Phase 1

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.ensemble import
BaggingClassifier,RandomForestClassifier,AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,precision_score,
recall_score, f1_score, classification_report
from sklearn import tree
```

Bagging

```
# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']

# Read data from CSV file
df = pd.read_csv('/content/drive/My Drive/1/Dataset1.csv')

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

# Scatter plot of Feature 1 vs Feature 2
plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
plt.title('Scatter Plot of Feature1 vs Feature2')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.grid(True)
plt.colorbar(ticks=range(len(np.unique(y))), label='Label')
plt.show()

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create Bagging model with different numbers of estimators
```

```
    bagging_clf =
BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=4,
splitter='random'),
                                    n_estimators=n,
                                    random_state=42)
    # Train the model on training data
    bagging_clf.fit(X_train, y_train)

    # Predict labels for training and testing data
    y_train_pred = bagging_clf.predict(X_train)
    y_test_pred = bagging_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred,
average='micro')
    test_precision = precision_score(y_test, y_test_pred,
average='micro')

    train_recall = recall_score(y_train, y_train_pred,
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators Bagging = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot Bagging accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
```

```python
plt.title('Bagging Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.xticks(num_estimators)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Display five random trees from the model
plt.figure(figsize=(20, 10))
for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Plot the tree
    plot_tree(bagging_clf.estimators_[i], filled=True)  # Use
plot_tree to plot the tree
    plt.title(f'Tree Bagging {i + 1}')

plt.tight_layout()
plt.show()

# Plot decision boundaries
plt.figure(figsize=(15, 10))

# Create a mesh grid
x_min, x_max = X['Feature 1'].min() - 1, X['Feature 1'].max() + 1
y_min, y_max = X['Feature 2'].min() - 1, X['Feature 2'].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Predict the class for each point in the mesh grid
    Z = bagging_clf.estimators_[i].predict(np.c_[xx.ravel(),
yy.ravel()])
    Z = Z.reshape(xx.shape)

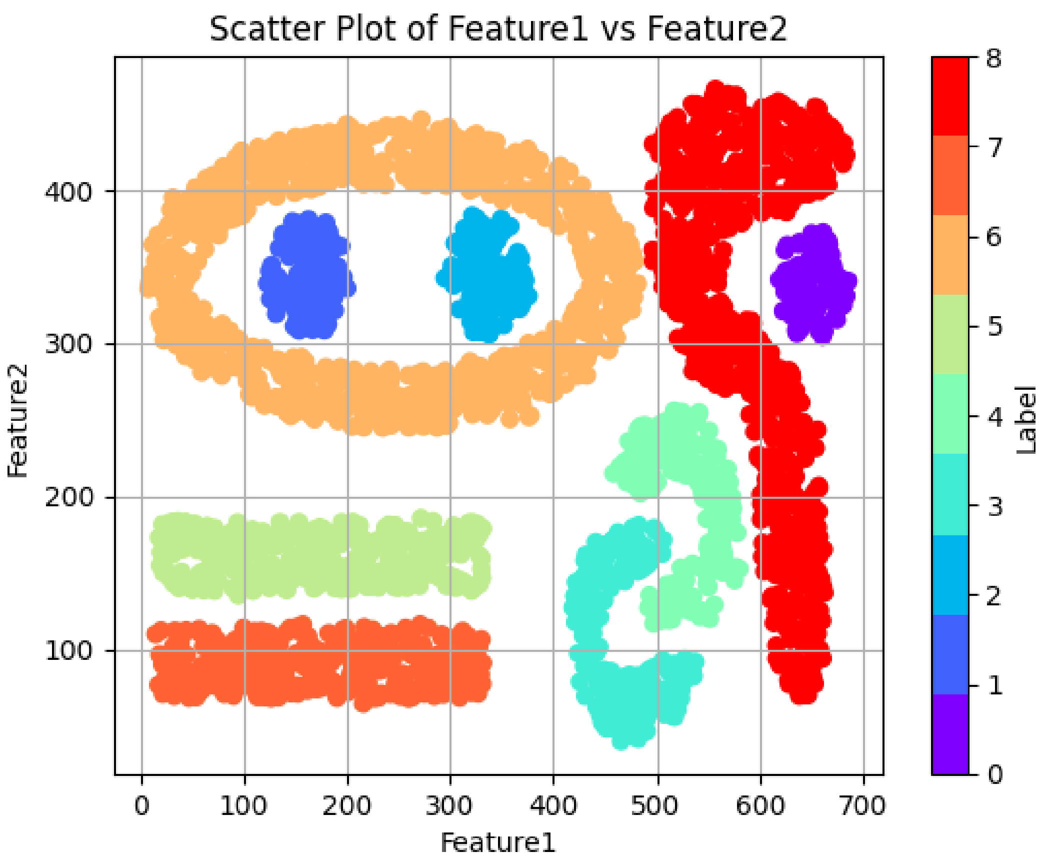
    # Plot decision boundaries
    plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))

    # Plot original data points with predicted labels
    y_pred_tree = bagging_clf.estimators_[i].predict(X)
    for label in np.unique(y):
        plt.scatter(X[y_pred_tree == label]['Feature 1'],
X[y_pred_tree == label]['Feature 2'],
                    color=colors[label], label=f'Label {label}')
```

```
    plt.title(f'Tree Bagging {i + 1}')
    plt.legend()

