S.Kavin Siva
3122215001306 CSE-A

UCS2612 Machine Learning Laboratory

ASSIGNMENT 8 : Applications of Random Forest and AdaBoost Ensemble Techniques

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

LOADING DATASET

```
url =
"https://archive.ics.uci.edu/ml/machine-learning-databases/breast-
cancer-wisconsin/wdbc.data"
names = ['ID', 'Diagnosis', 'mean_radius', 'mean_texture','mean_perimeter',
'mean_area',
         'mean_smoothness', 'mean_compactness', 'mean_concavity',
'mean_concave_points',
         'mean_symmetry', 'mean_fractal_dimension', 'se_radius','se_texture',
         'se_perimeter', 'se_area', 'se_smoothness', 'se_compactness',
'se_concavity',
         'se_concave_points', 'se_symmetry', 'se_fractal_dimension',
'worst_radius',
         'worst_texture', 'worst_perimeter', 'worst_area','worst_smoothness',
         'worst_compactness', 'worst_concavity',
'worst_concave_points',
         'worst_symmetry', 'worst_fractal_dimension']data

= pd.read_csv(url, names=names)

data

           ID Diagnosis mean_radius mean_texture mean_perimeter
mean_area \
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
```

```
564    926424         M        21.56         22.39            142.00
1479.0
565    926682         M        20.13         28.25            131.20
1261.0
566    926954         M        16.60         28.08            108.30
858.1
567    927241         M        20.60         29.33            140.10
1265.0
568     92751         B         7.76         24.54             47.92
181.0

     mean smoothness   ean_compactness  mean_concavity
mean_concave_points  \
0             0.11840           0.27760         0.30010
0.14710
1             0.08474           0.07864         0.08690
0.07017
2             0.10960           0.15990         0.19740
0.12790
3             0.14250           0.28390         0.24140
0.10520
4             0.10030           0.13280         0.19800
0.10430
..                ...               ...             ...
...
564           0.11100           0.11590         0.24390
0.13890
565           0.09780           0.10340         0.14400
0.09791
566           0.08455           0.10230         0.09251
0.05302
567           0.11780           0.27700         0.35140
0.15200
568           0.05263           0.04362         0.00000
0.00000

     ...  worst_radius  worst_texture  worst_perimeter  worst_area  \
0    ...        25.380          17.33           184.60      2019.0
1    ...        24.990          23.41           158.80      1956.0
2    ...        23.570          25.53           152.50      1709.0
3    ...        14.910          26.50            98.87       567.7
4    ...        22.540          16.67           152.20      1575.0
..   ...           ...            ...              ...         ...
564  ...        25.450          26.40           166.10      2027.0
565  ...        23.690          38.25           155.00      1731.0
566  ...        18.980          34.12           126.70      1124.0
567  ...        25.740          39.42           184.60      1821.0
568  ...         9.456          30.37            59.16       268.6

     worst_smoothness  worst_compactness  worst_concavity  \
```

```
0            0.16220          0.66560         0.7119
1            0.12380          0.18660         0.2416
2            0.14440          0.42450         0.4504
3            0.20980          0.86630         0.6869
4            0.13740          0.20500         0.4000
..               ...              ...            ...
564          0.14100          0.21130         0.4107
565          0.11660          0.19220         0.3215
566          0.11390          0.30940         0.3403
567          0.16500          0.86810         0.9387
568          0.08996          0.06444         0.0000

     worst_concave_points  worst_symmetry  worst_fractal_dimension
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
4                  0.1625          0.2364                  0.07678
..                    ...             ...                      ...
564                0.2216          0.2060                  0.07115
565                0.1628          0.2572                  0.06637
566                0.1418          0.2218                  0.07820
567                0.2650          0.4087                  0.12400
568                0.0000          0.2871                  0.07039

[569 rows x 32 columns]

data.head()

         ID Diagnosis mean_radius mean_texture mean_perimeter
mean area \
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

   mean_smoothness mean_compactness mean_concavity
mean concave points \
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

   ...  worst_radius  worst_texture  worst_perimeter  worst_area  \
0  ...         25.38          17.33           184.60      2019.0
1  ...         24.99          23.41           158.80      1956.0
2  ...         23.57          25.53           152.50      1709.0
3  ...         14.91          26.50            98.87       567.7
4  ...         22.54          16.67           152.20      1575.0

   worst_smoothness  worst_compactness  worst_concavity
worst_concave_points  \
0            0.1622             0.6656           0.7119
0.2654
1            0.1238             0.1866           0.2416
0.1860
2            0.1444             0.4245           0.4504
0.2430
3            0.2098             0.8663           0.6869
0.2575
4            0.1374             0.2050           0.4000
0.1625

   worst_symmetry  worst_fractal_dimension
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758
3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]

data.describe()

                 ID mean_radius mean_texture mean_perimeter
mean_area \
count  5.690000e+02   569.000000   569.000000      569.000000
569.000000
mean   3.037183e+07    14.127292    19.289649       91.969033
654.889104
std    1.250206e+08     3.524049     4.301036       24.298981
351.914129
min    8.670000e+03     6.981000     9.710000       43.790000
143.500000
25%    8.692180e+05    11.700000    16.170000       75.170000
420.300000
50%    9.060240e+05    13.370000    18.840000       86.240000
551.100000
```

```
75%    8.813129e+06    15.780000     21.800000      104.100000
782.700000
max    9.113205e+08    28.110000     39.280000      188.500000
2501.000000

       mean_smoothness mean_compactness mean_concavity
mean_concave_points \
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

       mean_symmetry ... worst_radius worst_texture
worst_perimeter \
count     569.000000  ...    569.000000     569.000000
569.000000
mean        0.181162  ...     16.269190      25.677223
107.261213
std         0.027414  ...      4.833242       6.146258
33.602542
min         0.106000  ...      7.930000      12.020000
50.410000
25%         0.161900  ...     13.010000      21.080000
84.110000
50%         0.179200  ...     14.970000      25.410000
97.660000
75%         0.195700  ...     18.790000      29.720000
125.400000
max         0.304000  ...     36.040000      49.540000
251.200000

        worst_area worst_smoothness worst_compactness
worst concavity \
count   569.000000        569.000000        569.000000
569.000000
mean    880.583128          0.132369          0.254265
0.272188
std     569.356993          0.022832          0.157336
```

```
0.208624
min     185.200000          0.071170           0.027290
0.000000
25%     515.300000          0.116600           0.147200
0.114500
50%     686.500000          0.131300           0.211900
0.226700
75%    1084.000000          0.146000           0.339100
0.382900
max    4254.000000          0.222600           1.058000
1.252000

       worst_concave_points  worst_symmetry  worst_fractal_dimension
count            569.000000      569.000000               569.000000
mean               0.114606        0.290076                 0.083946
std                0.065732        0.061867                 0.018061
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
50%                0.099930        0.282200                 0.080040
75%                0.161400        0.317900                 0.092080
max                0.291000        0.663800                 0.207500

[8 rows x 31 columns]
```

```python
num_rows, num_columns = data.shape

print("Number of rows:", num_rows)
print("Number of columns:", num_columns)
```

```
Number of rows: 569
Number of columns: 32
```

```python
data.nunique()
```

```
ID                         569
Diagnosis                    2
mean_radius                456
mean_texture               479
mean_perimeter             522
mean_area                  539
mean_smoothness            474
mean_compactness           537
mean_concavity             537
mean_concave_points        542
mean_symmetry              432
mean_fractal_dimension     499
se_radius                  540
se_texture                 519
se_perimeter               533
se_area                    528
```

```
se_smoothness              547
se_compactness             541
se_concavity               533
se_concave_points          507
se_symmetry                498
se_fractal_dimension       545
worst_radius               457
worst_texture              511
worst_perimeter            514
worst_area                 544
worst_smoothness           411
worst_compactness          529
worst_concavity            539
worst_concave_points       492
worst_symmetry             500
worst fractal dimension    535
dtype: int64
```

