1. Problem:

In [174]:

```
1
   import numpy as np
 2 import pandas as pd
 3 import sqlalchemy as sa
 4
 5 from statsmodels.stats.outliers influence import varia
   from sklearn.linear model import LogisticRegression
   from sklearn.model selection import train test split,
 7
 8
   from sklearn.metrics import accuracy score,f1 score,re
 9
   from sklearn.metrics import classification report, cor
11
   from sklearn.metrics import roc curve
12
   from sklearn.metrics import auc
13
   from imblearn.over sampling import SMOTE
14
   from imblearn.over sampling import RandomOverSampler
15
16
17
   from summarytools import dfSummary
18
   import seaborn as sns
   import matplotlib.pyplot as plt
19
   import plotly.express as px
20
   import pickle
21
22
23
   import warnings
   warnings.filterwarnings('ignore')
24
```

2. Data Gathering

```
In [ ]:
 1
 2
    This text was recognized by the built-in Ocrad engine
```

In [22]:

```
# connecting mySQL database to Jupyter Notebook for do
2 con = sa.create_engine("mysql+pymysql://root:@Localhos
 con
```

Out[22]:

```
Engine(mysql+pymysql://root:***@Localhost:3
306/diabetes db)
```

In [23]:

```
1 df = pd.read_sql_table('diabetes',con)
2 df
```

Out[23]:

	Glucose	BloodPressure	SkinThickness	Insulin	
0	148	50	35	0	;
1	85	66	29	0	2
2	183	64	0	0	1
3	150	66	23	94	2
4	150	40	35	168	2
	•••				
763	101	76	48	180	;
764	122	70	27	0	;
765	121	72	23	112	1
766	126	60	0	0	;
767	93	70	31	0	;

768 rows × 8 columns



```
In [24]:
```

```
1 df.head()
```

Out[24]:

	Glucose	BloodPressure	SkinThickness	Insulin	ВΝ
0	148	50	35	0	33.
1	85	66	29	0	26.
2	183	64	0	0	23.
3	150	66	23	94	28.
4	150	40	35	168	43.
4					•

3. Exploratory Data Analysis

```
In [25]:
```

```
1 df.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 768 entries, 0 to 767 Data columns (total 8 columns): # Column Non-Null Cou nt Dtype _____ ----0 Glucose 768 non-null int64 BloodPressure 768 non-null 1 int64 2 SkinThickness 768 non-null int64 Insulin 768 non-null 3 int64 4 BMI 768 non-null float64 DiabetesPedigreeFunction 768 non-null float64 6 Age 768 non-null int64 7 Outcome 768 non-null int64

dtypes: float64(2), int64(6)

memory usage: 48.1 KB

In [26]:

dfSummary(df) 1

Out[26]:

Data Frame Summary

Dimensions: 768 x 8

Duplicates: 0

No	Variable	Stats / Values	Freqs / (% of Valid)	Graph
1	Glucose [int64]	Mean (sd): 121.1 (31.8) min < med < max: 0.0 < 117.0 < 199.0 IQR (CV): 43.0 (3.8)	136 distinct values	. Allha
2	BloodPressure [int64]	Mean (sd): 69.1 (19.4) min < med < max: 0.0 < 72.0 < 122.0 IQR (CV): 18.0 (3.6)	47 distinct values	. عالد

No	Variable	Stats / Values	Freqs / (% of Valid)	Graph
3	SkinThickness [int64]	Mean (sd): 20.5 (16.0) min < med < 23.0 < 99.0 IQR (CV): 32.0 (1.3)	51 distinct values	lifls.
4	Insulin [int64]	Mean (sd): 79.8 (115.2) min < med < max: 0.0 < 30.5 < 846.0 IQR (CV): 127.2 (0.7)	186 distinct values	
5	BMI [float64]	Mean (sd): 32.0 (7.9) min < med < max: 0.0 < 32.0 < 67.1 IQR (CV): 9.3 (4.1)	248 distinct values	lli

```
Freas
                                Stats /
No
                      Variable
                                         / (% of
                                                Graph
                                Values
                                         Valid)
                                 Mean
                                  (sd):
                                   0.5
                                  (0.3)
                                 min <
                                 med <
                                           517
     DiabetesPedigreeFunction
                                  max:
                                        distinct
                       [float64]
                                  0.1 <
                                         values
                                  0.4 <
                                   2.4
                                   IQR
                                 (CV):
                                   0.4
                                  (1.4)
                                 Mean
                                  (sd):
                                  33.2
                                 (11.8)
                                 min <
                                 med <
                                            52
                          Age
                                  max:
  7
                                        distinct
                         [int64]
                                 21.0 <
                                         values
                                 29.0 <
                                  81.0
                                   IQR
                                 (CV):
                                  17.0
                                  (2.8)
In [27]:
                                 Mean
                                  (sd):
     \# x = df.drop('Outcome', 0@xis=1)
     # y = df['Outcome']
                                  (0.5)
  2
                                 min <
  3
                                 med <
     # x_train,x_test_split(x,
  4
                                        distinct
                         [int64]
                                  0.0 <
                                         values
                                  0.0 <
In [28]:
                                    1.0
                                   IQR
                                 (CV):
  1
     # x train
                                    1.0
                                  (0.7)
```

1. Glucose

```
In [29]:
 1 df['Glucose'].head()
Out[29]:
0
     148
1
      85
2
     183
3
     150
4
     150
Name: Glucose, dtype: int64
In [30]:
   df['Glucose'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: Glucose
Non-Null Count
                Dtype
-----
768 non-null
                int64
dtypes: int64(1)
memory usage: 6.1 KB
In [31]:
   df['Glucose'].isna().sum()
Out[31]:
0
```

In [32]:

```
1 df['Glucose'].value_counts()
```

Out[32]:

100	17
99	17
150	15
106	14
129	14
44	1
177	1
191	1
61	1

1

Name: Glucose, Length: 136, dtype: int64

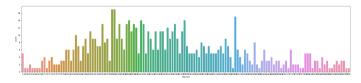
In [40]:

190

