Healthcare Capstone project

February 16, 2023

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.graphics.gofplots import qqplot
import numpy as np
from scipy import stats as st
import random
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪StratifiedKFold
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪roc_auc_score, roc_curve, precision_recall_curve, auc
from sklearn.dummy import DummyClassifier
from sklearn import svm
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

[2]:
```
Data = pd.read_csv("health care diabetes.csv")
```

[3]:
```
Data.head(10)
```

[3]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1
5            5      116             74              0        0  25.6
6            3       78             50             32       88  31.0
7           10      115              0              0        0  35.3
8            2      197             70             45      543  30.5
9            8      125             96              0        0   0.0
```

```
   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
5                     0.201   30        0
6                     0.248   26        1
7                     0.134   29        0
8                     0.158   53        1
9                     0.232   54        1
```

[4]:
```python
print('No. of rows and columns : ', Data.shape)
```

```
No. of rows and columns :  (768, 9)
```

[5]:
```python
print('Columns names :')
print('---------------')
print(Data.columns)
```

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

[6]:
```python
print('Dataset structure information :')
print('--------------------------------')
Data.info()
```

```
Dataset structure information :
--------------------------------
<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
```

[7]:
```python
print('Count of missing values : ')
print('---------------------------')
print(Data.isnull().sum())
```

```
Count of missing values :
---------------------------
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[8]:
```python
print('Dataset data description :')
print('---------------------------')
Data.describe()
```

```
Dataset data description :
---------------------------
```

[8]:

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

\

	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000
mean	31.992578	0.471876	33.240885	0.348958
std	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.078000	21.000000	0.000000
25%	27.300000	0.243750	24.000000	0.000000
50%	32.000000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

[9]:
```python
#Check for duplicate data
dup = Data.duplicated()
print('Is there any duplicate rows ?')
```

```
print('--------------------------------')
print(dup.value_counts())
```

```
Is there any duplicate rows ?
--------------------------------
False    768
dtype: int64
```

[10]:
```
#No duplicate rows present in data set
```

[11]:
```
#Exploration of the distribution of data of columns 'Glucose', 'BloodPressure',␣
↪'SkinThickness', 'Insulin' and 'BMI' using histogram and density plot.
```

[12]:
```
f, axes = plt.subplots(5, 2, figsize=(20, 25))
sns.distplot( Data["Glucose"] , color="skyblue", ax=axes[0,0])
qqplot(Data["Glucose"], line="45", fit=True, ax=axes[0,1])
sns.distplot( Data["BloodPressure"] , color="olive", ax=axes[1, 0])
qqplot(Data["BloodPressure"], line ="45", fit=True, ax=axes[1,1])
sns.distplot( Data["SkinThickness"] , color="Orange", ax=axes[2, 0])
qqplot(Data["SkinThickness"], line ="45", fit=True, ax=axes[2,1])
sns.distplot( Data["Insulin"] , color="teal", ax=axes[3, 0])
qqplot(Data["Insulin"], line ="45", fit=True, ax=axes[3,1])
sns.distplot(Data["BMI"], color="Pink", ax=axes[4, 0])
qqplot(Data["BMI"], line ="45", fit=True, ax=axes[4,1])
plt.show()
```

```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
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/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
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/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
```
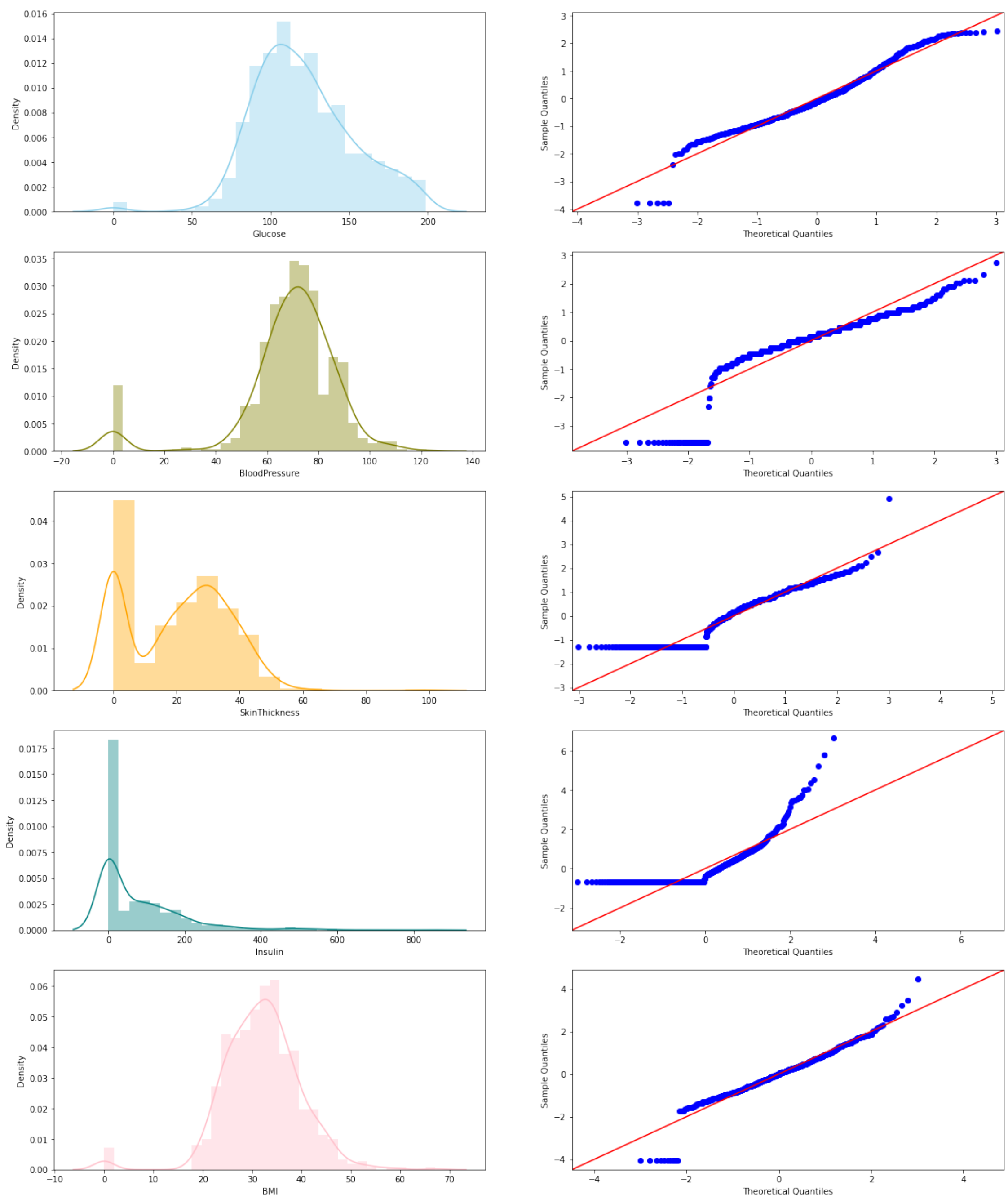

```
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



[13]:
```
#From above graphs it is clear that apart from Insulin all other features
↪follows alomst normal distribution. Insulin has a lot of zero value, so if
↪we fill those it may too follow normal distribution.

#A zero in columns 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin' and
↪'BMI' indicates a missing values. We need to  find all missing values in
↪these columns.
```

[14]:
```
print('Number of missing values in :')
print('-----------------------------')
print('1. Glucose        = ', (Data.Glucose == 0).sum())
print('2. Blood Pressure = ', (Data.BloodPressure == 0).sum())
print('3. Skin Thickness = ', (Data.SkinThickness == 0).sum())
print('4. Insilin        = ', (Data.Insulin == 0).sum())
print('5. BMI            = ', (Data.BMI == 0).sum())
```

```
Number of missing values in :
-----------------------------
1. Glucose        =  5
2. Blood Pressure =  35
3. Skin Thickness =  227
4. Insilin        =  374
5. BMI            =  11
```

[15]:
```
#Insulin and Skinthickness is missing most of its datas in given data set.
```

[16]:
```
Total_Records = Data.shape[0]
Insuline_Missing_Count = (Data.Insulin == 0).sum()
SkinThickness_Missing_Count = (Data.SkinThickness == 0).sum()
Insulin_Missing_Pct = (Insuline_Missing_Count / Total_Records) * 100
SkinThickness_Missing_Pct = (SkinThickness_Missing_Count / Total_Records) * 100
print('% of missing Insulin Data       = ', Insulin_Missing_Pct.round(2))
print('% of missing SkinThickness Data = ', SkinThickness_Missing_Pct.round(2))
```

```
% of missing Insulin Data       =  48.7
% of missing SkinThickness Data =  29.56
```

[17]:
```
#Filling up missing values.
#It is noticed that other than insulin all other features have almost similar
↪mean and median value. So, median value will be used to fill those features,
↪as median value is independent of outliers. The small difference in mean and
↪median these features have may be due to those outliers. The difference of
↪mean and median for Insulin is very high compare to others. So, for this
↪feature trim-mean will be used because I want to concentrate on the datas of
↪denser region.
```

[18]:
```
Insulin_Trim_Mean = st.trim_mean(Data.Insulin, .20, axis=0).astype(int)
print('Trim-Mean of Insulin : ', Insulin_Trim_Mean)
```

```
Trim-Mean of Insulin :  45
```

[19]:
```
Data.Glucose.replace(0, Data.Glucose.median(), inplace = True)
Data.BloodPressure.replace(0, Data.BloodPressure.median(), inplace = True)
Data.SkinThickness.replace(0, Data.SkinThickness.median(), inplace = True)
Data.Insulin.replace(0, Insulin_Trim_Mean, inplace = True)
Data.BMI.replace(0, Data.BMI.median(), inplace = True)
```

[20]:
```
Data.to_csv('Healthcare.csv')
```

[21]:
```
Data.Insulin.value_counts()
```

[21]:
```
45     377
105     11
140      9
130      9
120      8
      …
270      1
271      1
272      1
274      1
14       1
Name: Insulin, Length: 185, dtype: int64
```

[22]:
```
print('Number of missing values in :')
print('------------------------------')
print('1. Glucose        = ', (Data.Glucose == 0).sum())
print('2. Blood Pressure = ', (Data.BloodPressure == 0).sum())
print('3. Skin Thickness = ', (Data.SkinThickness == 0).sum())
print('4. Insilin        = ', (Data.Insulin == 0).sum())
print('5. BMI            = ', (Data.BMI == 0).sum())
```

```
Number of missing values in :
------------------------------
1. Glucose        =  0
2. Blood Pressure =  0
3. Skin Thickness =  0
4. Insilin        =  0
5. BMI            =  0
```

[23]:
```
#To find count of data types in the dataset.
```

[24]:
```python
D = pd.DataFrame(Data.dtypes)
D.rename(columns= {0: 'Type'}, inplace=True)
D.replace(['int64', 'float64'], ['Integer', 'Float'], inplace=True)
print("Types of data type :")
print('---------------------')
D
```

