Breast Cancer Prediction

Breast Cancer Prediction is a classification task aimed at predicting the diagnosis of a breast mass as either malignant or benign. The dataset used for this prediction consists of features computed from a digitized image of a fine needle aspirate (FNA) of the breast mass. These features describe various characteristics of the cell nuclei present in the image.

The dataset contains the following information for each instance:

1. ID number: A unique identifier for each sample.
2. Diagnosis: The target variable indicating the diagnosis, where 'M' represents malignant and 'B' represents benign.

For each cell nucleus, ten real-valued features are computed, which are:

1. Radius: The mean distance from the center to points on the perimeter of the nucleus.
2. Texture: The standard deviation of gray-scale values in the nucleus.
3. Perimeter: The perimeter of the nucleus.
4. Area: The area of the nucleus.
5. Smoothness: A measure of local variation in radius lengths.
6. Compactness: Computed as the square of the perimeter divided by the area minus 1.0.
7. Concavity: Describes the severity of concave portions of the nucleus contour.
8. Concave points: Represents the number of concave portions of the nucleus contour.
9. Symmetry: Measures the symmetry of the nucleus.
10. Fractal dimension: This feature approximates the "coastline" of the nucleus, using the concept of fractal geometry.

These features provide quantitative measurements that can be used to assess the characteristics of cell nuclei and aid in distinguishing between malignant and benign breast masses. By training a machine learning model on this dataset, it is possible to develop a predictive model that can assist in the early detection and diagnosis of breast cancer.

```python
# importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# importing the dataset
df=pd.read_csv('data.csv')
df.head()
```

```
         id diagnosis  radius_mean  texture_mean  perimeter_mean
area_mean  \
0    842302         M        17.99         10.38          122.80
1001.0
1    842517         M        20.57         17.77          132.90
```

```
1326.0
2  84300903         M        19.69         21.25          130.00
1203.0
3  84348301         M        11.42         20.38           77.58
386.1
4  84358402         M        20.29         14.34          135.10
1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave
points_mean  \
0          0.11840           0.27760          0.3001
0.14710
1          0.08474           0.07864          0.0869
0.07017
2          0.10960           0.15990          0.1974
0.12790
3          0.14250           0.28390          0.2414
0.10520
4          0.10030           0.13280          0.1980
0.10430

   ...  texture_worst  perimeter_worst  area_worst
smoothness_worst  \
0  ...          17.33           184.60      2019.0            0.1622

1  ...          23.41           158.80      1956.0            0.1238

2  ...          25.53           152.50      1709.0            0.1444

3  ...          26.50            98.87       567.7            0.2098

4  ...          16.67           152.20      1575.0            0.1374


   compactness_worst  concavity_worst  concave points_worst
symmetry_worst  \
0             0.6656           0.7119                0.2654
0.4601
1             0.1866           0.2416                0.1860
0.2750
2             0.4245           0.4504                0.2430
0.3613
3             0.8663           0.6869                0.2575
0.6638
4             0.2050           0.4000                0.1625
0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
```

```
2                   0.08758         NaN
3                   0.17300         NaN
4                   0.07678         NaN

[5 rows x 33 columns]
```