```
plt.figure(figsize= (30,6))
sns.countplot(x=df["Glucose"])
```

Out[40]:

```
<AxesSubplot:xlabel='Glucose', ylabel='coun
t'>
```

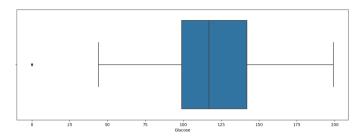


In [41]:

```
plt.figure(figsize=(15,5))
sns.boxplot(df['Glucose'])
```

Out[41]:

<AxesSubplot:xlabel='Glucose'>



2. BloodPressure

In [44]:

```
1 df['BloodPressure'].head()
```

Out[44]:

- 0 50
- 1 66
- 2 64
- 3 66
- 4 40

Name: BloodPressure, dtype: int64

```
In [45]:
 1 df['BloodPressure'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: BloodPressure
Non-Null Count Dtype
768 non-null
                int64
dtypes: int64(1)
memory usage: 6.1 KB
In [47]:
 1 df['BloodPressure'].isna().sum()
Out[47]:
0
```

```
In [48]:
```

1 df['BloodPressure'].value_counts()

Out[48]:

```
70
         57
74
         52
78
         45
68
         45
64
         43
72
         43
80
         40
76
         39
60
         37
0n [50]35
62
      plt3figure(figsize= (30,6))
      sns<sub>36</sub>ountplot(df["BloodPressure"])
88
Qut[50];3
90

$\frac{22}{2}\text{xesSubplot:xlabel='BloodPressure', ylabel} \frac{58}{86} \text{count'} \frac{21}{2}
92
           8
   [51]:7
65
85
      plt.figure(figsize= (15,5))
94
      sns.poxplot(df["BloodPressure"])
48<sup>2</sup>
96
Qut[51]:4
100
{AxesSubplot:xlabel='BloodPressure'>
```

```
102
        1
34 BloodPressure
38
49 [53]:1
114
Name df[1'StdpnTesisukme, sdt]vbeadi(n)t64
Out[53]:
0
     35
1
     29
2
      0
3
     23
4
     35
Name: SkinThickness, dtype: int64
In [54]:
 1 df['SkinThickness'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: SkinThickness
Non-Null Count Dtype
-----
768 non-null
                int64
dtypes: int64(1)
memory usage: 6.1 KB
In [56]:
   df['SkinThickness'].isna().sum()
Out[56]:
0
```

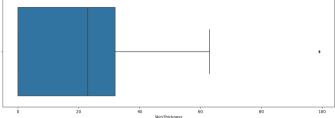
```
In [55]:
```

1 df['SkinThickness'].value_counts()

Out[55]:

```
0
       227
32
        31
30
        27
27
        23
23
        22
33
        20
28
        20
18
        20
31
        19
19
        18
39
        18
29
        17
40
        16
25 [57]16
26
plt figure(figsize= (30,6))
37<sup>2</sup> sns<sub>16</sub>countplot(df["SkinThickness"])
41
Qut[57]15
   xesSupplot:xlabel='SkinThickness', ylabel
4 4
46
          8
34
          8
12
         7
38
          7
11
          6
43
          6
16
          6
45
          6
14
          6
          5
44
10
          5
48
          4
47
          4
49
          3
```

```
50
ğη [58]:<sub>2</sub>
      plt.figure(figsize= (15,5))
sns.poxplot(df["SkinThickness"])
63
0ut[58]:1
₹ÁxesSub∱lot:xlabel='SkinThickness'>
```



4. Insulin

```
In [59]:
```

```
df['Insulin'].head()
```

Out[59]:

Name: Insulin, dtype: int64

```
In [60]:
 1 df['Insulin'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: Insulin
Non-Null Count
                Dtvpe
768 non-null
                 int64
dtypes: int64(1)
memory usage: 6.1 KB
In [61]:
 1 df['Insulin'].isna().sum()
Out[61]:
0
In [62]:
    df['Insulin'].value counts()
Out[62]:
0
       374
105
        11
130
         9
140
         9
120
         8
73
         1
171
         1
255
         1
52
         1
112
         1
Name: Insulin, Length: 186, dtype: int64
```

In [63]:

```
plt.figure(figsize= (30,6))
sns.countplot(df["Insulin"])
```

Out[63]:

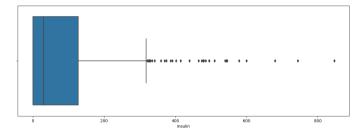
```
<AxesSubplot:xlabel='Insulin', ylabel='coun</pre>
t'>
```

In [64]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Insulin"])
```

Out[64]:

<AxesSubplot:xlabel='Insulin'>



5. BMI

```
In [65]:
 1 df['BMI'].head()
Out[65]:
0
     33.6
1
     26.6
2
     23.3
3
     28.1
4
     43.1
Name: BMI, dtype: float64
In [66]:
 1 df['BMI'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: BMI
Non-Null Count
                Dtype
-----
768 non-null
                float64
dtypes: float64(1)
memory usage: 6.1 KB
In [67]:
   df['BMI'].isna().sum()
Out[67]:
0
```

```
In [68]:
```

```
1 df['BMI'].value_counts()
```

Out[68]:

- 32.0 13
- 31.6 12
- 31.2 12
- 0.0 11
- 32.4 10
- 36.7 1
- 41.8 1
- 42.6 1
- 42.8 1
- 46.3 1

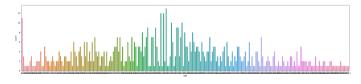
Name: BMI, Length: 248, dtype: int64

In [70]:

```
plt.figure(figsize= (30,6))
sns.countplot(df["BMI"])
```

Out[70]:

```
<AxesSubplot:xlabel='BMI', ylabel='count'>
```

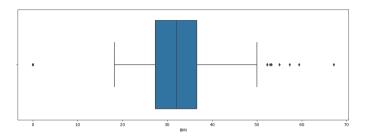


In [71]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["BMI"])
```

Out[71]:

<AxesSubplot:xlabel='BMI'>



6. DiabetesPedigreeFunction

In [72]:

```
1 df['DiabetesPedigreeFunction'].head()
```

Out[72]:

0 0.627

1 0.351

2 0.672

3 0.167

4 2.288

Name: DiabetesPedigreeFunction, dtype: floa

t64

```
In [73]:
 1 df['DiabetesPedigreeFunction'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: DiabetesPedigreeFunction
Non-Null Count Dtvpe
768 non-null
                float64
dtypes: float64(1)
memory usage: 6.1 KB
In [74]:
 1 df['DiabetesPedigreeFunction'].isna().sum()
Out[74]:
0
In [75]:
    df['DiabetesPedigreeFunction'].value counts()
Out[75]:
0.258
         6
0.254
         6
0.268
0.207
0.261
         5
1.353
         1
0.655
         1
0.092
         1
0.926
         1
0.171
         1
Name: DiabetesPedigreeFunction, Length: 51
7, dtype: int64
```

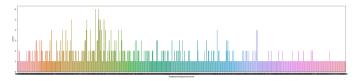
In [78]:

```
1 plt.figure(figsize= (30,6))
```

2 sns.countplot(df["DiabetesPedigreeFunction"])

Out[78]:

<AxesSubplot:xlabel='DiabetesPedigreeFuncti
on', ylabel='count'>



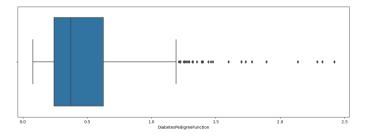
In [77]:

```
plt.figure(figsize= (15,5))
```

2 sns.boxplot(df["DiabetesPedigreeFunction"])

Out[77]:

<AxesSubplot:xlabel='DiabetesPedigreeFuncti
on'>



7. Age

```
In [80]:
 1 df['Age'].head()
Out[80]:
0
     50
1
     31
2
     52
3
     21
4
     33
Name: Age, dtype: int64
In [81]:
 1 df['Age'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: Age
Non-Null Count Dtype
768 non-null
                int64
dtypes: int64(1)
memory usage: 6.1 KB
In [82]:
   df['Age'].isna().sum()
Out[82]:
0
```

```
In [83]:
```

1 df['Age'].value_counts()

Out[83]:

```
22
       72
21
       63
25
       48
24
       46
23
       38
28
       35
26
       33
27
       32
29
       29
31
       24
41
       22
30
       21
37
       19
42
       18
3B [8517
38
     plts figure(figsize= (30,6))
36<sup>1</sup>
   sກໍ້ຮຸ້ countplot(df["Age"])
32^{2}
45
Qut[85]4
43
{AxesSupplot:xlabel='Age', ylabel='count'>
שכ
51
         8
44
         8
58
         7
47
         6
54
         6
49
         5
         5
48
57
         5
60
         5
66
         4
53
         4
62
         4
55
         4
63
         4
```

8. Outcome

```
In [89]:
    df['Outcome']
Out[89]:
0
        1
1
        0
2
        1
3
4
        1
763
764
765
766
        1
767
Name: Outcome, Length: 768, dtype: int64
```

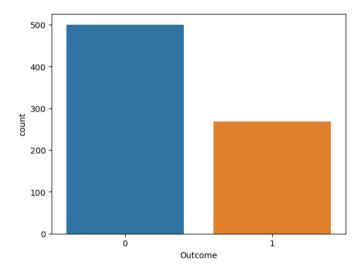
```
In [90]:
 1 df['Outcome'].info()
<class 'pandas.core.series.Series'>
RangeIndex: 768 entries, 0 to 767
Series name: Outcome
Non-Null Count Dtype
768 non-null
                int64
dtypes: int64(1)
memory usage: 6.1 KB
In [91]:
 1 df['Outcome'].isna().sum()
Out[91]:
0
```

In [94]:

sns.countplot(df['Outcome'])

Out[94]:

<AxesSubplot:xlabel='Outcome', ylabel='coun t'>

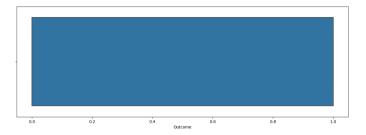


In [95]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Outcome"])
```

Out[95]:

<AxesSubplot:xlabel='Outcome'>



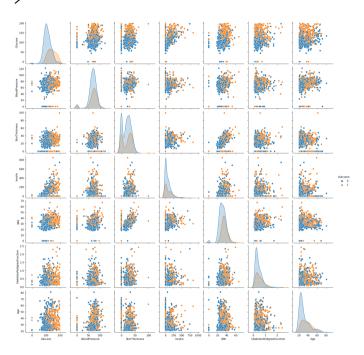
4. Feature Engineering

In [97]:

sns.pairplot(df, hue = 'Outcome') 1

Out[97]:

<seaborn.axisgrid.PairGrid at 0x198b6bdba30</pre>



4.1 zero value Imputation

```
In [113]:
```

```
num= df[df["SkinThickness"]==0]
num1= df[df["BloodPressure"]==0]
num2= df[df["Glucose"]==0]
num3= df[df["Insulin"]==0]
num4= df[df["BMI"]==0]
num.shape,num1.shape,num2.shape,num3.shape,num4.shape
```

Out[113]:

```
((227, 8), (35, 8), (5, 8), (374, 8), (11, 8))
```

In [114]:

In [115]:

```
1 df.isna().sum()
```

Out[115]:

dtype: int64

Glucose	5
BloodPressure	35
SkinThickness	227
Insulin	374
BMI	11
DiabetesPedigreeFunction	0
Age	0
Outcome	0

In [117]:

```
df[['Glucose', 'BloodPressure', 'BMI','Insulin','Skin
```

In [119]:

```
num= df[df["SkinThickness"]==0]
num1= df[df["BloodPressure"]==0]
num2= df[df["Glucose"]==0]
num3= df[df["Insulin"]==0]
num4= df[df["BMI"]==0]
num4= num1.shape,num2.shape,num3.shape,num4.shape
```

