Healthcare

Importing the libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
sns.set()
from pandas.plotting import scatter_matrix
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay, accuracy_score
from sklearn.pipeline import make_pipeline
from sklearn.datasets import fetch_openml
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import roc_curve
from sklearn.metrics import RocCurveDisplay
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
import warnings
warnings.filterwarnings('ignore')
```

Importing the dataset

```
dataset = pd.read_csv('health care diabetes.csv')
```

Checking dataset structure

```
dataset.head(2)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0

Setting features and label

```
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

Data Exploration

Checking the first `2` rows of dataset

```
dataset.head(2)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0

Checking concise summary of a DataFrame

```
dataset.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
```

Checking lebels of dataset

```
dataset.columns
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Checking data types in datafram

```
dataset.dtypes
```

```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

Checking descriptive statistics

```
dataset.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00000	17.00
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25000	199.00
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00000	122.00
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00000	99.00
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25000	846.00
BMI	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60000	67.10
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62625	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00000	1.00

Computing pairwise correlation of columns, excluding NA/null values

```
dataset.corr().T
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.221898
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.466581
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.065068
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.074752

Checking datatype for preape to make count frequency plot

```
dataset.dtypes.value_counts()
```

```
int64      7
float64    2
dtype: int64
```

Checking the balance of the data by count of outcomes by their values

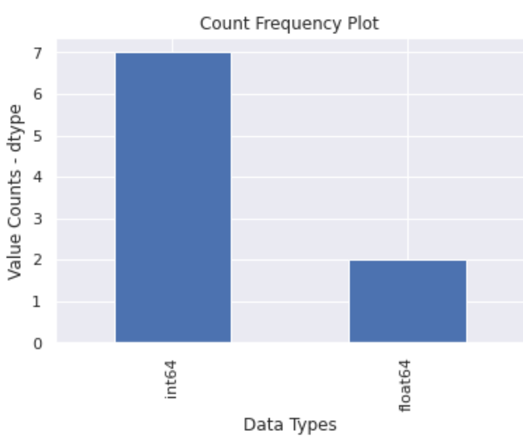
```
dataset.Outcome.value_counts(normalize = True)
```

```
0    0.651042
1    0.348958
Name: Outcome, dtype: float64
```

Data Visualization

Ploting count frequency plot for describing the data types and the count of variables

```
datatyp = dataset.dtypes.value_counts()
datatyp.plot.bar()
plt.title('Count Frequency Plot')
plt.xlabel('Data Types')
plt.ylabel('Value Counts - dtype')
plt.show()
```

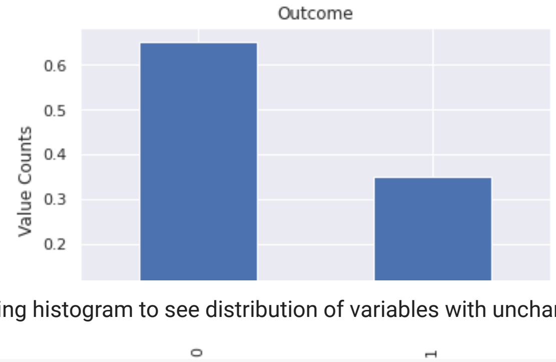


Ploting the count frequency plot for describing the 'Outcome' values

Findings :

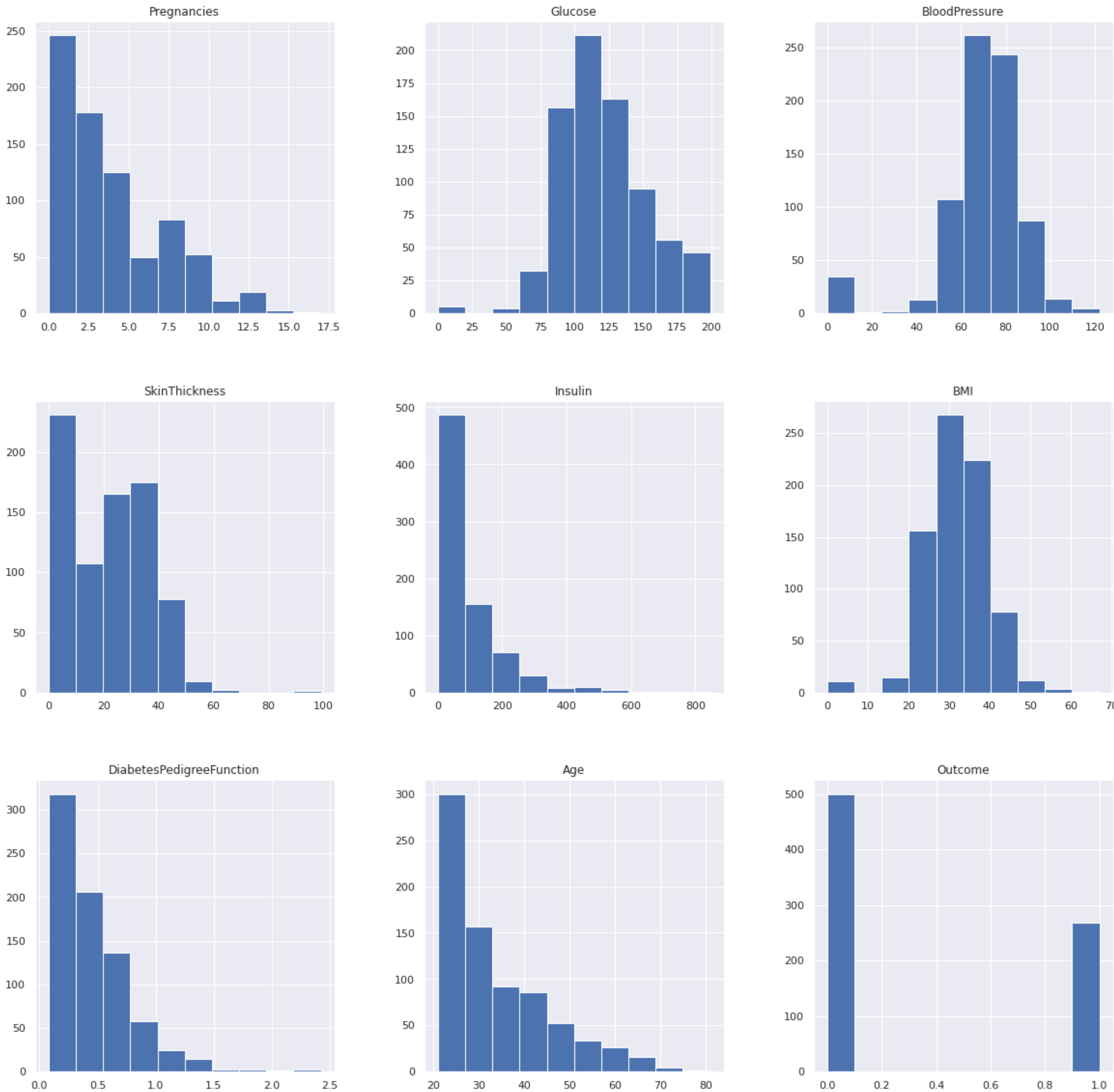
1. 65% Patients are non Diabetes and 35 % Patients are Diabetes

```
outcome_value = dataset.Outcome.value_counts(normalize = True)
outcome_value.plot.bar()
plt.title('Outcome')
plt.xlabel('Values')
plt.ylabel('Value Counts')
plt.show()
```



Ploting histogram to see distribution of variables with unchanged data

```
histogram = dataset.hist(figsize = (20, 20))
```

