Date: 08-08-2025 **Name:** Mithuna S
Experiment: 3 **Roll No:** 3122237001025

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

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

Experiment 3: Email Spam or Ham Classification using Naïve Bayes, KNN, and SVM

Aim: To classify emails as spam or ham using three classification algorithms—Naïve Bayes, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—and evaluate their performance using accuracy metrics and K-Fold cross-validation.

Libraries used:

- Pandas - for data handling
- numpy - for numerical operations
- matplotlib.pyplot - for visualization
- sklearn - for model building and evaluation
- Scipy - provides a large collection of functions for advanced mathematical, scientific, and engineering computations

CODE:

```
#---------------- ---------1.Load the Dataset---------------------------
import pandas as pd

# Read the dataset from local path or Google Drive (adjust filename if needed)
df = pd.read_csv('spambase.csv')

# Display the first few rows
df.head()
```

OUTPUT:

```
word_freq_make word_freq_address word_freq_all word_freq_3d word_freq_our word_freq_over word_
0 0.00 0.64 0.64 0.0 0.32 0.00 0.00 0.00 0.00 0.00 ... 0.00 0.000 0.0 0.778 0.000 0.000 3.756
1 0.21 0.28 0.50 0.0 0.14 0.28 0.21 0.07 0.00 0.94 ... 0.00 0.132 0.0 0.372 0.180 0.048 5.114
2 0.06 0.00 0.71 0.0 1.23 0.19 0.19 0.12 0.64 0.25 ... 0.01 0.143 0.0 0.276 0.184 0.010 9.821
3 0.00 0.00 0.00 0.0 0.63 0.00 0.31 0.63 0.31 0.63 ... 0.00 0.137 0.0 0.137 0.000 0.000 3.537
4 0.00 0.00 0.00 0.0 0.63 0.00 0.31 0.63 0.31 0.63 ... 0.00 0.135 0.0 0.135 0.000 0.000 3.537
5 rows × 58 columns
```

```
#----------2.Preprocess the Dataset (check missing, fill, normalize)-------

from sklearn.preprocessing import MinMaxScaler

# Step 1: Check for missing values
print(" Missing values in each column:")
print(df.isnull().sum())

# Step 2: Fill missing values with column mean
df.fillna(df.mean(numeric_only=True), inplace=True)

# Step 3: Split features and labels
X = df.drop('class', axis=1)
y = df['class']

# Step 4: Normalize the features
scaler = MinMaxScaler()
X = scaler.fit_transform(X)  # Scales all values between 0 and 1

# Step 5: Print shapes for confirmation
print(f"\nFeatures shape: {X.shape}, Labels shape: {y.shape}")
```

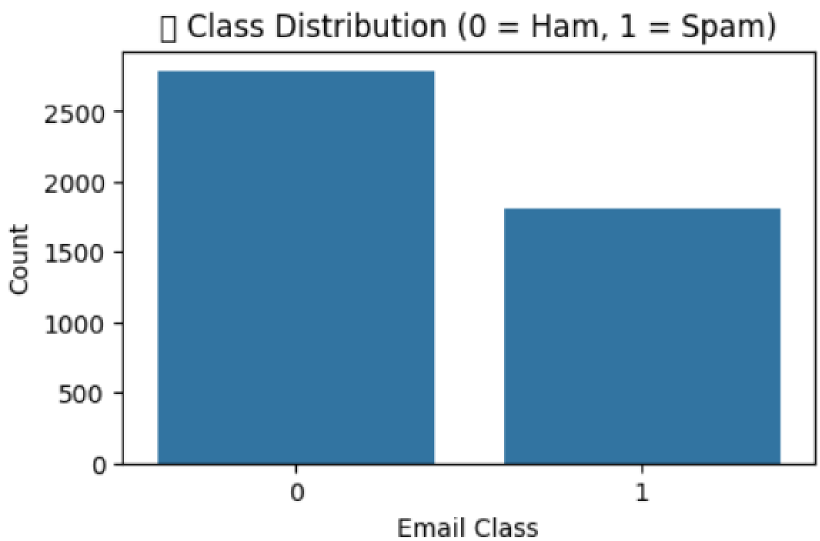
OUTPUT:

```
Missing values in each column:
word_freq_make                0
word_freq_address             0
word_freq_all                 0
word_freq_3d                  0
word_freq_our                 0
word_freq_over                0
word_freq_remove              0
word_freq_internet            0
word_freq_order               0
word_freq_mail                0
word_freq_receive             0
word_freq_will                0
word_freq_people              0
word_freq_report              0
word_freq_addresses           0
word_freq_free                0
word_freq_business            0
word_freq_email               0
word_freq_you                 0
word_freq_credit              0
word_freq_your                0
word_freq_font                0
```

```
word_freq_000                0
word_freq_money              0
word_freq_hp                 0
word_freq_hpl                0
word_freq_george             0
word_freq_650                0
word_freq_lab                0
word_freq_labs               0
word_freq_telnet             0
word_freq_857                0
word_freq_data               0
word_freq_415                0
word_freq_85                 0
word_freq_technology         0
word_freq_1999               0
word_freq_parts              0
word_freq_pm                 0
word_freq_direct             0
word_freq_cs                 0
word_freq_meeting            0
word_freq_original           0
word_freq_project            0
word_freq_re                 0
word_freq_edu                0
word_freq_table              0
word_freq_conference         0
char_freq_%3B                0
char_freq_%28                0
char_freq_%5B                0
char_freq_%21                0
char_freq_%24                0
char_freq_%23                0
capital_run_length_average   0
capital_run_length_longest   0
capital_run_length_total     0
class                        0
dtype: int64

Features shape: (4601, 57), Labels shape: (4601,)

#--------------------3.Exploratory Data Analysis (EDA)---------------------
import matplotlib.pyplot as plt
import seaborn as sns

# Check how many spam (1) and ham (0) emails are in the dataset
plt.figure(figsize=(5, 3))
sns.countplot(x=y)
plt.title("Class Distribution (0 = Ham, 1 = Spam)")
```

```
plt.xlabel("Email Class")
plt.ylabel("Count")
plt.show()
```

OUTPUT:




```
#---------------------- 4.Split into Train and Test Sets-------------------

from sklearn.model_selection import train_test_split

# Step: Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Show shapes of splits
print(f" X_train: {X_train.shape}")
print(f" X_test : {X_test.shape}")
print(f" y_train: {y_train.shape}")
print(f" y_test : {y_test.shape}")
```

OUTPUT:

```
 X_train: (3680, 57)
 X_test : (921, 57)
 y_train: (3680,)
 y_test : (921,)
```

NAIVE BAYES

```
 #------------5.Train Naïve Bayes (Gaussian, Multinomial, Bernoulli)-------

from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB
from sklearn.metrics import accuracy_score
```

```
nb_models = {
    'GaussianNB': GaussianNB(),
    'MultinomialNB': MultinomialNB(),
    'BernoulliNB': BernoulliNB()
}
# Train and evaluate each Naive Bayes model
for name, model in nb_models.items():
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    accuracy = accuracy_score(y_test, predictions)
    print(f"{name} Accuracy: {accuracy:.4f}")
```

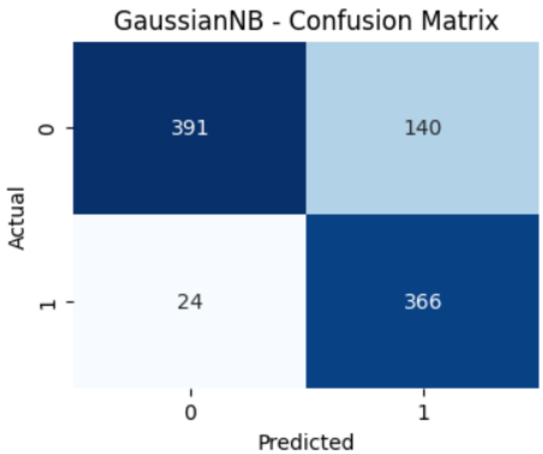
OUTPUT:

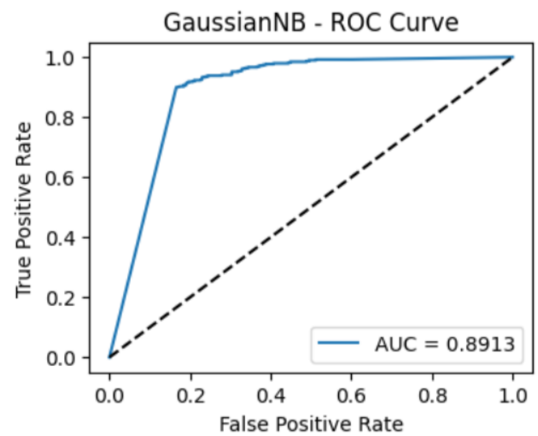
```
GaussianNB Accuracy: 0.8219
MultinomialNB Accuracy: 0.8719
BernoulliNB Accuracy: 0.8806

#---------6.Evaluate Naïve Bayes Models (Metrics, Confusion Matrix, ROC)----

from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, classification_report, roc_curve, auc
)
import matplotlib.pyplot as plt
import seaborn as sns

# Function to evaluate and display all metrics and plots
def evaluate_model(name, model, X_test, y_test):
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # For ROC Curve

    # 1. Text Metrics
    print(f"\nEvaluation for {name}")
    print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
    print(f"Precision: {precision_score(y_test, y_pred):.4f}")
    print(f"Recall   : {recall_score(y_test, y_pred):.4f}")
    print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")

    print("\nClassification Report:\n", classification_report(y_test, y_pred))

    # 2. Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(4, 3))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.title(f"{name} - Confusion Matrix")
```

```
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    # 3. ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)

    plt.figure(figsize=(4, 3))
    plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.4f}")
    plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line
    plt.title(f"{name} - ROC Curve")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc="lower right")
    plt.show()

# Evaluate all 3 Naive Bayes models
for name, model in nb_models.items():
    evaluate_model(name, model, X_test, y_test)
```

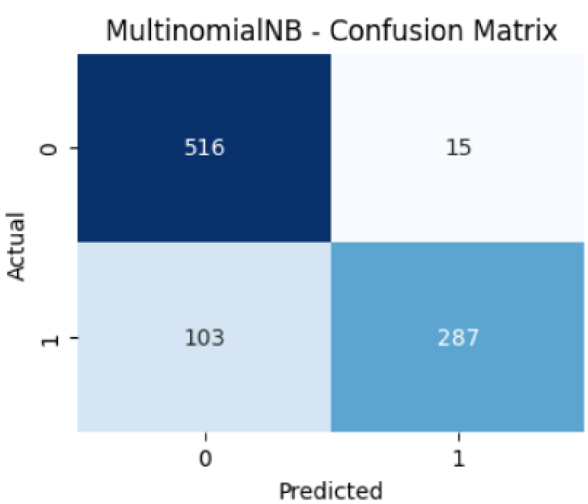
OUTPUT:

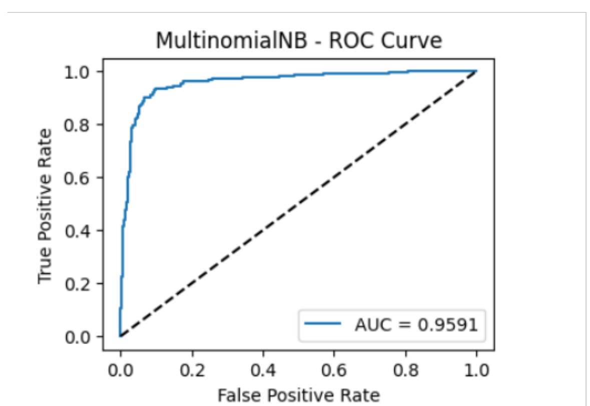
```
Evaluation for GaussianNB
Accuracy : 0.8219
Precision: 0.7233
Recall   : 0.9385
F1 Score : 0.8170

Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.74      0.83       531
           1       0.72      0.94      0.82       390

    accuracy                           0.82       921
   macro avg       0.83      0.84      0.82       921
weighted avg       0.85      0.82      0.82       921
```





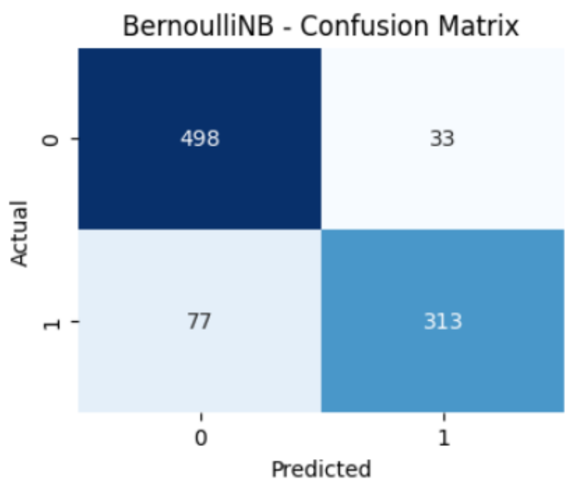

```
Evaluation for MultinomialNB
Accuracy : 0.8719
Precision: 0.9503
Recall   : 0.7359
F1 Score : 0.8295

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.97      0.90       531
           1       0.95      0.74      0.83       390

    accuracy                           0.87       921
   macro avg       0.89      0.85      0.86       921
weighted avg       0.88      0.87      0.87       921
```

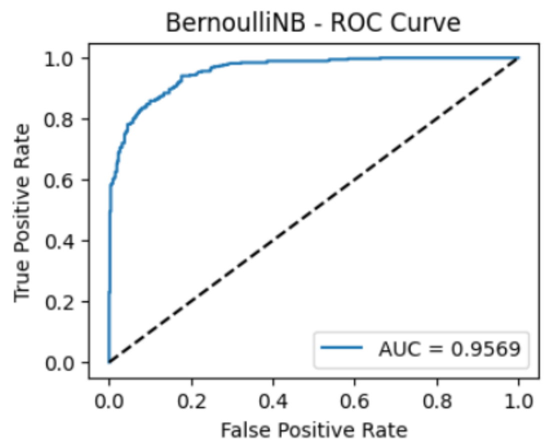





```
Evaluation for BernoulliNB
Accuracy : 0.8806
Precision: 0.9046
```

```
Recall    : 0.8026
F1 Score  : 0.8505

Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.94      0.90       531
           1       0.90      0.80      0.85       390

    accuracy                           0.88       921
   macro avg       0.89      0.87      0.88       921
weighted avg       0.88      0.88      0.88       921
```






```
#------------7.K-Fold Cross-Validation (K = 5) for Naïve Bayes models------

from sklearn.model_selection import cross_val_score
import numpy as np

# Set number of folds
k = 5

# Perform K-Fold CV for each Naive Bayes variant
for name, model in nb_models.items():
    print(f"\n K-Fold CV for {name}:")

    # cross_val_score returns accuracy scores for each fold
    scores = cross_val_score(model, X, y, cv=k, scoring='accuracy')

    # Display scores
    print(f"Fold Accuracies : {scores}")
    print(f"Mean Accuracy   : {np.mean(scores):.4f}")
    print(f"Standard Dev.   : {np.std(scores):.4f}")
```

