Diabetes Project

November 27 2023

DIABETIC PREDICTION USING CLASSIFICATION ALGORITHMS

In [48]:
```
#IMPORT LIBRARIES
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [49]:
```
df=pd.read_csv('diabetes (Task1).csv')
df
```

Out[49]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

In [50]:
```
 #generating the first five rows of the data
df.head()
```

Out[50]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [51]:
```
 #generating the last five rows of the data
df.tail()
```

Out[51]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

In [52]:
```
 #Checking the columns
df.describe()
```

Out[52]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

In [53]:

```
df.dtypes
```

Out[53]:

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

In [54]:

```
df.describe
```

Out[54]:

```
<bound method NDFrame.describe of      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
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     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
..                        ...  ...      ...
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]>
```

In [55]:

```
# Information about all the columns
df.info()
```

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

In [56]:

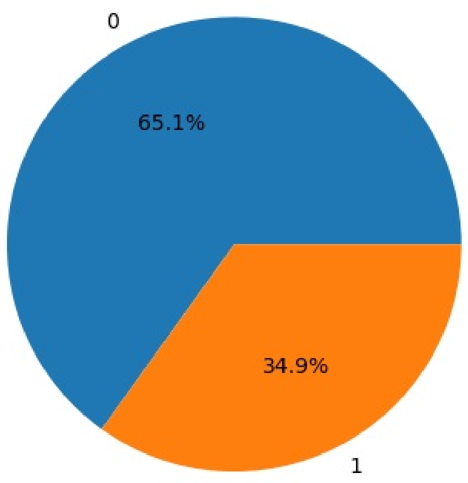
```
#To check null values
df.isna().sum()
```

Out[56]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [57]:
```python
#check the dataset is balanced or not
df["Outcome"].value_counts()
```

Out[57]:
```
Outcome
0    500
1    268
Name: count, dtype: int64
```

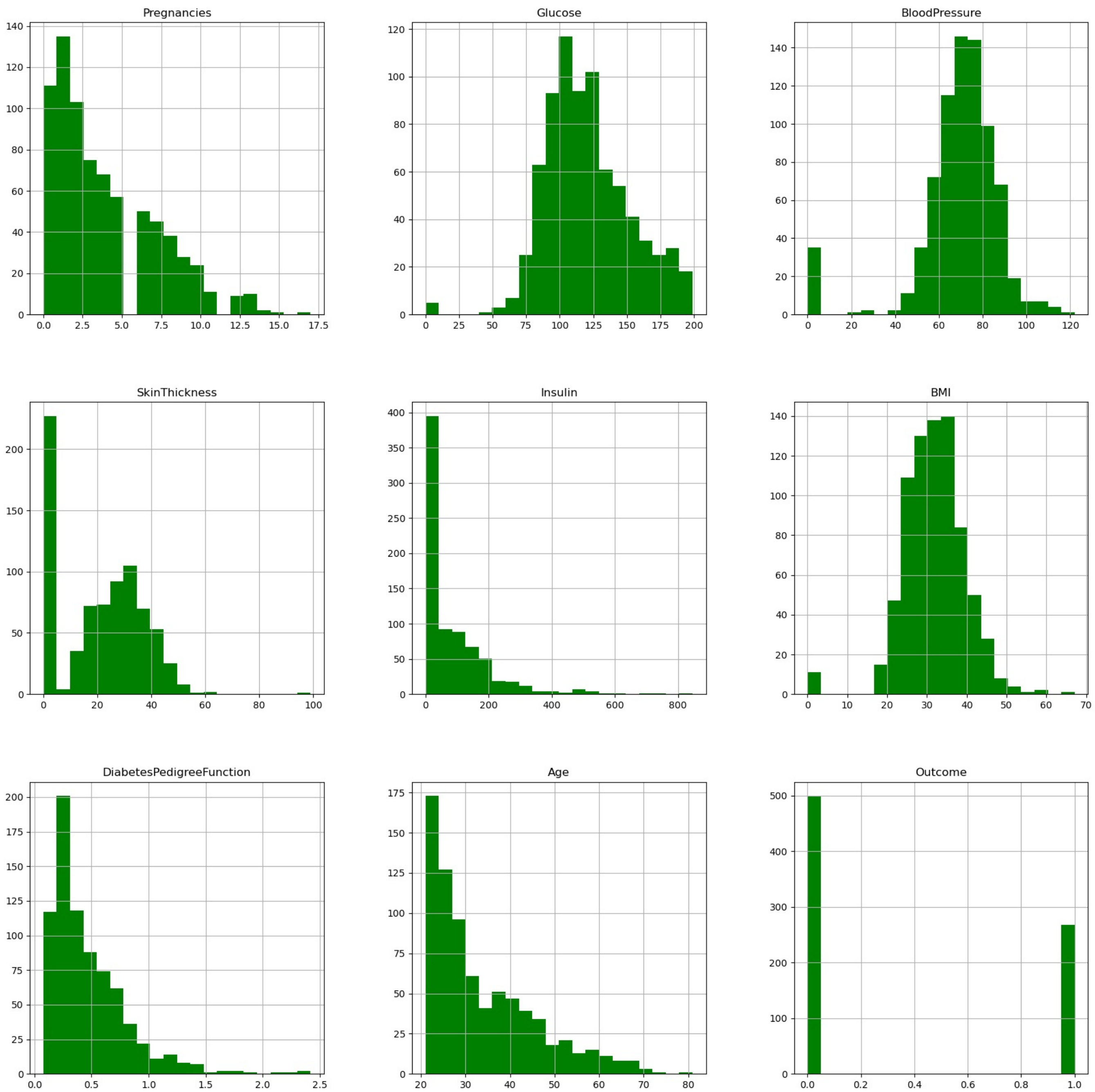
In [58]:
```python
#check the dataset is balanced or not using pie chart
plt.pie(df['Outcome'].value_counts(), labels=['0', '1'], autopct='%1.1f%%')
plt.show()
```



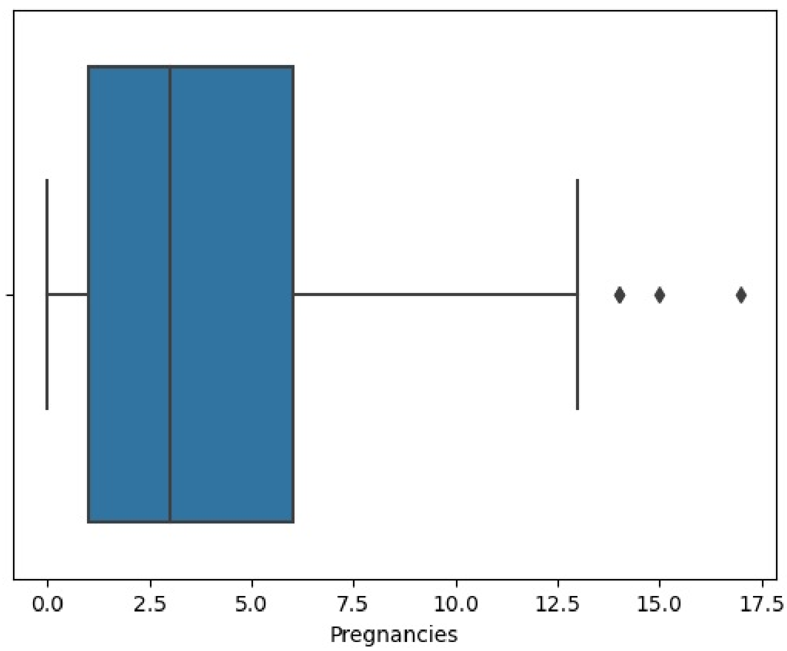
In [59]:
```python
sns.pairplot(df, hue = 'Outcome')