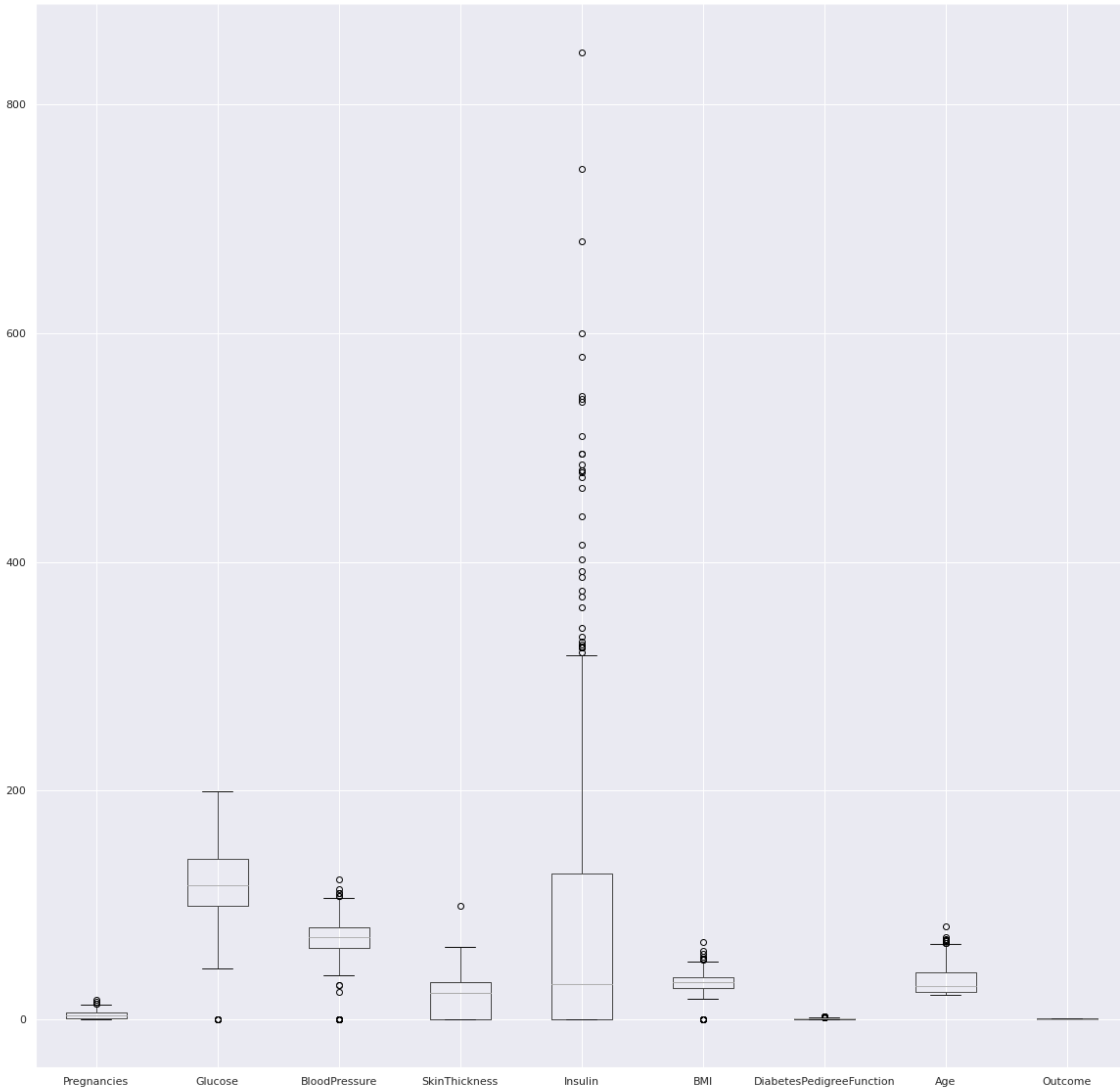


Checking outliers present in dataset

1. Insulin having hugh outlier present as '0' which is missing values

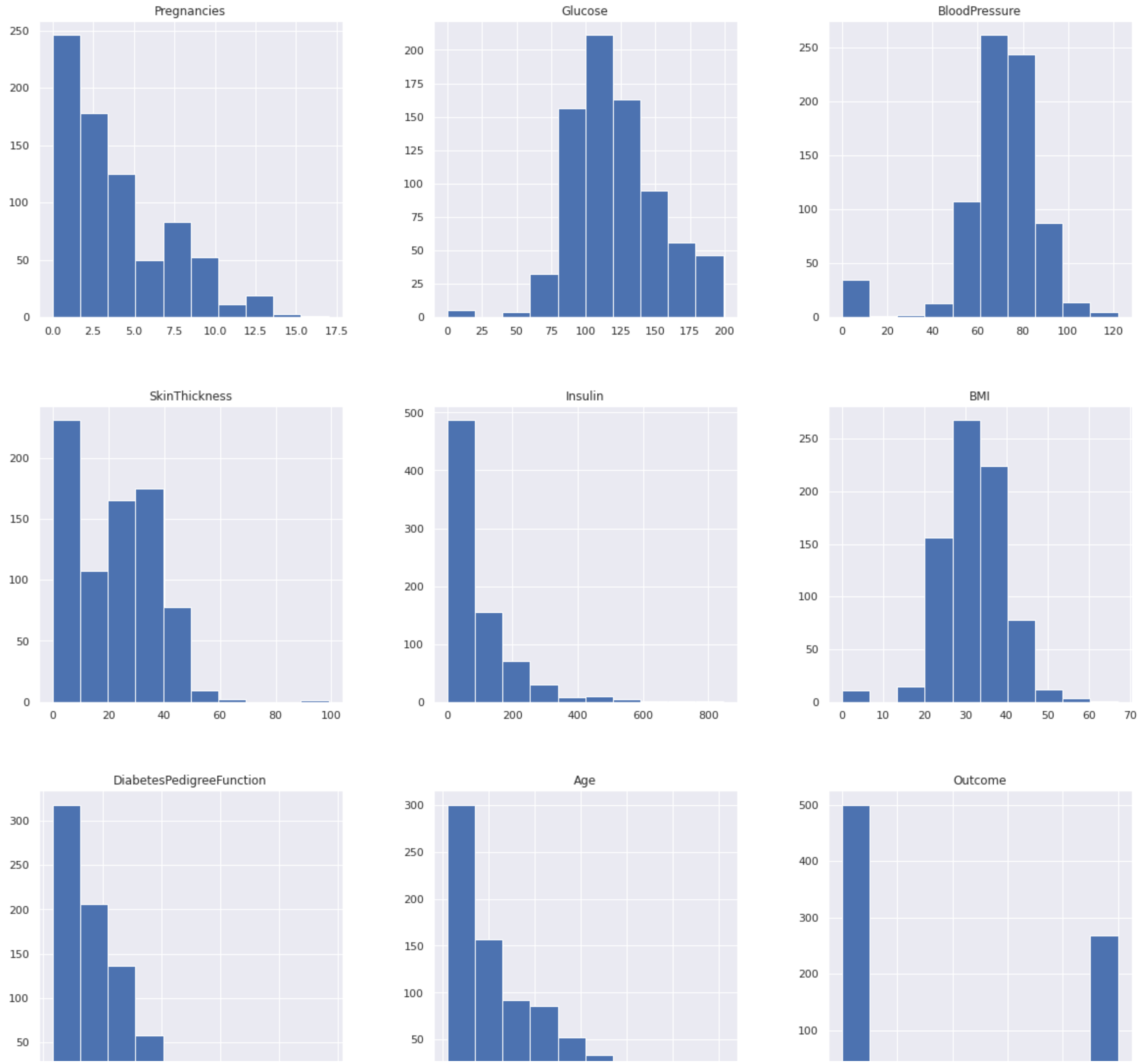
```
dataset.boxplot(figsize=(20, 20))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5b487cdd0>
```