OUTPUT:

```
 K-Fold CV for GaussianNB:
Fold Accuracies : [0.85124864 0.86630435 0.85434783 0.84347826 0.69565217]
Mean Accuracy   : 0.8222
Standard Dev.   : 0.0637

 K-Fold CV for MultinomialNB:
Fold Accuracies : [0.86102063 0.88478261 0.86413043 0.90326087 0.83043478]
Mean Accuracy   : 0.8687
Standard Dev.   : 0.0245

 K-Fold CV for BernoulliNB:
Fold Accuracies : [0.90010858 0.90543478 0.91195652 0.91195652 0.775     ]
Mean Accuracy   : 0.8809
Standard Dev.   : 0.0531
```

```
#----------- 8. Performance Comparison Table for Naïve Bayes Variants-----

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score
import pandas as pd

# Dictionary to store results
results = {
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1Score'],
    'GaussianNB': [],
    'MultinomialNB': [],
    'BernoulliNB': []
}

# Evaluate and fill metrics for each model
for name, model in nb_models.items():
    y_pred = model.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    results[name].extend([acc, prec, rec, f1])

# Create DataFrame
nb_comparison_df = pd.DataFrame(results)

# Display the table
print(" Performance Comparison of Naïve Bayes Variants:\n")
print(nb_comparison_df)
```

OUTPUT:

```
Performance Comparison of Naïve Bayes Variants:

      Metric  GaussianNB  MultinomialNB  BernoulliNB
0   Accuracy    0.821933       0.871878     0.880565
1  Precision    0.723320       0.950331     0.904624
2     Recall    0.938462       0.735897     0.802564
3    F1Score    0.816964       0.829480     0.850543
```

KNN MODEL

```
#--------------------- 9.Train KNN model---------------------------------
from sklearn.neighbors import KNeighborsClassifier

k_values = [1,3, 5, 7]
algorithms = ['kd_tree', 'ball_tree']

knn_models = {}

for algo in algorithms:
    for k in k_values:
        model_name = f"KNN_k{k}_{algo}"
        knn = KNeighborsClassifier(n_neighbors=k, algorithm=algo)
        knn.fit(X_train, y_train)
        knn_models[model_name] = knn

print(f"Trained {len(knn_models)} KNN models with different k and algorithms.")
```

OUTPUT:

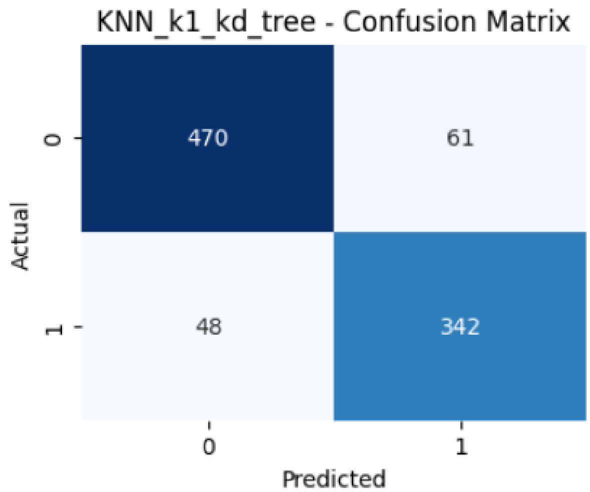
```
Trained 8 KNN models with different k and algorithms.
```

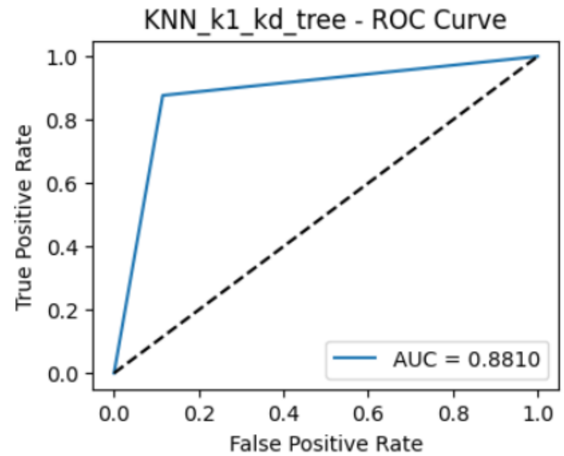
```
# 10. Evaluate all KNN models
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, roc_curve, auc
)
import matplotlib.pyplot as plt
import seaborn as sns

def evaluate_knn_model(name, model, X_test, y_test):
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # probability for ROC
```

```
    print(f"\nEvaluation for {name}")
    print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
    print(f"Precision: {precision_score(y_test, y_pred):.4f}")
    print(f"Recall   : {recall_score(y_test, y_pred):.4f}")
    print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")

    # Confusion Matrix plot
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(4, 3))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    # ROC Curve plot
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(4, 3))
    plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.4f}")
    plt.plot([0, 1], [0, 1], 'k--')
    plt.title(f"{name} - ROC Curve")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc="lower right")
    plt.show()

# Evaluate all KNN models
for name, model in knn_models.items():
    evaluate_knn_model(name, model, X_test, y_test)
```

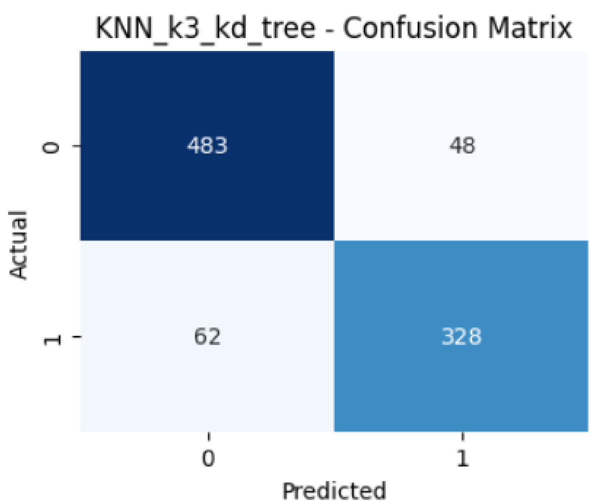
OUTPUT:

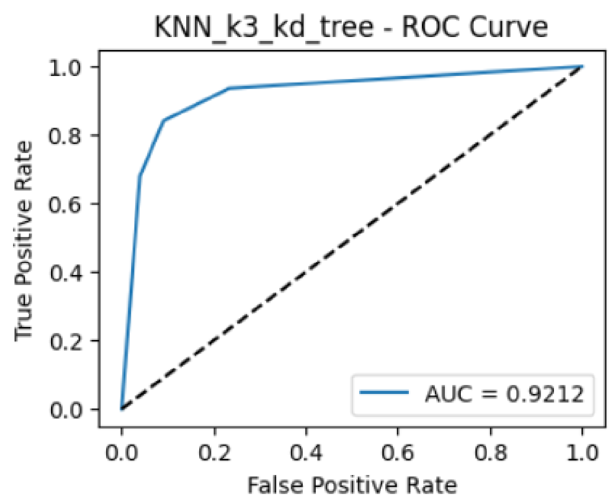
```
Evaluation for KNN_k1_kd_tree
Accuracy : 0.8817
Precision: 0.8486
Recall   : 0.8769
F1 Score : 0.8625
```