```

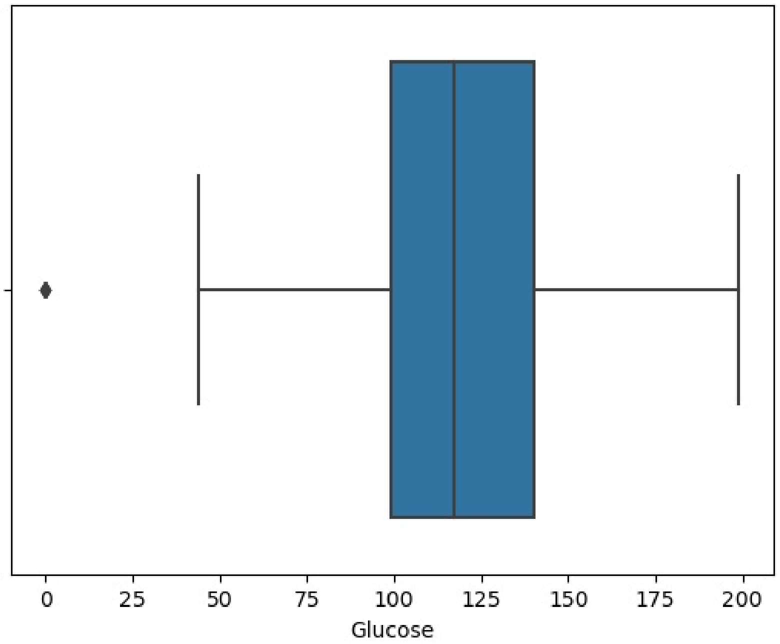
Out[59]:
```
<seaborn.axisgrid.PairGrid at 0x1a6fc84ae10>
```

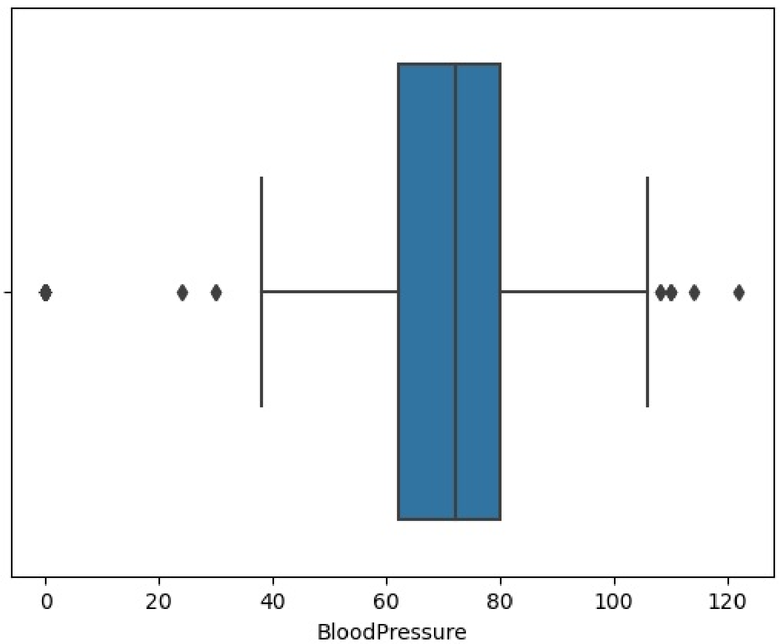
In [60]:
```
 df.hist(bins=20, figsize=(20, 20),color='green')
plt.show()
```

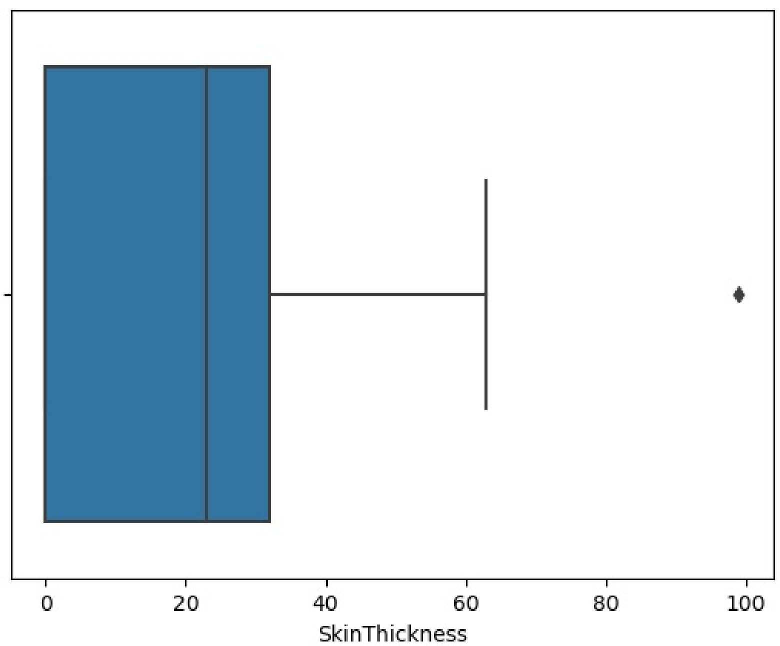


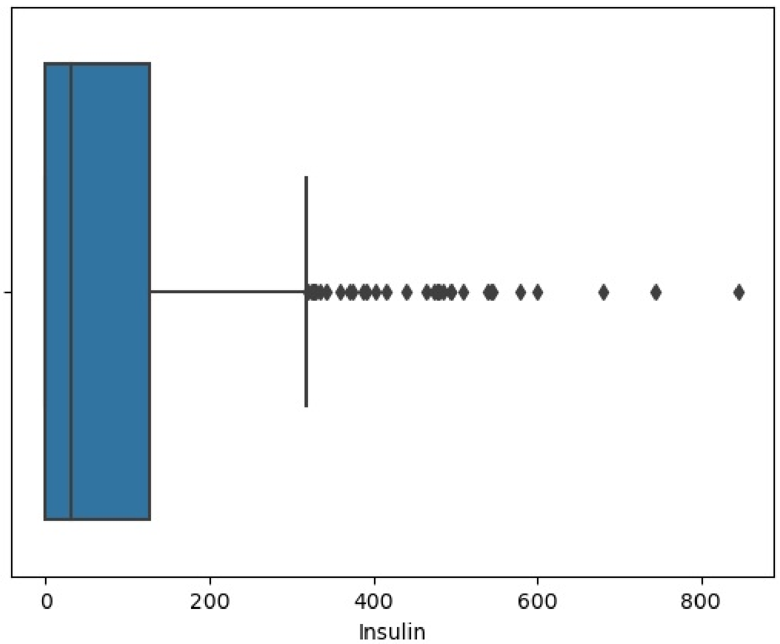
In [61]:
```
#To check the presence of outliers
for i in df:
  sns.boxplot(x=df[i])
  plt.show()
```

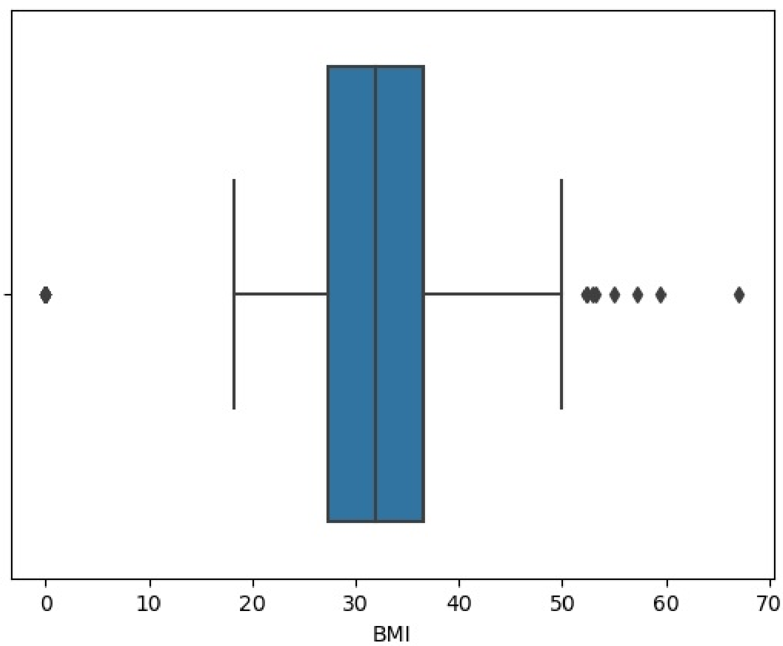


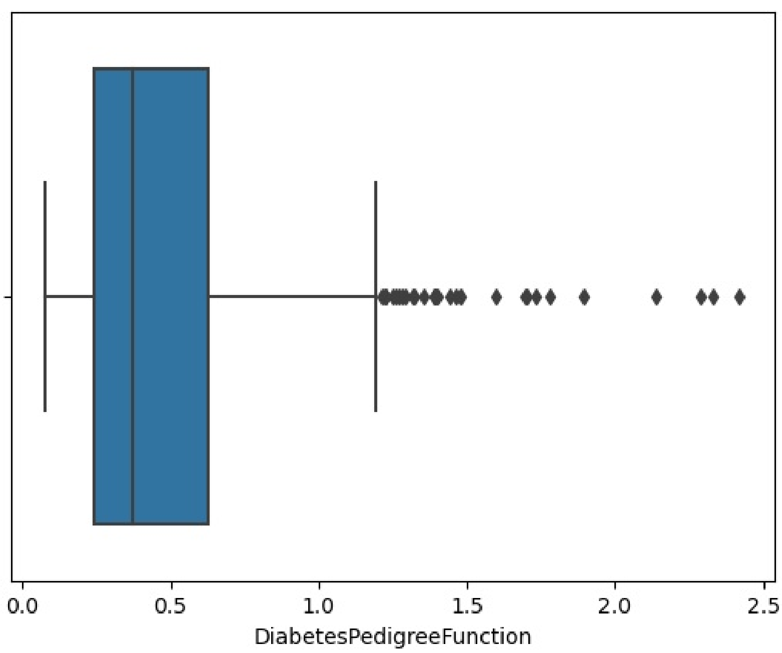

0
25
50
75
100
125
150
175
200
Glucose

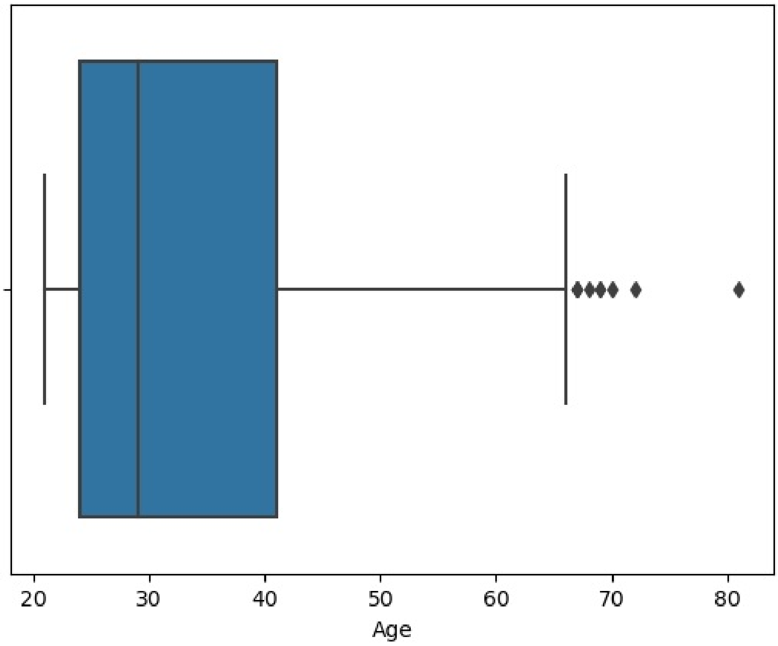

0
20
40
60
80
100
120
BloodPressure

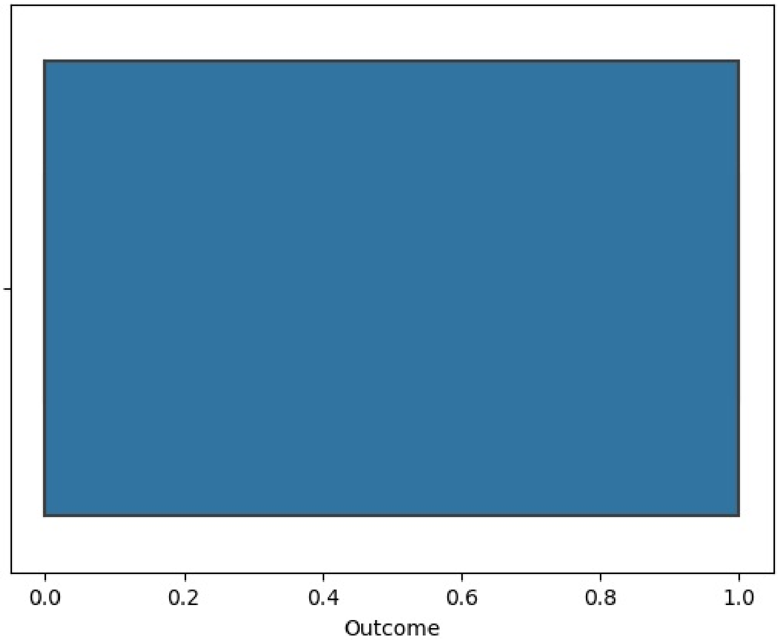

0
20
40
60
80
100
SkinThickness


0
200
400
600
800
Insulin


0
10
20
30
40
50
60
70
BMI

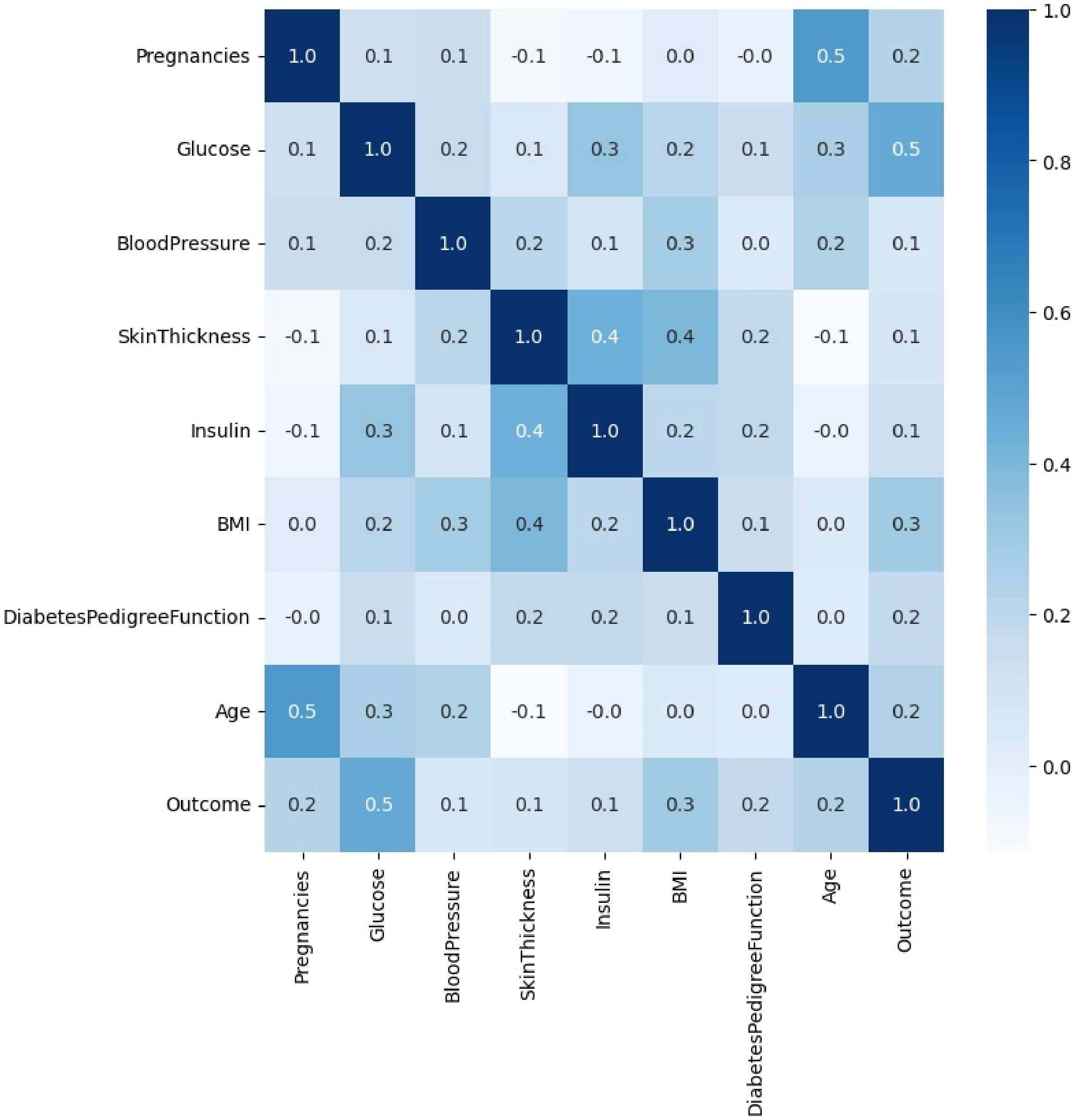

0.0
0.5
1.0
1.5
2.0
2.5
DiabetesPedigreeFunction





In [62]:
```
#Removing outliers using z_scores technique
from scipy import stats