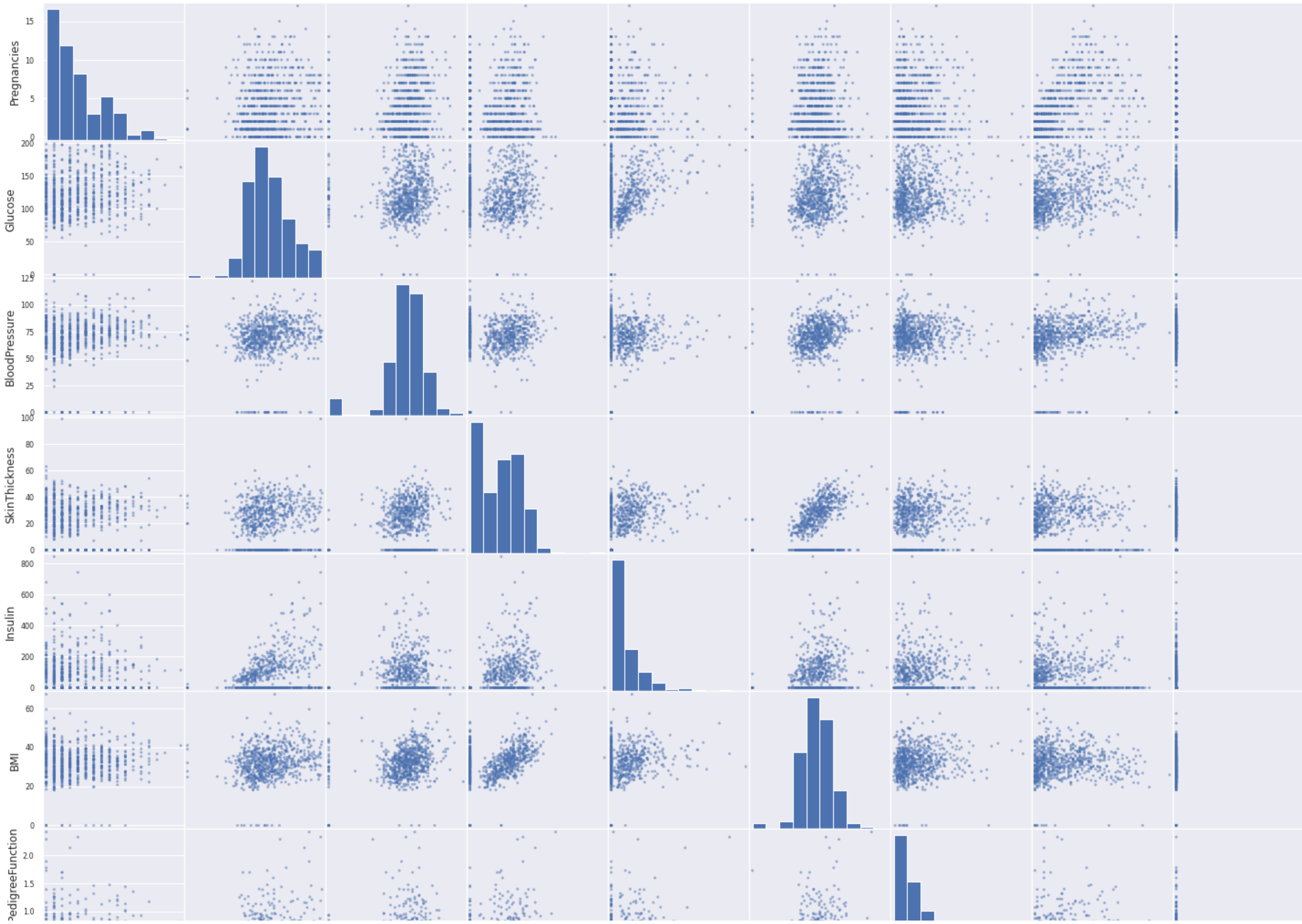
Ploting histogram to see distribution of variables after removing null values

```
histogram = dataset.hist(figsize = (20,20))
```



Ploting scatter charts between the pair of variables to understand the relationships

```
scatter = scatter_matrix(dataset,figsize=(25, 25))
```



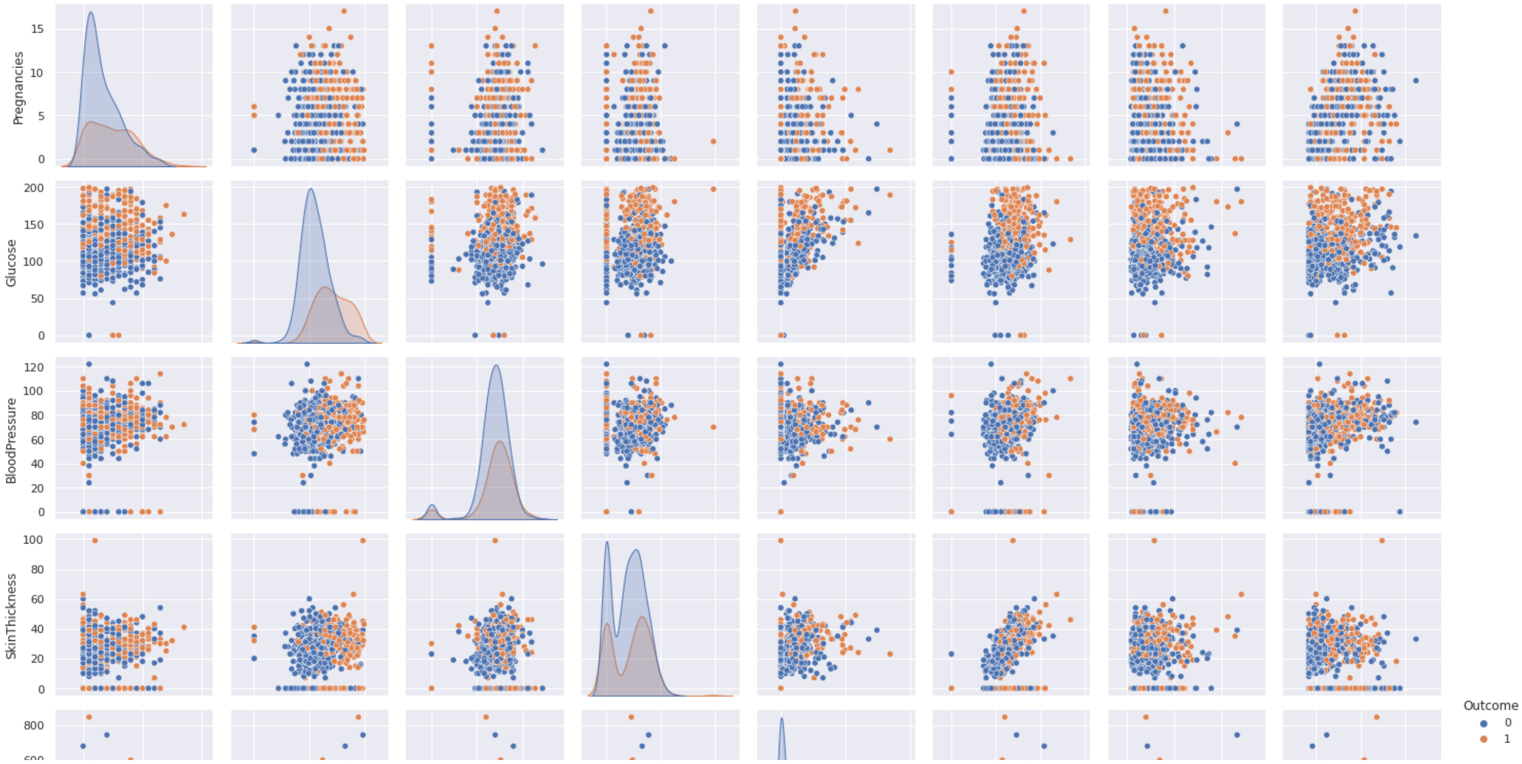
Ploting scatter charts between the pair of variables to understand the relationships