Out[119]:

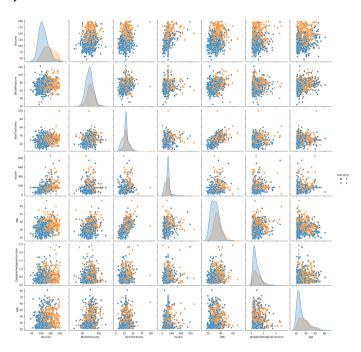
```
((0, 8), (0, 8), (0, 8), (0, 8), (0, 8))
```

In [132]:

1 sns.pairplot(df, hue = 'Outcome')

Out[132]:

<seaborn.axisgrid.PairGrid at 0x198bbefec40
>



4.2 Outlier Imputation

```
In [134]:
```

```
1 df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
     Column
                                Non-Null Cou
    Dtype
nt
 0
     Glucose
                                768 non-null
float64
                                768 non-null
 1
     BloodPressure
float64
     SkinThickness
                                768 non-null
float64
 3
     Insulin
                                768 non-null
float64
 4
     BMT
                                768 non-null
float64
     DiabetesPedigreeFunction 768 non-null
 5
float64
                                768 non-null
 6
     Age
int64
 7
     Outcome
                                768 non-null
int64
dtypes: float64(6), int64(2)
memory usage: 48.1 KB
```

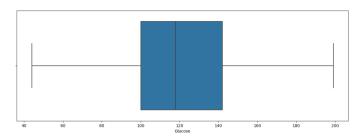
1.Glucose

In [136]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Glucose"])
```

Out[136]:

<AxesSubplot:xlabel='Glucose'>



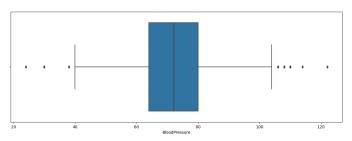
2. BloodPressure

In [137]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["BloodPressure"])
```

Out[137]:

<AxesSubplot:xlabel='BloodPressure'>



In [181]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['BloodPressure'].quantile(0.25)
   a2 = df['BloodPressure'].quantile(0.50)
   q3 = df['BloodPressure'].quantile(0.75)
   median = df['BloodPressure'].median()
 7
 8
   iqr = q3 - q1
9
10
   upper tail = q3 + 1.5 * iqr
   lower_tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
   print("Median :",median)
16
17
   print("upper tail :", upper tail)
18
   print("lower_tail :", lower_tail)
19
   a = df['BloodPressure'].loc[(df['BloodPressure'] > upr
20
   print("upper tail outliers:\n ", a)
21
   b= df['BloodPressure'].loc[(df['BloodPressure'] < lowe
22
   print("lower tail outliers: \n", b)
23
   df.loc[(df['BloodPressure']> upper_tail), 'BloodPressure'
24
   df.loc[(df['BloodPressure']< lower tail), 'BloodPressure']</pre>
25
26
   plt.figure(figsize=(15,3))
27
   sns.boxplot(df['BloodPressure'])
28
```

01:64.0

02: 72.18758526603001

03:80.0

Median: 72.18758526603001

upper_tail : 104.0 lower tail: 40.0 upper_tail outliers:

Series([], Name: BloodPressure, dtype: fl

oat64)

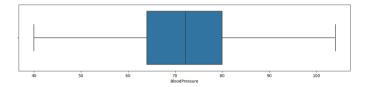
lower tail outliers:

18 30.0 125 30.0 597 24.0 599 38.0

Name: BloodPressure, dtype: float64

Out[181]:

<AxesSubplot:xlabel='BloodPressure'>



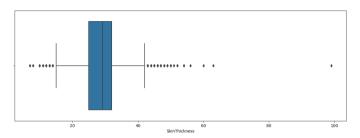
3. SkinThickness

In [138]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["SkinThickness"])
```

Out[138]:

<AxesSubplot:xlabel='SkinThickness'>



In [184]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['SkinThickness'].quantile(0.25)
   q2 = df['SkinThickness'].quantile(0.50)
   q3 = df['SkinThickness'].quantile(0.75)
   median = df['SkinThickness'].median()
 7
 8
   iqr = q3 - q1
9
10
   upper tail = q3 + 1.5 * iqr
   lower_tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
   print("Median :",median)
16
17
   print("upper tail :", upper tail)
18
   print("lower tail :", lower tail)
19
   a = df['SkinThickness'].loc[(df['SkinThickness'] > upr
20
   print("upper tail outliers:\n ", a)
21
   b= df['SkinThickness'].loc[(df['SkinThickness'] < lowe
22
   print("lower tail outliers: \n", b)
23
   df.loc[(df['SkinThickness']> upper_tail),'SkinThicknes
24
   df.loc[(df['SkinThickness']< lower_tail),'SkinThicknes</pre>
25
26
```

```
01:25.0
```

02: 29.153419593345657

03:32.0

Median: 29.153419593345657

upper tail: 42.5 lower tail: 14.5 upper tail outliers:

Series([], Name: SkinThickness, dtype: fl

oat64)

lower tail outliers:

Series([], Name: SkinThickness, dtype: flo

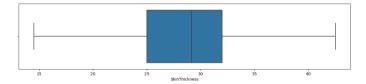
at64)

In [185]:

```
plt.figure(figsize=(15,3))
sns.boxplot(df['SkinThickness'])
```

Out[185]:

<AxesSubplot:xlabel='SkinThickness'>



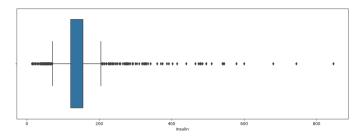
4. Insulin

In [139]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Insulin"])
```

Out[139]:

<AxesSubplot:xlabel='Insulin'>



In [187]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['Insulin'].quantile(0.25)
   a2 = df['Insulin'].quantile(0.50)
   q3 = df['Insulin'].quantile(0.75)
   median = df['Insulin'].median()
 7
 8
   iqr = q3 - q1
9
10
   upper tail = q3 + 1.5 * iqr
   lower tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
   print("Median :",median)
16
17
   print("upper tail :", upper tail)
18
   print("lower tail :", lower tail)
19
   a = df['Insulin'].loc[(df['Insulin'] > upper tail)]
20
   print("upper tail outliers:\n ", a)
21
   b= df['Insulin'].loc[(df['Insulin'] < lower tail)]</pre>
22
   print("lower tail outliers: \n", b)
23
   df.loc[(df['Insulin']> upper_tail), 'Insulin']= upper_t
24
   df.loc[(df['Insulin']< lower_tail), 'Insulin'] = lower_t</pre>
25
26
```

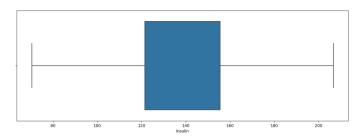
```
01:121.5
02: 155.5482233502538
03: 155.5482233502538
Median: 155.5482233502538
upper tail: 206.62055837563452
lower tail : 70.42766497461929
upper_tail outliers:
  8
        543.0
13
      846.0
16
      230.0
     235.0
20
31
      245.0
      . . .
707
      335.0
710 387.0
713 291.0
715 392.0
753
      510.0
Name: Insulin, Length: 82, dtype: float64
lower tail outliers:
 32
       54.0
40
      70.0
51
     36.0
52
      23.0
     38.0
68
      . . .
672
      49.0
680 45.0
711 22.0
747 57.0
760 16.0
Name: Insulin, Length: 82, dtype: float64
```

In [188]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Insulin"])
```

Out[188]:

<AxesSubplot:xlabel='Insulin'>



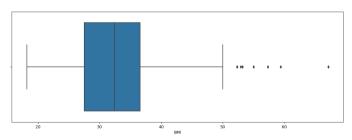
5. BMI

In [141]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["BMI"])
```

Out[141]:

<AxesSubplot:xlabel='BMI'>



In [189]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['BMI'].quantile(0.25)
4 q2 = df['BMI'].quantile(0.50)
   q3 = df['BMI'].quantile(0.75)
   median = df['BMI'].median()
 7
 8
   iqr = q3 - q1
9
10
   upper tail = q3 + 1.5 * iqr
   lower_tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
   print("Median :",median)
16
17
   print("upper tail :", upper tail)
18
   print("lower tail :", lower tail)
19
   a = df['BMI'].loc[(df['BMI'] > upper tail)]
20
   print("upper tail outliers:\n ", a)
21
   b= df['BMI'].loc[(df['BMI'] < lower tail)]</pre>
22
   print("lower tail outliers: \n", b)
23
   df.loc[(df['BMI']> upper tail), 'BMI']= upper tail
24
   df.loc[(df['BMI']< lower tail), 'BMI']= lower tail</pre>
25
26
```

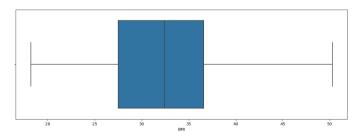
```
01:27.5
02:32.4
03:36.6
Median: 32.4
upper tail: 50.25
lower tail: 13.8499999999998
upper_tail outliers:
  120
        53.2
125
       55.0
177
      67.1
193
      52.3
193 52.3
247 52.3
303 52.9
445
     59.4
673 57.3
Name: BMI, dtype: float64
lower tail outliers:
 Series([], Name: BMI, dtype: float64)
```

In [190]:

```
plt.figure(figsize= (15,5))
2 sns.boxplot(df["BMI"])
```

Out[190]:

<AxesSubplot:xlabel='BMI'>



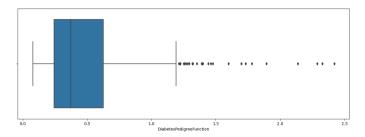
6. DiabetesPedigreeFunction

In [142]:

```
plt.figure(figsize= (15,5))
 sns.boxplot(df["DiabetesPedigreeFunction"])
```

Out[142]:

<AxesSubplot:xlabel='DiabetesPedigreeFuncti</pre> on'>



In [191]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['DiabetesPedigreeFunction'].quantile(0.25)
   q2 = df['DiabetesPedigreeFunction'].quantile(0.50)
   q3 = df['DiabetesPedigreeFunction'].quantile(0.75)
   median = df['DiabetesPedigreeFunction'].median()
 7
 8
    iqr = q3 - q1
 9
10
   upper tail = q3 + 1.5 * iqr
    lower_tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
    print("Median :",median)
16
17
    print("upper tail :", upper tail)
18
    print("lower tail :", lower tail)
19
   a = df['DiabetesPedigreeFunction'].loc[(df['DiabetesPe
20
    print("upper tail outliers:\n ", a)
21
    b= df['DiabetesPedigreeFunction'].loc[(df['DiabetesPedigreeFunction'].loc[(df['DiabetesPedigreeFunction'].loc]
22
    print("lower tail outliers: \n", b)
23
   df.loc[(df['DiabetesPedigreeFunction']> upper tail),'[
24
   df.loc[(df['DiabetesPedigreeFunction']< lower tail),'[</pre>
25
26
```

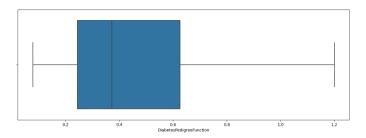
```
01: 0.24375
02 : 0.3725
03: 0.62625
Median : 0.3725
upper tail : 1.2
lower tail : -0.3299999999999996
upper_tail outliers:
        2.288
  4
12
      1.441
39
      1.390
45
      1.893
58
      1.781
100
      1.222
147
      1.400
187
      1.321
218
      1.224
      2.329
228
243
      1.318
      1.213
245
259
      1.353
292
308
      1.224
308
      1.391
330
      1.476
370
      2.137
371
      1.731
383
395
      1.268
395
      1.600
445 2.420
534
      1.251
593
      1.699
606
      1.258
      1.282
618
621
      1.698
622 1.461659 1.292
      1.394
661
Name: DiabetesPedigreeFunction, dtype: floa
t64
lower tail outliers:
 Series([], Name: DiabetesPedigreeFunction,
dtype: float64)
```

In [192]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["DiabetesPedigreeFunction"])
```