z_score_threshold = 3.0
z_scores = np.abs(stats.zscore(df))
outlier_mask = (z_scores > z_score_threshold).any(axis=1)
df1 = df[~outlier_mask]
```

In [63]:
```
plt.figure(figsize=(8,8))
sns.heatmap(df.corr(), annot=True, cmap="Blues", fmt=".1f")
plt.show()
```



In [64]:
```
x=df.iloc[:,:-1].values
x
y=df.iloc[:,-1].values
y
```

Out[64]:
```
array([1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0,
       1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0,
       0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0,
       1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0],
      dtype=int64)
```

In [65]:
```python
#Split data into Training and testing data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=42)
```

In [66]:
```python
 x_train
```

Out[66]:
```
array([[  1.   ,  95.   ,  60.   , ...,  23.9  ,   0.26 ,  22.   ],
       [  5.   , 105.   ,  72.   , ...,  36.9  ,   0.159,  28.   ],
       [  0.   , 135.   ,  68.   , ...,  42.3  ,   0.365,  24.   ],
       ...,
       [ 10.   , 101.   ,  86.   , ...,  45.6  ,   1.136,  38.   ],
       [  0.   , 141.   ,   0.   , ...,  42.4  ,   0.205,  29.   ],
       [  0.   , 125.   ,  96.   , ...,  22.5  ,   0.262,  21.   ]])
```

In [67]:
```python
 x_test
```

Out[67]:
```
array([[6.00e+00, 9.80e+01, 5.80e+01, ..., 3.40e+01, 4.30e-01, 4.30e+01],
       [2.00e+00, 1.12e+02, 7.50e+01, ..., 3.57e+01, 1.48e-01, 2.10e+01],
       [2.00e+00, 1.08e+02, 6.40e+01, ..., 3.08e+01, 1.58e-01, 2.10e+01],
       ...,
       [0.00e+00, 1.27e+02, 8.00e+01, ..., 3.63e+01, 8.04e-01, 2.30e+01],
       [6.00e+00, 1.05e+02, 7.00e+01, ..., 3.08e+01, 1.22e-01, 3.70e+01],
       [5.00e+00, 7.70e+01, 8.20e+01, ..., 3.58e+01, 1.56e-01, 3.50e+01]])
```

In [68]:
```python
 y_test
```

Out[68]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0], dtype=int64)
```