Findings:

- SkinThickness and BMI are highly correlated

```
sns.pairplot(dataset, hue = 'Outcome')
```

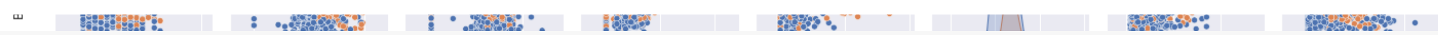
```
<seaborn.axisgrid.PairGrid at 0x7ff5b32fcb90>
```



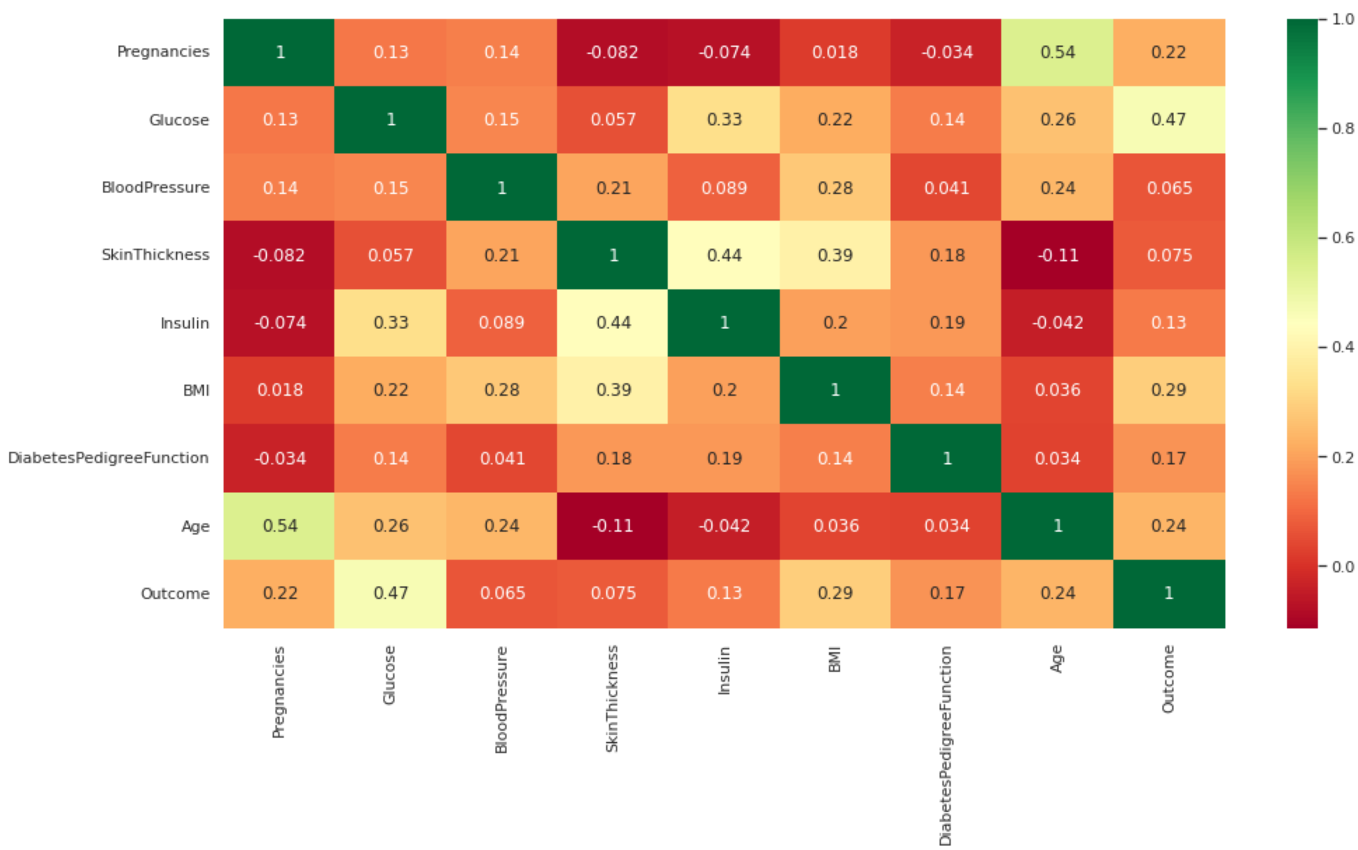
Ploting heatmap for performing correlation analysis

Finding:

1. Value 1 represent the correlation between variables with lighter
2. Value 0 represent the no correlation between variables with darker color color



```
plt.figure(figsize = (16, 8))
heatmap = sns.heatmap(dataset.corr(), annot=True, cmap ='RdYlGn')
```



Printing X and y as features and target variables

```
print(X)
```

```
[[  6.    148.     72.    ...  33.6     0.627  50.   ]
 [  1.     85.     66.    ...  26.6     0.351  31.   ]
 [  8.    183.     64.    ...  23.3     0.672  32.   ]
 ...
 [  5.    121.     72.    ...  26.2     0.245  30.   ]
 [  1.    126.     60.    ...  30.1     0.349  47.   ]
 [  1.     93.     70.    ...  30.4     0.315  23.   ]]
```

```
print(y)
```

```
[1 0 1 0 1 0 1 0 1 1 0 1 0 1 1 1 1 1 0 1 0 0 1 1 1 1 1 0 0 0 0 1 0 0 0 0 0
 1 1 1 0 0 0 1 0 1 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0
 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1
 1 0 0 1 1 1 0 0 0 1 0 0 0 1 1 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
 0 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 1 1 0 0 0 1 0 1 0 1 0 0 0 0 0
 1 1 1 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 0 0 0 1 1 0 1 0 0 0 1 1 1 1 0 1 1 1 1
 0 0 0 0 0 1 0 0 1 1 0 0 0 1 1 1 1 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0
 1 0 1 0 0 1 0 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 0 1 1 0 0 1 0 0 0 1 1 1 0 0
 1 0 1 0 1 1 0 1 0 0 1 0 1 1 0 0 1 0 1 0 0 1 0 1 0 1 1 1 0 0 1 0 1 0 0 0 1
 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 1 0 1 1 0 0 1 0 0 1 0 0 1
 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 1 0 0 1 0 0 1 0 0 1 0 1 1 0 1 0 1 0 1
 0 1 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 1
 1 1 0 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1
 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 1 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 1 1 0 0 1 1 0 0 0 0 0 0 0 0
 0 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1 0 0 0 1 0 1 0 1 0 1 0
 1 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0
 0 1 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 1 1 1 0 0 0 0 0 0 1 0 0 0 1 0 1 1 1 1 0
 1 1 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 1 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 0 0 1 1
 0 0 0 1 0 1 1 0 0 1 0 0 1 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 1
 1 0 0 1 0 0 1 0 1 1 1 0 0 1 1 1 0 1 0 1 0 1 0 0 0 0 0 1 0]
```

Taking care of missing data

Checking missing values in dataset

```
dataset.isnull().values.any()
```

```
False
```

Checking null values as '0' present in given dataset

```
dataset[dataset[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI']]==0].count()
```

```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

Percentage of NaN values present in dataset as '0'

```
for i in ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI']:
        print(i)
        print(dataset[i].value_counts(normalize = True)[0], '\n')

