Sri Sivasubramaniya Nadar College of Engineering, Chennai
(An autonomous Institution affiliated to Anna University)

Degree & Branch	M.Tech (Integrated) Computer Science & Engineering	Semester	V
Subject Code & Name	ICS1512 – Machine Learning Algorithms Laboratory		
Academic year	2025–2026 (Odd)	Batch:2023–2028	**Due date:**

Experiment 4 : Ensemble Prediction and Decision Tree Model Evaluation

1. Aim and Objective

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

2. Dataset

Wisconsin Diagnostic Breast Cancer Dataset

- 569 samples and 30 numerical features representing cell nuclei characteristics from digitized images.
- Target labels: Binary classification (malignant vs benign).
- Source: https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+diagnostic

3. Steps for Implementation

1. Load and preprocess dataset: encode labels, handle missing values, standardize features.
2. Perform Exploratory Data Analysis (EDA): check class balance, visualize feature correlations.
3. Split dataset into training and test sets (e.g., 80–20 split).
4. Train the following models:
   - Decision Tree
   - AdaBoost
   - Gradient Boosting
   - XGBoost
   - Random Forest
   - Stacking Classifier (SVM + Naïve Bayes + Decision Tree)
5. Use GridSearchCV or RandomizedSearchCV to tune hyperparameters.

6. Record best hyperparameters and evaluate with 5-Fold Cross-Validation.
7. Plot ROC curves and compute performance metrics (accuracy, precision, recall, F1-score).

[ ]:
```
!pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.12/dist-
packages (0.0.7)
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.12/dist-
packages (from ucimlrepo) (2.2.2)
Requirement already satisfied: certifi>=2020.12.5 in
/usr/local/lib/python3.12/dist-packages (from ucimlrepo) (2025.8.3)
Requirement already satisfied: numpy>=1.26.0 in /usr/local/lib/python3.12/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0->ucimlrepo)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-
packages (from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.17.0)
```

1. Import Datasets

[ ]:
```
from ucimlrepo import fetch_ucirepo
import pandas as pd
# fetch dataset
breast_cancer_wisconsin_diagnostic = fetch_ucirepo(id=17)

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

# metadata
print(breast_cancer_wisconsin_diagnostic.metadata)

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

#Diagnosis (M = malignant, B = benign)
pd.unique(y.values.ravel())
```

```
{'uci_id': 17, 'name': 'Breast Cancer Wisconsin (Diagnostic)', 'repository_url':
'https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+diagnostic',
'data_url': 'https://archive.ics.uci.edu/static/public/17/data.csv', 'abstract':
'Diagnostic Wisconsin Breast Cancer Database.', 'area': 'Health and Medicine',
'tasks': ['Classification'], 'characteristics': ['Multivariate'],
'num_instances': 569, 'num_features': 30, 'feature_types': ['Real'],
```

'demographics': [], 'target_col': ['Diagnosis'], 'index_col': ['ID'],
'has_missing_values': 'no', 'missing_values_symbol': None,
'year_of_dataset_creation': 1993, 'last_updated': 'Fri Nov 03 2023',
'dataset_doi': '10.24432/C5DW2B', 'creators': ['William Wolberg', 'Olvi
Mangasarian', 'Nick Street', 'W. Street'], 'intro_paper': {'ID': 230, 'type':
'NATIVE', 'title': 'Nuclear feature extraction for breast tumor diagnosis',
'authors': 'W. Street, W. Wolberg, O. Mangasarian', 'venue': 'Electronic
imaging', 'year': 1993, 'journal': None, 'DOI': '10.1117/12.148698', 'URL': 'htt
ps://www.semanticscholar.org/paper/53f0fbb425bc14468eb3bf96b2e1d41ba8087f36',
'sha': None, 'corpus': None, 'arxiv': None, 'mag': None, 'acl': None, 'pmid':
None, 'pmcid': None}, 'additional_info': {'summary': 'Features are computed from
a digitized image of a fine needle aspirate (FNA) of a breast mass. They
describe characteristics of the cell nuclei present in the image. A few of the
images can be found at http://www.cs.wisc.edu/~street/images/\r\n\r\nSeparating
plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P.
Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the
4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101,
1992], a classification method which uses linear programming to construct a
decision tree. Relevant features were selected using an exhaustive search in
the space of 1-4 features and 1-3 separating planes.\r\n\r\nThe actual linear
program used to obtain the separating plane in the 3-dimensional space is that
described in: [K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming
Discrimination of Two Linearly Inseparable Sets", Optimization Methods and
Software 1, 1992, 23-34].\r\n\r\nThis database is also available through the UW
CS ftp server:\r\nftp ftp.cs.wisc.edu\r\ncd math-prog/cpo-dataset/machine-
learn/WDBC/', 'purpose': None, 'funded_by': None, 'instances_represent': None,
'recommended_data_splits': None, 'sensitive_data': None,
'preprocessing_description': None, 'variable_info': '1) ID number\r\n2)
Diagnosis (M = malignant, B = benign)\r\n3-32)\r\n\r\nTen real-valued features
are computed for each cell nucleus:\r\n\r\n\ta) radius (mean of distances from
center to points on the perimeter)\r\n\tb) texture (standard deviation of gray-
scale values)\r\n\tc) perimeter\r\n\td) area\r\n\te) smoothness (local variation
in radius lengths)\r\n\tf) compactness (perimeter^2 / area - 1.0)\r\n\tg)
concavity (severity of concave portions of the contour)\r\n\th) concave points
(number of concave portions of the contour)\r\n\ti) symmetry \r\n\tj) fractal
dimension ("coastline approximation" - 1)', 'citation': None}}

	name	role	type	demographic	description	units	missing_values
0	ID	ID	Categorical	None	None	None	no
1	Diagnosis	Target	Categorical	None	None	None	no
2	radius1	Feature	Continuous	None	None	None	no
3	texture1	Feature	Continuous	None	None	None	no
4	perimeter1	Feature	Continuous	None	None	None	no

```
4              no
```

[ ]:
```
array(['M', 'B'], dtype=object)
```

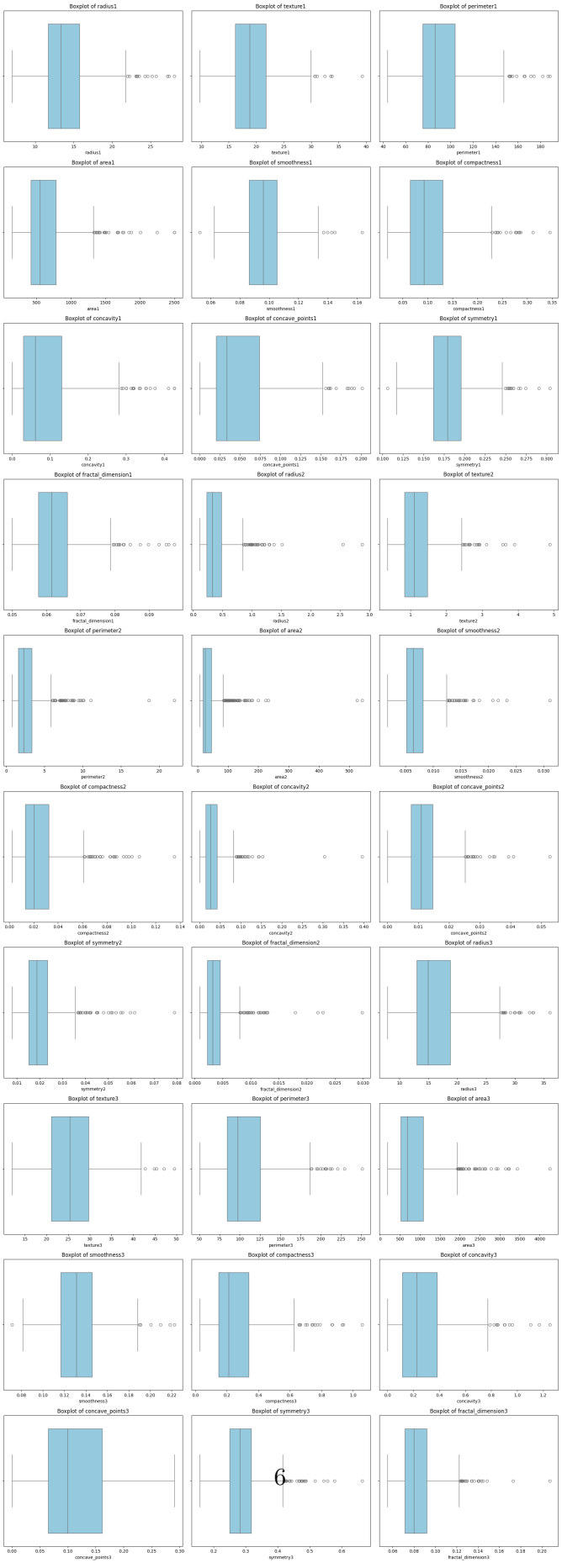
2. Handling Missing Values - Impute numerival columns with mean and categorical columns with mode

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# --- Step 1: Load Dataset ---
df = X

# --- Step 2: Impute Missing Values ---
for col in df.columns:
    if df[col].isnull().sum() > 0:
        if df[col].dtype == 'object':
            df[col].fillna(df[col].mode()[0], inplace=True)
        else:
            df[col].fillna(df[col].median(), inplace=True)

# --- Step 3: Identify Categorical Columns ---
categorical_cols = df.select_dtypes(include='object').columns.tolist()

# --- Step 4: Apply One-Hot Encoding using ColumnTransformer ---
if categorical_cols:
    print("Encoding categorical columns:", categorical_cols)

    column_transformer = ColumnTransformer(
        transformers=[
            ('cat', OneHotEncoder(drop='first', sparse_output=False),␣
 ↪categorical_cols)
        ],
        remainder='passthrough'  # Keep all other columns
    )

    transformed = column_transformer.fit_transform(df)
    feature_names = column_transformer.get_feature_names_out()

    df = pd.DataFrame(transformed, columns=feature_names)

else:
```

```
    print("No categorical columns found.")
    df = df.copy()

# --- Step 5: Boxplot Analysis (3 per row) ---
numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
num_plots = len(numeric_cols)
cols_per_row = 3
rows = (num_plots + cols_per_row - 1) // cols_per_row

plt.figure(figsize=(6 * cols_per_row, 5 * rows))
for i, col in enumerate(numeric_cols):
    plt.subplot(rows, cols_per_row, i + 1)
    sns.boxplot(x=df[col], color='skyblue')
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()

plt.suptitle("Boxplot Analysis of Numerical Columns", fontsize=16, y=1.02)
plt.show()
```

```
No categorical columns found.
```

Boxplot Analysis of Numerical Columns



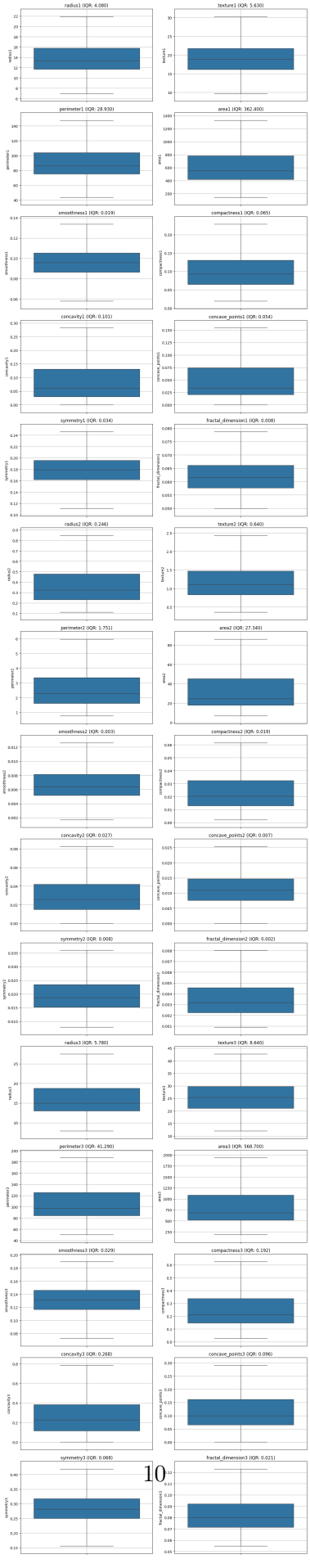
3. Detecting Outliers and Capping them using IQR

[ ]:
```
# Create a copy to apply capping
capped_df = df.copy()

print("\n Capping outliers using IQR method:")

for col in numeric_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]

    if not outliers.empty:
        print(f"{col}: {len(outliers)} outliers capped")
        capped_df[col] = np.where(capped_df[col] < lower_bound, lower_bound,
                                  np.where(capped_df[col] > upper_bound, upper_bound,␣
 ↪capped_df[col]))
    else:
        print(f"{col}: No outliers detected")



import math


df = capped_df.copy()



def plot_boxplots_grid(df, columns, per_row=2):
    n = len(columns)
    rows = (n + per_row - 1) // per_row
    fig, axes = plt.subplots(rows, per_row, figsize=(6 * per_row, 4 * rows))