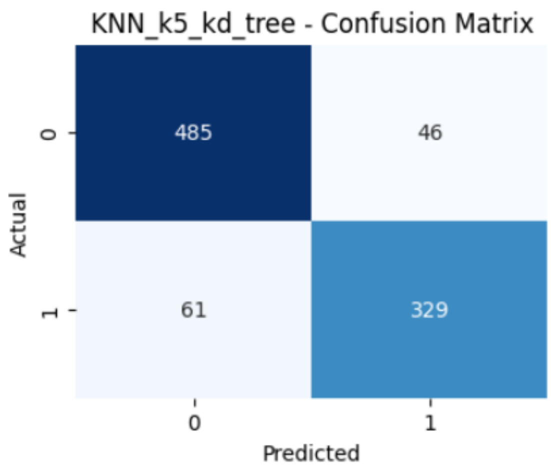


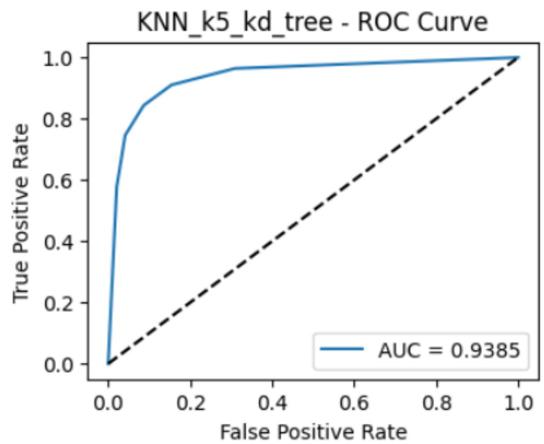

```
Evaluation for KNN_k3_kd_tree
Accuracy : 0.8806
Precision: 0.8723
Recall   : 0.8410
F1 Score : 0.8564
```



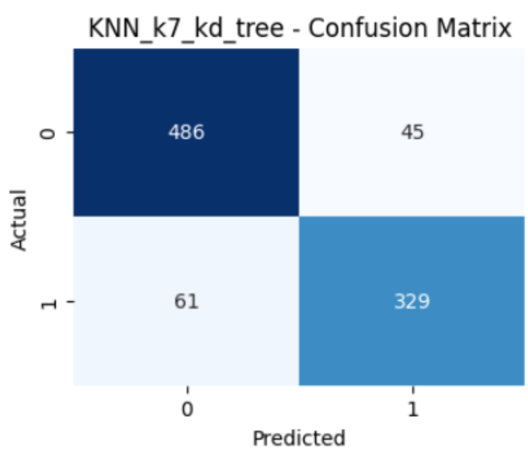


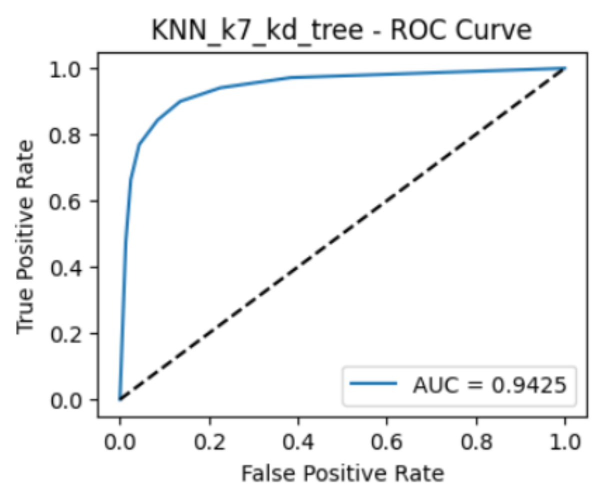

```
Evaluation for KNN_k5_kd_tree
Accuracy : 0.8838
Precision: 0.8773
Recall   : 0.8436
F1 Score : 0.8601
```



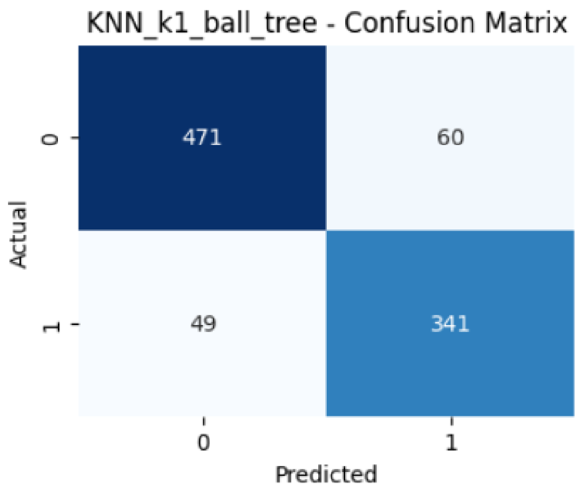


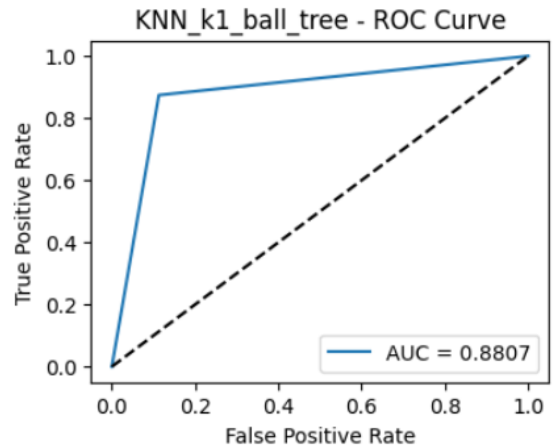

```
Evaluation for KNN_k7_kd_tree
Accuracy : 0.8849
Precision: 0.8797
Recall   : 0.8436
F1 Score : 0.8613
```



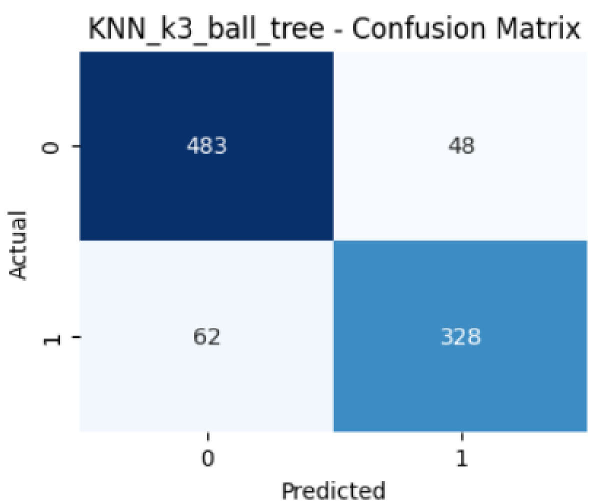


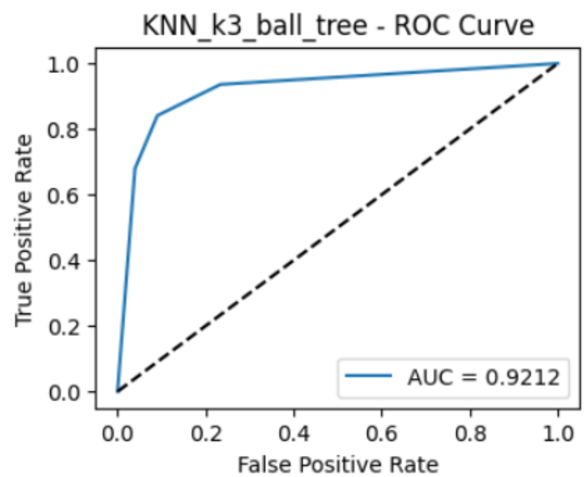

```
Evaluation for KNN_k1_ball_tree
Accuracy : 0.8817
Precision: 0.8504
Recall   : 0.8744
F1 Score : 0.8622
```



