explanatory

December 16, 2024

1 MODEL

[68]:
```
# ==================================================
# 1) Imports
# ==================================================
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

plt.style.use('seaborn')
pd.set_option('display.max_columns', None)
```

```
/tmp/ipykernel_16219/806087732.py:14: MatplotlibDeprecationWarning: The seaborn
styles shipped by Matplotlib are deprecated since 3.6, as they no longer
correspond to the styles shipped by seaborn. However, they will remain available
as 'seaborn-v0_8-<style>'. Alternatively, directly use the seaborn API instead.
  plt.style.use('seaborn')
```

[69]:
```
filename = 'Ndata.csv'
data = pd.read_csv(filename)
data.rename(columns={data.columns[0]: "id"}, inplace=True)
pd.set_option('display.max_columns', None) # To show all columns
data.sample(3)
```

[69]:
```
            id  ALT  HDL  Cholesterol  weight(kg)  LDL  age  hearing(left)  \
49237    49237   10   53          206          50  135   50              1
115817  115817   15   73          164          60   73   40              1
75344    75344   31   39          161          70   93   25              1

        waist(cm)  hemoglobin  height(cm)  smoking
49237        70.0        13.7         155        0
115817       72.0        12.5         165        0
```

```
75344         83.0         14.6          170        0
```

[70]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159256 entries, 0 to 159255
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   id              159256 non-null  int64
 1   ALT             159256 non-null  int64
 2   HDL             159256 non-null  int64
 3   Cholesterol     159256 non-null  int64
 4   weight(kg)      159256 non-null  int64
 5   LDL             159256 non-null  int64
 6   age             159256 non-null  int64
 7   hearing(left)   159256 non-null  int64
 8   waist(cm)       159256 non-null  float64
 9   hemoglobin      159256 non-null  float64
 10  height(cm)      159256 non-null  int64
 11  smoking         159256 non-null  int64
dtypes: float64(2), int64(10)
memory usage: 14.6 MB
```

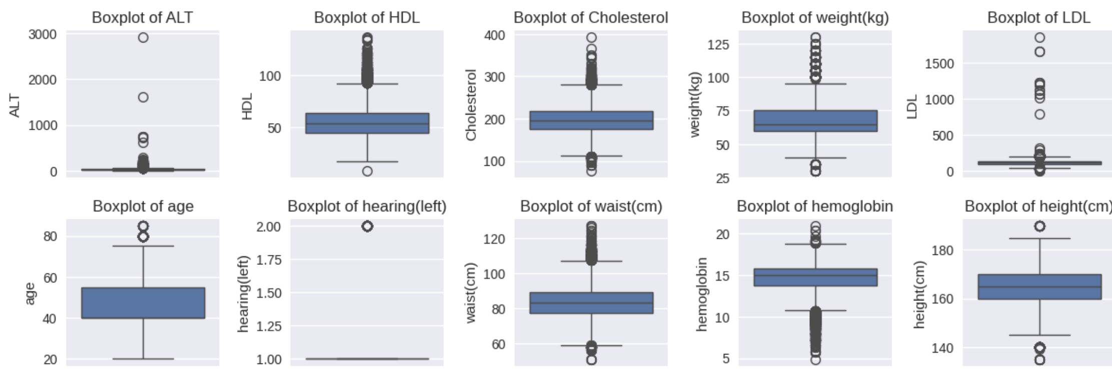
[71]:
```python
data.isna().sum()
```

[71]:
```
id                 0
ALT                0
HDL                0
Cholesterol        0
weight(kg)         0
LDL                0
age                0
hearing(left)      0
waist(cm)          0
hemoglobin         0
height(cm)         0
smoking            0
dtype: int64
```

[72]:
```python
numerical_cols = ['ALT', 'HDL', 'Cholesterol', 'weight(kg)', 'LDL', 'age',␣
↪'hearing(left)', 'waist(cm)', 'hemoglobin', 'height(cm)']
# [
#     'age', 'height(cm)', 'weight(kg)', 'waist(cm)', 'systolic',
#     'relaxation', 'fasting blood sugar', 'Cholesterol', 'triglyceride',
#     'HDL','hemoglobin'
# ]
```