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

```
<ipython-input-54-1fa8d6f22dc9>:11: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
```




```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
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```

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FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators Bagging = 1:
Train Accuracy: 0.81, Test Accuracy: 0.80
Train Precision: 0.81, Test Precision: 0.80
Train Recall: 0.81, Test Recall: 0.80
Train F1-score: 0.81, Test F1-score: 0.80

n_estimators Bagging = 2:
Train Accuracy: 0.83, Test Accuracy: 0.81
Train Precision: 0.83, Test Precision: 0.81
Train Recall: 0.83, Test Recall: 0.81
Train F1-score: 0.83, Test F1-score: 0.81

n_estimators Bagging = 5:
Train Accuracy: 0.85, Test Accuracy: 0.83
Train Precision: 0.85, Test Precision: 0.83
Train Recall: 0.85, Test Recall: 0.83
Train F1-score: 0.85, Test F1-score: 0.83

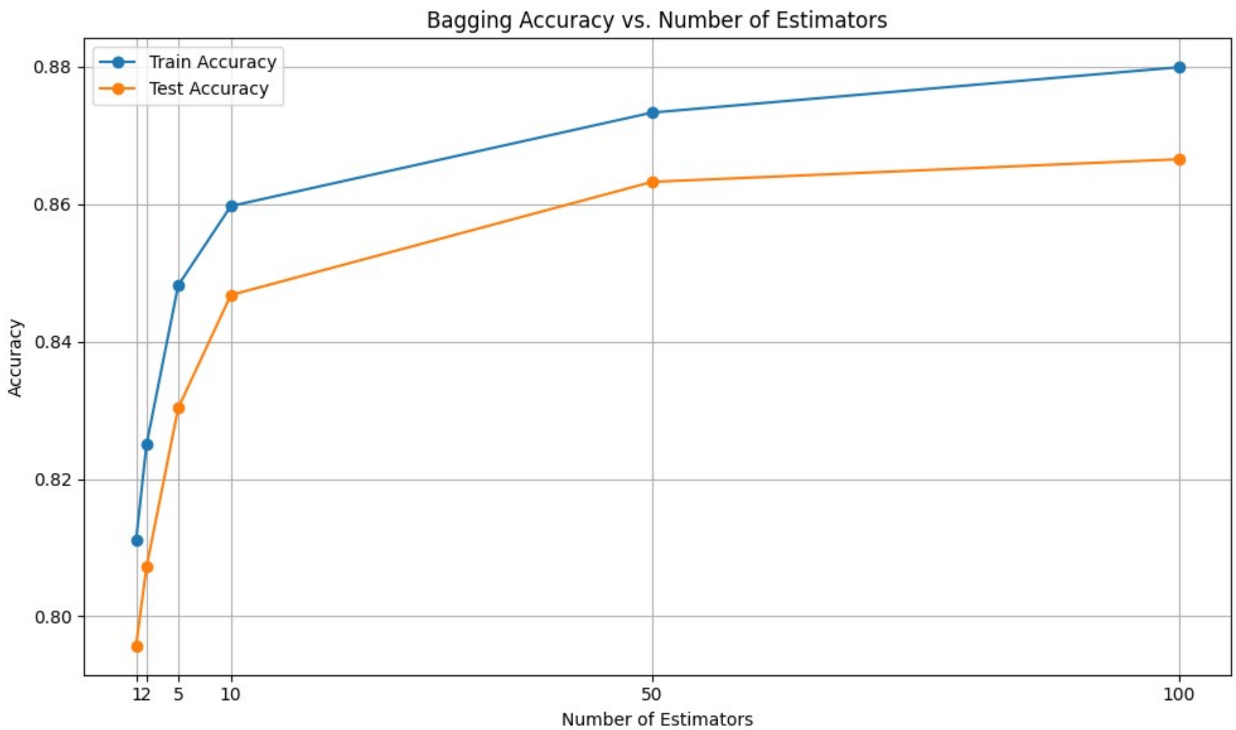
n_estimators Bagging = 10:
Train Accuracy: 0.86, Test Accuracy: 0.85
Train Precision: 0.86, Test Precision: 0.85
Train Recall: 0.86, Test Recall: 0.85
Train F1-score: 0.86, Test F1-score: 0.85

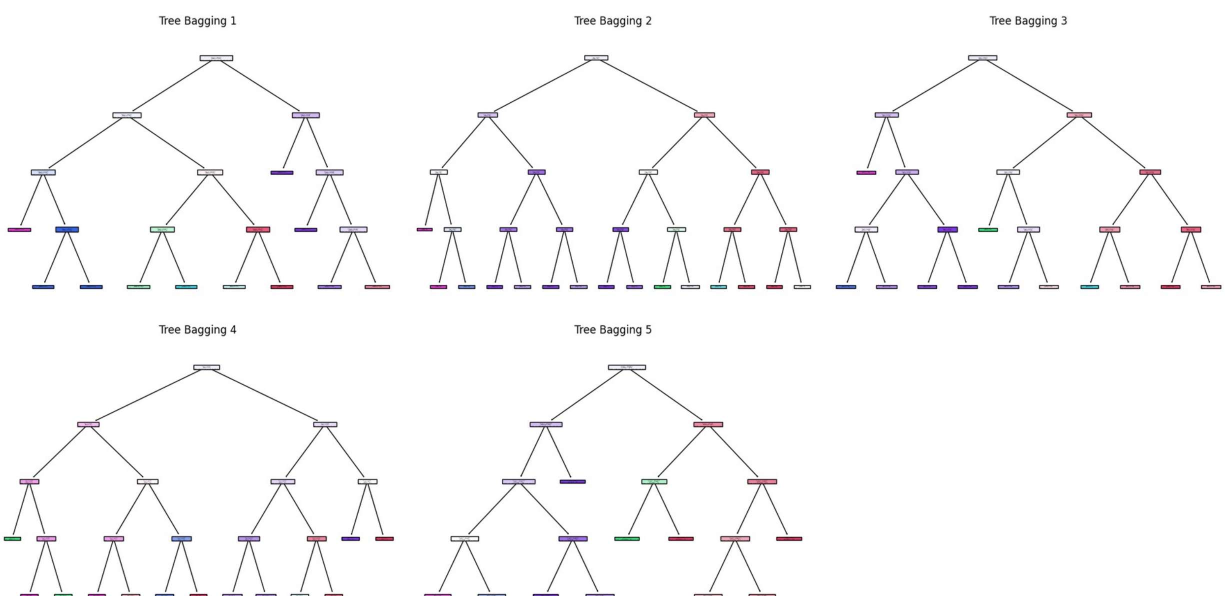

/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators Bagging = 50:
Train Accuracy: 0.87, Test Accuracy: 0.86
Train Precision: 0.87, Test Precision: 0.86
Train Recall: 0.87, Test Recall: 0.86
Train F1-score: 0.87, Test F1-score: 0.86


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
```

```
n_estimators Bagging = 100:
Train Accuracy: 0.88, Test Accuracy: 0.87
Train Precision: 0.88, Test Precision: 0.87
Train Recall: 0.88, Test Recall: 0.87
Train F1-score: 0.88, Test F1-score: 0.87
```





```
<ipython-input-54-1fa8d6f22dc9>:108: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
<ipython-input-54-1fa8d6f22dc9>:108: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
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  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
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  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
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/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
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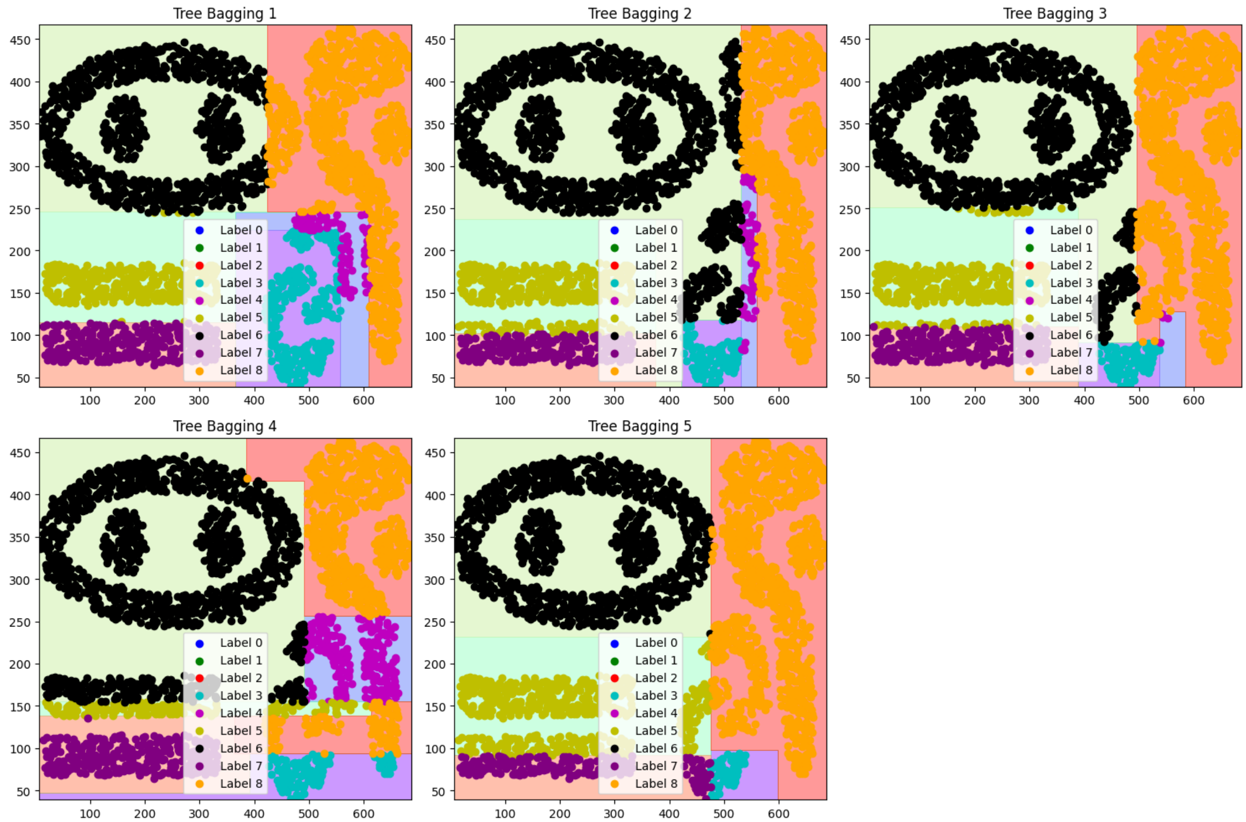
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
```

```
fitted without feature names
  warnings.warn(
```



RandomForest

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']

# Read data from CSV file
df = pd.read_csv('/content/drive/My Drive/1/Dataset1.csv')

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

# Scatter plot of Feature 1 vs Feature 2
```

```
plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
plt.title('Scatter Plot of Feature1 vs Feature2')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.grid(True)
plt.colorbar(ticks=range(len(np.unique(y))), label='Label')
plt.show()

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create RandomForest model with different numbers of estimators
    rf_clf = RandomForestClassifier(n_estimators=n, max_depth=4,
random_state=42)

    # Train the model on training data
    rf_clf.fit(X_train, y_train)

    # Predict labels for training and testing data
    y_train_pred = rf_clf.predict(X_train)
    y_test_pred = rf_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred,
average='micro')
    test_precision = precision_score(y_test, y_test_pred,
average='micro')

    train_recall = recall_score(y_train, y_train_pred,
```

```
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators RandomForest = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot RandomForest accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
plt.title('RandomForest Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.xticks(num_estimators)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Display five random trees from the model
plt.figure(figsize=(20, 10))
for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Plot the tree
    plot_tree(rf_clf.estimators_[i], filled=True)  # Use plot_tree to
plot the tree
    plt.title(f'Tree RandomForest {i + 1}')

plt.tight_layout()
plt.show()

# Plot decision boundaries
plt.figure(figsize=(15, 10))

# Create a mesh grid
x_min, x_max = X['Feature 1'].min() - 1, X['Feature 1'].max() + 1
y_min, y_max = X['Feature 2'].min() - 1, X['Feature 2'].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
```

```python
for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Predict the class for each point in the mesh grid
    Z = rf_clf.estimators_[i].predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

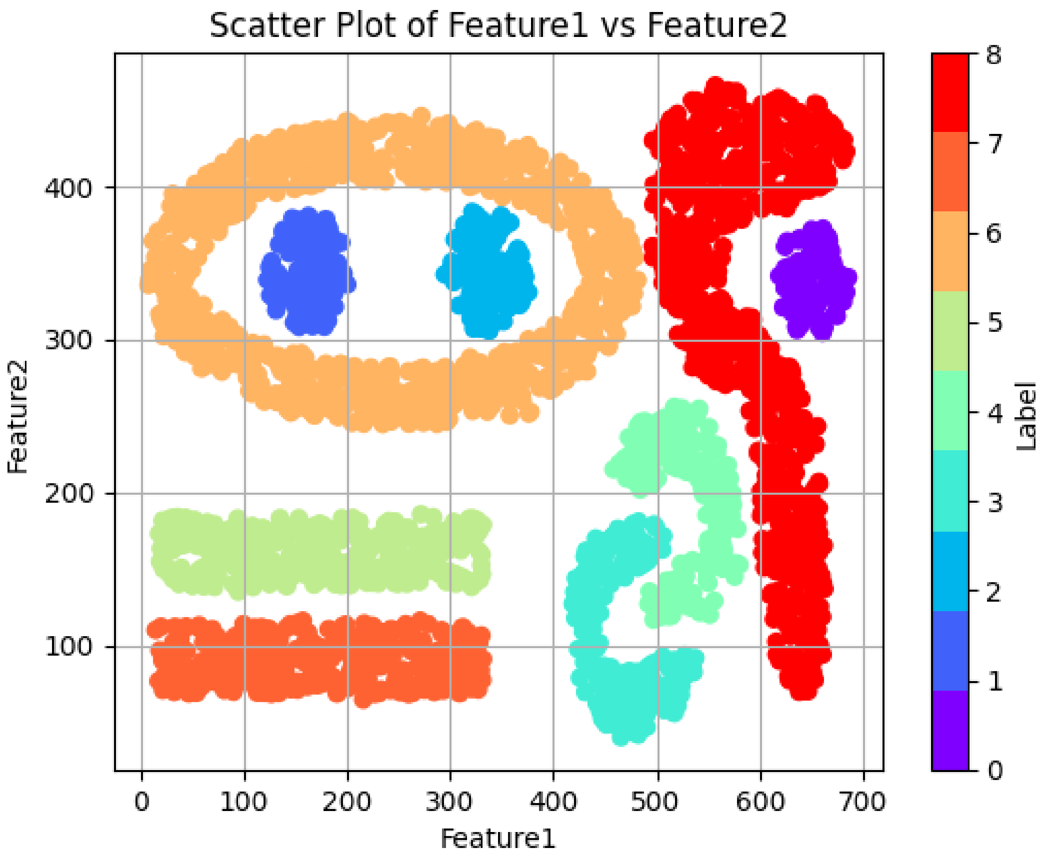
    # Plot decision boundaries
    plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))

