Final Project Code

April 10, 2024

[ ]:
```
import pandas as pd
import numpy as np
import copy
```

[ ]:
```
dataset = pd.read_csv('./dataset_ideal.csv')
```

[ ]:
```
# Data Exploration
dataset.shape[0]
dataset.head()
```

[ ]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   52    1   0       125   212    0        1      168      0      1.0      2
1   53    1   0       140   203    1        0      155      1      3.1      0
2   70    1   0       145   174    0        1      125      1      2.6      0
3   61    1   0       148   203    0        1      161      0      0.0      2
4   62    0   0       138   294    1        1      106      0      1.9      1

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

[ ]:
```
dataset.tail()
```

[ ]:
```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
1020   59    1   1       140   221    0        1      164      1      0.0
1021   60    1   0       125   258    0        0      141      1      2.8
1022   47    1   0       110   275    0        0      118      1      1.0
1023   50    0   0       110   254    0        0      159      0      0.0
1024   54    1   0       120   188    0        1      113      0      1.4

      slope  ca  thal  target
1020      2   0     2       1
1021      1   1     3       0
1022      1   1     2       0
1023      2   0     2       1
```

```
1024       1    1     3        0
```

[ ]:
```
dataset.describe()
```

[ ]:
```
                age          sex           cp     trestbps        chol  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.00000
mean     54.434146     0.695610     0.942439   131.611707   246.00000
std       9.072290     0.460373     1.029641    17.516718    51.59251
min      29.000000     0.000000     0.000000    94.000000   126.00000
25%      48.000000     0.000000     0.000000   120.000000   211.00000
50%      56.000000     1.000000     1.000000   130.000000   240.00000
75%      61.000000     1.000000     2.000000   140.000000   275.00000
max      77.000000     1.000000     3.000000   200.000000   564.00000

                fbs      restecg     thalach        exang      oldpeak  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.000000
mean      0.149268     0.529756   149.114146     0.336585     1.071512
std       0.356527     0.527878    23.005724     0.472772     1.175053
min       0.000000     0.000000    71.000000     0.000000     0.000000
25%       0.000000     0.000000   132.000000     0.000000     0.000000
50%       0.000000     1.000000   152.000000     0.000000     0.800000
75%       0.000000     1.000000   166.000000     1.000000     1.800000
max       1.000000     2.000000   202.000000     1.000000     6.200000

              slope           ca         thal       target
count  1025.000000  1025.000000  1025.000000  1025.000000
mean      1.385366     0.754146     2.323902     0.513171
std       0.617755     1.030798     0.620660     0.500070
min       0.000000     0.000000     0.000000     0.000000
25%       1.000000     0.000000     2.000000     0.000000
50%       1.000000     0.000000     2.000000     1.000000
75%       2.000000     1.000000     3.000000     1.000000
max       2.000000     4.000000     3.000000     1.000000
```

[ ]:
```
dataset.isnull().sum()
```

[ ]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
```

```
ca          0
thal        0
target      0
dtype: int64
```

```
[ ]: column_dtypes = dataset.dtypes

     print("Data types of each column:")
     print(column_dtypes)
```

```
Data types of each column:
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca            int64
thal          int64
target        int64
dtype: object
```

```
[ ]: %matplotlib inline
     import matplotlib.pyplot as plt
     import seaborn as sns
```

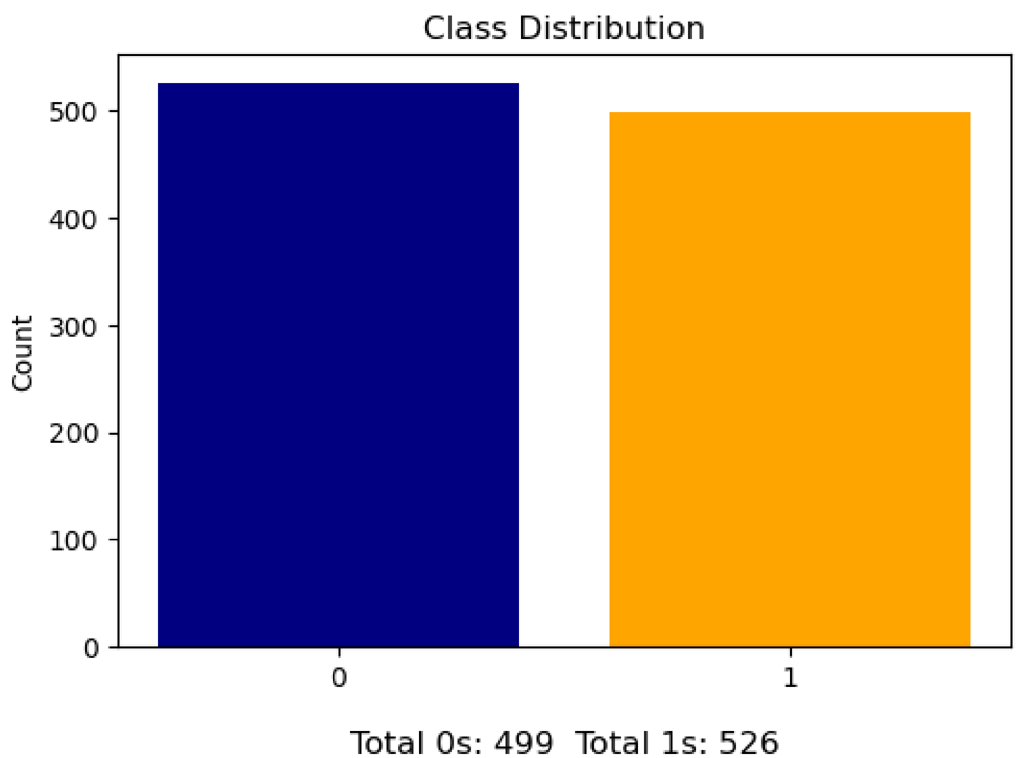
```
[ ]: import pandas_profiling as pp
     pp.ProfileReport(dataset)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

```
[ ]:
```

```
[ ]: class_distribution = dataset['target'].value_counts()
     # Labels
     labels = class_distribution.index.astype(str)
     targets = ['no disease', 'disease']

     # Plot
```

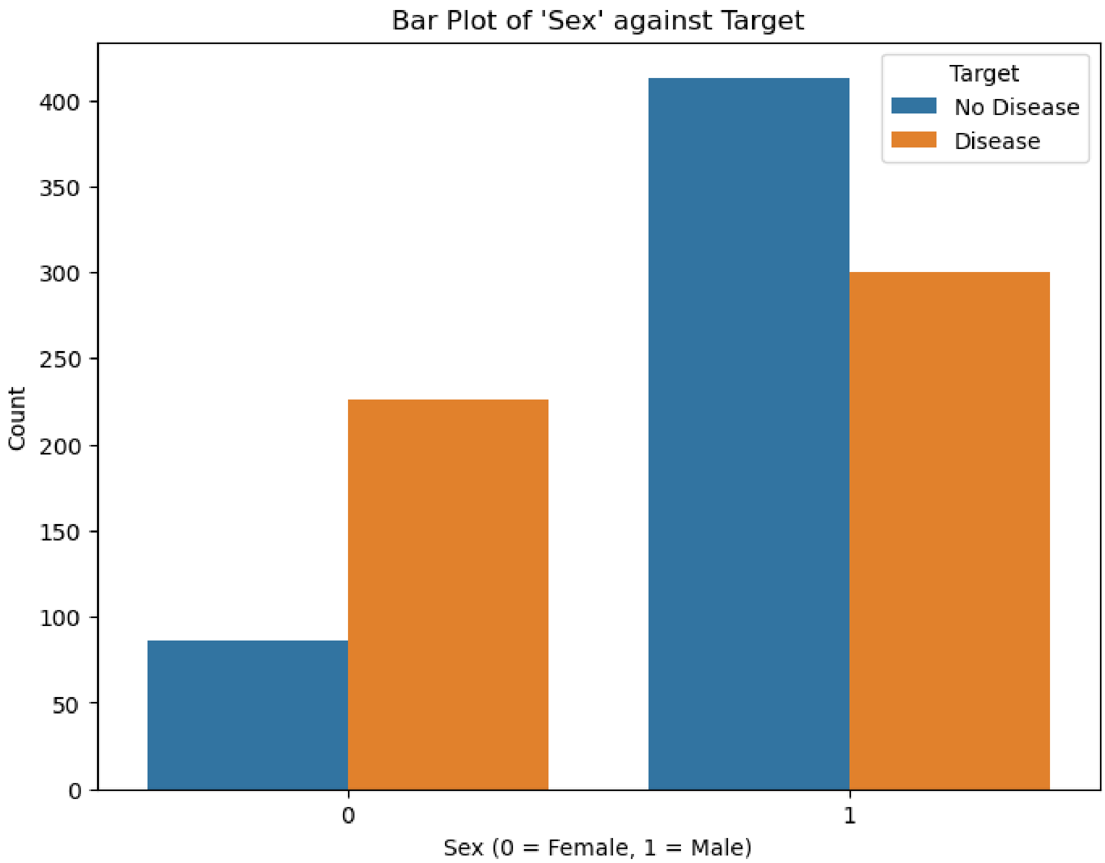
```
fig, ax = plt.subplots(figsize=(6, 4))
x = range(len(labels))
counts = class_distribution.values
bars = ax.bar(x, counts, color=['navy', 'orange'])
plt.title('Class Distribution')
total_count_0 = class_distribution[0]
total_count_1 = class_distribution[1]
plt.text(0.5, -100, f'Total 0s: {total_count_0}  Total 1s: {total_count_1}',␣
 ↪ha='center', fontsize=12)

plt.ylabel('Count')
plt.xticks(class_distribution.keys())

plt.show()
```



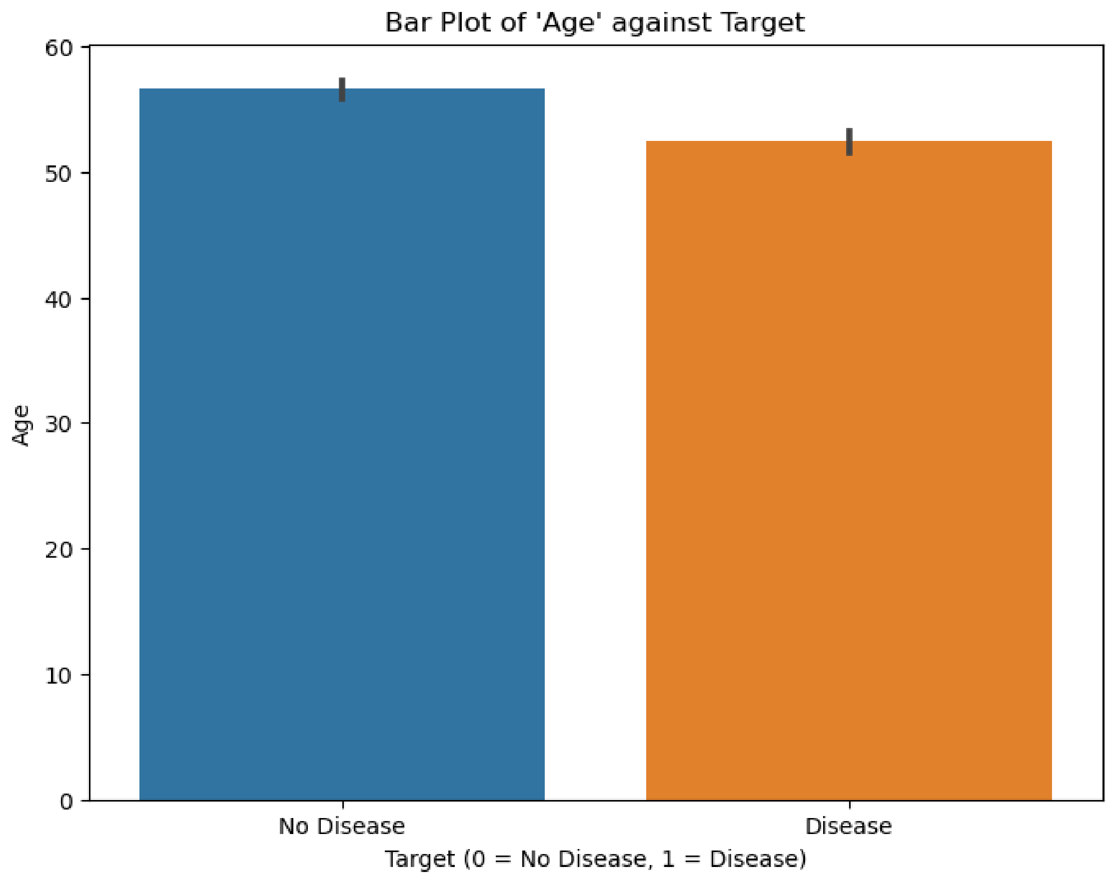
[ ]:

```
# Bar plot for 'sex' against the target
plt.figure(figsize=(8, 6))
sns.countplot(x='sex', hue='target', data=dataset)
plt.title("Bar Plot of 'Sex' against Target")
plt.xlabel("Sex (0 = Female, 1 = Male)")
plt.ylabel("Count")
plt.legend(title='Target', labels=['No Disease', 'Disease'])
```