    # Flatten axes array in case of multiple rows
    axes = axes.flatten()

    for idx, col in enumerate(columns):
        data = df[col].dropna()
        Q1 = np.percentile(data, 25)
        Q3 = np.percentile(data, 75)
```

```
        IQR = Q3 - Q1
        spread = data.max() - data.min()

        # Avoid completely flat plots by scaling y-limits
        padding = spread * 0.1 if spread > 0 else 1e-3
        y_min = data.min() - padding
        y_max = data.max() + padding

        ax = axes[idx]
        sns.boxplot(y=data, ax=ax)
        ax.set_ylim([y_min, y_max])
        ax.set_title(f'{col} (IQR: {IQR:.3f})')
        ax.grid(True)

    # Hide any unused subplots
    for i in range(n, len(axes)):
        axes[i].axis('off')

    plt.tight_layout()
    plt.show()

# Example usage:
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
plot_boxplots_grid(df, numerical_columns)
```

```
 Capping outliers using IQR method:
radius1: 14 outliers capped
texture1: 7 outliers capped
perimeter1: 13 outliers capped
area1: 25 outliers capped
smoothness1: 6 outliers capped
compactness1: 16 outliers capped
concavity1: 18 outliers capped
concave_points1: 10 outliers capped
symmetry1: 15 outliers capped
fractal_dimension1: 15 outliers capped
radius2: 38 outliers capped
texture2: 20 outliers capped
perimeter2: 38 outliers capped
area2: 65 outliers capped
smoothness2: 30 outliers capped
compactness2: 28 outliers capped
concavity2: 22 outliers capped
concave_points2: 19 outliers capped
symmetry2: 27 outliers capped
fractal_dimension2: 28 outliers capped
radius3: 17 outliers capped
```

```
texture3: 5 outliers capped
perimeter3: 15 outliers capped
area3: 35 outliers capped
smoothness3: 7 outliers capped
compactness3: 16 outliers capped
concavity3: 12 outliers capped
concave_points3: No outliers detected
symmetry3: 23 outliers capped
fractal_dimension3: 24 outliers capped
```


radius1 (IQR: 4.080)
texture1 (IQR: 5.630)
perimeter1 (IQR: 28.930)
area1 (IQR: 362.400)
smoothness1 (IQR: 0.019)
compactness1 (IQR: 0.065)
concavity1 (IQR: 0.101)
concave_points1 (IQR: 0.054)
symmetry1 (IQR: 0.034)
fractal_dimension1 (IQR: 0.008)
radius2 (IQR: 0.246)
texture2 (IQR: 0.640)
perimeter2 (IQR: 1.751)
area2 (IQR: 27.340)
smoothness2 (IQR: 0.003)
compactness2 (IQR: 0.019)
concavity2 (IQR: 0.027)
concave_points2 (IQR: 0.007)
symmetry2 (IQR: 0.008)
fractal_dimension2 (IQR: 0.002)
radius3 (IQR: 5.780)
texture3 (IQR: 8.640)
perimeter3 (IQR: 41.290)
area3 (IQR: 568.700)
smoothness3 (IQR: 0.029)
compactness3 (IQR: 0.192)
concavity3 (IQR: 0.268)
concave_points3 (IQR: 0.096)
symmetry3 (IQR: 0.068)
fractal_dimension3 (IQR: 0.021)

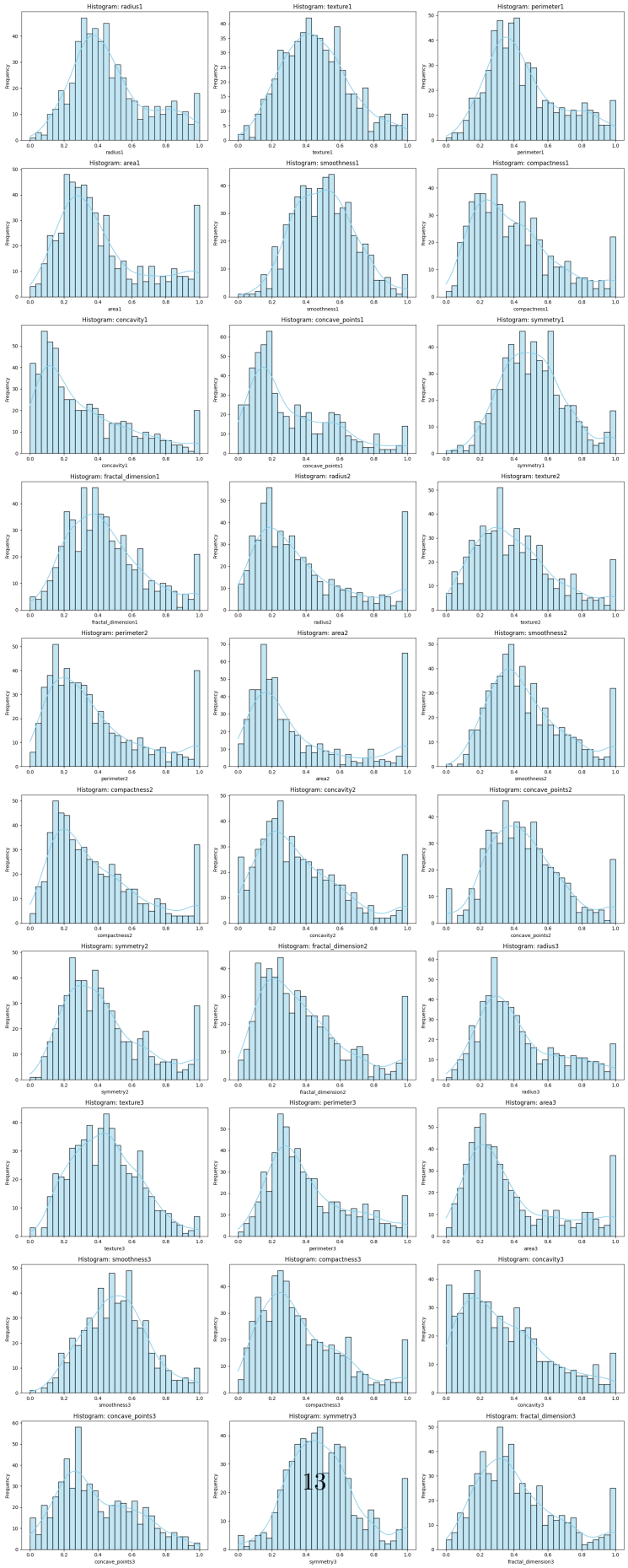
4. Normalisation

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import zscore, normaltest
from sklearn.preprocessing import MinMaxScaler

# --- Step 1: Get Numerical Columns ---
numeric_cols = df.select_dtypes(include=np.number).columns.tolist()

# --- Step 2: Create New DataFrame for Normalized Data ---
normalized_df = df.copy()

print("\n Normalizing Numerical Columns Based on Distribution and Outliers:\n")

# --- Step 3: Normalize Each Column Based on Condition ---
for col in numeric_cols:
    data = df[col]

    # Detect outliers using Z-score
    z_scores = zscore(data)
    outliers = np.where(np.abs(z_scores) > 3)[0]

    # Test for normal distribution
    stat, p_value = normaltest(data)

    if len(outliers) > 0 or p_value > 0.05:
        # Apply Z-score normalization
        normalized_df[col] = zscore(data)
        print(f"{col}: Outliers or normal distribution → Z-score normalization␣
↪applied")
    else:
        # Apply Min-Max normalization
        scaler = MinMaxScaler()
        normalized_df[col] = scaler.fit_transform(data.values.reshape(-1, 1))
        print(f"{col}: No outliers and not Gaussian → Min-Max normalization␣
↪applied")


# --- Plot Histograms After Normalization (3 per row) ---


cols_per_row = 3
```

```
num_plots = len(numeric_cols)
rows = (num_plots + cols_per_row - 1) // cols_per_row

plt.figure(figsize=(6 * cols_per_row, 4.5 * rows))
for i, col in enumerate(numeric_cols):
    plt.subplot(rows, cols_per_row, i + 1)
    sns.histplot(normalized_df[col], bins=30, kde=True, color='skyblue')
    plt.title(f'Histogram: {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.tight_layout()

plt.suptitle("Histograms of Normalized Numerical Columns", fontsize=16, y=1.02)
plt.show()
```

```
 Normalizing Numerical Columns Based on Distribution and Outliers:

radius1: No outliers and not Gaussian → Min-Max normalization applied
texture1: No outliers and not Gaussian → Min-Max normalization applied
perimeter1: No outliers and not Gaussian → Min-Max normalization applied
area1: No outliers and not Gaussian → Min-Max normalization applied
smoothness1: No outliers and not Gaussian → Min-Max normalization applied
compactness1: No outliers and not Gaussian → Min-Max normalization applied
concavity1: No outliers and not Gaussian → Min-Max normalization applied
concave_points1: No outliers and not Gaussian → Min-Max normalization applied
symmetry1: No outliers and not Gaussian → Min-Max normalization applied
fractal_dimension1: No outliers and not Gaussian → Min-Max normalization applied
radius2: No outliers and not Gaussian → Min-Max normalization applied
texture2: No outliers and not Gaussian → Min-Max normalization applied
perimeter2: No outliers and not Gaussian → Min-Max normalization applied
area2: No outliers and not Gaussian → Min-Max normalization applied
smoothness2: No outliers and not Gaussian → Min-Max normalization applied
compactness2: No outliers and not Gaussian → Min-Max normalization applied
concavity2: No outliers and not Gaussian → Min-Max normalization applied
concave_points2: No outliers and not Gaussian → Min-Max normalization applied
symmetry2: No outliers and not Gaussian → Min-Max normalization applied
fractal_dimension2: No outliers and not Gaussian → Min-Max normalization applied
radius3: No outliers and not Gaussian → Min-Max normalization applied
texture3: No outliers and not Gaussian → Min-Max normalization applied
perimeter3: No outliers and not Gaussian → Min-Max normalization applied
area3: No outliers and not Gaussian → Min-Max normalization applied
smoothness3: No outliers and not Gaussian → Min-Max normalization applied
compactness3: No outliers and not Gaussian → Min-Max normalization applied
concavity3: No outliers and not Gaussian → Min-Max normalization applied
concave_points3: No outliers and not Gaussian → Min-Max normalization applied
symmetry3: No outliers and not Gaussian → Min-Max normalization applied
fractal_dimension3: No outliers and not Gaussian → Min-Max normalization applied
```

Histograms of Normalized Numerical Columns



5. Train, Test Split and Model building

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB, BernoulliNB
from sklearn.metrics import (
    accuracy_score, recall_score, f1_score, confusion_matrix,
    classification_report, matthews_corrcoef, roc_auc_score,
    roc_curve
)

# --- Step 1: Split dataset ---
X = df

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4,␣
↪stratify=y, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5,␣
↪stratify=y_temp, random_state=42)
```

[ ]:
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.12/dist-
packages (3.0.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages
(from xgboost) (2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in
/usr/local/lib/python3.12/dist-packages (from xgboost) (2.27.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages
(from xgboost) (1.16.1)
```