PRE-PROCESSING DATA

1.HANDLING MISSING VALUES

```
print("The Number of Missing Values in the dataset\n")
data.isnull().sum()
```

```
The Number of Missing Values in the dataset
```

```
worst_radius               0
worst_texture              0
worst_perimeter            0
worst_area                 0
worst_smoothness           0
worst_compactness          0
worst_concavity            0
worst_concave_points       0
worst_symmetry             0
worst_fractal_dimension    0
dtype: int64
```

2. ENCODING CATEGORICAL TARGET VARIABLE

```
label_encoder = LabelEncoder()
data['Diagnosis'] = label_encoder.fit_transform(data['Diagnosis'])

data
```

```
           ID  Diagnosis  mean_radius  mean_texture  mean_perimeter  \
0      842302          1        17.99         10.38          122.80
1      842517          1        20.57         17.77          132.90
2    84300903          1        19.69         21.25          130.00
3    84348301          1        11.42         20.38           77.58
4    84358402          1        20.29         14.34          135.10
..        ...        ...          ...           ...             ...
564    926424          1        21.56         22.39          142.00
565    926682          1        20.13         28.25          131.20
566    926954          1        16.60         28.08          108.30
567    927241          1        20.60         29.33          140.10
568     92751          0         7.76         24.54           47.92

     mean_area  mean_smoothness  mean_compactness  mean_concavity  \
0       1001.0          0.11840           0.27760         0.30010
1       1326.0          0.08474           0.07864         0.08690
2       1203.0          0.10960           0.15990         0.19740
3        386.1          0.14250           0.28390         0.24140
4       1297.0          0.10030           0.13280         0.19800
..         ...              ...               ...             ...
564     1479.0          0.11100           0.11590         0.24390
565     1261.0          0.09780           0.10340         0.14400
566      858.1          0.08455           0.10230         0.09251
567     1265.0          0.11780           0.27700         0.35140
568      181.0          0.05263           0.04362         0.00000

     mean_concave_points ... worst_radius worst_texture
worst perimeter \
0                0.14710  ...        25.380          17.33
184.60
1                0.07017  ...        24.990          23.41
```

```
158.80
2                0.12790  ...       23.570         25.53
152.50
3                0.10520  ...       14.910         26.50
98.87
4                0.10430  ...       22.540         16.67
152.20
..                   ...  ...          ...           ...
...
564              0.13890  ...       25.450         26.40
166.10
565              0.09791  ...       23.690         38.25
155.00
566              0.05302  ...       18.980         34.12
126.70
567              0.15200  ...       25.740         39.42
184.60
568              0.00000  ...        9.456         30.37
59.16

     worst_area  worst_smoothness  worst_compactness  worst_concavity  \
0        2019.0           0.16220            0.66560           0.7119

1        1956.0           0.12380            0.18660           0.2416

2        1709.0           0.14440            0.42450           0.4504

3         567.7           0.20980            0.86630           0.6869

4        1575.0           0.13740            0.20500           0.4000

..          ...               ...                ...              ...

564      2027.0           0.14100            0.21130           0.4107

565      1731.0           0.11660            0.19220           0.3215

566      1124.0           0.11390            0.30940           0.3403

567      1821.0           0.16500            0.86810           0.9387

568       268.6           0.08996            0.06444           0.0000


     worst_concave_points  worst_symmetry  worst_fractal_dimension
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
```

```
4                  0.1625          0.2364                        0.07678
..                    ...             ...                            ...
564                0.2216          0.2060                        0.07115
565                0.1628          0.2572                        0.06637
566                0.1418          0.2218                        0.07820
567                0.2650          0.4087                        0.12400
568                0.0000          0.2871                        0.07039

[569 rows x 32 columns]
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype
----
 0   ID                       569 non-null    int64
 1   Diagnosis                569 non-null    int32
 2   mean_radius              569 non-null    float64
 3   mean_texture             569 non-null    float64
 4   mean_perimeter           569 non-null    float64
 5   mean_area                569 non-null    float64
 6   mean_smoothness          569 non-null    float64
 7   mean_compactness         569 non-null    float64
 8   mean_concavity           569 non-null    float64
 9   mean_concave_points      569 non-null    float64
 10  mean_symmetry            569 non-null    float64
 11  mean_fractal_dimension   569 non-null    float64
 12  se_radius                569 non-null    float64
 13  se_texture               569 non-null    float64
 14  se_perimeter             569 non-null    float64
 15  se_area                  569 non-null    float64
 16  se_smoothness            569 non-null    float64
 17  se_compactness           569 non-null    float64
 18  se_concavity             569 non-null    float64
 19  se_concave_points        569 non-null    float64
 20  se_symmetry              569 non-null    float64
 21  se_fractal_dimension     569 non-null    float64
 22  worst_radius             569 non-null    float64
 23  worst_texture            569 non-null    float64
 24  worst_perimeter          569 non-null    float64
 25  worst_area               569 non-null    float64
 26  worst_smoothness         569 non-null    float64
 27  worst_compactness        569 non-null    float64
 28  worst_concavity          569 non-null    float64
 29  worst_concave_points     569 non-null    float64
 30  worst_symmetry           569 non-null    float64
 31  worst_fractal_dimension  569 non-null    float64
```

```
dtypes: float64(30), int32(1), int64(1)
memory usage: 140.2 KB
```