Data Preprocessing

```
# dropping unnecessary columns
df.drop(['Unnamed: 32','id'],axis=1,inplace=True)

#checking for the missing values
df.isnull().sum()

diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64

#checking the data types of the columns
df.dtypes
```

```
diagnosis                   object
radius_mean                float64
texture_mean               float64
perimeter_mean             float64
area_mean                  float64
smoothness_mean            float64
compactness_mean           float64
concavity_mean             float64
concave points_mean        float64
symmetry_mean              float64
fractal_dimension_mean     float64
radius_se                  float64
texture_se                 float64
perimeter_se               float64
area_se                    float64
smoothness_se              float64
compactness_se             float64
concavity_se               float64
concave points_se          float64
symmetry_se                float64
fractal_dimension_se       float64
radius_worst               float64
texture_worst              float64
perimeter_worst            float64
area_worst                 float64
smoothness_worst           float64
compactness_worst          float64
concavity_worst            float64
concave points_worst       float64
symmetry_worst             float64
fractal_dimension_worst    float64
dtype: object

# checking the data description
df.describe()

       radius_mean  texture_mean  perimeter_mean    area_mean  \
count   569.000000    569.000000      569.000000   569.000000   
mean     14.127292     19.289649       91.969033   654.889104   
std       3.524049      4.301036       24.298981   351.914129   
min       6.981000      9.710000       43.790000   143.500000   
25%      11.700000     16.170000       75.170000   420.300000   
50%      13.370000     18.840000       86.240000   551.100000   
75%      15.780000     21.800000      104.100000   782.700000   
max      28.110000     39.280000      188.500000  2501.000000   

       smoothness_mean  compactness_mean  concavity_mean  concave 
points_mean  \
count       569.000000        569.000000      569.000000   
569.000000   
```

```
mean           0.096360          0.104341        0.088799
0.048919
std            0.014064          0.052813        0.079720
0.038803
min            0.052630          0.019380        0.000000
0.000000
25%            0.086370          0.064920        0.029560
0.020310
50%            0.095870          0.092630        0.061540
0.033500
75%            0.105300          0.130400        0.130700
0.074000
max            0.163400          0.345400        0.426800
0.201200

       symmetry_mean  fractal_dimension_mean  ...  radius_worst  \
count     569.000000              569.000000  ...    569.000000
mean        0.181162                0.062798  ...     16.269190
std         0.027414                0.007060  ...      4.833242
min         0.106000                0.049960  ...      7.930000
25%         0.161900                0.057700  ...     13.010000
50%         0.179200                0.061540  ...     14.970000
75%         0.195700                0.066120  ...     18.790000
max         0.304000                0.097440  ...     36.040000

       texture_worst  perimeter_worst   area_worst
smoothness_worst  \
count     569.000000       569.000000   569.000000        569.000000

mean       25.677223       107.261213   880.583128          0.132369

std         6.146258        33.602542   569.356993          0.022832

min        12.020000        50.410000   185.200000          0.071170

25%        21.080000        84.110000   515.300000          0.116600

50%        25.410000        97.660000   686.500000          0.131300

75%        29.720000       125.400000  1084.000000          0.146000

max        49.540000       251.200000  4254.000000          0.222600


       compactness_worst  concavity_worst  concave points_worst  \
count         569.000000       569.000000            569.000000
mean            0.254265         0.272188              0.114606
std             0.157336         0.208624              0.065732
min             0.027290         0.000000              0.000000
25%             0.147200         0.114500              0.064930
```

```
50%               0.211900         0.226700                0.099930
75%               0.339100         0.382900                0.161400
max               1.058000         1.252000                0.291000

       symmetry_worst  fractal_dimension_worst
count      569.000000               569.000000
mean         0.290076                 0.083946
std          0.061867                 0.018061
min          0.156500                 0.055040
25%          0.250400                 0.071460
50%          0.282200                 0.080040
75%          0.317900                 0.092080
max          0.663800                 0.207500

[8 rows x 30 columns]
```