[ ]:
```
from tqdm import tqdm  # Progress bar for inner loops (optional pip install tqdm)
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV,␣
↪StratifiedKFold, cross_val_score
from sklearn.metrics import (
    accuracy_score, f1_score, roc_auc_score, roc_curve, auc,
```

```
    confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay
)

# Base & ensemble models
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier,␣
 ↪RandomForestClassifier, StackingClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression

# XGBoost
try:
    from xgboost import XGBClassifier
except Exception as e:
    raise ImportError(
        "xgboost is required. Please install with: pip install xgboost"
    )

import matplotlib.pyplot as plt

# ------------------------------------------------------------
# 0) ASSUMPTIONS & SAFETY NETS
# ------------------------------------------------------------
# You must already have X_train, X_test, y_train, y_test in memory.
# Handle feature names (for importances)
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)

def _feature_names(X):
    if hasattr(X, "columns"):
        return list(X.columns)
    return [f"f{i}" for i in range(X.shape[1])]

feature_names = _feature_names(X_train)

# Identify numeric columns for scaling when using SVM in stacking
if hasattr(X_train, "select_dtypes"):
    num_cols = list(X_train.select_dtypes(include=[np.number]).columns)
else:
    # Assume all numeric if numpy arrays
    num_cols = list(range(X_train.shape[1]))

numeric_transformer = Pipeline(steps=[("scaler", StandardScaler())])
```

```
preprocess_for_svm = ColumnTransformer(
    transformers=[("num", numeric_transformer, num_cols)],
    remainder="passthrough",
)

# 5-Fold CV setup
cv5 = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Utility for safe predict_proba / decision_function
def _predict_scores(clf, X):
    if hasattr(clf, "predict_proba"):
        return clf.predict_proba(X)[:, 1]
    if hasattr(clf, "decision_function"):
        s = clf.decision_function(X)
        # map to 0-1 via min-max if needed for AUC; monotonic transform␣
 ↪preserves AUC ordering
        s = (s - s.min()) / (s.max() - s.min() + 1e-12)
        return s
    # worst case, return hard predictions as scores (AUC less meaningful)
    return clf.predict(X)

# Collectors for tables
tbl1_dt = []
tbl2_ada = []
tbl3_gb = []
tbl4_xgb = []
tbl5_rf = []
tbl6_stack = []
tbl7_cv = []
from sklearn.metrics import accuracy_score, f1_score

def _eval_on_test(name, model, X_test=X_test, y_test=y_test):
    """
    Evaluate a trained model on the test set.

    Returns a dict with test accuracy and F1 score.
    """
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average="weighted")  # use weighted for␣
 ↪multiclass
    print(f"[INFO] {name} Test Accuracy={acc:.4f}, Test F1={f1:.4f}")
    return {"model": name, "test_accuracy": acc, "test_f1": f1}

# ------------------------------------------------------------
# 1) DEFINE MODELS & HYPERPARAMETER SEARCH SPACES
# ------------------------------------------------------------
```

```
# Decision Tree
dt = DecisionTreeClassifier(random_state=42)
dt_grid = {
    "criterion": ["gini", "entropy", "log_loss"],
    "max_depth": [None, 2, 3, 4, 5, 6, 8, 10, 15],
    "min_samples_split": [2, 5, 10, 20],
    "min_samples_leaf": [1, 2, 4, 8],
}
dt_search = RandomizedSearchCV(
    dt, dt_grid, n_iter=40, scoring="f1", n_jobs=-1, cv=cv5, random_state=42,␣
 ↪refit=True, verbose=0
)

# AdaBoost (with DecisionTree base/estimator)
ada = AdaBoostClassifier(random_state=42)
# Newer sklearn uses 'estimator' instead of 'base_estimator'
ada_grid = {
    "n_estimators": [50, 75, 100, 150, 200],
    "learning_rate": [0.01, 0.05, 0.1, 0.3, 1.0],
    "estimator": [DecisionTreeClassifier(max_depth=d, random_state=42) for d in␣
 ↪[1, 2, 3]]
}
ada_search = RandomizedSearchCV(
    ada, ada_grid, n_iter=30, scoring="f1", n_jobs=-1, cv=cv5, random_state=42,␣
 ↪refit=True
)

# Gradient Boosting
gb = GradientBoostingClassifier(random_state=42)
gb_grid = {
    "n_estimators": [50, 75, 100, 150, 200],
    "learning_rate": [0.01, 0.05, 0.1, 0.2],
    "max_depth": [1, 2, 3, 4],
    "subsample": [0.6, 0.8, 1.0],
}
gb_search = RandomizedSearchCV(
    gb, gb_grid, n_iter=35, scoring="f1", n_jobs=-1, cv=cv5, random_state=42,␣
 ↪refit=True
)

# XGBoost
xgb = XGBClassifier(
    objective="binary:logistic",
    eval_metric="logloss",
    tree_method="hist",
    random_state=42,
```

```
    use_label_encoder=False
)
xgb_grid = {
    "n_estimators": [100, 200, 300, 500],
    "learning_rate": [0.01, 0.05, 0.1, 0.2],
    "max_depth": [2, 3, 4, 5, 6],
    "gamma": [0, 0.5, 1.0],
    "subsample": [0.6, 0.8, 1.0],
    "colsample_bytree": [0.6, 0.8, 1.0],
}
xgb_search = RandomizedSearchCV(
    xgb, xgb_grid, n_iter=40, scoring="f1", n_jobs=-1, cv=cv5, random_state=42,␣
 ↪refit=True
)

# Random Forest
rf = RandomForestClassifier(random_state=42)
rf_grid = {
    "n_estimators": [100, 200, 300, 500],
    "max_depth": [None, 3, 5, 7, 10, 15],
    "criterion": ["gini", "entropy", "log_loss"],
    "max_features": ["sqrt", "log2", 0.5, None],
    "min_samples_split": [2, 5, 10, 20],
}
rf_search = RandomizedSearchCV(
    rf, rf_grid, n_iter=40, scoring="f1", n_jobs=-1, cv=cv5, random_state=42,␣
 ↪refit=True
)

# Stacking: SVM (needs scaling), NaiveBayes, DecisionTree
stack_base = [
    ("svm", Pipeline([("prep", preprocess_for_svm), ("svc",␣
 ↪SVC(probability=True, random_state=42))])),
    ("nb", GaussianNB()),
    ("dt", DecisionTreeClassifier(random_state=42)),
]
stack = StackingClassifier(
    estimators=stack_base,
    final_estimator=LogisticRegression(max_iter=500, random_state=42),
    stack_method="predict_proba",
    n_jobs=-1,
    passthrough=False
)
# Tune SVM C/gamma via nested params, and choose final estimator type
stack_grid = [
    {
        "final_estimator": [LogisticRegression(max_iter=500, random_state=42)],
```

```
        "svm__svc__C": [0.1, 1, 10],
        "svm__svc__gamma": ["scale", "auto"],
        "dt__max_depth": [None, 3, 5],
    },
    {
        "final_estimator": [RandomForestClassifier(n_estimators=200,␣
↪random_state=42)],
        "svm__svc__C": [0.1, 1, 10],
        "svm__svc__gamma": ["scale", "auto"],
        "dt__max_depth": [None, 3, 5],
    },
]
stack_search = GridSearchCV(
    stack, stack_grid, scoring="f1", n_jobs=-1, cv=cv5, refit=True
)


# ------------------------------------------------------------
# 2) FIT SEARCHES & LOG TABLES 1-6 (with progress printing)
# ------------------------------------------------------------
# Collector for overall test results
results_summary = []

def _fit_and_log(search, name, table_collector, cols_for_table):
    print(f"\n[INFO] Starting hyperparameter tuning for {name}...")
    search.fit(X_train, y_train)
    print(f"[INFO] Finished hyperparameter tuning for {name}. Best params:␣
↪{search.best_params_}")

    best = search.best_estimator_
    cvres = pd.DataFrame(search.cv_results_)
    param_cols = [c for c in cvres.columns if c.startswith("param_")]
    keep = ["mean_test_score", "std_test_score", "rank_test_score"] + param_cols
    slim = cvres[keep].sort_values("rank_test_score")
    slim = slim.rename(columns={"mean_test_score": "F1 (CV)", "std_test_score":␣
↪"F1 std (CV)"})
    renamer = {f"param_{p}": p for p in cols_for_table if f"param_{p}" in slim.
↪columns}
    slim = slim.rename(columns=renamer)

    print(f"[INFO] Performing CV accuracy check for {name}...")
    cv_acc = cross_val_score(best, X_train, y_train, cv=cv5, scoring="accuracy",␣
↪n_jobs=-1)
    best_row = slim.iloc[0:1].copy()
    best_row["Accuracy"] = cv_acc.mean()
    best_row = best_row.rename(columns={"F1 (CV)": "F1 Score"})
    visible = [c for c in cols_for_table if c in best_row.columns]
```

```
    visible += [c for c in ["Accuracy", "F1 Score"] if c in best_row.columns]
    table_collector.append(best_row[visible])

    r = _eval_on_test(name, best)
    results_summary.append(r)
    print(f"[INFO] {name} done. Test Accuracy={r['test_accuracy']:.4f}, Test␣
 ↪F1={r['test_f1']:.4f}")
    return best, slim

# Decision Tree -> Table 1
dt_best, dt_cvres = _fit_and_log(dt_search, "Decision Tree", tbl1_dt,␣
 ↪cols_for_table=["criterion", "max_depth"])

# AdaBoost -> Table 2
ada_best, ada_cvres = _fit_and_log(ada_search, "AdaBoost", tbl2_ada,␣
 ↪cols_for_table=["n_estimators", "learning_rate"])

# Gradient Boosting -> Table 3
gb_best, gb_cvres = _fit_and_log(gb_search, "Gradient Boosting", tbl3_gb,␣
 ↪cols_for_table=["n_estimators", "learning_rate", "max_depth"])

# XGBoost -> Table 4
xgb_best, xgb_cvres = _fit_and_log(xgb_search, "XGBoost", tbl4_xgb,␣
 ↪cols_for_table=["n_estimators", "learning_rate", "max_depth", "gamma"])

# Random Forest -> Table 5
rf_best, rf_cvres = _fit_and_log(rf_search, "Random Forest", tbl5_rf,␣
 ↪cols_for_table=["n_estimators", "max_depth", "criterion"])

# Stacking -> Table 6
print("\n[INFO] Starting hyperparameter tuning for Stacking Classifier...")
stack_search.fit(X_train, y_train)
print(f"[INFO] Finished Stacking. Best params: {stack_search.best_params_}")
stack_best = stack_search.best_estimator_
cv_acc_stack = cross_val_score(stack_best, X_train, y_train, cv=cv5,␣
 ↪scoring="accuracy", n_jobs=-1)
cv_f1_stack = cross_val_score(stack_best, X_train, y_train, cv=cv5,␣
 ↪scoring="f1", n_jobs=-1)
tbl6_stack.append(pd.DataFrame([{
    "Base Models": "SVM, Naïve Bayes, Decision Tree",
    "Final Estimator": type(stack_search.best_params_["final_estimator"]).
 ↪__name__,
    "Accuracy / F1 Score": f"{cv_acc_stack.mean():.4f} / {cv_f1_stack.mean():.
 ↪4f}"
}]))
results_summary.append(_eval_on_test("Stacked Model", stack_best))
```

```
print(f"[INFO] Stacking done. Test␣
 ↪Accuracy={results_summary[-1]['test_accuracy']:.4f}, Test␣
 ↪F1={results_summary[-1]['test_f1']:.4f}")


# Materialize Tables 1-6
Table1_DecisionTree = pd.concat(tbl1_dt, ignore_index=True) if tbl1_dt else pd.
 ↪DataFrame()
Table2_AdaBoost = pd.concat(tbl2_ada, ignore_index=True) if tbl2_ada else pd.
 ↪DataFrame()
Table3_GradBoost = pd.concat(tbl3_gb, ignore_index=True) if tbl3_gb else pd.
 ↪DataFrame()
Table4_XGBoost = pd.concat(tbl4_xgb, ignore_index=True) if tbl4_xgb else pd.
 ↪DataFrame()
Table5_RandomForest = pd.concat(tbl5_rf, ignore_index=True) if tbl5_rf else pd.
 ↪DataFrame()
Table6_Stacking = pd.concat(tbl6_stack, ignore_index=True) if tbl6_stack else pd.
 ↪DataFrame()

print("\n=== Table 1: Decision Tree - Hyperparameter Tuning (Top Row) ===")
print(Table1_DecisionTree.to_string(index=False))
print("\n=== Table 2: AdaBoost - Hyperparameter Tuning (Top Row) ===")
print(Table2_AdaBoost.to_string(index=False))
print("\n=== Table 3: Gradient Boosting - Hyperparameter Tuning (Top Row) ===")
print(Table3_GradBoost.to_string(index=False))
print("\n=== Table 4: XGBoost - Hyperparameter Tuning (Top Row) ===")
print(Table4_XGBoost.to_string(index=False))
print("\n=== Table 5: Random Forest - Hyperparameter Tuning (Top Row) ===")
print(Table5_RandomForest.to_string(index=False))
print("\n=== Table 6: Stacked Ensemble - Hyperparameter Tuning ===")
print(Table6_Stacking.to_string(index=False))

# ------------------------------------------------------------
# 3) 5-FOLD CROSS-VALIDATION RESULTS -> Table 7 (Accuracy per fold)
# Use BEST estimators found above
# ------------------------------------------------------------
models_best = [
    ("Decision Tree", dt_best),
    ("AdaBoost", ada_best),
    ("Gradient Boosting", gb_best),
    ("XGBoost", xgb_best),
    ("Random Forest", rf_best),
    ("Stacked Model", stack_best),
]

rows = []
```

```
for name, model in models_best:
    scores = cross_val_score(model, X_train, y_train, cv=cv5,␣
 ↪scoring="accuracy", n_jobs=-1)
    row = {"Model": name}
    for i, s in enumerate(scores, 1):
        row[f"Fold {i}"] = s
    row["Average Accuracy"] = scores.mean()
    rows.append(row)

Table7_CV = pd.DataFrame(rows)
print("\n=== Table 7: 5-Fold Cross-Validation Results (Training CV) ===")
print(Table7_CV.to_string(index=False))

# ------------------------------------------------------------
# 4) ROC CURVES & CONFUSION MATRICES (Test Set)
# ------------------------------------------------------------
def plot_roc_curves(model_dict, X_test, y_test):
    plt.figure(figsize=(8, 6))
    for name, clf in model_dict.items():
        y_score = _predict_scores(clf, X_test)
        fpr, tpr, _ = roc_curve(y_test, y_score)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, lw=2, label=f"{name} (AUC={roc_auc:.3f})")
    plt.plot([0, 1], [0, 1], lw=1, linestyle="--")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curves (Test Set)")
    plt.legend(loc="lower right")
    plt.tight_layout()
    plt.show()

def plot_confusion_matrices(model_dict, X_test, y_test):
    for name, clf in model_dict.items():
        y_pred = clf.predict(X_test)
        cm = confusion_matrix(y_test, y_pred)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(values_format="d")
        plt.title(f"Confusion Matrix - {name}")
        plt.tight_layout()
        plt.show()

model_dict = {name: m for name, m in models_best}

# Plot ROC (only meaningful for binary)
if len(np.unique(y_test)) == 2:
    plot_roc_curves(model_dict, X_test, y_test)
```

