Adaboost

August 29, 2025

[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, roc_auc_score,␣
↪roc_curve,auc,confusion_matrix
)
import matplotlib.pyplot as plt
from sklearn.ensemble import AdaBoostClassifier
import seaborn as sns
```

[2]:
```
# 1. Load dataset
# wdbc.data does not have headers, so we define them
columns = ["ID", "Diagnosis"] + [f"feature_{i}" for i in range(1, 31)]
data = pd.read_csv("wdbc.data", header=None, names=columns)
```

[3]:
```
# 2. Prepare features and target
X = data.drop(["ID", "Diagnosis"], axis=1)
y = data["Diagnosis"].map({"M": 1, "B": 0})  # Malignant=1, Benign=0
```

[4]:
```
# 4. Preprocessor (scaling not needed for trees, but kept for pipeline␣
↪consistency)
num_features = X.columns.tolist()
preprocessor = ColumnTransformer(
    transformers=[("scale", StandardScaler(), num_features)],
    remainder="drop"
)
```

[5]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

[6]:
```
pipeline = Pipeline([
    ("scaler", StandardScaler()),
    ("clf",␣
 ↪AdaBoostClassifier(estimator=DecisionTreeClassifier(random_state=42),
                               random_state=42))
])
```

[7]:
```
param_grid = {
    "clf__n_estimators": [50, 100, 200],
    "clf__learning_rate": [0.01, 0.1, 1.0],
    "clf__estimator__max_depth": [1, 2]
}
```

[8]:
```
grid = GridSearchCV(
    estimator=pipeline,
    param_grid=param_grid,
    cv=5,
    scoring={"accuracy": "accuracy", "f1": "f1_macro"},  # both metrics
    refit="accuracy",    # model chosen based on accuracy
    n_jobs=-1,
    verbose=1
)

grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
```

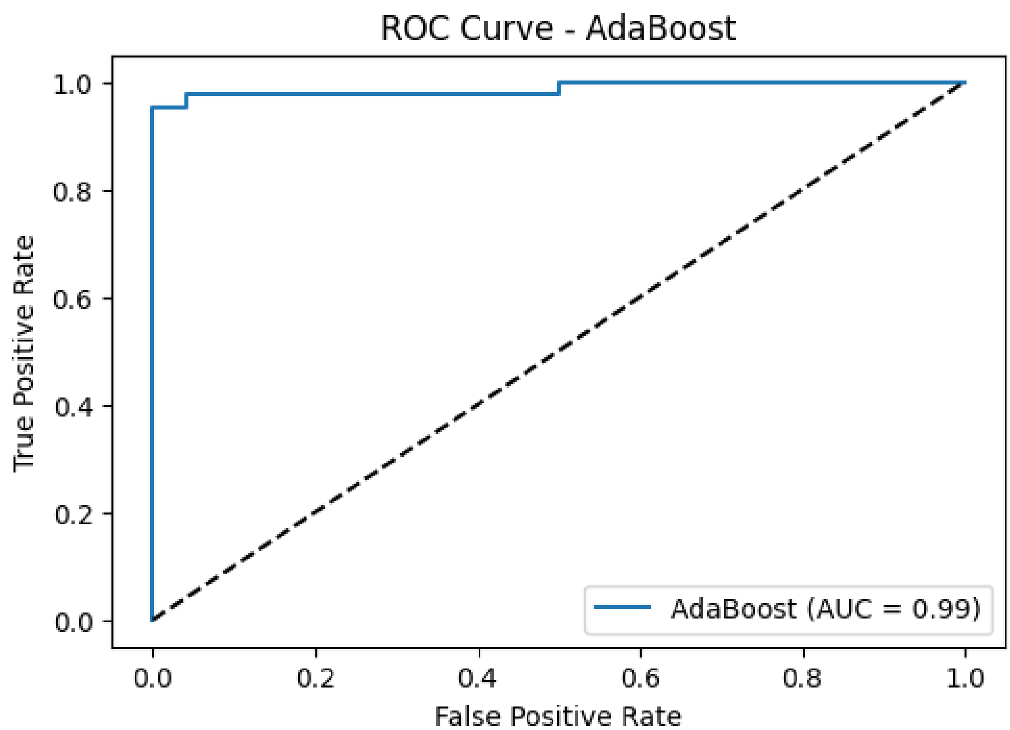
[8]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('clf',
AdaBoostClassifier(estimator=DecisionTreeClassifier(random_state=42),
                                                           random_state=42))]),
             n_jobs=-1,
             param_grid={'clf__estimator__max_depth': [1, 2],
                         'clf__learning_rate': [0.01, 0.1, 1.0],
                         'clf__n_estimators': [50, 100, 200]},
             refit='accuracy',
             scoring={'accuracy': 'accuracy', 'f1': 'f1_macro'}, verbose=1)
```