    # Plot original data points with predicted labels
    y_pred_tree = rf_clf.estimators_[i].predict(X)
    for label in np.unique(y):
        plt.scatter(X[y_pred_tree == label]['Feature 1'],
X[y_pred_tree == label]['Feature 2'],
                    color=colors[label], label=f'Label {label}')

    plt.title(f'Tree RandomForest {i + 1}')
    plt.legend()

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

```
<ipython-input-55-27a5bddb699e>:19: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
```




```
n_estimators RandomForest = 1:
Train Accuracy: 0.88, Test Accuracy: 0.85
Train Precision: 0.88, Test Precision: 0.85
Train Recall: 0.88, Test Recall: 0.85
Train F1-score: 0.88, Test F1-score: 0.85

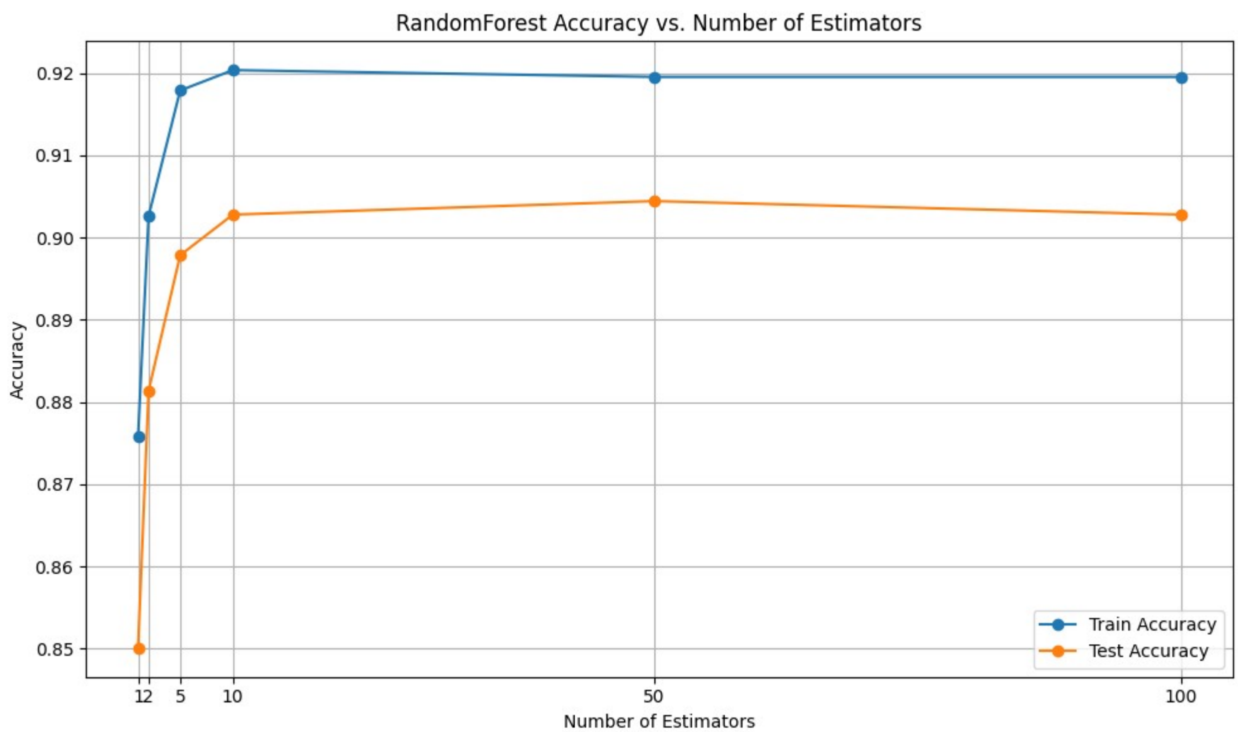
n_estimators RandomForest = 2:
Train Accuracy: 0.90, Test Accuracy: 0.88
Train Precision: 0.90, Test Precision: 0.88
Train Recall: 0.90, Test Recall: 0.88
Train F1-score: 0.90, Test F1-score: 0.88

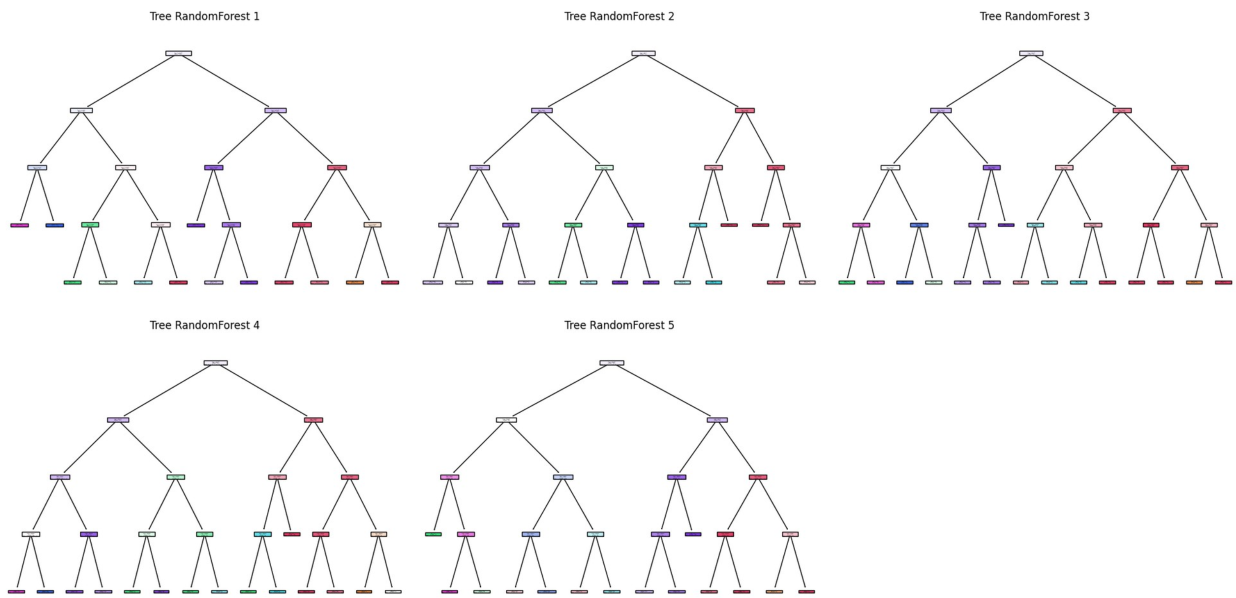
n_estimators RandomForest = 5:
Train Accuracy: 0.92, Test Accuracy: 0.90
Train Precision: 0.92, Test Precision: 0.90
Train Recall: 0.92, Test Recall: 0.90
Train F1-score: 0.92, Test F1-score: 0.90

n_estimators RandomForest = 10:
Train Accuracy: 0.92, Test Accuracy: 0.90
Train Precision: 0.92, Test Precision: 0.90
Train Recall: 0.92, Test Recall: 0.90
Train F1-score: 0.92, Test F1-score: 0.90
```

```
n_estimators RandomForest = 50:
Train Accuracy: 0.92, Test Accuracy: 0.90
Train Precision: 0.92, Test Precision: 0.90
Train Recall: 0.92, Test Recall: 0.90
Train F1-score: 0.92, Test F1-score: 0.90

n_estimators RandomForest = 100:
Train Accuracy: 0.92, Test Accuracy: 0.90
Train Precision: 0.92, Test Precision: 0.90
Train Recall: 0.92, Test Recall: 0.90
Train F1-score: 0.92, Test F1-score: 0.90
```






```
<ipython-input-55-27a5bddb699e>:115: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
<ipython-input-55-27a5bddb699e>:115: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
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``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
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```
<ipython-input-55-27a5bddb699e>:115: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
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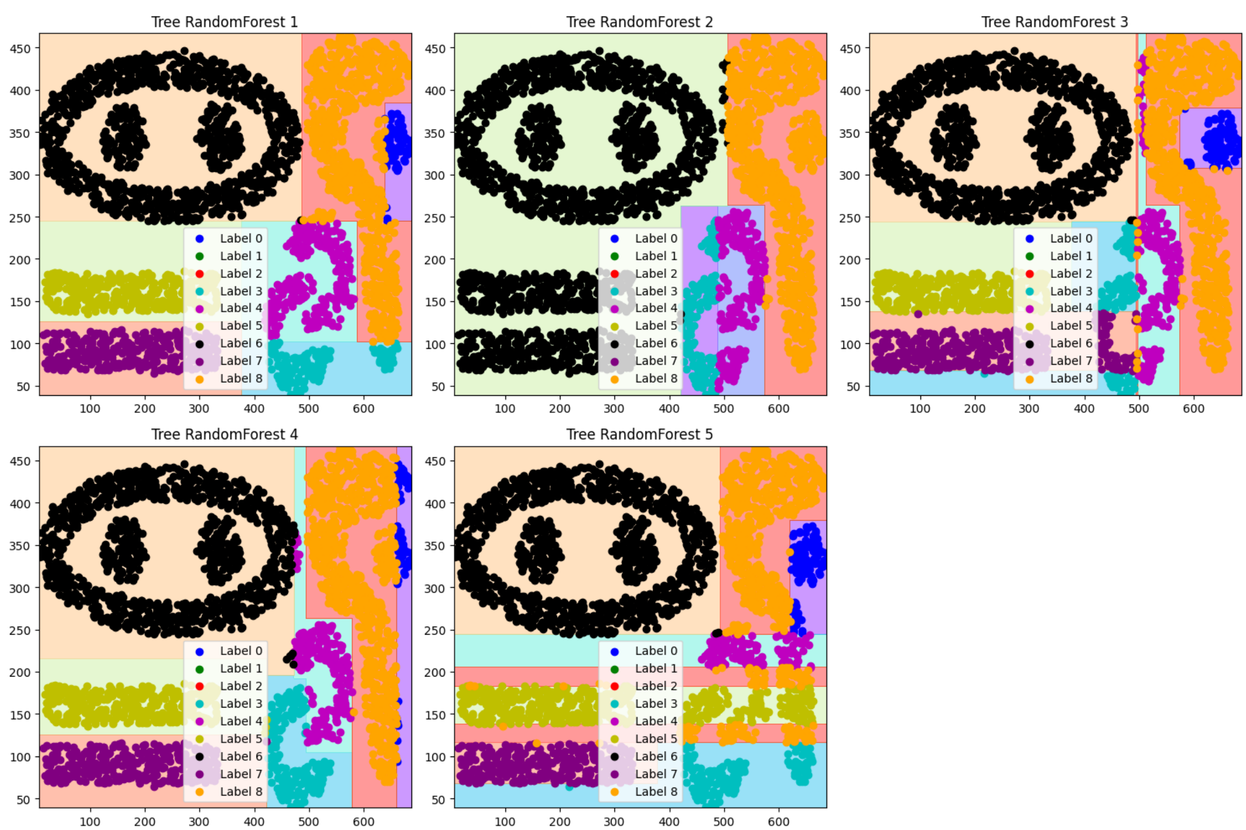
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
<ipython-input-55-27a5bddb699e>:115: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
```