In [69]:
```python
 from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(x_train)
x_train=scaler.fit_transform(x_train)
x_test=scaler.fit_transform(x_test)
```

MODEL CREATION USING CLASSIFICATION ALGORITHMS

k-Nearest Neighbors, NaiveBayes, SVM, Decision Tree Classifier, Random forest.

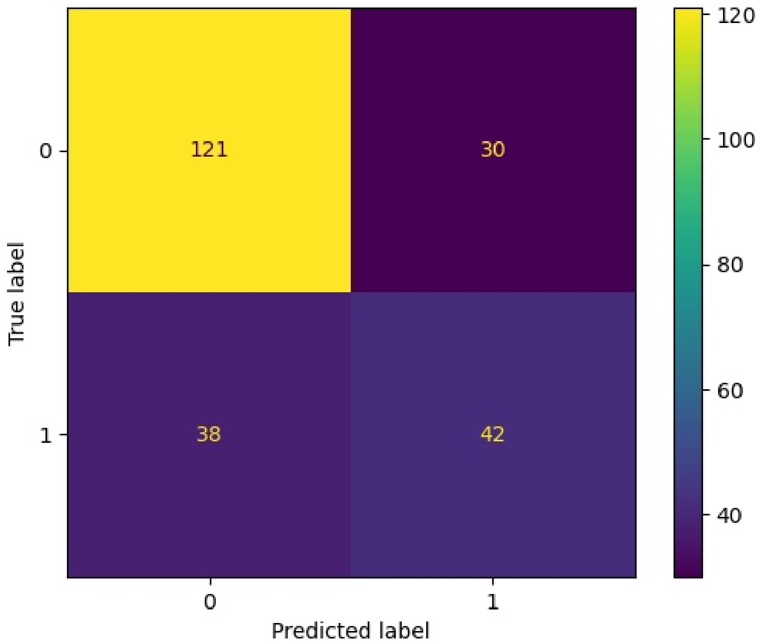
In [70]:
```python
 from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

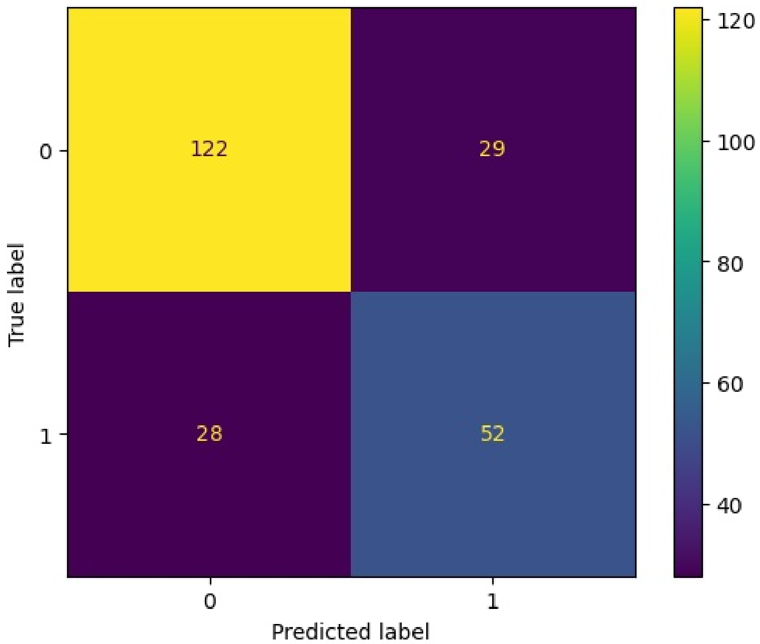
```python
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
knn=KNeighborsClassifier(n_neighbors=7)
nb=GaussianNB()
svm=SVC()
tree_model=DecisionTreeClassifier(criterion='entropy')
forest_model=RandomForestClassifier(n_estimators=100)
lst=[knn,nb,svm,tree_model,forest_model]
```

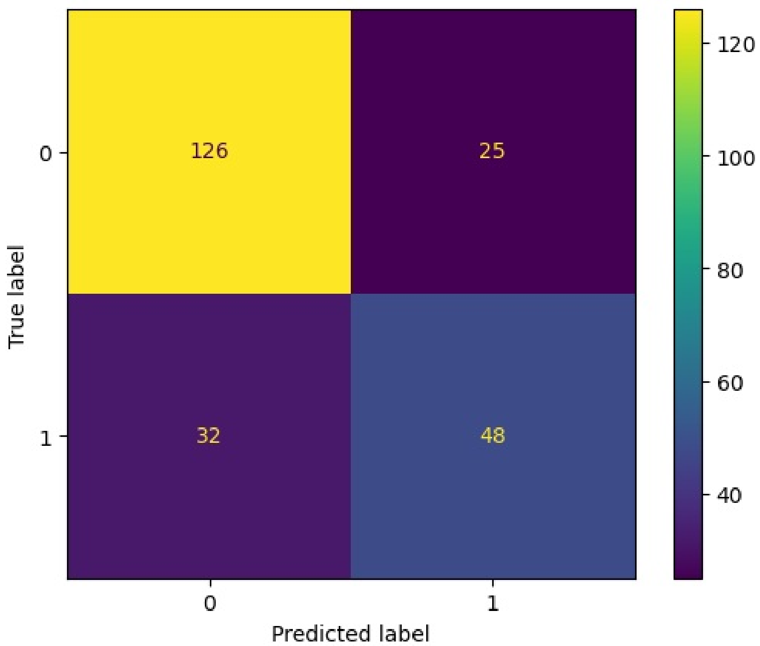