1. NORMALIZATION AND STANDARDIZATION

```
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data.drop(['ID', 'Diagnosis'],axis=1))
data_scaled = pd.DataFrame(data_scaled, columns=data.columns[2:])

data

           ID  Diagnosis  mean_radius  mean_texture  mean_perimeter  \
0      842302          1        17.99         10.38          122.80
1      842517          1        20.57         17.77          132.90
2    84300903          1        19.69         21.25          130.00
3    84348301          1        11.42         20.38           77.58
4    84358402          1        20.29         14.34          135.10
..        ...        ...          ...           ...             ...
564    926424          1        21.56         22.39          142.00
565    926682          1        20.13         28.25          131.20
566    926954          1        16.60         28.08          108.30
567    927241          1        20.60         29.33          140.10
568     92751          0         7.76         24.54           47.92

     mean_area  mean_smoothness  mean_compactness  mean_concavity  \
0       1001.0          0.11840           0.27760         0.30010
1       1326.0          0.08474           0.07864         0.08690
2       1203.0          0.10960           0.15990         0.19740
3        386.1          0.14250           0.28390         0.24140
4       1297.0          0.10030           0.13280         0.19800
..         ...              ...               ...             ...
564     1479.0          0.11100           0.11590         0.24390
565     1261.0          0.09780           0.10340         0.14400
566      858.1          0.08455           0.10230         0.09251
567     1265.0          0.11780           0.27700         0.35140
568      181.0          0.05263           0.04362         0.00000

     mean_concave_points ... worst_radius worst_texture
worst perimeter \
0                0.14710  ...       25.380         17.33
184.60
1                0.07017  ...       24.990         23.41
158.80
2                0.12790  ...       23.570         25.53
152.50
3                0.10520  ...       14.910         26.50
98.87
4                0.10430  ...       22.540         16.67
152.20
```

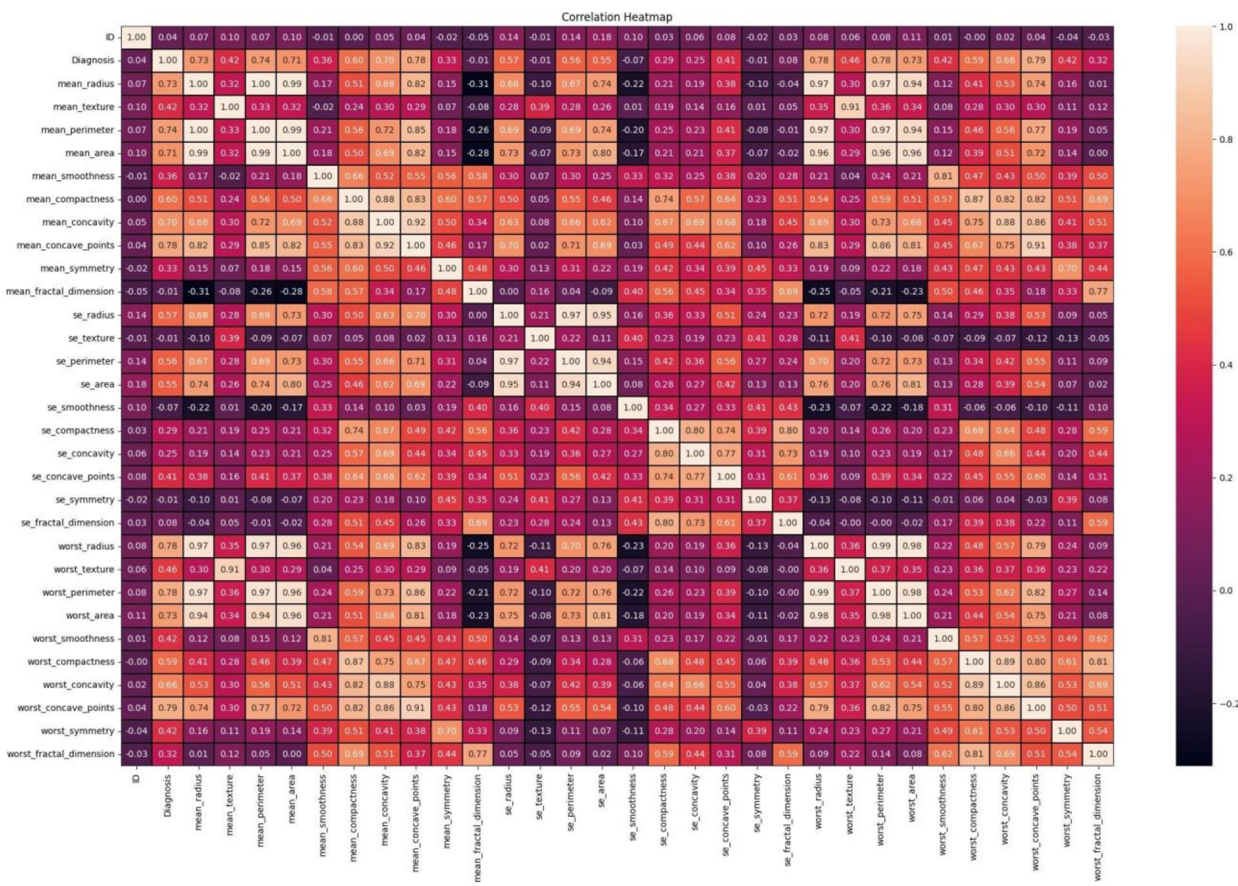
```
..                    ...  ...           ...          ...
...
564               0.13890  ...        25.450        26.40
166.10
565               0.09791  ...        23.690        38.25
155.00
566               0.05302  ...        18.980        34.12
126.70
567               0.15200  ...        25.740        39.42
184.60
568               0.00000  ...         9.456        30.37
59.16

     worst_area  worst_smoothness  worst_compactness  worst_concavity
\
0        2019.0           0.16220            0.66560           0.7119

1        1956.0           0.12380            0.18660           0.2416

2        1709.0           0.14440            0.42450           0.4504

3         567.7           0.20980            0.86630           0.6869

4        1575.0           0.13740            0.20500           0.4000

..          ...               ...                ...              ...

564      2027.0           0.14100            0.21130           0.4107

565      1731.0           0.11660            0.19220           0.3215

566      1124.0           0.11390            0.30940           0.3403

567      1821.0           0.16500            0.86810           0.9387

568       268.6           0.08996            0.06444           0.0000


     worst_concave_points  worst_symmetry  worst_fractal_dimension
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
4                  0.1625          0.2364                  0.07678
..                    ...             ...                      ...
564                0.2216          0.2060                  0.07115
565                0.1628          0.2572                  0.06637
566                0.1418          0.2218                  0.07820
567                0.2650          0.4087                  0.12400
568                0.0000          0.2871                  0.07039
```

```
[569 rows x 32 columns]
```