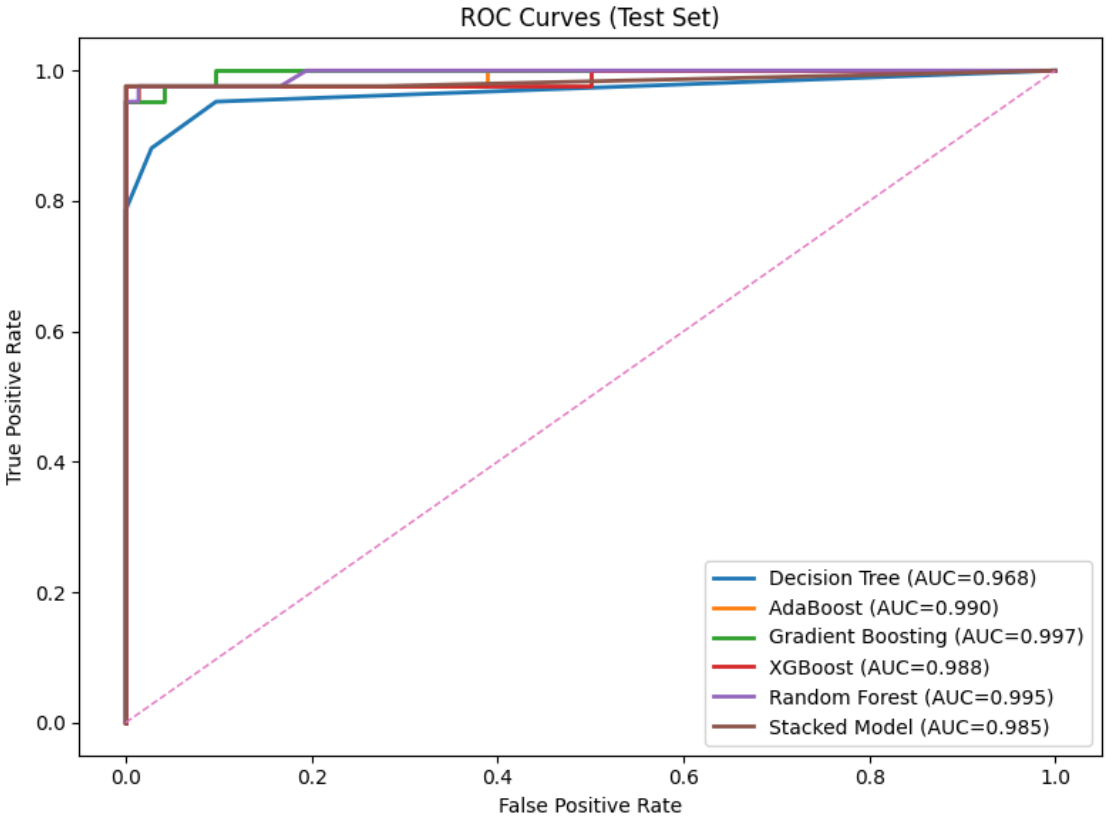
```
plot_confusion_matrices(model_dict, X_test, y_test)

# ------------------------------------------------------------
# 5) FEATURE IMPORTANCE (DT, RF, GB, XGB)
# ------------------------------------------------------------
def show_importances(name, clf, feature_names, top_k=15):
    if hasattr(clf, "feature_importances_"):
        importances = clf.feature_importances_
    elif hasattr(clf, "named_steps"):
        # Some pipelines/stacking may wrap the estimator-try to find the␣
 ↪attribute
        for step_name, step_est in getattr(clf, "named_steps", {}).items():
            if hasattr(step_est, "feature_importances_"):
                importances = step_est.feature_importances_
                break
        else:
            return
    else:
        return
    order = np.argsort(importances)[::-1][:top_k]
    plt.figure(figsize=(8, 5))
    plt.bar(range(len(order)), importances[order])
    plt.xticks(range(len(order)), [feature_names[i] for i in order],␣
 ↪rotation=60, ha="right")
    plt.title(f"Top {top_k} Feature Importances - {name}")
    plt.tight_layout()
    plt.show()

show_importances("Decision Tree", dt_best, feature_names)
show_importances("Random Forest", rf_best, feature_names)
show_importances("Gradient Boosting", gb_best, feature_names)
show_importances("XGBoost", xgb_best, feature_names)

# ------------------------------------------------------------
# 6) AUTO-GENERATED OBSERVATIONS
# ------------------------------------------------------------
summary_df = pd.DataFrame(results_summary).sort_values("test_accuracy",␣
 ↪ascending=False)
print("\n=== Test Set Summary (Best Estimators) ===")
print(summary_df.to_string(index=False))

def observations():
    best = summary_df.iloc[0]
    best_name = best["model"]
    # Compare DT vs Ensembles
    dt_row = summary_df[summary_df["model"] == "Decision Tree"].iloc[0]
    ensembles = summary_df[summary_df["model"] != "Decision Tree"]
```

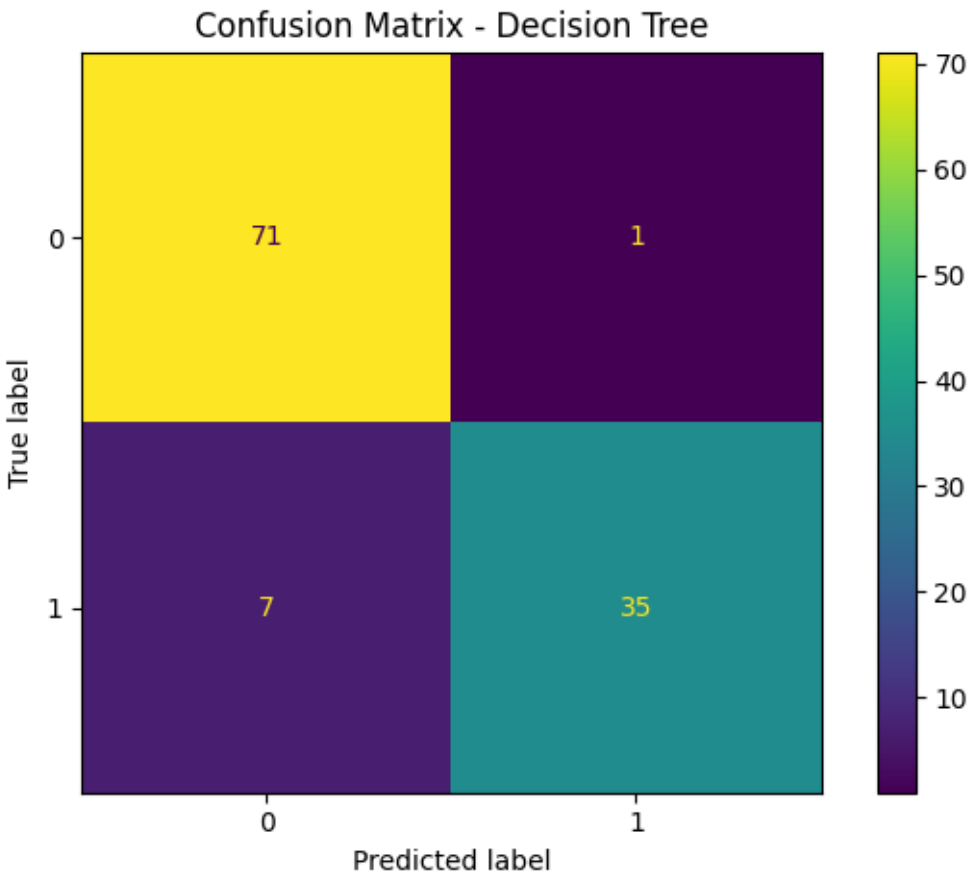
```
    ensembles_mean_acc = ensembles["test_accuracy"].mean()
    rf_tuned_gain = None
    # Effect of tuning on RF: compare cross-val mean of tuned RF vs default RF
    rf_default = RandomForestClassifier(random_state=42)
    rf_default_scores = cross_val_score(rf_default, X_train, y_train, cv=cv5,␣
↪scoring="accuracy", n_jobs=-1).mean()
    rf_tuned_scores = cross_val_score(rf_best, X_train, y_train, cv=cv5,␣
↪scoring="accuracy", n_jobs=-1).mean()
    rf_tuned_gain = rf_tuned_scores - rf_default_scores

    # Generalization: gap between CV accuracy and test accuracy (absolute␣
↪difference)
    gen_gaps = []
    for name, model in models_best:
        cv_acc = cross_val_score(model, X_train, y_train, cv=cv5,␣
↪scoring="accuracy", n_jobs=-1).mean()
        test_acc = summary_df[summary_df["model"] == name]["test_accuracy"].
↪values[0]
        gen_gaps.append((name, abs(cv_acc - test_acc)))
    gen_gaps = sorted(gen_gaps, key=lambda t: t[1])
    best_generalizer = gen_gaps[0][0]

    lines = []
    lines.append(f"Best accuracy on the test set: {best_name}␣
↪(Acc={best['test_accuracy']:.4f}, F1={best['test_f1']:.4f},␣
↪AUC={best['test_auc']:.4f}).")
    lines.append(f"Ensembles vs Decision Tree: Mean ensemble␣
↪accuracy={ensembles_mean_acc:.4f} vs Decision Tree␣
↪accuracy={dt_row['test_accuracy']:.4f}.")
    lines.append(f"Random Forest tuning effect: ΔCV accuracy  {rf_tuned_gain:.
↪4f} (tuned - default).")
    lines.append(f"Best generalization (smallest CV-Test gap):␣
↪{best_generalizer}.")
    # Stacking improvement over its base models (compare vs DT/SVM/NB␣
↪individually where available)
    base_refs = ["Decision Tree"]  # NB & SVM individually not evaluated alone␣
↪here
    stack_acc = summary_df[summary_df["model"] == "Stacked␣
↪Model"]["test_accuracy"].values[0]
    improvements = []
    for b in base_refs:
        improvements.append((b, stack_acc - summary_df[summary_df["model"] ==␣
↪b]["test_accuracy"].values[0]))
    imp_str = ", ".join([f"{b}: {d:+.4f}" for b, d in improvements])
    lines.append(f"Stacking improvement vs base references → {imp_str}.")
    return "\n".join(lines)
```