[9]:
```
best_model = grid.best_estimator_

y_pred = best_model.predict(X_test)
y_proba = best_model.predict_proba(X_test)[:, 1]

acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("\nBest Hyperparameters (from training CV):", grid.best_params_)
```

```
print("Test Accuracy:", acc)
print("Test F1 Score:", f1)
```

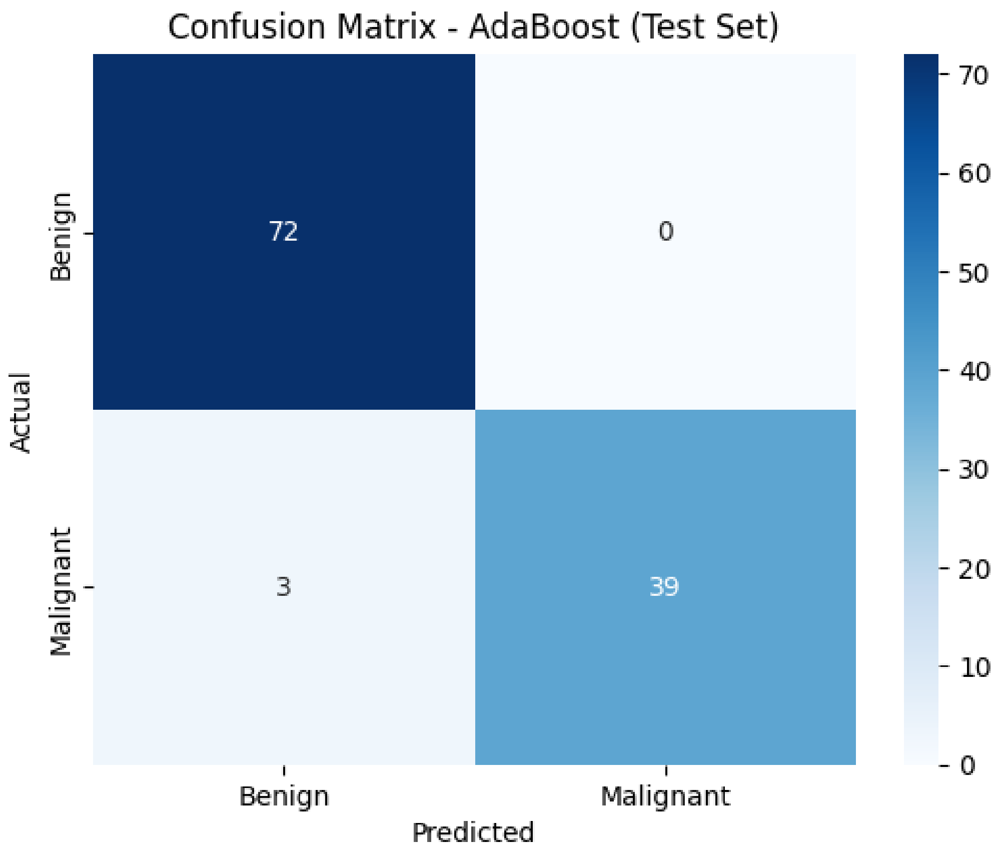
```
Best Hyperparameters (from training CV): {'clf__estimator__max_depth': 1,
'clf__learning_rate': 1.0, 'clf__n_estimators': 200}
Test Accuracy: 0.9736842105263158
Test F1 Score: 0.9629629629629629
```