EXPLORATORY DATA ANALYSIS

1.CORRELATION HEATMAP

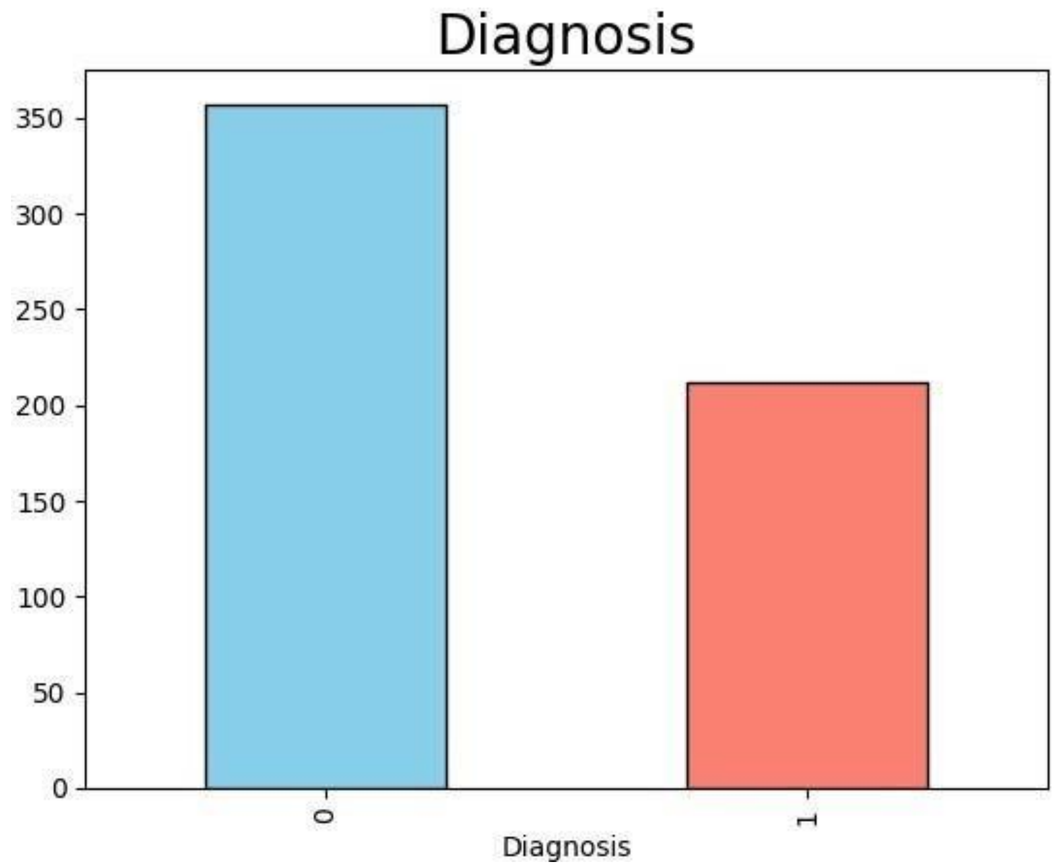
```
import matplotlib.pyplot as plt
import seaborn as sns
correlation_matrix = data.corr()

plt.figure(figsize=(25, 15))
sns.heatmap(correlation_matrix, annot=True, linecolor='black',
fmt='.2f', linewidths=.1)
plt.title('Correlation Heatmap')
plt.show()
```



1. BAR-CHART

```
data['Diagnosis'].value_counts().plot(kind='bar',edgecolor='black',col
or=['skyblue','salmon'])
plt.title("Diagnosis",fontsize=20)
```

```
plt.show()
data['Diagnosis'].value_counts()
```

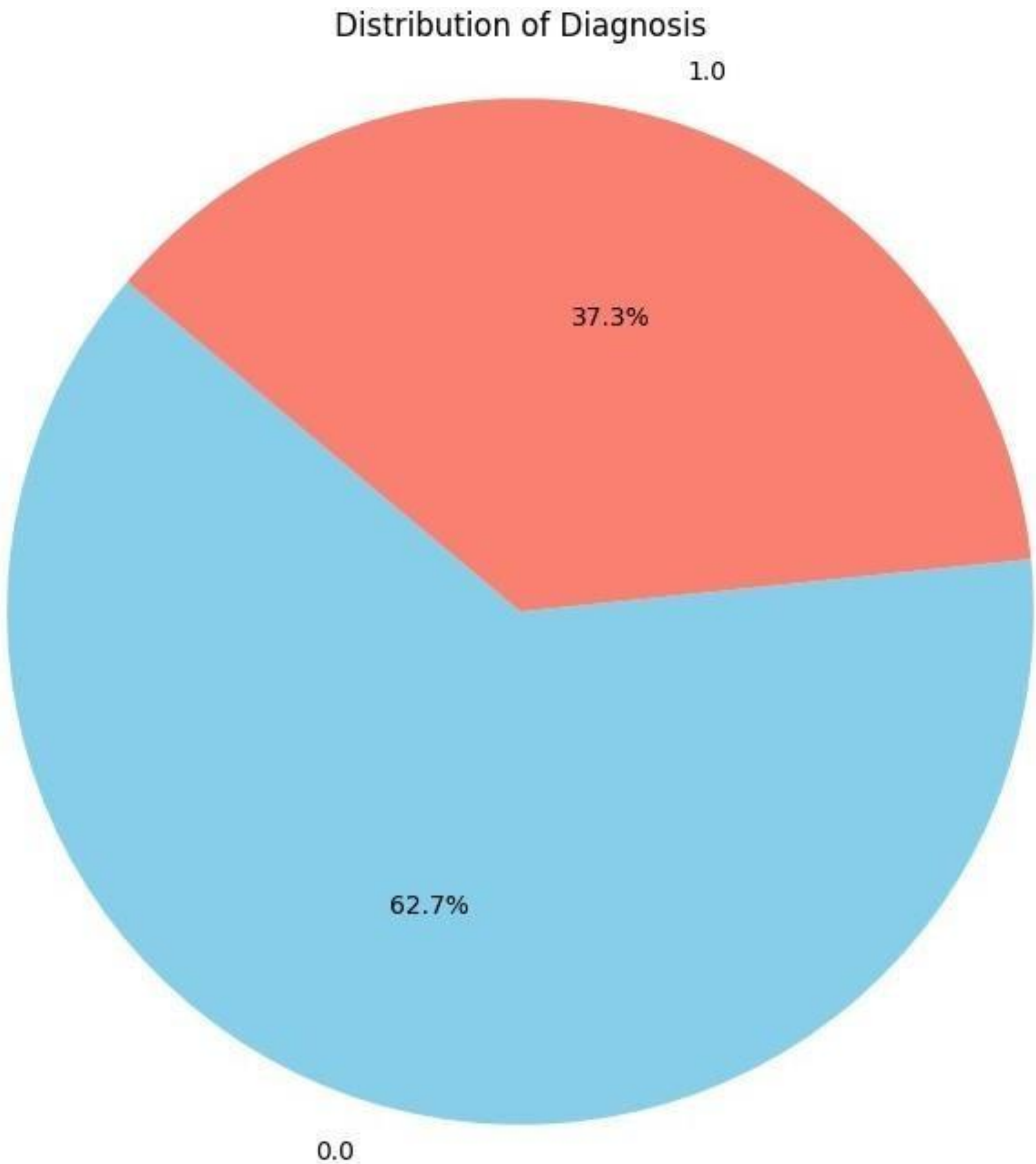



```
Diagnosis
0    357
1    212
Name: count, dtype: int64
```

