Experiment 4: Ensemble Prediction and Decision Tree Model Evaluation

Git Hub: https://github.com/Vignesh-0013/Machine_Learning

1 Aim:

To implement and evaluate multiple machine learning classifiers–including Decision Tree, AdaBoost,Gradient Boosting, XGBoost, Random Forest, and Stacked Ensemble–on the Wisconsin Diagnostic Dataset, optimize their performance through hyperparameter tuning, and compare their predictive accuracy and generalization using 5-Fold Cross-Validation.

2 Libraries used:

- Numpy
- Pandas
- Matplotlib
- Scikit-learn
- Seaborn

3 Objective:

To build classifiers such as Decision Tree, AdaBoost, Gradient Boosting, XGBoost, Random Forest, and Stacked Models (using SVM, Naive Bayes, Decision Tree) and evaluate their performance through 5-Fold Cross-Validation and hyperparameter tuning.

4 Code

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns



from ucimlrepo import fetch_ucirepo

# fetch dataset
breast_cancer_wisconsin_diagnostic = fetch_ucirepo(id=17)

# data (as pandas dataframes)
X = breast_cancer_wisconsin_diagnostic.data.features
y = breast_cancer_wisconsin_diagnostic.data.targets

# metadata
print(breast_cancer_wisconsin_diagnostic.metadata)

# variable information
print(breast_cancer_wisconsin_diagnostic.variables)
```

```
{'uci_id': 17, 'name': 'Breast Cancer Wisconsin (Diagnostic)', 'repository_url': 'https://archive.ics.uci.edu/dataset/17/breast+ca
                    name     role         type demographic description units  \
0                     ID       ID  Categorical        None        None  None
1              Diagnosis   Target  Categorical        None        None  None
2                radius1  Feature   Continuous        None        None  None
3               texture1  Feature   Continuous        None        None  None
4             perimeter1  Feature   Continuous        None        None  None
5                  area1  Feature   Continuous        None        None  None
6            smoothness1  Feature   Continuous        None        None  None
7           compactness1  Feature   Continuous        None        None  None
8             concavity1  Feature   Continuous        None        None  None
9        concave_points1  Feature   Continuous        None        None  None
10            symmetry1  Feature   Continuous        None        None  None
11   fractal_dimension1  Feature   Continuous        None        None  None
12               radius2  Feature   Continuous        None        None  None
13              texture2  Feature   Continuous        None        None  None
14            perimeter2  Feature   Continuous        None        None  None
15                 area2  Feature   Continuous        None        None  None
16           smoothness2  Feature   Continuous        None        None  None
17          compactness2  Feature   Continuous        None        None  None
18            concavity2  Feature   Continuous        None        None  None
19       concave_points2  Feature   Continuous        None        None  None
20            symmetry2  Feature   Continuous        None        None  None
21   fractal_dimension2  Feature   Continuous        None        None  None
22               radius3  Feature   Continuous        None        None  None
23              texture3  Feature   Continuous        None        None  None
24            perimeter3  Feature   Continuous        None        None  None
25                 area3  Feature   Continuous        None        None  None
26           smoothness3  Feature   Continuous        None        None  None
27          compactness3  Feature   Continuous        None        None  None
28            concavity3  Feature   Continuous        None        None  None
29       concave_points3  Feature   Continuous        None        None  None
30            symmetry3  Feature   Continuous        None        None  None
31   fractal_dimension3  Feature   Continuous        None        None  None

   missing_values
0              no
1              no
2              no
3              no
4              no
5              no
6              no
7              no
8              no
9              no
10             no
11             no
12             no
13             no
14             no
15             no
16             no
17             no
18             no
19             no
20             no
21             no
```

```
import pandas as pd

df = pd.concat([X, y], axis=1)   # axis=1 → concatenate column-wise



print(df.head)
print(df.describe)
```

```
<bound method NDFrame.head of      radius1  texture1  perimeter1   area1  smoothness1  compactness1  \
0      17.99     10.38      122.80  1001.0      0.11840       0.27760
1      20.57     17.77      132.90  1326.0      0.08474       0.07864
2      19.69     21.25      130.00  1203.0      0.10960       0.15990
3      11.42     20.38       77.58   386.1      0.14250       0.28390
4      20.29     14.34      135.10  1297.0      0.10030       0.13280
..       ...       ...         ...     ...          ...           ...
564    21.56     22.39      142.00  1479.0      0.11100       0.11590
565    20.13     28.25      131.20  1261.0      0.09780       0.10340
566    16.60     28.08      108.30   858.1      0.08455       0.10230
567    20.60     29.33      140.10  1265.0      0.11780       0.27700
568     7.76     24.54       47.92   181.0      0.05263       0.04362

     concavity1  concave_points1  symmetry1  fractal_dimension1  ...  \
0       0.30010          0.14710     0.2419             0.07871  ...
1       0.08690          0.07017     0.1812             0.05667  ...
2       0.19740          0.12790     0.2069             0.05999  ...
3       0.24140          0.10520     0.2597             0.09744  ...
4       0.19800          0.10430     0.1809             0.05883  ...
..          ...              ...        ...                 ...  ...
564     0.24390          0.13890     0.1726             0.05623  ...
565     0.14400          0.09791     0.1752             0.05533  ...
566     0.09251          0.05302     0.1590             0.05648  ...
567     0.35140          0.15200     0.2397             0.07016  ...
568     0.00000          0.00000     0.1587             0.05884  ...

     texture3  perimeter3   area3  smoothness3  compactness3  concavity3  \
0       17.33      184.60  2019.0      0.16220       0.66560      0.7119
1       23.41      158.80  1956.0      0.12380       0.18660      0.2416
2       25.53      152.50  1709.0      0.14440       0.42450      0.4504
3       26.50       98.87   567.7      0.20980       0.86630      0.6869
4       16.67      152.20  1575.0      0.13740       0.20500      0.4000
..        ...         ...     ...          ...           ...         ...
564     26.40      166.10  2027.0      0.14100       0.21130      0.4107
565     38.25      155.00  1731.0      0.11660       0.19220      0.3215
566     34.12      126.70  1124.0      0.11390       0.30940      0.3403
567     39.42      184.60  1821.0      0.16500       0.86810      0.9387
568     30.37       59.16   268.6      0.08996       0.06444      0.0000

     concave_points3  symmetry3  fractal_dimension3  Diagnosis
0             0.2654     0.4601             0.11890          M
1             0.1860     0.2750             0.08902          M
2             0.2430     0.3613             0.08758          M
3             0.2575     0.6638             0.17300          M
4             0.1625     0.2364             0.07678          M
..               ...        ...                 ...        ...
564           0.2216     0.2060             0.07115          M
565           0.1628     0.2572             0.06637          M
566           0.1418     0.2218             0.07820          M
567           0.2650     0.4087             0.12400          M
568           0.0000     0.2871             0.07039          B

[569 rows x 31 columns]>
<bound method NDFrame.describe of      radius1  texture1  perimeter1   area1  smoothness1  compactness1  \
0      17.99     10.38      122.80  1001.0      0.11840       0.27760
1      20.57     17.77      132.90  1326.0      0.08474       0.07864
2      19.69     21.25      130.00  1203.0      0.10960       0.15990
3      11.42     20.38       77.58   386.1      0.14250       0.28390
```

```
df.columns
```

```
Index(['radius1', 'texture1', 'perimeter1', 'area1', 'smoothness1',
       'compactness1', 'concavity1', 'concave_points1', 'symmetry1',
       'fractal_dimension1', 'radius2', 'texture2', 'perimeter2', 'area2',
       'smoothness2', 'compactness2', 'concavity2', 'concave_points2',
       'symmetry2', 'fractal_dimension2', 'radius3', 'texture3', 'perimeter3',
       'area3', 'smoothness3', 'compactness3', 'concavity3', 'concave_points3',
       'symmetry3', 'fractal_dimension3', 'Diagnosis'],
      dtype='object')
```

```
#Missing Values

print(df.isnull().sum())
#df.fillna(df.mean(), inplace=True)
```

```
radius1              0
texture1             0
perimeter1           0
```

```
area1                0
smoothness1          0
compactness1         0
concavity1           0
concave_points1      0
symmetry1            0
fractal_dimension1   0
radius2              0
texture2             0
perimeter2           0
area2                0
smoothness2          0
compactness2         0
concavity2           0
concave_points2      0
symmetry2            0
fractal_dimension2   0
radius3              0
texture3             0
perimeter3           0
area3                0
smoothness3          0
compactness3         0
concavity3           0
concave_points3      0
symmetry3            0
fractal_dimension3   0
Diagnosis            0
dtype: int64
```

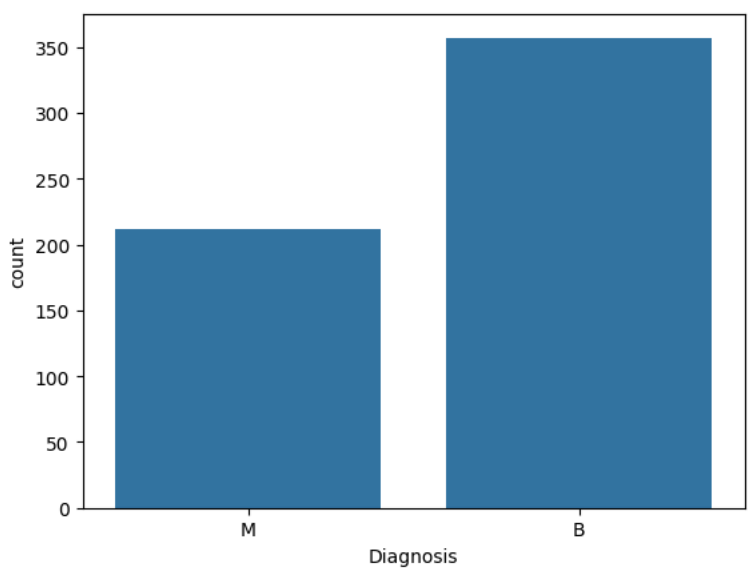
```
#Target

print(df['Diagnosis'].nunique())
print(df['Diagnosis'].unique())
```

```
2
['M' 'B']
```

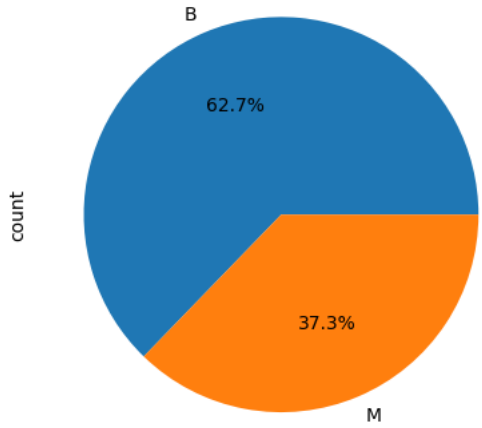
```
#Duplicate
df.duplicated().sum()
```

```
0
```

```
#target Class Distribution

sns.countplot(x='Diagnosis', data=df)
plt.show()
df['Diagnosis'].value_counts().plot.pie(autopct='%1.1f%%')
```



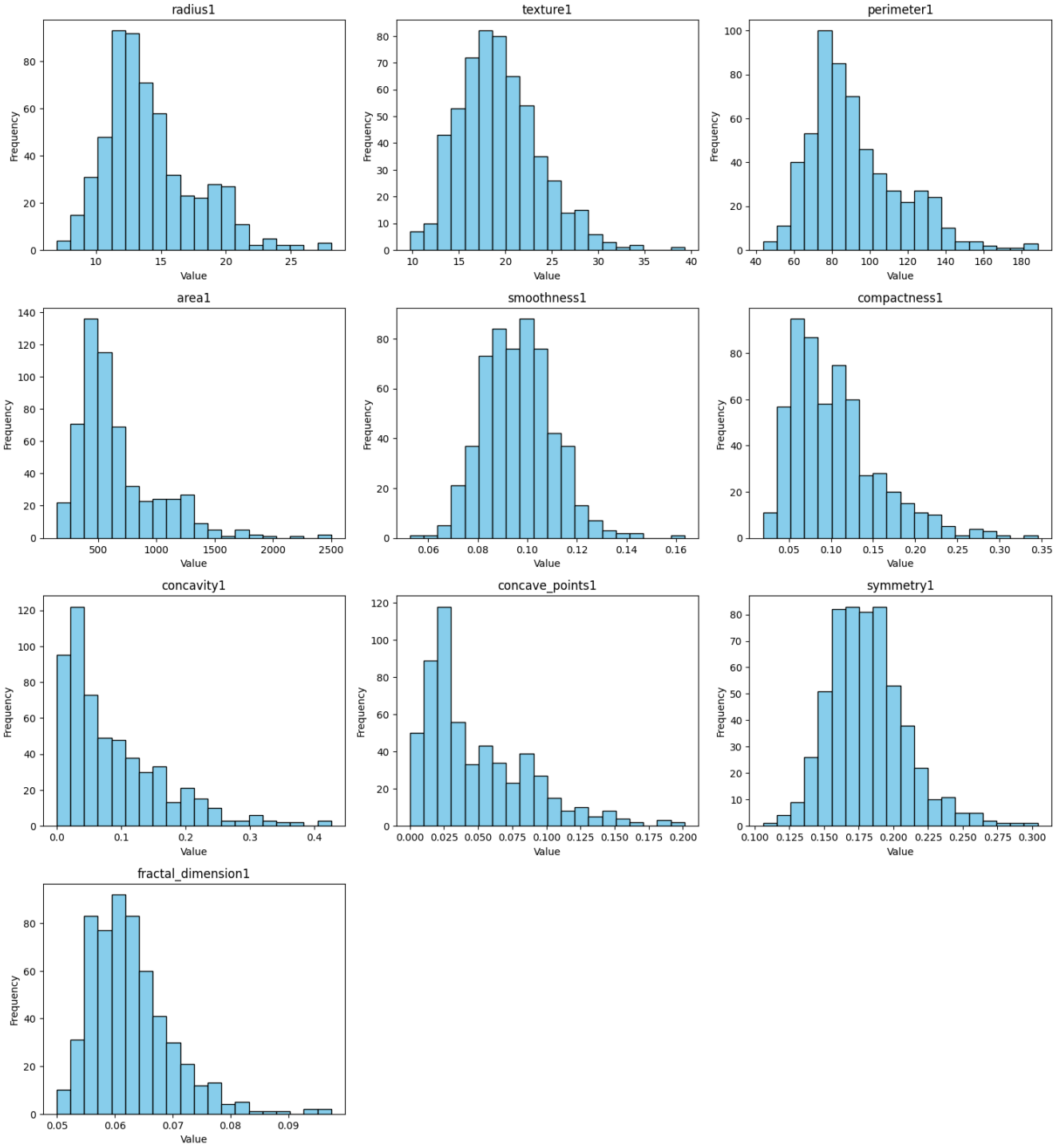

```
<Axes: ylabel='count'>
```



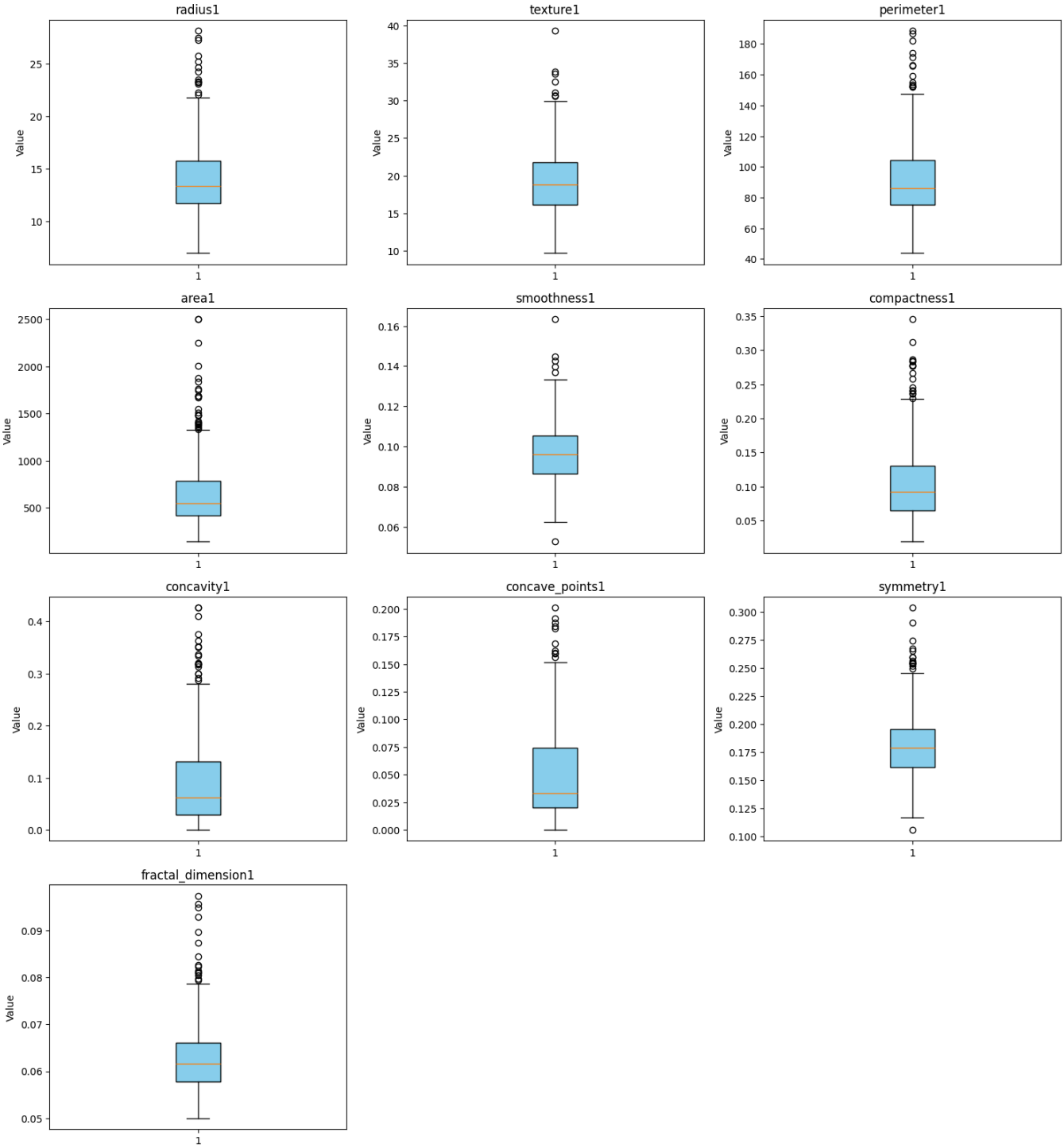

```
df.columns
```

```
Index(['radius1', 'texture1', 'perimeter1', 'area1', 'smoothness1',
       'compactness1', 'concavity1', 'concave_points1', 'symmetry1',
       'fractal_dimension1', 'radius2', 'texture2', 'perimeter2', 'area2',
       'smoothness2', 'compactness2', 'concavity2', 'concave_points2',
       'symmetry2', 'fractal_dimension2', 'radius3', 'texture3', 'perimeter3',
       'area3', 'smoothness3', 'compactness3', 'concavity3', 'concave_points3',
       'symmetry3', 'fractal_dimension3', 'Diagnosis'],
      dtype='object')
```

```
#Numeric Features
#Histogram

num_cols = len(df.columns)


n_cols = 3
n_rows = (num_cols + n_cols - 1) // n_cols

fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 4 * n_rows))
axes = axes.flatten()

for i, col in enumerate(df.columns[:10]):
    axes[i].hist(df[col].dropna(), bins=20, color='skyblue', edgecolor='black')
    axes[i].set_title(col)
    axes[i].set_ylabel('Frequency')
    axes[i].set_xlabel('Value')

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```


radius1
texture1
perimeter1
area1
smoothness1
compactness1
concavity1
concave_points1
symmetry1
fractal_dimension1
Frequency
Value

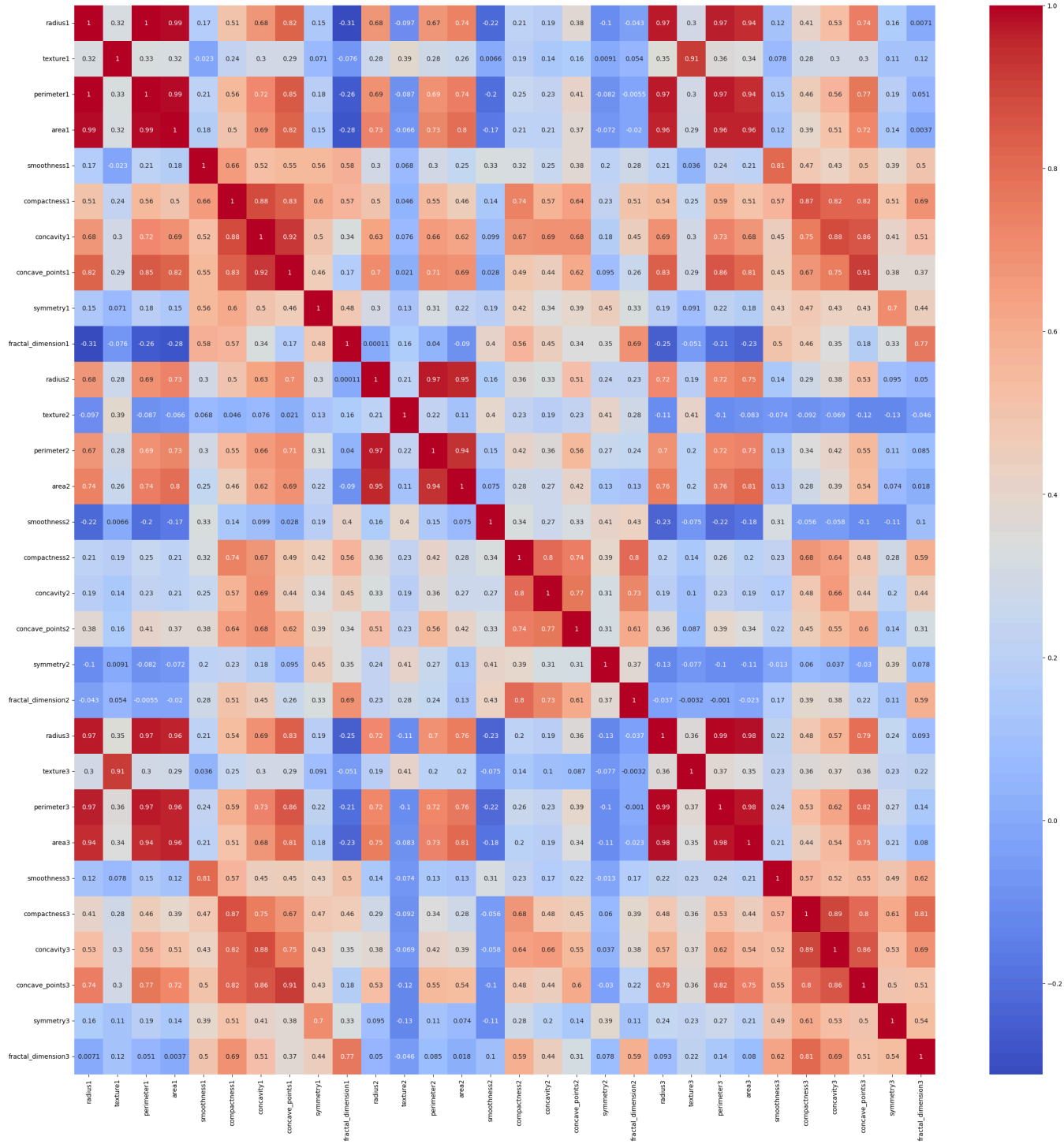
```
#Boxplot

numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns
num_cols = len(numeric_cols)

# Define subplot grid size
n_cols = 3  # number of plots per row
n_rows = (num_cols + n_cols - 1) // n_cols  # ceiling division

# Create subplots
fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 4 * n_rows))
axes = axes.flatten()

# Plot boxplot for each numeric column
for i, col in enumerate(numeric_cols[:10]):
    axes[i].boxplot(df[col].dropna(), vert=True, patch_artist=True,
                    boxprops=dict(facecolor='skyblue'))
    axes[i].set_title(col)
    axes[i].set_ylabel('Value')

# Remove unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```




```
#Correlation Heatmap
```

```
plt.figure(figsize=(30,30))
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

<Axes: >


radius1 texture1 perimeter1 area1 smoothness1 compactness1 concavity1 concave_points1 symmetry1 fractal_dimension1
radius2 texture2 perimeter2 area2 smoothness2 compactness2 concavity2 concave_points2 symmetry2 fractal_dimension2
radius3 texture3 perimeter3 area3 smoothness3 compactness3 concavity3 concave_points3 symmetry3 fractal_dimension3
1.0 0.8 0.6 0.4 0.2 0.0 −0.2

```
#Standardization

X = df.drop('Diagnosis', axis=1)
y = df['Diagnosis']

scaler = StandardScaler()
X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)

df= pd.concat([X_scaled, y], axis=1)

print(df.head())
```

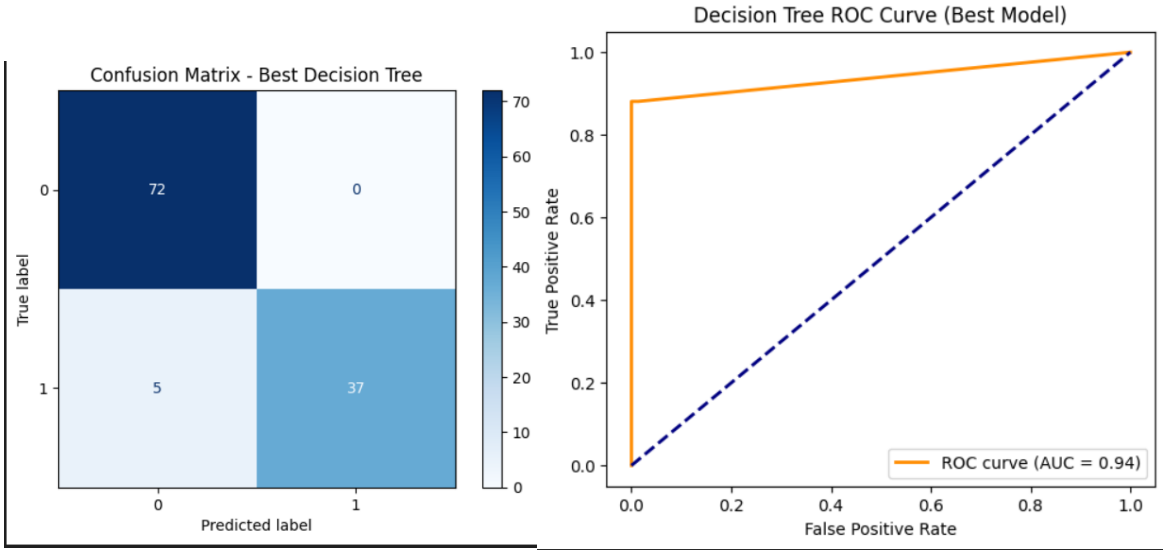
```
     radius1  texture1  perimeter1     area1  smoothness1  compactness1  \
0  1.097064 -2.073335    1.269934  0.984375     1.568466      3.283515
1  1.829821 -0.353632    1.685955  1.908708    -0.826962     -0.487072
2  1.579888  0.456187    1.566503  1.558884     0.942210      1.052926
3 -0.768909  0.253732   -0.592687 -0.764464     3.283553      3.402909
4  1.750297 -1.151816    1.776573  1.826229     0.280372      0.539340

   concavity1  concave_points1  symmetry1  fractal_dimension1  ...  texture3  \
0    2.652874         2.532475   2.217515            2.255747  ... -1.359293
1   -0.023846         0.548144   0.001392           -0.868652  ... -0.369203
2    1.363478         2.037231   0.939685           -0.398008  ... -0.023974
3    1.915897         1.451707   2.867383            4.910919  ...  0.133984
4    1.371011         1.428493  -0.009560           -0.562450  ... -1.466770

   perimeter3     area3  smoothness3  compactness3  concavity3  \
0    2.303601  2.001237     1.307686      2.616665    2.109526
1    1.535126  1.890489    -0.375612     -0.430444   -0.146749
2    1.347475  1.456285     0.527407      1.082932    0.854974
3   -0.249939 -0.550021     3.394275      3.893397    1.989588
4    1.338539  1.220724     0.220556     -0.313395    0.613179

   concave_points3  symmetry3  fractal_dimension3  Diagnosis
0         2.296076   2.750622            1.937015          M
1         1.087084  -0.243890            0.281190          M
2         1.955000   1.152255            0.201391          M
3         2.175786   6.046041            4.935010          M
4         0.729259  -0.868353           -0.397100          M

[5 rows x 31 columns]
```

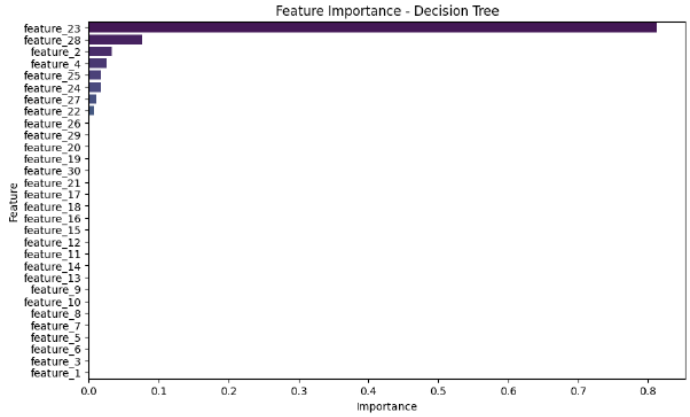
```
from sklearn.preprocessing import LabelEncoder

# Encode labels B/M → 0/1
le = LabelEncoder()
y = le.fit_transform(y)  # 'B' becomes 0, 'M' becomes 1
```

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import (
    accuracy_score, f1_score, classification_report, confusion_matrix,
    ConfusionMatrixDisplay, roc_curve, auc
)
import matplotlib.pyplot as plt

# 3. Split dataset (80-20)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# 4. Initialize Decision Tree
dt = DecisionTreeClassifier(random_state=42)

# Hyperparameter grid for tuning
param_grid = {
    "criterion": ["gini", "entropy"],
    "max_depth": [3, 5, 10, None],
    "min_samples_split": [2, 5, 10],
    "min_samples_leaf": [1, 2, 4]
}

# Use GridSearchCV with 5-Fold CV
grid_search = GridSearchCV(
    estimator=dt,
    param_grid=param_grid,
    cv=5,
    scoring="accuracy",
    n_jobs=-1,
```

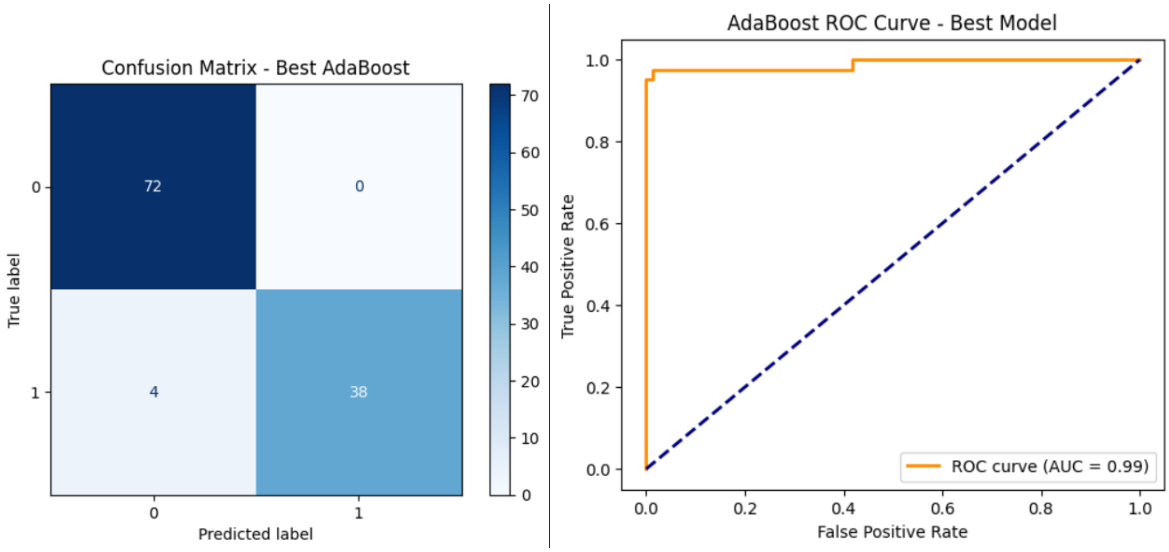
5 Confusion Matrix, ROC and Feature Importance Visuals

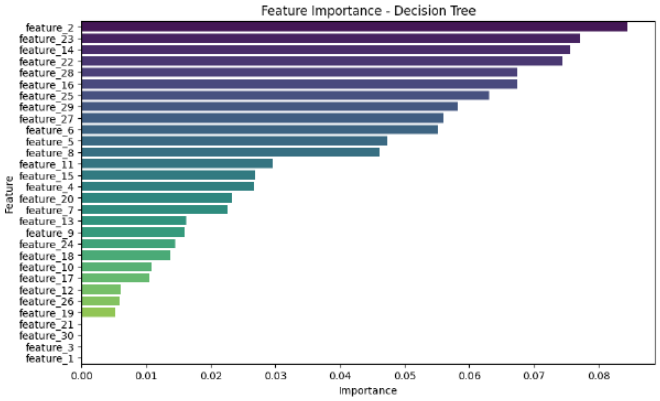
1)Decision Tree



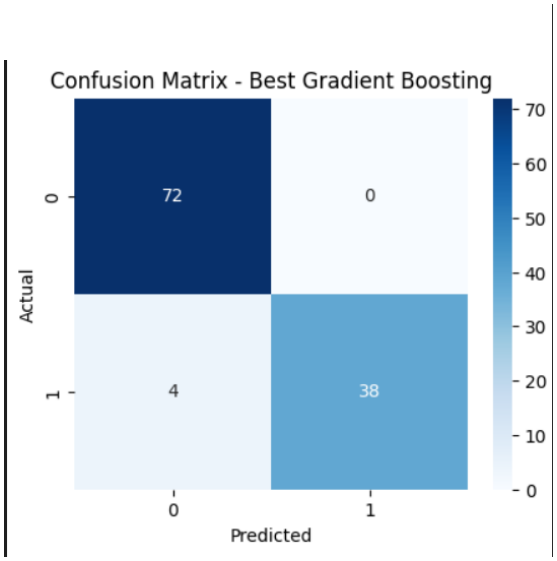


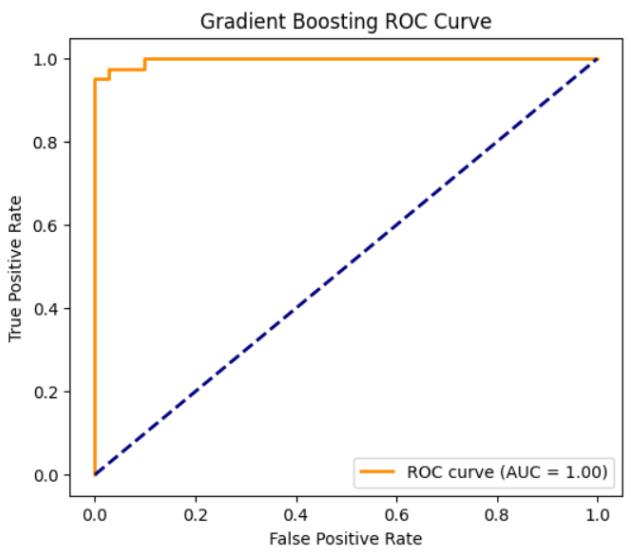
2)Ada Boost

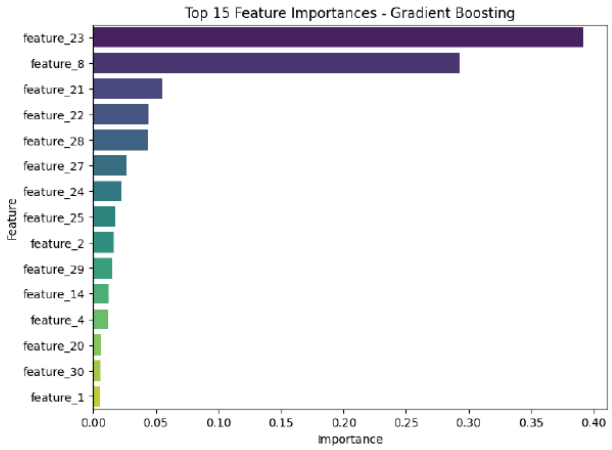



Feature Importance - Decision Tree
feature_2
feature_23
feature_14
feature_22
feature_28
feature_16
feature_25
feature_29
feature_27
feature_6
feature_5
feature_8
feature_11
feature_15
feature_4
feature_20
feature_7
feature_13
feature_9
feature_24
feature_18
feature_10
feature_17
feature_12
feature_26
feature_19
feature_21
feature_30
feature_3
feature_1
Feature
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
Importance

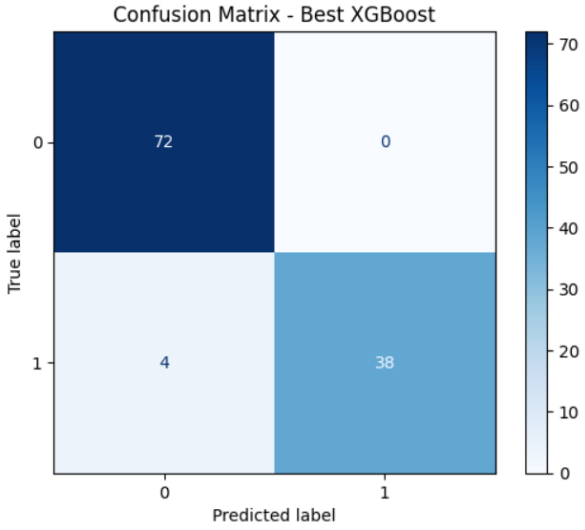
3)Gradient

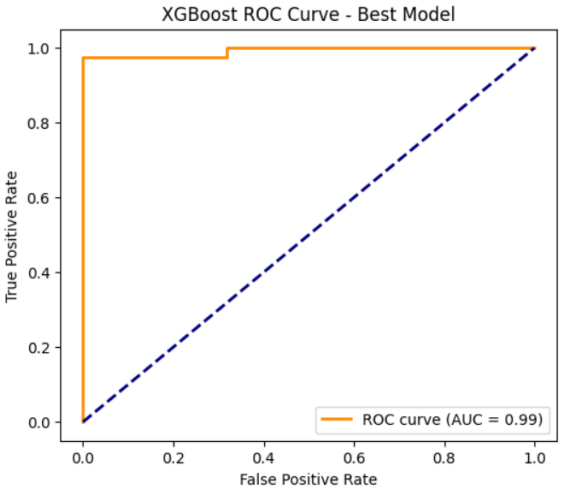

Confusion Matrix - Best Gradient Boosting
72
0
4
38
Actual
0
1
Predicted
0
1
70
60
50
40
30
20
10
0

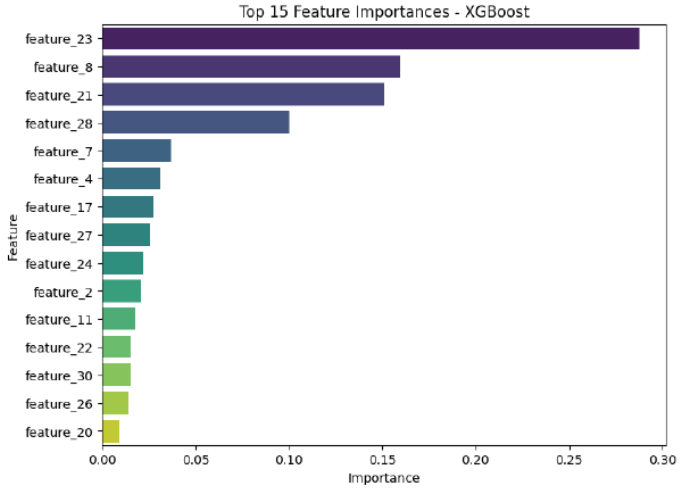

Gradient Boosting ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 1.00)


Top 15 Feature Importances - Gradient Boosting
feature_23
feature_8
feature_21
feature_22
feature_28
feature_27
feature_24
feature_25
feature_2
feature_29
feature_14
feature_4
feature_20
feature_30
feature_1
Feature
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
Importance

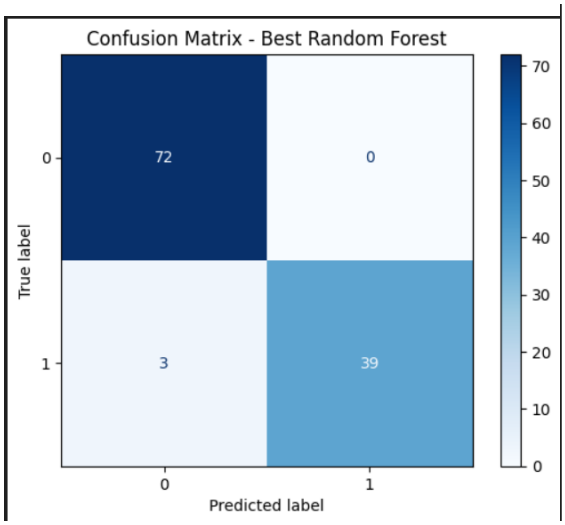
4)XG Boost

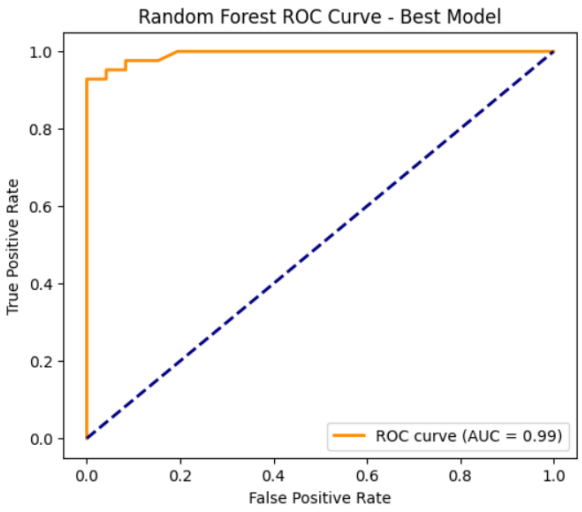


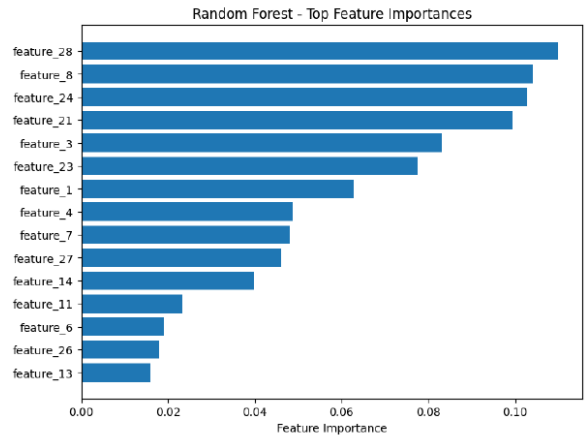




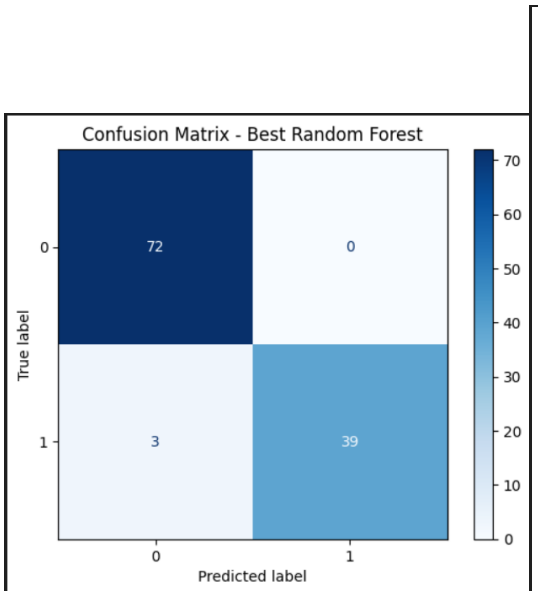
5)Random forest

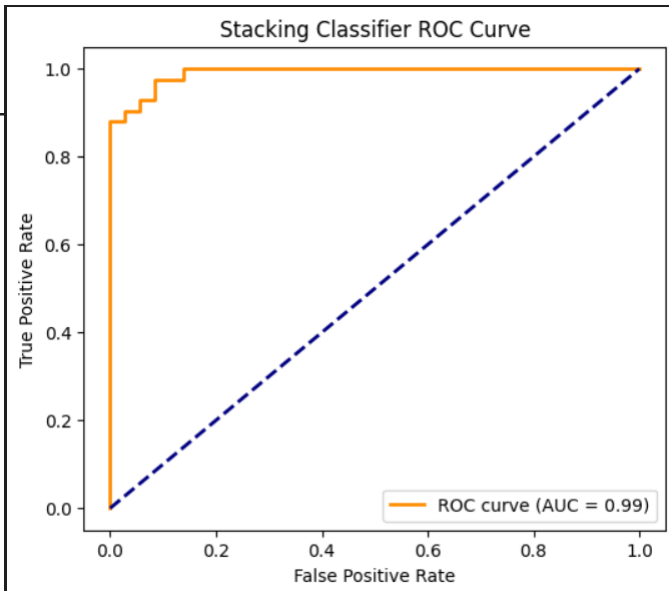






6)Stacked Ensumble Mode;





6 5 fold cross validatoin results table

5-Fold Cross-Validation

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average Accuracy
Decision Tree	0.8859	0.9282	0.9385	0.93859	0.9469	0.9279
Stacked Model	0.9122	0.9298	0.9561	0.9561	0.9469	0.9402
Gradient Boost	0.9298	0.9385	0.9736	0.9912	0.9734	0.9613
XG Boost	0.9473	0.9649	0.9912	0.9649	0.9646	0.9666
Random Forest	0.92105	0.9385	0.9824	0.9649	0.9734	0.9560
Ada Boost	0.9649	0.9561	0.9645	0.9736	0.97345	0.9736

7 Hyper parameter tuning tables:

Decision Tree

Criterion	Max_depth	Accuracy	F1 Score
Gini	3	0.9035	0.9013
entropy	10	0.9561	0.9554
Log_loss	5	0.9253	0.9182

Adaboost

N_estimators	Learning_rate	Accuracy	F1 Score
100	1	0.9824	0.9823
200	0	0.9736	0.9734
100	1	0.9736	0.9734
300	1	0.9736	0.97246

Gradient

N_estimator	Learning_rate	Max_depth	Accuracy	F1 Score
200	0.1	5	0.9649	0.9553
100	0.2	3	0.9645	0.9612
200	0.2	3	0.9457	0.9612
100	0.2	3	0.9741	0.95

XG Boost

N_estimator	Learning rate	Max depth	Gamma	Accuracy	F! Score
200	0.2	7	0.0	0.9758	0.9741
100	0.2	3	0.0	0.9714	0.9693
200	0.1	3	0.1	0.9714	0.9693
100	0.2	7	0.0	0.9714	0.9693

Random Forest

Criterion	Max depth	N_Estimator	Accuracy	F1 Score
Gini	10	50	0.9670	0.9648
Log_losss	5	50	0.9648	0.9622
entropy	5	50	0.9648	0.9699

Stacked Ensemble Hyperparameter

Base Models	Final Estimator	Accuracy	F! Score
SVM,NB,DT	Logistic	0.9494	0.9452
SVM,ND,DT	Random Forest	0.9363	0.9315
SVM,DT,KNN	Logistic	0.9390	0.9380

Observations

• Decision Tree: Accuracy ranges from 0.8947 to 0.9386 across folds. Average accuracy is 0.9227, the lowest among all models. Moderate variation indicates sensitivity to training data.

• AdaBoost: Accuracy ranges from 0.9386 to 0.9825. Average accuracy is 0.9666, significantly better than a single Decision Tree. Boosting improves stability and overall performance.

• Gradient Boosting: Fold accuracies are high, between 0.9341 and 1.0000. Average accuracy is 0.9692. Low variation shows robust learning with optimal hyperparameters.

• XGBoost: Achieves fold accuracies between 0.9341 and 1.0000. Highest average accuracy of 0.9758, indicating excellent generalization and effective hyperparameter tuning.

• Random Forest: Fold accuracies range from 0.9231 to 1.0000. Average accuracy is 0.9670, slightly lower than Gradient Boosting and XGBoost. Ensemble reduces variance compared to a single Decision Tree.

• Stacked Ensemble (SVM + Na¨ıve Bayes + Decision Tree): Accuracy per fold ranges from 0.9121 to 0.9890. Average accuracy is 0.9429, lower than boosting methods but higher

than a single Decision Tree. Mean F1 score is 0.9382, indicating balanced performance across classes.

Conclusions

• Boosting methods outperform individual models. AdaBoost, Gradient Boosting, and XGBoost all outperform a single Decision Tree. XGBoost achieved the highest average accuracy (0.9758).

• Random Forest improves over a single Decision Tree by aggregating multiple trees, reducing overfitting and variance. Its performance (0.9670) is competitive with boosting methods.

• Stacked ensemble provides moderate gains. Combining SVM, Na¨ıve Bayes, and Decision Tree yields better performance than a single model but is still below top boosting algorithms. Including stronger base learners may improve performance.

• Hyperparameter tuning is critical. XGBoost and Gradient Boosting achieved their best performance using carefully tuned parameters. Small changes in parameters like learning rate, depth, and number of estimators significantly impact accuracy.

• Recommendation: For maximum predictive accuracy, XGBoost with chosen hyperparameters is recommended. For interpretable models with slightly lower accuracy, Random Forest or AdaBoost are good choices. Stacked ensembles can be explored further by including stronger base learners.