[10]:
```
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f"AdaBoost (AUC = {roc_auc:.2f})")
plt.plot([0,1],[0,1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - AdaBoost")
plt.legend()
plt.show()
```



[11]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
```

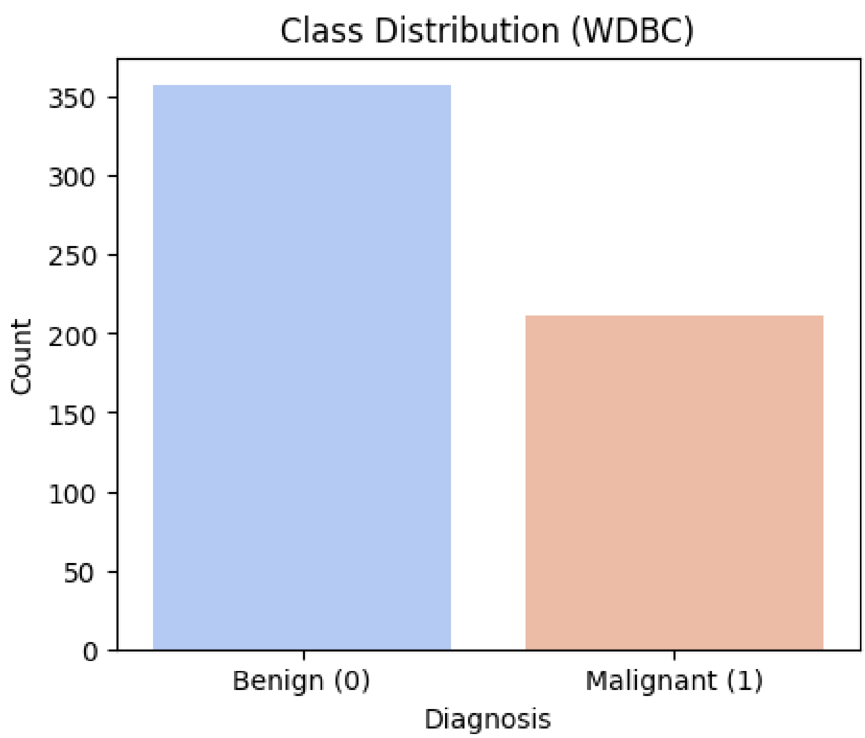
```
            xticklabels=["Benign","Malignant"],
            yticklabels=["Benign","Malignant"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - AdaBoost (Test Set)")
plt.show()
```



[12]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

# ---- Class distribution ----
plt.figure(figsize=(5,4))
sns.countplot(x=y, palette="coolwarm")
plt.xticks([0,1], ["Benign (0)", "Malignant (1)"])
plt.title("Class Distribution (WDBC)")
plt.xlabel("Diagnosis")
plt.ylabel("Count")
plt.show()
```