        #print(dataset[i].value_counts(normalize = True).head(), '\n')
        #print(dataset[i].value_counts(normalize = True).to_frame().iloc[0, :], '\n')
        #print(dataset[dataset[value_count()==0].value_counts()]).value_count()
```

```
Glucose
0.006510416666666667

BloodPressure
0.045572916666666664

SkinThickness
```

```
0.2955729166666667

Insulin
0.4869791666666667

BMI
0.014322916666666666
```

Findings:

1. In given dataset we have null values represented as '0'

Imputing missing values with 'median'

```
for i in ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI']:
    print(i)

    median_values = dataset[dataset[i]!=0][i].median()
    print(median_values,'\n')

    dataset[i].replace(0, median_values, inplace = True)
```

```
Glucose
117.0

BloodPressure
72.0

SkinThickness
29.0

Insulin
125.0

BMI
32.3
```

```
print(X)
```

```
[[  6.    148.     72.    ...  33.6     0.627  50.   ]
 [  1.     85.     66.    ...  26.6     0.351  31.   ]
 [  8.    183.     64.    ...  23.3     0.672  32.   ]
 ...
 [  5.    121.     72.    ...  26.2     0.245  30.   ]
 [  1.    126.     60.    ...  30.1     0.349  47.   ]
 [  1.     93.     70.    ...  30.4     0.315  23.   ]]
```

Checking dataset after removing null values

```
dataset[dataset[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI']] == 0].count()
```

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

```
dataset.head(2)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	125	33.6	0.627	50	1
1	1	85	66	29	125	26.6	0.351	31	0

```
print(X)
```

```
[[  6.    148.     72.    ...  33.6     0.627  50.   ]
 [  1.     85.     66.    ...  26.6     0.351  31.   ]
```

```
 [  8.    183.     64.    ...  23.3     0.672  32.   ]
 ...
 [  5.    121.     72.    ...  26.2     0.245  30.   ]
 [  1.    126.     60.    ...  30.1     0.349  47.   ]
 [  1.     93.     70.    ...  30.4     0.315  23.   ]]
```

```
print(y)
```

```
[1 0 1 0 1 0 1 0 1 1 0 1 0 1 1 1 1 1 0 1 0 0 1 1 1 1 1 0 0 0 0 1 0 0 0 0 0
 1 1 1 0 0 0 1 0 1 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0
 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1
 1 0 0 1 1 1 0 0 0 1 0 0 0 1 1 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
 0 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 1 1 0 0 0 1 0 1 0 1 0 0 0 0 0
 1 1 1 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 0 0 0 1 1 0 1 0 0 0 1 1 1 1 0 1 1 1 1
 0 0 0 0 0 1 0 0 1 1 0 0 0 1 1 1 1 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0
 1 0 1 0 0 1 0 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 0 1 1 0 0 1 0 0 0 1 1 1 0 0
 1 0 1 0 1 1 0 1 0 0 1 0 1 1 0 0 1 0 1 0 0 1 0 1 0 1 1 1 0 0 1 0 1 0 0 0 1
 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 1 0 1 1 0 0 1 0 0 1 0 0 1
 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 1 0 0 1 0 0 1 0 0 1 0 1 1 0 1 0 1 0 1
 0 1 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 1
 1 1 0 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1
 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 1 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 1 1 0 0 1 1 0 0 0 0 0 0 0 0
 0 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1 0 0 0 1 0 1 0 1 0 1 0
 1 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0
 0 1 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 1 1 1 0 0 0 0 0 0 1 0 0 0 1 0 1 1 1 1 0
 1 1 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 1 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 0 0 1 1
 0 0 0 1 0 1 1 0 0 1 0 0 1 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 1
 1 0 0 1 0 0 1 0 1 1 1 0 0 1 1 1 0 1 0 1 0 1 0 0 0 0 1 0]
```

Splitting the dataset into the Training set and Test set

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state = 0, stratify = y)
```

```
print(X_train)
```

```
[[  7.    196.     90.    ...  39.8     0.451  41.   ]
 [  2.     81.     72.    ...  30.1     0.547  25.   ]
 [  2.    127.     58.    ...  27.7     1.6    25.   ]
 ...
 [  3.     82.     70.    ...  21.1     0.389  25.   ]
 [  7.    103.     66.    ...  39.1     0.344  31.   ]
 [  0.    161.     50.    ...  21.9     0.254  65.   ]]
```

```
print(X_test)
```

```
[[2.00e+00 5.60e+01 5.60e+01 ... 2.42e+01 3.32e-01 2.20e+01]
 [1.00e+00 9.20e+01 6.20e+01 ... 1.95e+01 4.82e-01 2.50e+01]
 [1.00e+00 1.00e+02 7.40e+01 ... 1.95e+01 1.49e-01 2.80e+01]
 ...
 [5.00e+00 1.66e+02 7.60e+01 ... 4.57e+01 3.40e-01 2.70e+01]
 [1.00e+00 1.06e+02 7.00e+01 ... 3.42e+01 1.42e-01 2.20e+01]
 [2.00e+00 1.12e+02 6.80e+01 ... 3.41e+01 3.15e-01 2.60e+01]]
```

```
print(y_train)
```

```
[1 0 0 0 0 0 0 0 1 1 0 1 1 1 0 1 1 0 1 1 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 1 0
 1 0 0 0 0 1 1 0 0 1 1 0 0 1 1 1 0 0 1 0 1 0 0 0 0 0 0 1 0 1 0 0 1 0 1 1 0
 0 0 1 0 1 1 1 1 0 0 0 0 1 1 0 0 0 1 0 0 0 1 1 0 0 0 1 0 1 1 1 0 0 1 1 0 1
 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 1 0 1 1 1 0
 0 1 0 0 0 0 1 1 1 0 1 1 0 0 1 1 0 1 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 1 1
 0 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0 1 1 1 1 1 0 1 0 0 0 1 0 0 0 0 1 1 1
 0 0 1 0 1 1 0 0 1 1 0 0 1 0 1 0 0 0 0 0 1 0 0 0 1 1 1 0 0 0 1 0 0 0 0 1 1
 1 0 1 0 0 1 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 0 1 1
 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 1 1 1 0 0 0 1 1
 0 1 1 1 0 1 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1
 0 1 1 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0
 1 0 0 1 0 0 1 0 0 0 0 0 1 0 1 1 1 1 0 1 0 0 0 1 0 0 1 1 0 0 1 0 0 0 1 0 0
 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 1 0 1 0 1 1 1 0 0 0 1 0 1 1 0 0 0 0 1
 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 1 1 0 1 1 1 0 1 0 1 1 0 0 0 0 0 0 1 0 0
 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 1 0
 1 1 0 0 1 0 1 0 0 0 1 1 0 1 0 0 1 0 0 1 0 1 0 0 0 0 1 0 1 0 1 1 0 0 1 0 0
 0 0 0 1 0 0 1 0 1 0 0 0 1 1 1 0 0 0 1 0 1 0]
```

```
print(y_test)
```

```
[0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 1 0 1 0 0 1 1 0 0 1 0 1 1 1 0 1
 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 1 0 0 1 0 1 1 0 0 1 1 0
```

