Q. Write a program to implement Boosting and Bagging methods. Analyze using suitable dataset.

Importing necessary library

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import BaggingClassifier, AdaBoostClassifier,
GradientBoostingClassifier, RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score,
confusion_matrix, precision_score, recall_score, f1_score
from sklearn.preprocessing import LabelEncoder
```

Load the dataset and displaying head of the dataset.

```
df = pd.read_csv('Almond.csv')
df.head()

   Unnamed: 0  Length (major axis)  Width (minor axis)   Thickness (depth)  \
0           0                  NaN          227.940628          127.759132
1           1                  NaN          234.188126          128.199509
2           2                  NaN          229.418610          125.796547
3           3                  NaN          232.763153          125.918808
4           4                  NaN          230.150742          107.253448

      Area   Perimeter  Roundness  Solidity  Compactness     Aspect Ratio  \
0  22619.0  643.813269        NaN  0.973384     1.458265             NaN
1  23038.0  680.984841        NaN  0.957304     1.601844             NaN
2  22386.5  646.943212        NaN  0.967270     1.487772             NaN
3  22578.5  661.227483        NaN  0.965512     1.540979             NaN
4  19068.0  624.842706        NaN  0.951450     1.629395             NaN

   Eccentricity    Extent  Convex hull(convex area)   Type
0           NaN  0.681193                   23237.5  MAMRA
1           NaN  0.656353                   24065.5  MAMRA
2           NaN  0.683620                   23144.0  MAMRA
3           NaN  0.685360                   23385.0  MAMRA
4           NaN  0.714800                   20041.0  MAMRA
```

Displaying info

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2803 entries, 0 to 2802
Data columns (total 14 columns):
 #   Column                      Non-Null Count  Dtype
```

```
---  -------                        --------------  ------
 0   Unnamed: 0                     2803 non-null   int64
 1   Length (major axis)            1946 non-null   float64
 2   Width (minor axis)             1861 non-null   float64
 3   Thickness (depth)              1799 non-null   float64
 4   Area                           2803 non-null   float64
 5   Perimeter                      2803 non-null   float64
 6   Roundness                      1946 non-null   float64
 7   Solidity                       2803 non-null   float64
 8   Compactness                    2803 non-null   float64
 9   Aspect Ratio                   1004 non-null   float64
 10  Eccentricity                   1004 non-null   float64
 11  Extent                         2803 non-null   float64
 12  Convex hull(convex area)      2803 non-null   float64
 13  Type                           2803 non-null   object
dtypes: float64(12), int64(1), object(1)
memory usage: 306.7+ KB
```

Checking for null values

```
df.isnull().sum()
```

```
Unnamed: 0                     0
Length (major axis)          857
Width (minor axis)           942
Thickness (depth)           1004
Area                           0
Perimeter                      0
Roundness                    857
Solidity                       0
Compactness                    0
Aspect Ratio                1799
Eccentricity                1799
Extent                         0
Convex hull(convex area)       0
Type                           0
dtype: int64
```

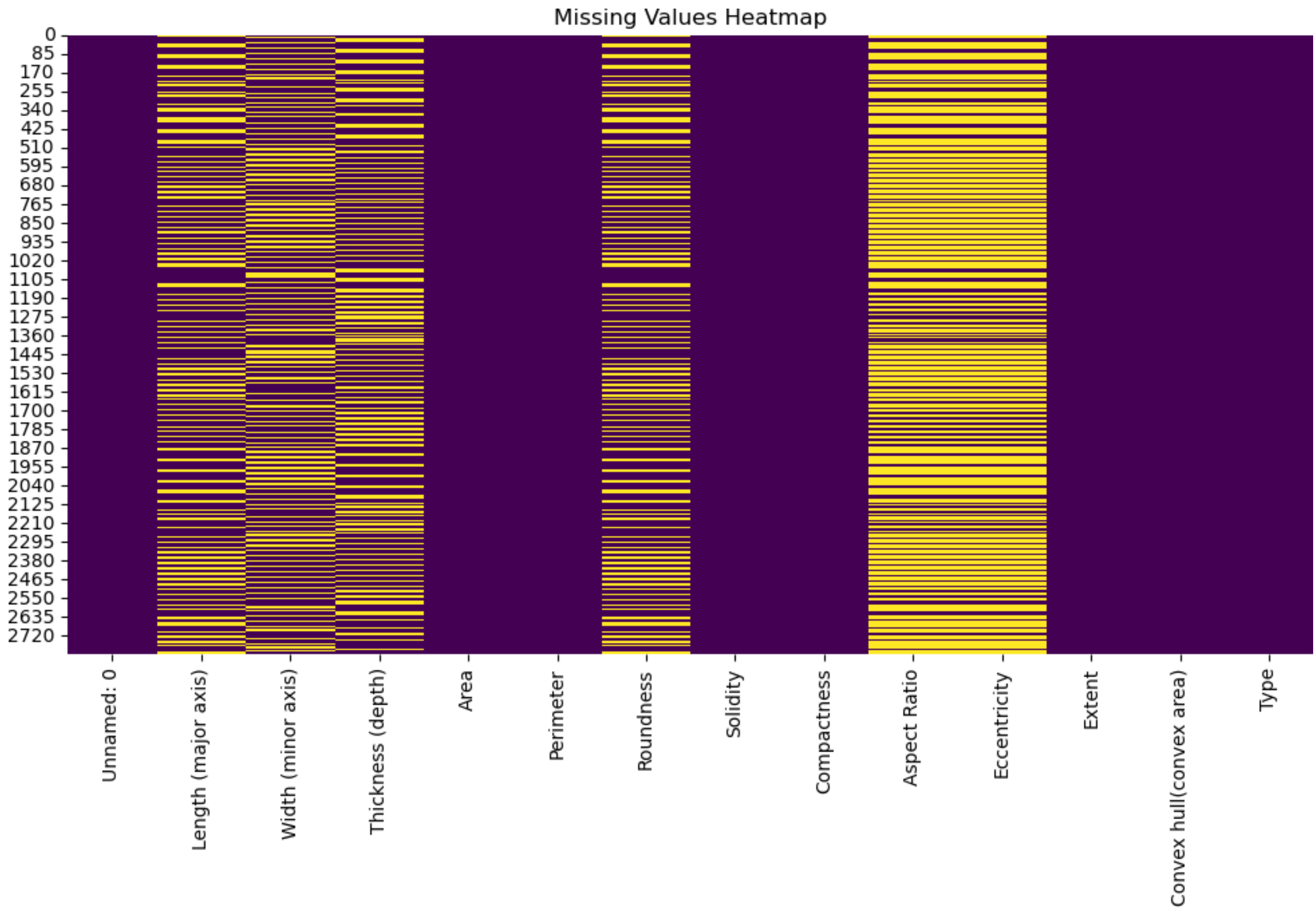
Plotting Null values

```
# Plotting missing values heatmap
plt.figure(figsize=(12, 6))
sns.heatmap (df.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Values Heatmap')
plt.show()

# Summary statistics
summary_stats = df.describe()

# Distribution of the 'Type' column
type_distribution = df['Type'].value_counts()

summary_stats, type_distribution
```




```
(         Unnamed: 0  Length (major axis)  Width (minor axis)  \
 count  2803.000000          1946.000000         1861.000000
 mean   1401.000000           290.609274          171.025915
 std     809.300727            62.719433           29.916529
 min       0.000000           151.335266           88.050529
 25%     700.500000           245.966293          149.453659
 50%    1401.000000           279.879883          170.168365
 75%    2101.500000           330.508575          190.640427
 max    2802.000000           515.352478          258.569794

        Thickness (depth)          Area    Perimeter    Roundness      Solidity
\
 count        1799.000000   2803.000000  2803.000000  1946.000000  2803.000000

 mean          109.705378  26511.117374   743.863770     0.470466     0.955828

 std            18.940597  13782.561344   230.632076     0.118673     0.039596

 min            59.494278   6037.000000   311.563489     0.173748     0.718772

 25%            97.091682  16211.500000   571.730009     0.384810     0.944579

 50%           110.280136  23440.500000   707.487369     0.472718     0.970422

 75%           121.392773  33451.000000   878.896530     0.577553     0.981484

 max           181.845200  89282.000000  1864.947387     0.697293     0.992889


        Compactness  Aspect Ratio  Eccentricity       Extent  \
 count  2803.000000   1004.000000   1004.000000  2803.000000
```

```
mean       1.825233       1.753216       0.813114      0.724587
std        0.794058       0.206616       0.041312      0.047474
min        1.164469       1.400082       0.699897      0.454538
25%        1.357398       1.612490       0.784476      0.701673
50%        1.576412       1.705716       0.810120      0.733720
75%        1.965953       1.833339       0.838141      0.757551
max        9.660057       2.731251       0.930563      0.845813

        Convex hull(convex area)
count             2803.000000
mean             27696.218159
std              14237.347610
min               6355.000000
25%              17088.500000
50%              24589.000000
75%              34863.250000
max              90642.500000  ,
Type
SANORA      943
MAMRA       933
REGULAR     927
Name: count, dtype: int64)
```