```
plt.figure(figsize=(12, 10))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(5, 5, i)
    sns.boxplot(y=data[col])
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()

plt.show()
```



[73]:
```
for col in data.select_dtypes(include=[np.number]).columns:
    if col =='dental caries':
        continue
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    upper_bound = Q3 + 1.8 * IQR
    lower_bound = Q1 - 1.5 * IQR
    outliers_below = data[data[col] < lower_bound].shape[0]
    outliers_above = data[data[col] > upper_bound].shape[0]
    if outliers_below + outliers_above > 500:
        # handle values above the upper bound
        data[col] = np.where(data[col] > upper_bound, upper_bound, data[col])
        # handle values below the lower bound
        data[col] = np.where(data[col] < lower_bound, lower_bound, data[col])
    else :
        upper_bound = Q3 + 1.6 * IQR
        lower_bound = Q1 - IQR
        data[col] = np.where(data[col] > upper_bound, upper_bound, data[col])
        data[col] = np.where(data[col] < lower_bound, lower_bound, data[col])
```

[74]:
```
data.describe()
```

[74]:

```
                 id            ALT            HDL    Cholesterol  \
count  159256.000000  159256.000000  159256.000000  159256.000000
mean    79627.500000      25.923458      55.826788     195.835558
std     45973.391572      12.916673      13.872204      28.163075
min         0.000000       1.000000      16.500000     133.000000
25%     39813.750000      16.000000      45.000000     175.000000
50%     79627.500000      22.000000      54.000000     196.000000
75%    119441.250000      32.000000      64.000000     217.000000
max    159255.000000      60.800000      98.200000     284.200000

          weight(kg)            LDL            age  hearing(left)  \
count  159256.000000  159256.000000  159256.000000       159256.0
mean       67.113562     114.546457      44.421366            1.0
std        12.483615      25.761897      11.601336            0.0
min        37.500000      57.000000      25.000000            1.0
25%        60.000000      95.000000      40.000000            1.0
50%        65.000000     114.000000      40.000000            1.0
75%        75.000000     133.000000      55.000000            1.0
max       102.000000     193.800000      79.000000            1.0

           waist(cm)     hemoglobin     height(cm)        smoking
count  159256.000000  159256.000000  159256.000000  159256.000000
mean       83.034845      14.807563     165.378290       0.437365
std         8.822533       1.393455       8.577791       0.496063
min        65.000000      10.800000     150.000000       0.000000
25%        77.000000      13.800000     160.000000       0.000000
50%        83.000000      15.000000     165.000000       0.000000
75%        89.000000      15.800000     170.000000       1.000000
max       108.200000      19.400000     186.000000       1.000000
```

[75]:

```python
X = data.drop(['id', 'smoking'], axis=1)
y = data['smoking']
print("Features shape:", X.shape)
print("Target shape:", y.shape)
```

```
Features shape: (159256, 10)
Target shape: (159256,)
```

[76]:

```python
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y,
    test_size=0.4,
    random_state=42,
    stratify=y
)

X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp,
    test_size=0.5,
```

```
    random_state=42,
    stratify=y_temp
)

print("Train shape:", X_train.shape, y_train.shape)
print("Validation shape:", X_val.shape, y_val.shape)
print("Test shape:", X_test.shape, y_test.shape)
```

```
Train shape: (95553, 10) (95553,)
Validation shape: (31851, 10) (31851,)
Test shape: (31852, 10) (31852,)
```

[77]:
```
lr_model = LogisticRegression(max_iter=1000, random_state=42)
lr_model.fit(X_train, y_train)

y_pred_lr = lr_model.predict(X_test)
acc_lr = accuracy_score(y_test, y_pred_lr)

print(" Logistic Regression Model")
print("Accuracy:", acc_lr)
print("Classification Report:\n", classification_report(y_test, y_pred_lr))
```

```
 Logistic Regression Model
Accuracy: 0.7263594122818033
Classification Report:
               precision    recall  f1-score   support

         0.0       0.77      0.73      0.75     17921
         1.0       0.68      0.72      0.70     13931

    accuracy                           0.73     31852
   macro avg       0.72      0.73      0.72     31852
weighted avg       0.73      0.73      0.73     31852
```

[78]:
```
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)

y_pred_dt = dt_model.predict(X_test)
acc_dt = accuracy_score(y_test, y_pred_dt)

print(" Decision Tree ")
print("Accuracy:", acc_dt)
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
```