```
 1 0 0 0 0 0 0 1 1 0 1 1 1 0 1 0 0 0 0 1 1 1 0 1 0 1 1 0 0 0 0 0 1 1 0 0 0
 0 0 1 0 0 0 1 0 0 1 0 1 0 1 0 1 0 0 0 0 0 0 0 1 1 0 1 0 1 0 0 1 1 0 0 0 0
 1 0 0 1 0 0]
```

Feature Scaling

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
print(X_train)
```

```
[[ 7.00000000e+00  2.36205262e+00  1.05918965e+00 ...  1.01966869e+00
   4.51000000e-01  4.10000000e+01]
 [ 2.00000000e+00 -1.24433342e+00  1.27466950e-01 ... -2.40277946e-01
   5.47000000e-01  2.50000000e+01]
 [ 2.00000000e+00  1.98220992e-01 -5.97206265e-01 ... -5.52017321e-01
   1.60000000e+00  2.50000000e+01]
 ...
 [ 3.00000000e+00 -1.21297355e+00  2.39422049e-02 ... -1.40930060e+00
   3.89000000e-01  2.50000000e+01]
 [ 7.00000000e+00 -5.54416095e-01 -1.83107285e-01 ...  9.28744709e-01
   3.44000000e-01  3.10000000e+01]
 [ 0.00000000e+00  1.26445686e+00 -1.01130525e+00 ... -1.30538748e+00
   2.54000000e-01  6.50000000e+01]]
```

```
print(X_test)
```

```
[[ 2.00000000e+00 -2.02833039e+00 -7.00731010e-01 ... -1.00663724e+00
   3.32000000e-01  2.20000000e+01]
 [ 1.00000000e+00 -8.99374760e-01 -3.90156775e-01 ... -1.61712685e+00
   4.82000000e-01  2.50000000e+01]
 [ 1.00000000e+00 -6.48495731e-01  2.30991695e-01 ... -1.61712685e+00
   1.49000000e-01  2.80000000e+01]
 ...
 [ 5.00000000e+00  1.42125626e+00  3.34516440e-01 ...  1.78602799e+00
   3.40000000e-01  2.70000000e+01]
 [ 1.00000000e+00 -4.60336459e-01  2.39422049e-02 ...  2.92276819e-01
   1.42000000e-01  2.20000000e+01]
 [ 2.00000000e+00 -2.72177188e-01 -7.95825401e-02 ...  2.79287678e-01
   3.15000000e-01  2.60000000e+01]]
```

Data Modeling

Checking the train and test data

```
print(X_train.shape)
```

```
(614, 8)
```

```
print(X_test.shape)
```

```
(154, 8)
```

```
print(y_train.shape)
```

```
(614,)
```

```
print(y_test.shape)
```

```
(154,)
```

Training the K-NN model on the Training set

```
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)
```

```
KNeighborsClassifier()
```

Predicting the Test set results

```
y_pred = classifier.predict(X_test)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
[[0 0]
 [0 0]
 [0 0]
 [0 1]
 [0 0]
 [0 0]
 [0 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 1]
 [1 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 1]
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 [0 1]
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 [1 1]
 [0 1]
 [1 1]
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 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 1]
 [1 0]
 [0 0]
 [0 0]
 [1 0]
 [0 0]
 [0 0]
 [0 0]
 [0 1]
 [0 1]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
```

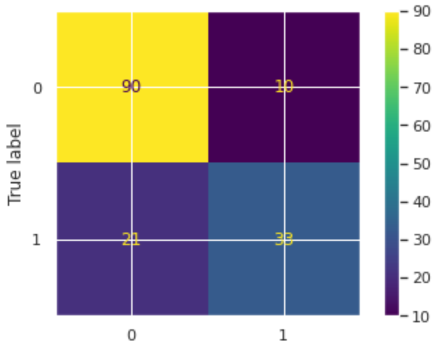
Making the Confusion Matrix

```
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test,y_pred))
```

```
[[86 14]
 [26 28]]
0.7402597402597403
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Check accuracy of model on training data

```
classifier.score(X_train, y_train)
```

```
0.7882736156351792
```

Check accuracy of model on testing data

```
classifier.score(X_test, y_test)
```

```
0.7402597402597403
```

Classification report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.86      0.81       100
           1       0.67      0.52      0.58        54

    accuracy                           0.74       154
   macro avg       0.72      0.69      0.70       154
weighted avg       0.73      0.74      0.73       154
```

Plotting pipeline steps

```
X, y = fetch_openml(data_id=1464, return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y)

clf = make_pipeline(StandardScaler(), KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2))
clf.fit(X_train, y_train)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('kneighborsclassifier', KNeighborsClassifier())])
```

Training the Naive Bayes model on the Training set

```
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

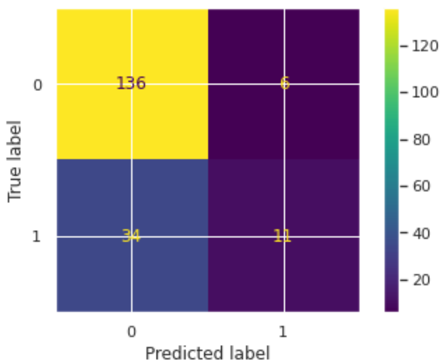
```
GaussianNB()
```

Making the Confusion Matrix

```
# print(confusion_matrix(y_test, y_pred))
# print(accuracy_score(y_test,y_pred))
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Check accuracy of model on training data

```
classifier.score(X_train, y_train)
```

```
0.7629233511586453
```

Check accuracy of model on testing data

```
classifier.score(X_test, y_test)
```

```
0.786096256684492
```

Classification report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.80      0.96      0.87       142
           2       0.65      0.24      0.35        45

    accuracy                           0.79       187
   macro avg       0.72      0.60      0.61       187
weighted avg       0.76      0.79      0.75       187
```

Plotting pipeline steps

```
X, y = fetch_openml(data_id=1464, return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y)

clf = make_pipeline(StandardScaler(), GaussianNB())
clf.fit(X_train, y_train)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('gaussiannb', GaussianNB())])
```

Training the Random Forest Classification model on the Training set

```
classifier = RandomForestClassifier(n_estimators = 5, criterion = 'entropy', random_state = 0,)
classifier.fit(X_train, y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=5, random_state=0)
```

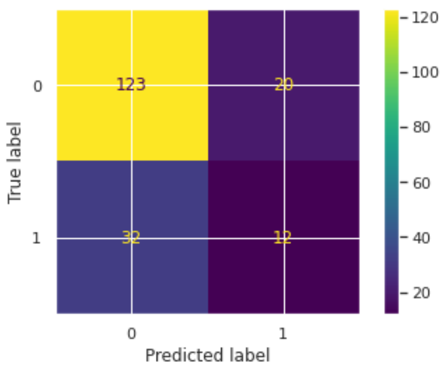
Making the Confusion Matrix

```
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test,y_pred))
```

```
[[130  13]
 [ 40   4]]
0.7165775401069518
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Check accuracy of model on training data

```
classifier.score(X_test, y_test)
```

```
0.7219251336898396
```

Check accuracy of model on testing data

```
classifier.score(X_test, y_test)
```

```
0.7219251336898396
```

Classification report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.79      0.86      0.83       143
           2       0.38      0.27      0.32        44

    accuracy                           0.72       187
   macro avg       0.58      0.57      0.57       187
weighted avg       0.70      0.72      0.71       187
```

Plotting pipeline steps

```
X, y = fetch_openml(data_id=1464, return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y)

clf = make_pipeline(StandardScaler(), RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0))
clf.fit(X_train, y_train)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('randomforestclassifier',
                 RandomForestClassifier(criterion='entropy', n_estimators=10,
                                        random_state=0))])
```

Training the SVM model on the Training set

```
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)
```

```
SVC(kernel='linear', random_state=0)
```

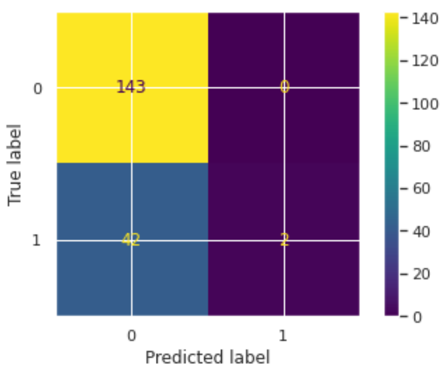
Making the Confusion Matrix