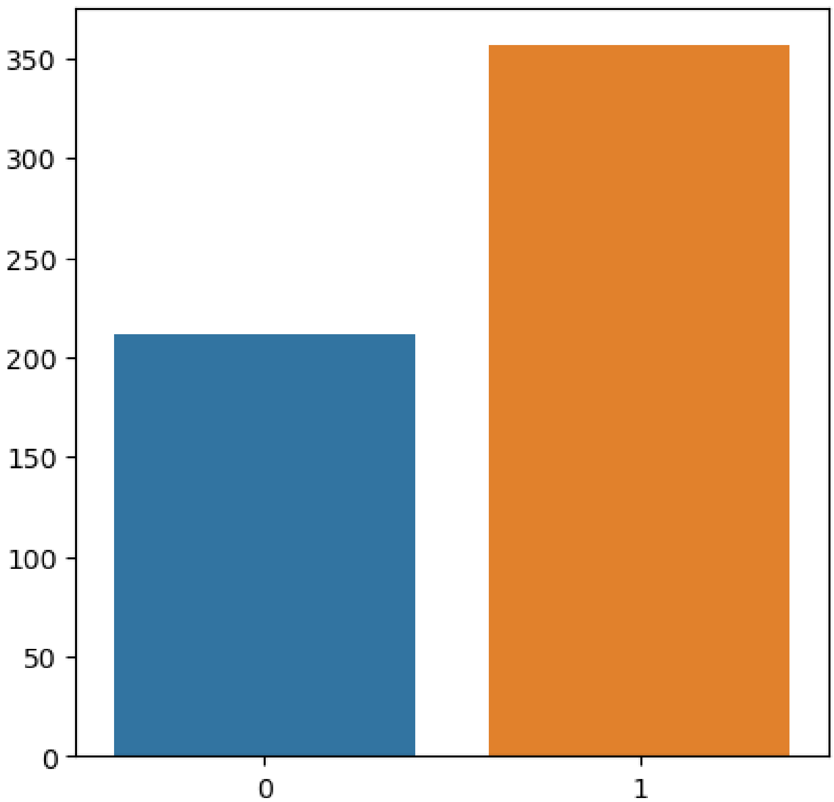
Exploratory Data Analysis

```
#Lets explore the target varibale
df['diagnosis'].value_counts()

B    357
M    212
Name: diagnosis, dtype: int64

# Now encode the target variable
df['diagnosis']=df['diagnosis'].map({'M':0,'B':1})
df['diagnosis'].head()

0    0
1    0
2    0
3    0
4    0
Name: diagnosis, dtype: int64

# coorelation between the columns diagnosis and the other columns
df.corr()['diagnosis'].sort_values()

concave points_worst      -0.793566
perimeter_worst           -0.782914
concave points_mean       -0.776614
radius_worst              -0.776454
perimeter_mean            -0.742636
area_worst                -0.733825
radius_mean               -0.730029
area_mean                 -0.708984
concavity_mean            -0.696360
concavity_worst           -0.659610
compactness_mean          -0.596534
```

```
compactness_worst          -0.590998
radius_se                  -0.567134
perimeter_se               -0.556141
area_se                    -0.548236
texture_worst              -0.456903
smoothness_worst           -0.421465
symmetry_worst             -0.416294
texture_mean               -0.415185
concave points_se          -0.408042
smoothness_mean            -0.358560
symmetry_mean              -0.330499
fractal_dimension_worst    -0.323872
compactness_se             -0.292999
concavity_se               -0.253730
fractal_dimension_se       -0.077972
symmetry_se                 0.006522
texture_se                  0.008303
fractal_dimension_mean      0.012838
smoothness_se               0.067016
diagnosis                   1.000000
Name: diagnosis, dtype: float64
```