```
Types of data type :
---------------------
```

[24]:

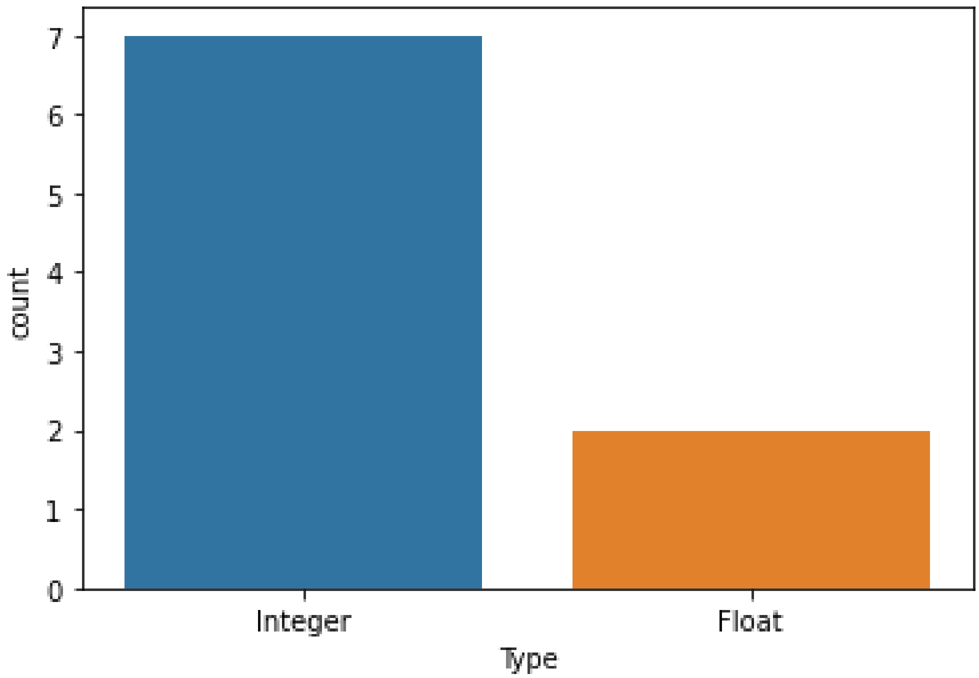
	Type
Pregnancies	Integer
Glucose	Integer
BloodPressure	Integer
SkinThickness	Integer
Insulin	Integer
BMI	Float
DiabetesPedigreeFunction	Float
Age	Integer
Outcome	Integer

[25]:
```python
print('Count of data types :')
print('---------------------')
print(D.Type.value_counts())
```

```
Count of data types :
---------------------
Integer    7
Float      2
Name: Type, dtype: int64
```

[26]:
```python
#Plotting the data type count using bar graph
sns.countplot(x = 'Type', data = D)
```

[26]:
```
<AxesSubplot:xlabel='Type', ylabel='count'>
```



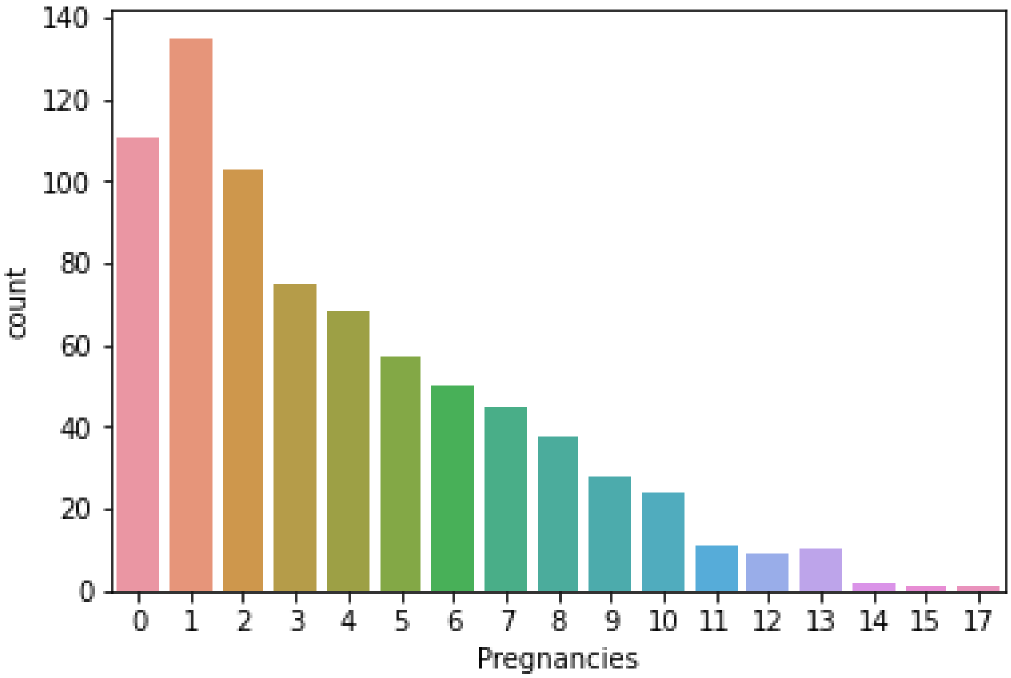
[27]:
```
#Univariate analysis
```

[28]:
```
print('Count of Values in Pregnancies :')
print('--------------------------------')
P = Data.Pregnancies.value_counts().sort_index()
print(P)
sns.countplot(x='Pregnancies', data = Data)
```

```
Count of Values in Pregnancies :
--------------------------------
0     111
1     135
2     103
3      75
4      68
5      57
6      50
7      45
8      38
9      28
10     24
11     11
12      9
13     10
14      2
```

```
15      1
17      1
Name: Pregnancies, dtype: int64
```

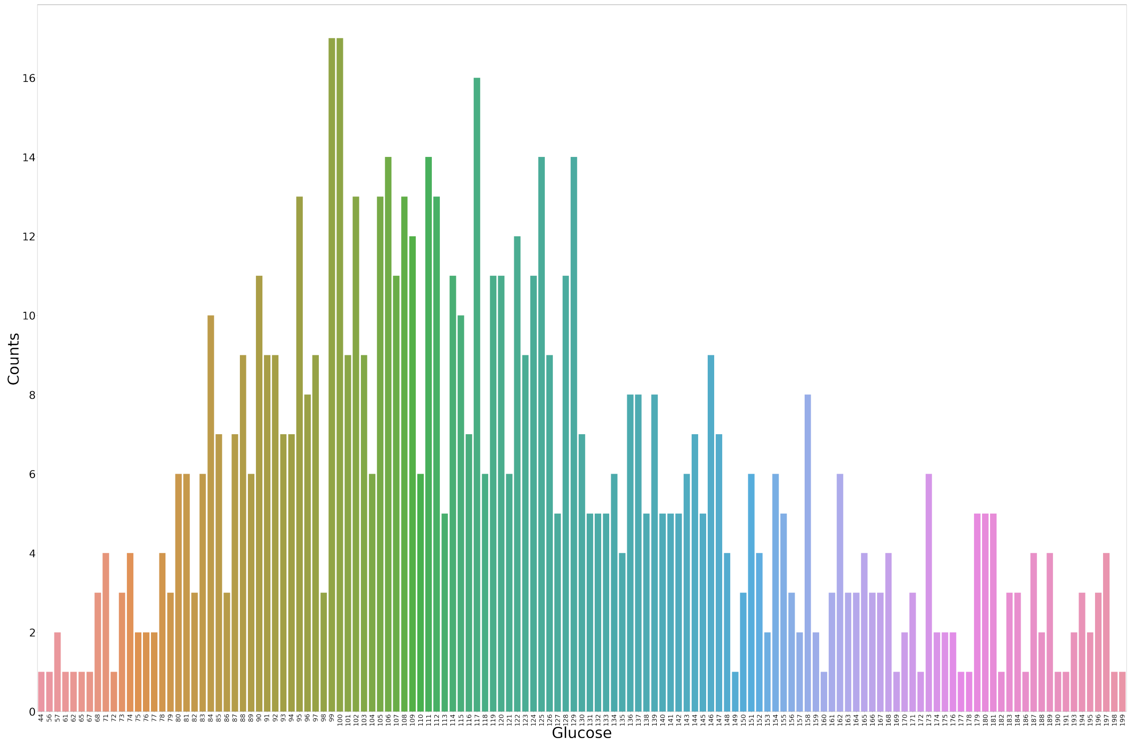
[28]: <AxesSubplot:xlabel='Pregnancies', ylabel='count'>



[29]:
```
print('Count of Values in Glucose :')
print('----------------------------')
P = Data.Glucose.value_counts().sort_index()
print(P)
plt.figure(figsize=(90,60))
sns.countplot(x='Glucose', data = Data)
plt.xticks(rotation='vertical', fontsize = 30)
plt.xlabel('Glucose', fontsize=70)
plt.yticks(fontsize = 50)
plt.ylabel('Counts', fontsize =70)
plt.show()
```

```
Count of Values in Glucose :
----------------------------
44     1
56     1
57     2
61     1
62     1
```

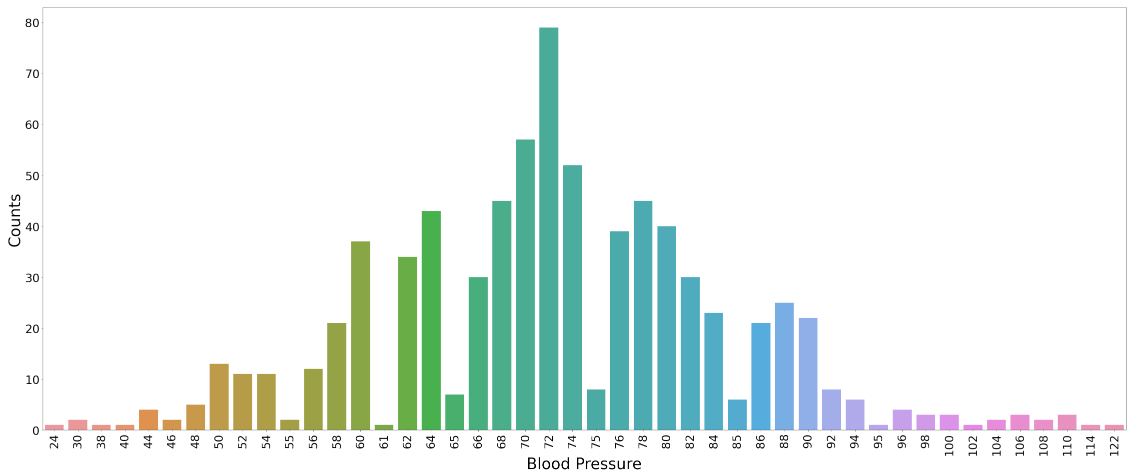
```
       ..
195    2
196    3
197    4
198    1
199    1
Name: Glucose, Length: 135, dtype: int64
```



[30]:
```python
print('Count of Values in Blood Presure :')
print('----------------------------------')
P = Data.BloodPressure.value_counts().sort_index()
print(P)
plt.figure(figsize = (50, 20))
sns.countplot(x='BloodPressure', data = Data)
plt.xticks(rotation='vertical', fontsize=30)
plt.xlabel('Blood Pressure', fontsize =40)
plt.yticks(fontsize = 30)
plt.ylabel('Counts', fontsize = 40)
plt.show()
```