```
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test,y_pred))
```

```
[[119  24]
 [ 36   8]]
0.679144385026738
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Check accuracy of model on training data

```
classifier.score(X_test, y_test)
```

```
0.7754010695187166
```

Check accuracy of model on testing data

```
classifier.score(X_test, y_test)
```

```
0.7754010695187166
```

Classification report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.77      1.00      0.87       143
           2       1.00      0.05      0.09        44

    accuracy                           0.78       187
   macro avg       0.89      0.52      0.48       187
weighted avg       0.83      0.78      0.69       187
```

Plotting pipeline steps

```
X, y = fetch_openml(data_id=1464, return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y)

clf = make_pipeline(StandardScaler(), SVC(kernel = 'linear', random_state = 0))
clf.fit(X_train, y_train)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('svc', SVC(kernel='linear', random_state=0))])
```

Training the Logistic Regression model on the Training set

```
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

```
LogisticRegression(random_state=0)
```

Double-click (or enter) to edit

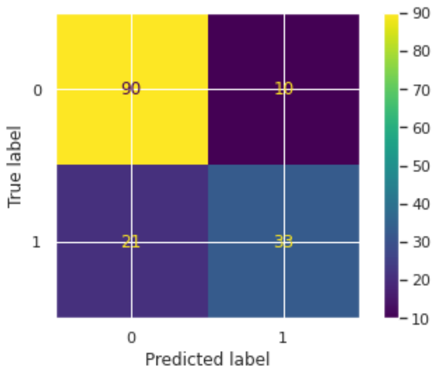
Making the Confusion Matrix

```
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test,y_pred))
```

```
[[90 10]
 [21 33]]
0.7987012987012987
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Check accuracy of model on training data

```
classifier.score(X_test, y_test)
```

```
0.7987012987012987
```

Check accuracy of model on testing data

```
classifier.score(X_test, y_test)
```

```
0.7987012987012987
```

Classification report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.90      0.85       100
           1       0.77      0.61      0.68        54

    accuracy                           0.80       154
   macro avg       0.79      0.76      0.77       154
```

```
weighted avg       0.80      0.80      0.79       154
```

Plotting pipeline steps

```
X, y = fetch_openml(data_id=1464, return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y)

clf = make_pipeline(StandardScaler(), LogisticRegression(random_state = 0))
clf.fit(X_train, y_train)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('logisticregression', LogisticRegression(random_state=0))])
```

Double-click (or enter) to edit

Training XGBoost on the Training set

```
classifier = XGBClassifier()
classifier.fit(X_train, y_train)
```

```
XGBClassifier()
```

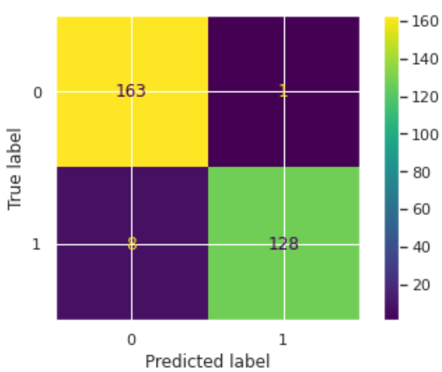
Making the Confusion Matrix

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[163   1]
 [  8 128]]
0.97
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Applying k-Fold Cross Validation

```
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

```
Accuracy: 98.29 %
Standard Deviation: 2.29 %
```

Training CatBoost on the Training set

```
classifier = CatBoostClassifier()
classifier.fit(X_train, y_train)
```

```
Learning rate set to 0.008847
0:      learn: 0.6754537        total: 6.97ms   remaining: 6.96s
1:      learn: 0.6647391        total: 12.9ms   remaining: 6.46s
2:      learn: 0.6477755        total: 19ms     remaining: 6.3s
3:      learn: 0.6336509        total: 24.7ms   remaining: 6.15s
4:      learn: 0.6181298        total: 30.5ms   remaining: 6.08s
5:      learn: 0.6083051        total: 36.8ms   remaining: 6.09s
6:      learn: 0.5964469        total: 42.7ms   remaining: 6.06s
7:      learn: 0.5856739        total: 49.2ms   remaining: 6.1s
8:      learn: 0.5745829        total: 55.5ms   remaining: 6.11s
9:      learn: 0.5641862        total: 61.7ms   remaining: 6.11s
10:     learn: 0.5547426        total: 68ms     remaining: 6.11s
11:     learn: 0.5441845        total: 74.2ms   remaining: 6.11s
12:     learn: 0.5338379        total: 80.6ms   remaining: 6.12s
13:     learn: 0.5228911        total: 86.6ms   remaining: 6.1s
14:     learn: 0.5137442        total: 92.6ms   remaining: 6.08s
15:     learn: 0.5066484        total: 98.7ms   remaining: 6.07s
16:     learn: 0.4950612        total: 105ms    remaining: 6.05s
17:     learn: 0.4848489        total: 111ms    remaining: 6.05s
18:     learn: 0.4754352        total: 117ms    remaining: 6.04s
19:     learn: 0.4659835        total: 123ms    remaining: 6.03s
20:     learn: 0.4570217        total: 129ms    remaining: 6.02s
21:     learn: 0.4479403        total: 135ms    remaining: 6.02s
22:     learn: 0.4376009        total: 142ms    remaining: 6.01s
23:     learn: 0.4285101        total: 148ms    remaining: 6s
24:     learn: 0.4192471        total: 154ms    remaining: 6.01s
25:     learn: 0.4125068        total: 161ms    remaining: 6.02s
26:     learn: 0.4072776        total: 167ms    remaining: 6.01s
27:     learn: 0.3981821        total: 176ms    remaining: 6.1s
28:     learn: 0.3935254        total: 182ms    remaining: 6.1s
29:     learn: 0.3859005        total: 188ms    remaining: 6.09s
30:     learn: 0.3799484        total: 198ms    remaining: 6.19s
31:     learn: 0.3744175        total: 205ms    remaining: 6.19s
32:     learn: 0.3680900        total: 211ms    remaining: 6.17s
33:     learn: 0.3631674        total: 219ms    remaining: 6.23s
34:     learn: 0.3589614        total: 225ms    remaining: 6.2s
35:     learn: 0.3523123        total: 230ms    remaining: 6.17s
36:     learn: 0.3457715        total: 236ms    remaining: 6.15s
37:     learn: 0.3407114        total: 242ms    remaining: 6.14s
38:     learn: 0.3348761        total: 248ms    remaining: 6.12s
39:     learn: 0.3287771        total: 255ms    remaining: 6.11s
40:     learn: 0.3226084        total: 261ms    remaining: 6.1s
41:     learn: 0.3174941        total: 267ms    remaining: 6.09s
42:     learn: 0.3103495        total: 273ms    remaining: 6.08s
43:     learn: 0.3066958        total: 279ms    remaining: 6.06s
44:     learn: 0.3009912        total: 285ms    remaining: 6.05s
45:     learn: 0.2944978        total: 291ms    remaining: 6.04s
46:     learn: 0.2889641        total: 297ms    remaining: 6.03s
47:     learn: 0.2861764        total: 303ms    remaining: 6.01s
48:     learn: 0.2800491        total: 309ms    remaining: 6s
49:     learn: 0.2770871        total: 315ms    remaining: 5.99s
50:     learn: 0.2714638        total: 321ms    remaining: 5.98s
51:     learn: 0.2661450        total: 327ms    remaining: 5.97s
52:     learn: 0.2616959        total: 334ms    remaining: 5.96s
53:     learn: 0.2585701        total: 340ms    remaining: 5.95s
54:     learn: 0.2559810        total: 346ms    remaining: 5.94s
55:     learn: 0.2510415        total: 354ms    remaining: 5.97s
56:     learn: 0.2463600        total: 360ms    remaining: 5.96s
```

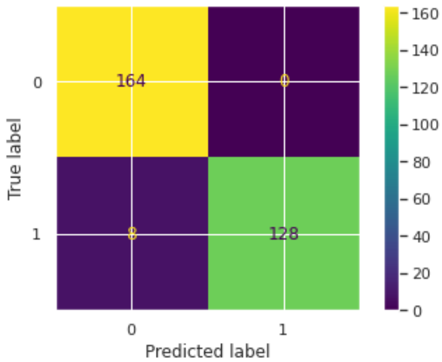
Making the Confusion Matrix

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[164   0]
 [  8 128]]
0.9733333333333334
```