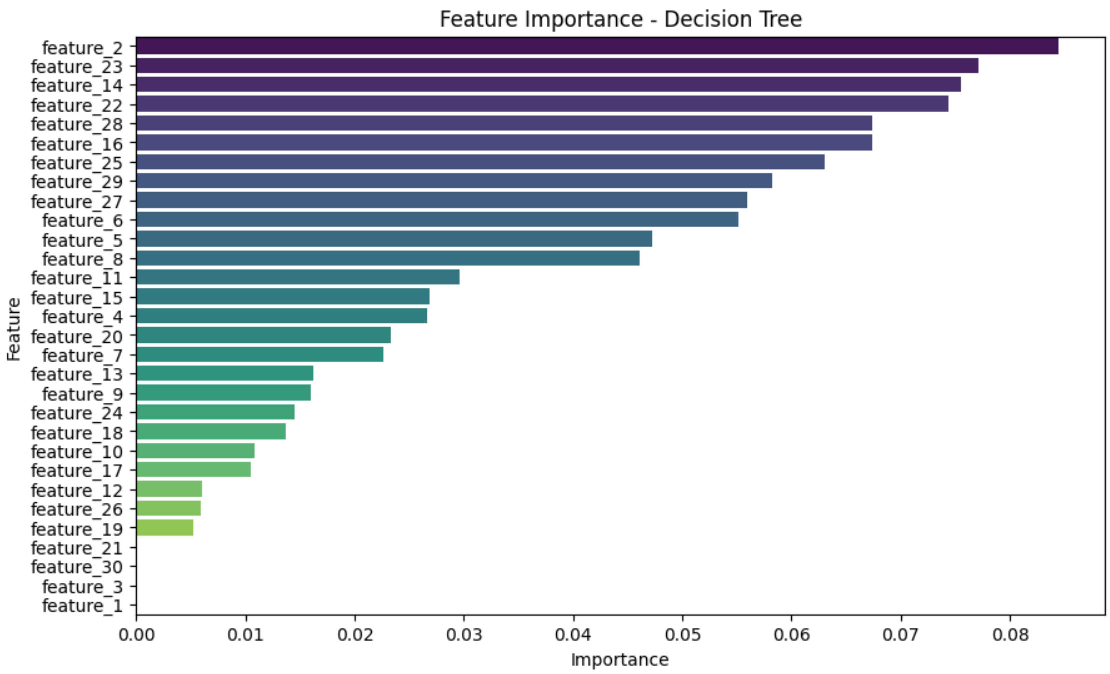
```python
# ---- Feature importance (from Decision Tree) ----
best_clf = best_model.named_steps["clf"]
importances = best_clf.feature_importances_
features = X.columns

# Sort feature importances
indices = np.argsort(importances)[::-1]
plt.figure(figsize=(10,6))
sns.barplot(x=importances[indices], y=features[indices], palette="viridis")
plt.title("Feature Importance - Decision Tree")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```

```
/tmp/ipykernel_9161/1424558563.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x=y, palette="coolwarm")
```




```
/tmp/ipykernel_9161/1424558563.py:22: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=importances[indices], y=features[indices], palette="viridis")
```



[13]:
```python
results = pd.DataFrame(grid.cv_results_)

table = results[[
    "param_clf__n_estimators",
    "param_clf__learning_rate",
    "param_clf__estimator__max_depth",
    "mean_test_accuracy",
    "mean_test_f1"
]].copy()

table = table.rename(columns={
    "param_clf__n_estimators": "n_estimators",
    "param_clf__learning_rate": "learning_rate",
    "param_clf__estimator__max_depth": "max_depth",
    "mean_test_accuracy": "Accuracy",
    "mean_test_f1": "F1_score"
})
```

```python
print("Table 2: AdaBoost - Hyperparameter Tuning")
print(table[["n_estimators", "learning_rate", "max_depth", "Accuracy", "F1_score"]])
```

Table 2: AdaBoost - Hyperparameter Tuning

	n_estimators	learning_rate	max_depth	Accuracy	F1_score
0	50	0.01	1	0.923077	0.915693
1	100	0.01	1	0.925275	0.918724
2	200	0.01	1	0.931868	0.926145
3	50	0.10	1	0.949451	0.945670
4	100	0.10	1	0.951648	0.948440
5	200	0.10	1	0.951648	0.948224
6	50	1.00	1	0.962637	0.959723
7	100	1.00	1	0.960440	0.957480
8	200	1.00	1	0.964835	0.962262
9	50	0.01	2	0.938462	0.933790
10	100	0.01	2	0.936264	0.931637
11	200	0.01	2	0.945055	0.941220
12	50	0.10	2	0.953846	0.950840
13	100	0.10	2	0.960440	0.957714
14	200	0.10	2	0.964835	0.962218
15	50	1.00	2	0.964835	0.962352
16	100	1.00	2	0.964835	0.962390
17	200	1.00	2	0.964835	0.962141