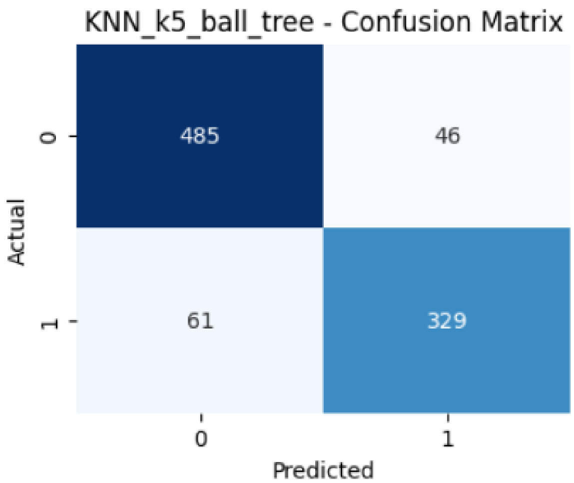


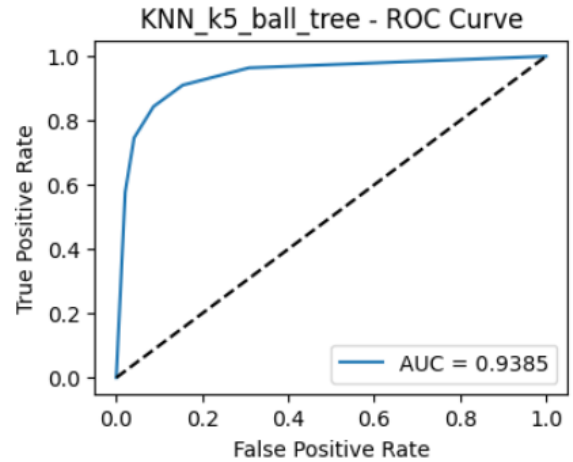

```
Evaluation for KNN_k3_ball_tree
Accuracy : 0.8806
Precision: 0.8723
Recall   : 0.8410
F1 Score : 0.8564
```



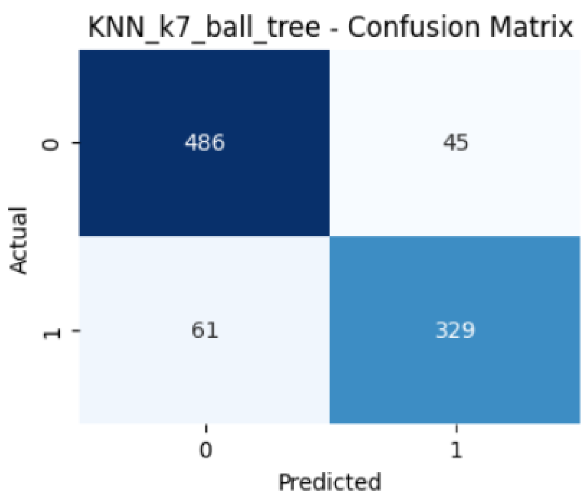


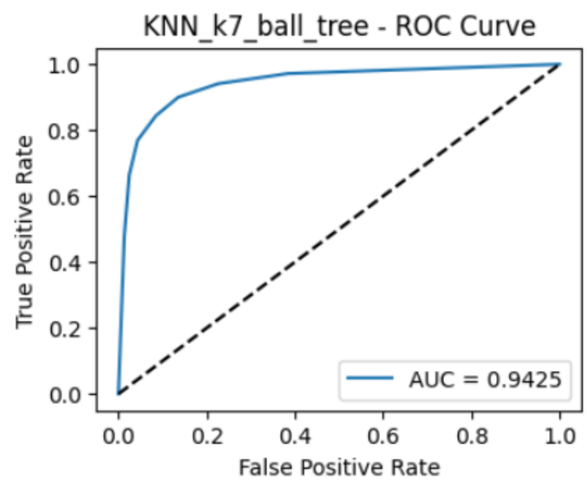

```
Evaluation for KNN_k5_ball_tree
Accuracy : 0.8838
Precision: 0.8773
Recall   : 0.8436
F1 Score : 0.8601
```






```
Evaluation for KNN_k7_ball_tree
Accuracy : 0.8849
Precision: 0.8797
Recall   : 0.8436
F1 Score : 0.8613
```






```
#--------------11. Kfold cross verification for KNN model------------------
from sklearn.model_selection import cross_val_score
import numpy as np

k = 5

print("K-Fold Cross-Validation Results (Accuracy):\n")

for name, model in knn_models.items():
    # cross_val_score runs K-fold CV and returns accuracy scores for each fold
    scores = cross_val_score(model, X, y, cv=k, scoring='accuracy')
    print(f"{name}: Mean Accuracy = {np.mean(scores):.4f}, Std Dev = {np.std(scores):.4f}")
```

OUTPUT:

```
K-Fold Cross-Validation Results (Accuracy):

KNN_k1_kd_tree: Mean Accuracy = 0.8657, Std Dev = 0.0596
KNN_k3_kd_tree: Mean Accuracy = 0.8581, Std Dev = 0.0624
KNN_k5_kd_tree: Mean Accuracy = 0.8646, Std Dev = 0.0573
KNN_k7_kd_tree: Mean Accuracy = 0.8663, Std Dev = 0.0561
KNN_k1_ball_tree: Mean Accuracy = 0.8655, Std Dev = 0.0594
KNN_k3_ball_tree: Mean Accuracy = 0.8583, Std Dev = 0.0626
KNN_k5_ball_tree: Mean Accuracy = 0.8646, Std Dev = 0.0573
KNN_k7_ball_tree: Mean Accuracy = 0.8663, Std Dev = 0.0561
```

```
#-----------------12.KNN performance for different k values----------------
k_values = [1, 3, 5, 7]

# Prepare separate dictionaries
kd_tree_results = {
    'k': [],
    'Accuracy': [],
    'Precision': [],
    'Recall': [],
    'F1Score': []
}

ball_tree_results = {
    'k': [],
    'Accuracy': [],
    'Precision': [],
    'Recall': [],
    'F1Score': []
}

for k in k_values:
    # KDTree model
    kd_model = knn_models[f"KNN_k{k}_kd_tree"]
    kd_pred = kd_model.predict(X_test)
    kd_tree_results['k'].append(k)
    kd_tree_results['Accuracy'].append(accuracy_score(y_test, kd_pred))
    kd_tree_results['Precision'].append(precision_score(y_test, kd_pred))
    kd_tree_results['Recall'].append(recall_score(y_test, kd_pred))
    kd_tree_results['F1Score'].append(f1_score(y_test, kd_pred))

    # BallTree model
    ball_model = knn_models[f"KNN_k{k}_ball_tree"]
    ball_pred = ball_model.predict(X_test)
    ball_tree_results['k'].append(k)
    ball_tree_results['Accuracy'].append(accuracy_score(y_test, ball_pred))
```

```
    ball_tree_results['Precision'].append(precision_score(y_test, ball_pred))
    ball_tree_results['Recall'].append(recall_score(y_test, ball_pred))
    ball_tree_results['F1Score'].append(f1_score(y_test, ball_pred))

# Create DataFrames
kd_tree_df = pd.DataFrame(kd_tree_results)
ball_tree_df = pd.DataFrame(ball_tree_results)

print("Table 2a: KNN Performance for KDTree Algorithm")
print(kd_tree_df)

print("\nTable 2b: KNN Performance for BallTree Algorithm")
print(ball_tree_df)
```