Handling missing values by filling with the mean (imputation)
Pairplot for visualizing relationships between features and 'Type'

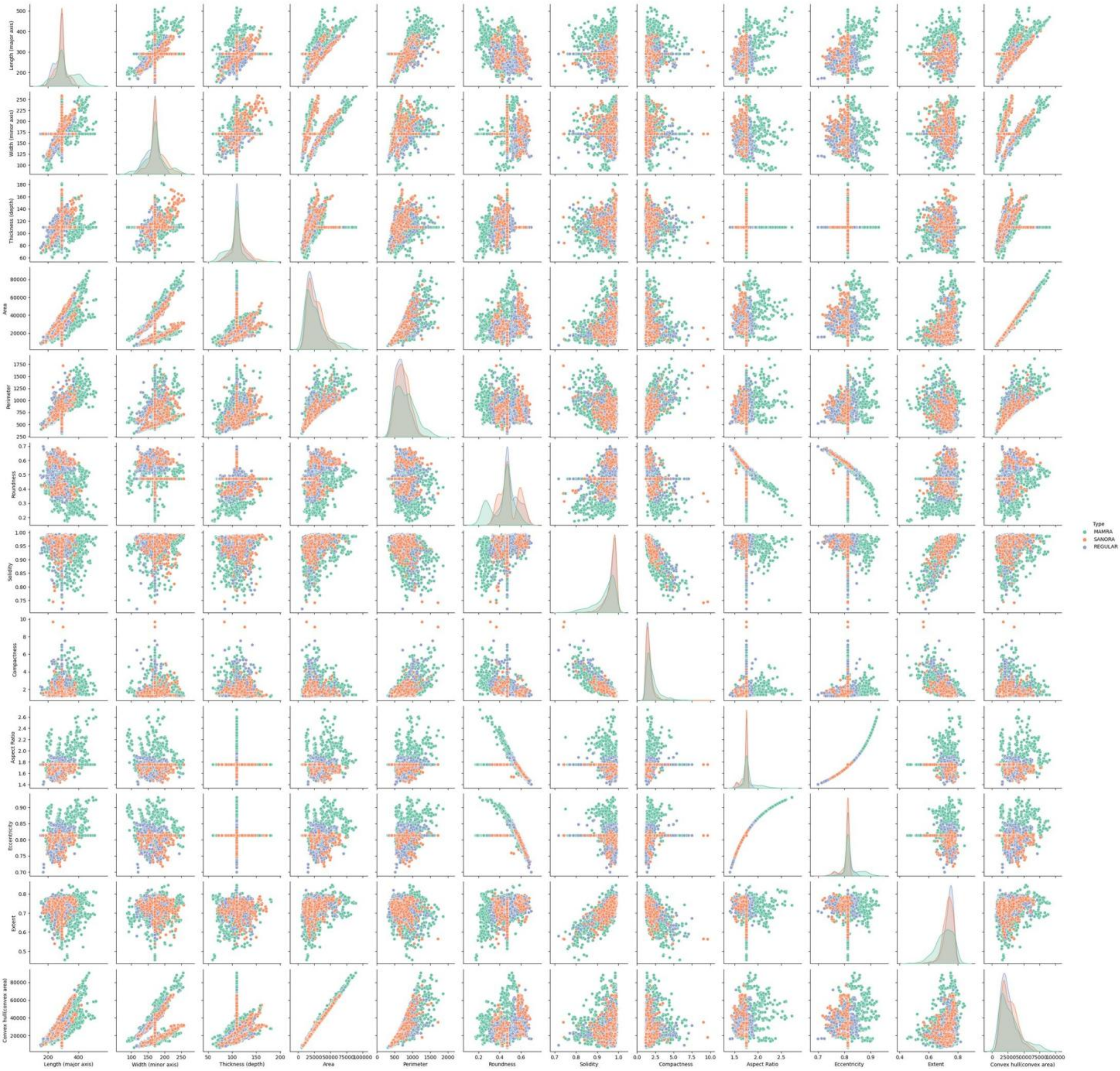
```python
data_filled = df.copy()
columns_with_missing_values = ['Length (major axis)', 'Width (minor axis)',
'Thickness (depth)', 'Roundness', 'Aspect Ratio', 'Eccentricity']

for col in columns_with_missing_values:
    data_filled[col].fillna(data_filled[col].mean(), inplace=True)

data_cleaned = data_filled.drop(columns=['Unnamed: 0'])

sns.pairplot(data_cleaned, hue='Type', diag_kind='kde', palette='Set2')
plt.show()
```

```
d:\Anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure
layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Displaying head of the cleaned dataset