Adaboost

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']

# Read data from CSV file
df = pd.read_csv('/content/drive/My Drive/1/Dataset1.csv')

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

# Scatter plot of Feature 1 vs Feature 2
plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
plt.title('Scatter Plot of Feature1 vs Feature2')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.grid(True)
plt.colorbar(ticks=range(len(np.unique(y))), label='Label')
plt.show()

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create AdaBoost model with different numbers of estimators
    ada_clf =
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=4,
splitter='random'),
                                 n_estimators=n, random_state=42)

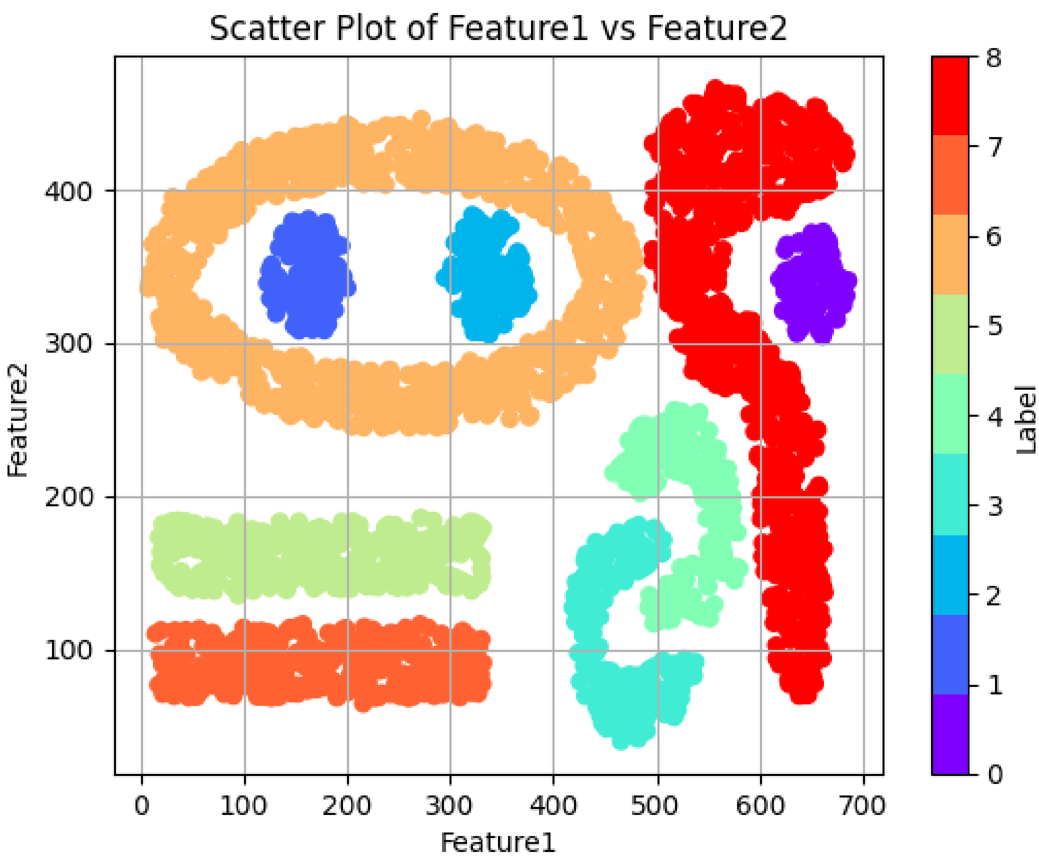
    # Train the model on training data
    ada_clf.fit(X_train, y_train)
```

```python
    # Predict labels for training and testing data
    y_train_pred = ada_clf.predict(X_train)
    y_test_pred = ada_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred,
average='micro')
    test_precision = precision_score(y_test, y_test_pred,
average='micro')

    train_recall = recall_score(y_train, y_train_pred,
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators AdaBoost = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot AdaBoost accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
plt.title('AdaBoost Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.xticks(num_estimators)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
# Display five random trees from the model
plt.figure(figsize=(20, 10))
for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Plot the tree
    plot_tree(ada_clf.estimators_[i], filled=True)  # Use plot_tree to
plot the tree
    plt.title(f'Tree AdaBoost {i + 1}')

plt.tight_layout()
plt.show()

# Plot decision boundaries
plt.figure(figsize=(15, 10))

# Create a mesh grid
x_min, x_max = X['Feature 1'].min() - 1, X['Feature 1'].max() + 1
y_min, y_max = X['Feature 2'].min() - 1, X['Feature 2'].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

for i in range(5):
    plt.subplot(2, 3, i + 1)

    # Predict the class for each point in the mesh grid
    Z = ada_clf.estimators_[i].predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    # Plot decision boundaries
    plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))

    # Plot original data points with predicted labels
    y_pred_tree = ada_clf.estimators_[i].predict(X)
    for label in np.unique(y):
        plt.scatter(X[y_pred_tree == label]['Feature 1'],
X[y_pred_tree == label]['Feature 2'],
                    color=colors[label], label=f'Label {label}')

    plt.title(f'Tree AdaBoost {i + 1}')
    plt.legend()

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

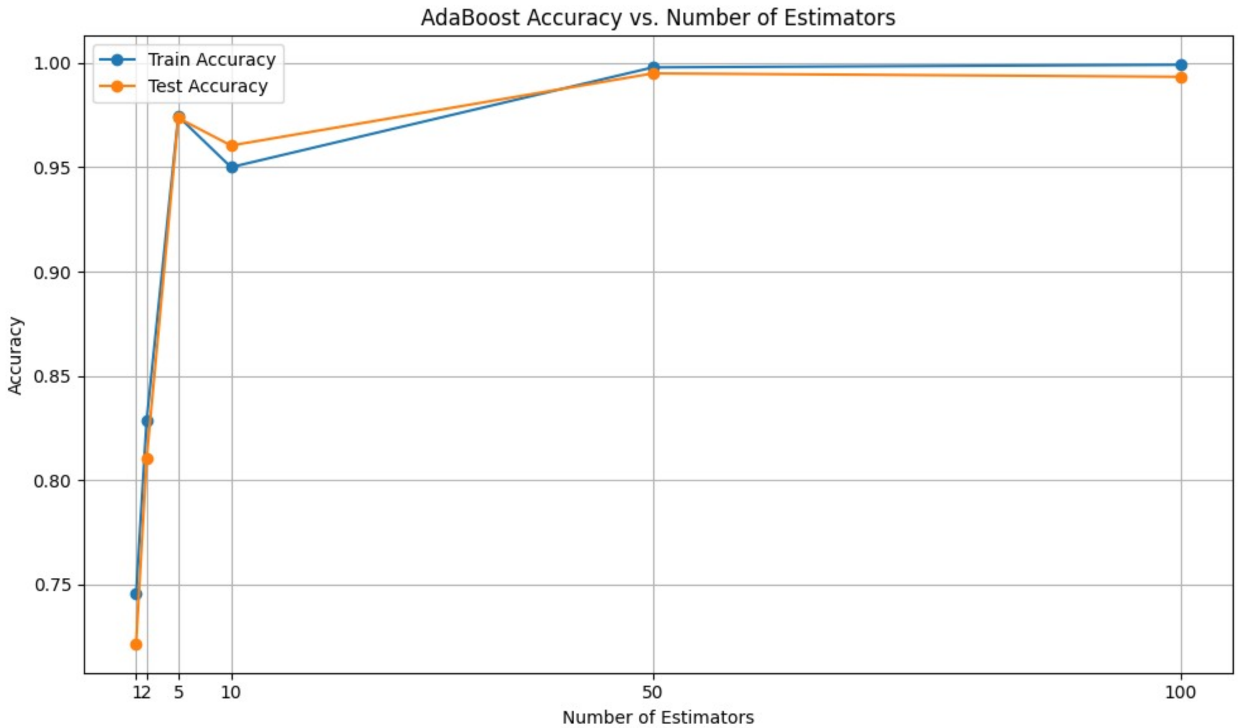
```
<ipython-input-56-9d42626d182c>:19: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
```

