot=annot, fmt='')# cmap= "GnBu"

def conf_mat_plot(all_models):
    plt.figure(figsize=[20,7])

    for i in range(len(all_models)):
        plt.subplot(2,4,i+1)
        pred = all_models[i].predict(Test_X_std)
        plot_cm(Test_Y, pred)
        plt.title(Evaluation_Results.index[i])
    plt.tight_layout()
    plt.show()

conf_mat_plot([LR,DT,RF,NB,SV,KNN,GB,XGB])
```



In [327]:

```
#Comparing all the models Scores

#plt.figure(figsize=[12,5])
sns.heatmap(Evaluation_Results, annot=True, vmin=65.0, vmax=85.0, cmap='YlGnBu', fmt='.1f')
plt.show()
```



7. Project Outcomes & Conclusions

Here are some of the key outcomes of the project:

- The Dataset was quiet small totally just 768 samples & after preprocessing 17.2% of the datasamples were dropped.
- The diabetic samples were 30% more than non-diabetic ones, hence SMOTE Technique was applied on the data to balance the classes, adding 11.8% more samples to the dataset.
- Visualising the distribution of data & their relationships, helped us to get some insights on the class seperability.
- Feature selection or feature extracting was not exercised, as there were only 8 features, which overall contributed towards the right prediction.
- Testing multiple algorithms with default hyperparamters gave us some understanding for various models performance on this specific dataset.
- Random Forest perform the best on the current dataset, followed by Support Vector Machines & Boosting Algorithms
- Yet it wise to also consider simpler models as they are more generalisable & take lesser training time.

In [ ]:

```
<<<----------------------------------------------------THE END-----------------------------
```