```
 Decision Tree
Accuracy: 0.6690945623508728
Classification Report:
               precision    recall  f1-score   support
```

```
         0.0       0.71      0.71      0.71     17921
         1.0       0.62      0.62      0.62     13931

    accuracy                           0.67     31852
   macro avg       0.66      0.66      0.66     31852
weighted avg       0.67      0.67      0.67     31852
```

[79]:

```python
def bagging_from_scratch(X_train, y_train, X_test, n_estimators=10,␣
 ↪max_samples_ratio=0.8, random_state=42):
    np.random.seed(random_state)
    n_samples = X_train.shape[0]
    max_samples = int(max_samples_ratio * n_samples)

    X_train_np = X_train.values
    y_train_np = y_train.values

    estimators = []

    for i in range(n_estimators):
        indices = np.random.choice(n_samples, size=max_samples, replace=True)
        X_bootstrap = X_train_np[indices]
        y_bootstrap = y_train_np[indices]

        tree = DecisionTreeClassifier(random_state=random_state + i)
        tree.fit(X_bootstrap, y_bootstrap)
        estimators.append(tree)


    preds = []
    for tree in estimators:
        p = tree.predict(X_test)
        preds.append(p)

    preds = np.array(preds).T

    final_predictions = []
    for row in preds:
        vals, counts = np.unique(row, return_counts=True)
        majority_vote = vals[np.argmax(counts)]
        final_predictions.append(majority_vote)

    return np.array(final_predictions)
```

```python
y_pred_bag = bagging_from_scratch(X_train, y_train, X_test, n_estimators=50,␣
↪max_samples_ratio=0.8, random_state=42)
acc_bag = accuracy_score(y_test, y_pred_bag)

print("=== Bagging (from scratch) ===")
print("Accuracy:", acc_bag)
print("Classification Report:\n", classification_report(y_test, y_pred_bag))
```

```
/usr/lib/python3/dist-packages/sklearn/base.py:486: UserWarning: X has feature
names, but DecisionTreeClassifier was fitted without feature names
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```

```
=== Bagging (from scratch) ===
Accuracy: 0.7373163380635439
Classification Report:
              precision    recall  f1-score   support

         0.0       0.79      0.72      0.75     17921
         1.0       0.68      0.76      0.72     13931

    accuracy                           0.74     31852
   macro avg       0.74      0.74      0.74     31852
weighted avg       0.74      0.74      0.74     31852
```

[80]:

```
# ================================================
# AdaBoost (From Scratch) in a Single Jupyter Cell
# ================================================

import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

# -------------------------------
# AdaBoost from Scratch
# -------------------------------
def adaboost_from_scratch(X_train, y_train, X_test, n_estimators=10,␣
 ↪random_state=42):
    """
    Simple AdaBoost implementation from scratch using Decision Tree stumps␣
 ↪(max_depth=1).
    Returns predictions for X_test.
```

```
    Parameters:
    -----------
    X_train : pd.DataFrame or np.ndarray
        Training features.
    y_train : pd.Series or np.ndarray
        Training labels (assumed binary: 0/1).
    X_test  : pd.DataFrame or np.ndarray
        Test features on which we want predictions.
    n_estimators : int
        Number of weak learners (stumps) to train.
    random_state : int
        Seed for reproducibility.

    Returns:
    --------
    final_preds : np.ndarray
        Predicted labels (0 or 1) for X_test.
    """
    np.random.seed(random_state)

    # Convert data to numpy arrays if needed
    if isinstance(X_train, pd.DataFrame):
        X_train = X_train.values
    if isinstance(y_train, pd.Series):
        y_train = y_train.values
    if isinstance(X_test, pd.DataFrame):
        X_test = X_test.values

    n_samples = X_train.shape[0]

    # Initialize sample weights equally
    w = np.ones(n_samples) / n_samples

    # Store the stump classifiers and their alpha weights
    learners = []
    alphas = []

    for i in range(n_estimators):
        # Train a stump (max_depth=1)
        stump = DecisionTreeClassifier(max_depth=1, random_state=random_state +
 ↪i)
        stump.fit(X_train, y_train, sample_weight=w)

        # Predictions on training data
        y_pred = stump.predict(X_train)

        # Compute weighted error
```

```
        misclassified = (y_pred != y_train)
        err = np.sum(w * misclassified)

        # Avoid division by zero
        err = max(err, 1e-10)

        # Compute alpha
        alpha = 0.5 * np.log((1 - err) / err)

        # Store this weak learner and its weight
        learners.append(stump)
        alphas.append(alpha)

        # Update sample weights
        w = w * np.exp(alpha * misclassified)
        w = w / np.sum(w)  # normalize

    # Inference on X_test
    final_scores = np.zeros(X_test.shape[0])

    for alpha, stump in zip(alphas, learners):
        preds = stump.predict(X_test)
        # Convert 0/1 to +1/-1 for easier accumulation
        preds_binary = np.where(preds == 1, 1, -1)
        final_scores += alpha * preds_binary

    # Convert back to 0/1
    final_preds = np.where(final_scores >= 0, 1, 0)
    return final_preds

# ============================
# Demonstration with Iris Data
# ===========================
```