```
Count of Values in Blood Presure :
----------------------------------
24      1
30      2
```

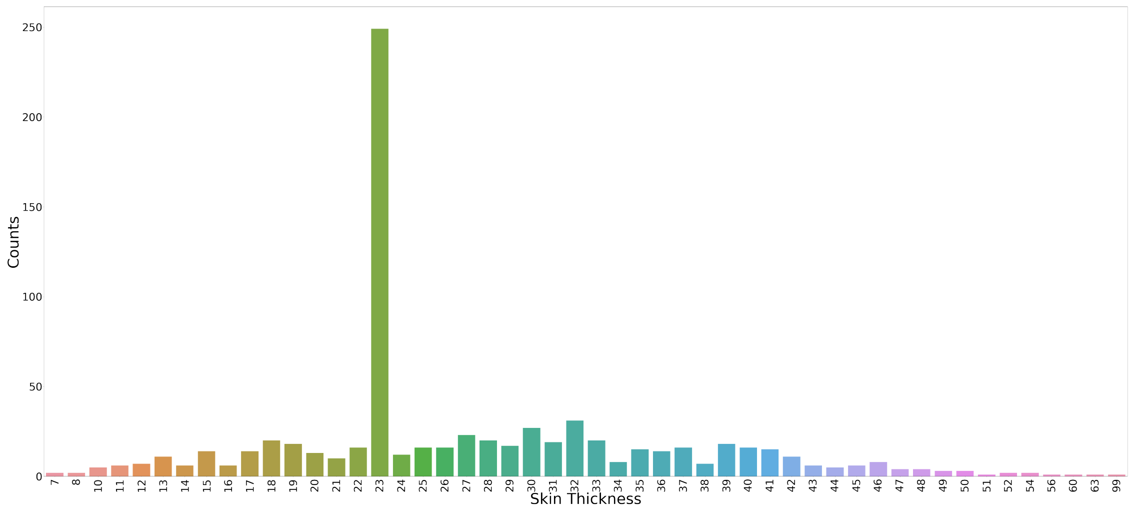
```
38      1
40      1
44      4
46      2
48      5
50     13
52     11
54     11
55      2
56     12
58     21
60     37
61      1
62     34
64     43
65      7
66     30
68     45
70     57
72     79
74     52
75      8
76     39
78     45
80     40
82     30
84     23
85      6
86     21
88     25
90     22
92      8
94      6
95      1
96      4
98      3
100     3
102     1
104     2
106     3
108     2
110     3
114     1
122     1
Name: BloodPressure, dtype: int64
```



[31]:
```
print('Count of Values in Skin Thickness :')
print('-------------------------------------')
P = Data.SkinThickness.value_counts().sort_index()
print(P)
plt.figure(figsize = (90, 40))
sns.countplot(x='SkinThickness', data = Data)
plt.xticks(rotation='vertical', fontsize=50)
plt.xlabel('Skin Thickness', fontsize=70)
plt.yticks(fontsize = 50)
plt.ylabel('Counts', fontsize=70)
plt.show()
```

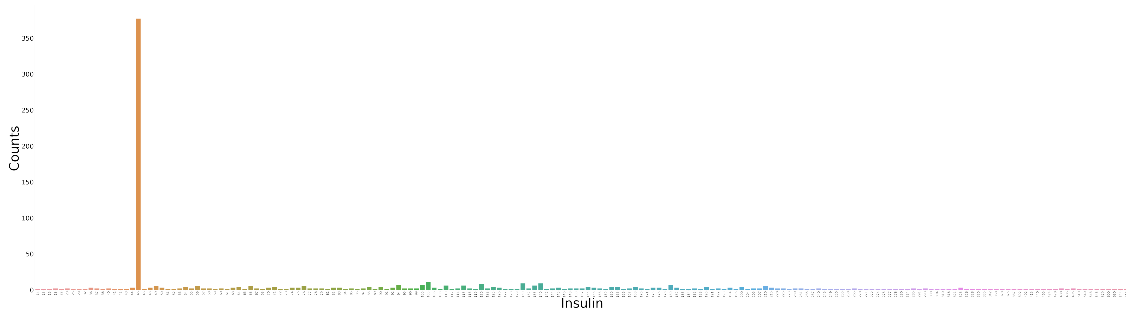
```
Count of Values in Skin Thickness :
-------------------------------------
7        2
8        2
10       5
11       6
12       7
13      11
14       6
15      14
16       6
17      14
18      20
19      18
20      13
21      10
22      16
23     249
24      12
```

```
25     16
26     16
27     23
28     20
29     17
30     27
31     19
32     31
33     20
34      8
35     15
36     14
37     16
38      7
39     18
40     16
41     15
42     11
43      6
44      5
45      6
46      8
47      4
48      4
49      3
50      3
51      1
52      2
54      2
56      1
60      1
63      1
99      1
Name: SkinThickness, dtype: int64
```



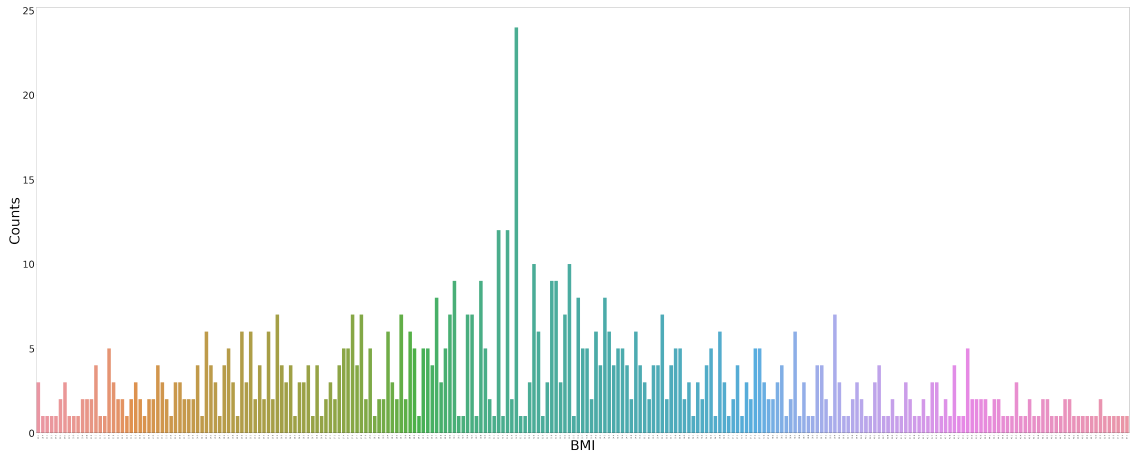
[32]:
```
print('Count of Values in Insulin :')
print('------------------------------')
P = Data.Insulin.value_counts().sort_index()
print(P)
plt.figure(figsize = (150, 40))
sns.countplot(data=Data, x="Insulin")
plt.xticks(rotation='vertical', fontsize=25)
plt.xlabel('Insulin', fontsize=100)
plt.yticks(fontsize = 50)
plt.ylabel('Counts', fontsize=100)
plt.show()
```

```
Count of Values in Insulin :
------------------------------
14     1
15     1
16     1
18     2
22     1
      ..
579    1
600    1
680    1
744    1
846    1
Name: Insulin, Length: 185, dtype: int64
```



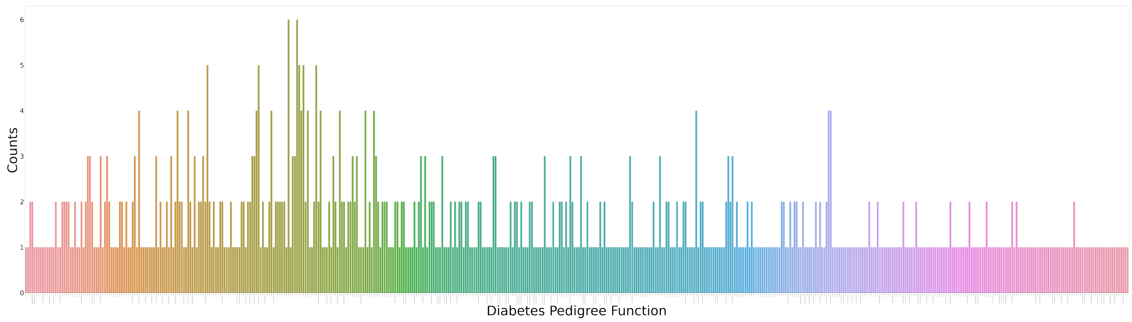
[33]:
```
print('Count of Values in BMI :')
print('-------------------------')
P = Data.BMI.value_counts().sort_index()
print(P)
plt.figure(figsize = (100, 40))
sns.countplot(data=Data, x="BMI")
plt.xticks(rotation='vertical', fontsize= 10)
plt.xlabel('BMI', fontsize=70)
plt.yticks(fontsize =50)
plt.ylabel("Counts", fontsize=70)
plt.show()
```

```
Count of Values in BMI :
-------------------------
18.2    3
18.4    1
19.1    1
19.3    1
19.4    1
       ..
53.2    1
55.0    1
57.3    1
59.4    1
67.1    1
Name: BMI, Length: 247, dtype: int64
```




```
[34]: print('Count of Values in Diabetes Pedigree Function :')
print('------------------------------------------------')
P = Data.DiabetesPedigreeFunction.value_counts().sort_index()
print(P)
plt.figure(figsize = (150, 40))
sns.countplot(data=Data, x="DiabetesPedigreeFunction")
plt.xticks(rotation='vertical', fontsize=7)
plt.xlabel('Diabetes Pedigree Function', fontsize=100)
plt.yticks(fontsize = 50)
plt.ylabel('Counts', fontsize=100)
plt.show()
```

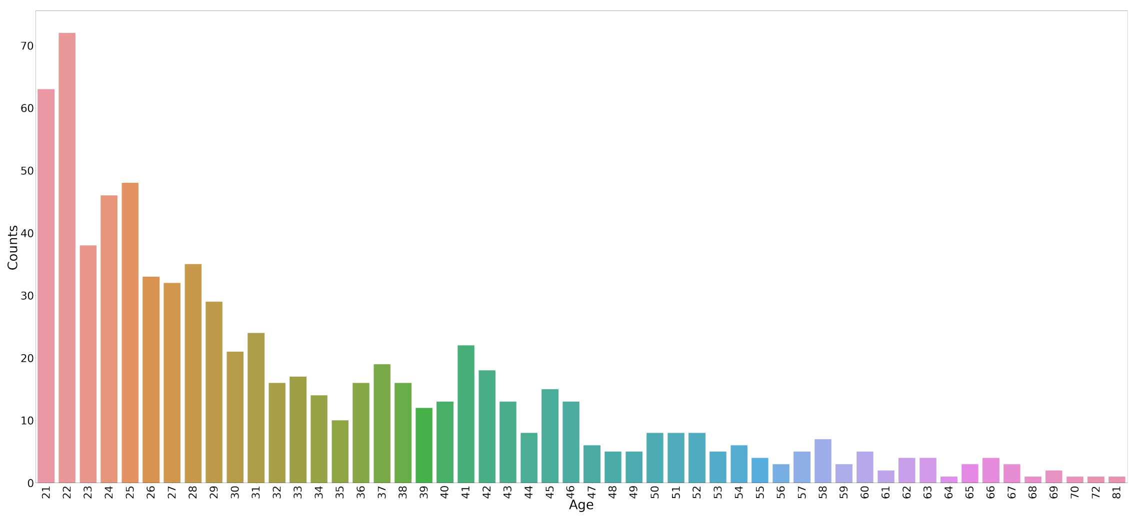
```
Count of Values in Diabetes Pedigree Function :
------------------------------------------------
0.078    1
0.084    1
0.085    2
0.088    2
0.089    1
        ..
1.893    1
2.137    1
2.288    1
2.329    1
2.420    1
Name: DiabetesPedigreeFunction, Length: 517, dtype: int64
```



[35]:
```
print('Count of Values in Age :')
print('-------------------------')
P = Data.Age.value_counts().sort_index()
print(P)
plt.figure(figsize = (90, 40))
sns.countplot(data=Data, x="Age")
plt.xticks(rotation='vertical', fontsize=50)
plt.xlabel('Age', fontsize=60)
plt.yticks(fontsize =50)
plt.ylabel('Counts', fontsize=60)
plt.show()
```