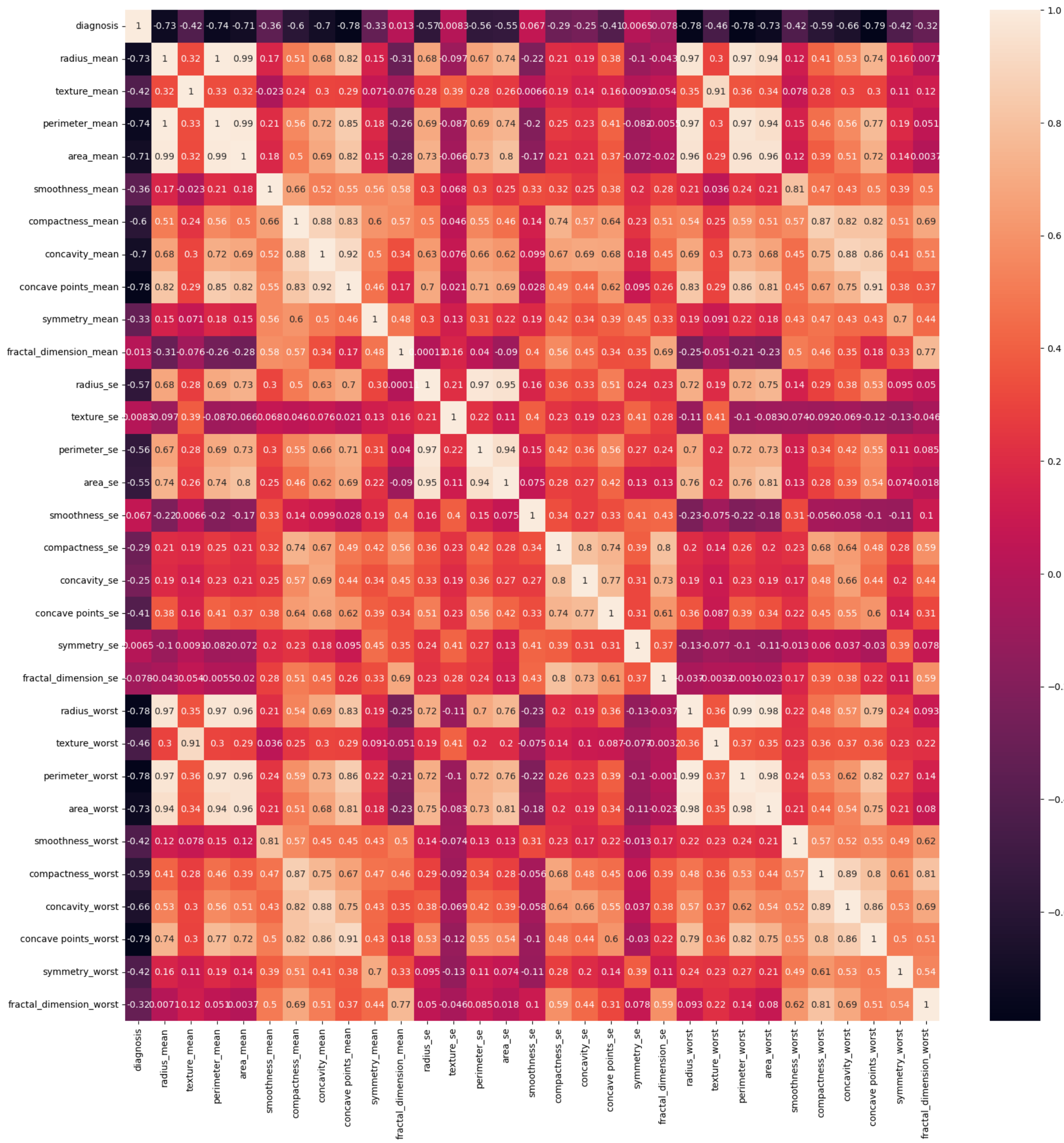
```python
# bar plot for the number of diagnosis
plt.figure(figsize=(5,5))
sns.barplot(x=df['diagnosis'].value_counts().index,y=df['diagnosis'].v
alue_counts().values)
```

```
<Axes: >
```




```
# create a heatmap to check the correlation
plt.figure(figsize=(20,20))
sns.heatmap(df.corr(),annot=True)
```

```
<Axes: >
```



Train Test Split

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(df.drop(['diagnosis'],axis=1),df['diagnosis'],test_si
ze=0.3,random_state=42)
```

Using Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train,y_train)
```

```
DecisionTreeClassifier()
```

```
#predicting the diagnosis
y_pred = dtree.predict(X_test)
```

Model Evaluation

```
# printing samples from predicted and actual values
print('Predicted values: ',y_pred[:10])
print('Actual values: ',y_test[:10])
```

```
Predicted values:  [1 0 0 1 1 0 0 0 1 1]
Actual values:  204    1
70     0
131    0
431    1
540    1
567    0
369    0
29     0
81     1
477    1
Name: diagnosis, dtype: int64
```

```
# model evaluation
print(dtree.score(X_test,y_test))
```

```
0.9415204678362573
```