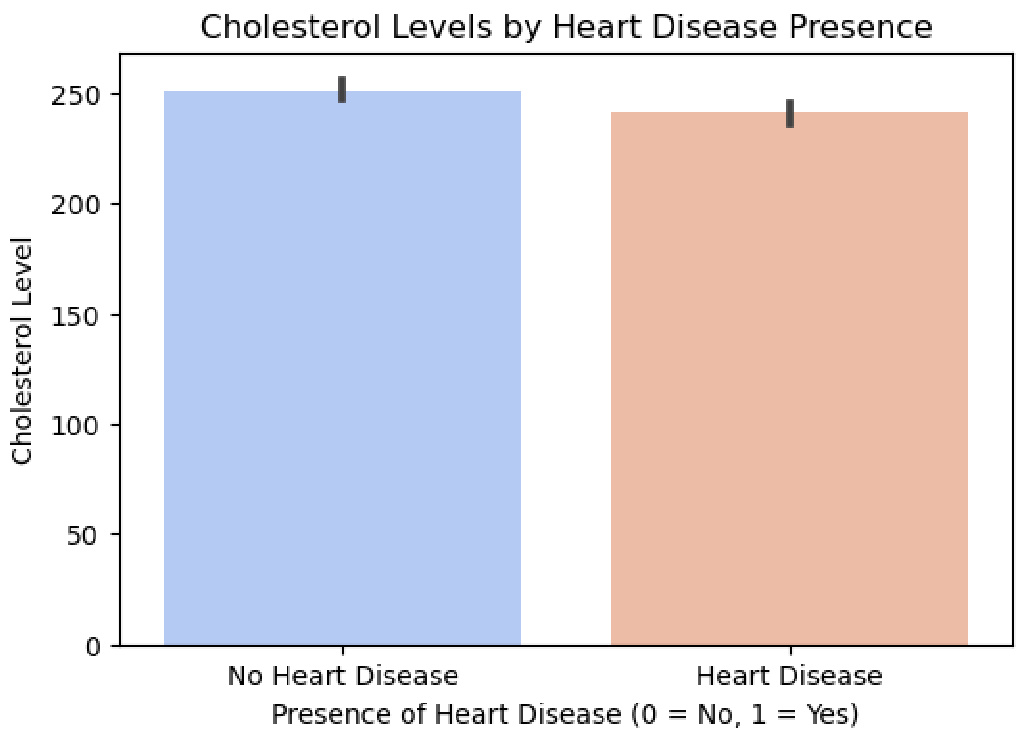
```
plt.show()
```



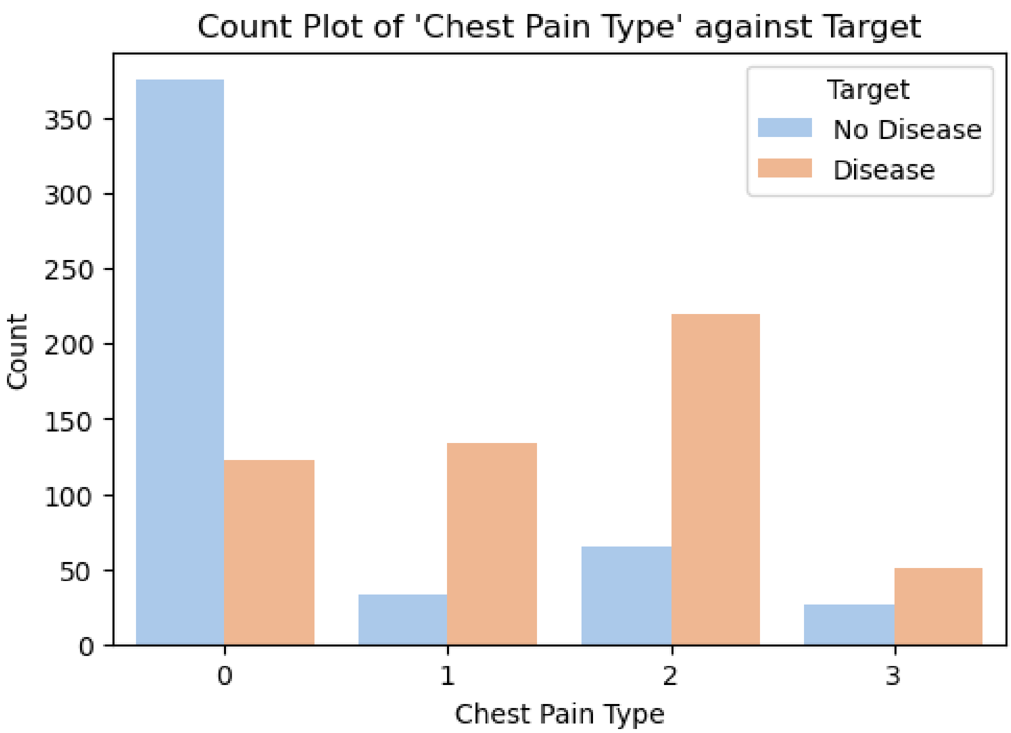

```
[ ]: # Box plot for 'age' against the target
plt.figure(figsize=(8, 6))
sns.barplot(x='target', y='age', data=dataset)
plt.title("Bar Plot of 'Age' against Target")
plt.xlabel("Target (0 = No Disease, 1 = Disease)")
plt.ylabel("Age")
plt.xticks(ticks=[0, 1], labels=['No Disease', 'Disease'])
plt.show()
```



[ ]:
```
# Box plot for 'cholesterol' against the target
plt.figure(figsize=(6, 4))
sns.barplot(x='target', y='chol', data=dataset, palette='coolwarm')
plt.title("Cholesterol Levels by Heart Disease Presence")
plt.xlabel("Presence of Heart Disease (0 = No, 1 = Yes)")
plt.ylabel("Cholesterol Level")
plt.xticks(ticks=[0, 1], labels=['No Heart Disease', 'Heart Disease'])
plt.show()
```



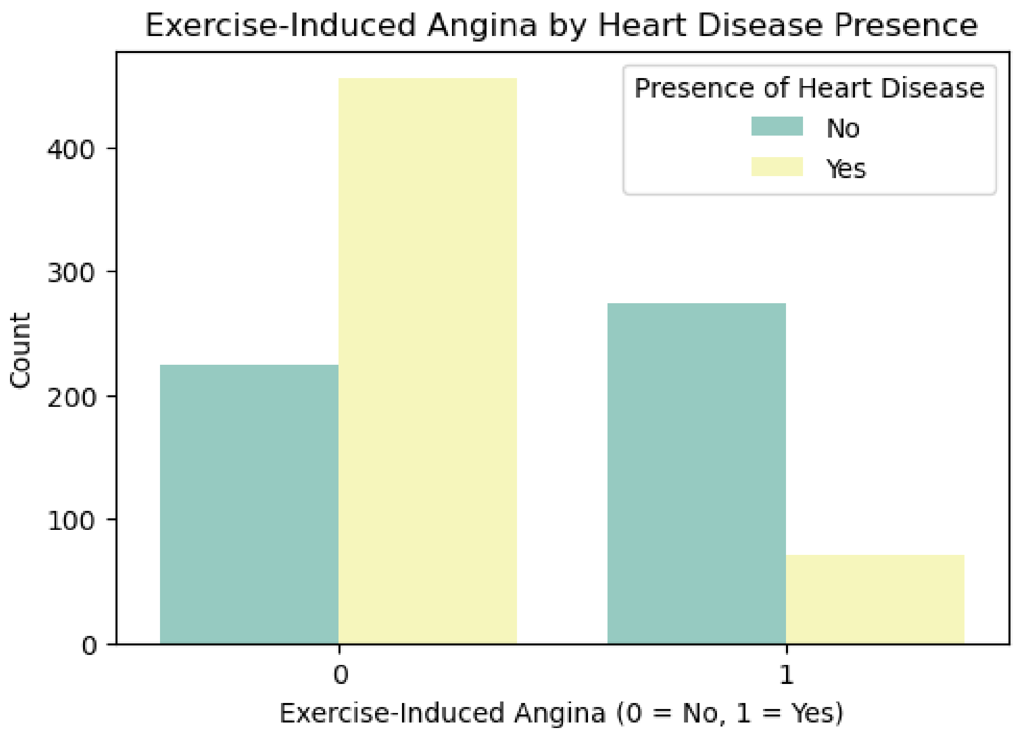
[ ]:
```
# Box plot for 'chest pain type' against the target
plt.figure(figsize=(6, 4))
sns.countplot(x='cp', hue='target', data=dataset, palette='pastel')
plt.title("Count Plot of 'Chest Pain Type' against Target")
plt.xlabel("Chest Pain Type")
plt.ylabel("Count")
plt.legend(title='Target', labels=['No Disease', 'Disease'])
plt.show()

# Count of chest pain type by target
chest_pain_counts = dataset.groupby(['cp', 'target']).size().
 ↪reset_index(name='Count')

# Print the count information
print("Count of Chest Pain Type by Target:")
print(chest_pain_counts)
```




```
Count of Chest Pain Type by Target:
   cp  target  Count
0   0       0    375
1   0       1    122
2   1       0     33
3   1       1    134
4   2       0     65
5   2       1    219
6   3       0     26
7   3       1     51
```

[ ]:
```
#Count Plot of Exercise Induced Angina

plt.figure(figsize=(6, 4))
sns.countplot(x='exang', hue='target', data=dataset, palette='Set3')
plt.title("Exercise-Induced Angina by Heart Disease Presence")
plt.xlabel("Exercise-Induced Angina (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.legend(title="Presence of Heart Disease", labels=['No', 'Yes'])
plt.show()

exeang_counts = dataset.groupby(['exang', 'target']).size().
 ↪reset_index(name='Count')
```

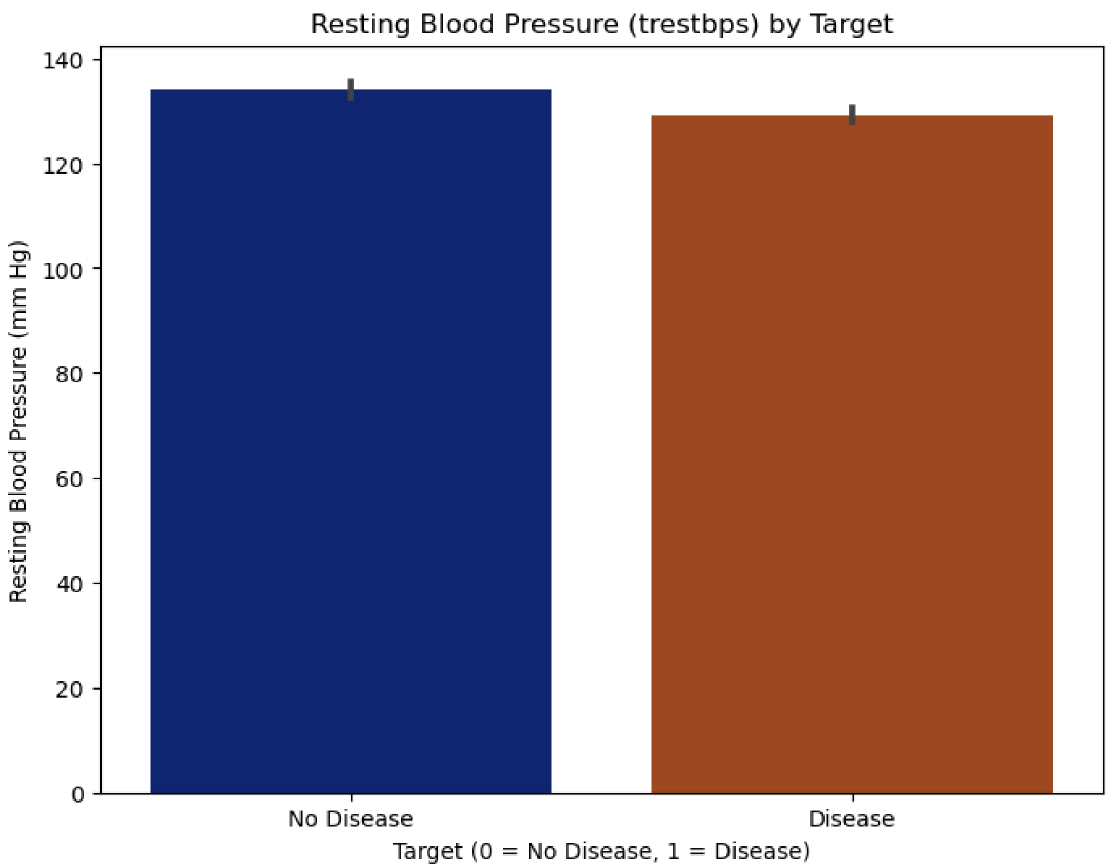
```
# Print the count information
print("Count of Exercise-Induced Angina by Target:")
print(chest_pain_counts)
```




```
Count of Exercise-Induced Angina by Target:
   cp  target  Count
0   0       0    375
1   0       1    122
2   1       0     33
3   1       1    134
4   2       0     65
5   2       1    219
6   3       0     26
7   3       1     51
```

[ ]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x='target', y='trestbps', data=dataset, palette='dark')
plt.title("Resting Blood Pressure (trestbps) by Target")
plt.xlabel("Target (0 = No Disease, 1 = Disease)")
plt.ylabel("Resting Blood Pressure (mm Hg)")
plt.xticks(ticks=[0, 1], labels=['No Disease', 'Disease'])
plt.show()
```

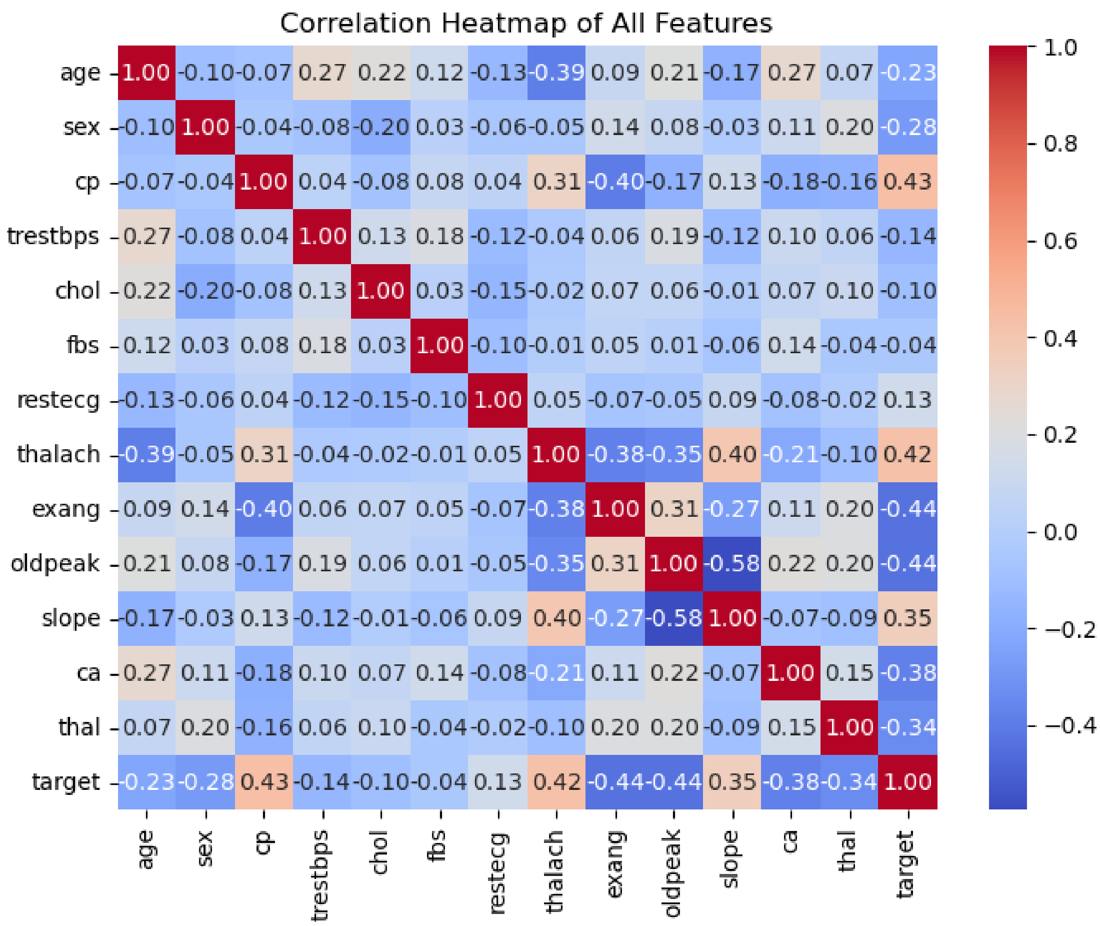
```
exeang_counts = dataset.groupby(['trestbps', 'target']).size().
↪reset_index(name='Count')

# Print the count information
print("Count of Resting Blood Pressure by Target:")
print(chest_pain_counts)
```




```
Count of Resting Blood Pressure by Target:
   cp  target  Count
0   0       0    375
1   0       1    122
2   1       0     33
3   1       1    134
4   2       0     65
5   2       1    219
6   3       0     26
7   3       1     51
```

[ ]:

```
# Compute the correlation matrix
correlation_matrix = dataset.corr()

# Plot the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
↪annot_kws={"size": 10})
plt.title("Correlation Heatmap of All Features")
plt.show()
```



[ ]:

```
# cp (chest pain type) - Strongest positive correlation (0.43)
# thalach (maximum heart rate achieved) - Second strongest positive correlation␣
↪(0.42)
# exang (exercise induced angina) - Strongest negative correlation (-0.44)
# oldpeak (ST depression induced by exercise) - Strongest negative correlation␣
↪(-0.44)
```

```
# trestbps (resting blood pressure) - Second strongest positive correlation (0.
↪42)
# ca (number of major vessels colored) - Second strongest negative correlation␣
↪(-0.38)
# thal (thalassemia) - Third strongest negative correlation (-0.34)
# slope (the slope of the peak exercise ST segment) - Third strongest negative␣
↪correlation (0.34)
```

[ ]:
```
# Check number of unique values for each categorical feature
categorical_columns = []
for column in dataset.columns:
    if dataset[column].dtype == 'object' or dataset[column].nunique() < 10:
        categorical_columns.append(column)

print("Categorical columns:", categorical_columns)
for feature in categorical_columns:
    unique_values = dataset[feature].nunique()
    print(f"Feature '{feature}' has {unique_values} unique values:␣
↪{dataset[feature].unique()}")
```

```
Categorical columns: ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca',
'thal', 'target']
Feature 'sex' has 2 unique values: [1 0]
Feature 'cp' has 4 unique values: [0 1 2 3]
Feature 'fbs' has 2 unique values: [0 1]
Feature 'restecg' has 3 unique values: [1 0 2]
Feature 'exang' has 2 unique values: [0 1]
Feature 'slope' has 3 unique values: [2 0 1]
Feature 'ca' has 5 unique values: [2 0 1 3 4]
Feature 'thal' has 4 unique values: [3 2 1 0]
Feature 'target' has 2 unique values: [0 1]
```

[ ]:
```
X = dataset.drop('target',axis=1)
y = dataset["target"]

# data splitting
from sklearn.model_selection import train_test_split

# Assuming X and y are your feature matrix and target vector
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.
↪20, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
↪test_size=0.25, random_state=42)

# Print the dimensions of each set
print("Training set:", X_train.shape, y_train.shape)
print("Validation set:", X_val.shape, y_val.shape)
```

```
print("Test set:", X_test.shape, y_test.shape)
```

```
Training set: (615, 13) (615,)
Validation set: (205, 13) (205,)
Test set: (205, 13) (205,)
```

[ ]:
```
#Data Preprocessing
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)
```

[ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪confusion_matrix, roc_auc_score, roc_curve, auc
```

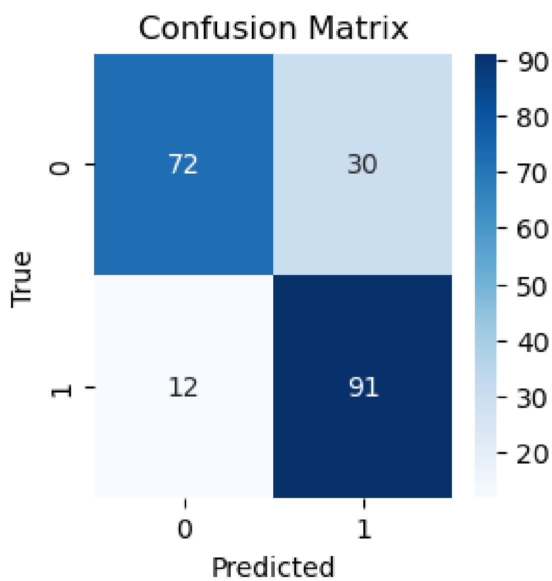
[ ]:
```
#Logistic Regression

from sklearn.linear_model import LogisticRegression
logistic_regression = LogisticRegression(max_iter=10000)

loss_values = []
# for i in range(1, 5001, 50):  # Assuming 100 iterations
#     loss = -np.sum(np.log(logistic_regression.predict_proba(X_train)[np.
↪arange(len(X_train)), y_train])) / len(X_train)
#     print(f"epoch {i}, loss {loss}")
#     loss_values.append(loss)

logistic_regression.fit(X_train, y_train)
```

[ ]:
```
LogisticRegression(max_iter=10000)
```

[ ]:
```
# Logistic Regression: Make predictions on the test set
y_pred_lr = logistic_regression.predict(X_test)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred_lr)
precision = precision_score(y_test, y_pred_lr)
recall = recall_score(y_test, y_pred_lr)
conf_matrix = confusion_matrix(y_test, y_pred_lr)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_lr)

# Print evaluation metrics
print("Accuracy:", accuracy)
```

```
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)
print(conf_matrix)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.7951219512195122
Precision: 0.7520661157024794
Recall: 0.883495145631068
Specificity: 0.7058823529411765
F1 Score: 0.8125000000000001
ROC AUC Score: 0.7946887492861221
[[72 30]
 [12 91]]
```



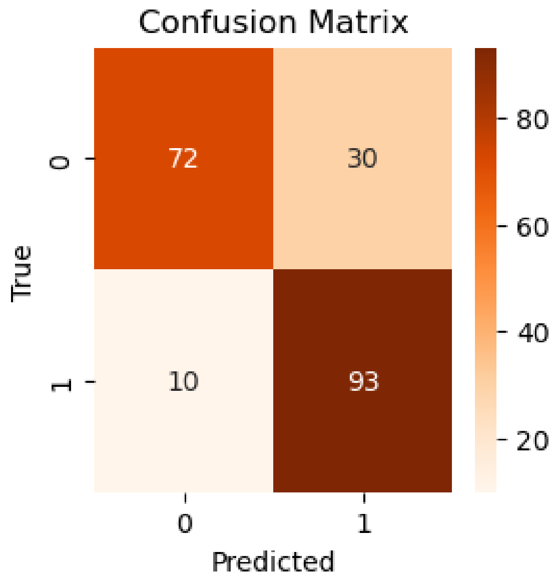
[ ]:
```
#Naive Bayes

from sklearn.naive_bayes import GaussianNB
```

```
naive_bayes_classifier = GaussianNB()

naive_bayes_classifier.fit(X_train, y_train)
```

[ ]: GaussianNB()

[ ]:
```
# Naive Bayes: Make predictions on the test set
y_pred_nb = naive_bayes_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy_nb = accuracy_score(y_test, y_pred_nb)
precision_nb = precision_score(y_test, y_pred_nb)
recall_nb = recall_score(y_test, y_pred_nb)
conf_matrix_nb = confusion_matrix(y_test, y_pred_nb)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_nb = tn / (tn + fp)
f1_score_nb = 2 * (precision_nb * recall_nb) / (precision_nb + recall_nb)
roc_auc_nb = roc_auc_score(y_test, y_pred_nb)

# Print evaluation metrics
print("Accuracy:", accuracy_nb)
print("Precision:", precision_nb)
print("Recall:", recall_nb)
print("Specificity:", specificity_nb)
print("F1 Score:", f1_score_nb)
print("ROC AUC Score:", roc_auc_nb)

print(conf_matrix_nb)
plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_nb, annot=True, cmap='Oranges', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.8048780487804879
Precision: 0.7560975609756098
Recall: 0.9029126213592233
Specificity: 0.7058823529411765
F1 Score: 0.8230088495575221
ROC AUC Score: 0.8043974871501998
[[72 30]
 [10 93]]
```



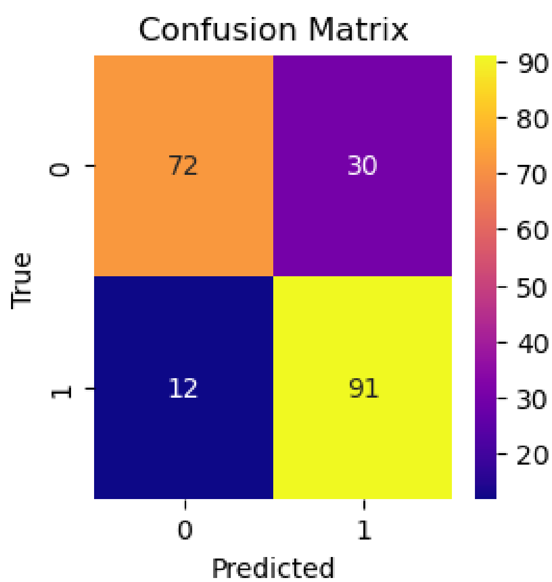
[ ]:
```
#Random Forest

from sklearn.ensemble import RandomForestClassifier

random_forest_classifier = RandomForestClassifier()

random_forest_classifier.fit(X_train, y_train)
```

[ ]: RandomForestClassifier()

[ ]:
```
# Random Forest: Make predictions on the test set
y_pred_rf = random_forest_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
specificity_rf = tn / (tn + fp)
f1_score_rf = 2 * (precision_rf * recall_rf) / (precision_rf + recall_rf)
roc_auc_rf = roc_auc_score(y_test, y_pred_rf)

# Print evaluation metrics
print("Accuracy:", accuracy_rf)
print("Precision:", precision_rf)
print("Recall:", recall_rf)
print("Specificity:", specificity_rf)
```

```
print("F1 Score:", f1_score_rf)
print("ROC AUC Score:", roc_auc_rf)

print('Confusion Matrix', conf_matrix_rf)
plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix, annot=True, cmap='plasma', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.975609756097561
Precision: 0.9803921568627451
Recall: 0.970873786407767
Specificity: 0.7058823529411765
F1 Score: 0.975609756097561
ROC AUC Score: 0.975632971635256
Confusion Matrix [[100   2]
 [  3 100]]
```



[ ]:
```
#K Nearest Neighbors

from sklearn.neighbors import KNeighborsClassifier

knn_classifier = KNeighborsClassifier()

knn_classifier.fit(X_train, y_train)
```

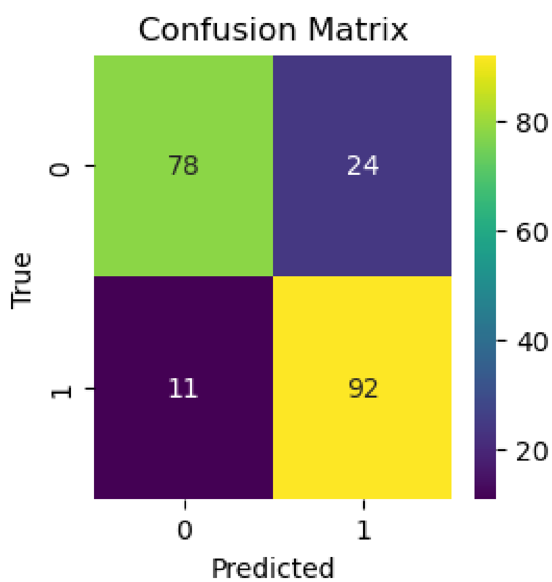
```
knn_classifier.get_params()
```

[ ]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 5,
 'p': 2,
 'weights': 'uniform'}
```

[ ]:
```
# K Nearest Neighbors Make predictions on the test set
y_pred_knn = knn_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred_knn)
precision = precision_score(y_test, y_pred_knn)
recall = recall_score(y_test, y_pred_knn)
conf_matrix = confusion_matrix(y_test, y_pred_knn)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
sensitivity = tp / (tp + fn)
npv = tn / (tn + fn)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_knn)

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("ROC AUC Score:", roc_auc)


print(conf_matrix)
plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix, annot=True, cmap='viridis', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
# Plot ROC curve
# fpr, tpr, thresholds = roc_curve(y_test, y_pred_knn)
# roc_auc = auc(fpr, tpr)

# plt.figure()
```

```
# plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)'␣
↪% roc_auc)
# plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
# plt.xlim([0.0, 1.0])
# plt.ylim([0.0, 1.05])
# plt.xlabel('False Positive Rate')
# plt.ylabel('True Positive Rate')
# plt.title('Receiver Operating Characteristic (ROC) Curve')
# plt.legend(loc="lower right")
# plt.show()
```

```
Accuracy: 0.8292682926829268
Precision: 0.7931034482758621
Recall: 0.8932038834951457
Specificity: 0.7647058823529411
ROC AUC Score: 0.8289548829240434
[[78 24]
 [11 92]]
```

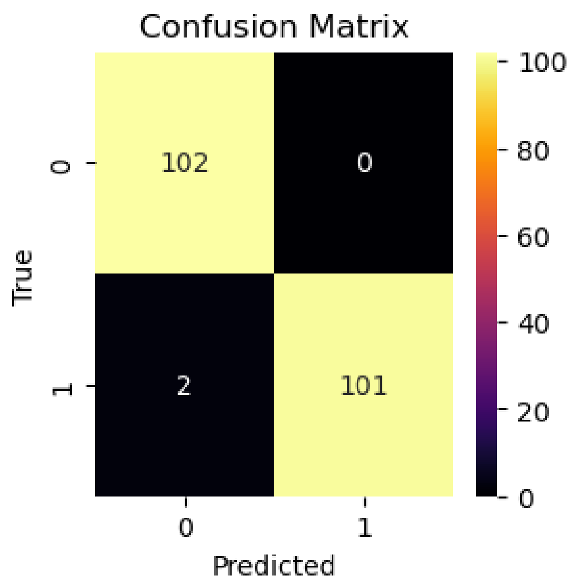


[ ]:
```
#Decision Tree

from sklearn.tree import DecisionTreeClassifier

decision_tree_classifier = DecisionTreeClassifier()

decision_tree_classifier.fit(X_train, y_train)
```

[ ]: DecisionTreeClassifier()

[ ]:
```python
# #Decision Tree Make predictions on the test set
y_pred_dt = decision_tree_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred_dt)
precision = precision_score(y_test, y_pred_dt)
recall = recall_score(y_test, y_pred_dt)
conf_matrix = confusion_matrix(y_test, y_pred_dt)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
sensitivity = tp / (tp + fn)
npv = tn / (tn + fn)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_dt)

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("ROC AUC Score:", roc_auc)

print(conf_matrix)
plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix, annot=True, cmap='inferno', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.9902439024390244
Precision: 1.0
Recall: 0.9805825242718447
Specificity: 1.0
ROC AUC Score: 0.9902912621359223
[[102   0]
 [  2 101]]
```



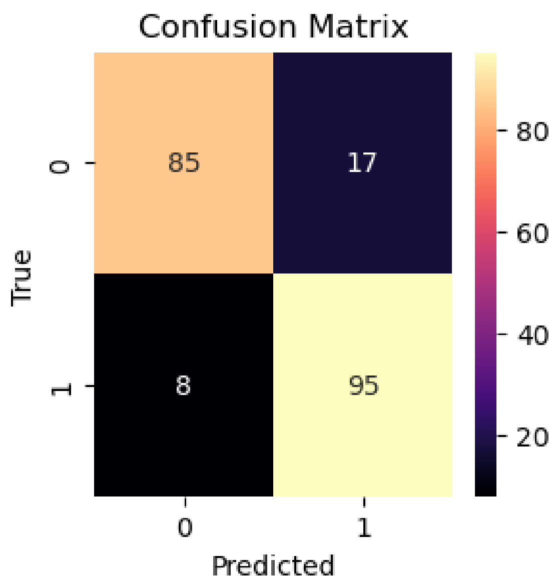

```
[ ]: # Support Vector Machines

     from sklearn.svm import SVC

     svc_classifier = SVC()

     svc_classifier.fit(X_train, y_train)
     svc_classifier.get_params()
```

```
[ ]: {'C': 1.0,
      'break_ties': False,
      'cache_size': 200,
      'class_weight': None,
      'coef0': 0.0,
      'decision_function_shape': 'ovr',
      'degree': 3,
      'gamma': 'scale',
      'kernel': 'rbf',
      'max_iter': -1,
      'probability': False,
      'random_state': None,
      'shrinking': True,
      'tol': 0.001,
      'verbose': False}
```

```
[ ]: # Support Vector Machines Make predictions on the test set
     y_pred_svc = svc_classifier.predict(X_test)
```

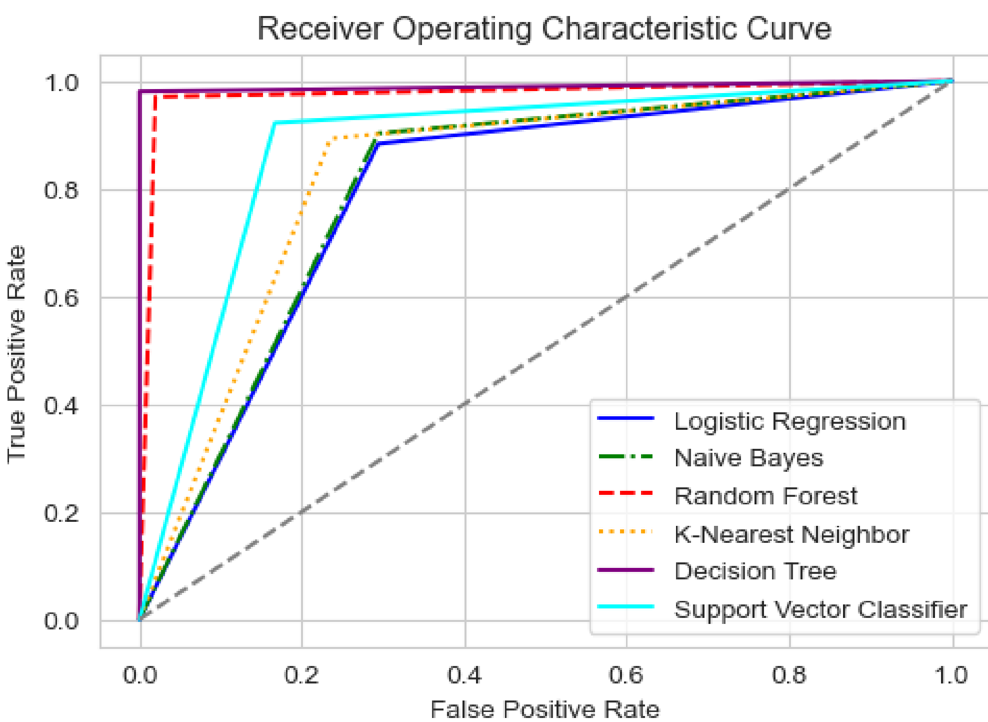
```
# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred_svc)
precision = precision_score(y_test, y_pred_svc)
recall = recall_score(y_test, y_pred_svc)
conf_matrix = confusion_matrix(y_test, y_pred_svc)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_svc)

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)
print(conf_matrix)
plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix, annot=True, cmap='magma', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.8780487804878049
Precision: 0.8482142857142857
Recall: 0.9223300970873787
Specificity: 0.8333333333333334
F1 Score: 0.8837209302325582
ROC AUC Score: 0.8778317152103561
[[85 17]
 [ 8 95]]
```




```
[ ]: lr_false_positive_rate,lr_true_positive_rate,lr_threshold =␣
      ↪roc_curve(y_test,y_pred_lr)
     nb_false_positive_rate,nb_true_positive_rate,nb_threshold =␣
      ↪roc_curve(y_test,y_pred_nb)
     rf_false_positive_rate,rf_true_positive_rate,rf_threshold =␣
      ↪roc_curve(y_test,y_pred_rf)
     knn_false_positive_rate,knn_true_positive_rate,knn_threshold =␣
      ↪roc_curve(y_test,y_pred_knn)
     dt_false_positive_rate,dt_true_positive_rate,dt_threshold =␣
      ↪roc_curve(y_test,y_pred_dt)
     svc_false_positive_rate,svc_true_positive_rate,svc_threshold =␣
      ↪roc_curve(y_test,y_pred_svc)
     sns.set_style('whitegrid')
     plt.figure(figsize=(6,4))
     plt.title('Receiver Operating Characteristic Curve')

     # Plot ROC curves for each classifier with different line styles and colors
     plt.plot(lr_false_positive_rate, lr_true_positive_rate, label='Logistic␣
      ↪Regression', color='blue', linestyle='-')
     plt.plot(nb_false_positive_rate, nb_true_positive_rate, label='Naive Bayes',␣
      ↪color='green', linestyle='-.')
     plt.plot(rf_false_positive_rate, rf_true_positive_rate, label='Random Forest',␣
      ↪color='red', linestyle='--')
     plt.plot(knn_false_positive_rate, knn_true_positive_rate, label='K-Nearest␣
      ↪Neighbor', color='orange', linestyle=':')
```

```
plt.plot(dt_false_positive_rate, dt_true_positive_rate, label='Decision Tree',␣
 ↪color='purple', linestyle='-')
plt.plot(svc_false_positive_rate, svc_true_positive_rate, label='Support Vector␣
 ↪Classifier', color='cyan', linestyle='-')

# Plot the diagonal reference line
plt.plot([0, 1], [0, 1], ls='--', color='.5')

# Add labels and legend
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()

# Show the plot
plt.show()
```



[ ]:
```
# Let's do Hyperparameter tuning!!
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.ensemble import StackingClassifier
```

[ ]:
```
# Define hyperparameters for logistic regression
param_lr = {
    'C': [0.001, 0.01, 0.1, 1, 10],
```

```
    'solver': ['lbfgs', 'sag', 'saga'],
    }

# Create grid search using 5-fold cross validation
grid_search_lr = GridSearchCV(LogisticRegression(max_iter=20000), param_lr,␣
 ↪cv=5, scoring='accuracy')

# Perform grid search
grid_search_lr.fit(X_train, y_train)


# Print best parameters
print("Best parameters for Logistic Regression with validation set (Grid␣
 ↪Search):", grid_search_lr.best_params_)
```

```
Best parameters for Logistic Regression with validation set (Grid Search): {'C':
1, 'solver': 'lbfgs'}
```

[ ]:
```
#Logistic Regression: Testing

logistic_regression_best = LogisticRegression(C=0.1, max_iter=10000)
logistic_regression_best.fit(X_train, y_train)

# Before hyperparameter tuning
y_pred_lr_before = logistic_regression.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_lr_before)
precision = precision_score(y_test, y_pred_lr_before)
recall = recall_score(y_test, y_pred_lr_before)
conf_matrix = confusion_matrix(y_test, y_pred_lr_before)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_lr_before)

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)


logistic_tuned_model = grid_search_lr.best_estimator_
y_pred_lr_best = logistic_tuned_model.predict(X_val)
```

```
# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_val, y_pred_lr_best)
precision_after = precision_score(y_val, y_pred_lr_best)
recall_after = recall_score(y_val, y_pred_lr_best)
conf_matrix = confusion_matrix(y_val, y_pred_lr_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_val, y_pred_lr_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (Val Set):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Accuracy: 0.7951219512195122
Precision: 0.7520661157024794
Recall: 0.883495145631068
Specificity: 0.7058823529411765
F1 Score: 0.8125000000000001
ROC AUC Score: 0.7946887492861221

Evaluation Metrics after Hyperparameter Tuning (Val Set):
Accuracy: 0.9073170731707317
Precision: 0.8728813559322034
Recall: 0.9626168224299065
Specificity: 0.8469387755102041
F1 Score: 0.8125000000000001
ROC AUC Score: 0.9047777989700553
```

[ ]:
```
# Make predictions on the test set using the tuned logistic regression model
logistic_tuned_model = grid_search_lr.best_estimator_
y_pred_lr_test = logistic_tuned_model.predict(X_test)

# Calculate evaluation metrics for the tuned model on the test set
accuracy_test = accuracy_score(y_test, y_pred_lr_test)
precision_test = precision_score(y_test, y_pred_lr_test)
recall_test = recall_score(y_test, y_pred_lr_test)
conf_matrix_test = confusion_matrix(y_test, y_pred_lr_test)
tn_test, fp_test, fn_test, tp_test = conf_matrix_test.ravel()
specificity_test = tn_test / (tn_test + fp_test)
sensitivity_test = tp_test / (tp_test + fn_test)
npv_test = tn_test / (tn_test + fn_test)
```

```
f1_score_test = 2 * (precision_test * recall_test) / (precision_test +␣
↪recall_test)
roc_auc_test = roc_auc_score(y_test, y_pred_lr_test)

# Print the evaluation metrics for the tuned model on the test set
print("\nEvaluation Metrics for Tuned Logistic Regression Model on Test Set:")
print("Accuracy:", accuracy_test)
print("Precision:", precision_test)
print("Recall:", recall_test)
print("Specificity:", specificity_test)
print("Sensitivity:", sensitivity_test)
print("NPV:", npv_test)
print("F1 Score:", f1_score_test)
print("ROC AUC Score:", roc_auc_test)
```

```
Evaluation Metrics for Tuned Logistic Regression Model on Test Set:
Accuracy: 0.7951219512195122
Precision: 0.7520661157024794
Recall: 0.883495145631068
Specificity: 0.7058823529411765
Sensitivity: 0.883495145631068
NPV: 0.8571428571428571
F1 Score: 0.8125000000000001
ROC AUC Score: 0.7946887492861221
```

[ ]:
```
# Random Forest
rf_param_grid = {
   'n_estimators': [50, 100],
    'max_depth': [None, 10],
    'min_samples_split': [2, 5, 7, 10],
    'min_samples_leaf': [1, 2],
    'max_features': ['auto', 'sqrt']



}

grid_search_rf = GridSearchCV(RandomForestClassifier(), rf_param_grid, cv=5,␣
↪scoring='accuracy')

grid_search_rf.fit(X_train, y_train)

best_params_grid_rf = grid_search_rf.best_params_
best_estimator_grid_rf = grid_search_rf.best_estimator_

print("Results for Random Forest - GridSearchCV:")
print("Best parameters:", best_params_grid_rf)
```

```
print("Best estimator:", best_estimator_grid_rf)
```

```
D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
160 fits failed out of a total of 320.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
160 fits failed with the following error:
Traceback (most recent call last):
  File "D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_validation.py", line 732, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "D:\Anaconda\envs\workingenv\lib\site-packages\sklearn\base.py", line
1144, in wrapper
    estimator._validate_params()
  File "D:\Anaconda\envs\workingenv\lib\site-packages\sklearn\base.py", line
637, in _validate_params
    validate_parameter_constraints(
  File "D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\utils\_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of RandomForestClassifier must be an int in the range [1, inf), a
float in the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got 'auto'
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_search.py:976: UserWarning: One or more of the
test scores are non-finite: [       nan        nan        nan        nan
nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan 0.97073171 0.96910569
 0.95284553 0.95772358 0.9495935  0.94471545 0.92357724 0.9398374
 0.9495935  0.9495935  0.95121951 0.94471545 0.93658537 0.93821138
 0.92682927 0.92357724        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.95772358 0.97073171 0.95121951 0.95609756 0.94634146 0.94146341
 0.93821138 0.94308943 0.93821138 0.95121951 0.94308943 0.94634146
 0.93821138 0.93658537 0.92682927 0.9203252 ]
  warnings.warn(
```

```
Results for Random Forest - GridSearchCV:
Best parameters: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf':
1, 'min_samples_split': 2, 'n_estimators': 50}
Best estimator: RandomForestClassifier(n_estimators=50)
```

[ ]:
```
#Random Forest: Testing

random_forest_best = RandomForestClassifier()
random_forest_best.fit(X_train, y_train)

# Before hyperparameter tuning
y_pred_rf_before = random_forest_best.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_rf_before)
precision = precision_score(y_test, y_pred_rf_before)
recall = recall_score(y_test, y_pred_rf_before)
conf_matrix = confusion_matrix(y_test, y_pred_rf_before)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_rf_before)

# Print evaluation metrics
print("Before HyperParameters Tuning")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)


random_forest_tuned_model = grid_search_rf.best_estimator_
y_pred_rf_best = random_forest_tuned_model.predict(X_val)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_val, y_pred_rf_best)
precision_after = precision_score(y_val, y_pred_rf_best)
recall_after = recall_score(y_val, y_pred_rf_best)
conf_matrix = confusion_matrix(y_val, y_pred_rf_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_val, y_pred_rf_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (Val Set):")
```

```
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Before HyperParameters Tuning
Accuracy: 0.975609756097561
Precision: 0.9803921568627451
Recall: 0.970873786407767
Specificity: 0.9803921568627451
F1 Score: 0.975609756097561
ROC AUC Score: 0.975632971635256

Evaluation Metrics after Hyperparameter Tuning (Val Set):
Accuracy: 0.9951219512195122
Precision: 0.9907407407407407
Recall: 1.0
Specificity: 0.9897959183673469
F1 Score: 0.975609756097561
ROC AUC Score: 0.9948979591836734
```

[ ]:

```
# Make predictions on the test set using the tuned random forest model
random_forest_tuned_model = grid_search_rf.best_estimator_
y_pred_rf_test = random_forest_tuned_model.predict(X_test)

# Calculate evaluation metrics for the tuned model on the test set
accuracy_test = accuracy_score(y_test, y_pred_rf_test)
precision_test = precision_score(y_test, y_pred_rf_test)
recall_test = recall_score(y_test, y_pred_rf_test)
conf_matrix_test = confusion_matrix(y_test, y_pred_rf_test)
tn_test, fp_test, fn_test, tp_test = conf_matrix_test.ravel()
specificity_test = tn_test / (tn_test + fp_test)
sensitivity_test = tp_test / (tp_test + fn_test)
npv_test = tn_test / (tn_test + fn_test)
f1_score_test = 2 * (precision_test * recall_test) / (precision_test +
 ↪recall_test)
roc_auc_test = roc_auc_score(y_test, y_pred_rf_test)

# Print the evaluation metrics for the tuned model on the test set
print("\nEvaluation Metrics for Tuned Logistic Regression Model on Test Set:")
print("Accuracy:", accuracy_test)
print("Precision:", precision_test)
print("Recall:", recall_test)
print("Specificity:", specificity_test)
print("Sensitivity:", sensitivity_test)
```

```
print("NPV:", npv_test)
print("F1 Score:", f1_score_test)
print("ROC AUC Score:", roc_auc_test)
```

```
Evaluation Metrics for Tuned Logistic Regression Model on Test Set:
Accuracy: 0.975609756097561
Precision: 0.9803921568627451
Recall: 0.970873786407767
Specificity: 0.9803921568627451
Sensitivity: 0.970873786407767
NPV: 0.970873786407767
F1 Score: 0.975609756097561
ROC AUC Score: 0.975632971635256
```

[ ]:

```
# K-Nearest Neighbors (KNN)
param_grid_knn = {
    'n_neighbors': range(5, 50),
    'weights': ['uniform', 'distance'],
    'algorithm': ['ball_tree', 'kd_tree', 'brute'],
    'metric' : ['minkowski','euclidean','manhattan']
}

grid_search_knn = GridSearchCV(KNeighborsClassifier(), param_grid_knn, cv=5,␣
 ↪scoring='accuracy')

grid_search_knn.fit(X_train, y_train)

best_params_grid_knn = grid_search_knn.best_params_
best_estimator_grid_knn = grid_search_knn.best_estimator_

print("Results for K Nearest Neighbors - GridSearchCV:")
print("Best parameters:", best_params_grid_knn)
print("Best estimator:", best_estimator_grid_knn)
```

```
Results for K Nearest Neighbors - GridSearchCV:
Best parameters: {'algorithm': 'ball_tree', 'metric': 'manhattan',
'n_neighbors': 44, 'weights': 'distance'}
Best estimator: KNeighborsClassifier(algorithm='ball_tree', metric='manhattan',
n_neighbors=44,
                     weights='distance')
```

[ ]:

```
#K Nearest Neighbors: Testing

# Before hyperparameter tuning
y_pred_knn_before = knn_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_knn_before)
```

```
precision = precision_score(y_test, y_pred_knn_before)
recall = recall_score(y_test, y_pred_knn_before)
conf_matrix = confusion_matrix(y_test, y_pred_knn_before)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_knn_before)

# Print evaluation metrics
print("Before Hyper Parameters Tuning")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)

# After hyperparameter tuning
# Make predictions on the test set using tuned model

knn_tuned_model = grid_search_knn.best_estimator_
y_pred_knn_after_gridSearch = knn_tuned_model.predict(X_val)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_val, y_pred_knn_after_gridSearch)
precision_after = precision_score(y_val, y_pred_knn_after_gridSearch)
recall_after = recall_score(y_val, y_pred_knn_after_gridSearch)
conf_matrix = confusion_matrix(y_val, y_pred_knn_after_gridSearch)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_val, y_pred_knn_after_gridSearch)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Before Hyper Parameters Tuning
Accuracy: 0.8292682926829268
Precision: 0.7931034482758621
Recall: 0.8932038834951457
Specificity: 0.7647058823529411
F1 Score: 0.8401826484018265
```

```
ROC AUC Score: 0.8289548829240434

Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.9804878048780488
Precision: 0.9904761904761905
Recall: 0.9719626168224299
Specificity: 0.9897959183673469
F1 Score: 0.8401826484018265
ROC AUC Score: 0.9808792675948884
```

[ ]:
```
# After hyperparameter tuning
# Make predictions on the test set using tuned model

knn_tuned_model_test = grid_search_knn.best_estimator_
y_pred_knn_after_gridSearch_test = knn_tuned_model_test.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_knn_after_gridSearch_test)
precision_after = precision_score(y_test, y_pred_knn_after_gridSearch_test)
recall_after = recall_score(y_test, y_pred_knn_after_gridSearch_test)
conf_matrix = confusion_matrix(y_test, y_pred_knn_after_gridSearch_test)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_knn_after_gridSearch_test)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("Sensitivity:", sensitivity_after)
print("NPV:", npv_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.9902439024390244
Precision: 0.9809523809523809
Recall: 1.0
Specificity: 0.9803921568627451
Sensitivity: 1.0
NPV: 1.0
F1 Score: 0.8401826484018265
```

```
ROC AUC Score: 0.9901960784313725
```

[ ]:
```python
# Decision Trees:
# Define the parameter grid

param_grid = {
    'max_depth': [2, 10, 20, 30],
    'min_samples_split': [2, 4, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
# Initialize the decision tree classifier
decision_tree = DecisionTreeClassifier(random_state=42)

# Initialize GridSearchCV
grid_search_decision_tree = GridSearchCV(estimator=decision_tree,␣
 ↪param_grid=param_grid, cv=5, scoring='accuracy')

# Perform hyperparameter tuning
grid_search_decision_tree.fit(X_train, y_train)

# Best parameters found during grid search
best_params = grid_search_decision_tree.best_params_
print("Best Parameters:", best_params)
```

```
Best Parameters: {'max_depth': 20, 'max_features': 'sqrt', 'min_samples_leaf':
1, 'min_samples_split': 2}
```

```
D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
180 fits failed out of a total of 540.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
180 fits failed with the following error:
Traceback (most recent call last):
  File "D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_validation.py", line 732, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "D:\Anaconda\envs\workingenv\lib\site-packages\sklearn\base.py", line
1144, in wrapper
    estimator._validate_params()
  File "D:\Anaconda\envs\workingenv\lib\site-packages\sklearn\base.py", line
637, in _validate_params
```

```
    validate_parameter_constraints(
  File "D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\utils\_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of DecisionTreeClassifier must be an int in the range [1, inf), a
float in the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got 'auto'
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
D:\Anaconda\envs\workingenv\lib\site-
packages\sklearn\model_selection\_search.py:976: UserWarning: One or more of the
test scores are non-finite: [        nan        nan        nan        nan
nan        nan
        nan        nan        nan 0.68292683 0.68292683 0.68292683
 0.68292683 0.68292683 0.68292683 0.68292683 0.68292683 0.68292683
 0.68292683 0.68292683 0.68292683 0.68292683 0.68292683 0.68292683
 0.68292683 0.68292683 0.68292683        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.93821138 0.91869919 0.86829268 0.89593496 0.89593496 0.85528455
 0.89105691 0.89105691 0.8601626  0.93821138 0.91869919 0.86829268
 0.89593496 0.89593496 0.85528455 0.89105691 0.89105691 0.8601626
        nan        nan        nan        nan        nan        nan
        nan        nan        nan 0.95121951 0.91869919 0.86829268
 0.90731707 0.90731707 0.85528455 0.89105691 0.89105691 0.8601626
 0.95121951 0.91869919 0.86829268 0.90731707 0.90731707 0.85528455
 0.89105691 0.89105691 0.8601626         nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.95121951 0.91869919 0.86829268 0.90731707 0.90731707 0.85528455
 0.89105691 0.89105691 0.8601626  0.95121951 0.91869919 0.86829268
 0.90731707 0.90731707 0.85528455 0.89105691 0.89105691 0.8601626 ]
  warnings.warn(
```

[ ]:
```
#Decision Trees: Testing

# Before hyperparameter tuning
y_pred_dt_before = decision_tree_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_dt_before)
precision = precision_score(y_test, y_pred_dt_before)
recall = recall_score(y_test, y_pred_dt_before)
conf_matrix = confusion_matrix(y_test, y_pred_dt_before)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
sensitivity = tp / (tp + fn)
npv = tn / (tn + fn)
```

```python
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_dt_before)

# Print evaluation metrics
print("Before Hyper parameters tuning")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)

# After hyperparameter tuning
# Make predictions on the test set using tuned model

decision_tree_tuned_model = grid_search_decision_tree.best_estimator_
y_pred_dt_after_gridSearch = decision_tree_tuned_model.predict(X_val)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_val, y_pred_dt_after_gridSearch)
precision_after = precision_score(y_val, y_pred_dt_after_gridSearch)
recall_after = recall_score(y_val, y_pred_dt_after_gridSearch)
conf_matrix = confusion_matrix(y_val, y_pred_dt_after_gridSearch)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_val, y_pred_dt_after_gridSearch)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Before Hyper parameters tuning
Accuracy: 0.9707317073170731
Precision: 0.9619047619047619
Recall: 0.9805825242718447
Specificity: 0.9607843137254902
F1 Score: 0.9711538461538461
ROC AUC Score: 0.9706834189986675

Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.9902439024390244
Precision: 0.981651376146789
```

```
Recall: 1.0
Specificity: 0.9795918367346939
F1 Score: 0.9711538461538461
ROC AUC Score: 0.9897959183673469
```

[ ]:
```
# After hyperparameter tuning
# Make predictions on the test set using tuned model

decision_tree_tuned_model = grid_search_decision_tree.best_estimator_
y_pred_dt_after_gridSearch_test = decision_tree_tuned_model.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_dt_after_gridSearch_test)
precision_after = precision_score(y_test, y_pred_dt_after_gridSearch_test)
recall_after = recall_score(y_test, y_pred_dt_after_gridSearch_test)
conf_matrix = confusion_matrix(y_test, y_pred_dt_after_gridSearch_test)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision_after * recall_after) / (precision_after +
 ↪recall_after)
roc_auc = roc_auc_score(y_test, y_pred_dt_after_gridSearch_test)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("Sensitivity:", sensitivity_after)
print("NPV:", npv_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.9609756097560975
Precision: 0.9523809523809523
Recall: 0.970873786407767
Specificity: 0.9509803921568627
Sensitivity: 0.970873786407767
NPV: 0.97
F1 Score: 0.9615384615384616
ROC AUC Score: 0.9609270892823149
```

[ ]:
```
# Support Vector Machine (SVM)
param_grid_svc = {
```

```
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'gamma': ['scale', 'auto']
}

grid_search_svc = GridSearchCV(SVC(), param_grid_svc, cv=5, scoring='accuracy')
# random_search_svc = RandomizedSearchCV(SVC(), param_grid_svc, cv=5,␣
 ↪n_iter=100, scoring='accuracy')

grid_search_svc.fit(X_train, y_train)
# random_search_svc.fit(X_val, y_val)

best_params_grid_svc = grid_search_svc.best_params_
best_estimator_grid_svc = grid_search_svc.best_estimator_

# best_params_random_svc = random_search_svc.best_params_
# best_estimator_random_svc = random_search_svc.best_estimator_

print("Results for Support Vector Machines - GridSearchCV:")
print("Best parameters:", best_params_grid_svc)
print("Best estimator:", best_estimator_grid_svc)

# print("\nResults for Support Vector Machines - RandomizedSearchCV:")
# print("Best parameters:", best_params_random_svc)
# print("Best estimator:", best_estimator_random_svc)
```

```
Results for Support Vector Machines - GridSearchCV:
Best parameters: {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
Best estimator: SVC(C=10)
```

[ ]:

```
#Support Vector Machines: Testing

# Before hyperparameter tuning
y_pred_svc_before = svc_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_svc_before)
precision = precision_score(y_test, y_pred_svc_before)
recall = recall_score(y_test, y_pred_svc_before)
conf_matrix = confusion_matrix(y_test, y_pred_svc_before)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_svc_before)

# Print evaluation metrics
print('Before Hyper Parameters tuning')
print("Accuracy:", accuracy)
```

```python
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)


# After hyperparameter tuning
# Make predictions on the test set using tuned mode
best_svm_grid = grid_search_svc.best_estimator_
y_test_svc_after_gridSearch = best_svm_grid.predict(X_val)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_val, y_test_svc_after_gridSearch)
precision_after = precision_score(y_val, y_test_svc_after_gridSearch)
recall_after = recall_score(y_val, y_test_svc_after_gridSearch)
conf_matrix = confusion_matrix(y_val, y_test_svc_after_gridSearch)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_val, y_test_svc_after_gridSearch)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

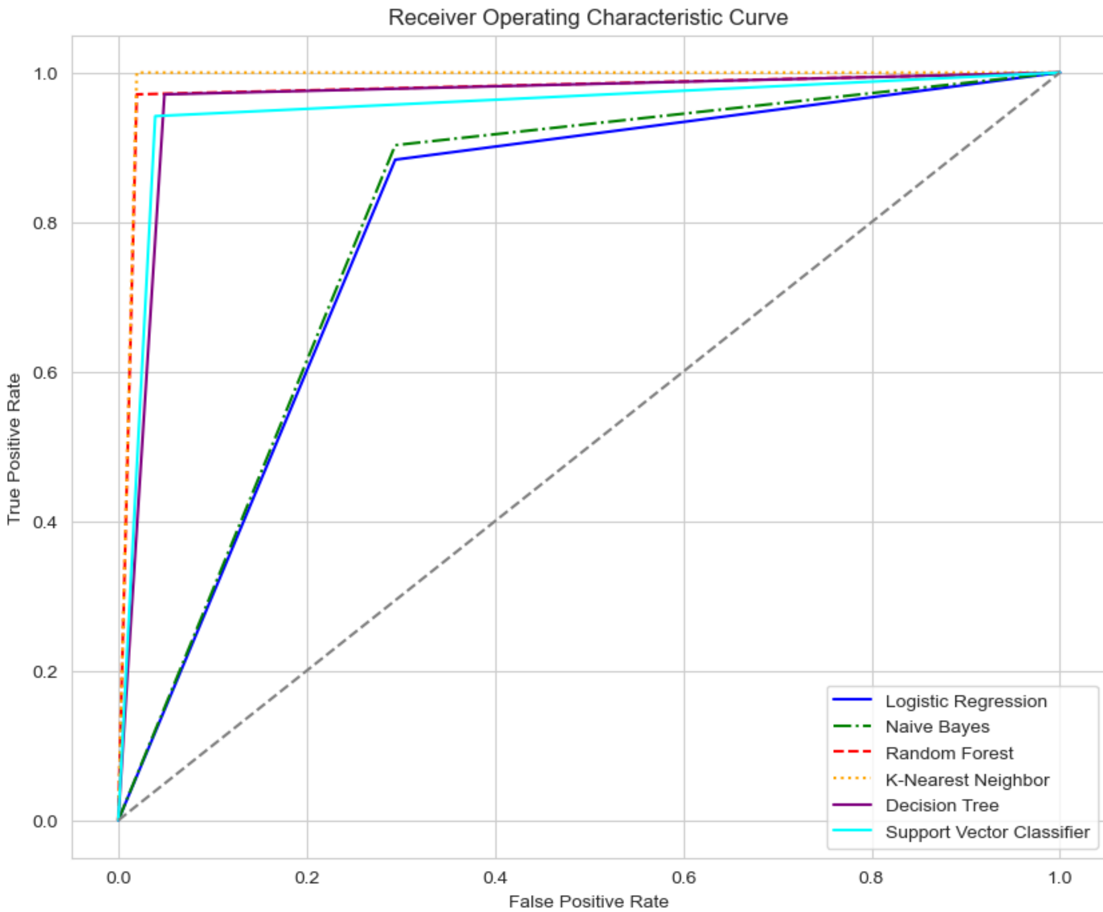
```
Before Hyper Parameters tuning
Accuracy: 0.8780487804878049
Precision: 0.8482142857142857
Recall: 0.9223300970873787
Specificity: 0.8333333333333334
F1 Score: 0.8837209302325582
ROC AUC Score: 0.8778317152103561

Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.975609756097561
Precision: 0.9811320754716981
Recall: 0.9719626168224299
Specificity: 0.9795918367346939
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9757772267785619
```

```
[ ]: # After hyperparameter tuning
     # Make predictions on the test set using tuned mode
     best_svm_grid_test = grid_search_svc.best_estimator_
     y_svc_after_gridSearch_test = best_svm_grid_test.predict(X_test)

     # Calculate evaluation metrics after tuning
     accuracy_after = accuracy_score(y_test, y_svc_after_gridSearch_test)
     precision_after = precision_score(y_test, y_svc_after_gridSearch_test)
     recall_after = recall_score(y_test, y_svc_after_gridSearch_test)
     conf_matrix = confusion_matrix(y_test, y_svc_after_gridSearch_test)
     tn, fp, fn, tp = conf_matrix.ravel()
     specificity_after = tn / (tn + fp)
     sensitivity_after = tp / (tp + fn)
     npv_after = tn / (tn + fn)
     f1_score_after = 2 * (precision * recall) / (precision + recall)
     roc_auc = roc_auc_score(y_test, y_svc_after_gridSearch_test)

     # Print evaluation metrics after tuning
     print("\nEvaluation Metrics after Hyperparameter Tuning (GridSearch):")
     print("Accuracy:", accuracy_after)
     print("Precision:", precision_after)
     print("Recall:", recall_after)
     print("Specificity:", specificity_after)
     print("Sensitivity:", sensitivity_after)
     print("NPV:", npv_after)
     print("F1 Score:", f1_score_after)
     print("ROC AUC Score:", roc_auc)
```

```
Evaluation Metrics after Hyperparameter Tuning (GridSearch):
Accuracy: 0.9512195121951219
Precision: 0.9603960396039604
Recall: 0.941747572815534
Specificity: 0.9607843137254902
Sensitivity: 0.941747572815534
NPV: 0.9423076923076923
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9512659432705121
```

```
[ ]: lr_false_positive_rate,lr_true_positive_rate,lr_threshold =␣
      ↪roc_curve(y_test,y_pred_lr_test)
     nb_false_positive_rate,nb_true_positive_rate,nb_threshold =␣
      ↪roc_curve(y_test,y_pred_nb)
     rf_false_positive_rate,rf_true_positive_rate,rf_threshold =␣
      ↪roc_curve(y_test,y_pred_rf_test)
     knn_false_positive_rate,knn_true_positive_rate,knn_threshold =␣
      ↪roc_curve(y_test,y_pred_knn_after_gridSearch_test)
```

```
dt_false_positive_rate,dt_true_positive_rate,dt_threshold =␣
 ↪roc_curve(y_test,y_pred_dt_after_gridSearch_test)
svc_false_positive_rate,svc_true_positive_rate,svc_threshold =␣
 ↪roc_curve(y_test,y_svc_after_gridSearch_test)
sns.set_style('whitegrid')
plt.figure(figsize=(10,8))
plt.title('Receiver Operating Characteristic Curve')

# Plot ROC curves for each classifier with different line styles and colors
plt.plot(lr_false_positive_rate, lr_true_positive_rate, label='Logistic␣
 ↪Regression', color='blue', linestyle='-')
plt.plot(nb_false_positive_rate, nb_true_positive_rate, label='Naive Bayes',␣
 ↪color='green', linestyle='-.')
plt.plot(rf_false_positive_rate, rf_true_positive_rate, label='Random Forest',␣
 ↪color='red', linestyle='--')
plt.plot(knn_false_positive_rate, knn_true_positive_rate, label='K-Nearest␣
 ↪Neighbor', color='orange', linestyle=':')
plt.plot(dt_false_positive_rate, dt_true_positive_rate, label='Decision Tree',␣
 ↪color='purple', linestyle='-')
plt.plot(svc_false_positive_rate, svc_true_positive_rate, label='Support Vector␣
 ↪Classifier', color='cyan', linestyle='-')

# Plot the diagonal reference line
plt.plot([0, 1], [0, 1], ls='--', color='.5')

# Add labels and legend
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()

# Show the plot
plt.show()
```




```
[ ]: # LETS DO Feature Selection
     from sklearn.feature_selection import RFECV
     from sklearn.model_selection import StratifiedKFold
```

```
[ ]: #Logistic Regression
     # Wrapper-based feature selection with Recursive Feature Elimination (RFE) for␣
      ↪Logistic Regression

     cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

     logistic_regression_rfecv = RFECV(estimator=logistic_regression_best, step=1,␣
      ↪cv=cv, scoring='accuracy')

     logistic_regression_rfecv.fit(X_train, y_train)

     print("Optimal number of features:", logistic_regression_rfecv.n_features_)
```

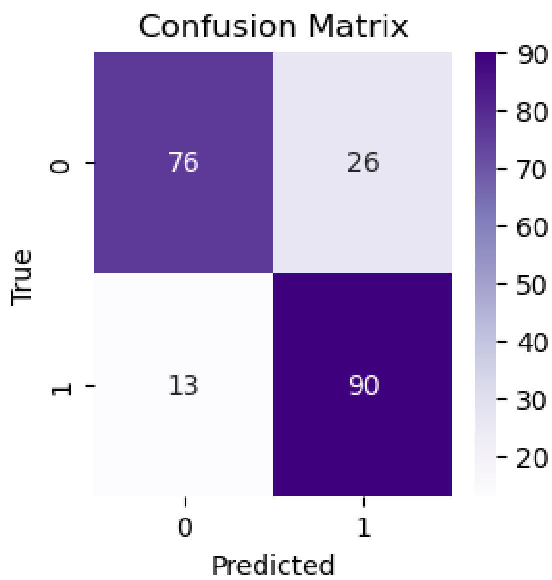
```
X_train_selected_wrapper = logistic_regression_rfecv.fit_transform(X_train,␣
↪y_train)

selected_features = X.columns[logistic_regression_rfecv.get_support()]

print("Selected features for Random Forest (Wrapper-Based):", selected_features)
```

```
Optimal number of features: 6
Selected features for Random Forest (Wrapper-Based): Index(['sex', 'cp',
'thalach', 'oldpeak', 'ca', 'thal'], dtype='object')
```

[ ]:
```
# After hyperparameter tuning
y_pred_lr_best = logistic_regression_best.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_lr_best)
precision_after = precision_score(y_test, y_pred_lr_best)
recall_after = recall_score(y_test, y_pred_lr_best)
conf_matrix = confusion_matrix(y_test, y_pred_lr_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_lr_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


# After feature selection
# X_test_selected_features = logistic_regression_rfecv.transform(X_test)

y_pred_lr_filtered = logistic_regression_rfecv.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_lr_filtered)
precision_after = precision_score(y_test, y_pred_lr_filtered)
recall_after = recall_score(y_test, y_pred_lr_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_lr_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
f1_score_after = 2 * (precision * recall) / (precision + recall)
```

```
roc_auc = roc_auc_score(y_test, y_pred_lr_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)

print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='Purples', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Evaluation Metrics before Feature Selection:
Accuracy: 0.7951219512195122
Precision: 0.7520661157024794
Recall: 0.883495145631068
Specificity: 0.7058823529411765
F1 Score: 0.8837209302325582
ROC AUC Score: 0.7946887492861221

Evaluation Metrics after Feature Selection:
Accuracy: 0.8097560975609757
Precision: 0.7758620689655172
Recall: 0.8737864077669902
Specificity: 0.7058823529411765
F1 Score: 0.8837209302325582
ROC AUC Score: 0.8094422234913383
[[76 26]
 [13 90]]
```



[ ]:

```
# Naive Bayes

from sklearn.feature_selection import SelectKBest, mutual_info_classif
from sklearn.preprocessing import MinMaxScaler

# Apply Min-Max scaling to ensure non-negative values
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)

naive_bayes_selector = SelectKBest(score_func=mutual_info_classif, k=8)


X_train_selected = naive_bayes_selector.fit_transform(X_train_scaled, y_train)

nb_filtered = GaussianNB()

nb_filtered.fit(X_train_selected, y_train)

selected_features_mask = naive_bayes_selector.get_support()

# Count the number of selected features
num_selected_features = np.sum(selected_features_mask)

print("Number of selected features:", num_selected_features)

selected_feature_indices = naive_bayes_selector.get_support(indices=True)
```

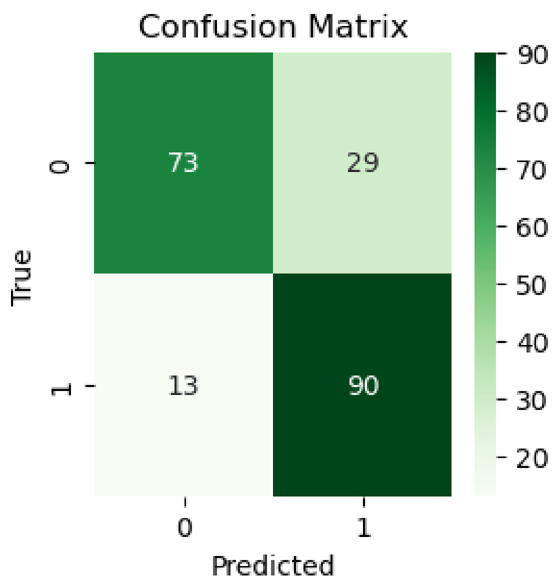
```
# Get the names of selected features
selected_features = X.columns[selected_feature_indices]

print("Selected features:", selected_features)
```

```
Number of selected features: 8
Selected features: Index(['cp', 'trestbps', 'chol', 'thalach', 'exang',
'oldpeak', 'ca', 'thal'], dtype='object')
```

[ ]:
```
# Naive Bayes Model
y_pred_nb = naive_bayes_classifier.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_nb)
precision_after = precision_score(y_test, y_pred_nb)
recall_after = recall_score(y_test, y_pred_nb)
conf_matrix = confusion_matrix(y_test, y_pred_nb)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_nb)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


# After feature selection
X_test_scaled = scaler.fit_transform(X_test)
X_test_filtered = naive_bayes_selector.transform(X_test_scaled)
y_pred_nb_filtered = nb_filtered.predict(X_test_filtered)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_nb_filtered)
precision_after = precision_score(y_test, y_pred_nb_filtered)
recall_after = recall_score(y_test, y_pred_nb_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_nb_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
```

```
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_nb_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)

print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='Greens', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Evaluation Metrics before Feature Selection:
Accuracy: 0.8048780487804879
Precision: 0.7560975609756098
Recall: 0.9029126213592233
Specificity: 0.7058823529411765
F1 Score: 0.8837209302325582
ROC AUC Score: 0.8043974871501998

Evaluation Metrics after Feature Selection:
Accuracy: 0.7951219512195122
Precision: 0.7563025210084033
Recall: 0.8737864077669902
Specificity: 0.7058823529411765
F1 Score: 0.8837209302325582
ROC AUC Score: 0.7947363411383972
[[73 29]
 [13 90]]
```



[ ]:
```python
# K Nearest Neighbors

from sklearn.feature_selection import SelectKBest, mutual_info_classif

knn_selector = SelectKBest(score_func=mutual_info_classif, k=10)

X_train_selected = knn_selector.fit_transform(X_train, y_train)

# Train KNeighborsClassifier using the selected features


grid_search_knn_filtered = copy.copy(grid_search_knn)
best_params_knn = grid_search_knn_filtered.best_params_

knn_classifier_filtered = KNeighborsClassifier(**best_params_knn)
knn_classifier_filtered.fit(X_train_selected, y_train)

selected_features_mask = knn_selector.get_support()

# Count the number of selected features
num_selected_features = np.sum(selected_features_mask)

print("Number of selected features:", num_selected_features)


selected_feature_indices = knn_selector.get_support(indices=True)
```

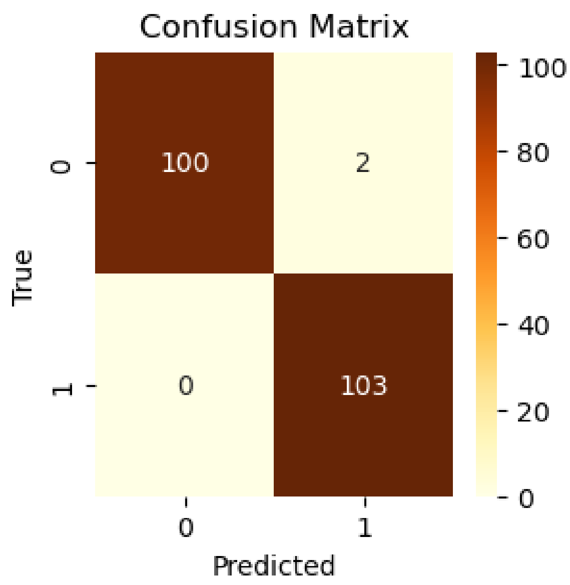
```
# Get the names of selected features
selected_features = X.columns[selected_feature_indices]

print("Selected features:", selected_features)
```

```
Number of selected features: 10
Selected features: Index(['age', 'cp', 'trestbps', 'chol', 'thalach', 'exang',
'oldpeak', 'slope',
       'ca', 'thal'],
      dtype='object')
```

[ ]:
```
# After hyperparameter tuning
y_pred_knn_after_gridSearch = knn_tuned_model.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_knn_after_gridSearch)
precision_after = precision_score(y_test, y_pred_knn_after_gridSearch)
recall_after = recall_score(y_test, y_pred_knn_after_gridSearch)
conf_matrix = confusion_matrix(y_test, y_pred_knn_after_gridSearch)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_knn_after_gridSearch)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Hyperparameter Tuning:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)

# After feature selection
X_test_selected = knn_selector.transform(X_test)
print(X_test_selected.shape)
y_pred_knn_filtered = knn_classifier_filtered.predict(X_test_selected)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_knn_filtered)
precision_after = precision_score(y_test, y_pred_knn_filtered)
recall_after = recall_score(y_test, y_pred_knn_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_knn_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
```

```
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_knn_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='YlOrBr', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Evaluation Metrics after Hyperparameter Tuning:
Accuracy: 0.9902439024390244
Precision: 0.9809523809523809
Recall: 1.0
Specificity: 0.9803921568627451
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9901960784313725
(205, 10)

Evaluation Metrics before Feature Selection:
Accuracy: 0.9902439024390244
Precision: 0.9809523809523809
Recall: 1.0
Specificity: 0.9803921568627451
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9901960784313725
[[100   2]
 [  0 103]]
```




```
[ ]: # Random Forest: Feature Selection
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

random_forest_filtering = RandomForestClassifier()

random_forest_rfecv = RFECV(estimator=random_forest_classifier, step=1, cv=cv,␣
 ↪scoring='accuracy')

random_forest_rfecv.fit(X_train, y_train)

print("Optimal number of features:", random_forest_rfecv.n_features_)

X_train_selected_wrapper = random_forest_rfecv.fit_transform(X_train, y_train)

selected_features = X.columns[random_forest_rfecv.get_support()]

print("Selected features for Random Forest (Wrapper-Based):", selected_features)
```

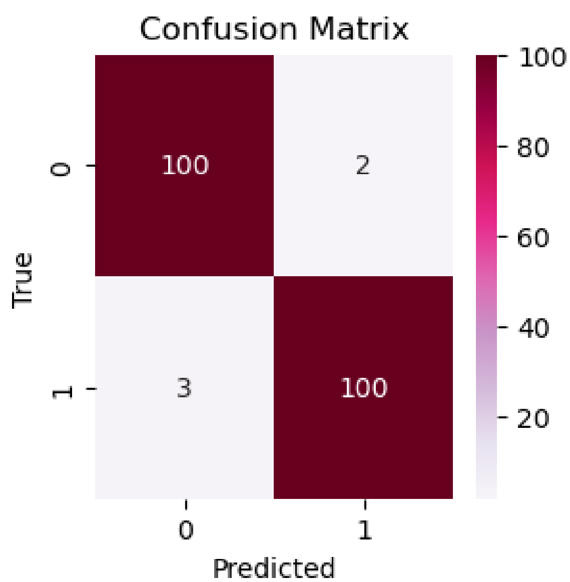
```
Optimal number of features: 8
Selected features for Random Forest (Wrapper-Based): Index(['age', 'cp',
'trestbps', 'chol', 'thalach', 'oldpeak', 'ca', 'thal'], dtype='object')
```

```
[ ]: # After hyperparameter tuning
y_pred_random_forest_best = random_forest_classifier.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_random_forest_best)
```

```
precision_after = precision_score(y_test, y_pred_random_forest_best)
recall_after = recall_score(y_test, y_pred_random_forest_best)
conf_matrix = confusion_matrix(y_test, y_pred_random_forest_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_random_forest_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


# After feature selection
# X_test_selected_features = logistic_regression_rfecv.transform(X_test)

y_pred_random_forest_filtered = random_forest_rfecv.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_random_forest_filtered)
precision_after = precision_score(y_test, y_pred_random_forest_filtered)
recall_after = recall_score(y_test, y_pred_random_forest_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_random_forest_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision_after * recall_after) / (precision_after +
 ↪recall_after)
roc_auc = roc_auc_score(y_test, y_pred_random_forest_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```
print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='PuRd', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Evaluation Metrics before Feature Selection:
Accuracy: 0.975609756097561
Precision: 0.9803921568627451
Recall: 0.970873786407767
Specificity: 0.9803921568627451
F1 Score: 0.8837209302325582
ROC AUC Score: 0.975632971635256

Evaluation Metrics after Feature Selection:
Accuracy: 0.975609756097561
Precision: 0.9803921568627451
Recall: 0.970873786407767
Specificity: 0.9803921568627451
F1 Score: 0.975609756097561
ROC AUC Score: 0.975632971635256
[[100   2]
 [  3 100]]
```



[ ]:
```python
# Decision Trees: Feature Selection

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

decision_trees_rfecv = RFECV(estimator=decision_tree_classifier, step=1, cv=cv,
 ↪scoring='accuracy')

decision_trees_rfecv.fit(X_train, y_train)

print("Optimal number of features:", decision_trees_rfecv.n_features_)

X_train_selected_wrapper = decision_trees_rfecv.fit_transform(X_train, y_train)

selected_features = X.columns[decision_trees_rfecv.get_support()]

print("Selected features for Decision Trees (Wrapper-Based):",
 ↪selected_features)
```

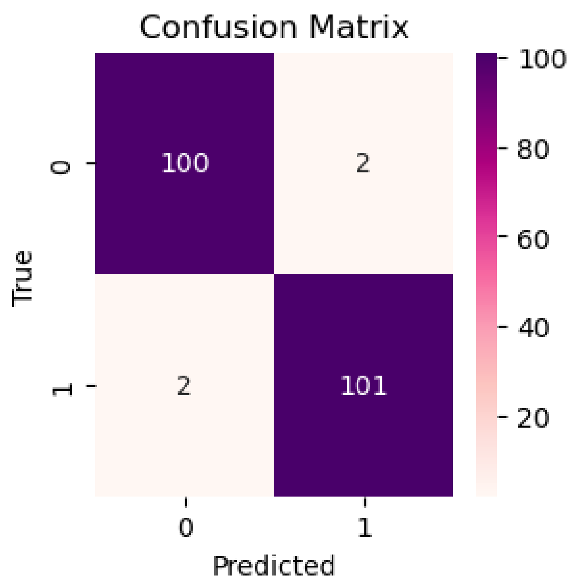
```
Optimal number of features: 8
Selected features for Decision Trees (Wrapper-Based): Index(['age', 'sex', 'cp',
'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal'],
      dtype='object')
```

[ ]:
```python
# After hyperparameter tuning
y_pred_decision_best = decision_tree_classifier.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_decision_best)
precision_after = precision_score(y_test, y_pred_decision_best)
recall_after = recall_score(y_test, y_pred_decision_best)
conf_matrix = confusion_matrix(y_test, y_pred_decision_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_decision_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
```

```python
# After feature selection
# X_test_selected_features = logistic_regression_rfecv.transform(X_test)

y_pred_decision_trees_filtered = decision_trees_rfecv.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_decision_trees_filtered)
precision_after = precision_score(y_test, y_pred_decision_trees_filtered)
recall_after = recall_score(y_test, y_pred_decision_trees_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_decision_trees_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision_after * recall_after) / (precision_after +␣
↪recall_after)
roc_auc = roc_auc_score(y_test, y_pred_decision_trees_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='RdPu', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Evaluation Metrics before Feature Selection:
Accuracy: 0.9707317073170731
Precision: 0.9619047619047619
Recall: 0.9805825242718447
Specificity: 0.9607843137254902
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9706834189986675
```

```
Evaluation Metrics after Feature Selection:
Accuracy: 0.9804878048780488
Precision: 0.9805825242718447
Recall: 0.9805825242718447
Specificity: 0.9607843137254902
F1 Score: 0.9805825242718447
ROC AUC Score: 0.9804873405672949
[[100   2]
 [  2 101]]
```



[ ]:
```
# Support Vector Machines: Feature Selection
svm_selector = SelectKBest(score_func=mutual_info_classif, k=13)
X_train_selected = svm_selector.fit_transform(X_train, y_train)

feature_scores = svm_selector.scores_

# Get the p-values of all features (if applicable)
# p_values = svm_selector.pvalues_  # Uncomment if using a scoring function␣
↪that supports p-values

# Get the indices of the selected features
selected_feature_indices = svm_selector.get_support(indices=True)

# Get the names of the selected features
selected_features = X.columns[selected_feature_indices]

# Print details
```

```
print("Selected Features:")
for feature, score in zip(selected_features,␣
↪feature_scores[selected_feature_indices]):
    print(f"Feature: {feature}, Score: {score}")
# Train SVM Classifier using the selected features

grid_search_svm_filtered = copy.copy(grid_search_svc)
best_params_svm = grid_search_svm_filtered.best_params_

svm_classifier_filtered = SVC(**best_params_svm)
svm_classifier_filtered.fit(X_train_selected, y_train)
```

```
Selected Features:
Feature: age, Score: 0.11943488155505566
Feature: sex, Score: 0.04326817650116621
Feature: cp, Score: 0.14450529811040713
Feature: trestbps, Score: 0.0623124022070245
Feature: chol, Score: 0.1785400598151876
Feature: fbs, Score: 0.0
Feature: restecg, Score: 0.02645413897071247
Feature: thalach, Score: 0.15982183438875674
Feature: exang, Score: 0.08456900931628786
Feature: oldpeak, Score: 0.16354731339701334
Feature: slope, Score: 0.08910389414085573
Feature: ca, Score: 0.1147388091937962
Feature: thal, Score: 0.12563386431926427
```

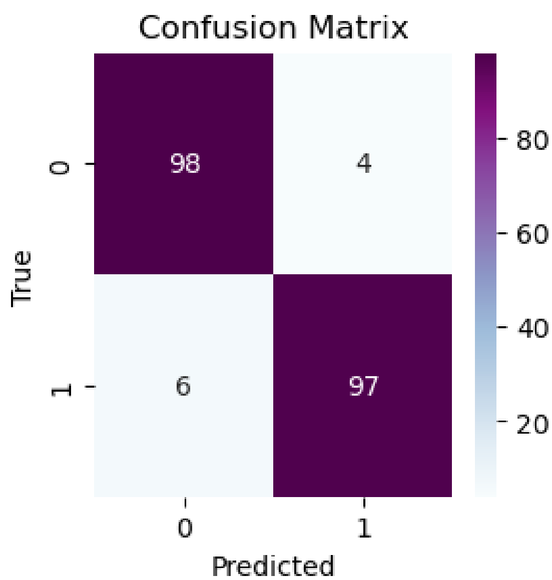
[ ]: SVC(C=10)

[ ]:
```
# After hyperparameter tuning
y_pred_svm_best = best_svm_grid_test.predict(X_test)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_svm_best)
precision_after = precision_score(y_test, y_pred_svm_best)
recall_after = recall_score(y_test, y_pred_svm_best)
conf_matrix = confusion_matrix(y_test, y_pred_svm_best)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_svm_best)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics before Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
```

```python
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)


# After feature selection
# X_test_selected_features = logistic_regression_rfecv.transform(X_test)

X_test_filtered = svm_selector.transform(X_test)
y_pred_svm_filtered = svm_classifier_filtered.predict(X_test_filtered)

# Calculate evaluation metrics after tuning
accuracy_after = accuracy_score(y_test, y_pred_svm_filtered)
precision_after = precision_score(y_test, y_pred_svm_filtered)
recall_after = recall_score(y_test, y_pred_svm_filtered)
conf_matrix_test = confusion_matrix(y_test, y_pred_svm_filtered)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision_after * recall_after) / (precision_after +␣
↪recall_after)
roc_auc = roc_auc_score(y_test, y_pred_svm_filtered)

# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Feature Selection:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)

print(conf_matrix_test)

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_test, annot=True, cmap='BuPu', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

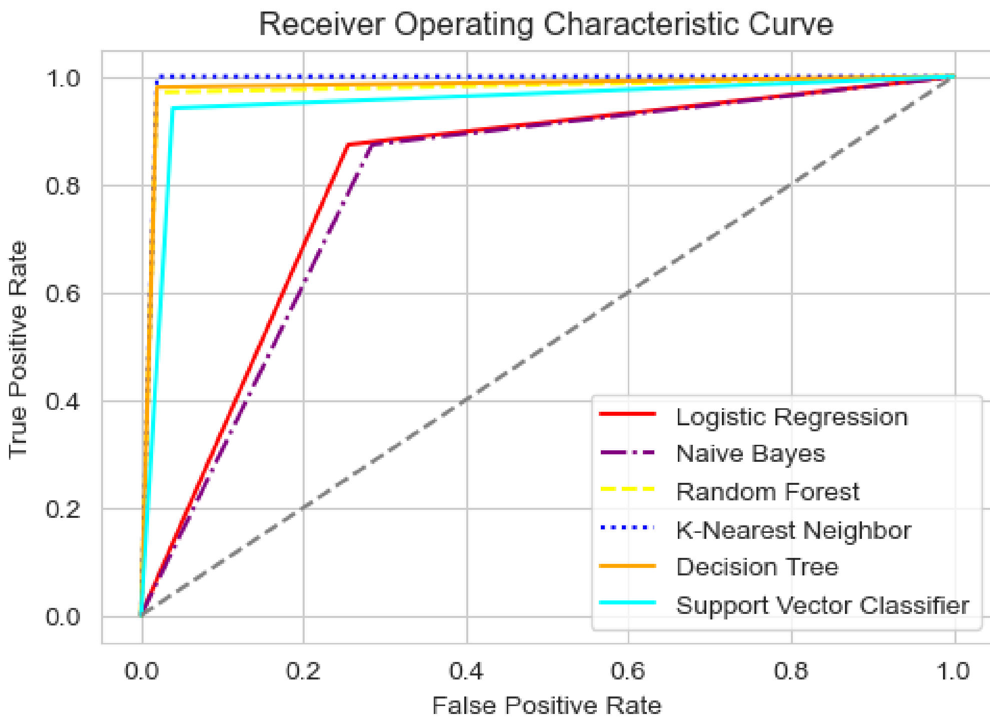
```
Evaluation Metrics before Feature Selection:
Accuracy: 0.9512195121951219
Precision: 0.9603960396039604
Recall: 0.941747572815534
```

```
Specificity: 0.9607843137254902
F1 Score: 0.8837209302325582
ROC AUC Score: 0.9512659432705121

Evaluation Metrics after Feature Selection:
Accuracy: 0.9512195121951219
Precision: 0.9603960396039604
Recall: 0.941747572815534
Specificity: 0.9607843137254902
F1 Score: 0.9509803921568628
ROC AUC Score: 0.9512659432705121
[[98  4]
 [ 6 97]]
```




```
[ ]: lr_false_positive_rate,lr_true_positive_rate,lr_threshold =␣
      ↪roc_curve(y_test,y_pred_lr_filtered)
     nb_false_positive_rate,nb_true_positive_rate,nb_threshold =␣
      ↪roc_curve(y_test,y_pred_nb_filtered)
     rf_false_positive_rate,rf_true_positive_rate,rf_threshold =␣
      ↪roc_curve(y_test,y_pred_random_forest_filtered)
     knn_false_positive_rate,knn_true_positive_rate,knn_threshold =␣
      ↪roc_curve(y_test,y_pred_knn_filtered)
     dt_false_positive_rate,dt_true_positive_rate,dt_threshold =␣
      ↪roc_curve(y_test,y_pred_decision_trees_filtered)
     svc_false_positive_rate,svc_true_positive_rate,svc_threshold =␣
      ↪roc_curve(y_test,y_pred_svm_filtered)
     sns.set_style('whitegrid')
```

```python
plt.figure(figsize=(6,4))
plt.title('Receiver Operating Characteristic Curve')

# Plot ROC curves for each classifier with different line styles and colors
plt.plot(lr_false_positive_rate, lr_true_positive_rate, label='Logistic Regression', color='red', linestyle='-')
plt.plot(nb_false_positive_rate, nb_true_positive_rate, label='Naive Bayes', color='purple', linestyle='-.')
plt.plot(rf_false_positive_rate, rf_true_positive_rate, label='Random Forest', color='yellow', linestyle='--')
plt.plot(knn_false_positive_rate, knn_true_positive_rate, label='K-Nearest Neighbor', color='blue', linestyle=':')
plt.plot(dt_false_positive_rate, dt_true_positive_rate, label='Decision Tree', color='orange', linestyle='-')
plt.plot(svc_false_positive_rate, svc_true_positive_rate, label='Support Vector Classifier', color='cyan', linestyle='-')

# Plot the diagonal reference line
plt.plot([0, 1], [0, 1], ls='--', color='.5')

# Add labels and legend
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()

# Show the plot
plt.show()
```



[ ]:
```
print("Logistic Regression ROC Curve:")
for fpr, tpr, threshold in zip(lr_false_positive_rate, lr_true_positive_rate, lr_threshold):
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")

print("\nNaive Bayes ROC Curve:")
for fpr, tpr, threshold in zip(nb_false_positive_rate, nb_true_positive_rate, nb_threshold):
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")

print("\nRandom Forest ROC Curve:")
for fpr, tpr, threshold in zip(rf_false_positive_rate, rf_true_positive_rate, rf_threshold):
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")

print("\nK Nearest Neighbors ROC Curve:")
for fpr, tpr, threshold in zip(knn_false_positive_rate, knn_true_positive_rate, knn_threshold):
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")

print("\nDecision Trees ROC Curve:")
for fpr, tpr, threshold in zip(dt_false_positive_rate, dt_true_positive_rate, dt_threshold):
```

```
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")

print("\nSupport Vector Machines ROC Curve:")
for fpr, tpr, threshold in zip(svc_false_positive_rate, svc_true_positive_rate,␣
 ↪svc_threshold):
    print(f"FPR: {fpr}, TPR: {tpr}, Threshold: {threshold}")
```

```
Logistic Regression ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.2549019607843137, TPR: 0.8737864077669902, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0

Naive Bayes ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.28431372549019607, TPR: 0.8737864077669902, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0

Random Forest ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.0196078431372549, TPR: 0.970873786407767, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0

K Nearest Neighbors ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.0196078431372549, TPR: 1.0, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0

Decision Trees ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.0196078431372549, TPR: 0.9805825242718447, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0

Support Vector Machines ROC Curve:
FPR: 0.0, TPR: 0.0, Threshold: inf
FPR: 0.0392156862745098, TPR: 0.941747572815534, Threshold: 1.0
FPR: 1.0, TPR: 1.0, Threshold: 0.0
```

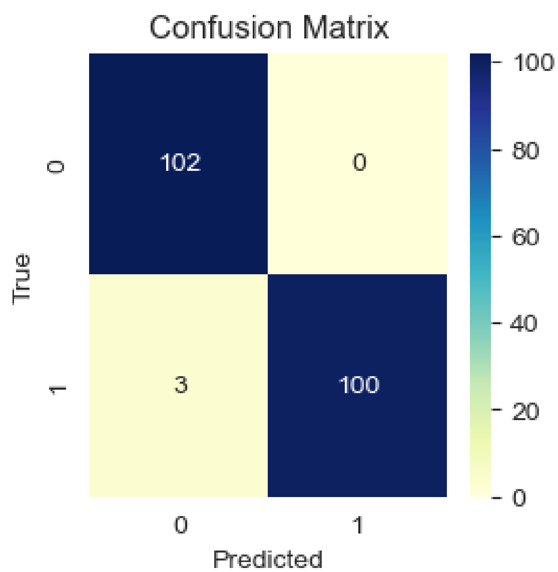
[ ]:
```
#Ensemble Techniques

from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import StackingClassifier
from sklearn.pipeline import Pipeline
```

[ ]:
```
#Bagging Ensemble (Homogeneous)

# Create a base classifier (e.g., Decision Tree)
base_classifier = DecisionTreeClassifier(random_state=42)
```

```
# Create a BaggingClassifier
bagging_clf = BaggingClassifier(base_estimator=base_classifier,␣
 ↪n_estimators=30, random_state=42)

# Train the BaggingClassifier
bagging_clf.fit(X_train, y_train)

# Make predictions
y_pred_bagging = bagging_clf.predict(X_test)

accuracy_bagging = accuracy_score(y_test, y_pred_bagging)
recall_bagging = recall_score(y_test, y_pred_bagging)
precision_bagging = precision_score(y_test, y_pred_bagging)
conf_matrix_bagging = confusion_matrix(y_test, y_pred_bagging)
tn, fp, fn, tp = conf_matrix.ravel()
specificity_after = tn / (tn + fp)
sensitivity_after = tp / (tp + fn)
npv_after = tn / (tn + fn)
f1_score_after = 2 * (precision_bagging * recall_bagging) / (precision_bagging␣
 ↪+ recall_bagging)
roc_auc = roc_auc_score(y_test, y_pred_bagging)
confusion_matrix_bagging = confusion_matrix(y_test, y_pred_bagging)


# Print evaluation metrics after tuning
print("\nEvaluation Metrics after Bagging:")
print("Accuracy:", accuracy_after)
print("Precision:", precision_after)
print("Recall:", recall_after)
print("Specificity:", specificity_after)
print("F1 Score:", f1_score_after)
print("ROC AUC Score:", roc_auc)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_bagging))

plt.figure(figsize=(3, 3))
sns.heatmap(conf_matrix_bagging, annot=True, cmap='YlGnBu', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
D:\Anaconda\envs\workingenv\lib\site-packages\sklearn\ensemble\_base.py:156:
FutureWarning: `base_estimator` was renamed to `estimator` in version 1.2 and
will be removed in 1.4.
  warnings.warn(
```

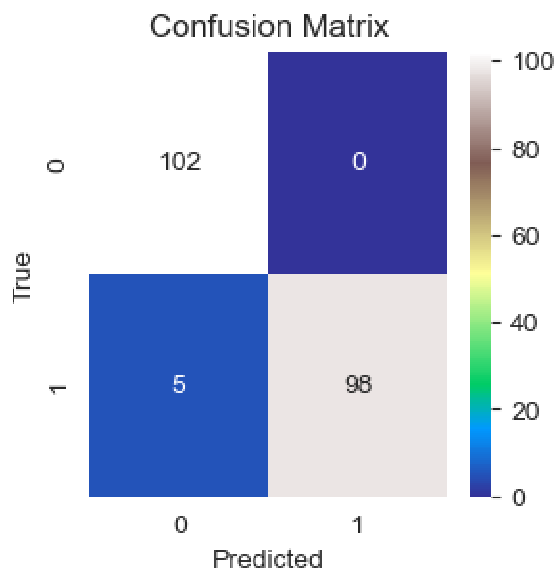
```
Evaluation Metrics after Bagging:
Accuracy: 0.9609756097560975
Precision: 0.9523809523809523
Recall: 0.970873786407767
Specificity: 0.9509803921568627
F1 Score: 0.9852216748768473
ROC AUC Score: 0.9854368932038835
Confusion Matrix:
[[102   0]
 [  3 100]]
```



[ ]:
```
# Ensemble Tuned Models (heterogeneous)
base_models = [
    ('Logistic Regression', grid_search_lr.best_estimator_),
    ('Naive Bayes', naive_bayes_classifier),
    ('Random Forest', grid_search_rf.best_estimator_),
    # ('Decision Tree', grid_search_decision_tree.best_estimator_),
    ('K Nearest Neighbors', grid_search_knn.best_estimator_),
    ('Support Vector Machines', grid_search_svc.best_estimator_)
]

stacking_clf = StackingClassifier(
    estimators=base_models,
    final_estimator=grid_search_decision_tree.best_estimator_
)

# Train the stacking classifier on the training set
```

```python
stacking_clf.fit(X_train, y_train)

# Evaluate the stacking classifier on the test set
y_pred_test_stacking = stacking_clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_test_stacking)
precision = precision_score(y_test, y_pred_test_stacking)
recall = recall_score(y_test, y_pred_test_stacking)
conf_matrix = confusion_matrix(y_test, y_pred_test_stacking)
tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
sensitivity = tp / (tp + fn)
npv = tn / (tn + fn)
f1_score = 2 * (precision * recall) / (precision + recall)
roc_auc = roc_auc_score(y_test, y_pred_test_stacking)
confusion_matrix_stacking  = confusion_matrix(y_test,
y_pred_test_stacking)

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("F1 Score:", f1_score)
print("ROC AUC Score:", roc_auc)

print(confusion_matrix_stacking)

plt.figure(figsize=(3, 3))
sns.heatmap(confusion_matrix_stacking, annot=True, cmap='terrain', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.975609756097561
Precision: 1.0
Recall: 0.9514563106796117
Specificity: 1.0
F1 Score: 0.9751243781094527
ROC AUC Score: 0.9757281553398058
[[102   0]
 [  5  98]]
```



[ ]:
```
# # Ensemble Tuned Models
# base_models = [
#     ('Logistic Regression', logistic_regression),
#     ('Naive Bayes', naive_bayes_classifier),
#     ('Random Forest', random_forest_classifier),
#     # ('Decision Tree', grid_search_decision_tree.best_estimator_),
#     ('K Nearest Neighbors', knn_classifier),
#     ('Support Vector Machines', svc_classifier)
# ]

# stacking_clf = StackingClassifier(
#     estimators=base_models,
#     final_estimator=decision_tree_classifier
# )

# # Train the stacking classifier on the training set
# stacking_clf.fit(X_train, y_train)

# # Evaluate the stacking classifier on the test set
# y_pred_test_stacking = stacking_clf.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred_test_stacking)
# precision = precision_score(y_test, y_pred_test_stacking)
# recall = recall_score(y_test, y_pred_test_stacking)
# conf_matrix = confusion_matrix(y_test, y_pred_test_stacking)
# tn, fp, fn, tp = conf_matrix.ravel()
# specificity = tn / (tn + fp)
# sensitivity = tp / (tp + fn)
```

```
# npv = tn / (tn + fn)
# f1_score = 2 * (precision * recall) / (precision + recall)
# roc_auc = roc_auc_score(y_test, y_pred_test_stacking)
# confusion_matrix_stacking  = confusion_matrix(y_test,
# y_pred_test_stacking)

# # Print evaluation metrics
# print("Accuracy:", accuracy)
# print("Precision:", precision)
# print("Recall:", recall)
# print("Specificity:", specificity)
# print("F1 Score:", f1_score)
# print("ROC AUC Score:", roc_auc)

# print(confusion_matrix_stacking)

# plt.figure(figsize=(3, 3))
# sns.heatmap(confusion_matrix_stacking, annot=True, cmap='terrain', fmt='g')
# plt.xlabel('Predicted')
# plt.ylabel('True')
# plt.title('Confusion Matrix')
# plt.show()
```

[ ]:

```
# # Ensemble Feature Selection
# base_models = [
#     ('Logistic Regression', grid_search_lr.best_estimator_),
#     ('Naive Bayes', naive_bayes_classifier),
#     ('Random Forest', grid_search_rf.best_estimator_),
#     ('Decision Tree', grid_search_decision_tree.best_estimator_),
#     ('K Nearest Neighbors', grid_search_knn.best_estimator_),
#     ('Support Vector Machines', grid_search_svc.best_estimator_)
# ]

# # Define feature selection models
# cv_lr = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
# cv_rf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# feature_selection_models = [
#     ('RFECV Logistic', RFECV(estimator=LogisticRegression(), step=1,
↪cv=cv_lr, scoring='accuracy')),
#     ('SelectKBest Naive Bayes', SelectKBest(score_func=mutual_info_classif,
↪k=10)),
#     ('SelectKBest KNN', SelectKBest(score_func=mutual_info_classif, k=10)),
#     ('RFECV Random Forest', RFECV(estimator=RandomForestClassifier(), step=1,
↪cv=cv_rf, scoring='accuracy')),
#     ('SelectKBest SVM', SelectKBest(score_func=mutual_info_classif, k=11))
# ]
```

```
# estimators = []
# for model, fs_model in feature_selection_models:
#     for base_name, base_model in base_models:
#         estimators.append((f"{model} + {base_name}", Pipeline([('Feature␣
↪Selection', fs_model), (base_name, base_model)])))

# stacking_clf = StackingClassifier(
#     estimators=base_models,
#     final_estimator= grid_search_knn
# )



# # Train the stacking classifier on the training set
# stacking_clf.fit(X_train, y_train)

# # Evaluate the stacking classifier on the test set
# y_pred_test_stacking = stacking_clf.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred_test_stacking)
# precision = precision_score(y_test, y_pred_test_stacking)
# recall = recall_score(y_test, y_pred_test_stacking)
# conf_matrix = confusion_matrix(y_test, y_pred_test_stacking)
# tn, fp, fn, tp = conf_matrix.ravel()
# specificity = tn / (tn + fp)
# sensitivity = tp / (tp + fn)
# npv = tn / (tn + fn)
# f1_score = 2 * (precision * recall) / (precision + recall)
# roc_auc = roc_auc_score(y_test, y_pred_test_stacking)

# # Print evaluation metrics
# print("Accuracy:", accuracy)
# print("Precision:", precision)
# print("Recall:", recall)
# print("Specificity:", specificity)
# print("F1 Score:", f1_score)
# print("ROC AUC Score:", roc_auc)
```

[ ]:
```
# # Stacking Ensemble Technique (heterogeneous)
# # Pre-trained and tuned models
# base_models = [
#     ('Logistic Regression', LogisticRegression()),
#     ('Naive Bayes', GaussianNB()),
#     ('Random Forest', RandomForestClassifier()),
#     ('Decision Tree', DecisionTreeClassifier()),
#     ('K Nearest Neighbors', KNeighborsClassifier()),
#     ('Support Vector Machines', SVC())
# ]
```

```
# cv_lr = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
# cv_rf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)


#     # Define feature selection models
# feature_selection_models = [
#     ('RFECV Logistic', RFECV(estimator=LogisticRegression(), step=1,␣
↪cv=cv_lr, scoring='accuracy')),
#     ('SelectKBest Naive Bayes', SelectKBest(score_func=mutual_info_classif,␣
↪k=10)),
#     ('SelectKBest KNN', SelectKBest(score_func=mutual_info_classif, k=10)),
#     ('RFECV Random Forest', RFECV(estimator=RandomForestClassifier(), step=1,␣
↪cv=cv_rf, scoring='accuracy')),
#     ('SelectKBest SVM', SelectKBest(score_func=mutual_info_classif, k=11))
# ]

# estimators = []
# for model, fs_model in feature_selection_models:
#     for base_name, base_model in base_models:
#         estimators.append((f"{model} + {base_name}", Pipeline([('Feature␣
↪Selection', fs_model), (base_name, base_model)])))

# stacking_clf = StackingClassifier(
#     estimators=base_models,
#     final_estimator= decision_trees_rfecv
# )

# # Train the stacking classifier on the training set
# stacking_clf.fit(X_train, y_train)

# # Evaluate the stacking classifier on the test set
# y_pred_test_stacking = stacking_clf.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred_test_stacking)
# precision = precision_score(y_test, y_pred_test_stacking)
# recall = recall_score(y_test, y_pred_test_stacking)
# conf_matrix = confusion_matrix(y_test, y_pred_test_stacking)
# tn, fp, fn, tp = conf_matrix.ravel()
# specificity = tn / (tn + fp)
# sensitivity = tp / (tp + fn)
# npv = tn / (tn + fn)
# f1_score = 2 * (precision * recall) / (precision + recall)
# roc_auc = roc_auc_score(y_test, y_pred_test_stacking)

# # Print evaluation metrics
# print("Accuracy:", accuracy)
# print("Precision:", precision)
```

```python
# print("Recall:", recall)
# print("Specificity:", specificity)
# print("F1 Score:", f1_score)
# print("ROC AUC Score:", roc_auc)
```