In [71]:

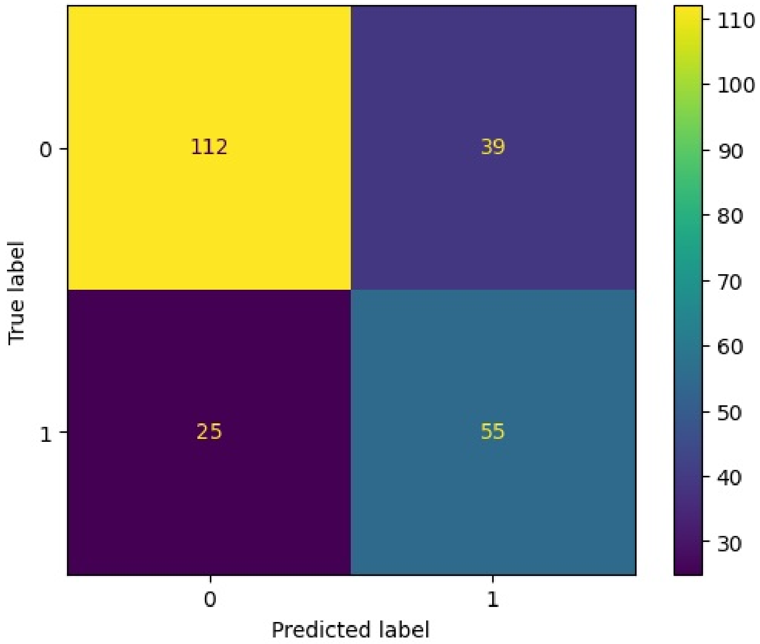
```python
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report,ConfusionMatrixDisplay
for i in lst:
 print(i)
 print('**********************************************************************')
 i.fit(x_train,y_train)
 y_pred=i.predict(x_test)
 print(confusion_matrix(y_test,y_pred))
 print(classification_report(y_test,y_pred))
 labels=[0,1]
 result=confusion_matrix(y_test,y_pred)
 cmd=ConfusionMatrixDisplay(result,display_labels=labels)
 cmd.plot()
```

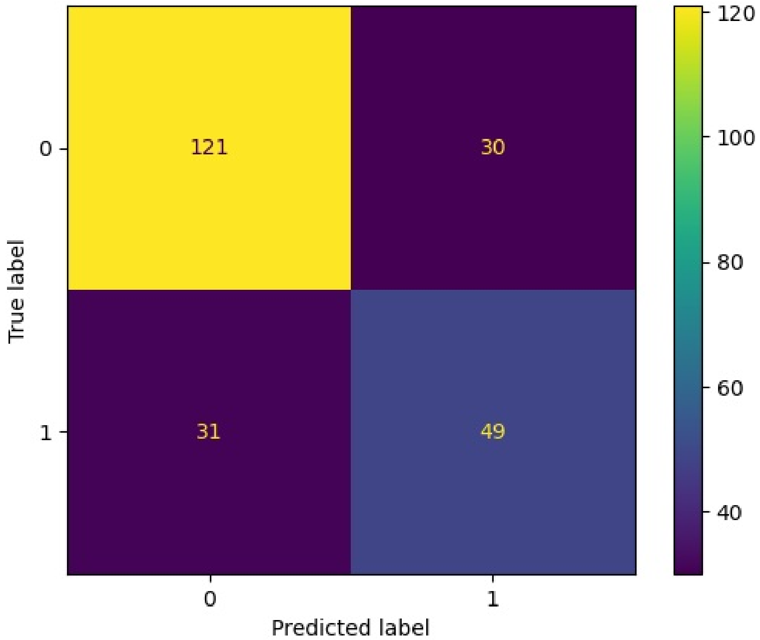
```
KNeighborsClassifier(n_neighbors=7)
**********************************************************************
[[121  30]
 [ 38  42]]
              precision    recall  f1-score   support