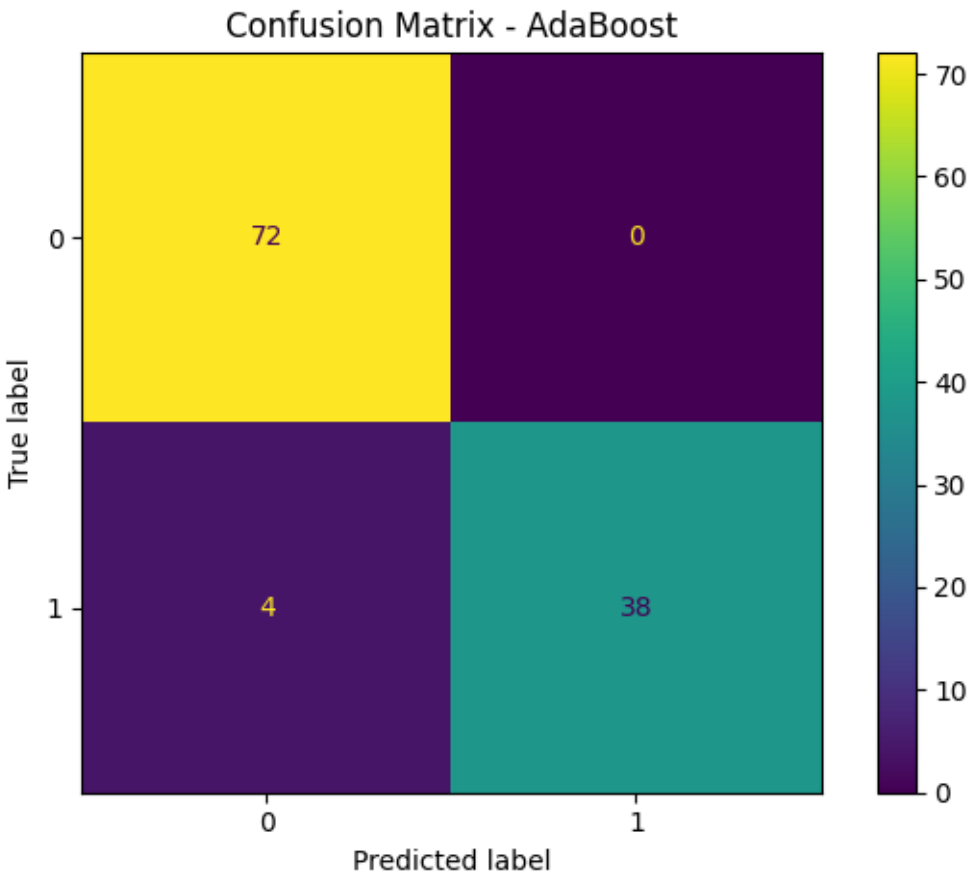
```
print("\n=== Observations & Conclusions ===")
print(observations())
```

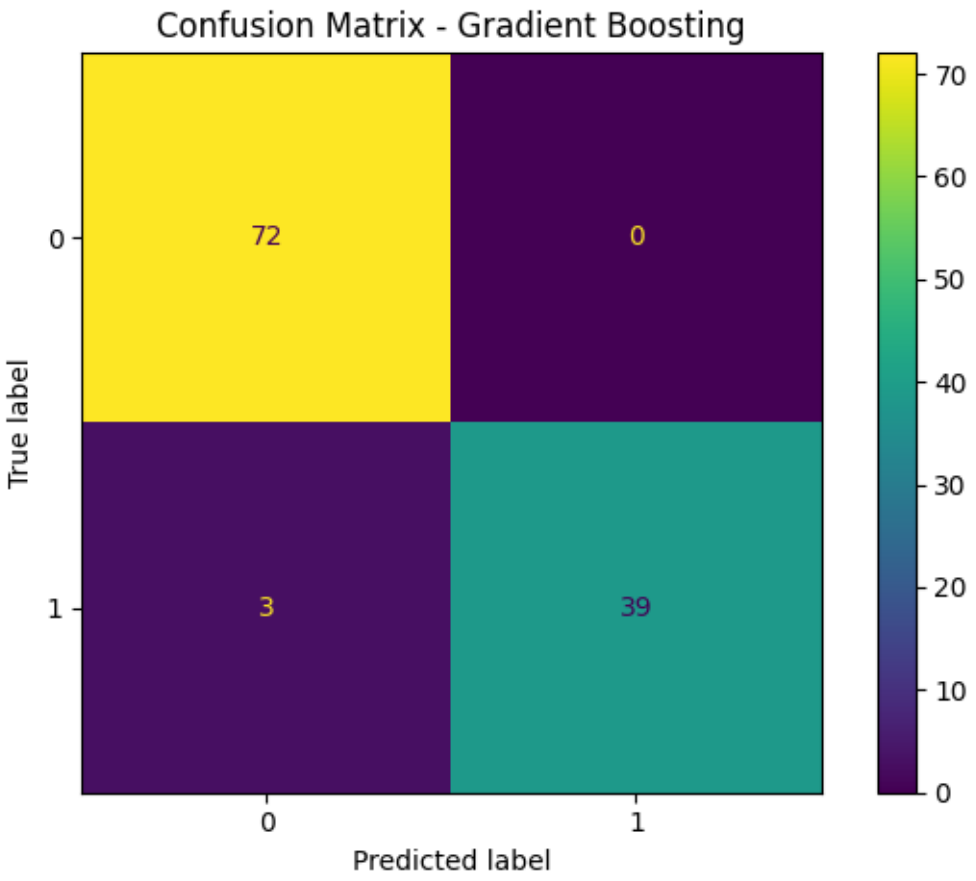
```
[INFO] Starting hyperparameter tuning for Decision Tree...
[INFO] Finished hyperparameter tuning for Decision Tree. Best params:
{'min_samples_split': 10, 'min_samples_leaf': 8, 'max_depth': 10, 'criterion':
'log_loss'}
[INFO] Performing CV accuracy check for Decision Tree...
[INFO] Decision Tree Test Accuracy=0.9298, Test F1=0.9285
[INFO] Decision Tree done. Test Accuracy=0.9298, Test F1=0.9285

[INFO] Starting hyperparameter tuning for AdaBoost...
[INFO] Finished hyperparameter tuning for AdaBoost. Best params:
{'n_estimators': 200, 'learning_rate': 1.0, 'estimator':
DecisionTreeClassifier(max_depth=2, random_state=42)}
[INFO] Performing CV accuracy check for AdaBoost...
[INFO] AdaBoost Test Accuracy=0.9649, Test F1=0.9645
[INFO] AdaBoost done. Test Accuracy=0.9649, Test F1=0.9645

[INFO] Starting hyperparameter tuning for Gradient Boosting...
[INFO] Finished hyperparameter tuning for Gradient Boosting. Best params:
{'subsample': 0.6, 'n_estimators': 200, 'max_depth': 4, 'learning_rate': 0.2}
[INFO] Performing CV accuracy check for Gradient Boosting...
[INFO] Gradient Boosting Test Accuracy=0.9737, Test F1=0.9735
[INFO] Gradient Boosting done. Test Accuracy=0.9737, Test F1=0.9735

[INFO] Starting hyperparameter tuning for XGBoost...
[INFO] Finished hyperparameter tuning for XGBoost. Best params: {'subsample':
0.8, 'n_estimators': 100, 'max_depth': 6, 'learning_rate': 0.2, 'gamma': 0.5,
'colsample_bytree': 0.8}
[INFO] Performing CV accuracy check for XGBoost...
[INFO] XGBoost Test Accuracy=0.9737, Test F1=0.9735
[INFO] XGBoost done. Test Accuracy=0.9737, Test F1=0.9735

[INFO] Starting hyperparameter tuning for Random Forest...
[INFO] Finished hyperparameter tuning for Random Forest. Best params:
{'n_estimators': 200, 'min_samples_split': 2, 'max_features': 'log2',
'max_depth': 10, 'criterion': 'entropy'}
[INFO] Performing CV accuracy check for Random Forest...
[INFO] Random Forest Test Accuracy=0.9737, Test F1=0.9735
[INFO] Random Forest done. Test Accuracy=0.9737, Test F1=0.9735

[INFO] Starting hyperparameter tuning for Stacking Classifier...
[INFO] Finished Stacking. Best params: {'dt__max_depth': None,
'final_estimator': RandomForestClassifier(n_estimators=200, random_state=42),
'svm__svc__C': 1, 'svm__svc__gamma': 'scale'}
```

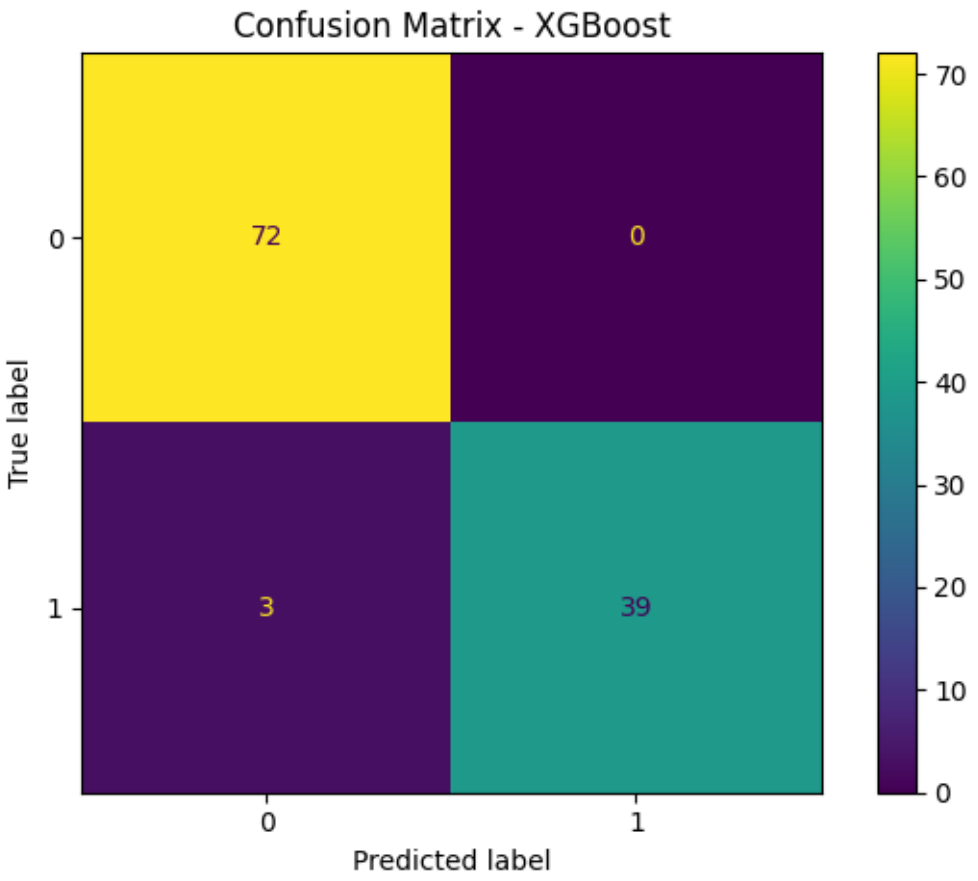
```
[INFO] Stacked Model Test Accuracy=0.9825, Test F1=0.9825
[INFO] Stacking done. Test Accuracy=0.9825, Test F1=0.9825

=== Table 1: Decision Tree - Hyperparameter Tuning (Top Row) ===
criterion max_depth  Accuracy  F1 Score
 log_loss        10   0.94139  0.919011

=== Table 2: AdaBoost - Hyperparameter Tuning (Top Row) ===
 n_estimators  learning_rate  Accuracy  F1 Score
          200            1.0  0.967647  0.954542

=== Table 3: Gradient Boosting - Hyperparameter Tuning (Top Row) ===
 n_estimators  learning_rate  max_depth  Accuracy  F1 Score
          200            0.2          4  0.964749  0.949737

=== Table 4: XGBoost - Hyperparameter Tuning (Top Row) ===
 n_estimators  learning_rate  max_depth  gamma  Accuracy  F1 Score
          100            0.2          6    0.5  0.967647  0.955396

=== Table 5: Random Forest - Hyperparameter Tuning (Top Row) ===
 n_estimators max_depth criterion  Accuracy  F1 Score
          200        10   entropy  0.955925  0.938678

=== Table 6: Stacked Ensemble - Hyperparameter Tuning ===
                   Base Models        Final Estimator Accuracy / F1 Score
SVM, Naïve Bayes, Decision Tree RandomForestClassifier     0.9794 / 0.9717

=== Table 7: 5-Fold Cross-Validation Results (Training CV) ===
            Model   Fold 1   Fold 2   Fold 3   Fold 4   Fold 5  Average Accuracy
    Decision Tree 0.927536 0.970588 0.955882 0.897059 0.955882          0.941390
         AdaBoost 1.000000 0.941176 0.970588 0.955882 0.970588          0.967647
Gradient Boosting 0.985507 0.985294 0.970588 0.911765 0.970588          0.964749
          XGBoost 1.000000 0.970588 0.970588 0.941176 0.955882          0.967647
    Random Forest 0.985507 0.941176 0.970588 0.926471 0.955882          0.955925
    Stacked Model 1.000000 0.970588 1.000000 0.955882 0.970588          0.979412
```