Out[192]:

<AxesSubplot:xlabel='DiabetesPedigreeFuncti
on'>



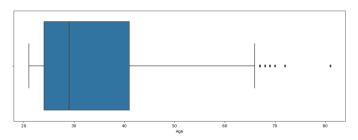
7. Age

In [143]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Age"])
```

Out[143]:

<AxesSubplot:xlabel='Age'>



In [193]:

```
1
   # Removing outliers with IOR method
 2
   q1 = df['Age'].quantile(0.25)
4 q2 = df['Age'].quantile(0.50)
   q3 = df['Age'].quantile(0.75)
   median = df['Age'].median()
 7
 8
   iqr = q3 - q1
9
10
   upper tail = q3 + 1.5 * iqr
   lower_tail = q1 - 1.5 * iqr
11
12
13
   print("Q1 :", q1)
   print("Q2 :", q2)
14
   print("Q3 :", q3)
15
   print("Median :",median)
16
17
   print("upper tail :", upper tail)
18
   print("lower tail :", lower tail)
19
   a = df['Age'].loc[(df['Age'] > upper tail)]
20
   print("upper tail outliers:\n ", a)
21
   b= df['Age'].loc[(df['Age'] < lower tail)]</pre>
22
   print("lower tail outliers: \n", b)
23
   df.loc[(df['Age']> upper tail), 'Age']= upper tail
24
   df.loc[(df['Age']< lower tail), 'Age']= lower tail</pre>
25
26
```

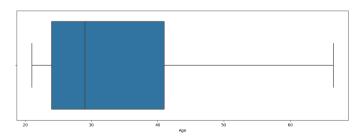
```
01:24.0
02:29.0
03:41.0
Median: 29.0
upper tail: 66.5
lower tail : -1.5
upper_tail outliers:
  123
        69
363
       67
453
      72
459
      81
489
      67
537 67
666
      70
674
      68
684
      69
Name: Age, dtype: int64
lower tail outliers:
Series([], Name: Age, dtype: int64)
```

In [194]:

```
plt.figure(figsize= (15,5))
sns.boxplot(df["Age"])
```

Out[194]:

<AxesSubplot:xlabel='Age'>



5. Feature Selection

5.1 Assumption

In [144]:

1 df.corr()

Out[144]:

	Glucose	BloodPressure	Sk
Glucose	1.000000	0.215938	
BloodPressure	0.215938	1.000000	
SkinThickness	0.192013	0.190815	
Insulin	0.395345	0.072356	
ВМІ	0.232153	0.280253	
DiabetesPedigreeFunction	0.134736	-0.003836	
Age	0.259389	0.319440	
Outcome	0.489601	0.162449	
4			•

In [145]:

plt.figure(figsize=(15,5))
sns.heatmap(df.corr(), annot=True)

Out[145]:

<AxesSubplot:>



5.2. No Multicolinearity

In [148]:

```
1 df1 = df.drop('Outcome', axis= 1)
  df1.head()
```

Out[148]:

	Glucose	BloodPressure	SkinThickness	Insulin
0	148.0	50.0	35.00000	155.548223
1	85.0	66.0	29.00000	155.548223
2	183.0	64.0	29.15342	155.548223
3	150.0	66.0	23.00000	94.000000
4	150.0	40.0	35.00000	168.000000
4				•

In [151]:

```
vif data = pd.DataFrame()
  vif data["feature"] = df1.columns
2
3
  # calculating VIF for each feature
  vif data["VIF"] = [variance inflation factor(df1.value
5
   for i in range(len(df1.columns))]
6
7
8
  print(vif data)
```

```
feature
                                   VIF
                    Glucose 21.347959
0
1
              BloodPressure 31.335650
2
              SkinThickness 17.360263
3
                    Insulin 5.232267
4
                             33.628317
                        BMI
  DiabetesPedigreeFunction 3.131796
5
6
                        Age
                             10.680453
```

6. Model Building

6.1. sampling

```
In [ ]:
  1
```

6.2. Splitting the data into Training data and Testing data

In [227]:

```
1 # regular Model
2 # independent variable(x)
3 x = df.drop('Outcome', axis= 1)
4 # dependent variable(v)
5 v = df['Outcome']
6 x_train, x_test, y_train, y_test = train_test_split(x)
```

In [228]:

```
1 print("shape of x train:",x train.shape)
2 print("shape of y train:",y train.shape)
3 print("shape of x_test:",x_test.shape)
4 print("shape of y test:",y test.shape)
```

```
shape of x train: (537, 7)
shape of y_train: (537,)
shape of x test: (231, 7)
shape of y test: (231,)
```

6.3 Model Training

Logistic Regression

```
In [229]:
```

```
logistic_model = LogisticRegression()
logistic_model.fit(x_train,y_train)
```

Out[229]:

LogisticRegression()

In [230]:

```
1 logistic_pred =logistic_model.predict(x_test)
2 logistic_pred[:5]
```

Out[230]:

```
array([0, 0, 1, 0, 0], dtype=int64)
```

6.4 Model Evaluation

Fucntion for test and train

In [231]:

```
1
   # Testing Data
   def testing evalution(model,x,y):
 2
       prediction = model.predict(x)
 3
 4
       cnf matrix = confusion matrix(y, prediction)
 5
       print("Confusion Matrix:\n", cnf matrix)
 6
 7
       print("*"*45)
 8
 9
       accuracy = accuracy_score(y, prediction)
       print('Accuracy \n',accuracy)
10
       print("*"*45)
11
12
13
       clf report= classification report(y, prediction)
       print("Classification Report\n", clf report)
14
```

In [232]:

```
# Training Data
 1
 2
   def training evalution(model,x,v):
 3
       prediction = model.predict(x)
 4
 5
       cnf matrix = confusion matrix(v, prediction)
       print("Confusion Matrix:\n", cnf matrix)
 6
7
       print("*"*45)
 8
 9
       accuracy = accuracy score(y, prediction)
       print('Accuracy \n',accuracy)
10
       print("*"*45)
11
12
       clf report= classification report(y, prediction)
13
       print("Classification Report\n", clf report)
14
```

regular Model

In [233]:

```
1 # Testing Data
2 testing_evalution(logistic_model,x_test,y_test)
```

```
Confusion Matrix:
```

```
[[135 15]
[ 35 4611
```

Accuracy

0.7835497835497836

Classification Report

	suppost.	precision	recall	f1-scor
е	support			
450	0	0.79	0.90	0.84
150	1	0.75	0.57	0.65
81				
221	accuracy			0.78
231				

macro avg 231

weighted avg 0.78 0.78 0.78

0.77

0.73

0.75

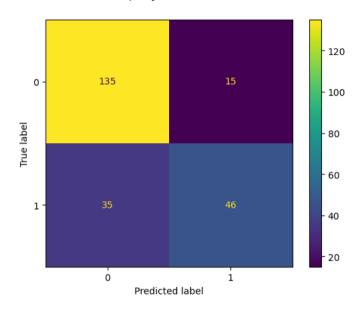
231

In [234]:

1 plot_confusion_matrix(logistic_model,x_test,y_test)

Out[234]:

<sklearn.metrics._plot.confusion_matrix.Con
fusionMatrixDisplay at 0x198c466ae50>



In [235]:

```
1 # Training Data
2 training_evalution(logistic_model,x_train,y_train)
```

```
Confusion Matrix:
```

```
[[309 41]
[ 84 103]]
```

Accuracy

0.7672253258845437

Classification Report

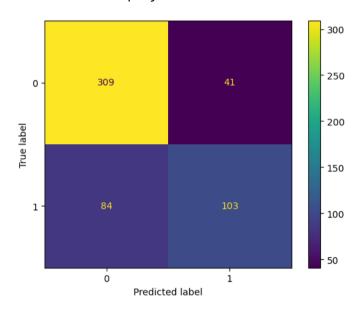
CIa	SSTITCACTOII	precision	recall	f1-scor
e	support	•		
250	0	0.79	0.88	0.83
350	1	0.72	0.55	0.62
187				
	accuracy			0.77
	macro avg	0.75	0.72	0.73
537 wei; 537	ghted avg	0.76	0.77	0.76
<i>J J J J</i>				

In [236]:

1 plot_confusion_matrix(logistic_model,x_train,y_train)

Out[236]:

<sklearn.metrics._plot.confusion_matrix.Con
fusionMatrixDisplay at 0x198c7033d60>



checking roc curve:

In [237]:

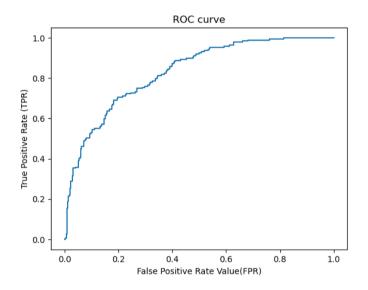
- 1 y_pred_proba = logistic_model.predict_proba(x_train)
 - 2 y_pred_proba[:,1]
 - 3 fpr,tpr,thresh = roc_curve(y_train,y_pred_proba[:,1])

In [238]:

```
plt.plot(fpr,tpr)
plt.xlabel("False Positive Rate Value(FPR)")
plt.ylabel("True Positive Rate (TPR)")
plt.title("ROC curve")
```

Out[238]:

Text(0.5, 1.0, 'ROC curve')



In [239]:

```
1 ### auc value
2 auc_value = auc(fpr,tpr)
3 auc_value
```

Out[239]:

0.8310313216195568

In [240]:

```
thresh = np.arange(0,1,0.1)
 1
   info df = pd.DataFrame()
 2
 3
 4
   for i in thresh:
        preds = (logistic_model.predict_proba(x_test)[:,1]
 5
 6
        thresh df=pd.DataFrame(data=[accuracy score(y test
 7
                               index=["Accuracy", "Recall", "
 8
        info df = pd.concat([info df,thresh df],axis=1)
 9
10
11
   info_df.columns=thresh
12
   info df
13
```

Out[240]:

	0.0	0.1	0.2	0.3	
Accuracy	0.350649	0.571429	0.718615	0.774892	0.78
Recall	1.000000	1.000000	0.913580	0.765432	0.66
Precision	0.350649	0.450000	0.560606	0.652632	0.71
F1-score	0.519231	0.620690	0.694836	0.704545	0.68
4					•

Hyper-Parameter Tunning:

In [241]:

```
weights = np.linspace(0,0.99,num=100)
1
2
  param_grid = {"C":np.arange(0.1,20), "penalty":['l1',"]
3
4
  gscv_model = GridSearchCV(logistic_model,param_grid)
5
  gscv model.fit(x train,y train)
```

Out[241]:

```
GridSearchCV(estimator=LogisticRegression
(),
              param_grid={'C': array([ 0.1,
1.1, 2.1, 3.1, 4.1, 5.1, 6.1, 7.1,
8.1, 9.1, 10.1,
       11.1, 12.1, 13.1, 14.1, 15.1, 16.1,
17.1, 18.1, 19.1]),
                            'class weight':
\{0: 0.0, 1: 1.0\}, \{0: 0.01, 1: 0.99\},
\{0: 0.02, 1: 0.98\},\
\{0: 0.03, 1: 0.97\},\
{0: 0.04, 1: 0.96},
\{0: 0.05, 1: 0.95\},\
{0: 0.06, 1: 0.94},
{0: 0.07, 1: 0.929999999999999999},
\{0: 0.08, 1: 0.92\},\
\{0: [0409; 1: 0.91\}, \{0:...: 0.9\},
61 gscv_model.best_params_
Pot[044]: 1: 0.88},
{'C': 13.1, 'class_weight': {0: 0.55, 1: 0. 4499999999999996}; 'penalty': 'l2'}
{0: 0.14, 1: 0.86},
{0: 0.15, 1: 0.85},
{0: 0.16, 1: 0.84},
{0: 0.17, 1: 0.83},
{0: 0.18, 1: 0.8200000000000001},
```