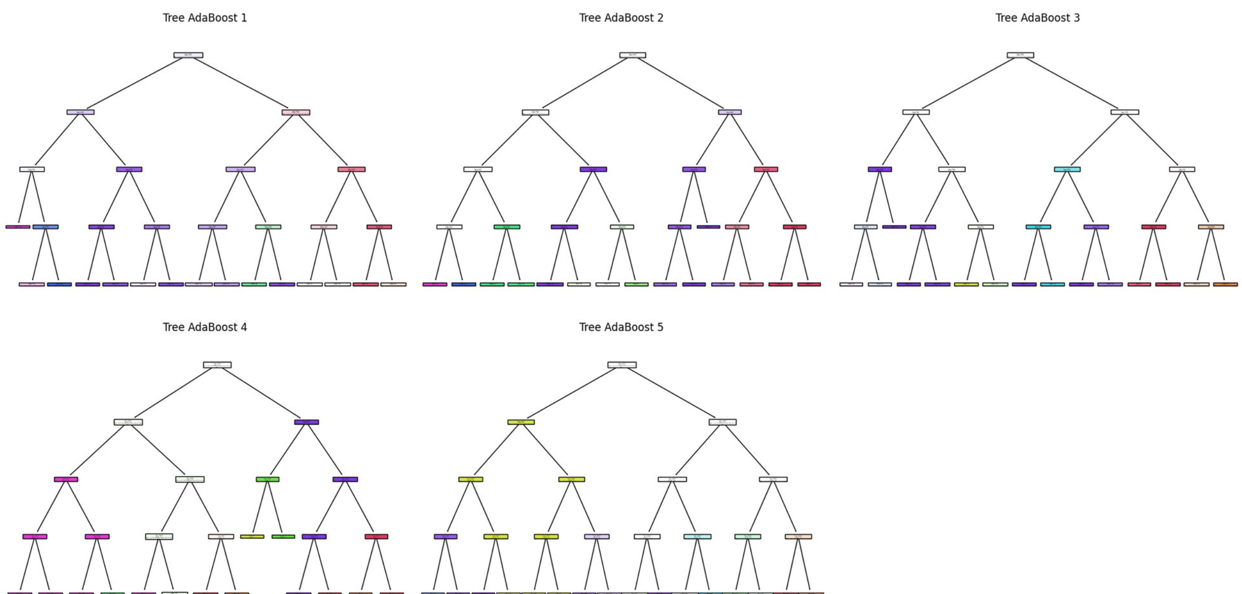
```
  plt.scatter(df['Feature 1'], df['Feature 2'], c=y,
cmap=plt.cm.get_cmap('rainbow', len(np.unique(y))))
```




```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators AdaBoost = 1:
Train Accuracy: 0.75, Test Accuracy: 0.72
```

```
Train Precision: 0.75, Test Precision: 0.72
Train Recall: 0.75, Test Recall: 0.72
Train F1-score: 0.75, Test F1-score: 0.72

n_estimators AdaBoost = 2:
Train Accuracy: 0.83, Test Accuracy: 0.81
Train Precision: 0.83, Test Precision: 0.81
Train Recall: 0.83, Test Recall: 0.81
Train F1-score: 0.83, Test F1-score: 0.81

n_estimators AdaBoost = 5:
Train Accuracy: 0.97, Test Accuracy: 0.97
Train Precision: 0.97, Test Precision: 0.97
Train Recall: 0.97, Test Recall: 0.97
Train F1-score: 0.97, Test F1-score: 0.97

n_estimators AdaBoost = 10:
Train Accuracy: 0.95, Test Accuracy: 0.96
Train Precision: 0.95, Test Precision: 0.96
Train Recall: 0.95, Test Recall: 0.96
Train F1-score: 0.95, Test F1-score: 0.96


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators AdaBoost = 50:
Train Accuracy: 1.00, Test Accuracy: 1.00
Train Precision: 1.00, Test Precision: 1.00
Train Recall: 1.00, Test Recall: 1.00
Train F1-score: 1.00, Test F1-score: 1.00


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators AdaBoost = 100:
Train Accuracy: 1.00, Test Accuracy: 0.99
Train Precision: 1.00, Test Precision: 0.99
Train Recall: 1.00, Test Recall: 0.99
Train F1-score: 1.00, Test F1-score: 0.99
```






```
<ipython-input-56-9d42626d182c>:116: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
```

```
fitted without feature names
  warnings.warn(
<ipython-input-56-9d42626d182c>:116: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
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len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
<ipython-input-56-9d42626d182c>:116: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
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two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
<ipython-input-56-9d42626d182c>:116: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.get_cmap('rainbow',
len(np.unique(y))))
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432:
UserWarning: X has feature names, but DecisionTreeClassifier was
fitted without feature names
  warnings.warn(
```

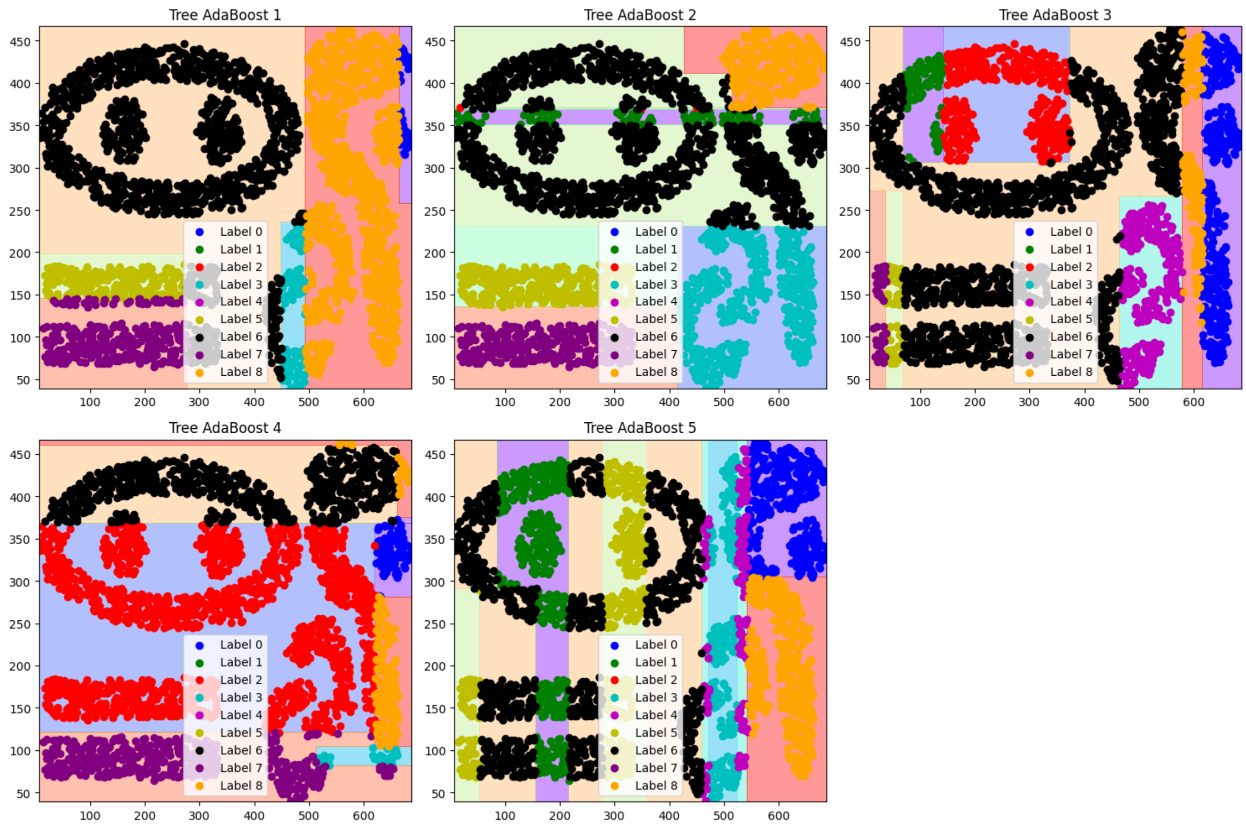

Stacked Learning

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

# Load the dataset
df = pd.read_csv('/content/drive/My Drive/1/Dataset1.csv')

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

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Define base classifiers
base_classifiers = {
```

```
    'knn': KNeighborsClassifier(n_neighbors=3),
    'decision_tree': DecisionTreeClassifier(max_depth=4,
random_state=42),
    'random_forest': RandomForestClassifier(n_estimators=10,
max_depth=4, random_state=42),
    'adaboost':
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=4),
n_estimators=10, random_state=42)
}

# Train base classifiers
for name, clf in base_classifiers.items():
    clf.fit(X_train, y_train)
    y_train_pred = clf.predict(X_train)
    y_test_pred = clf.predict(X_test)
    print(f'{name} - Train Accuracy: {accuracy_score(y_train,
y_train_pred):.2f}, Test Accuracy: {accuracy_score(y_test,
y_test_pred):.2f}')

# Create new features for the meta-classifier
meta_features_train = np.column_stack([clf.predict(X_train) for clf in
base_classifiers.values()])
meta_features_test = np.column_stack([clf.predict(X_test) for clf in
base_classifiers.values()])

# Define and train the meta-classifier
meta_classifier = DecisionTreeClassifier(max_depth=4, random_state=42)
meta_classifier.fit(meta_features_train, y_train)

# Evaluate the stacked model
y_train_pred_meta = meta_classifier.predict(meta_features_train)
y_test_pred_meta = meta_classifier.predict(meta_features_test)

train_accuracy = accuracy_score(y_train, y_train_pred_meta)
test_accuracy = accuracy_score(y_test, y_test_pred_meta)

train_precision = precision_score(y_train, y_train_pred_meta,
average='micro')
test_precision = precision_score(y_test, y_test_pred_meta,
average='micro')

train_recall = recall_score(y_train, y_train_pred_meta,
average='micro')
test_recall = recall_score(y_test, y_test_pred_meta, average='micro')

train_f1 = f1_score(y_train, y_train_pred_meta, average='micro')
test_f1 = f1_score(y_test, y_test_pred_meta, average='micro')

print(f'Stacked Model:')
print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
```

```
{test_accuracy:.2f}')
print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
print(f'Train F1-score: {train_f1:.2f}, Test F1-score: {test_f1:.2f}')
```

```
knn - Train Accuracy: 1.00, Test Accuracy: 1.00
decision_tree - Train Accuracy: 0.91, Test Accuracy: 0.89
random_forest - Train Accuracy: 0.92, Test Accuracy: 0.90
adaboost - Train Accuracy: 1.00, Test Accuracy: 0.99
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
```

```
Stacked Model:
Train Accuracy: 0.90, Test Accuracy: 0.89
Train Precision: 0.90, Test Precision: 0.89
Train Recall: 0.90, Test Recall: 0.89
Train F1-score: 0.90, Test F1-score: 0.89
```

Phase 2

Preprocess

```
import pandas as pd
df = pd.read_csv('/content/drive/My Drive/1/Dataset2.csv')