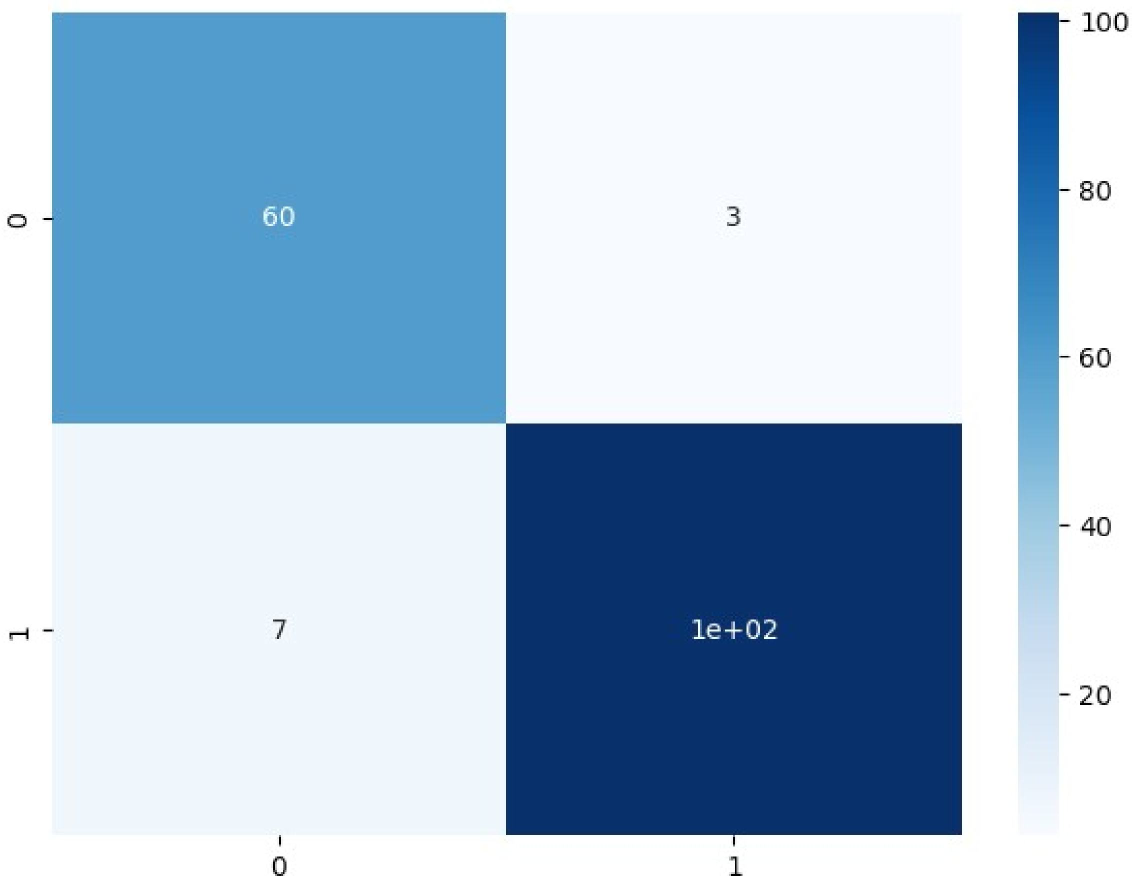
```
from sklearn.metrics import confusion_matrix

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

```
[[ 60   3]
 [  7 101]]
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.95      0.92        63
           1       0.97      0.94      0.95       108

    accuracy                           0.94       171
```

```
   macro avg       0.93      0.94      0.94       171
weighted avg       0.94      0.94      0.94       171


# helper function
from sklearn.metrics import confusion_matrix
def plot_confusionmatrix(a,b,dom):
    print(f'{dom} Confusion matrix')
    cf = confusion_matrix(a,b)
    sns.heatmap(cf,annot=True,cmap='Blues')#For g and G , the maximum
number of significant digits
    plt.tight_layout()
    plt.show()

plot_confusionmatrix(y_test,y_pred,dom='Test Data')