```
data_cleaned.head()

   Length (major axis)  Width (minor axis)  Thickness (depth)     Area  \
0           290.609274          227.940628         127.759132  22619.0
1           290.609274          234.188126         128.199509  23038.0
2           290.609274          229.418610         125.796547  22386.5
3           290.609274          232.763153         125.918808  22578.5
4           290.609274          230.150742         107.253448  19068.0

    Perimeter  Roundness  Solidity  Compactness  Aspect Ratio    Eccentricity  \
0  643.813269   0.470466  0.973384     1.458265       1.753216       0.813114
1  680.984841   0.470466  0.957304     1.601844       1.753216       0.813114
2  646.943212   0.470466  0.967270     1.487772       1.753216       0.813114
3  661.227483   0.470466  0.965512     1.540979       1.753216       0.813114
4  624.842706   0.470466  0.951450     1.629395       1.753216       0.813114

     Extent  Convex hull(convex area)   Type
0  0.681193                   23237.5  MAMRA
```

```
1  0.656353                    24065.5   MAMRA
2  0.683620                    23144.0   MAMRA
3  0.685360                    23385.0   MAMRA
4  0.714800                    20041.0   MAMRA
```

Displaying info of the cleaned dataset

```
data_cleaned.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2803 entries, 0 to 2802
Data columns (total 13 columns):
 #   Column                      Non-Null Count   Dtype
---  -------                     --------------   ------
 0   Length (major axis)         2803 non-null    float64
 1   Width (minor axis)          2803 non-null    float64
 2   Thickness (depth)           2803 non-null    float64
 3   Area                        2803 non-null    float64
 4   Perimeter                   2803 non-null    float64
 5   Roundness                   2803 non-null    float64
 6   Solidity                    2803 non-null    float64
 7   Compactness                 2803 non-null    float64
 8   Aspect Ratio                2803 non-null    float64
 9   Eccentricity                2803 non-null    float64
 10  Extent                      2803 non-null    float64
 11  Convex hull(convex area)   2803 non-null    float64
 12  Type                        2803 non-null    object
dtypes: float64(12), object(1)
memory usage: 284.8+ KB
```

Encoding Categorical data.

```
le = LabelEncoder()
for column in data_cleaned.columns:
    data_cleaned[column] = le.fit_transform(data_cleaned[column])
```

Displaying Head after converting

```
data_cleaned.head(20)

    Length (major axis)  Width (minor axis)  Thickness (depth)   Area  \
0                  1138                1780               1525   1316
1                  1138                1808               1539   1334
2                  1138                1788               1467   1306
3                  1138                1800               1473   1315
4                  1138                1792                781   1020
5                  1138                1796                801   1052
6                  1138                1770                752    965
7                  1138                1769                594    902
8                  1852                 947               1684   2384
9                  1865                 947               1566   2360
10                 1885                 947               1411   2315
11                 1860                 947               1601   2389
12                 1718                 947                534   1771
13                 1673                 947                473   1680
14                 1651                 947                496   1644
15                 1663                 947                417   1621
16                 1364                 903                873   2280
```

```
17                  1384                    886                 873  2288
18                  1399                    883                 873  2306
19                  1375                    870                 873  2299
```

	Extent	Convex hull(convex area)	Type
0	420	1292	0
1	234	1335	0
2	443	1286	0
3	468	1303	0
4	931	1005	0
5	1216	1023	0
6	1215	932	0
7	1586	846	0
8	2374	2384	0
9	2135	2362	0
10	2474	2331	0
11	1822	2387	0
12	2602	1761	0
13	2099	1669	0
14	2695	1648	0
15	2541	1605	0
16	2600	2226	0
17	2529	2245	0
18	2689	2267	0
19	2494	2263	0

Displaying tail after converting