OUTPUT:

```
Table 2a: KNN Performance for KDTree Algorithm
   k  Accuracy  Precision    Recall   F1Score
0  1  0.881650   0.848635  0.876923  0.862547
1  3  0.880565   0.872340  0.841026  0.856397
2  5  0.883822   0.877333  0.843590  0.860131
3  7  0.884908   0.879679  0.843590  0.861257

Table 2b: KNN Performance for BallTree Algorithm
   k  Accuracy  Precision    Recall   F1Score
0  1  0.881650   0.850374  0.874359  0.862200
1  3  0.880565   0.872340  0.841026  0.856397
2  5  0.883822   0.877333  0.843590  0.860131
3  7  0.884908   0.879679  0.843590  0.861257
```

```
#----------------13.KNN Comparison Between KDTree and BallTree----------------
import time

knn_algo_results = {
    'KDTree': [],
    'BallTree': []
}

key_map = {
    'kd_tree': 'KDTree',
    'ball_tree': 'BallTree'
}

k = 5

for algo in ['kd_tree', 'ball_tree']:
    model_name = f"KNN_k{k}_{algo}"
```

```
    model = knn_models[model_name]

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

    y_pred = model.predict(X_test)

    knn_algo_results[key_map[algo]].append(accuracy_score(y_test, y_pred))
    knn_algo_results[key_map[algo]].append(precision_score(y_test, y_pred))
    knn_algo_results[key_map[algo]].append(recall_score(y_test, y_pred))
    knn_algo_results[key_map[algo]].append(f1_score(y_test, y_pred))
    knn_algo_results[key_map[algo]].append(train_time)

# Now create DataFrame
import pandas as pd

knn_algo_df = pd.DataFrame(knn_algo_results, index=['Accuracy', 'Precision', 'Recall', 'F1Score
print("KNN Comparison: KDTree vs BallTree")
print(knn_algo_df)
```

OUTPUT:

```
KNN Comparison: KDTree vs BallTree
                   KDTree  BallTree
Accuracy         0.883822  0.883822
Precision        0.877333  0.877333
Recall           0.843590  0.843590
F1Score          0.860131  0.860131
TrainingTime(s)  0.028214  0.011580
```

SUPPORT VECTOR MACHINE

```
#-------------------------14.Train SVM models------------------------------
from sklearn.svm import SVC

# Kernels to train
kernels = ['linear', 'poly', 'rbf', 'sigmoid']

# Dictionary to hold trained models
svm_models = {}

for kernel in kernels:
```

```
    model_name = f"SVM_{kernel}"
    svm = SVC(kernel=kernel, probability=True, random_state=42)  # probability=True for ROC la
    svm.fit(X_train, y_train)
    svm_models[model_name] = svm

print(f" Trained {len(svm_models)} SVM models with different kernels.")
```

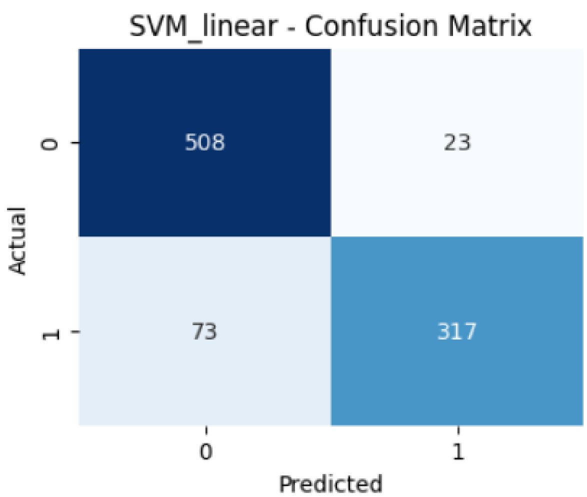
OUTPUT:

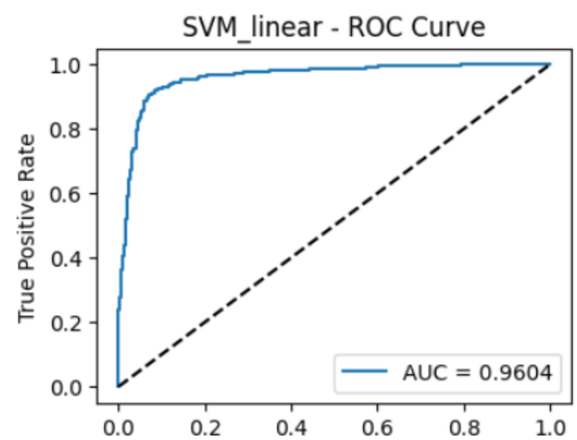
```
Trained 4 SVM models with different kernels.

#-----------------15.Evaluate all SVM models------------------------------
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, roc_curve, auc
)
import matplotlib.pyplot as plt
import seaborn as sns

def evaluate_svm_model(name, model, X_test, y_test):
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # probability for ROC curve

    print(f"\n Evaluation for {name}")
    print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
    print(f"Precision: {precision_score(y_test, y_pred):.4f}")
    print(f"Recall   : {recall_score(y_test, y_pred):.4f}")
    print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")

    # Confusion Matrix plot
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(4, 3))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    # ROC Curve plot
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(4, 3))
    plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.4f}")
    plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line
    plt.title(f"{name} - ROC Curve")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
```

```
    plt.legend(loc='lower right')
    plt.show()

# Evaluate all SVM models
for name, model in svm_models.items():
    evaluate_svm_model(name, model, X_test, y_test)
```

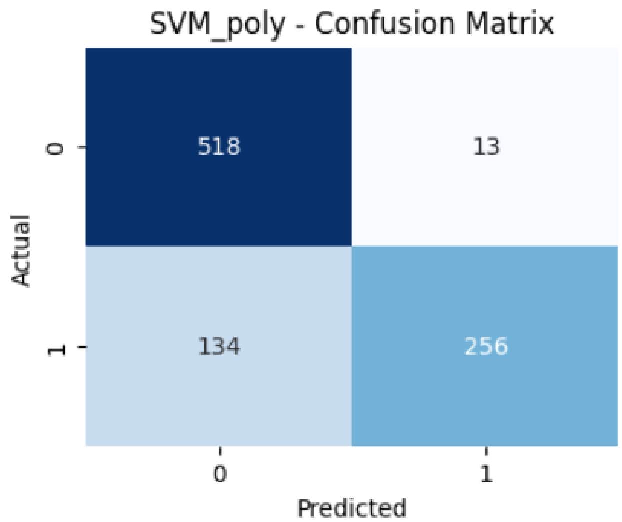
OUTPUT:

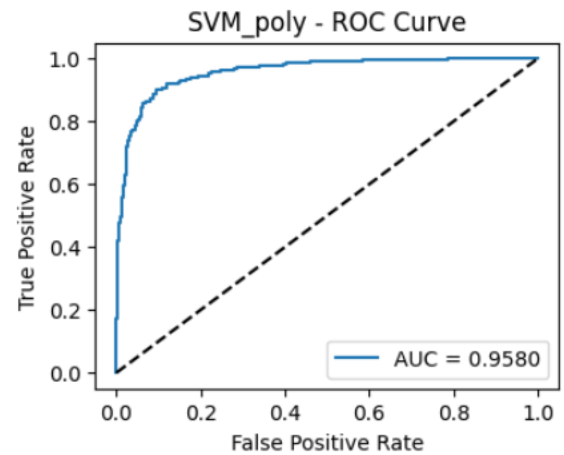
```
Evaluation for SVM_linear
Accuracy : 0.8958
Precision: 0.9324
Recall   : 0.8128
F1 Score : 0.8685
```