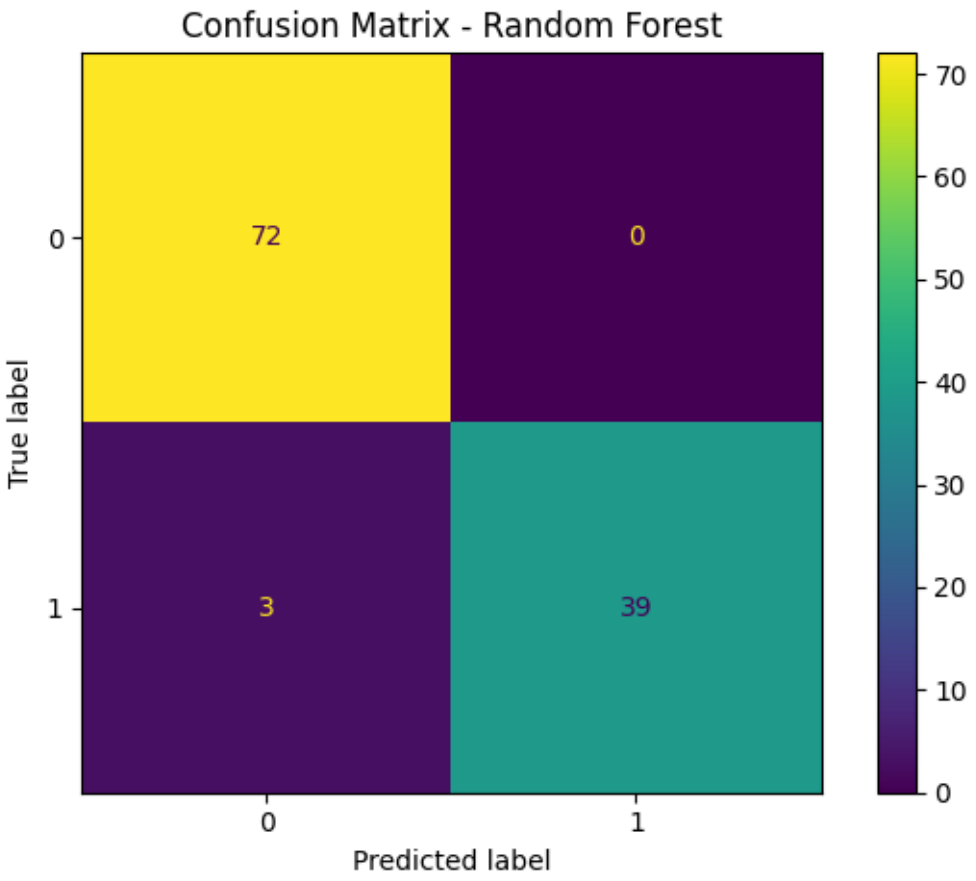

ROC Curves (Test Set)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Decision Tree (AUC=0.968)
AdaBoost (AUC=0.990)
Gradient Boosting (AUC=0.997)
XGBoost (AUC=0.988)
Random Forest (AUC=0.995)
Stacked Model (AUC=0.985)

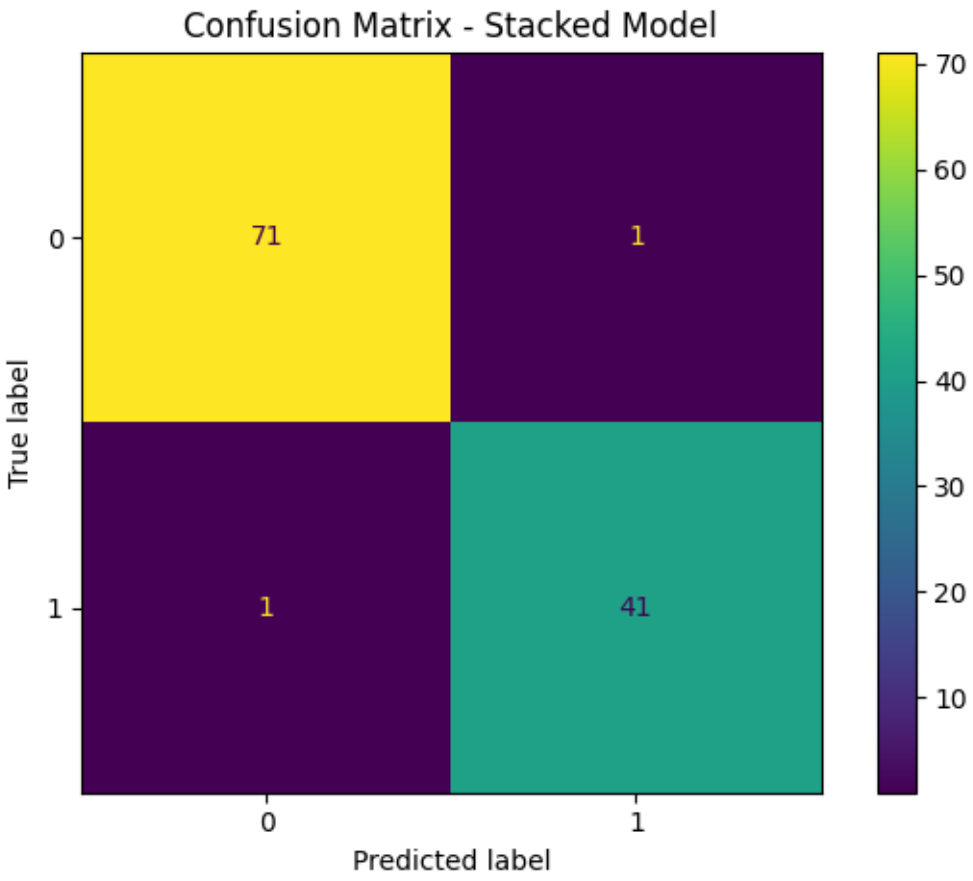

Confusion Matrix - Decision Tree
71
1
7
35
0
1
True label
0
1
Predicted label
70
60
50
40
30
20
10

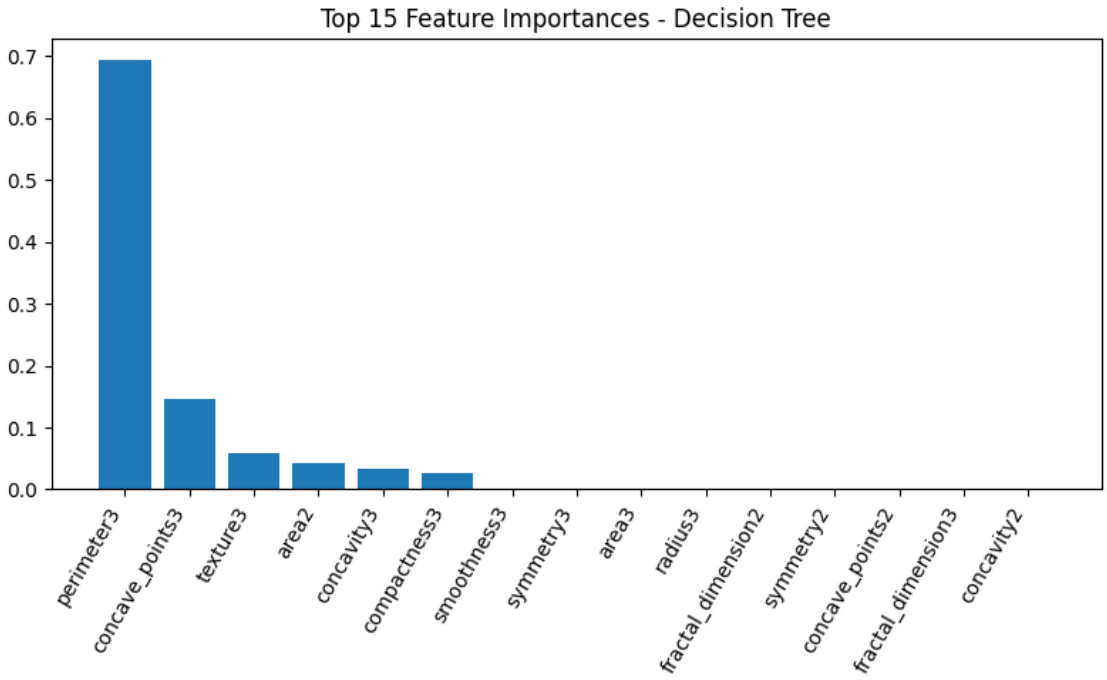

Confusion Matrix - AdaBoost
72
0
4
38
0
1
True label
0
1
Predicted label
70
60
50
40
30
20
10
0

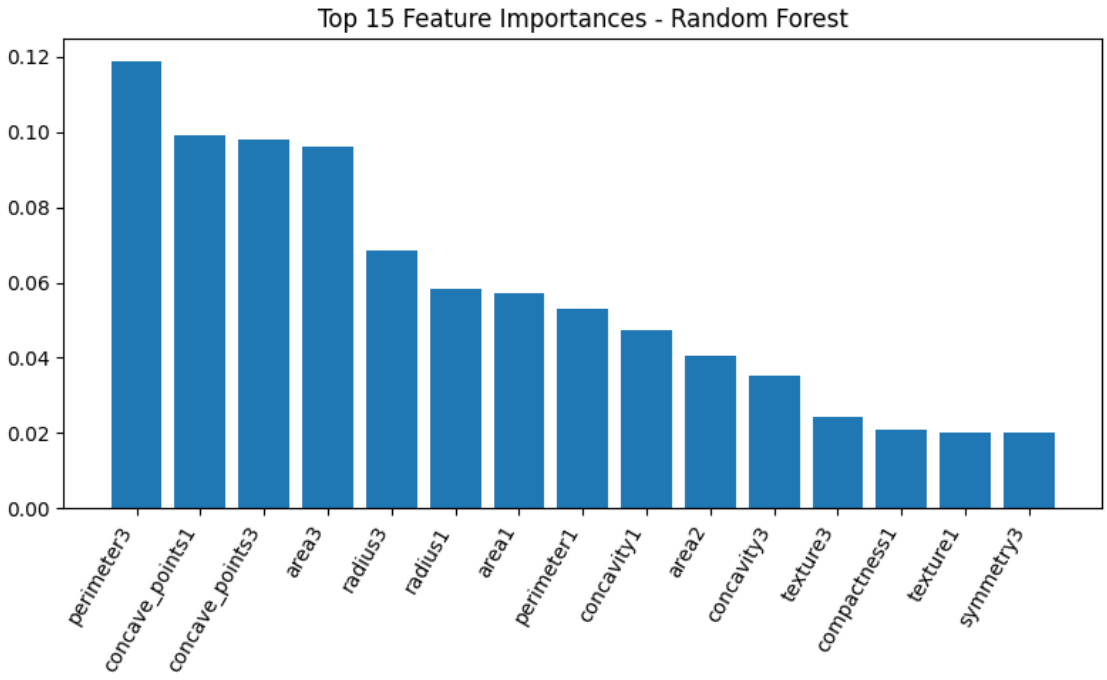

Confusion Matrix - Gradient Boosting
72
0
3
39
0
1
True label
0
1
Predicted label
70
60
50
40
30
20
10
0