1. PIE-CHART OF TARGET COLUMN

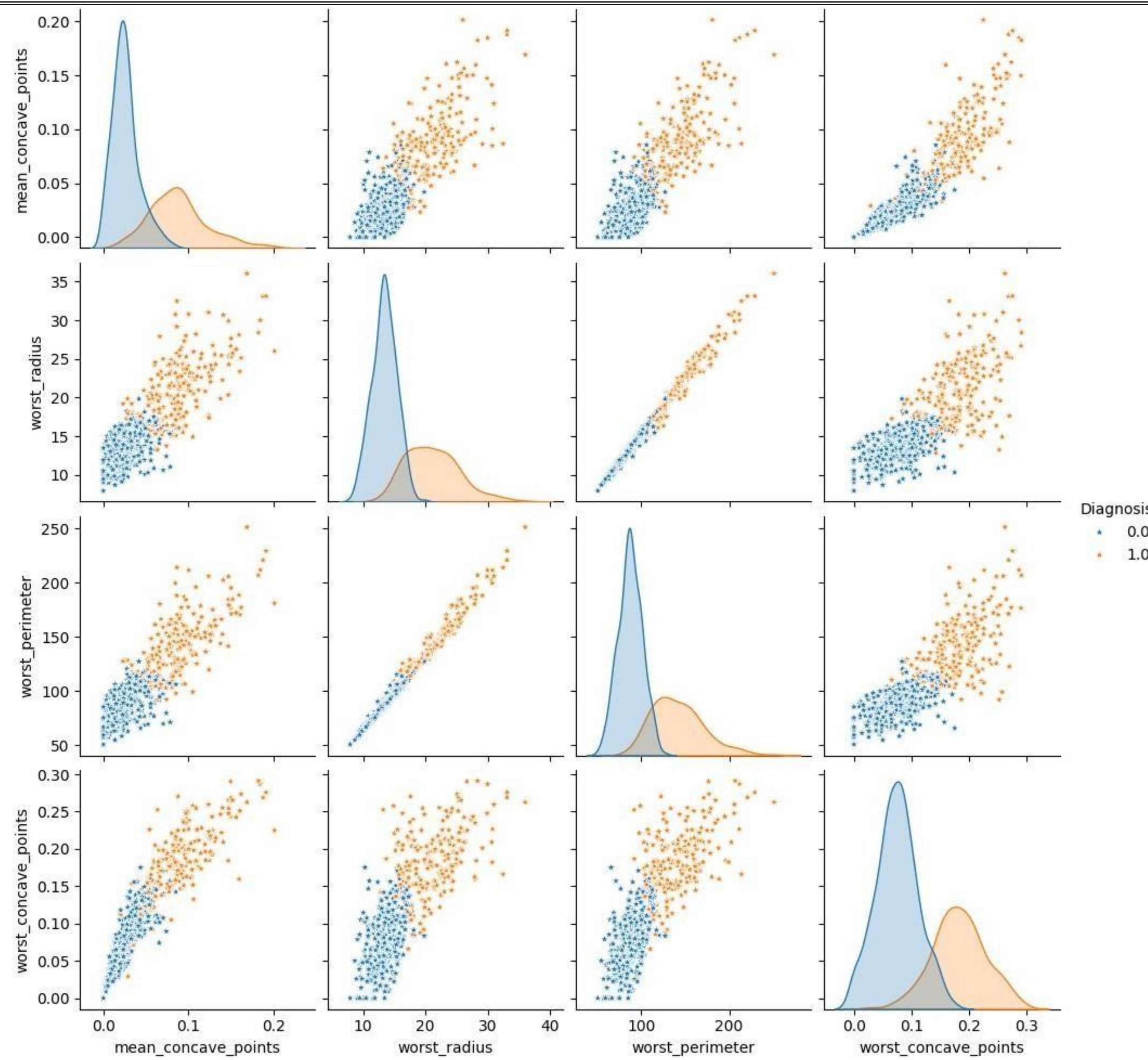
```
# Count occurrences of each unique value in the 'Diagnosis' column
diagnosis_counts = data['Diagnosis'].value_counts()

# Define colors for each slice
colors = ['skyblue', 'salmon']

# Plotting the pie chart with custom colors
plt.figure(figsize=(8, 8))
plt.pie(diagnosis_counts, labels=diagnosis_counts.index,
autopct='%1.1f%%', startangle=140, colors=colors)
plt.title('Distribution of Diagnosis')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a
```

```
circle.
plt.show()
```



1. PAIRPLOT FOR HIGHLY CORRELATED FEATURES

```
threshold = 0.75
filtre = np.abs(correlation_matrix["Diagnosis"] > threshold)
corr_features = correlation_matrix .columns[filtre].tolist()
sns.pairplot(data[corr_features], diag_kind = "kde" , markers = "*",
hue="Diagnosis")
plt.show()
```




```
# Remove 'ID' column
data.drop('ID', axis=1, inplace=True)

# Convert 'Diagnosis' column to float64
data['Diagnosis'] = data['Diagnosis'].astype(float)

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
 #   Column                    Non-Null Count  Dtype
                                               -----
 0   Diagnosis                 569 non-null    float64
 1   mean_radius               569 non-null    float64
 2   mean_texture              569 non-null    float64
```

```
 3   mean_perimeter           569 non-null    float64
 4   mean_area                569 non-null    float64
 5   mean_smoothness          569 non-null    float64
 6   mean_compactness         569 non-null    float64
 7   mean_concavity           569 non-null    float64
 8   mean_concave_points      569 non-null    float64
 9   mean_symmetry            569 non-null    float64
 10  mean_fractal_dimension   569 non-null    float64
 11  se_radius                569 non-null    float64
 12  se_texture               569 non-null    float64
 13  se_perimeter             569 non-null    float64
 14  se_area                  569 non-null    float64
 15  se_smoothness            569 non-null    float64
 16  se_compactness           569 non-null    float64
 17  se_concavity             569 non-null    float64
 18  se_concave_points        569 non-null    float64
 19  se_symmetry              569 non-null    float64
 20  se_fractal_dimension     569 non-null    float64
 21  worst_radius             569 non-null    float64
 22  worst_texture            569 non-null    float64
 23  worst_perimeter          569 non-null    float64
 24  worst_area               569 non-null    float64
 25  worst_smoothness         569 non-null    float64
 26  worst_compactness        569 non-null    float64
 27  worst_concavity          569 non-null    float64
 28  worst_concave_points     569 non-null    float64
 29  worst_symmetry           569 non-null    float64
 30  worst_fractal_dimension  569 non-null    float64
dtypes: float64(31)
memory usage: 137.9 KB
```