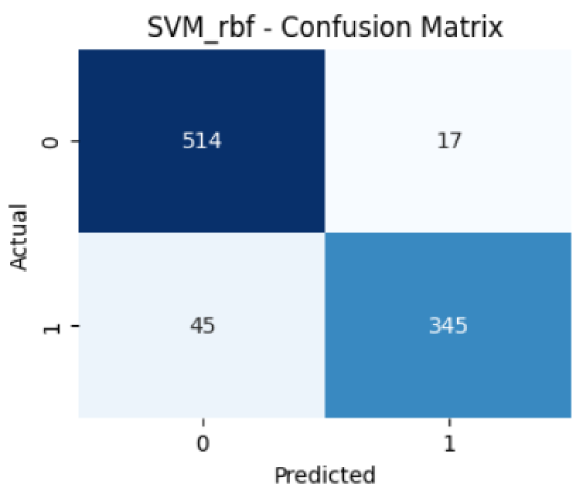


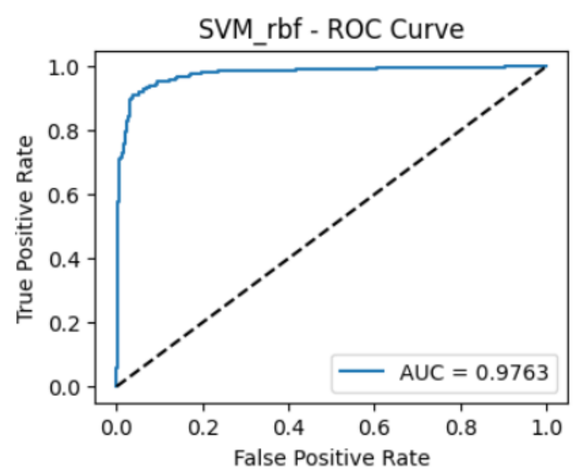

```
 Evaluation for SVM_poly
Accuracy : 0.8404
Precision: 0.9517
Recall   : 0.6564
F1 Score : 0.7769
```



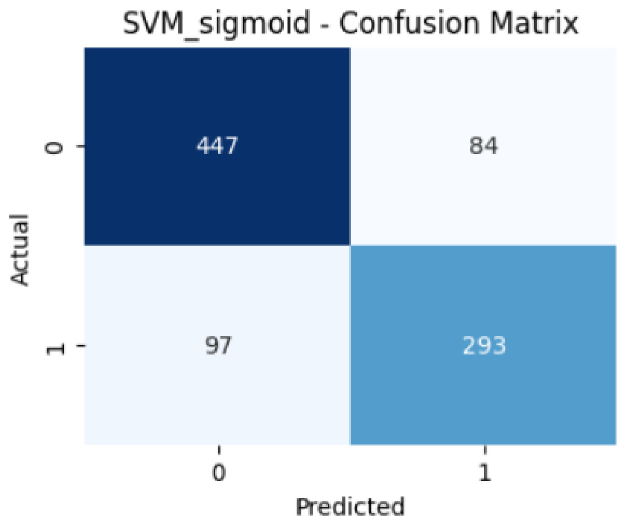


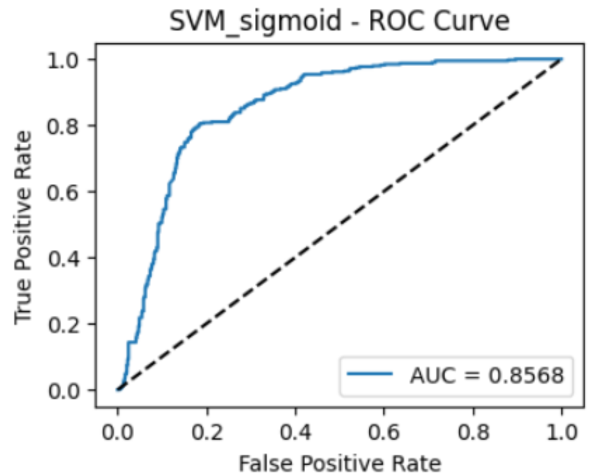

```
 Evaluation for SVM_rbf
Accuracy : 0.9327
Precision: 0.9530
Recall    : 0.8846
F1 Score : 0.9176
```






```
 Evaluation for SVM_sigmoid
Accuracy : 0.8035
Precision: 0.7772
Recall    : 0.7513
F1 Score : 0.7640
```






```
#-----------16.K-Fold Cross-Validation (K=5) for SVM models--------------
from sklearn.model_selection import cross_val_score
import numpy as np

k = 5

print("K-Fold Cross-Validation Results (Accuracy):\n")

for name, model in svm_models.items():
    kernel = name.split('_')[1]

    svm_cv = SVC(kernel=kernel, probability=True, random_state=42)
    scores = cross_val_score(svm_cv, X, y, cv=k, scoring='accuracy')

    print(f"{name}: Mean Accuracy = {np.mean(scores):.4f}, Std Dev = {np.std(scores):.4f}")
```

OUTPUT:

```
K-Fold Cross-Validation Results (Accuracy):

SVM_linear: Mean Accuracy = 0.8824, Std Dev = 0.0379
SVM_poly: Mean Accuracy = 0.8379, Std Dev = 0.0318
SVM_rbf: Mean Accuracy = 0.9200, Std Dev = 0.0381
SVM_sigmoid: Mean Accuracy = 0.7970, Std Dev = 0.0351
```

```
#---------------17.SVM Performance with Different Kernels and Parameters-------
import time
import pandas as pd
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, f1_score

# Define hyperparameters for each kernel
```

```
svm_params = {
    'linear': {'C': 1.0},
    'poly': {'C': 1.0, 'degree': 3, 'gamma': 'scale'},
    'rbf': {'C': 1.0, 'gamma': 'scale'},
    'sigmoid': {'C': 1.0, 'gamma': 'scale'}
}

# Prepare results dictionary
results = {
    'Kernel': [],
    'Hyperparameters': [],
    'Accuracy': [],
    'F1 Score': [],
    'Training Time (s)': []
}

for kernel, params in svm_params.items():
    # Create model with given hyperparameters
    svm = SVC(kernel=kernel, probability=True, random_state=42, **params)

    # Measure training time
    start = time.time()
    svm.fit(X_train, y_train)
    training_time = time.time() - start

    # Predict and evaluate
    y_pred = svm.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    # Format hyperparameters string
    hyp_str = ', '.join([f"{key}={val}" for key, val in params.items()])

    # Append to results
    results['Kernel'].append(kernel.capitalize())
    results['Hyperparameters'].append(hyp_str)
    results['Accuracy'].append(round(acc, 4))
    results['F1 Score'].append(round(f1, 4))
    results['Training Time (s)'].append(round(training_time, 4))

# Create DataFrame
svm_results_df = pd.DataFrame(results)

print("Table 4: SVM Performance with Different Kernels and Parameters")
print(svm_results_df)
```