Test Data Confusion matrix
```



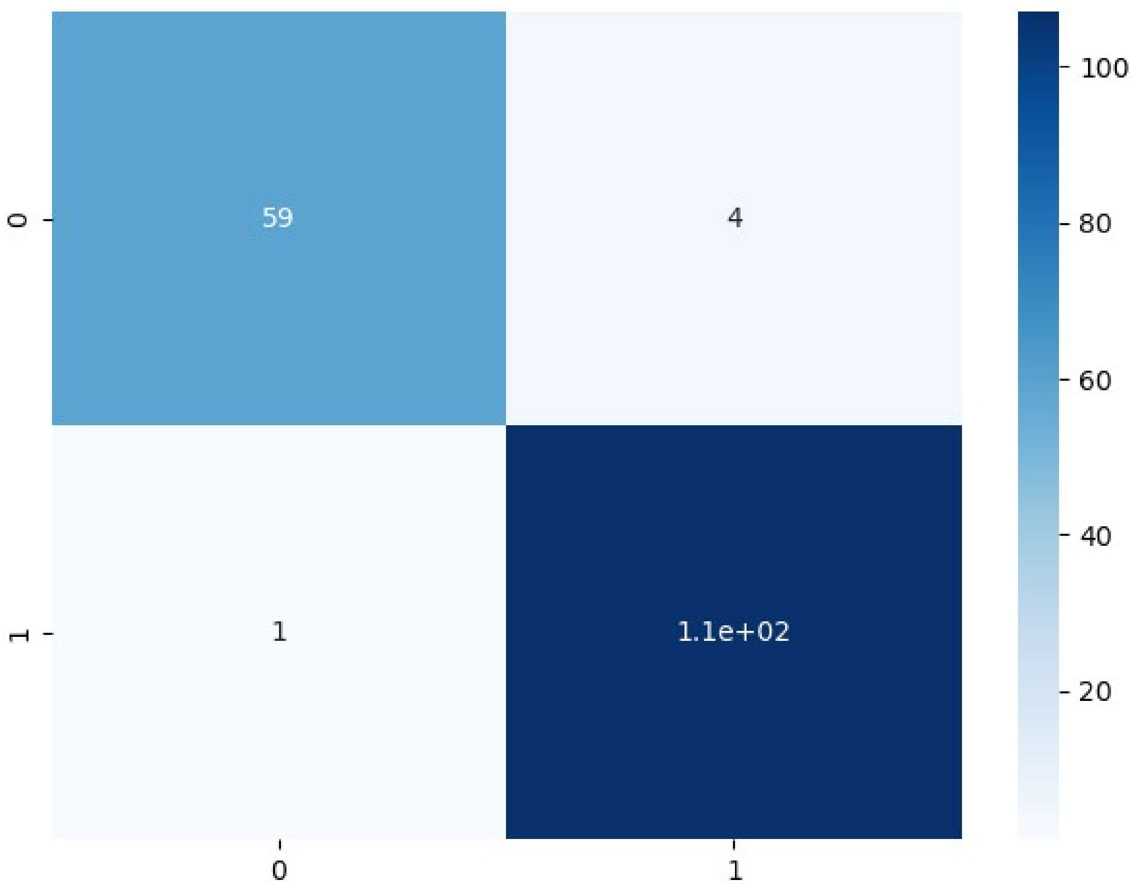
Using logistic regression

```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)

C:\Users\admin\anaconda3\Lib\site-packages\sklearn\linear_model\
_logistic.py:460: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

LogisticRegression()

yhat = logmodel.predict(X_test)
```

Model Evaluation

```
# printing samples from predicted and actual values
print('Predicted values: ',yhat[:10])
print('Actual values: ',y_test[:10])

Predicted values:  [1 0 0 1 1 0 0 0 1 1]
Actual values:  204    1
70     0
131    0
431    1
540    1
567    0
369    0
29     0
81     1
477    1
Name: diagnosis, dtype: int64

# model evaluation
print(logmodel.score(X_test,y_test))

0.9707602339181286

from sklearn.metrics import confusion_matrix
```

```
confusion_matrix = confusion_matrix(y_test,yhat)
print(confusion_matrix)

[[ 59   4]
 [  1 107]]

from sklearn.metrics import classification_report
print(classification_report(y_test, yhat))

              precision    recall  f1-score   support

           0       0.98      0.94      0.96        63
           1       0.96      0.99      0.98       108

    accuracy                           0.97       171
   macro avg       0.97      0.96      0.97       171
weighted avg       0.97      0.97      0.97       171


plot_confusionmatrix(y_test,yhat,dom='Test Data')

Test Data Confusion matrix
```



Conclusion

From both the models we can see that the accuracy is 94% and 97% respectively. But we can see that the recall value for the logistic regression is 97% which is better than the decision tree classifier. So we can say in this case that the logistic regression is better than the decision tree classifier.