SPLITTING DATA INTO TRAIN , TEST AND VALIDATION SETS

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import BaggingClassifier,
RandomForestClassifier, AdaBoostClassifier
import matplotlib.pyplot as plt

# Step 5: Split the data into training, testing, and validation sets
X = data.drop('Diagnosis', axis=1)
y = data['Diagnosis']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
test_size=0.25, random_state=42) # 60% train, 20% validation, 20%
test
```

```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 10, criterion =
'entropy', random_state = 0)
classifier.fit(X_train, y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10,
random_state=0)
```

TRAINING AND TESTING MODEL

```
#Train the model
models = {
    "Bagging": BaggingClassifier(),
    "Random Forest": RandomForestClassifier(),
    "AdaBoost": AdaBoostClassifier()
}

for name, model in models.items():
    model.fit(X_train, y_train)

#Test the model
results = {}
for name, model in models.items():
    y_pred = model.predict(X_test)
    results[name] = y_pred
```

```
c:\Users\HP\AppData\Local\Programs\Python\Python311\Lib\site-packages\
sklearn\ensemble\_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use
the SAMME algorithm to circumvent this warning.
  warnings.warn(
```

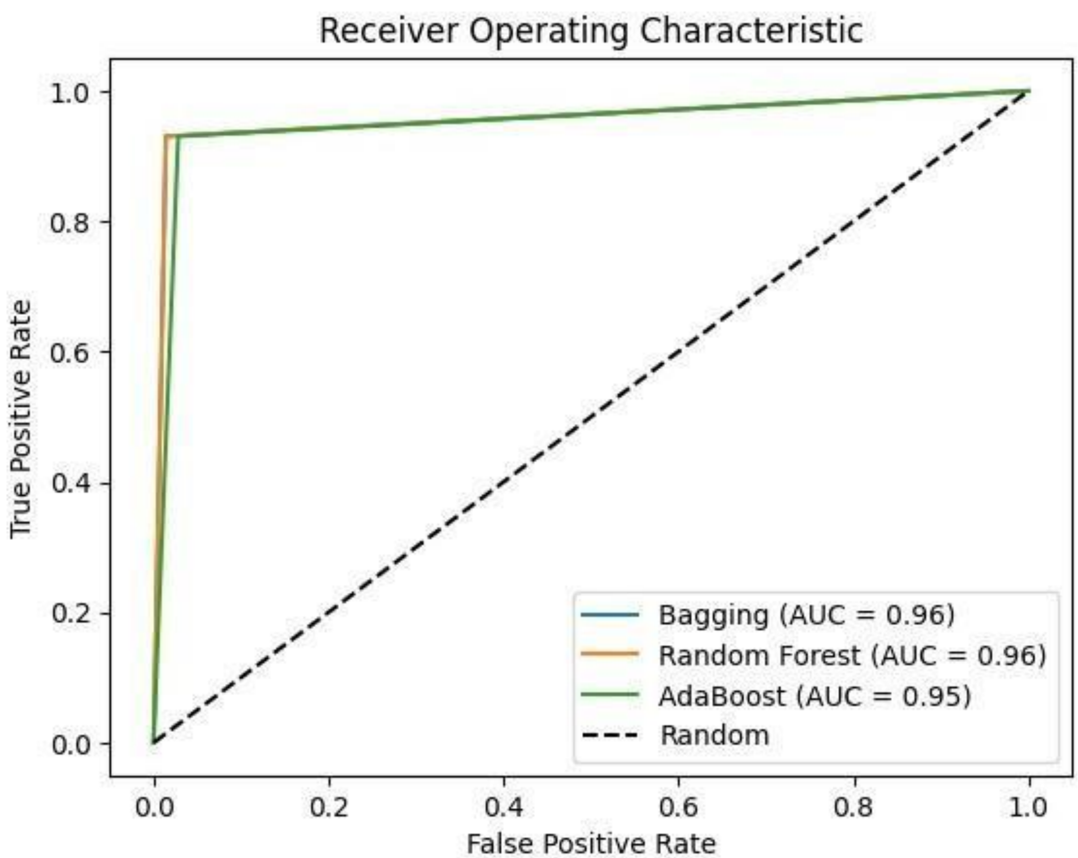
```
# Step 8: Measure the performance of the trained model
# (Assuming binary classification)
# (Assuming binary classification)
def calculate_roc(y_true, y_pred):
    fpr, tpr, thresholds = roc_curve(y_true, y_pred)
    roc_auc = auc(fpr, tpr)
    return fpr, tpr, roc_auc

plt.figure(figsize=(8, 6))
```

```
<Figure size 800x600 with 0 Axes>
```

```
# Step 9: Compare the results of each ensemble model using graphs
for name, y_pred in results.items():
    fpr, tpr, roc_auc = calculate_roc(y_test, y_pred)
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

    accuracy = accuracy_score(y_test, y_pred)
```

```
    print(f"{name}: Accuracy = {accuracy:.4f}")

plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc='lower right')
plt.show()
```

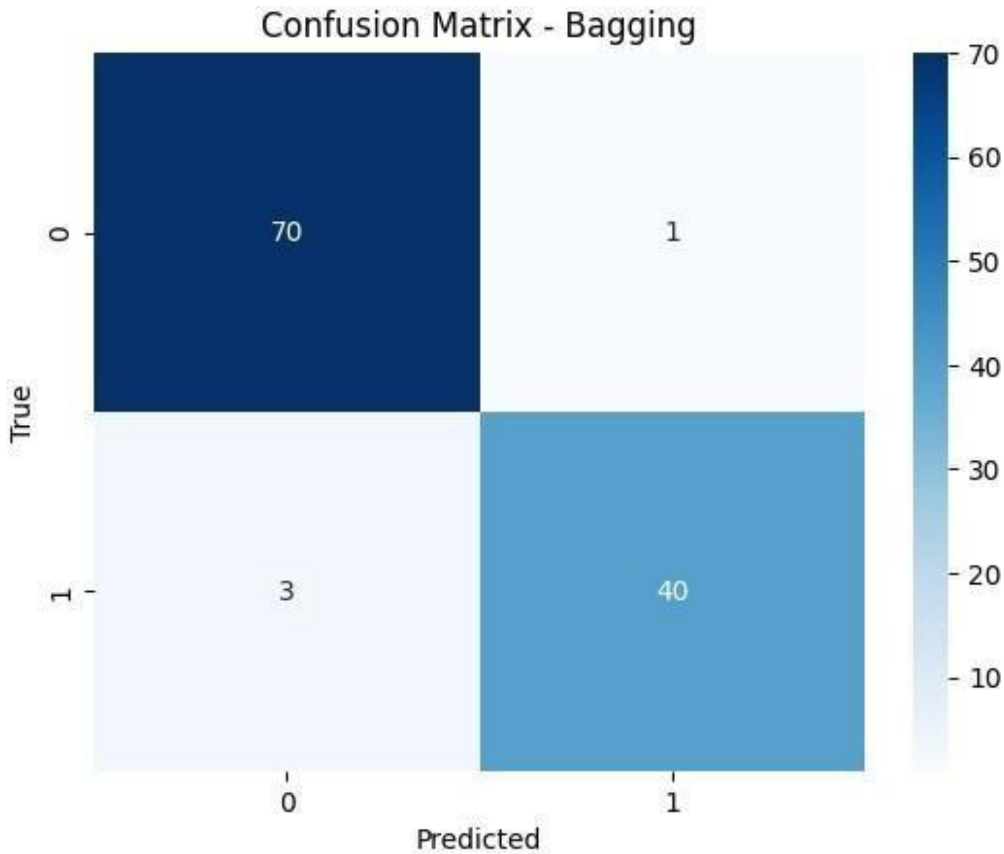
```
Bagging: Accuracy = 0.9649
Random Forest: Accuracy = 0.9649
AdaBoost: Accuracy = 0.9561
```



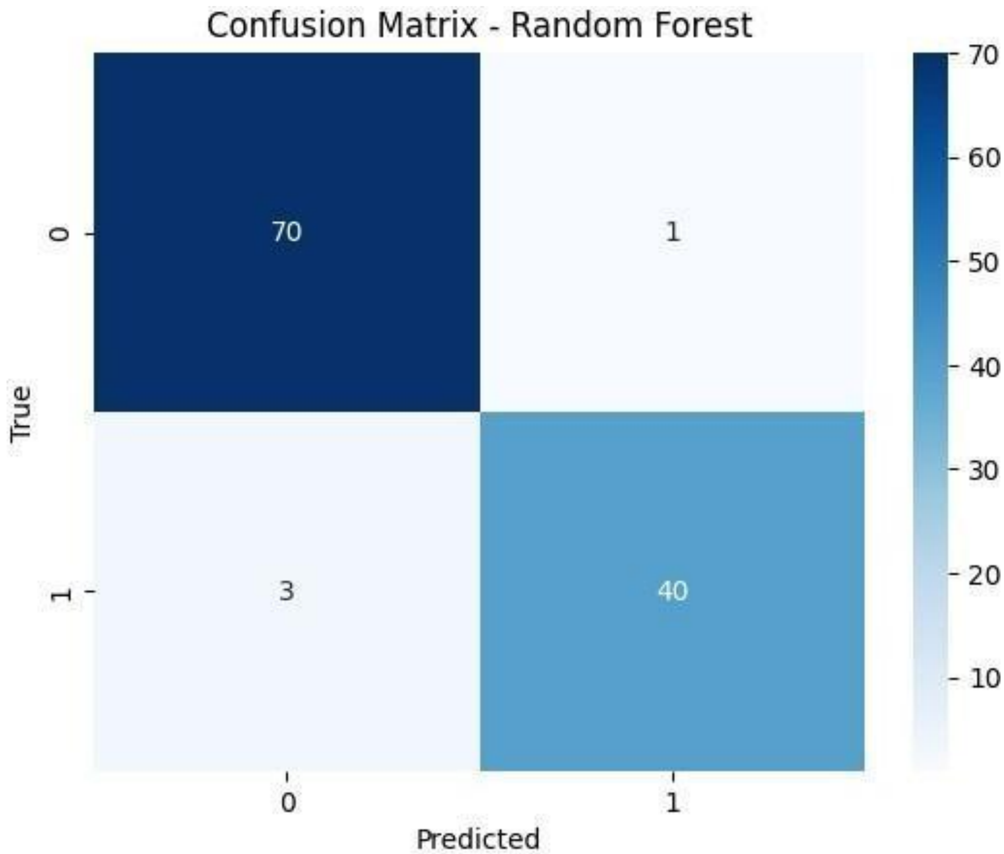

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Step 9: Compare the results of each ensemble model using graphs
for name, y_pred in results.items():


    accuracy = accuracy_score(y_test, y_pred)
    print(f"{name}: Accuracy = {accuracy:.4f}")
```

```
    # Print classification report
    print(f"\n{name} Classification Report:\
n{classification_report(y_test, y_pred)}")

    # Plot confusion matrix
    plt.figure()
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
    plt.title(f'Confusion Matrix - {name}')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()
```

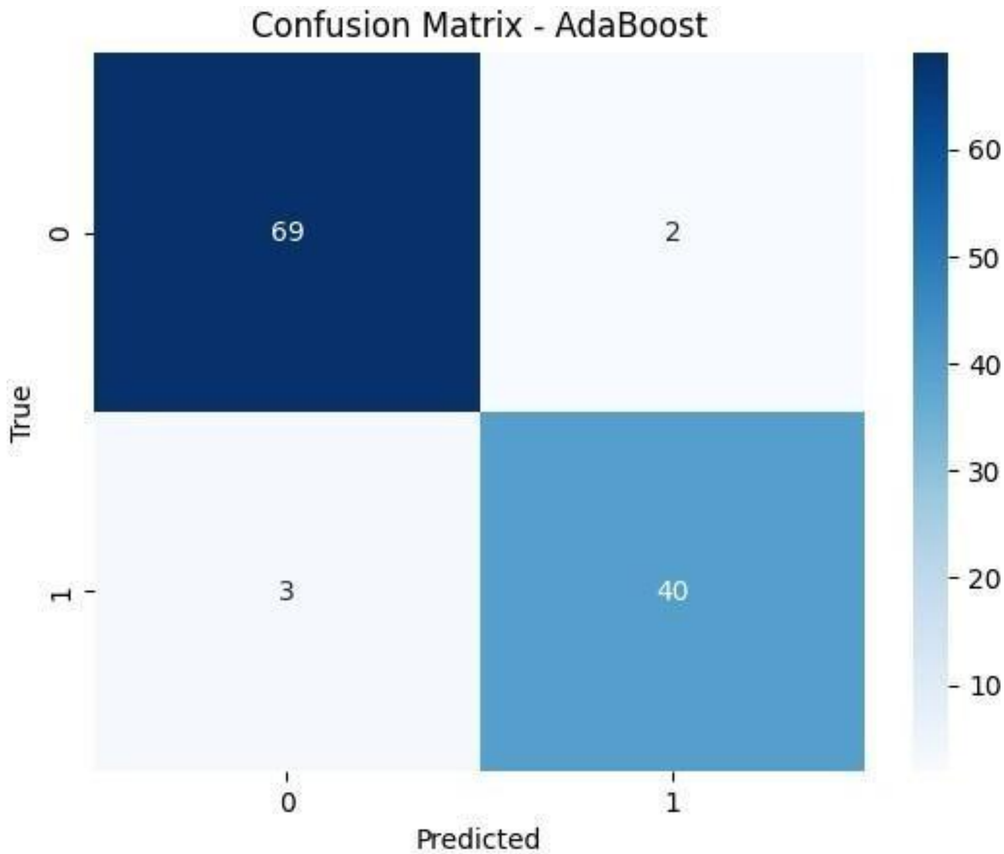
```
Bagging: Accuracy = 0.9649

Bagging Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97        71
         1.0       0.98      0.93      0.95        43

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114
```