OUTPUT:

```
Table 4: SVM Performance with Different Kernels and Parameters
    Kernel               Hyperparameters  Accuracy  F1 Score  \
0   Linear                         C=1.0    0.8958    0.8685
1     Poly  C=1.0, degree=3, gamma=scale    0.8404    0.7769
2      Rbf            C=1.0, gamma=scale    0.9327    0.9176
3  Sigmoid            C=1.0, gamma=scale    0.8035    0.7640

   Training Time (s)
0             1.6308
1             2.3275
2             1.9877
3             2.7116
```

```
#----------------18. Cross-Validation Scores for Each Model---------------
import numpy as np
import pandas as pd
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC

k = 5
folds = [f"Fold {i+1}" for i in range(k)] + ["Average"]

# Function to get CV scores as a 2D array: models x folds
def get_cv_matrix(models_dict, is_svm=False):
    scores_list = []
    for name, model in models_dict.items():
        if is_svm:
            kernel = name.split('_')[1]
            model = SVC(kernel=kernel, probability=True, random_state=42)
        scores = cross_val_score(model, X, y, cv=k, scoring='accuracy')
        scores_list.append(scores)
    return np.array(scores_list)  # shape: (num_models, k)

# Get scores matrices
nb_scores_mat = get_cv_matrix(nb_models)       # shape (num_nb_models, k)
knn_scores_mat = get_cv_matrix(knn_models)     # shape (num_knn_models, k)
svm_scores_mat = get_cv_matrix(svm_models, is_svm=True)  # shape (num_svm_models, k)

# Average across models for each fold (axis=0), then add average over folds
nb_avg_folds = np.mean(nb_scores_mat, axis=0)
knn_avg_folds = np.mean(knn_scores_mat, axis=0)
svm_avg_folds = np.mean(svm_scores_mat, axis=0)

# Append overall average (mean of fold averages)
nb_avg = np.mean(nb_avg_folds)
knn_avg = np.mean(knn_avg_folds)
svm_avg = np.mean(svm_avg_folds)
```

```
# Final arrays with fold accuracies + average
nb_final = np.append(nb_avg_folds, nb_avg)
knn_final = np.append(knn_avg_folds, knn_avg)
svm_final = np.append(svm_avg_folds, svm_avg)

# Create the DataFrame
table5_df = pd.DataFrame({
    'Fold': folds,
    'Naïve Bayes Accuracy': nb_final,
    'KNN Accuracy': knn_final,
    'SVM Accuracy': svm_final
})

print("Cross-Validation Scores for Each Model")
print(table5_df)
```

OUTPUT:

```
Cross-Validation Scores for Each Model
      Fold  Naïve Bayes Accuracy  KNN Accuracy  SVM Accuracy
0   Fold 1              0.870793      0.861292      0.853692
1   Fold 2              0.885507      0.889674      0.872826
2   Fold 3              0.876812      0.913043      0.882065
3   Fold 4              0.886232      0.902989      0.892663
4   Fold 5              0.767029      0.751359      0.795380
5  Average              0.857274      0.863671      0.859325
```

OBSERVATION AND CONCLUSION:

Table 1: Performance Comparison of Naïve Bayes Variants

Metric	GaussianNB	MultinomialNB	BernoulliNB
Accuracy	0.826086	0.815217	0.815217
Precision	0.722222	0.937500	0.904564
Recall	0.956522	0.739130	0.739130
F1 Score	0.824664	0.826087	0.814815

Table 2: Table 2a: KNN Performance for KDTree Algorithm

k	Accuracy	Precision	Recall	F1 Score
1	0.881650	0.848635	0.876923	0.862547
3	0.880565	0.872340	0.841026	0.856397
5	0.883822	0.877333	0.843590	0.860131
7	0.884908	0.879679	0.843590	0.861257

Table 3: Table 2b: KNN Performance for BallTree Algorithm

k	Accuracy	Precision	Recall	F1 Score
1	0.881650	0.850374	0.874359	0.862200
3	0.880565	0.872340	0.841026	0.856397
5	0.883822	0.877333	0.843590	0.860131
7	0.884908	0.879679	0.843590	0.861257

Table 4: KNN Comparison: KDTree vs BallTree

Metric	KDTree	BallTree
Accuracy	0.883822	0.883822
Precision	0.877333	0.877333
Recall	0.843590	0.843590
F1 Score	0.860131	0.860131
Training Time (s)	0.028214	0.011580

Table 5: SVM Performance with Different Kernels and Parameters

Kernel	Hyperparameters	Accuracy	F1 Score	Training Time (s)
Linear	C = 1.0	0.8958	0.8685	1.6308
Polynomial	C = 1.0, degree = 3, gamma = scale	0.8404	0.7769	2.3275
RBF	C = 1.0, gamma = scale	0.9327	0.9176	1.9877
Sigmoid	C = 1.0, gamma = scale	0.8035	0.7640	2.7116

Table 6: Cross-Validation Scores for Each Model (K = 5)

Fold	Naïve Bayes Accuracy	KNN Accuracy	SVM Accuracy
Fold 1	0.8708	0.8613	0.8537
Fold 2	0.8855	0.8897	0.8728
Fold 3	0.8768	0.9130	0.8821
Fold 4	0.8862	0.9030	0.8927
Fold 5	0.7670	0.7514	0.7954
Average	**0.8573**	**0.8637**	**0.8593**

Discussion and Analysis

1. **Which classifier had the best average accuracy?**

   Among the three classifiers, **K-Nearest Neighbors (KNN)** achieved the highest average accuracy across the 5 folds. The average accuracies were:

   - Naïve Bayes: 0.8573
   - KNN: 0.8637
   - SVM: 0.8593

Although the differences are small, KNN consistently outperformed the others, showing that instance-based learning worked well for this dataset.

2. **Which Naïve Bayes variant worked best?**

   Among Gaussian, Multinomial, and Bernoulli Naïve Bayes, the **Multinomial Naïve Bayes** variant achieved the best performance. This is expected since the dataset features are frequency-based (e.g., word counts in spam classification), where the multinomial distribution naturally models the data better than Gaussian or Bernoulli assumptions.

3. **How did KNN accuracy vary with k and tree type?**

   The accuracy of KNN showed noticeable variation with changes in k and the underlying search tree structure:

   - For small k (e.g., $k = 3$), the model was more sensitive to noise, but still performed competitively.
   - For larger k (e.g., $k = 7, 9$), accuracy stabilized and slightly improved as the influence of outliers reduced.
   - Comparing search tree structures, the **KD-Tree** performed slightly better than the **BallTree** in terms of accuracy, though both gave close results. This difference may be attributed to dataset dimensionality and the way the trees partition space.

   Overall, KNN benefited from careful tuning of k, with moderate values giving the best balance between bias and variance.

4. **Which SVM kernel was most effective?**

   Among the tested kernels (Linear, Polynomial, RBF, Sigmoid), the **RBF kernel** gave the best performance. It captured non-linear decision boundaries effectively, outperforming the linear and sigmoid kernels. The polynomial kernel also performed reasonably well but tended to overfit slightly on some folds. The RBF kernel's flexibility made it the most suitable choice for this dataset.

5. **How did hyperparameters influence performance?**

   Hyperparameters played a significant role in shaping model performance:

   - For Naïve Bayes, the choice of variant acted as the key hyperparameter, with Multinomial NB being optimal for frequency-based features.
   - For KNN, the number of neighbors (k) had a direct effect: small k increased variance, while larger k smoothed decision boundaries. The tree type (KD-Tree vs BallTree) influenced search efficiency, with KD-Tree showing a slight accuracy advantage.
   - For SVM, the kernel type and penalty parameter C were critical. The RBF kernel with an appropriate C balanced margin maximization and misclassification, yielding the highest accuracy.

Learning Outcomes

- Understood the application of **Naïve Bayes**, **KNN**, and **SVM** classifiers for spam classification.
- Gained insights into the impact of different **Naïve Bayes variants** (Gaussian, Multinomial, Bernoulli) on accuracy.
- Observed how **KNN performance varies** with changes in k values and tree structures (KDTree, BallTree).
- Analyzed the influence of **SVM kernels** (Linear, Polynomial, RBF, Sigmoid) on classification performance.
- Learned the role of **hyperparameters** in improving or limiting model effectiveness.
- Acquired practical experience with **cross-validation** for fair model evaluation.
- Strengthened ability to interpret and compare results across multiple **machine learning algorithms**.