```
Count of Values in Age :
-------------------------
21    63
22    72
23    38
24    46
25    48
26    33
27    32
28    35
29    29
30    21
31    24
32    16
33    17
34    14
35    10
36    16
37    19
38    16
39    12
40    13
41    22
42    18
```

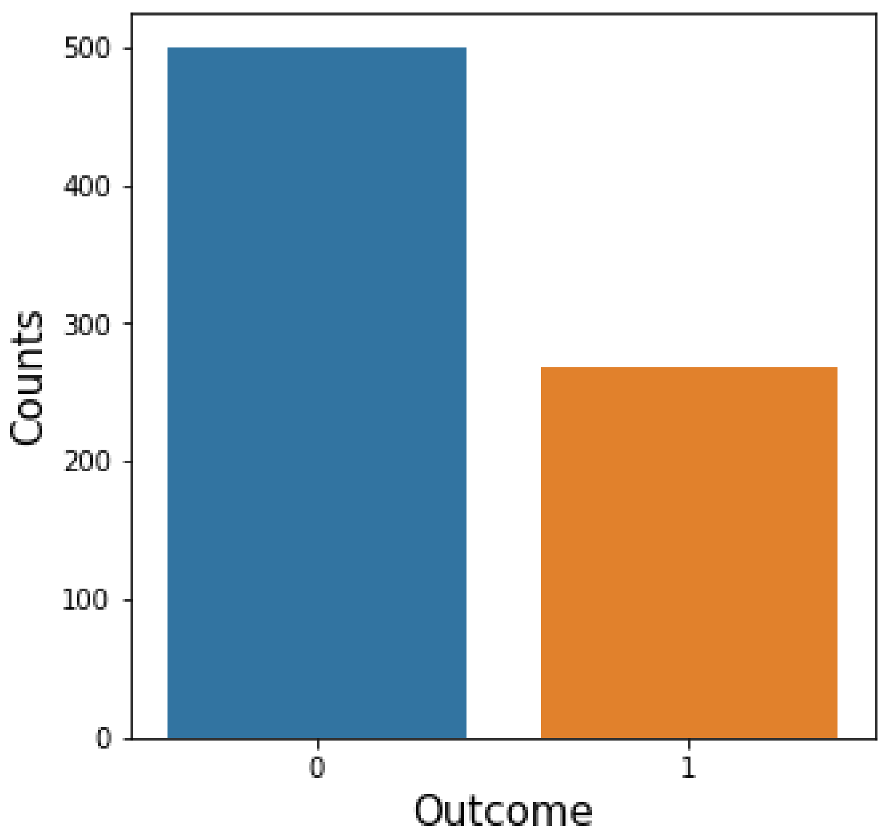
```
43    13
44     8
45    15
46    13
47     6
48     5
49     5
50     8
51     8
52     8
53     5
54     6
55     4
56     3
57     5
58     7
59     3
60     5
61     2
62     4
63     4
64     1
65     3
66     4
67     3
68     1
69     2
70     1
72     1
81     1
Name: Age, dtype: int64
```



[36]:

```
print('Count of Values in Outcome :')
print('------------------------------')
P = Data.Outcome.value_counts().sort_index()
print(P)
plt.figure(figsize = (5, 5))
sns.countplot(data=Data, x="Outcome")
plt.xticks(fontsize=10)
plt.xlabel('Outcome', fontsize=15)
plt.yticks(fontsize =10)
plt.ylabel('Counts', fontsize=15)
plt.show()
```

```
Count of Values in Outcome :
------------------------------
0    500
1    268
Name: Outcome, dtype: int64
```

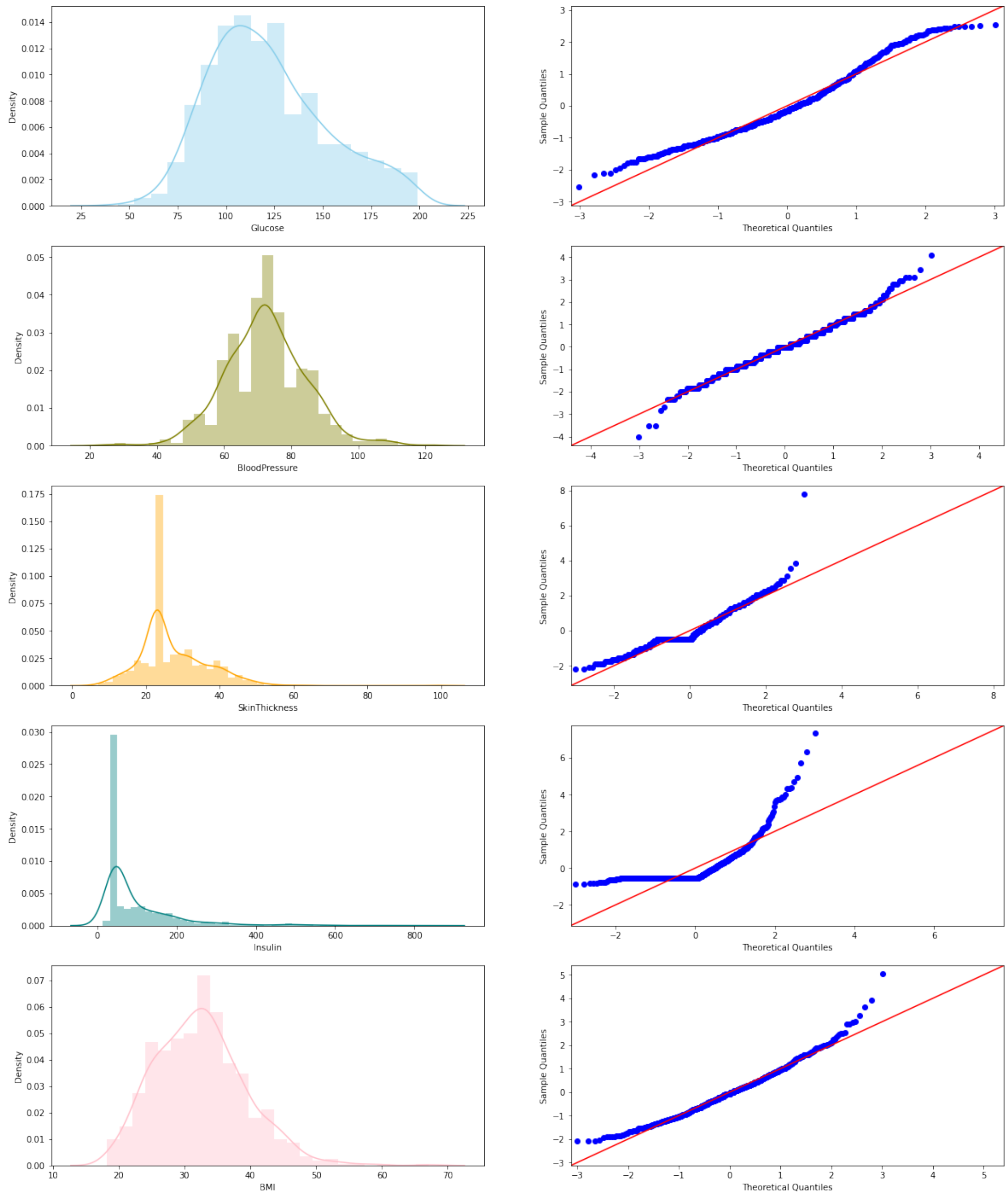


[37]:

```
#Analysis of the distribution of data after filling all missing values.
```

[38]:
```
f, axes = plt.subplots(5, 2, figsize=(20, 25))
sns.distplot( Data["Glucose"] , color="skyblue", ax=axes[0,0])
qqplot(Data["Glucose"], line="45", fit=True, ax=axes[0,1])
sns.distplot( Data["BloodPressure"] , color="olive", ax=axes[1, 0])
qqplot(Data["BloodPressure"], line ="45", fit=True, ax=axes[1,1])
sns.distplot( Data["SkinThickness"] , color="Orange", ax=axes[2, 0])
qqplot(Data["SkinThickness"], line ="45", fit=True, ax=axes[2,1])
sns.distplot( Data["Insulin"] , color="teal", ax=axes[3, 0])
qqplot(Data["Insulin"], line ="45", fit=True, ax=axes[3,1])
sns.distplot(Data["BMI"], color="Pink", ax=axes[4, 0])
qqplot(Data["BMI"], line ="45", fit=True, ax=axes[4,1])
plt.show()
```

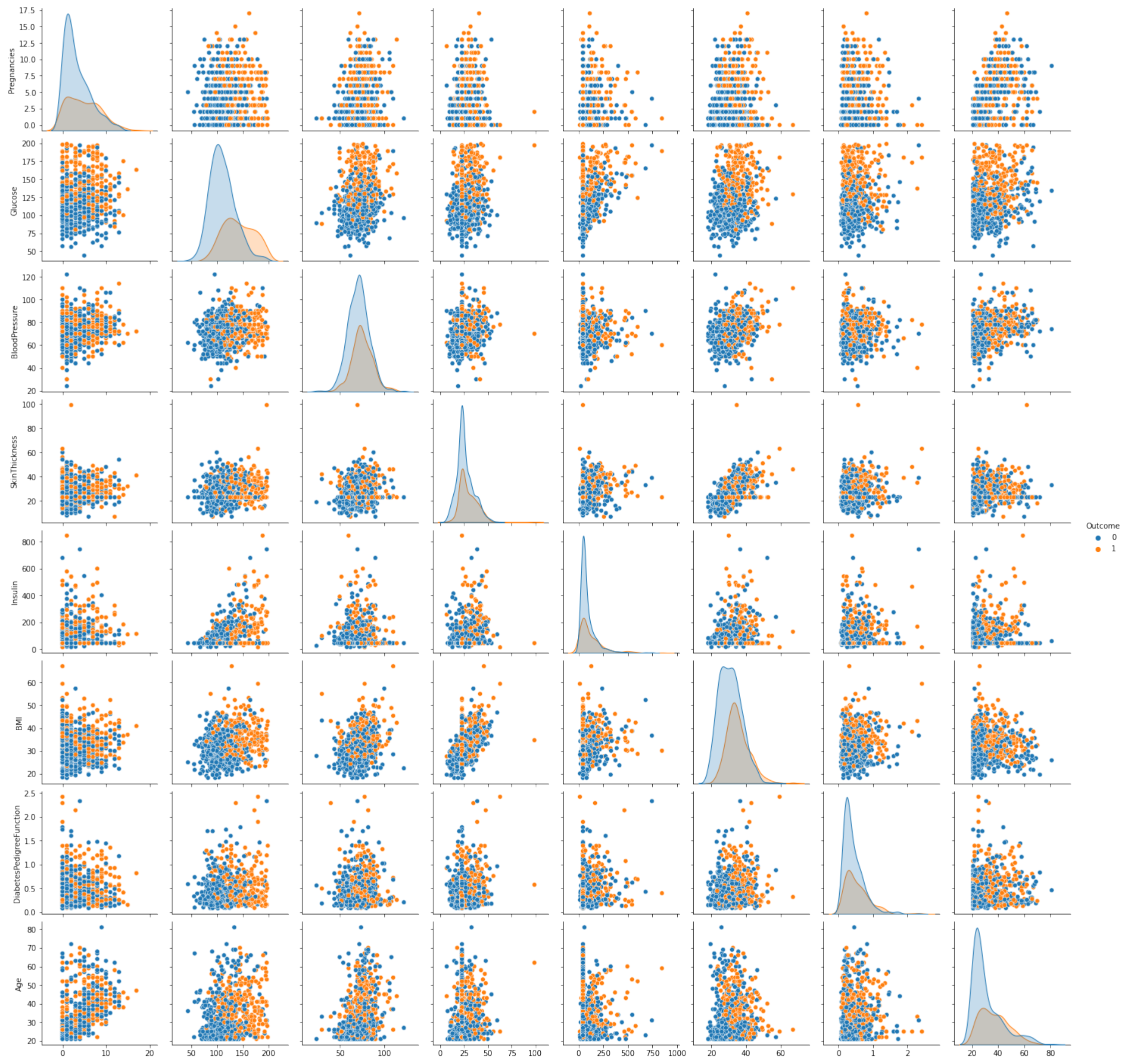
```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