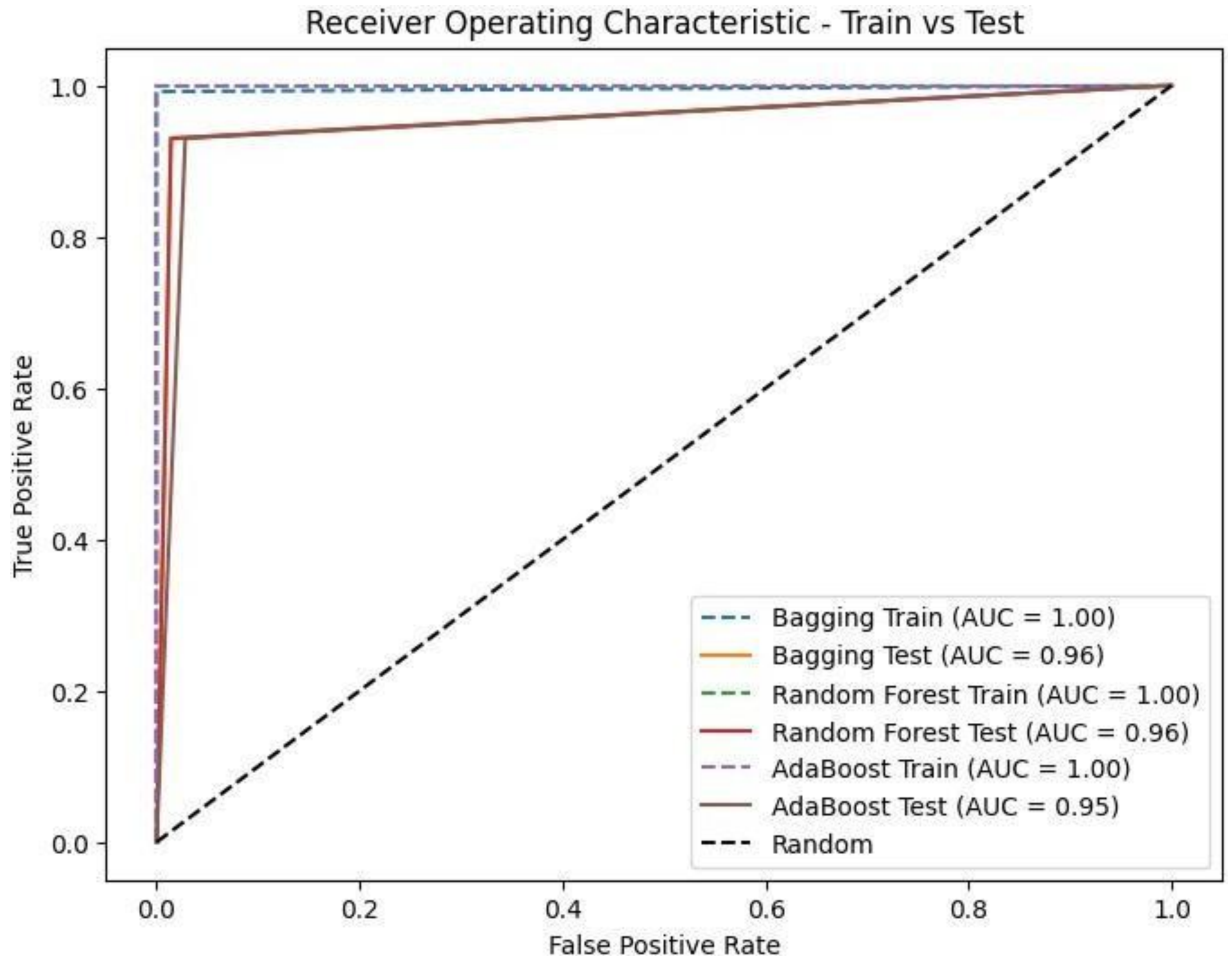

```
Random Forest: Accuracy = 0.9649

Random Forest Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97        71
         1.0       0.98      0.93      0.95        43

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114
```




```
AdaBoost: Accuracy = 0.9561

AdaBoost Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      0.97      0.97        71
         1.0       0.95      0.93      0.94        43

    accuracy                           0.96       114
   macro avg       0.96      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114
```




```
# Step 10: Represent the ROC of training and test results in the
graphs
plt.figure(figsize=(8, 6))
for name, model in models.items():
    y_train_pred = model.predict(X_train)
    fpr_train, tpr_train, roc_auc_train = calculate_roc(y_train,
y_train_pred)
    plt.plot(fpr_train, tpr_train, label=f'{name} Train (AUC =
{roc_auc_train:.2f})', linestyle='--')

    fpr_test, tpr_test, roc_auc_test = calculate_roc(y_test,
results[name])
    plt.plot(fpr_test, tpr_test, label=f'{name} Test (AUC =
{roc_auc_test:.2f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic - Train vs Test')
plt.legend(loc='lower right')
plt.show()
```



INFERENCE :

- Bagging and Random Forest models achieved identical accuracy scores of 0.9649, while AdaBoost had a slightly lower accuracy of 0.9561.
- Precision, recall, and F1-score metrics indicate high performance across all models, suggesting strong predictive capability.
- Detailed classification reports provide insights into the performance of each model for both classes (0 and 1), demonstrating their ability to correctly classify instances.
- Overall, Bagging and Random Forest models slightly outperform AdaBoost in diagnosing breast cancer.
- The models exhibit high accuracy and robustness, as evidenced by the AUC values.
- Visualizations of ROC curves can offer further insights into the comparative performance of the models.

LEARNING OUTCOMES :

- Ensemble Learning: Understanding and applying ensemble techniques for classification tasks.
- Data Preprocessing: Handling missing data, encoding categorical variables, and scaling features for model training.
- Model Evaluation: Using classification metrics to assess model performance.
- Feature Engineering: Implementing techniques to enhance model predictive capability.
- Model Evaluation: Familiarity with classification metrics like accuracy, precision, recall, and F1-score for assessing model performance.

GITHUB LINK :

https://github.com/KavinSiva13/ML-A4/tree/main/Assignment-8