[81]:
```
y_pred_bag = adaboost_from_scratch(X_train, y_train, X_test)
acc_bag = accuracy_score(y_test, y_pred_bag)

print("=== AdaBoost (from scratch) ===")
print("Accuracy:", acc_bag)
print("Classification Report:\n", classification_report(y_test, y_pred_bag))
```

```
=== AdaBoost (from scratch) ===
Accuracy: 0.7166582946125832
Classification Report:
               precision    recall  f1-score   support

         0.0       0.82      0.64      0.72     17921
         1.0       0.64      0.82      0.72     13931
```

```
    accuracy                           0.72     31852
   macro avg       0.73      0.73      0.72     31852
weighted avg       0.74      0.72      0.72     31852
```

[82]:
```python
# ================================================
# Random Forest (From Scratch) - Single Jupyter Cell
# ================================================

import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

def random_forest_from_scratch(
    X_train,
    y_train,
    X_test,
    n_estimators=10,
    max_samples_ratio=0.8,
    max_features_ratio=0.8,
    random_state=42
):
    """
    A rudimentary Random Forest from scratch.

    For each of the n_estimators:
      - Draw a bootstrap sample (with replacement) of size = max_samples_ratio␣
↪* n_samples.
      - Randomly select a subset of features (size = max_features_ratio *␣
↪total_features).
      - Train a Decision Tree on (bootstrap_sample_rows,␣
↪random_subset_of_features).
    At prediction time, use majority vote across all trees.

    Parameters:
    -----------
    X_train: pd.DataFrame or np.ndarray
        Training features.
    y_train: pd.Series or np.ndarray
        Training labels (assumed binary: 0 or 1).
    X_test : pd.DataFrame or np.ndarray
        Test features on which we want predictions.
    n_estimators : int
        Number of decision trees in the forest.
```

```
    max_samples_ratio : float
        Fraction of the training set used for bootstrap sampling.
    max_features_ratio : float
        Fraction of features used for each tree.
    random_state : int
        Seed for reproducibility.

    Returns:
    --------
    final_predictions : np.ndarray
        Predicted labels (0 or 1) for X_test.
    """
    np.random.seed(random_state)

    # Convert to numpy if needed
    if isinstance(X_train, pd.DataFrame):
        X_train_np = X_train.values
    else:
        X_train_np = X_train

    if isinstance(y_train, pd.Series):
        y_train_np = y_train.values
    else:
        y_train_np = y_train

    if isinstance(X_test, pd.DataFrame):
        X_test_np = X_test.values
    else:
        X_test_np = X_test

    n_samples = X_train_np.shape[0]
    n_features = X_train_np.shape[1]

    max_samples = int(max_samples_ratio * n_samples)
    max_features = int(max_features_ratio * n_features)

    estimators = []
    feature_subsets = []

    # Train n_estimators decision trees
    for i in range(n_estimators):
        # 1) Bootstrap sampling of rows
        row_indices = np.random.choice(n_samples, size=max_samples,␣
↪replace=True)
        X_bootstrap = X_train_np[row_indices]
        y_bootstrap = y_train_np[row_indices]
```

```
        # 2) Random subset of columns (features)
        feature_indices = np.random.choice(n_features, size=max_features,␣
↪replace=False)
        feature_subsets.append(feature_indices)

        # 3) Train a Decision Tree on the (bootstrapped rows, subset of␣
↪features)
        tree = DecisionTreeClassifier(random_state=random_state + i)
        tree.fit(X_bootstrap[:, feature_indices], y_bootstrap)
        estimators.append(tree)

    # --------------------------
    # Inference (Majority Vote)
    # --------------------------
    all_preds = []
    for i, tree in enumerate(estimators):
        preds = tree.predict(X_test_np[:, feature_subsets[i]])
        all_preds.append(preds)

    all_preds = np.array(all_preds).T  # shape (#samples_test, n_estimators)

    final_predictions = []
    for row in all_preds:
        vals, counts = np.unique(row, return_counts=True)
        majority_vote = vals[np.argmax(counts)]
        final_predictions.append(majority_vote)

    return np.array(final_predictions)

# ============================
# USE ON YOUR OWN DATASET
# ============================
```