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4240 entries, 0 to 4239
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   male             4240 non-null   int64
 1   age              4240 non-null   int64
 2   education        4135 non-null   float64
 3   currentSmoker    4240 non-null   int64
 4   cigsPerDay       4211 non-null   float64
 5   BPMeds           4187 non-null   float64
 6   prevalentStroke  4240 non-null   int64
 7   prevalentHyp     4240 non-null   int64
 8   diabetes         4240 non-null   int64
 9   totChol          4190 non-null   float64
 10  sysBP            4240 non-null   float64
```

```
 11  diaBP            4240 non-null   float64
 12  BMI              4221 non-null   float64
 13  heartRate        4239 non-null   float64
 14  glucose          3852 non-null   float64
 15  TenYearCHD       4240 non-null   int64
dtypes: float64(9), int64(7)
memory usage: 530.1 KB
```

```
df['education'].unique()
```

```
array([ 4.,  2.,  1.,  3., nan])
```

```
# Calculate the mode of the column
mode_value = df['education'].mode()[0]

# Fill NaN values with the mode
df['education'].fillna(mode_value, inplace=True)
```

```
df['cigsPerDay'].unique()
```

```
array([ 0., 20., 30., 23., 15.,  9., 10.,  5., 35., 43.,  1., 40.,
3.,
        2., nan, 12.,  4., 18., 25., 60., 14., 45.,  8., 50., 13.,
11.,
        7.,  6., 38., 29., 17., 16., 19., 70.])
```

```
# Calculate the median of the column
median_value = df['cigsPerDay'].median()

# Fill NaN values with the median
df['cigsPerDay'].fillna(median_value, inplace=True)
```

```
df['BPMeds'].unique()
```

```
array([ 0.,  1., nan])
```

```
df = df.dropna(subset=['BPMeds'])
```

```
# Calculate the median of the column
median_value = df['totChol'].median()

# Fill NaN values with the median
df['totChol'].fillna(median_value, inplace=True)
```

```
<ipython-input-66-6f836d55e12c>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['totChol'].fillna(median_value, inplace=True)
```

```python
# Calculate the median of the column
mean_value = df['BMI'].mean()

# Fill NaN values with the median
df['BMI'].fillna(mean_value, inplace=True)
```

```
<ipython-input-67-a33f1e4e780a>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['BMI'].fillna(mean_value, inplace=True)
```

```python
# Calculate the median of the column
median_value = df['heartRate'].median()

# Fill NaN values with the median
df['heartRate'].fillna(median_value, inplace=True)
```

```
<ipython-input-68-25274b80e945>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['heartRate'].fillna(median_value, inplace=True)
```

```python
# Calculate the median of the column
median_value = df['glucose'].median()

# Fill NaN values with the median
df['glucose'].fillna(median_value, inplace=True)
```

```
<ipython-input-69-3502970513b1>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['glucose'].fillna(median_value, inplace=True)
```

```python
df.head()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 4187,\n  \"fields\":
[\n    {\n      \"column\": \"male\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          0,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"age\",\n      \"properties\": {\n        \"dtype\":
```

```
\"number\",\n        \"std\": 8,\n        \"min\": 32,\n
\"max\": 70,\n        \"num_unique_values\": 39,\n        \"samples\":
[\n          34,\n          70\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"education\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 1.01787672260344,\n
\"min\": 1.0,\n        \"max\": 4.0,\n        \"num_unique_values\":
4,\n        \"samples\": [\n          2.0,\n          3.0\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"currentSmoker\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          1,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"cigsPerDay\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 11.901904311142495,\n        \"min\":
0.0,\n        \"max\": 70.0,\n        \"num_unique_values\": 33,\n
\"samples\": [\n          19.0,\n          4.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"BPMeds\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
0.16954428739626196,\n        \"min\": 0.0,\n        \"max\": 1.0,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          1.0,\n
0.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"prevalentStroke\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"prevalentHyp\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"diabetes\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"totChol\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 44.2237265788299,\n        \"min\":
107.0,\n        \"max\": 696.0,\n        \"num_unique_values\": 248,\n
\"samples\": [\n          311.0,\n          205.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"sysBP\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 21.98290660966593,\n
\"min\": 83.5,\n        \"max\": 295.0,\n
```

```
\"num_unique_values\": 233,\n        \"samples\": [\n          117.0,\
n          191.5\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
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\"std\": 11.878463990074186,\n        \"min\": 48.0,\n        \"max\":
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\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"BMI\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 4.067178635883306,\n        \"min\": 15.54,\n        \"max\":
56.8,\n        \"num_unique_values\": 1360,\n        \"samples\": [\n
19.66,\n          30.99\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"heartRate\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 12.053463897069951,\n
\"min\": 44.0,\n        \"max\": 143.0,\n
\"num_unique_values\": 73,\n        \"samples\": [\n          85.0,\n
47.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"glucose\",\n      \"properties\": {\n        \"dtype\": \"number\",\
n        \"std\": 22.932432152397404,\n        \"min\": 40.0,\n
\"max\": 394.0,\n        \"num_unique_values\": 142,\n
\"samples\": [\n          332.0,\n          74.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"TenYearCHD\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          1,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df"}

# Calculate the correlation matrix
correlation_matrix = df.corr()

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 8))

# Draw the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1,
vmax=1, center=0)

# Add title and labels
plt.title('Correlation Matrix Heatmap')
plt.show()
```

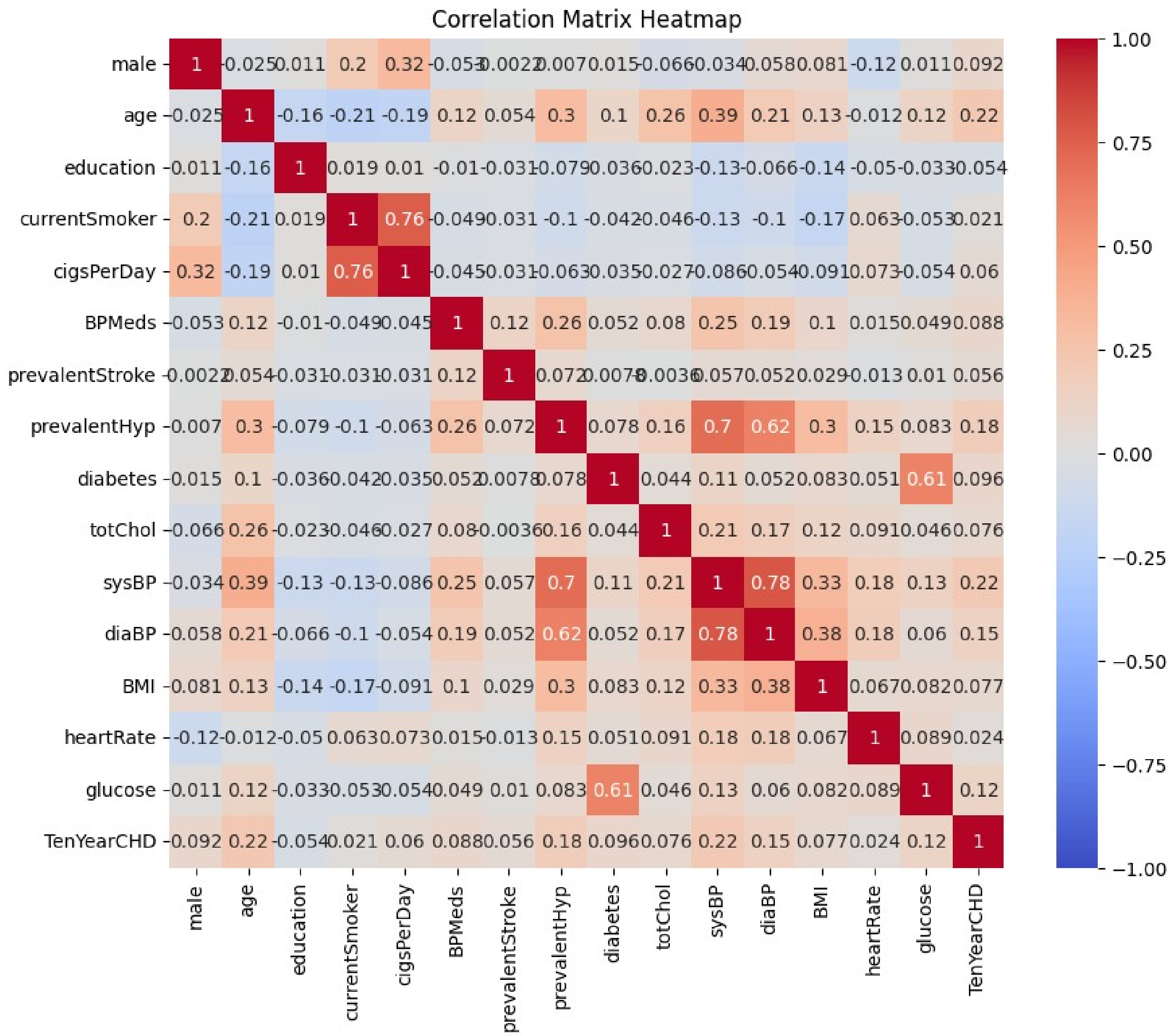


```
columns_to_drop = set()

# Iterate through the correlation matrix
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > threshold:
            column_to_drop = correlation_matrix.columns[i]
            columns_to_drop.add(column_to_drop)

# Create a new DataFrame with only the columns that have low
correlation
df_low_corr = df.drop(columns=columns_to_drop)

print("Columns to drop due to high correlation:")
print(columns_to_drop)
print("\nDataFrame with only low correlated columns:")
print(df_low_corr)
```