```
data_cleaned.tail(20)
```

	Length (major axis)	Width (minor axis)	Thickness (depth)	Area \
2783	1289	1230	873	2424
2784	1242	1047	873	2367
2785	1234	1080	873	2379
2786	1107	947	1374	1616
2787	1241	947	1311	1645
2788	998	947	1285	1515

2789	1043	947	1219	1516
2790	1291	947	904	1573
2791	1254	947	1120	1624
2792	1212	947	923	1536
2793	1189	947	914	1513
2794	1138	1715	1501	1214
2795	1138	1661	1513	1184
2796	1138	1664	1454	1135
2797	1138	1662	1476	1151
2798	1138	1439	1383	948
2799	1138	1298	1257	799
2800	1138	1296	1271	844
2801	1138	1351	1323	885
2802	805	1066	873	2206

	Perimeter	Roundness	Solidity	Compactness	Aspect Ratio	Eccentricity
\						
2783	2165	1610	1193	1138	381	381
2784	2199	1480	1228	1514	515	515
2785	2127	1554	1470	1224	460	460
2786	2164	647	733	2435	622	541
2787	2028	503	523	2308	622	541
2788	1968	616	731	2344	622	541
2789	2043	573	462	2402	622	541
2790	1874	345	867	2193	622	541
2791	1892	469	711	2149	622	541
2792	1677	427	962	1913	622	541
2793	1666	435	942	1926	622	541
2794	1274	961	710	1852	622	541
2795	1218	961	896	1801	622	541
2796	1393	961	717	2092	622	541
2797	1122	961	1005	1690	622	541
2798	1110	961	483	1939	622	541
2799	745	961	861	1364	622	541
2800	887	961	789	1718	622	541
2801	999	961	701	1843	622	541
2802	2132	1872	761	1761	75	75

	Extent	Convex hull(convex area)	Type
2783	2127	2423	2
2784	1626	2358	2

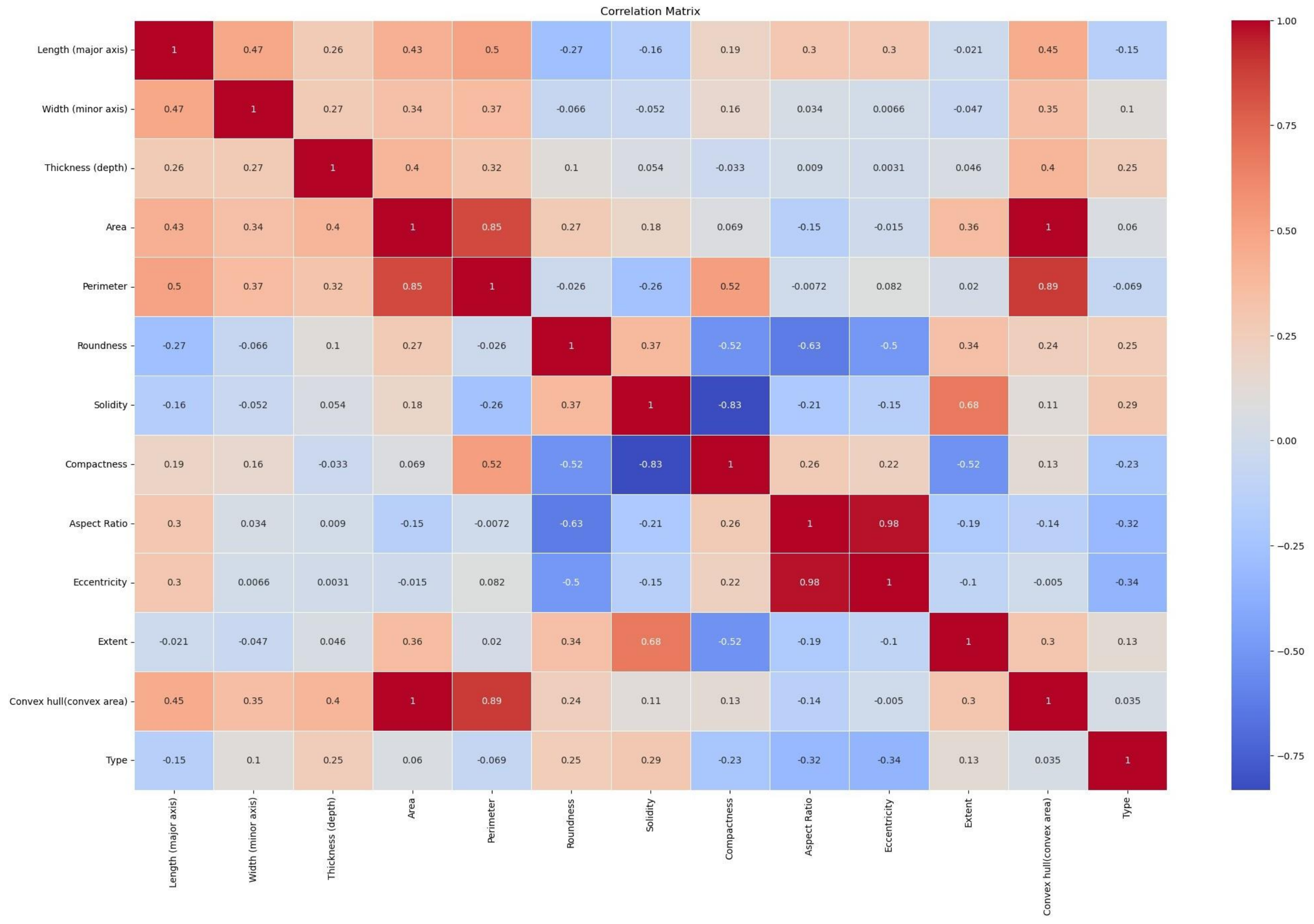
```
2785     2197                           2359     2
2786     2023                           1650     2
2787      913                           1699     2
2788     2166                           1524     2
2789      522                           1566     2
2790      741                           1572     2
2791      168                           1658     2
2792      532                           1529     2
2793      428                           1500     2
2794      799                           1231     2
2795     1063                           1188     2
2796     1007                           1148     2
2797     1334                           1136     2
2798     1161                            980     2
2799      912                            786     2
2800      999                            827     2
2801     1524                            881     2
2802     1078                           2207     2
```

Finding correlation

```
correlation_matrix = data_cleaned.corr()
```

Plotting correlation

```
plt.figure(figsize=(25, 15))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



Defining X ('Feature') and y ('Target')

```
X = data_cleaned.drop(columns=['Type'])
y = data_cleaned['Type']
```

Splitting Dataset into train and test

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
```

Function to plot the confusion matrix

```
def plot_confusion_matrix(y_test, y_pred, model_name):
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=True,
yticklabels=True)
    plt.title(f"Confusion Matrix - {model_name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```

Function to plot feature importance

```
def plot_feature_importance(model, X_train, model_name):
    feature_importance = model.feature_importances_
    sorted_idx = feature_importance.argsort()
    plt.barh(X_train.columns[sorted_idx], feature_importance[sorted_idx])
    plt.xlabel("Feature Importance")
    plt.title(f"Feature Importance - {model_name}")
    plt.show()
```

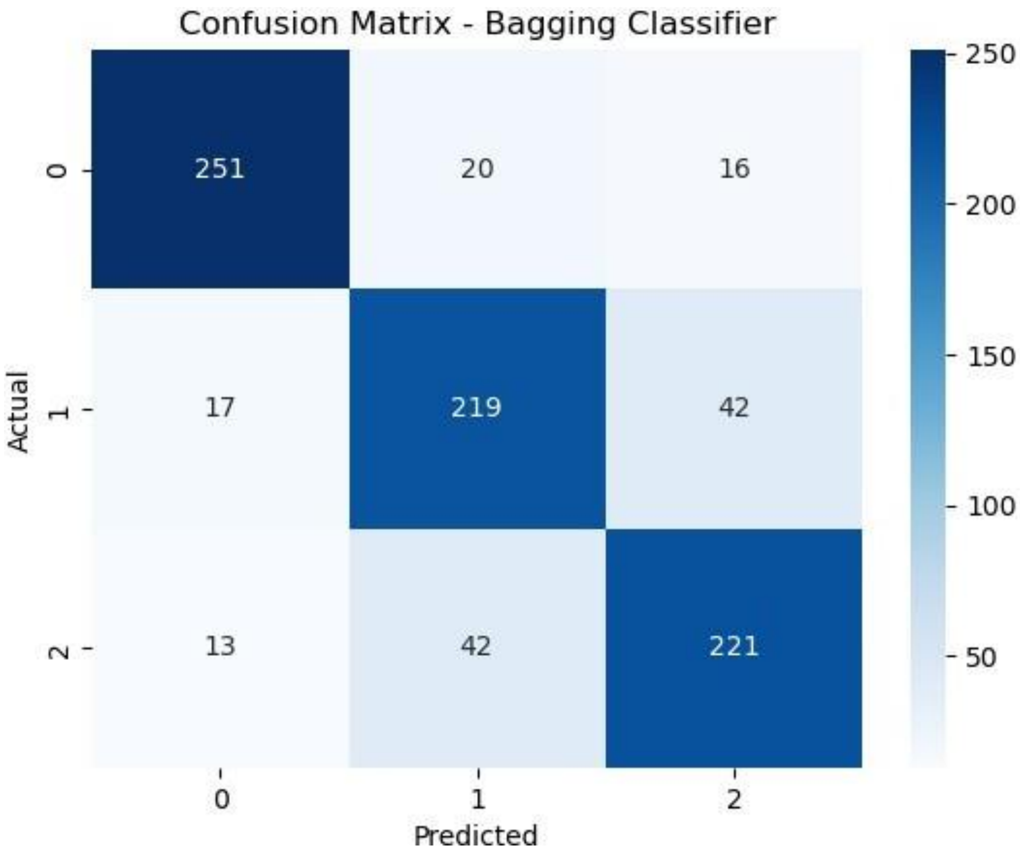
Bagging Classifier

```
bagging_model = BaggingClassifier(random_state=42)
bagging_model.fit(X_train, y_train)
y_pred_bagging = bagging_model.predict(X_test)
print("Bagging Classifier Accuracy:", accuracy_score(y_test, y_pred_bagging))
print(classification_report(y_test, y_pred_bagging))
plot_confusion_matrix(y_test, y_pred_bagging, "Bagging Classifier")
```

```
Bagging Classifier Accuracy: 0.821640903686088
              precision    recall  f1-score   support

           0       0.89      0.87      0.88       287
           1       0.78      0.79      0.78       278
           2       0.79      0.80      0.80       276

    accuracy                           0.82       841
   macro avg       0.82      0.82      0.82       841
weighted avg       0.82      0.82      0.82       841
```



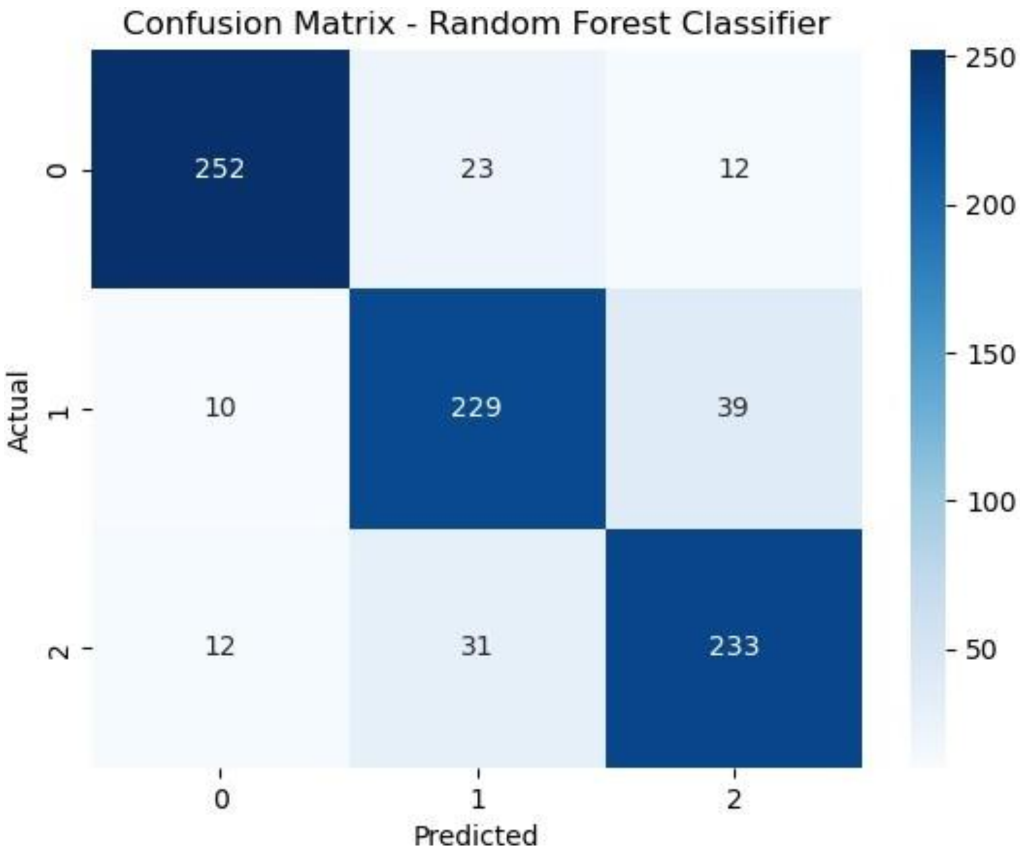
Random Forest Classifier

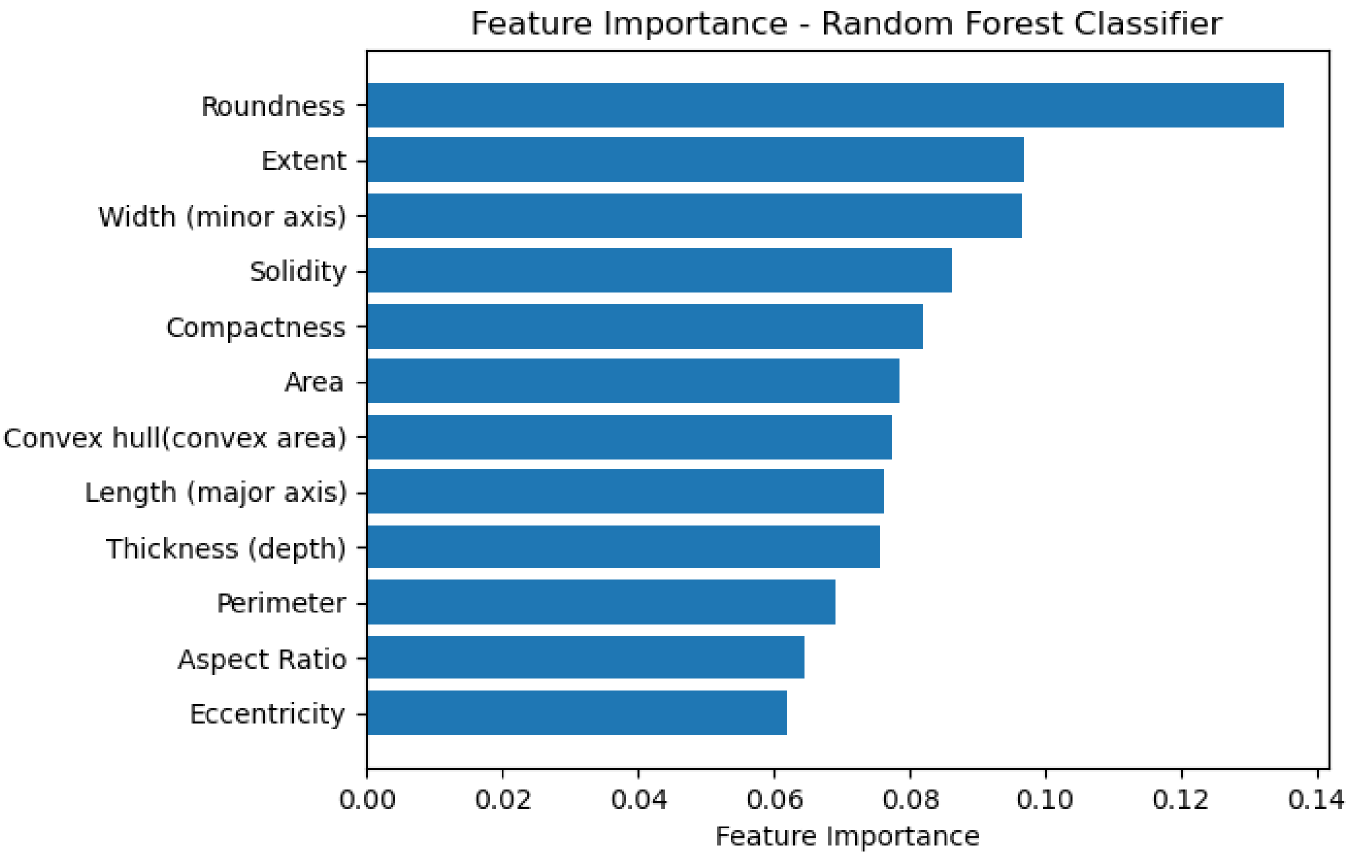
```
random_forest_model = RandomForestClassifier(random_state=42)
random_forest_model.fit(X_train, y_train)
y_pred_random_forest = random_forest_model.predict(X_test)
y_pred_random_forest_prob = random_forest_model.predict_proba(X_test)[:, 1]
print("Random Forest Classifier Accuracy:", accuracy_score(y_test,
y_pred_random_forest))
print(classification_report(y_test, y_pred_random_forest))
plot_confusion_matrix(y_test, y_pred_random_forest, "Random Forest
Classifier")
plot_feature_importance(random_forest_model, X_train, "Random Forest
Classifier")
```

```
Random Forest Classifier Accuracy: 0.8489892984542212
              precision    recall  f1-score   support

           0       0.92      0.88      0.90       287
           1       0.81      0.82      0.82       278
           2       0.82      0.84      0.83       276

    accuracy                           0.85       841
   macro avg       0.85      0.85      0.85       841
weighted avg       0.85      0.85      0.85       841
```





AdaBoost Classifier

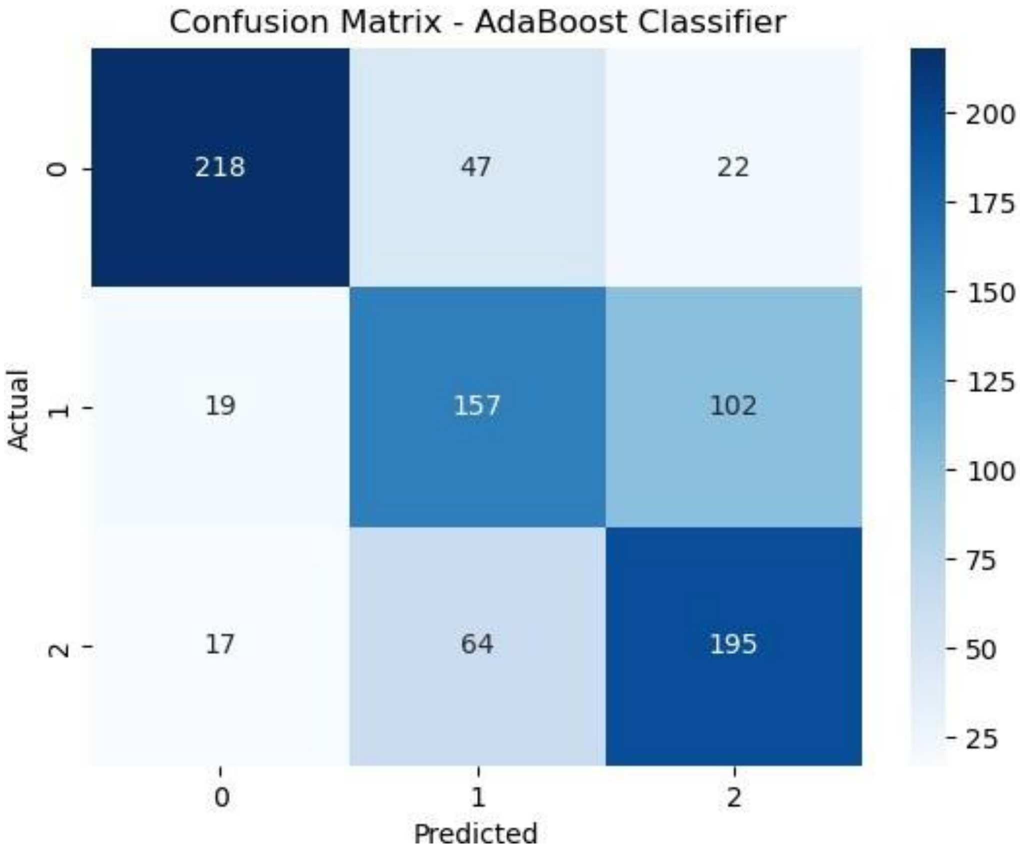
```
adaboost_model = AdaBoostClassifier(random_state=42)
adaboost_model.fit(X_train, y_train)
y_pred_adaboost = adaboost_model.predict(X_test)
y_pred_adaboost_prob = adaboost_model.predict_proba(X_test)[:, 1]
print("AdaBoost Classifier Accuracy:", accuracy_score(y_test,
```

```
y_pred_adaboost))
print(classification_report(y_test, y_pred_adaboost))
plot_confusion_matrix(y_test, y_pred_adaboost, "AdaBoost Classifier")
```

```
AdaBoost Classifier Accuracy: 0.6777645659928656
              precision    recall  f1-score   support

           0       0.86      0.76      0.81       287
           1       0.59      0.56      0.58       278
           2       0.61      0.71      0.66       276

    accuracy                           0.68       841
   macro avg       0.69      0.68      0.68       841
weighted avg       0.69      0.68      0.68       841
```



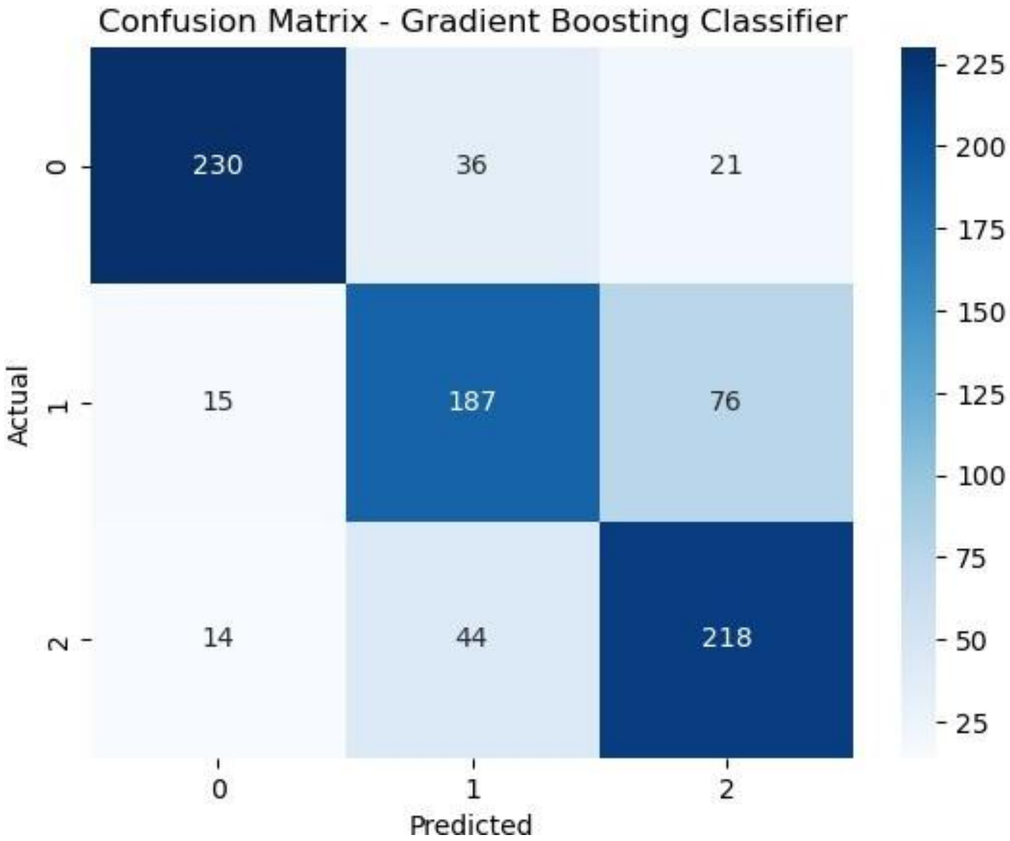
Gradient Boosting Classifier

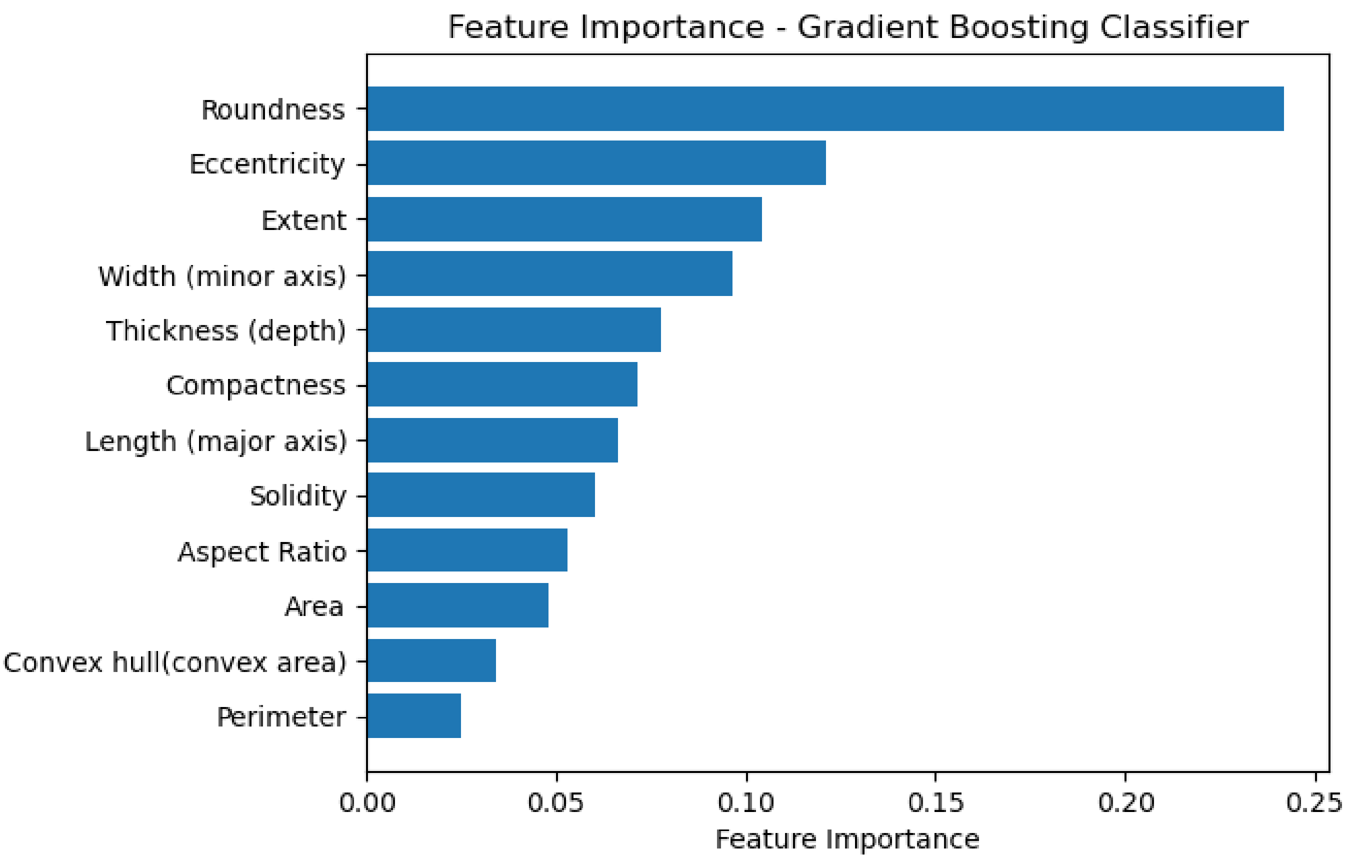
```
gradientboost_model = GradientBoostingClassifier(random_state=42)
gradientboost_model.fit(X_train, y_train)
y_pred_gradientboost = gradientboost_model.predict(X_test)
y_pred_gradientboost_prob = gradientboost_model.predict_proba(X_test)[:, 1]
print("Gradient Boosting Classifier Accuracy:", accuracy_score(y_test,
y_pred_gradientboost))
print(classification_report(y_test, y_pred_gradientboost))
plot_confusion_matrix(y_test, y_pred_gradientboost, "Gradient Boosting
Classifier")
plot_feature_importance(gradientboost_model, X_train, "Gradient Boosting
Classifier")
```

```
Gradient Boosting Classifier Accuracy: 0.7550535077288941
              precision    recall  f1-score   support
```

```
           0       0.89      0.80      0.84       287
           1       0.70      0.67      0.69       278
           2       0.69      0.79      0.74       276

    accuracy                           0.76       841
   macro avg       0.76      0.75      0.76       841
weighted avg       0.76      0.76      0.76       841
```





Function to print summary

```
def print_model_summary(model_name, y_test, y_pred):
    print(f"Summary for {model_name}:")
    print(" ---------------------------------------------------- ")
    print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
    print(f"Precision: {precision_score(y_test, y_pred,
average='weighted'):.4f}")
    print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")
    print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
```

Printing summary of the model

```
# Bagging Classifier
print_model_summary("Bagging Classifier", y_test, y_pred_bagging)

# AdaBoost Classifier
print_model_summary("AdaBoost Classifier", y_test, y_pred_adaboost)

# Gradient Boosting Classifier
print_model_summary("Gradient Boosting Classifier", y_test,
y_pred_gradientboost)

# Random Forest Classifier
print_model_summary("Random Forest Classifier", y_test, y_pred_random_forest)
```

```
Summary for Bagging Classifier:
-----------------------------------
Accuracy: 0.8216
Precision: 0.8224
Recall: 0.8216
F1 Score: 0.8220
Summary for AdaBoost Classifier:
```

```
------------------------------
Accuracy: 0.6778
Precision: 0.6872
Recall: 0.6778
F1 Score: 0.6802
Summary for Gradient Boosting Classifier:
------------------------------
Accuracy: 0.7551
Precision: 0.7617
Recall: 0.7551
F1 Score: 0.7565
Summary for Random Forest Classifier:
------------------------------
Accuracy: 0.8490
Precision: 0.8506
Recall: 0.8490
F1 Score: 0.8495
```