[83]:

```
# Assuming you've already defined the function:
# def random_forest_from_scratch(X_train, y_train, X_test, n_estimators=10, ...
↪):

# Call the random_forest_from_scratch function, similar to your AdaBoost usage
y_pred_rf = random_forest_from_scratch(
    X_train,
    y_train,
    X_test,
    n_estimators=10,          # number of trees
    max_samples_ratio=0.8,    # fraction of training data in each bootstrap
    max_features_ratio=0.8,   # fraction of features for each tree
    random_state=42
)
```

```
# Evaluate
acc_rf = accuracy_score(y_test, y_pred_rf)

print("=== Random Forest (from scratch) ===")
print("Accuracy:", acc_rf)
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
=== Random Forest (from scratch) ===
Accuracy: 0.7077106618108753
Classification Report:
               precision    recall  f1-score   support

         0.0       0.73      0.75      0.74     17921
         1.0       0.67      0.65      0.66     13931

    accuracy                           0.71     31852
   macro avg       0.70      0.70      0.70     31852
weighted avg       0.71      0.71      0.71     31852
```

[ ]:

```

```

1.1 Hyper-parameter tuning

[84]:

```
# ========================================
# Cell 1: Imports & Bagging Function
# ========================================
import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

def bagging_from_scratch(
    X_train,
    y_train,
    X_test,
    n_estimators=10,
    max_samples_ratio=0.8,
    random_state=42
):
    """
    Simple Bagging (from scratch) using Decision Trees as base learners.

    Parameters
    ----------
```

```
    X_train : pd.DataFrame or np.ndarray
        Training features.
    y_train : pd.Series or np.ndarray
        Training labels (assumed binary classification).
    X_test : pd.DataFrame or np.ndarray
        Test features for which we want predictions.
    n_estimators : int
        Number of base estimators (Decision Trees).
    max_samples_ratio : float
        Fraction of the training data used for each bootstrap sample.
    random_state : int
        Random seed for reproducibility.

    Returns
    -------
    final_predictions : np.ndarray
        Predicted labels (0 or 1) for X_test based on majority vote.
    """
    np.random.seed(random_state)

    # Convert data to numpy if needed
    if isinstance(X_train, pd.DataFrame):
        X_train_np = X_train.values
    else:
        X_train_np = X_train

    if isinstance(y_train, pd.Series):
        y_train_np = y_train.values
    else:
        y_train_np = y_train

    if isinstance(X_test, pd.DataFrame):
        X_test_np = X_test.values
    else:
        X_test_np = X_test

    n_samples = X_train_np.shape[0]
    max_samples = int(max_samples_ratio * n_samples)

    estimators = []

    # Train multiple Decision Trees on bootstrap samples
    for i in range(n_estimators):
        # Bootstrap sampling of rows
        indices = np.random.choice(n_samples, size=max_samples, replace=True)
        X_bootstrap = X_train_np[indices]
        y_bootstrap = y_train_np[indices]
```

```python
        # Train a Decision Tree
        tree = DecisionTreeClassifier(random_state=random_state + i)
        tree.fit(X_bootstrap, y_bootstrap)
        estimators.append(tree)

    # Majority vote on X_test
    preds_list = []
    for tree in estimators:
        preds = tree.predict(X_test_np)
        preds_list.append(preds)

    # Transpose to shape (#test_samples, #n_estimators)
    preds_array = np.array(preds_list).T

    final_predictions = []
    for row in preds_array:
        vals, counts = np.unique(row, return_counts=True)
        majority_vote = vals[np.argmax(counts)]
        final_predictions.append(majority_vote)

    return np.array(final_predictions)
```