```
Columns to drop due to high correlation:
{'cigsPerDay', 'diaBP'}

DataFrame with only low correlated columns:
      male  age  education  currentSmoker  BPMeds  prevalentStroke  \
0        1   39        4.0              0     0.0                0
1        0   46        2.0              0     0.0                0
2        1   48        1.0              1     0.0                0
3        0   61        3.0              1     0.0                0
4        0   46        3.0              1     0.0                0
...    ...  ...        ...            ...     ...              ...
4234     1   51        3.0              1     0.0                0
4236     0   44        1.0              1     0.0                0
4237     0   52        2.0              0     0.0                0
4238     1   40        3.0              0     0.0                0
4239     0   39        3.0              1     0.0                0

      prevalentHyp  diabetes  totChol  sysBP    BMI  heartRate
glucose  \
0                0         0    195.0  106.0  26.97       80.0
77.0
1                0         0    250.0  121.0  28.73       95.0
76.0
2                0         0    245.0  127.5  25.34       75.0
70.0
3                1         0    225.0  150.0  28.58       65.0
103.0
4                0         0    285.0  130.0  23.10       85.0
85.0
...            ...       ...      ...    ...    ...        ...      ..
.
4234             0         0    207.0  126.5  19.71       65.0
68.0
4236             0         0    210.0  126.5  19.16       86.0
78.0
4237             0         0    269.0  133.5  21.47       80.0
107.0
4238             1         0    185.0  141.0  25.60       67.0
72.0
4239             0         0    196.0  133.0  20.91       85.0
80.0

      TenYearCHD
0              0
1              0
2              0
3              1
4              0
...          ...
4234           0
```

```
4236           0
4237           0
4238           0
4239           0

[4187 rows x 14 columns]
```

df_low_corr

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```
[\n          1,\n          0\n        ],\n        \"semantic_type\":
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\"column\": \"totChol\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 44.2237265788299,\n        \"min\":
107.0,\n        \"max\": 696.0,\n        \"num_unique_values\": 248,\n
\"samples\": [\n          311.0,\n          205.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"sysBP\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 21.98290660966593,\n
\"min\": 83.5,\n        \"max\": 295.0,\n
\"num_unique_values\": 233,\n        \"samples\": [\n          117.0,\
n          191.5\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"BMI\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 4.067178635883306,\n        \"min\": 15.54,\n        \"max\":
56.8,\n        \"num_unique_values\": 1360,\n        \"samples\": [\n
19.66,\n          30.99\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"heartRate\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 12.053463897069951,\n
\"min\": 44.0,\n        \"max\": 143.0,\n
\"num_unique_values\": 73,\n        \"samples\": [\n          85.0,\n
47.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"glucose\",\n      \"properties\": {\n        \"dtype\": \"number\",\
n        \"std\": 22.932432152397404,\n        \"min\": 40.0,\n
\"max\": 394.0,\n        \"num_unique_values\": 142,\n
\"samples\": [\n          332.0,\n          74.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"TenYearCHD\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          1,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df_low_corr"}
```


Bagging

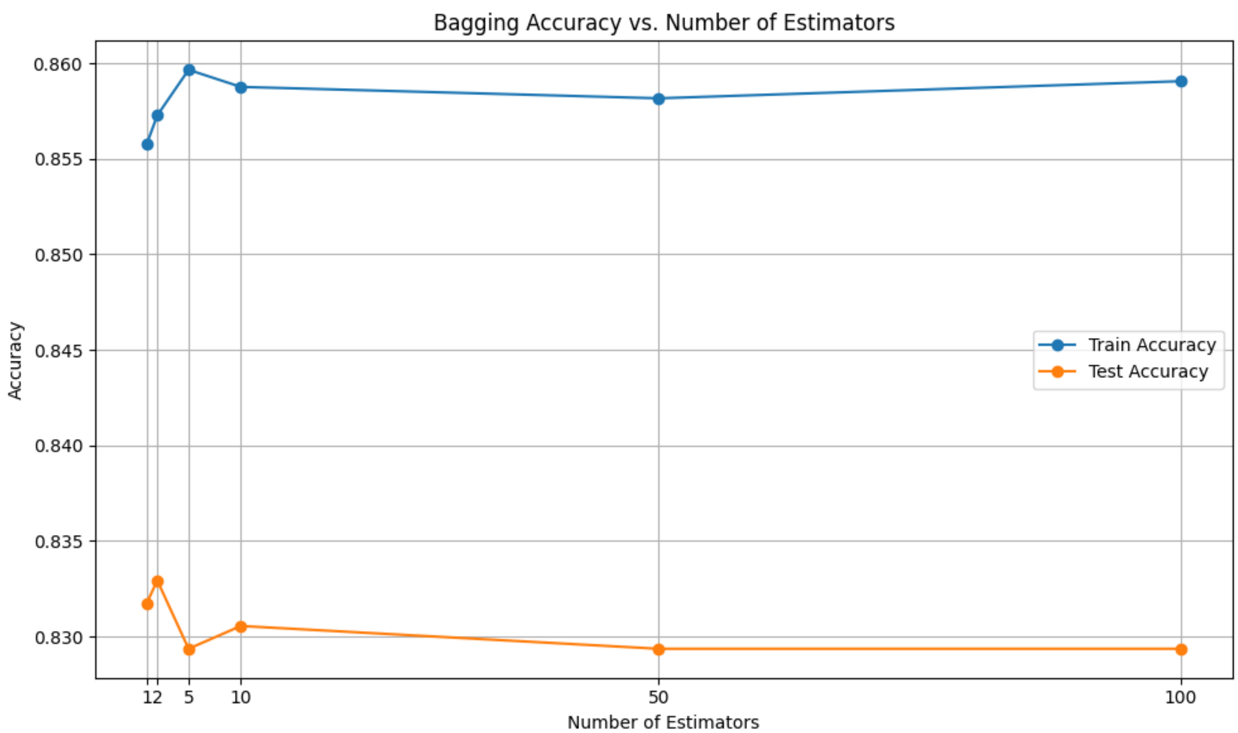
```
# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']


X = df_low_corr.drop('TenYearCHD', axis=1)
y = df_low_corr['TenYearCHD']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

```python
# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create Bagging model with different numbers of estimators
    bagging_clf = 
BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=4, 
splitter='random'),
                                    n_estimators=n,
                                    random_state=42)
    # Train the model on training data
    bagging_clf.fit(X_train, y_train)

    # Predict labels for training and testing data
    y_train_pred = bagging_clf.predict(X_train)
    y_test_pred = bagging_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred, 
average='micro')
    test_precision = precision_score(y_test, y_test_pred, 
average='micro')

    train_recall = recall_score(y_train, y_train_pred, 
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators Bagging = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy: 
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision: 
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall: 
{test_recall:.2f}')
```

```
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot Bagging accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
plt.title('Bagging Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.xticks(num_estimators)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
n_estimators Bagging = 1:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators Bagging = 2:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
```

```
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators Bagging = 5:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators Bagging = 10:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators Bagging = 50:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators Bagging = 100:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83
```



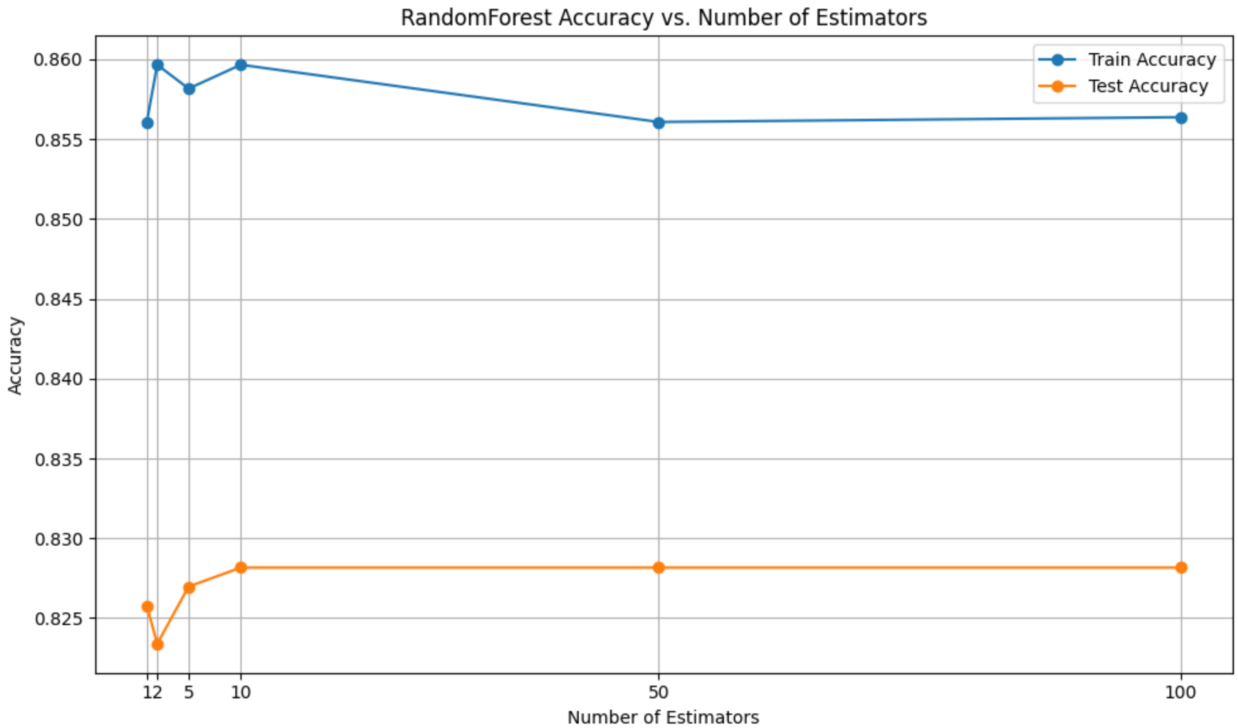
RandomForest

```
# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']



X = df_low_corr.drop('TenYearCHD', axis=1)
y = df_low_corr['TenYearCHD']


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create RandomForest model with different numbers of estimators
    rf_clf = RandomForestClassifier(n_estimators=n, max_depth=4,
random_state=42)
```

```
    # Train the model on training data
    rf_clf.fit(X_train, y_train)

    # Predict labels for training and testing data
    y_train_pred = rf_clf.predict(X_train)
    y_test_pred = rf_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred,
average='micro')
    test_precision = precision_score(y_test, y_test_pred,
average='micro')

    train_recall = recall_score(y_train, y_train_pred,
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators RandomForest = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot RandomForest accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
plt.title('RandomForest Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.xticks(num_estimators)
plt.legend()
```