Ploting confusion matrix display visual

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm_display = ConfusionMatrixDisplay(cm).plot()
```



Applying k-Fold Cross Validation

```
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

```
Streaming output truncated to the last 5000 lines.
6:	learn: 0.6069159	total: 38.9ms	remaining: 5.52s
7:	learn: 0.5966027	total: 44.2ms	remaining: 5.48s
8:	learn: 0.5856913	total: 49.6ms	remaining: 5.46s
9:	learn: 0.5760461	total: 54.8ms	remaining: 5.43s
10:	learn: 0.5672112	total: 60ms	remaining: 5.39s
11:	learn: 0.5568810	total: 65.5ms	remaining: 5.39s
12:	learn: 0.5471381	total: 72.3ms	remaining: 5.49s
13:	learn: 0.5364776	total: 84.6ms	remaining: 5.96s
14:	learn: 0.5257723	total: 90.1ms	remaining: 5.92s
15:	learn: 0.5189652	total: 95.8ms	remaining: 5.89s
16:	learn: 0.5077214	total: 102ms	remaining: 5.87s
17:	learn: 0.4981857	total: 107ms	remaining: 5.86s
18:	learn: 0.4914058	total: 114ms	remaining: 5.87s
19:	learn: 0.4821758	total: 120ms	remaining: 5.86s
20:	learn: 0.4739371	total: 125ms	remaining: 5.85s
21:	learn: 0.4643209	total: 131ms	remaining: 5.84s
22:	learn: 0.4542510	total: 144ms	remaining: 6.1s
23:	learn: 0.4455842	total: 150ms	remaining: 6.09s
24:	learn: 0.4364911	total: 156ms	remaining: 6.09s
25:	learn: 0.4298995	total: 162ms	remaining: 6.08s
26:	learn: 0.4248616	total: 168ms	remaining: 6.06s
27:	learn: 0.4158486	total: 174ms	remaining: 6.04s
28:	learn: 0.4112165	total: 180ms	remaining: 6.03s
29:	learn: 0.4037789	total: 186ms	remaining: 6.02s
30:	learn: 0.3976996	total: 192ms	remaining: 6.01s
31:	learn: 0.3922534	total: 198ms	remaining: 5.99s
32:	learn: 0.3844608	total: 204ms	remaining: 5.97s
33:	learn: 0.3796078	total: 210ms	remaining: 5.96s
34:	learn: 0.3753508	total: 216ms	remaining: 5.96s
35:	learn: 0.3685849	total: 222ms	remaining: 5.95s
36:	learn: 0.3620838	total: 228ms	remaining: 5.93s
37:	learn: 0.3569738	total: 234ms	remaining: 5.92s
38:	learn: 0.3512006	total: 240ms	remaining: 5.91s
39:	learn: 0.3451061	total: 246ms	remaining: 5.89s
40:	learn: 0.3390674	total: 251ms	remaining: 5.88s
41:	learn: 0.3354994	total: 257ms	remaining: 5.87s
42:	learn: 0.3282447	total: 263ms	remaining: 5.85s
43:	learn: 0.3245163	total: 278ms	remaining: 6.04s
44:	learn: 0.3187397	total: 286ms	remaining: 6.07s
45:	learn: 0.3145742	total: 292ms	remaining: 6.05s
46:	learn: 0.3089212	total: 298ms	remaining: 6.04s
47:	learn: 0.3060941	total: 304ms	remaining: 6.02s
48:	learn: 0.2998508	total: 309ms	remaining: 6s
49:	learn: 0.2964866	total: 315ms	remaining: 5.99s
50:	learn: 0.2907251	total: 321ms	remaining: 5.97s
51:	learn: 0.2854233	total: 326ms	remaining: 5.95s
52:	learn: 0.2802471	total: 332ms	remaining: 5.94s
53:	learn: 0.2769830	total: 338ms	remaining: 5.93s
54:	learn: 0.2743580	total: 344ms	remaining: 5.91s
55:	learn: 0.2693188	total: 350ms	remaining: 5.9s
56:	learn: 0.2645324	total: 356ms	remaining: 5.89s
57:	learn: 0.2601882	total: 362ms	remaining: 5.88s
58:	learn: 0.2557942	total: 368ms	remaining: 5.87s
59:	learn: 0.2508667	total: 374ms	remaining: 5.86s
60:	learn: 0.2467156	total: 380ms	remaining: 5.85s
61:	learn: 0.2432984	total: 386ms	remaining: 5.84s
62:	learn: 0.2396241	total: 392ms	remaining: 5.83s
```

ROC and AUC Curves

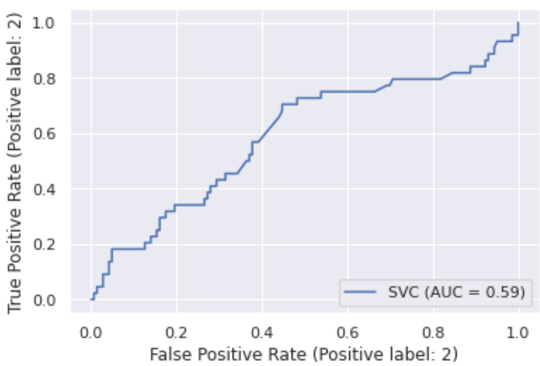
Training SVC model

```
X, y = make_classification(random_state=0)
classifier = SVC(random_state = 0)
classifier.fit(X_train, y_train)
```

```
SVC(random_state=0)
```

Create a ROC Curve display from an estimator

```
RocCurveDisplay.from_estimator(classifier, X_test, y_test)
plt.show()
```



Plot ROC curve given the true and predicted values

```
# generate two class dataset
X, y = make_classification(n_samples=1000, n_classes=2, n_features=20, random_state=27)

# split into train-test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=27)
```

```
# train models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

# logistic regression
model1 = LogisticRegression()
# knn
model2 = KNeighborsClassifier(n_neighbors=4)

# fit model
model1.fit(X_train, y_train)
model2.fit(X_train, y_train)

# predict probabilities
pred_prob1 = model1.predict_proba(X_test)
pred_prob2 = model2.predict_proba(X_test)
```

```
# roc curve for models
fpr1, tpr1, thresh1 = roc_curve(y_test, pred_prob1[:,1], pos_label=1)
fpr2, tpr2, thresh2 = roc_curve(y_test, pred_prob2[:,1], pos_label=1)

# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

```
# auc scores
auc_score1 = roc_auc_score = (y_test, pred_prob1[:,1])
auc_score2 = roc_auc_score = (y_test, pred_prob2[:,1])
```

```
# plot roc curves
plt.plot(fpr1, tpr1, linestyle='--',color='orange', label='Logistic Regression')
plt.plot(fpr2, tpr2, linestyle='--',color='green', label='KNN')
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
```

```
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show();
```