[86]:
```python
# =========================================
# Cell 3: Manual Hyperparameter Search
# =========================================

n_estimators_list = [50, 100, 150]
max_samples_ratios = [0.6, 0.8, 1.0]

best_accuracy = 0.0
best_params = (None, None)  # (n_estimators, max_samples_ratio)

for n_est in n_estimators_list:
    for ms_ratio in max_samples_ratios:
        y_pred = bagging_from_scratch(
            X_train,
            y_train,
            X_test,
            n_estimators=n_est,
            max_samples_ratio=ms_ratio,
            random_state=42
        )
        acc = accuracy_score(y_test, y_pred)

        if acc > best_accuracy:
            best_accuracy = acc
```

```
            best_params = (n_est, ms_ratio)

print(f"Best Accuracy: {best_accuracy:.3f}")
print("Best Params (n_estimators, max_samples_ratio):", best_params)
```

```
Best Accuracy: 0.745
Best Params (n_estimators, max_samples_ratio): (150, 0.6)
```

[ ]:

```

```

[87]:

```
# ==============================================
# Cell 4: Final Model with Best Hyperparameters
# ==============================================

best_n_est, best_ms_ratio = best_params

y_pred_final = bagging_from_scratch(
    X_train,
    y_train,
    X_test,
    n_estimators=best_n_est,
    max_samples_ratio=best_ms_ratio,
    random_state=42
)

acc_final = accuracy_score(y_test, y_pred_final)
print("=== Bagging (from scratch) - Final Model ===")
print("Using Hyperparams:", best_params)
print("Accuracy:", acc_final)
print("Classification Report:\n", classification_report(y_test, y_pred_final))
```

```
=== Bagging (from scratch) - Final Model ===
Using Hyperparams: (150, 0.6)
Accuracy: 0.7452907195780485
Classification Report:
               precision    recall  f1-score   support

         0.0       0.81      0.71      0.76     17921
         1.0       0.68      0.79      0.73     13931

    accuracy                           0.75     31852
   macro avg       0.75      0.75      0.74     31852
weighted avg       0.75      0.75      0.75     31852
```

[88]:

```
import random

# =========================================================
```

```python
# Randomized Search for Bagging (or Random Forest)
# ==========================================================

# Define the range of hyperparameters
param_ranges = {
    "n_estimators": (5, 50),          # Range for number of trees
    "max_samples_ratio": (0.5, 1.0), # Range for fraction of samples in bootstrap
}

# Number of random combinations to test
n_iterations = 10

best_accuracy = 0.0
best_params = None

# Perform Randomized Search
for _ in range(n_iterations):
    # Randomly sample hyperparameters
    n_estimators = random.randint(*param_ranges["n_estimators"])
    max_samples_ratio = random.uniform(*param_ranges["max_samples_ratio"])

    # Train and evaluate Bagging or Random Forest model
    y_pred = bagging_from_scratch(
        X_train,
        y_train,
        X_test,
        n_estimators=n_estimators,
        max_samples_ratio=max_samples_ratio,
        random_state=42
    )

    # Evaluate model
    acc = accuracy_score(y_test, y_pred)

    # Track the best performing parameters
    if acc > best_accuracy:
        best_accuracy = acc
        best_params = (n_estimators, max_samples_ratio)

# Output the best parameters and accuracy
print(f"Best Accuracy: {best_accuracy:.3f}")
print("Best Params (n_estimators, max_samples_ratio):", best_params)
```

```
Best Accuracy: 0.739
Best Params (n_estimators, max_samples_ratio): (48, 0.689088317164462)
```