[39]:
```
#Bivariate analysis
#Scatter chart to understand the relation between two variables.
```

[40]:
```
sns.pairplot(data=Data, hue='Outcome')
plt.xticks(fontsize = 50)
```

[40]:
```
(array([  0.,  20.,  40.,  60.,  80., 100.]),
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```



[41]:
```
#Analysis of correlation among different variables.
```

[42]:
```
Cor = Data.corr()
print('Correlation Chart for the dataset :')
print('-----------------------------------')
Cor
```

```
Correlation Chart for the dataset :
-----------------------------------
```

[42]:

```
                          Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                  1.000000  0.128213       0.208615       0.032568
Glucose                      0.128213  1.000000       0.218937       0.172143
BloodPressure                0.208615  0.218937       1.000000       0.147809
SkinThickness                0.032568  0.172143       0.147809       1.000000
Insulin                     -0.045797  0.369850      -0.019376       0.233785
BMI                          0.021546  0.231400       0.281132       0.546951
DiabetesPedigreeFunction    -0.033523  0.137327      -0.002378       0.142977
Age                          0.544341  0.266909       0.324915       0.054514
Outcome                      0.221898  0.492782       0.165723       0.189065

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies              -0.045797  0.021546                 -0.033523
Glucose                   0.369850  0.231400                  0.137327
BloodPressure            -0.019376  0.281132                 -0.002378
SkinThickness             0.233785  0.546951                  0.142977
Insulin                   1.000000  0.190107                  0.173381
BMI                       0.190107  1.000000                  0.153506
DiabetesPedigreeFunction  0.173381  0.153506                  1.000000
Age                      -0.000889  0.025744                  0.033561
Outcome                   0.157428  0.312249                  0.173844

                               Age   Outcome
Pregnancies               0.544341  0.221898
Glucose                   0.266909  0.492782
BloodPressure             0.324915  0.165723
SkinThickness             0.054514  0.189065
Insulin                  -0.000889  0.157428
BMI                       0.025744  0.312249
DiabetesPedigreeFunction  0.033561  0.173844
Age                       1.000000  0.238356
Outcome                   0.238356  1.000000
```

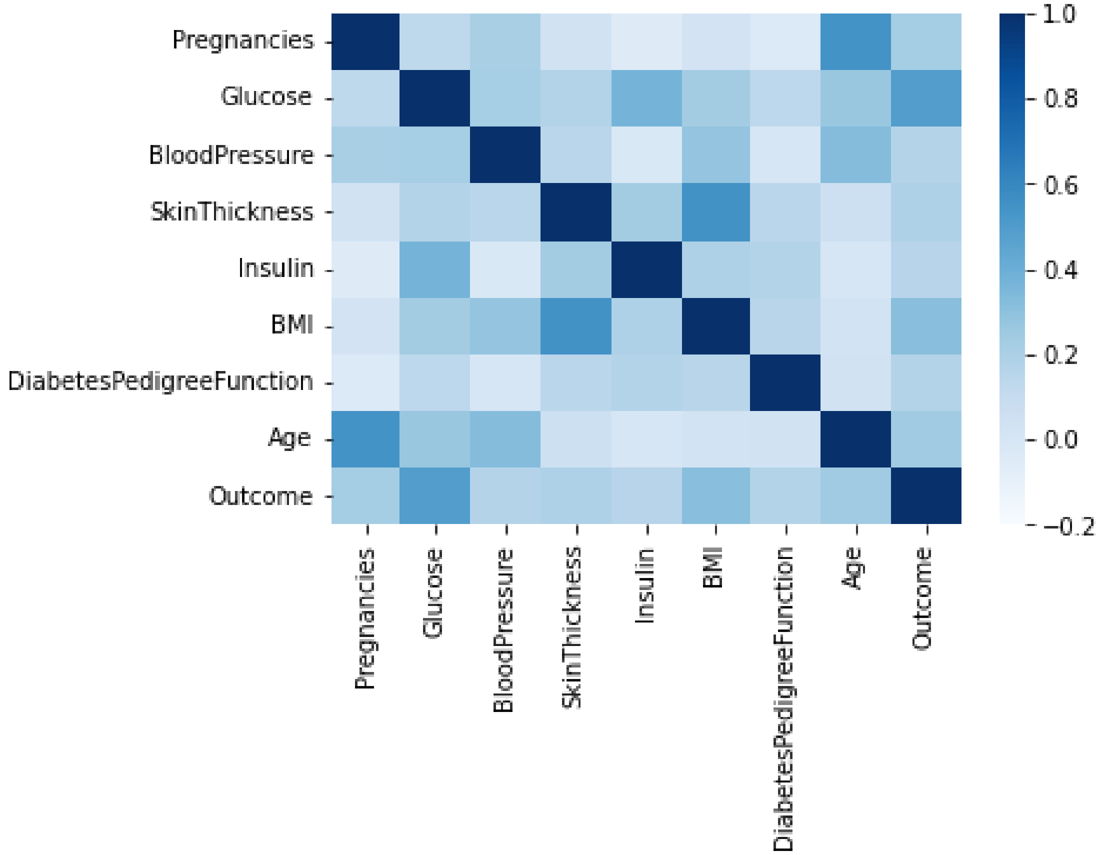
[43]:

```python
#Visiualization of the correlation using heatmap
```

[44]:

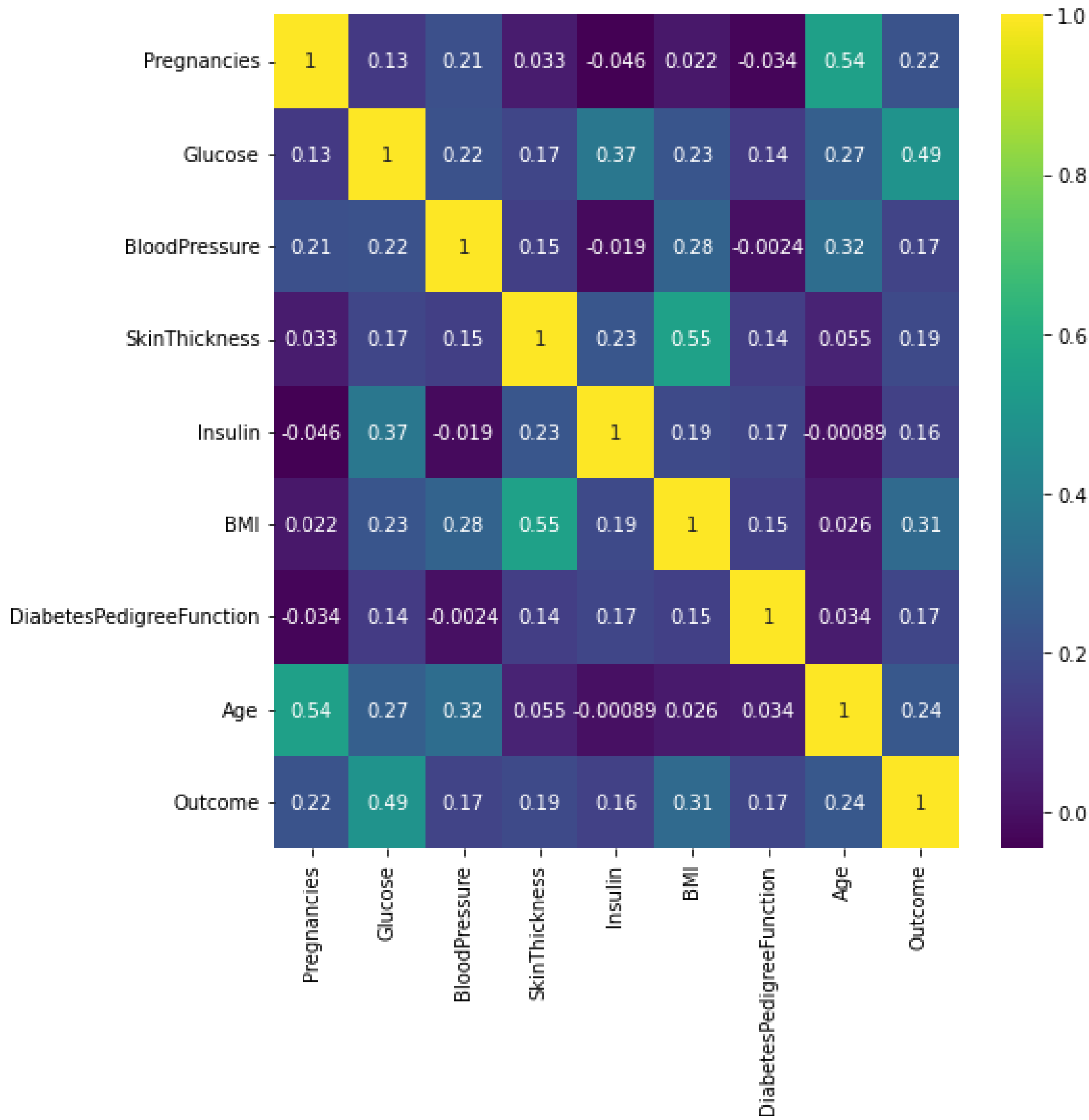
```python
sns.heatmap(data=Cor, vmin=-0.2, vmax=1.0, cmap='Blues')
```

[44]: <AxesSubplot:>




```
[47]: plt.subplots(figsize=(8,8))
      sns.heatmap(data=Cor,annot=True,cmap='viridis')   ### gives correlation value
```

```
[47]: <AxesSubplot:>
```



[48]:
```
#Data Modeling
```

[49]:
```
Model_Data = Data.copy()
```

[50]:
```
Model_Comparision_Report = pd.DataFrame(columns = ['Classifier', 'Accuracy',␣
↪'Precision', 'Specificity',
                                                   'Recall/Sensitivity', 'F1',␣
↪'ROC-AUC-Score', 'PR-AUC-Score'])
```

[51]:
```
#Data preprocessing
```

[52]:
```
#Selection of independent and target variables
```

[53]:
```
x = pd.DataFrame(Model_Data.iloc[:, [0, 1, 2, 3, 4, 5, 6, 7]])
y = Data.iloc[:, -1]
```

[54]:
```
#Splitting dataset into train and test set in the ratio of 80:20
```

[55]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.20,␣
 ↪random_state = 60)
xtrain.shape, xtest.shape, ytrain.shape, ytest.shape
```

[55]:
```
((614, 8), (154, 8), (614,), (154,))
```

[56]:
```
#Scaling of data
```

[57]:
```
scaler = StandardScaler()
scaled_xtrain = scaler.fit_transform(xtrain)
scaled_xtest = scaler.fit_transform(xtest)
```