           0       0.76      0.80      0.78       151
           1       0.58      0.53      0.55        80

    accuracy                           0.71       231
   macro avg       0.67      0.66      0.67       231
weighted avg       0.70      0.71      0.70       231

GaussianNB()
**********************************************************************
[[122  29]
 [ 28  52]]
              precision    recall  f1-score   support

           0       0.81      0.81      0.81       151
           1       0.64      0.65      0.65        80

    accuracy                           0.75       231
   macro avg       0.73      0.73      0.73       231
weighted avg       0.75      0.75      0.75       231

SVC()
**********************************************************************
[[126  25]
 [ 32  48]]
              precision    recall  f1-score   support

           0       0.80      0.83      0.82       151
           1       0.66      0.60      0.63        80

    accuracy                           0.75       231
   macro avg       0.73      0.72      0.72       231
weighted avg       0.75      0.75      0.75       231

DecisionTreeClassifier(criterion='entropy')
**********************************************************************
[[112  39]
 [ 25  55]]
              precision    recall  f1-score   support

           0       0.82      0.74      0.78       151
           1       0.59      0.69      0.63        80

    accuracy                           0.72       231
   macro avg       0.70      0.71      0.70       231
weighted avg       0.74      0.72      0.73       231

RandomForestClassifier()
**********************************************************************
[[121  30]
 [ 31  49]]
              precision    recall  f1-score   support

           0       0.80      0.80      0.80       151
           1       0.62      0.61      0.62        80

    accuracy                           0.74       231
   macro avg       0.71      0.71      0.71       231
weighted avg       0.74      0.74      0.74       231
```


121
30
38
42
0
1
True label
0
1
Predicted label
120
100
80
60
40


122
29
28
52
0
1
True label
0
1
Predicted label
120
100
80
60
40


126
25
32
48
0
1
True label
0
1
Predicted label
120
100
80
60
40





In [72]:

```
data=nb.predict(scaler.transform([[5,200,90,52,290,32,0.300,27]]))
if data==0:
 print('diabetic patient')
else:
 print('not diabetic')
```

```
not diabetic
```

CONCLUSION

From above observation we concluded that in comparision to other models Naive Bayes works more better(accuracy-73%).