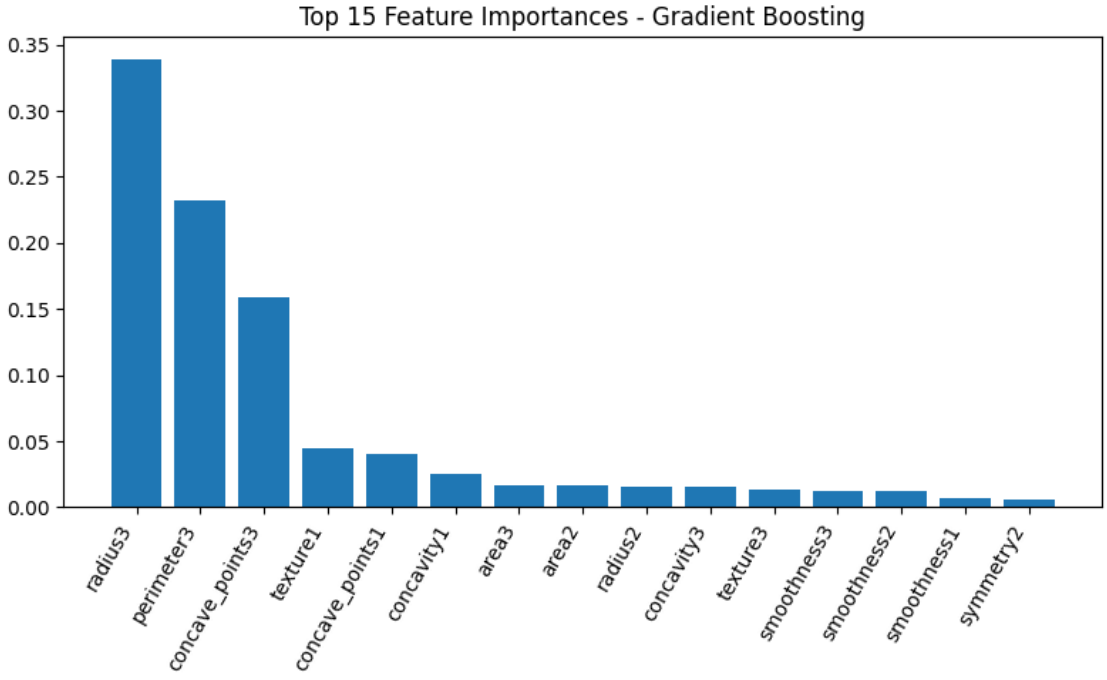

Confusion Matrix - XGBoost
72
0
3
39
0
1
True label
0
1
Predicted label
70
60
50
40
30
20
10
0

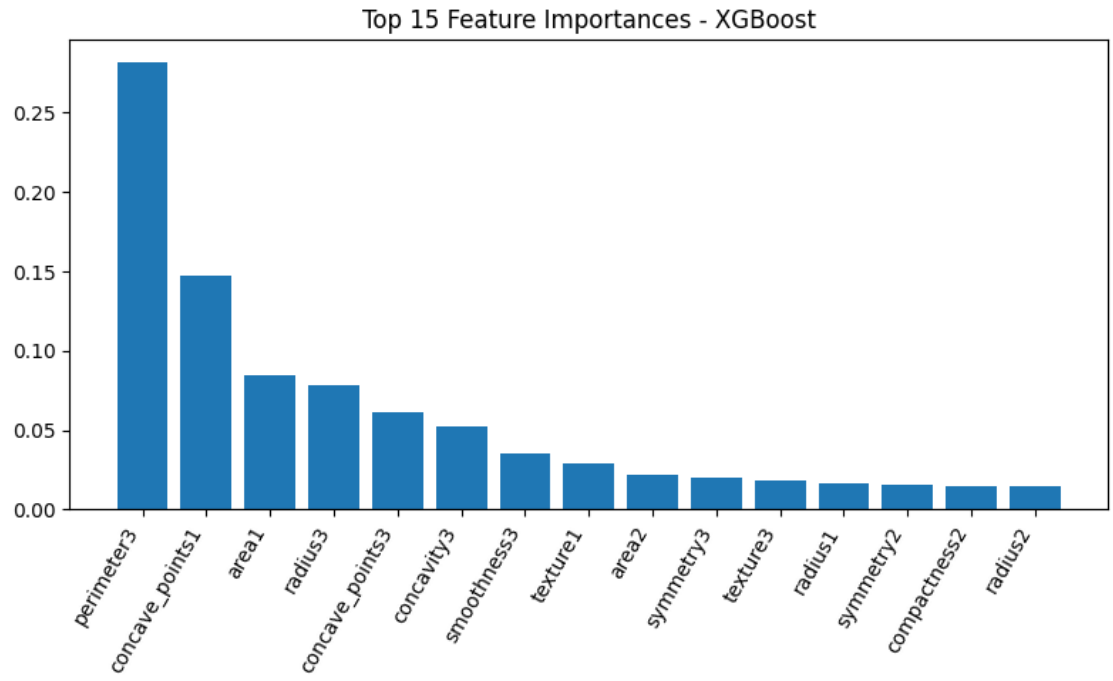

Confusion Matrix - Random Forest
True label
Predicted label
0
1
0
1
72
0
3
39
70
60
50
40
30
20
10
0


Confusion Matrix - Stacked Model
71
1
1
41
0
1
True label
Predicted label
70
60
50
40
30
20
10


Top 15 Feature Importances - Decision Tree
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
perimeter3
concave_points3
texture3
area2
concavity3
compactness3
smoothness3
symmetry3
area3
radius3
fractal_dimension2
symmetry2
concave_points2
fractal_dimension3
concavity2


Top 15 Feature Importances - Random Forest
0.12
0.10
0.08
0.06
0.04
0.02
0.00
perimeter3
concave_points1
concave_points3
area3
radius3
radius1
area1
perimeter1
concavity1
area2
concavity3
texture3
compactness1
texture1
symmetry3


Top 15 Feature Importances - Gradient Boosting
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
radius3
perimeter3
concave_points3
texture1
concave_points1
concavity1
area3
area2
radius2
concavity3
texture3
smoothness3
smoothness2
smoothness1
symmetry2




```
=== Test Set Summary (Best Estimators) ===
             model  test_accuracy  test_f1
    Stacked Model       0.982456 0.982456
Gradient Boosting       0.973684 0.973465
          XGBoost       0.973684 0.973465
    Random Forest       0.973684 0.973465
         AdaBoost       0.964912 0.964509
    Decision Tree       0.929825 0.928529

=== Observations & Conclusions ===
Best accuracy on the test set: Stacked Model (Acc=0.9825, F1=0.9762,
AUC=0.9848).
Ensembles vs Decision Tree: Mean ensemble accuracy=0.9727 vs Decision Tree
accuracy=0.9298.
Random Forest tuning effect: ΔCV accuracy  0.0029 (tuned - default).
Best generalization (smallest CV-Test gap): AdaBoost.
Stacking improvement vs base references → Decision Tree: +0.0526.
```