[58]:
```
#Creation of ROC curve for tpr=fpr or no-skill classifier
```

[59]:
```
random_probs = [0 for i in range(len(ytest))]
fpr_ns, tpr_ns, thd = roc_curve(ytest, random_probs, pos_label=1)
```

[60]:
```
#No skill model, stratified random class predictions for Precision_Recall curve
```

[61]:
```
no_skill = len(y[y==1]) / len(y)
model = DummyClassifier(strategy='stratified', random_state=0)
model.fit(xtrain, ytrain)
yhat = model.predict_proba(xtest)
dummy_probs = yhat[:, 1]
precision, recall, _ = precision_recall_curve(ytest, dummy_probs)
ns_roc_score = metrics.roc_auc_score(ytest, dummy_probs)
ns_pr_score = metrics.auc(recall, precision)
print('ROC-AUC Score for no skill classifier = ', ns_roc_score)
print('Precision_Recal Score for no skill classifier = ', ns_pr_score)
```

```
ROC-AUC Score for no skill classifier =  0.5163715971825623
Precision_Recal Score for no skill classifier =  0.46609653962595143
```

[62]:
```
#KNN Modeling
```

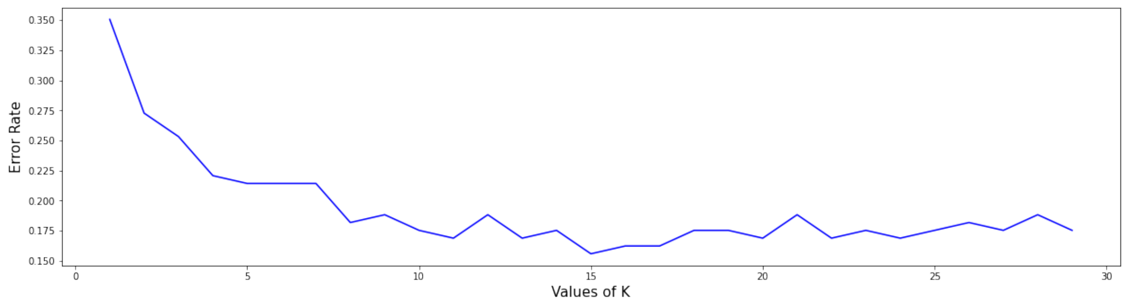
[63]:
```
#Elbow method to find optimum value of K.
```

[64]:
```
error_rate = []
for i in range(1,30):
    model = KNeighborsClassifier(n_neighbors=i)
    model.fit(scaled_xtrain, ytrain)
    pred_i = model.predict(scaled_xtest)
```

```
    error_rate.append(np.mean(pred_i != ytest))
```

[65]:
```
plt.figure(figsize=(20,5))
plt.plot(range(1,30), error_rate,color='blue')
plt.xlabel('Values of K', fontsize=15)
plt.ylabel('Error Rate', fontsize=15)
```

[65]: Text(0, 0.5, 'Error Rate')



[66]:
```
#Elbow method is showing K=15 gives the lowest error rate.
```

[67]:
```
knn_classifier = KNeighborsClassifier(n_neighbors = 15)
knn_model = knn_classifier.fit(scaled_xtrain, ytrain)
knn_model
```

[67]: KNeighborsClassifier(n_neighbors=15)

[68]:
```
ypredict = knn_classifier.predict(scaled_xtest)
prob_predict = knn_classifier.predict_proba(scaled_xtest)
```

[69]:
```
print('Training model score for KNN : ', knn_model.score(scaled_xtrain, ytrain))
print('Test model score for KNN     : ', knn_model.score(scaled_xtest, ytest))
```

```
Training model score for KNN :  0.7931596091205212
Test model score for KNN     :  0.8441558441558441
```

[70]:
```
train_matrix = confusion_matrix(ytrain, knn_classifier.predict(scaled_xtrain))
test_matrix = confusion_matrix(ytest, ypredict)
print('Confusion matrix for train data for KNN :')
print('-----------------------------------------')
print(train_matrix, '\n')
print('Confusion matrix for test data for KNN :')
print('---------------------------------------')
print(test_matrix)
```

```
Confusion matrix for train data for KNN :
-----------------------------------------
[[359  38]
 [ 89 128]]

Confusion matrix for test data for KNN :
---------------------------------------
[[93 10]
 [14 37]]
```

[71]:
```
print('Classification report for train data for KNN :')
print('-------------------------------------------------')
print(classification_report(ytrain, knn_classifier.predict(scaled_xtrain)))
print('Classification report for train data for KNN :')
print('------------------------------------------------')
print(classification_report(ytest, ypredict))
```

```
Classification report for train data for KNN :
------------------------------------------------
              precision    recall  f1-score   support

           0       0.80      0.90      0.85       397
           1       0.77      0.59      0.67       217

    accuracy                           0.79       614
   macro avg       0.79      0.75      0.76       614
weighted avg       0.79      0.79      0.79       614

Classification report for train data for KNN :
-----------------------------------------------
              precision    recall  f1-score   support

           0       0.87      0.90      0.89       103
           1       0.79      0.73      0.76        51

    accuracy                           0.84       154
   macro avg       0.83      0.81      0.82       154
weighted avg       0.84      0.84      0.84       154
```

[72]:
```
spec = round((test_matrix[0,0]/(test_matrix[0,0] + test_matrix[0,1]) * 100), 1)
spec
```

[72]: 90.3

[73]:
```
fpr_knn, tpr_knn, thresh = roc_curve(ytest, prob_predict[:,1], pos_label=1)
```

```
precision_knn, recall_knn, _ = precision_recall_curve(ytest, prob_predict[:,1],␣
↪pos_label=1)
auc_score = roc_auc_score(ytest, prob_predict[:,1])
pr_auc_score = auc(recall_knn, precision_knn)
auc_score =  round((auc_score * 100), 1)
pr_auc_score = round((pr_auc_score * 100), 1)
print('ROC_AUC_Score for KNN : ', auc_score)
print('Precision-Recall Score for KNN : ', pr_auc_score)
```

```
ROC_AUC_Score for KNN :  87.2
Precision-Recall Score for KNN :  77.3
```

[74]:
```
ac = round(((metrics.accuracy_score(ytest, ypredict))*100), 1)
f1 = round(((metrics.f1_score(ytest, ypredict))*100), 1)
re = round(((metrics.recall_score(ytest, ypredict))*100), 1)
pr = round(((metrics.precision_score(ytest, ypredict))*100), 1)
Model_Comparision_Report = Model_Comparision_Report.append({'Classifier':␣
↪'KNN', 'Accuracy': ac, 'Recall/Sensitivity': re,
                                                            'Specificity':␣
↪spec, 'Precision': pr, 'F1': f1,
                                                            'ROC-AUC-Score':␣
↪auc_score, 'PR-AUC-Score': pr_auc_score},
                                                             ignore_index=True)
```

[75]:
```
#SVM Modeling
```

[76]:
```
#Using Standardized data as it is distance based algorithm.
```

[77]:
```
#Finding best parameter
```

[78]:
```
param_grid = ({'C': [10, 100, 1000],
              'kernel': ['rbf', 'linear', 'poly'],
              'gamma': ['auto', 'scale']})
```

[79]:
```
cls_svm = svm.SVC()
grid_search = GridSearchCV(cls_svm, param_grid)
grid_search_model = grid_search.fit(scaled_xtrain, ytrain)
```

[80]:
```
print('Best Parameters : ', grid_search_model.best_params_, '\n')
print('Best Estimator  : ', grid_search_model.best_estimator_)
```

```
Best Parameters :  {'C': 1000, 'gamma': 'auto', 'kernel': 'linear'}

Best Estimator  :  SVC(C=1000, gamma='auto', kernel='linear')
```

[81]:
```
svm_classifier = svm.SVC(kernel = 'linear', gamma='auto', C=1000)
svm_model = svm_classifier.fit(scaled_xtrain, ytrain)
```

[82]:
```
ypredict = svm_model.predict(scaled_xtest)
prob_predict = svm_classifier.decision_function(scaled_xtest)
```

[83]:
```
print('Training model score for SVM : ', svm_model.score(scaled_xtrain, ytrain))
print('Test model score for SVM     : ', svm_model.score(scaled_xtest, ytest))
```

```
Training model score for SVM :  0.7736156351791531
Test model score for SVM     :  0.7727272727272727
```

[84]:
```
train_matrix = confusion_matrix(ytrain, svm_classifier.predict(scaled_xtrain))
test_matrix = confusion_matrix(ytest, ypredict)
print('Confusion matrix for train data for SVM :')
print('---------------------------------------')
print(train_matrix, '\n')
print('Confusion matrix for test data for SVM :')
print('---------------------------------------')
print(test_matrix)
```

```
Confusion matrix for train data for SVM :
---------------------------------------
[[352  45]
 [ 94 123]]

Confusion matrix for test data for SVM :
---------------------------------------
[[90 13]
 [22 29]]
```

[85]:
```
print('Classification report for train data for SVM :')
print('----------------------------------------------')
print(classification_report(ytrain, svm_classifier.predict(scaled_xtrain)))
print('Classification report for test data for SVM :')
print('----------------------------------------------')
print(classification_report(ytest, ypredict))
```

```
Classification report for train data for SVM :
----------------------------------------------
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       397
           1       0.73      0.57      0.64       217

    accuracy                           0.77       614
   macro avg       0.76      0.73      0.74       614
weighted avg       0.77      0.77      0.77       614

Classification report for test data for SVM :
----------------------------------------------
```

```
              precision    recall  f1-score   support

           0       0.80      0.87      0.84       103
           1       0.69      0.57      0.62        51

    accuracy                           0.77       154
   macro avg       0.75      0.72      0.73       154
weighted avg       0.77      0.77      0.77       154
```

[86]:
```
spec = round((test_matrix[0,0]/(test_matrix[0,0] + test_matrix[0,1]) * 100), 1)
spec
```

[86]:
```
87.4
```

[87]:
```
fpr_svm, tpr_svm, thresh = roc_curve(ytest, prob_predict, pos_label=1)
precision_svm, recall_svm, _ = precision_recall_curve(ytest, prob_predict,␣
 ↪pos_label=1)
auc_score = metrics.roc_auc_score(ytest, prob_predict)
pr_auc_score = metrics.auc(recall_svm, precision_svm)
auc_score =  round((auc_score * 100), 1)
pr_auc_score = round((pr_auc_score * 100), 1)
print('ROC_AUC_Score for SVM : ', auc_score)
print('Precision-Recall Score for SVM : ', pr_auc_score)
#prob_predict
```

```
ROC_AUC_Score for SVM :  83.7
Precision-Recall Score for SVM :  71.0
```

[88]:
```
ac = round(((metrics.accuracy_score(ytest, ypredict))*100), 1)
f1 = round(((metrics.f1_score(ytest, ypredict))*100), 1)
re = round(((metrics.recall_score(ytest, ypredict))*100), 1)
pr = round(((metrics.precision_score(ytest, ypredict))*100), 1)
Model_Comparision_Report = Model_Comparision_Report.append({'Classifier':␣
 ↪'SVM', 'Accuracy': ac, 'Recall/Sensitivity': re,
                                                            'Specificity':␣
 ↪spec, 'Precision': pr, 'F1': f1,
                                                            'ROC-AUC-Score':␣
 ↪auc_score, 'PR-AUC-Score': pr_auc_score},
                                                             ignore_index=True)
```