```
₹0:[0439; 1: 0.81}, {0: 0.2, 1: 0.8},
1 ht_logistic_model = LogisticRegression(penalty='12',C=
2 ht_logistic_model.fit(x_train,y_train)
{0: 0.22, 1: 0.78},
out[243]:
[0gi9t12Regre9s17] (C=6.1, class_weight={0:
0.5, 1: 0.5})
{0: 0.24, 1: 0.76},
\{0: 0.25, 1: 0.75\},\
\{0: 0.26, 1: 0.74\},\
\{0: 0.27, 1: 0.73\},\
\{0: 0.28, 1: 0.72\},\
{0: 0.29, 1: 0.71}, ...], 'penalty': ['l1',
'12']})
```

```
In [244]:
```

```
# testing data :
 2
    testing_evalution(ht_logistic_model,x_test,y_test)
Confusion Matrix:
```

[[134 16] [35 46]]

Accuracy

0.7792207792207793

231

Classification Report

e support	precision	recall	f1-scor
0 150	0.79	0.89	0.84
1 81	0.74	0.57	0.64
accuracy 231			0.78
macro avg	0.77	0.73	0.74
weighted avg	0.78	0.78	0.77

```
In [245]:
```

```
1
   # training data
 2
   training evalution(ht logistic model,x train,y train)
Confusion Matrix:
[[310 40]
[ 84 103]]
************
Accuracy
0.7690875232774674
**************
Classification Report
            precision recall f1-scor
e
   support
         0
               0.79
                       0.89
                                0.83
```

0.55

0.72

0.77

0.62

0.73

537 macro avg 537

weighted avg 0.76 0.77 0.76

0.75

537

6.3 Model Training aftter outlier removing

```
In [195]:
    logistic_model_OR = LogisticRegression()
    logistic model OR.fit(x train, y train)
Out[195]:
LogisticRegression()
In [196]:
    logistic_pred =logistic_model_OR.predict(x_test)
 2 logistic pred[:5]
Out[196]:
array([0, 0, 0, 1, 0], dtype=int64)
```

6.4 Model Evaluation

In [197]:

```
1 # Testing Data
2 testing_evalution(logistic_model_OR,x_test,y_test)
```

```
Confusion Matrix:
```

```
[[134 16]
[ 42 3911
```

Accuracy

0.7489177489177489

231

Classification Report

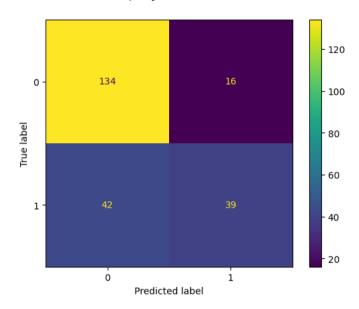
CIassilica	ICIOII	precision	recall	f1-scor
e suppor	'nτ			
150	0	0.76	0.89	0.82
150	1	0.71	0.48	0.57
81				
accura 231	су			0.75
macro a	ıvg	0.74	0.69	0.70
weighted a	ıvg	0.74	0.75	0.73

In [198]:

plot_confusion_matrix(logistic_model_OR,x_test,y_test)

Out[198]:

<sklearn.metrics._plot.confusion_matrix.Con</pre> fusionMatrixDisplay at 0x198c40af670>



In [199]:

```
1 # Training Data
2 training_evalution(logistic_model_OR,x_train,y_train)
```

```
Confusion Matrix:
```

[[309 41]

[70 117]]

Accuracy

0.7932960893854749

Classification Report

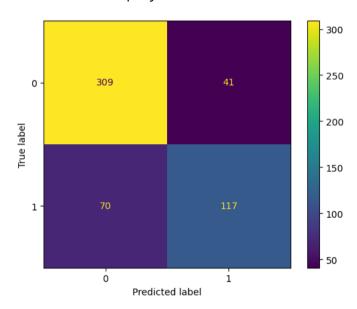
		precision	recall	f1-scor
е	support			
350	0	0.82	0.88	0.85
	1	0.74	0.63	0.68
187				
	accuracy			0.79
537	macro avg	0.78	0.75	0.76
537	ilaci o avg	0.78	0.75	0.70
wei 537	ghted avg	0.79	0.79	0.79

In [200]:

plot confusion matrix(logistic model OR,x train,y train

Out[200]:

<sklearn.metrics._plot.confusion_matrix.Con</pre> fusionMatrixDisplay at 0x198c432d6a0>



Pickle File

In [246]:

```
with open('Logistic model.pkl', 'wb') as f:
      pickle.dump(logistic model,f)
2
```

Single user Input Testing

In [247]:

```
1 x test.iloc[35]
```

Out[247]:

Glucose 141.000000 BloodPressure 72.375171 SkinThickness 29.153420 Insulin 155.548223 BMT 42,400000 DiabetesPedigreeFunction 0.205000 29.000000 Age

Name: 435, dtype: float64

In [248]:

```
Glucose = 141.000000
1
2 | BloodPressure = 72.375171
3 SkinThickness = 29.153420
4 Insulin = 155.548223
5 \mid BMI = 42.400000
6 DiabetesPedigreeFunction = 0.205000
7 \text{ Age} = 29.000000
```

In [249]:

```
1 test array = np.array([[Glucose, BloodPressure, SkinTl
2 test array
```

Out[249]:

```
array([[141. , 72.375171, 29.15342,
155.548223, 42.4
                         11)
        0.205 , 29.
```

```
In [250]:
```

```
prediction = logistic model.predict(test array)
prediction
```

Out[250]:

```
array([1], dtype=int64)
```

In [251]:

```
if prediction==1:
1
      print("Yes, You are Having Diabetics")
3 else:
      print("No, You are not Having Diabetics")
4
```

Yes, You are Having Diabetics

In []:

1