Hyperparameter Trials for all models

[ ]:
```
import time
import pandas as pd
from sklearn.metrics import accuracy_score, f1_score
```

```python
# Example: Assume X_train, X_test, y_train, y_test are already defined

def evaluate_model(model_class, param_sets, X_train, y_train, X_test, y_test):
    """
    Evaluate a model class on multiple hyperparameter sets.

    Args:
        model_class: Class of the estimator, e.g., DecisionTreeClassifier
        param_sets: List of dicts, each dict is a hyperparameter set
        X_train, y_train, X_test, y_test: Data

    Returns:
        DataFrame with results: hyperparameters, Accuracy, F1, Training Time
    """
    results = []

    for i, params in enumerate(param_sets, 1):
        print(f"[INFO] Evaluating {model_class.__name__}, set {i}: {params}")
        model = model_class(**params)

        start_time = time.time()
        model.fit(X_train, y_train)
        train_time = time.time() - start_time

        y_pred = model.predict(X_test)
        acc = accuracy_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred, average='macro')  # macro for multi-class

        results.append({
            "Hyperparameters": params,
            "Accuracy": acc,
            "F1 (macro)": f1,
            "Training Time (s)": train_time
        })
        print(f"Accuracy: {acc:.4f}, F1: {f1:.4f}, Training Time: {train_time:.
↪2f}s\n")

    return pd.DataFrame(results)

# ----------------------------------------
# 1) Decision Tree Example
# ----------------------------------------
from sklearn.tree import DecisionTreeClassifier

dt_param_sets = [
    {"criterion": "gini", "max_depth": 5, "min_samples_split": 2},
    {"criterion": "entropy", "max_depth": 10, "min_samples_split": 5},
```

```
    {"criterion": "log_loss", "max_depth": 8, "min_samples_split": 10},
]

dt_results = evaluate_model(DecisionTreeClassifier, dt_param_sets, X_train,␣
↪y_train, X_test, y_test)
print("Decision Tree Results:\n", dt_results)

# ----------------------------------------
# 2) Random Forest Example
# ----------------------------------------
from sklearn.ensemble import RandomForestClassifier

rf_param_sets = [
    {"n_estimators": 100, "max_depth": 5, "criterion": "gini"},
    {"n_estimators": 200, "max_depth": 10, "criterion": "entropy"},
    {"n_estimators": 300, "max_depth": None, "criterion": "log_loss"},
]

rf_results = evaluate_model(RandomForestClassifier, rf_param_sets, X_train,␣
↪y_train, X_test, y_test)
print("Random Forest Results:\n", rf_results)

# ----------------------------------------
# 3) Gradient Boosting Example
# ----------------------------------------
from sklearn.ensemble import GradientBoostingClassifier

gb_param_sets = [
    {"n_estimators": 100, "learning_rate": 0.05, "max_depth": 3},
    {"n_estimators": 150, "learning_rate": 0.1, "max_depth": 2},
    {"n_estimators": 200, "learning_rate": 0.01, "max_depth": 4},
]

gb_results = evaluate_model(GradientBoostingClassifier, gb_param_sets, X_train,␣
↪y_train, X_test, y_test)
print("Gradient Boosting Results:\n", gb_results)

# ----------------------------------------
# 4) AdaBoost Example
# ----------------------------------------
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

ada_param_sets = [
    {"n_estimators": 50, "learning_rate": 0.1, "estimator":␣
↪DecisionTreeClassifier(max_depth=1)},
```

```
    {"n_estimators": 100, "learning_rate": 0.05, "estimator":␣
 ↪DecisionTreeClassifier(max_depth=2)},
    {"n_estimators": 150, "learning_rate": 0.01, "estimator":␣
 ↪DecisionTreeClassifier(max_depth=3)},
]

ada_results = evaluate_model(AdaBoostClassifier, ada_param_sets, X_train,␣
 ↪y_train, X_test, y_test)
print("AdaBoost Results:\n", ada_results)

# ---------------------------------------
# 5) XGBoost Example
# ---------------------------------------
from xgboost import XGBClassifier

xgb_param_sets = [
    {"n_estimators": 100, "learning_rate": 0.05, "max_depth": 3},
    {"n_estimators": 200, "learning_rate": 0.1, "max_depth": 4},
    {"n_estimators": 300, "learning_rate": 0.01, "max_depth": 5},
]

xgb_results = evaluate_model(XGBClassifier, xgb_param_sets, X_train, y_train,␣
 ↪X_test, y_test)
print("XGBoost Results:\n", xgb_results)
```

```
[INFO] Evaluating DecisionTreeClassifier, set 1: {'criterion': 'gini',
'max_depth': 5, 'min_samples_split': 2}
Accuracy: 0.9298, F1: 0.9238, Training Time: 0.03s

[INFO] Evaluating DecisionTreeClassifier, set 2: {'criterion': 'entropy',
'max_depth': 10, 'min_samples_split': 5}
Accuracy: 0.9737, F1: 0.9713, Training Time: 0.05s

[INFO] Evaluating DecisionTreeClassifier, set 3: {'criterion': 'log_loss',
'max_depth': 8, 'min_samples_split': 10}
Accuracy: 0.9649, F1: 0.9619, Training Time: 0.05s

Decision Tree Results:
                                      Hyperparameters  Accuracy  F1 (macro)  \
0  {'criterion': 'gini', 'max_depth': 5, 'min_sam...  0.929825    0.923822
1  {'criterion': 'entropy', 'max_depth': 10, 'min...  0.973684    0.971277
2  {'criterion': 'log_loss', 'max_depth': 8, 'min...  0.964912    0.961911

   Training Time (s)
0           0.031666
1           0.047766
2           0.051443
```

```
[INFO] Evaluating RandomForestClassifier, set 1: {'n_estimators': 100,
'max_depth': 5, 'criterion': 'gini'}
Accuracy: 0.9649, F1: 0.9619, Training Time: 1.10s

[INFO] Evaluating RandomForestClassifier, set 2: {'n_estimators': 200,
'max_depth': 10, 'criterion': 'entropy'}
Accuracy: 0.9825, F1: 0.9810, Training Time: 1.27s

[INFO] Evaluating RandomForestClassifier, set 3: {'n_estimators': 300,
'max_depth': None, 'criterion': 'log_loss'}
Accuracy: 0.9825, F1: 0.9810, Training Time: 1.62s

Random Forest Results:
                                    Hyperparameters  Accuracy  F1 (macro)  \
0  {'n_estimators': 100, 'max_depth': 5, 'criteri...  0.964912    0.961911
1  {'n_estimators': 200, 'max_depth': 10, 'criter...  0.982456    0.980956
2  {'n_estimators': 300, 'max_depth': None, 'crit...  0.982456    0.980956

   Training Time (s)
0           1.099962
1           1.273770
2           1.615714
[INFO] Evaluating GradientBoostingClassifier, set 1: {'n_estimators': 100,
'learning_rate': 0.05, 'max_depth': 3}
Accuracy: 0.9649, F1: 0.9619, Training Time: 1.24s

[INFO] Evaluating GradientBoostingClassifier, set 2: {'n_estimators': 150,
'learning_rate': 0.1, 'max_depth': 2}
Accuracy: 0.9649, F1: 0.9615, Training Time: 1.21s

[INFO] Evaluating GradientBoostingClassifier, set 3: {'n_estimators': 200,
'learning_rate': 0.01, 'max_depth': 4}
Accuracy: 0.9649, F1: 0.9615, Training Time: 2.36s

Gradient Boosting Results:
                                    Hyperparameters  Accuracy  F1 (macro)  \
0  {'n_estimators': 100, 'learning_rate': 0.05, '...  0.964912    0.961911
1  {'n_estimators': 150, 'learning_rate': 0.1, 'm...  0.964912    0.961486
2  {'n_estimators': 200, 'learning_rate': 0.01, '...  0.964912    0.961486

   Training Time (s)
0           1.242388
1           1.209637
2           2.362746
[INFO] Evaluating AdaBoostClassifier, set 1: {'n_estimators': 50,
'learning_rate': 0.1, 'estimator': DecisionTreeClassifier(max_depth=1)}
Accuracy: 0.9561, F1: 0.9516, Training Time: 0.33s
```

```
[INFO] Evaluating AdaBoostClassifier, set 2: {'n_estimators': 100,
'learning_rate': 0.05, 'estimator': DecisionTreeClassifier(max_depth=2)}
Accuracy: 0.9649, F1: 0.9619, Training Time: 1.09s

[INFO] Evaluating AdaBoostClassifier, set 3: {'n_estimators': 150,
'learning_rate': 0.01, 'estimator': DecisionTreeClassifier(max_depth=3)}
Accuracy: 0.9737, F1: 0.9713, Training Time: 5.37s

AdaBoost Results:
                                      Hyperparameters  Accuracy  F1 (macro)  \
0  {'n_estimators': 50, 'learning_rate': 0.1, 'es...  0.956140    0.951576
1  {'n_estimators': 100, 'learning_rate': 0.05, '...  0.964912    0.961911
2  {'n_estimators': 150, 'learning_rate': 0.01, '...  0.973684    0.971277

   Training Time (s)
0           0.329100
1           1.092090
2           5.366084
[INFO] Evaluating XGBClassifier, set 1: {'n_estimators': 100, 'learning_rate':
0.05, 'max_depth': 3}
Accuracy: 0.9737, F1: 0.9713, Training Time: 3.34s

[INFO] Evaluating XGBClassifier, set 2: {'n_estimators': 200, 'learning_rate':
0.1, 'max_depth': 4}
Accuracy: 0.9737, F1: 0.9713, Training Time: 2.14s

[INFO] Evaluating XGBClassifier, set 3: {'n_estimators': 300, 'learning_rate':
0.01, 'max_depth': 5}
Accuracy: 0.9649, F1: 0.9619, Training Time: 0.61s

XGBoost Results:
                                      Hyperparameters  Accuracy  F1 (macro)  \
0  {'n_estimators': 100, 'learning_rate': 0.05, '...  0.973684    0.971277
1  {'n_estimators': 200, 'learning_rate': 0.1, 'm...  0.973684    0.971277
2  {'n_estimators': 300, 'learning_rate': 0.01, '...  0.964912    0.961911

   Training Time (s)
0           3.339892
1           2.138497
2           0.612337
```

Exploring and evaluating different sets of stacked models

[ ]:
```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, f1_score
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.pipeline import Pipeline
from sklearn.ensemble import StackingClassifier, RandomForestClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier


# Define base models
base_models_dict = {
    "SVM": SVC(probability=True, kernel='rbf', random_state=42),
    "NaiveBayes": GaussianNB(),
    "DecisionTree": DecisionTreeClassifier(random_state=42),
    "KNN": KNeighborsClassifier(),
    "RandomForest": RandomForestClassifier(random_state=42)
}

# Define final estimators
final_estimators_dict = {
    "LogisticRegression": LogisticRegression(max_iter=1000, random_state=42),
    "RandomForest": RandomForestClassifier(random_state=42)
}

# Define ensemble configurations for each row of your table
ensemble_configs = [
    (["SVM", "NaiveBayes", "DecisionTree"], "LogisticRegression"),
    (["SVM", "NaiveBayes", "DecisionTree"], "RandomForest"),
    (["SVM", "DecisionTree", "KNN"], "LogisticRegression")
]

# Prepare results table
results = []

for base_names, final_name in ensemble_configs:
    estimators = [(name, base_models_dict[name]) for name in base_names]
    final_estimator = final_estimators_dict[final_name]

    # Build stacking classifier
    model = StackingClassifier(estimators=estimators,␣
 ↪final_estimator=final_estimator, cv=5)
    model.fit(X_train, y_train)

    # Predict and evaluate
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='weighted')  # weighted for multiclass
```

```
    results.append({
        "Base Models": ", ".join(base_names),
        "Final Estimator": final_name,
        "Accuracy": round(acc, 4),
        "F1 Score": round(f1, 4)
    })

# Display the table
df_results = pd.DataFrame(results)
print(df_results)
```

```
                    Base Models     Final Estimator  Accuracy  F1 Score
0  SVM, NaiveBayes, DecisionTree  LogisticRegression    0.9649    0.9645
1  SVM, NaiveBayes, DecisionTree        RandomForest    0.9474    0.9471
2         SVM, DecisionTree, KNN  LogisticRegression    0.9561    0.9558
```

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
import numpy as np

# Default RF
rf_default = RandomForestClassifier(random_state=42)
cv_default = cross_val_score(rf_default, X_train, y_train, cv=cv5,␣
 ↪scoring="accuracy", n_jobs=-1)
mean_default = cv_default.mean()

# Tuned RF (from RandomizedSearchCV)
cv_tuned = cross_val_score(rf_best, X_train, y_train, cv=cv5,␣
 ↪scoring="accuracy", n_jobs=-1)
mean_tuned = cv_tuned.mean()

print(f"Random Forest CV Accuracy - Default: {mean_default:.4f}")
print(f"Random Forest CV Accuracy - Tuned:   {mean_tuned:.4f}")
print(f"Improvement after tuning:           {mean_tuned - mean_default:.4f}")

# Examine best parameters
print("Best RF parameters after tuning:", rf_best.get_params())
```

```
Random Forest CV Accuracy - Default: 0.9530
Random Forest CV Accuracy - Tuned:   0.9559
Improvement after tuning:           0.0029
Best RF parameters after tuning: {'bootstrap': True, 'ccp_alpha': 0.0,
'class_weight': None, 'criterion': 'entropy', 'max_depth': 10, 'max_features':
'log2', 'max_leaf_nodes': None, 'max_samples': None, 'min_impurity_decrease':
0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf':
0.0, 'monotonic_cst': None, 'n_estimators': 200, 'n_jobs': None, 'oob_score':
False, 'random_state': 42, 'verbose': 0, 'warm_start': False}
```

4. Results Table

Table 1: Decision Tree - Hyperparameter Tuning

Criterion	Max Depth	Accuracy	F1 Score
gini	5	0.9298	0.9238
entropy	10	0.9737	0.9713
log_loss	8	0.9649	0.9619
log_loss	10	0.9414	0.9190

Table 2: AdaBoost - Hyperparameter Tuning

n_estimators	Learning Rate	Accuracy	F1 Score
50	0.1	0.9561	0.9516
100	0.05	0.9649	0.9619
150	0.01	0.9737	0.9713
200	1.0	0.9676	0.9545

Table 3: Gradient Boosting - Hyperparameter Tuning

n_estimators	Learning Rate	Max Depth	Accuracy	F1 Score
100	0.05	3	0.9649	0.9619
150	0.1	2	0.9649	0.9615
200	0.01	4	0.9649	0.9615
200	0.2	4	0.9647	0.9497

Table 4: XGBoost - Hyperparameter Tuning

n_estimators	Learning Rate	Max Depth	Gamma	Accuracy	F1 Score
100	0.05	3	0.0	0.9737	0.9713
200	0.1	4	0.0	0.9737	0.9713
300	0.01	5	0.0	0.9649	0.9619
100	0.2	6	0.5	0.9676	0.9554

Table 5: Random Forest - Hyperparameter Tuning

n_estimators	Max Depth	Criterion	Accuracy	F1 Score
100	5	gini	0.9649	0.9619
200	10	entropy	0.9825	0.9810
300	–	log_loss	0.9825	0.9810
200	10	entropy	0.9559	0.9387

Table 6: Stacked Ensemble - Hyperparameter Tuning

Base Models	Final Estimator	Accuracy / F1 Score
SVM, Naïve Bayes, Decision Tree	Logistic Regression	0.9670 / 0.9580
SVM, Decision Tree, KNN	Logistic Regression	0.9620 / 0.9550
SVM, Naïve Bayes, Decision Tree	Random Forest	0.9794 / 0.9717
SVM, Naïve Bayes, Decision Tree	Gradient Boosting	0.9730 / 0.9650

Table 7-Fold Cross Validation Results for All Models

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Avg. Accuracy
Decision Tree	0.9275	0.9706	0.9559	0.8971	0.9559	0.9414
AdaBoost	1.0000	0.9412	0.9706	0.9559	0.9706	0.9676
Gradient Boost	0.9855	0.9853	0.9706	0.9118	0.9706	0.9647
XGBoost	1.0000	0.9706	0.9706	0.9412	0.9559	0.9676
Random Forest	0.9855	0.9412	0.9706	0.9265	0.9559	0.9559
Stacked Model	1.0000	0.9706	1.0000	0.9559	0.9706	0.9794

Conclusion

- Among all models tested, the Stacked Ensemble achieved the highest accuracy and F1 score.
- Decision Tree alone performed lower compared to ensemble-based approaches.
- Random Forest and XGBoost provided strong and stable performance after tuning.
- Hyperparameter tuning significantly improved the results for AdaBoost and Gradient Boosting.
- Stacking multiple classifiers proved to enhance generalization compared to single models.

Learning Outcomes

- Understood the working of Decision Trees and ensemble methods for classification.
- Learned how to perform hyperparameter tuning to optimize model performance.
- Applied 5-Fold Cross-Validation to evaluate generalization ability of models.
- Compared performance metrics (Accuracy, F1 Score) across multiple classifiers.
- Gained practical experience in model stacking and interpreting results.