[89]:
```
#Naive Bayes Modeling
```

[90]:
```
#Using original data as the algorithm is not distance based
```

[91]:
```
nb_classifier = GaussianNB()
nb_model = nb_classifier.fit(xtrain, ytrain)
```

[92]:
```
ypredict = nb_classifier.predict(xtest)
prob_predict = nb_classifier.predict_proba(scaled_xtest)
```

```
/usr/local/lib/python3.7/site-packages/sklearn/base.py:451: UserWarning: X does
not have valid feature names, but GaussianNB was fitted with feature names
  "X does not have valid feature names, but"
```

[93]:
```
print('Training model score for Naive_Bayes : ', nb_model.score(xtrain, ytrain))
print('Test model score for Naive_Bayes     : ', nb_model.score(xtest, ytest))
```

```
Training model score for Naive_Bayes :  0.745928338762215
Test model score for Naive_Bayes     :  0.7662337662337663
```

[94]:
```
train_matrix = confusion_matrix(ytrain, nb_classifier.predict(xtrain))
test_matrix = confusion_matrix(ytest, ypredict)
print('Confusion matrix for train data for naive bayes :')
print('--------------------------------------------------')
print(train_matrix, '\n')
print('Confusion matrix for test data for naive bayes :')
print('------------------------------------------------')
print(test_matrix)
```

```
Confusion matrix for train data for naive bayes :
--------------------------------------------------
[[332  65]
 [ 91 126]]

Confusion matrix for test data for naive bayes :
------------------------------------------------
[[83 20]
 [16 35]]
```

[95]:
```
print('Classification report for train data for naive bayes :')
print('------------------------------------------------------')
print(classification_report(ytrain, nb_classifier.predict(xtrain)))
print('Classification report for test data for naive bayes :')
print('-------------------------------------------------------')
print(classification_report(ytest, ypredict))
```

```
Classification report for train data for naive bayes :
------------------------------------------------------
              precision    recall  f1-score   support

           0       0.78      0.84      0.81       397
           1       0.66      0.58      0.62       217

    accuracy                           0.75       614
   macro avg       0.72      0.71      0.71       614
```

```
weighted avg       0.74      0.75      0.74       614

Classification report for test data for naive bayes :
----------------------------------------------------
              precision    recall  f1-score   support

           0       0.84      0.81      0.82       103
           1       0.64      0.69      0.66        51

    accuracy                           0.77       154
   macro avg       0.74      0.75      0.74       154
weighted avg       0.77      0.77      0.77       154
```

[96]:
```
spec = round((test_matrix[0,0]/(test_matrix[0,0] + test_matrix[0,1]) * 100), 1)
spec
```

[96]:
```
80.6
```

[97]:
```
fpr_nb, tpr_nb, thresh = roc_curve(ytest, prob_predict[:,1], pos_label=1)
precision_nb, recall_nb, _ = precision_recall_curve(ytest, prob_predict[:,1],␣
 ↪pos_label=1)
auc_score = metrics.roc_auc_score(ytest, prob_predict[:,1])
pr_auc_score = metrics.auc(recall_nb, precision_nb)
auc_score =  round((auc_score * 100), 1)
pr_auc_score = round((pr_auc_score * 100), 1)
print('ROC_AUC_Score for Naive Bayes : ', auc_score)
print('Precision-Recall Score for Naive Bayes : ', pr_auc_score)
```

```
ROC_AUC_Score for Naive Bayes :  52.6
Precision-Recall Score for Naive Bayes :  40.8
```

[98]:
```
ac = round(((metrics.accuracy_score(ytest, ypredict))*100), 1)
f1 = round(((metrics.f1_score(ytest, ypredict))*100), 1)
re = round(((metrics.recall_score(ytest, ypredict))*100), 1)
pr = round(((metrics.precision_score(ytest, ypredict))*100), 1)
Model_Comparision_Report = Model_Comparision_Report.append({'Classifier':␣
 ↪'Naive Bayes', 'Accuracy': ac,
                                                            'Recall/
 ↪Sensitivity': re, 'Specificity': spec,
                                                            'Precision': pr,␣
 ↪'F1': f1, 'ROC-AUC-Score': auc_score,
                                                            'PR-AUC-Score':␣
 ↪pr_auc_score}, ignore_index=True)
```

[99]:
```
#Random Forest Modeling
```

[100]:
```
rf_classifier = RandomForestClassifier(n_estimators=150, max_depth=15,␣
↪max_features='log2', random_state=95)
rf_model = rf_classifier.fit(scaled_xtrain, ytrain)
```

[101]:
```
ypredict = rf_classifier.predict(scaled_xtest)
prob_predict = rf_classifier.predict_proba(scaled_xtest)
```

[102]:
```
print('Training model score for Random_Forest : ', rf_model.
↪score(scaled_xtrain, ytrain))
print('Test model score for Random_Forest     : ', rf_model.score(scaled_xtest,␣
↪ytest))
```

```
Training model score for Random_Forest :  1.0
Test model score for Random_Forest     :  0.7987012987012987
```

[103]:
```
train_matrix = confusion_matrix(ytrain, rf_classifier.predict(scaled_xtrain))
test_matrix = confusion_matrix(ytest, ypredict)
print('Confusion matrix for train data for random forest :')
print('---------------------------------------------------')
print(train_matrix, '\n')
print('Confusion matrix for test data for random forest :')
print('-------------------------------------------------')
print(test_matrix)
```

```
Confusion matrix for train data for random forest :
---------------------------------------------------
[[397   0]
 [  0 217]]

Confusion matrix for test data for random forest :
-------------------------------------------------
[[86 17]
 [14 37]]
```

[104]:
```
print('Classification report for train data for random forest :')
print('-------------------------------------------------------')
print(classification_report(ytrain, rf_classifier.predict(scaled_xtrain)))
print('Classification report for test data for random forest :')
print('--------------------------------------------------------')
print(classification_report(ytest, ypredict))
```

```
Classification report for train data for random forest :
-------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       397
           1       1.00      1.00      1.00       217
```

```
    accuracy                           1.00       614
   macro avg       1.00      1.00      1.00       614
weighted avg       1.00      1.00      1.00       614

Classification report for test data for random forest :
--------------------------------------------------------
              precision    recall  f1-score   support

           0       0.86      0.83      0.85       103
           1       0.69      0.73      0.70        51

    accuracy                           0.80       154
   macro avg       0.77      0.78      0.78       154
weighted avg       0.80      0.80      0.80       154
```

[105]:
```
spec = round((test_matrix[0,0]/(test_matrix[0,0] + test_matrix[0,1]) * 100), 1)
spec
```

[105]:
```
83.5
```

[106]:
```
fpr_rf, tpr_rf, thresh = roc_curve(ytest, prob_predict[:,1], pos_label=1)
precision_rf, recall_rf, _ = precision_recall_curve(ytest, prob_predict[:,1],␣
↪pos_label=1)
auc_score = metrics.roc_auc_score(ytest, prob_predict[:,1])
pr_auc_score = metrics.auc(recall_rf, precision_rf)
auc_score =  round((auc_score * 100), 1)
pr_auc_score = round((pr_auc_score * 100), 1)
print('ROC_AUC_Score for Random Forest : ', auc_score)
print('Precision-Recall Score for Random Forest : ', pr_auc_score)
```

```
ROC_AUC_Score for Random Forest :  83.9
Precision-Recall Score for Random Forest :  70.1
```

[107]:
```
ac = round(((metrics.accuracy_score(ytest, ypredict))*100), 1)
f1 = round(((metrics.f1_score(ytest, ypredict))*100), 1)
re = round(((metrics.recall_score(ytest, ypredict))*100), 1)
pr = round(((metrics.precision_score(ytest, ypredict))*100), 1)
Model_Comparision_Report = Model_Comparision_Report.append({'Classifier':␣
↪'Random Forest', 'Accuracy': ac,
                                                            'Recall/
↪Sensitivity': re, 'Specificity': spec,
                                                            'Precision': pr,␣
↪'F1': f1, 'ROC-AUC-Score': auc_score,
                                                            'PR-AUC-Score':␣
↪pr_auc_score}, ignore_index=True)
```

[108]:
```
#Logistic Regression
```

[109]:
```
lr_classifier = LogisticRegression()
lr_model = lr_classifier.fit(scaled_xtrain, ytrain)
```

[110]:
```
ypredict = lr_classifier.predict(scaled_xtest)
prob_predict = lr_classifier.predict_proba(scaled_xtest)
```

[111]:
```
print('Training model score for Logistic_Regression : ', lr_model.
↪score(scaled_xtrain, ytrain))
print('Test model score for Logistic_Regression     : ', lr_model.
↪score(scaled_xtest, ytest))
```

```
Training model score for Logistic_Regression :  0.7736156351791531
Test model score for Logistic_Regression     :  0.7727272727272727
```

[112]:
```
train_matrix = confusion_matrix(ytrain, lr_classifier.predict(scaled_xtrain))
test_matrix = confusion_matrix(ytest, ypredict)
print('Confusion matrix for train data for logistic regression :')
print('----------------------------------------------------------')
print(train_matrix, '\n')
print('Confusion matrix for test data for logistic regression :')
print('---------------------------------------------------------')
print(test_matrix)
```

```
Confusion matrix for train data for logistic regression :
----------------------------------------------------------
[[348  49]
 [ 90 127]]

Confusion matrix for test data for logistic regression :
---------------------------------------------------------
[[90 13]
 [22 29]]
```

[113]:
```
print('Classification report for train data for logistic regression :')
print('----------------------------------------------------------------')
print(classification_report(ytrain, lr_classifier.predict(scaled_xtrain)))
print('Classification report for test data for logistic regression :')
print('----------------------------------------------------------------')
print(classification_report(ytest, ypredict))
```

```
Classification report for train data for logistic regression :
----------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.79      0.88      0.83       397
           1       0.72      0.59      0.65       217
```

```
    accuracy                           0.77       614
   macro avg       0.76      0.73      0.74       614
weighted avg       0.77      0.77      0.77       614

Classification report for test data for logistic regression :
---------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.80      0.87      0.84       103
           1       0.69      0.57      0.62        51

    accuracy                           0.77       154
   macro avg       0.75      0.72      0.73       154
weighted avg       0.77      0.77      0.77       154
```

[114]:
```
spec = round((test_matrix[0,0]/(test_matrix[0,0] + test_matrix[0,1]) * 100), 1)
spec
```