```
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
n_estimators RandomForest = 1:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators RandomForest = 2:
Train Accuracy: 0.86, Test Accuracy: 0.82
Train Precision: 0.86, Test Precision: 0.82
Train Recall: 0.86, Test Recall: 0.82
Train F1-score: 0.86, Test F1-score: 0.82

n_estimators RandomForest = 5:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators RandomForest = 10:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators RandomForest = 50:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83

n_estimators RandomForest = 100:
Train Accuracy: 0.86, Test Accuracy: 0.83
Train Precision: 0.86, Test Precision: 0.83
Train Recall: 0.86, Test Recall: 0.83
Train F1-score: 0.86, Test F1-score: 0.83
```



Adaboost

```
# Define 9 different colors
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']



X = df_low_corr.drop('TenYearCHD', axis=1)
y = df_low_corr['TenYearCHD']


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Number of estimators to evaluate
num_estimators = [1, 2, 5, 10, 50, 100]

train_accuracies = []
test_accuracies = []

# Loop to test different numbers of estimators
for n in num_estimators:
    # Create AdaBoost model with different numbers of estimators
    ada_clf =
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=4,
splitter='random'),
```

```
                                 n_estimators=n, random_state=42)

    # Train the model on training data
    ada_clf.fit(X_train, y_train)

    # Predict labels for training and testing data
    y_train_pred = ada_clf.predict(X_train)
    y_test_pred = ada_clf.predict(X_test)

    # Compute model accuracy
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracies in lists
    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

    # Evaluate the model for training and testing data
    train_f1 = f1_score(y_train, y_train_pred, average='micro')
    test_f1 = f1_score(y_test, y_test_pred, average='micro')

    train_precision = precision_score(y_train, y_train_pred,
average='micro')
    test_precision = precision_score(y_test, y_test_pred,
average='micro')

    train_recall = recall_score(y_train, y_train_pred,
average='micro')
    test_recall = recall_score(y_test, y_test_pred, average='micro')

    print(f'n_estimators AdaBoost = {n}:')
    print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
    print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
    print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
    print(f'Train F1-score: {train_f1:.2f}, Test F1-score:
{test_f1:.2f}')
    print()

# Plot AdaBoost accuracy versus number of estimators
plt.figure(figsize=(10, 6))
plt.plot(num_estimators, train_accuracies, marker='o', label='Train
Accuracy')
plt.plot(num_estimators, test_accuracies, marker='o', label='Test
Accuracy')
plt.title('AdaBoost Accuracy vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
```

```
plt.xticks(num_estimators)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
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  warnings.warn(
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  warnings.warn(

n_estimators AdaBoost = 1:
Train Accuracy: 0.86, Test Accuracy: 0.82
Train Precision: 0.86, Test Precision: 0.82
Train Recall: 0.86, Test Recall: 0.82
Train F1-score: 0.86, Test F1-score: 0.82

n_estimators AdaBoost = 2:
Train Accuracy: 0.86, Test Accuracy: 0.82
Train Precision: 0.86, Test Precision: 0.82
Train Recall: 0.86, Test Recall: 0.82
Train F1-score: 0.86, Test F1-score: 0.82

n_estimators AdaBoost = 5:
Train Accuracy: 0.86, Test Accuracy: 0.82
Train Precision: 0.86, Test Precision: 0.82
Train Recall: 0.86, Test Recall: 0.82
Train F1-score: 0.86, Test F1-score: 0.82

n_estimators AdaBoost = 10:
Train Accuracy: 0.87, Test Accuracy: 0.81
Train Precision: 0.87, Test Precision: 0.81
Train Recall: 0.87, Test Recall: 0.81
```
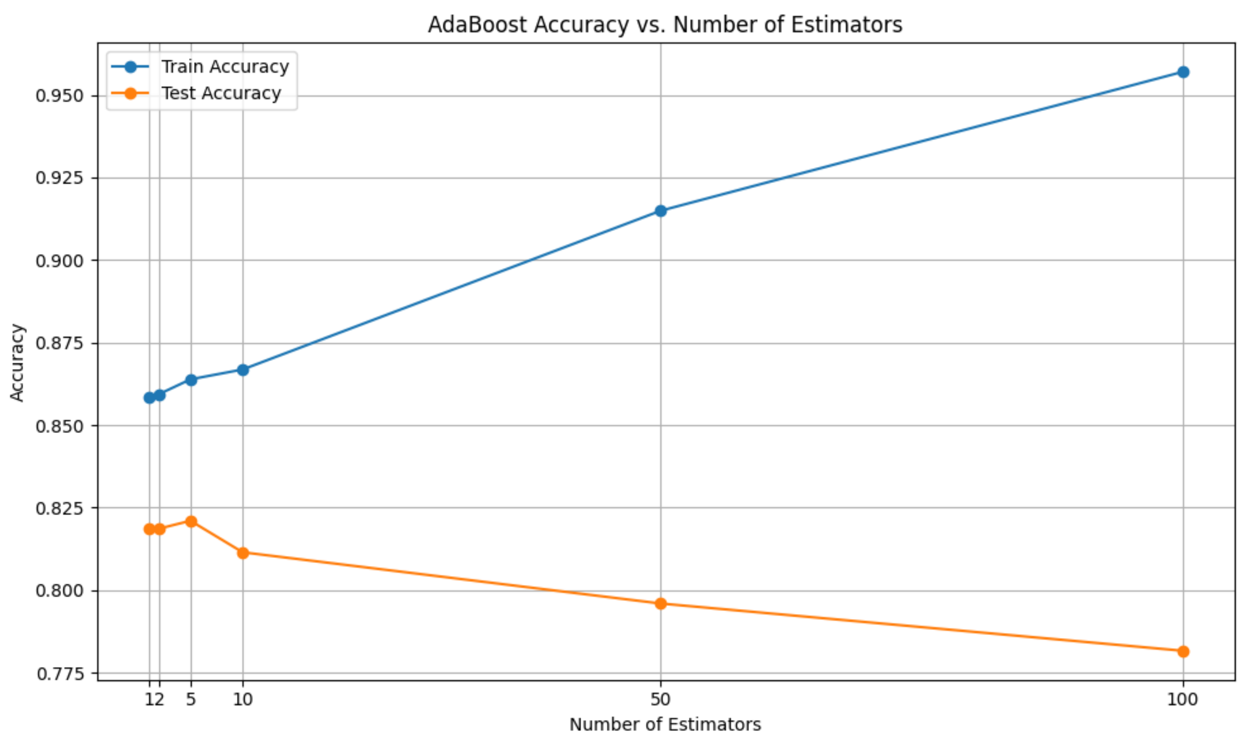

```
Train F1-score: 0.87, Test F1-score: 0.81

n_estimators AdaBoost = 50:
Train Accuracy: 0.91, Test Accuracy: 0.80
Train Precision: 0.91, Test Precision: 0.80
Train Recall: 0.91, Test Recall: 0.80
Train F1-score: 0.91, Test F1-score: 0.80


/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

n_estimators AdaBoost = 100:
Train Accuracy: 0.96, Test Accuracy: 0.78
Train Precision: 0.96, Test Precision: 0.78
Train Recall: 0.96, Test Recall: 0.78
Train F1-score: 0.96, Test F1-score: 0.78
```



Stacked Learner

```python
import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

X = df_low_corr.drop('TenYearCHD', axis=1)
y = df_low_corr['TenYearCHD']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Define base classifiers
base_classifiers = {
    'knn': KNeighborsClassifier(n_neighbors=3),
    'decision_tree': DecisionTreeClassifier(max_depth=4,
random_state=42),
    'random_forest': RandomForestClassifier(n_estimators=10,
max_depth=4, random_state=42),
    'adaboost':
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=4),
n_estimators=10, random_state=42)
}

# Train base classifiers
for name, clf in base_classifiers.items():
    clf.fit(X_train, y_train)
    y_train_pred = clf.predict(X_train)
    y_test_pred = clf.predict(X_test)
    print(f'{name} - Train Accuracy: {accuracy_score(y_train,
y_train_pred):.2f}, Test Accuracy: {accuracy_score(y_test,
y_test_pred):.2f}')

# Create new features for the meta-classifier
meta_features_train = np.column_stack([clf.predict(X_train) for clf in
base_classifiers.values()])
meta_features_test = np.column_stack([clf.predict(X_test) for clf in
base_classifiers.values()])

# Define and train the meta-classifier
meta_classifier = DecisionTreeClassifier(max_depth=4, random_state=42)
meta_classifier.fit(meta_features_train, y_train)

# Evaluate the stacked model
y_train_pred_meta = meta_classifier.predict(meta_features_train)
y_test_pred_meta = meta_classifier.predict(meta_features_test)
```

```python
train_accuracy = accuracy_score(y_train, y_train_pred_meta)
test_accuracy = accuracy_score(y_test, y_test_pred_meta)

train_precision = precision_score(y_train, y_train_pred_meta,
average='micro')
test_precision = precision_score(y_test, y_test_pred_meta,
average='micro')

train_recall = recall_score(y_train, y_train_pred_meta,
average='micro')
test_recall = recall_score(y_test, y_test_pred_meta, average='micro')

train_f1 = f1_score(y_train, y_train_pred_meta, average='micro')
test_f1 = f1_score(y_test, y_test_pred_meta, average='micro')

print(f'Stacked Model:')
print(f'Train Accuracy: {train_accuracy:.2f}, Test Accuracy:
{test_accuracy:.2f}')
print(f'Train Precision: {train_precision:.2f}, Test Precision:
{test_precision:.2f}')
print(f'Train Recall: {train_recall:.2f}, Test Recall:
{test_recall:.2f}')
print(f'Train F1-score: {train_f1:.2f}, Test F1-score: {test_f1:.2f}')
```

```
knn - Train Accuracy: 0.89, Test Accuracy: 0.79
decision_tree - Train Accuracy: 0.86, Test Accuracy: 0.82
random_forest - Train Accuracy: 0.86, Test Accuracy: 0.83
adaboost - Train Accuracy: 0.88, Test Accuracy: 0.80

/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166:
FutureWarning: `base_estimator` was renamed to `estimator` in version
1.2 and will be removed in 1.4.
  warnings.warn(

Stacked Model:
Train Accuracy: 0.89, Test Accuracy: 0.78
Train Precision: 0.89, Test Precision: 0.78
Train Recall: 0.89, Test Recall: 0.78
Train F1-score: 0.89, Test F1-score: 0.78
```