[114]:
```
87.4
```

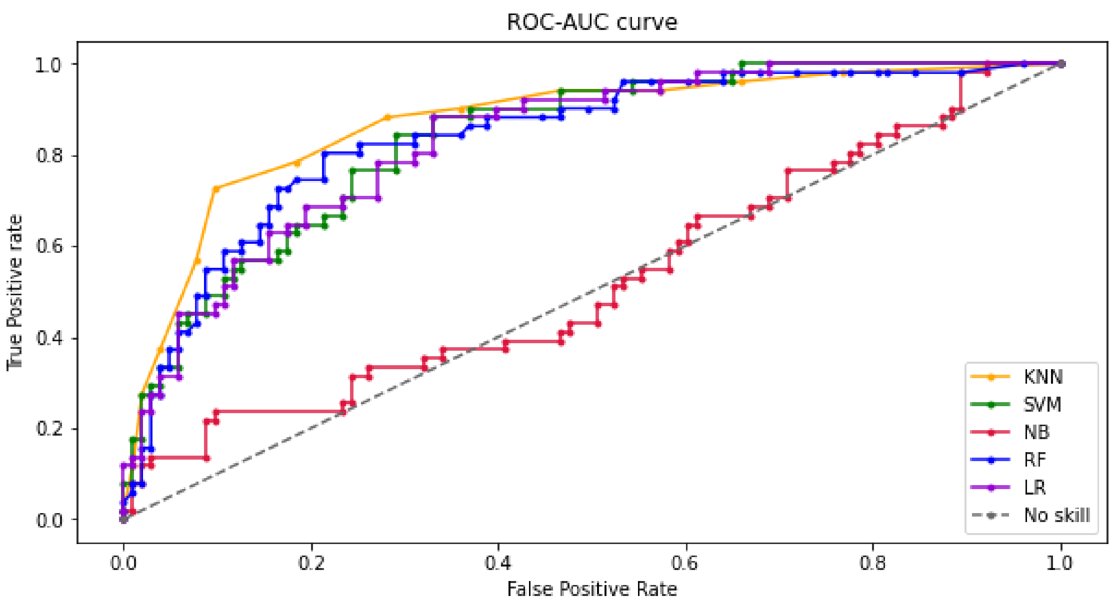
[115]:
```
fpr_lr, tpr_lr, thresh = roc_curve(ytest, prob_predict[:,1], pos_label=1)
precision_lr, recall_lr, _ = precision_recall_curve(ytest, prob_predict[:,1],␣
 ↪pos_label=1)
auc_score = metrics.roc_auc_score(ytest, prob_predict[:,1])
pr_auc_score = metrics.auc(recall_lr, precision_lr)
auc_score =  round((auc_score * 100), 1)
pr_auc_score = round((pr_auc_score * 100), 1)
print('ROC_AUC_Score for Logistic Regression : ', auc_score)
print('Precision-Recall Score for Logistic Regression : ', pr_auc_score)
```

```
ROC_AUC_Score for Logistic Regression :  83.3
Precision-Recall Score for Logistic Regression :  70.8
```

[116]:
```
ac = round(((metrics.accuracy_score(ytest, ypredict))*100), 1)
f1 = round(((metrics.f1_score(ytest, ypredict))*100), 1)
re = round(((metrics.recall_score(ytest, ypredict))*100), 1)
pr = round(((metrics.precision_score(ytest, ypredict))*100), 1)
Model_Comparision_Report = Model_Comparision_Report.append({'Classifier':␣
 ↪'Logistic Regression', 'Accuracy': ac,
                                                            'Recall/
 ↪Sensitivity': re, 'Specificity': spec,
                                                            'Precision': pr,␣
 ↪'F1': f1, 'ROC-AUC-Score': auc_score,
                                                             'PR-AUC-Score':␣
 ↪pr_auc_score}, ignore_index=True)
```

[117]:
```
#ROC - AUC Plot
```

[118]:
```
plt.figure(figsize=(10, 5))
plt.plot(fpr_knn, tpr_knn, color='orange', label='KNN', marker='.')
plt.plot(fpr_svm, tpr_svm, color='green', label='SVM', marker='.')
plt.plot(fpr_nb, tpr_nb, color='crimson', label='NB', marker='.')
plt.plot(fpr_rf, tpr_rf, color='blue', label='RF', marker='.')
plt.plot(fpr_lr, tpr_lr, color='darkviolet', label='LR', marker='.')
plt.plot(fpr_ns, tpr_ns, linestyle='--', color='dimgrey', label='No skill',␣
 ↪marker='.')

plt.title('ROC-AUC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')

plt.show()
```

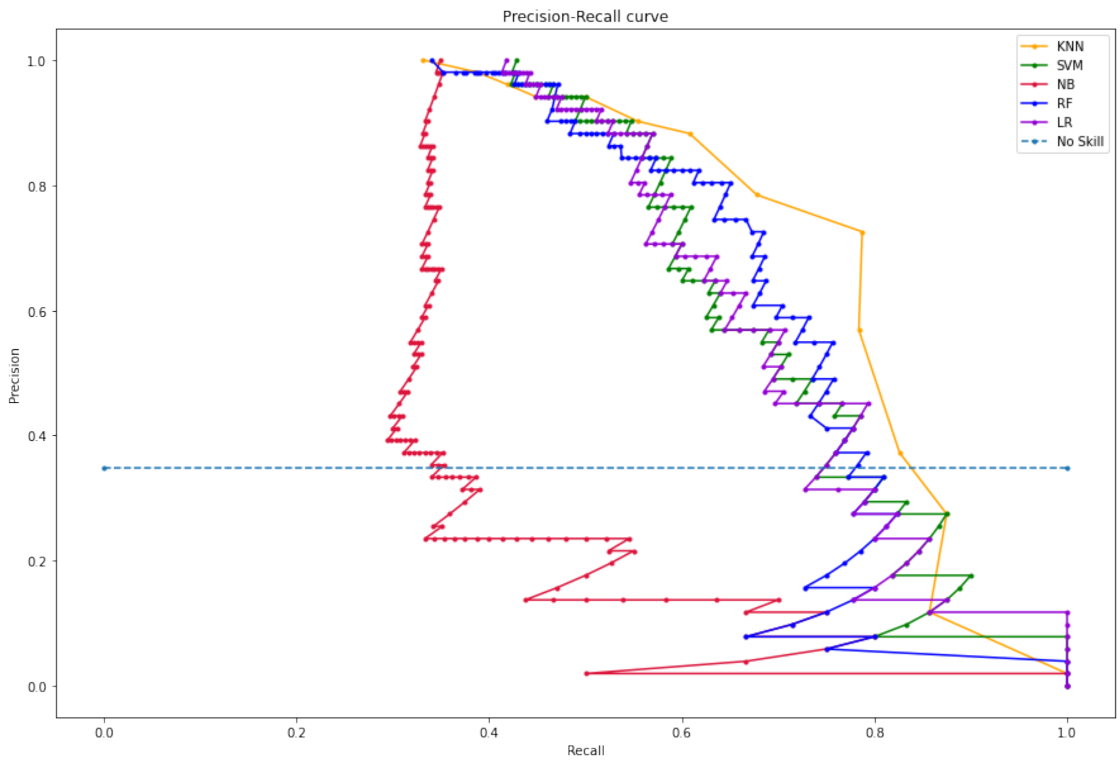


[119]:
```
#Precesion - Recall Curve
```

[120]:
```
#For imbalance data set Precesion-Recall Curve is used.
```

[121]:
```
plt.figure(figsize=(15, 10))
plt.plot(precision_knn, recall_knn, color='orange', label='KNN', marker='.')
plt.plot(precision_svm, recall_svm, color='green', label='SVM', marker='.')
plt.plot(precision_nb, recall_nb, color='crimson', label='NB', marker='.')
plt.plot(precision_rf, recall_rf, color='blue', label='RF', marker='.')
```

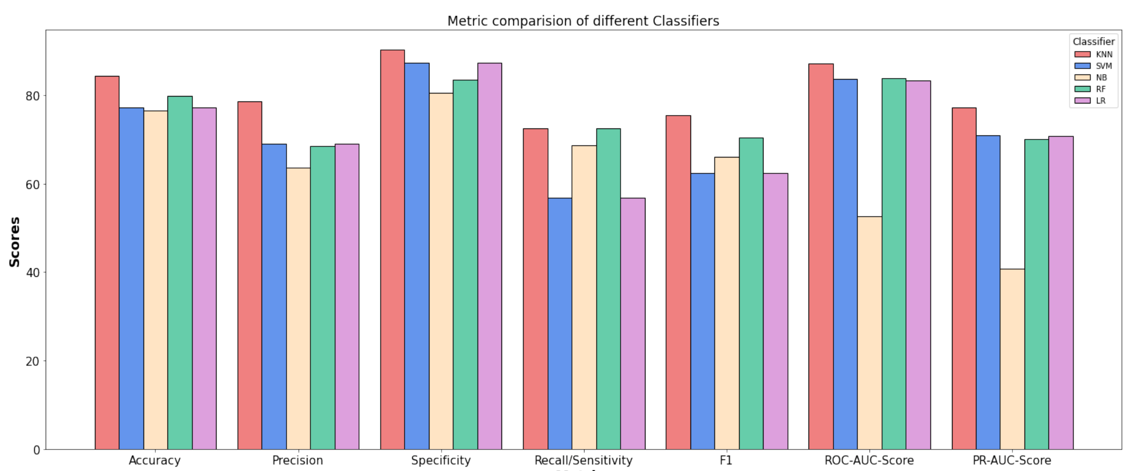
```
plt.plot(precision_lr, recall_lr, color='darkviolet', label='LR', marker='.')
plt.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill',␣
 ↪marker='.')

plt.title('Precision-Recall curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.legend(loc='best')

plt.show()
```



[122]:

```
plt.figure(figsize=(25, 10))
barWidth = 0.17

bars1 = Model_Comparision_Report.iloc[0, 1:8]
bars2 = Model_Comparision_Report.iloc[1, 1:8]
bars3 = Model_Comparision_Report.iloc[2, 1:8]
bars4 = Model_Comparision_Report.iloc[3, 1:8]
bars5 = Model_Comparision_Report.iloc[4, 1:8]

r1 = np.arange(len(bars1))
r2 = [x + barWidth for x in r1]
r3 = [x + barWidth for x in r2]
```

```
r4 = [x + barWidth for x in r3]
r5 = [x + barWidth for x in r4]

plt.bar(r1, bars1, color='lightcoral', width=barWidth, edgecolor='black',␣
 ↪label='KNN')
plt.bar(r2, bars2, color='cornflowerblue', width=barWidth, edgecolor='black',␣
 ↪label='SVM')
plt.bar(r3, bars3, color='bisque', width=barWidth, edgecolor='black',␣
 ↪label='NB')
plt.bar(r4, bars4, color='mediumaquamarine', width=barWidth, edgecolor='black',␣
 ↪label='RF')
plt.bar(r5, bars5, color='plum', width=barWidth, edgecolor='black', label='LR')

plt.title('Metric comparision of different Classifiers', fontsize=17)
plt.xlabel('Metrics', fontsize=18, fontweight='bold')
plt.ylabel('Scores', fontsize=18, fontweight='bold')
plt.xticks([r + 2*barWidth for r in range(len(bars1))], ['Accuracy',␣
 ↪'Precision', 'Specificity',
                                                         'Recall/Sensitivity',␣
 ↪'F1', 'ROC-AUC-Score', 'PR-AUC-Score'],
           fontsize=15)

plt.yticks(fontsize = 15)
plt.legend(title='Classifier', fontsize=10, title_fontsize=12, loc='best')
plt.show()
```



[123]:
```
#Classification report
```

[124]:
```
Model_Comparision_Report
```

[124]:

	Classifier	Accuracy	Precision	Specificity	Recall/Sensitivity
0	KNN	84.4	78.7	90.3	72.5
1	SVM	77.3	69.0	87.4	56.9
2	Naive Bayes	76.6	63.6	80.6	68.6
3	Random Forest	79.9	68.5	83.5	72.5
4	Logistic Regression	77.3	69.0	87.4	56.9

	F1	ROC-AUC-Score	PR-AUC-Score
0	75.5	87.2	77.3
1	62.4	83.7	71.0
2	66.0	52.6	40.8
3	70.5	83.9	70.1
4	62.4	83.3	70.8

[125]:
```
#From the above table it is clear that KNN is the best clustering algorithm for
 ↪the given dataset. It performs best in all the parameters. Its accuracy is
 ↪the highest.
```

[ ]: