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

1. Aim

To classify emails as spam or ham using Naïve Bayes, K-Nearest Neighbors, and Support Vector Machine, and evaluate their performance with accuracy, precision, recall, F1-score, and cross-validation.

2. Libraries Used

- **NumPy:** For numerical operations and array handling.
  - `np.mean()`, `np.std()`, `np.array()`
- **Pandas:** For dataset loading, cleaning, and preprocessing.
  - `pd.read_csv()`, `df.info()`, `df.describe()`, `df.isnull()`
- **Matplotlib & Seaborn:** For visualization of class distribution, feature trends, and confusion matrices.
  - `plt.plot()`, `plt.bar()`, `sns.heatmap()`
- **scikit-learn (sklearn):** For implementing models and evaluation metrics.
  - `naive_bayes.GaussianNB`, `naive_bayes.MultinomialNB`, `naive_bayes.BernoulliNB`
  - `neighbors.KNeighborsClassifier` with `kd_tree`, `ball_tree`
  - `svm.SVC` with kernels (linear, polynomial, rbf, sigmoid)
  - `train_test_split()`, `cross_val_score()`, `classification_report()`, `confusion_matrix()`
  - `accuracy_score()`, `precision_score()`, `recall_score()`, `f1_score()`

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3. Python Implementation

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

1. Import Datasets

[ ]:
```
import pandas as pd
import numpy as np

# --- Step 1: Load the Dataset ---
file_path = '/content/drive/MyDrive/spambase/spambase_csv.csv'  # Replace with your␣
 ↪file path
df = pd.read_csv(file_path)

# --- Step 2: Initial Dataset Summary ---
print(" Dataset Shape:", df.shape)
print("\n First 5 Rows:\n", df.head())
print("\n Summary Statistics:\n", df.describe(include='all'))
print("\n Column Info:")
df.info()

# --- Step 3: Missing Value Analysis ---
missing_counts = df.isnull().sum()
print("\n Missing Values per Column:\n", missing_counts[missing_counts > 0])

# --- Step 4: Imputation (Handling Missing Values) ---
for col in df.columns:
    if df[col].isnull().sum() > 0:
        if df[col].dtype == 'object':
            # Fill categorical columns with mode
```

```
            mode_value = df[col].mode()[0]
            df[col].fillna(mode_value, inplace=True)
            print(f"Filled missing values in '{col}' with mode: {mode_value}")
        else:
            # Fill numeric columns with median
            median_value = df[col].median()
            df[col].fillna(median_value, inplace=True)
            print(f"Filled missing values in '{col}' with median: {median_value}")

# --- Step 5: Final Check ---
print("\n Missing Values After Imputation:\n", df.isnull().sum().sum())

# (Optional) Save cleaned dataset
# df.to_csv('/content/drive/MyDrive/cleaned_dataset.csv', index=False)
```

```
 Dataset Shape: (4601, 58)

 First 5 Rows:
   word_freq_make  word_freq_address  word_freq_all  word_freq_3d  \
0            0.00               0.64           0.64           0.0
1            0.21               0.28           0.50           0.0
2            0.06               0.00           0.71           0.0
3            0.00               0.00           0.00           0.0
4            0.00               0.00           0.00           0.0

   word_freq_our  word_freq_over  word_freq_remove  word_freq_internet  \
0           0.32            0.00              0.00                0.00
1           0.14            0.28              0.21                0.07
2           1.23            0.19              0.19                0.12
3           0.63            0.00              0.31                0.63
4           0.63            0.00              0.31                0.63

   word_freq_order  word_freq_mail  ...  char_freq_%3B  char_freq_%28  \
0             0.00            0.00  ...           0.00          0.000
1             0.00            0.94  ...           0.00          0.132
2             0.64            0.25  ...           0.01          0.143
3             0.31            0.63  ...           0.00          0.137
4             0.31            0.63  ...           0.00          0.135

   char_freq_%5B  char_freq_%21  char_freq_%24  char_freq_%23  \
0            0.0          0.778          0.000          0.000
1            0.0          0.372          0.180          0.048
2            0.0          0.276          0.184          0.010
3            0.0          0.137          0.000          0.000
4            0.0          0.135          0.000          0.000

   capital_run_length_average  capital_run_length_longest  \
0                       3.756                          61
```

```
1                       5.114                           101
2                       9.821                           485
3                       3.537                            40
4                       3.537                            40

   capital_run_length_total  class
0                       278      1
1                      1028      1
2                      2259      1
3                       191      1
4                       191      1

[5 rows x 58 columns]

 Summary Statistics:
        word_freq_make  word_freq_address  word_freq_all  word_freq_3d  \
count     4601.000000        4601.000000    4601.000000   4601.000000   
mean         0.104553           0.213015       0.280656      0.065425   
std          0.305358           1.290575       0.504143      1.395151   
min          0.000000           0.000000       0.000000      0.000000   
25%          0.000000           0.000000       0.000000      0.000000   
50%          0.000000           0.000000       0.000000      0.000000   
75%          0.000000           0.000000       0.420000      0.000000   
max          4.540000          14.280000       5.100000     42.810000   

       word_freq_our  word_freq_over  word_freq_remove  word_freq_internet  \
count    4601.000000     4601.000000       4601.000000         4601.000000   
mean        0.312223        0.095901          0.114208            0.105295   
std         0.672513        0.273824          0.391441            0.401071   
min         0.000000        0.000000          0.000000            0.000000   
25%         0.000000        0.000000          0.000000            0.000000   
50%         0.000000        0.000000          0.000000            0.000000   
75%         0.380000        0.000000          0.000000            0.000000   
max        10.000000        5.880000          7.270000           11.110000   

       word_freq_order  word_freq_mail  ...  char_freq_%3B  char_freq_%28  \
count      4601.000000     4601.000000  ...    4601.000000    4601.000000   
mean          0.090067        0.239413  ...       0.038575       0.139030   
std           0.278616        0.644755  ...       0.243471       0.270355   
min           0.000000        0.000000  ...       0.000000       0.000000   
25%           0.000000        0.000000  ...       0.000000       0.000000   
50%           0.000000        0.000000  ...       0.000000       0.065000   
75%           0.000000        0.160000  ...       0.000000       0.188000   
max           5.260000       18.180000  ...       4.385000       9.752000   

       char_freq_%5B  char_freq_%21  char_freq_%24  char_freq_%23  \
count    4601.000000    4601.000000    4601.000000    4601.000000   
mean        0.016976       0.269071       0.075811       0.044238   
```

```
std         0.109394       0.815672       0.245882       0.429342
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.315000       0.052000       0.000000
max         4.081000      32.478000       6.003000      19.829000

       capital_run_length_average  capital_run_length_longest  \
count                 4601.000000                 4601.000000
mean                     5.191515                   52.172789
std                     31.729449                  194.891310
min                      1.000000                    1.000000
25%                      1.588000                    6.000000
50%                      2.276000                   15.000000
75%                      3.706000                   43.000000
max                   1102.500000                 9989.000000

       capital_run_length_total        class
count               4601.000000  4601.000000
mean                 283.289285     0.394045
std                  606.347851     0.488698
min                    1.000000     0.000000
25%                   35.000000     0.000000
50%                   95.000000     0.000000
75%                  266.000000     1.000000
max                15841.000000     1.000000

[8 rows x 58 columns]

 Column Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4601 entries, 0 to 4600
Data columns (total 58 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   word_freq_make              4601 non-null   float64
 1   word_freq_address           4601 non-null   float64
 2   word_freq_all               4601 non-null   float64
 3   word_freq_3d                4601 non-null   float64
 4   word_freq_our               4601 non-null   float64
 5   word_freq_over              4601 non-null   float64
 6   word_freq_remove            4601 non-null   float64
 7   word_freq_internet          4601 non-null   float64
 8   word_freq_order             4601 non-null   float64
 9   word_freq_mail              4601 non-null   float64
 10  word_freq_receive           4601 non-null   float64
 11  word_freq_will              4601 non-null   float64
 12  word_freq_people            4601 non-null   float64
```

```
 13  word_freq_report            4601 non-null   float64
 14  word_freq_addresses         4601 non-null   float64
 15  word_freq_free              4601 non-null   float64
 16  word_freq_business          4601 non-null   float64
 17  word_freq_email             4601 non-null   float64
 18  word_freq_you               4601 non-null   float64
 19  word_freq_credit            4601 non-null   float64
 20  word_freq_your              4601 non-null   float64
 21  word_freq_font              4601 non-null   float64
 22  word_freq_000               4601 non-null   float64
 23  word_freq_money             4601 non-null   float64
 24  word_freq_hp                4601 non-null   float64
 25  word_freq_hpl               4601 non-null   float64
 26  word_freq_george            4601 non-null   float64
 27  word_freq_650               4601 non-null   float64
 28  word_freq_lab               4601 non-null   float64
 29  word_freq_labs              4601 non-null   float64
 30  word_freq_telnet            4601 non-null   float64
 31  word_freq_857               4601 non-null   float64
 32  word_freq_data              4601 non-null   float64
 33  word_freq_415               4601 non-null   float64
 34  word_freq_85                4601 non-null   float64
 35  word_freq_technology        4601 non-null   float64
 36  word_freq_1999              4601 non-null   float64
 37  word_freq_parts             4601 non-null   float64
 38  word_freq_pm                4601 non-null   float64
 39  word_freq_direct            4601 non-null   float64
 40  word_freq_cs                4601 non-null   float64
 41  word_freq_meeting           4601 non-null   float64
 42  word_freq_original          4601 non-null   float64
 43  word_freq_project           4601 non-null   float64
 44  word_freq_re                4601 non-null   float64
 45  word_freq_edu               4601 non-null   float64
 46  word_freq_table             4601 non-null   float64
 47  word_freq_conference        4601 non-null   float64
 48  char_freq_%3B               4601 non-null   float64
 49  char_freq_%28               4601 non-null   float64
 50  char_freq_%5B               4601 non-null   float64
 51  char_freq_%21               4601 non-null   float64
 52  char_freq_%24               4601 non-null   float64
 53  char_freq_%23               4601 non-null   float64
 54  capital_run_length_average  4601 non-null   float64
 55  capital_run_length_longest  4601 non-null   int64
 56  capital_run_length_total    4601 non-null   int64
 57  class                       4601 non-null   int64
dtypes: float64(55), int64(3)
memory usage: 2.0 MB
```

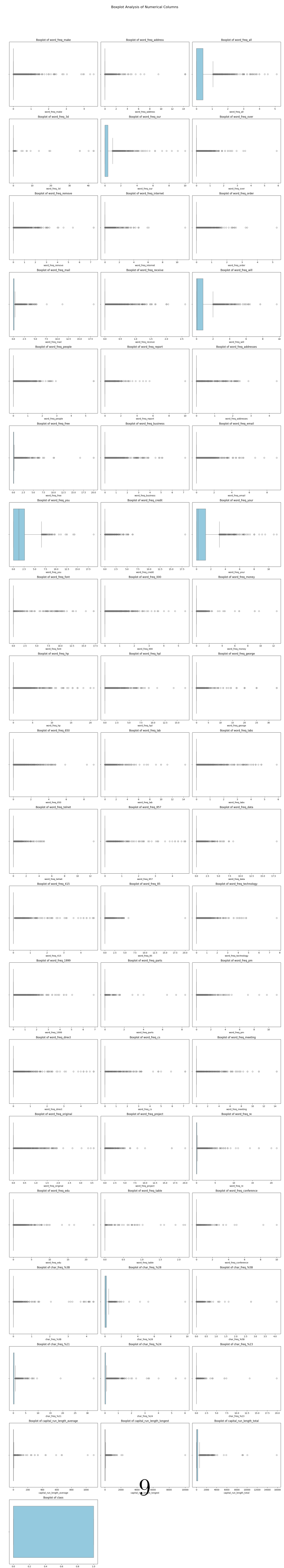
```
Missing Values per Column:
Series([], dtype: int64)

Missing Values After Imputation:
0
```

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 ---
file_path = '/content/drive/MyDrive/spambase/spambase_csv.csv'
df = pd.read_csv(file_path)

# --- 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.
```



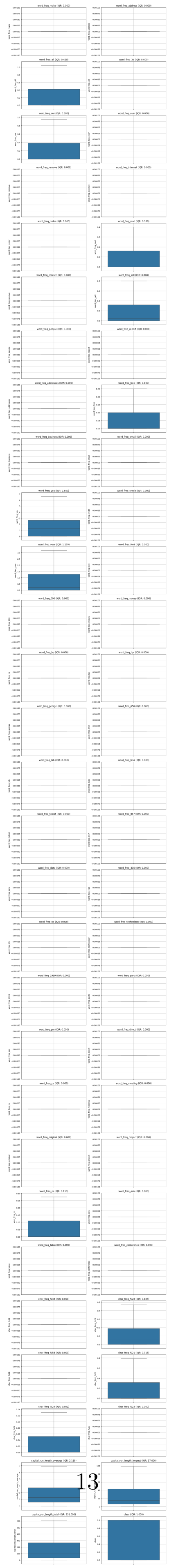
3. Detecting Outliers and Capping them using IQR

[ ]:
```python
# 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:
word_freq_make: 1053 outliers capped
word_freq_address: 898 outliers capped
word_freq_all: 338 outliers capped
word_freq_3d: 47 outliers capped
word_freq_our: 501 outliers capped
word_freq_over: 999 outliers capped
word_freq_remove: 807 outliers capped
word_freq_internet: 824 outliers capped
word_freq_order: 773 outliers capped
word_freq_mail: 852 outliers capped
word_freq_receive: 709 outliers capped
word_freq_will: 270 outliers capped
word_freq_people: 852 outliers capped
word_freq_report: 357 outliers capped
word_freq_addresses: 336 outliers capped
word_freq_free: 957 outliers capped
word_freq_business: 963 outliers capped
word_freq_email: 1038 outliers capped
word_freq_you: 75 outliers capped
word_freq_credit: 424 outliers capped
word_freq_your: 229 outliers capped
```

```
word_freq_font: 117 outliers capped
word_freq_000: 679 outliers capped
word_freq_money: 735 outliers capped
word_freq_hp: 1090 outliers capped
word_freq_hpl: 811 outliers capped
word_freq_george: 780 outliers capped
word_freq_650: 463 outliers capped
word_freq_lab: 372 outliers capped
word_freq_labs: 469 outliers capped
word_freq_telnet: 293 outliers capped
word_freq_857: 205 outliers capped
word_freq_data: 405 outliers capped
word_freq_415: 215 outliers capped
word_freq_85: 485 outliers capped
word_freq_technology: 599 outliers capped
word_freq_1999: 829 outliers capped
word_freq_parts: 83 outliers capped
word_freq_pm: 384 outliers capped
word_freq_direct: 453 outliers capped
word_freq_cs: 148 outliers capped
word_freq_meeting: 341 outliers capped
word_freq_original: 375 outliers capped
word_freq_project: 327 outliers capped
word_freq_re: 1001 outliers capped
word_freq_edu: 517 outliers capped
word_freq_table: 63 outliers capped
word_freq_conference: 203 outliers capped
char_freq_%3B: 790 outliers capped
char_freq_%28: 296 outliers capped
char_freq_%5B: 529 outliers capped
char_freq_%21: 411 outliers capped
char_freq_%24: 811 outliers capped
char_freq_%23: 750 outliers capped
capital_run_length_average: 363 outliers capped
capital_run_length_longest: 463 outliers capped
capital_run_length_total: 550 outliers capped
class: No outliers detected
```



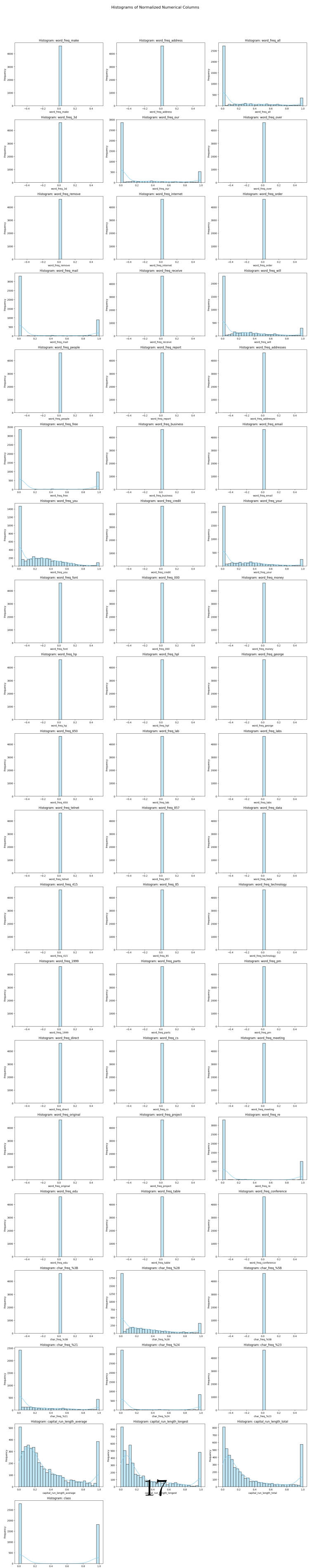
4. Normalisation

```
[ ]: 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)
```

```python
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:

word_freq_make: No outliers and not Gaussian → Min-Max normalization applied
word_freq_address: No outliers and not Gaussian → Min-Max normalization applied
word_freq_all: No outliers and not Gaussian → Min-Max normalization applied
word_freq_3d: No outliers and not Gaussian → Min-Max normalization applied
word_freq_our: No outliers and not Gaussian → Min-Max normalization applied
word_freq_over: No outliers and not Gaussian → Min-Max normalization applied
word_freq_remove: No outliers and not Gaussian → Min-Max normalization applied
word_freq_internet: No outliers and not Gaussian → Min-Max normalization applied
word_freq_order: No outliers and not Gaussian → Min-Max normalization applied
word_freq_mail: No outliers and not Gaussian → Min-Max normalization applied
word_freq_receive: No outliers and not Gaussian → Min-Max normalization applied
word_freq_will: No outliers and not Gaussian → Min-Max normalization applied
word_freq_people: No outliers and not Gaussian → Min-Max normalization applied
word_freq_report: No outliers and not Gaussian → Min-Max normalization applied
word_freq_addresses: No outliers and not Gaussian → Min-Max normalization
applied
word_freq_free: No outliers and not Gaussian → Min-Max normalization applied
word_freq_business: No outliers and not Gaussian → Min-Max normalization applied
word_freq_email: No outliers and not Gaussian → Min-Max normalization applied
word_freq_you: No outliers and not Gaussian → Min-Max normalization applied
word_freq_credit: No outliers and not Gaussian → Min-Max normalization applied
word_freq_your: No outliers and not Gaussian → Min-Max normalization applied
word_freq_font: No outliers and not Gaussian → Min-Max normalization applied
word_freq_000: No outliers and not Gaussian → Min-Max normalization applied
word_freq_money: No outliers and not Gaussian → Min-Max normalization applied
word_freq_hp: No outliers and not Gaussian → Min-Max normalization applied
word_freq_hpl: No outliers and not Gaussian → Min-Max normalization applied
word_freq_george: No outliers and not Gaussian → Min-Max normalization applied
word_freq_650: No outliers and not Gaussian → Min-Max normalization applied
word_freq_lab: No outliers and not Gaussian → Min-Max normalization applied
word_freq_labs: No outliers and not Gaussian → Min-Max normalization applied
```

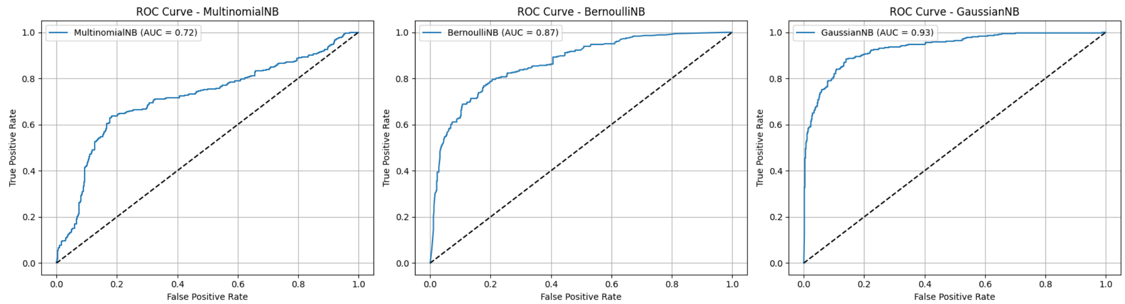
```
word_freq_telnet: No outliers and not Gaussian → Min-Max normalization applied
word_freq_857: No outliers and not Gaussian → Min-Max normalization applied
word_freq_data: No outliers and not Gaussian → Min-Max normalization applied
word_freq_415: No outliers and not Gaussian → Min-Max normalization applied
word_freq_85: No outliers and not Gaussian → Min-Max normalization applied
word_freq_technology: No outliers and not Gaussian → Min-Max normalization
applied
word_freq_1999: No outliers and not Gaussian → Min-Max normalization applied
word_freq_parts: No outliers and not Gaussian → Min-Max normalization applied
word_freq_pm: No outliers and not Gaussian → Min-Max normalization applied
word_freq_direct: No outliers and not Gaussian → Min-Max normalization applied
word_freq_cs: No outliers and not Gaussian → Min-Max normalization applied
word_freq_meeting: No outliers and not Gaussian → Min-Max normalization applied
word_freq_original: No outliers and not Gaussian → Min-Max normalization applied
word_freq_project: No outliers and not Gaussian → Min-Max normalization applied
word_freq_re: No outliers and not Gaussian → Min-Max normalization applied
word_freq_edu: No outliers and not Gaussian → Min-Max normalization applied
word_freq_table: No outliers and not Gaussian → Min-Max normalization applied
word_freq_conference: No outliers and not Gaussian → Min-Max normalization
applied
char_freq_%3B: No outliers and not Gaussian → Min-Max normalization applied
char_freq_%28: No outliers and not Gaussian → Min-Max normalization applied
char_freq_%5B: No outliers and not Gaussian → Min-Max normalization applied
char_freq_%21: No outliers and not Gaussian → Min-Max normalization applied
char_freq_%24: No outliers and not Gaussian → Min-Max normalization applied
char_freq_%23: No outliers and not Gaussian → Min-Max normalization applied
capital_run_length_average: No outliers and not Gaussian → Min-Max normalization
applied
capital_run_length_longest: No outliers and not Gaussian → Min-Max normalization
applied
capital_run_length_total: No outliers and not Gaussian → Min-Max normalization
applied
class: No outliers and not Gaussian → Min-Max normalization applied
```

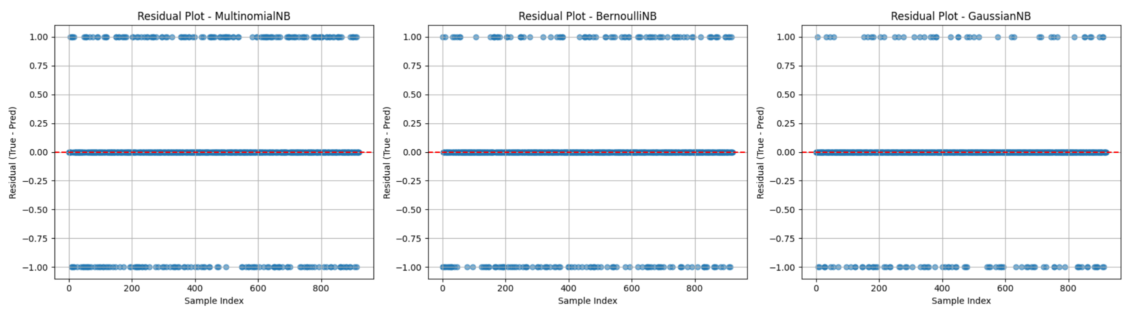

Histograms of Normalized Numerical Columns

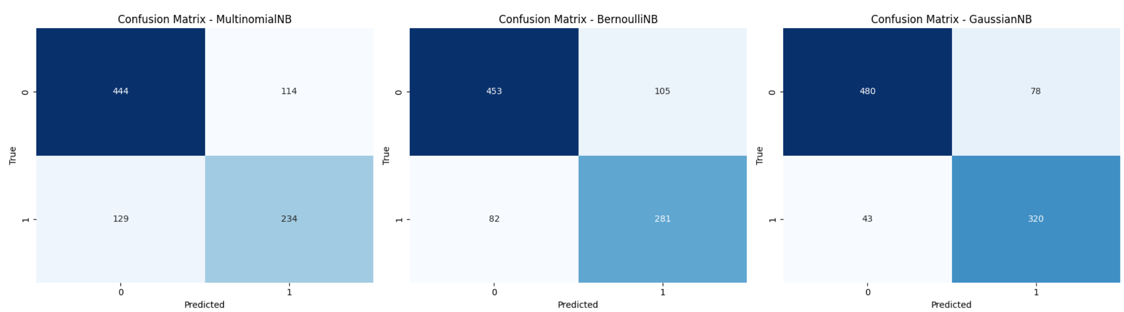
5. Train, Test Split and Model building

[ ]:
```python
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, GaussianNB

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.drop("class", axis=1)  # features
y = df["class"]  # target

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)

# --- Step 2: Train Models ---
models = {
    "MultinomialNB": MultinomialNB(),
    "BernoulliNB": BernoulliNB(),
    "GaussianNB": GaussianNB()

}

preds = {}
probas = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]
    preds[name] = y_pred
    probas[name] = y_proba
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, confusion_matrix

# --- ROC Curve Plots in 1 row ---
```

```python
fig, axs = plt.subplots(1, 3, figsize=(18, 5))
for i, name in enumerate(models):
    fpr, tpr, _ = roc_curve(y_test, probas[name])
    axs[i].plot(fpr, tpr, label=f'{name} (AUC = {roc_auc_score(y_test,␣
 ↪probas[name]):.2f})')
    axs[i].plot([0, 1], [0, 1], 'k--')
    axs[i].set_title(f"ROC Curve - {name}")
    axs[i].set_xlabel("False Positive Rate")
    axs[i].set_ylabel("True Positive Rate")
    axs[i].legend()
    axs[i].grid()
plt.tight_layout()
plt.show()

# --- Residual Plots in 1 row ---
fig, axs = plt.subplots(1, 3, figsize=(18, 5))
for i, name in enumerate(models):
    residuals = y_test - preds[name]
    axs[i].scatter(range(len(residuals)), residuals, alpha=0.6)
    axs[i].axhline(0, color='red', linestyle='--')
    axs[i].set_title(f"Residual Plot - {name}")
    axs[i].set_xlabel("Sample Index")
    axs[i].set_ylabel("Residual (True - Pred)")
    axs[i].grid()
plt.tight_layout()
plt.show()

# --- Confusion Matrix Heatmaps in 1 row ---
fig, axs = plt.subplots(1, 3, figsize=(18, 5))
for i, (name, model) in enumerate(models.items()):
    cm = confusion_matrix(y_test, preds[name])
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, ax=axs[i],
                xticklabels=model.classes_ if hasattr(model, "classes_") else None,
                yticklabels=model.classes_ if hasattr(model, "classes_") else None)
    axs[i].set_title(f"Confusion Matrix - {name}")
    axs[i].set_xlabel("Predicted")
    axs[i].set_ylabel("True")
plt.tight_layout()
plt.show()
```



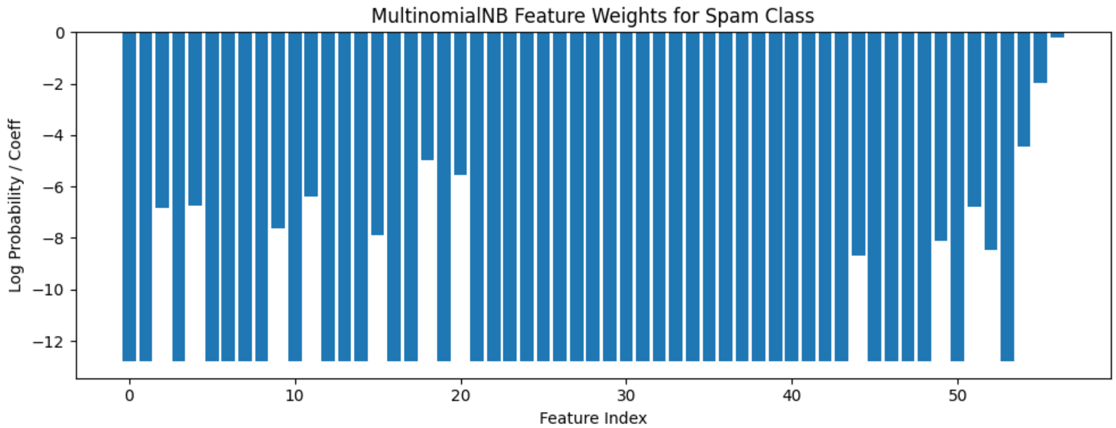


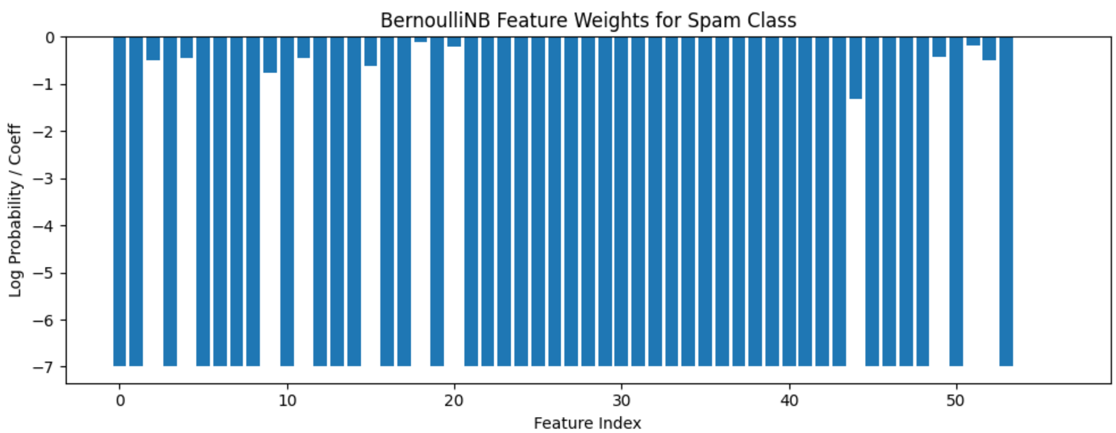


[ ]:
```python
# --- Step 6: Correlation Heatmap (Larger Plot) ---
plt.figure(figsize=(18, 10))  # Increased width and height
sns.heatmap(X.corr(), annot=True, fmt=".2f", cmap="coolwarm", cbar=True, square=True)
plt.title("Feature Correlation Heatmap", fontsize=16)
plt.xticks(rotation=45, ha='right', fontsize=8)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()
```

[ ]:

```python
# --- Step 7: Coefficient Weights Plot (Naive Bayes only) ---
def plot_coefficients(model, model_name):
    if hasattr(model, 'coef_'):
        coef = model.coef_[0]
    else:
        coef = model.feature_log_prob_[1]  # Class 1 (spam)
    plt.figure(figsize=(10, 4))
    plt.bar(range(len(coef)), coef)
    plt.title(f"{model_name} Feature Weights for Spam Class")
    plt.xlabel("Feature Index")
    plt.ylabel("Log Probability / Coeff")
    plt.tight_layout()
    plt.show()

plot_coefficients(models["MultinomialNB"], "MultinomialNB")
plot_coefficients(models["BernoulliNB"], "BernoulliNB")
```





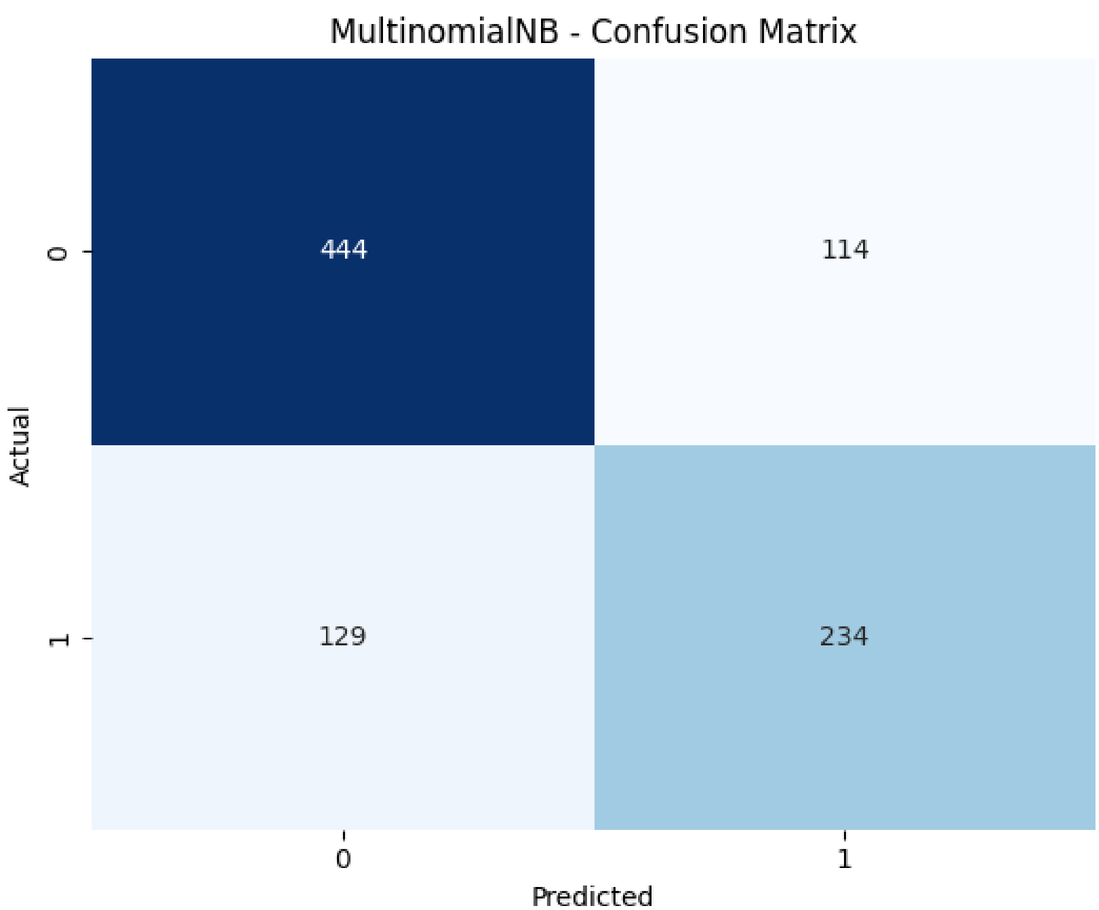
Evaluation

[ ]:
```
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, classification_report, roc_auc_score,
    log_loss, roc_curve, auc
)
import matplotlib.pyplot as plt
import seaborn as sns

def evaluate_model(name, y_true, y_pred, y_proba=None):
    print(f"\n Performance of {name} Model:")

    # Basic metrics
    acc = accuracy_score(y_true, y_pred)
    prec = precision_score(y_true, y_pred, average='weighted', zero_division=0)
    rec = recall_score(y_true, y_pred, average='weighted')
```

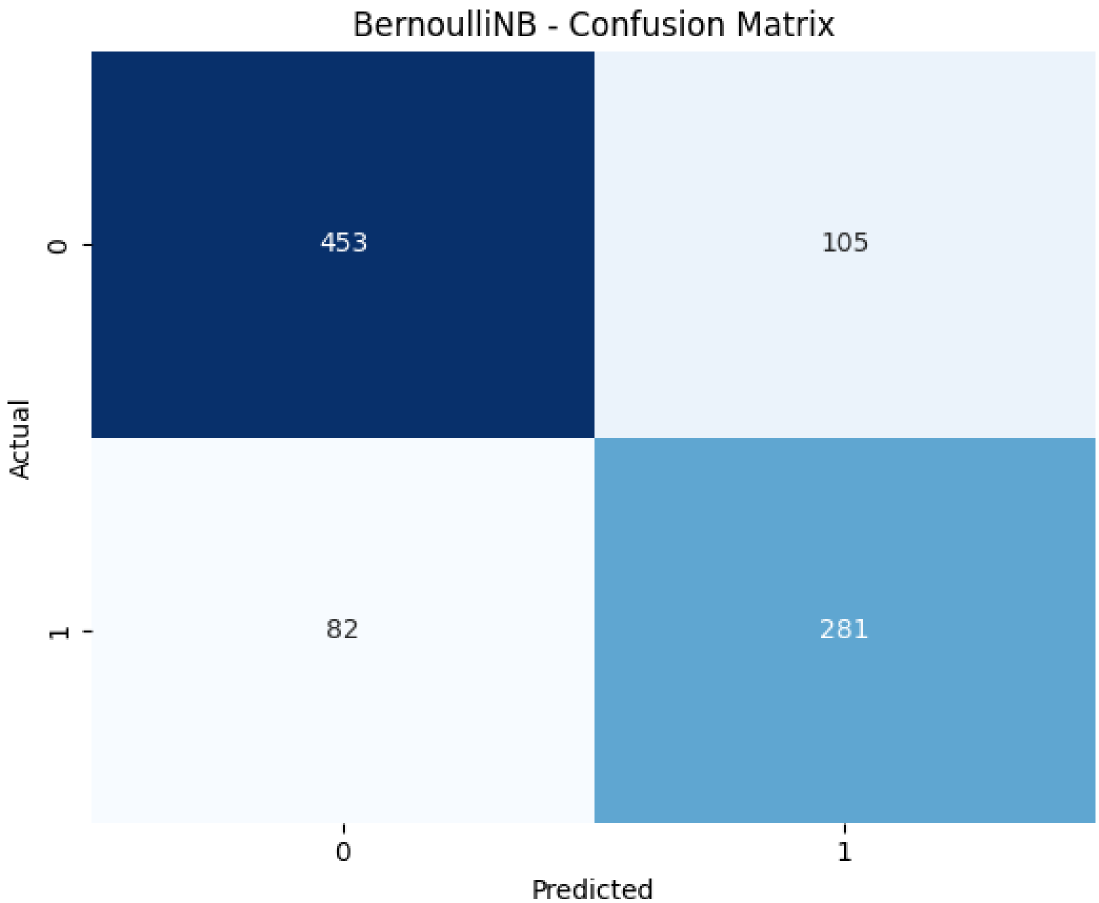
```python
    f1 = f1_score(y_true, y_pred, average='weighted')

    print(f" Accuracy          : {acc:.4f}")
    print(f" Precision (Wgt)   : {prec:.4f}")
    print(f" Recall    (Wgt)   : {rec:.4f}")
    print(f" F1 Score  (Wgt)   : {f1:.4f}")

    # Confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    print("\n Confusion Matrix:")
    print(cm)

    # Classification report
    print("\n Classification Report:")
    print(classification_report(y_true, y_pred, zero_division=0))

    # ROC-AUC and Log Loss (only if probabilities are given)
    if y_proba is not None:
        try:
            # Handle both binary and multiclass cases
            if len(set(y_true)) == 2:
                auc_score = roc_auc_score(y_true, y_proba[:, 1])
            else:
                auc_score = roc_auc_score(y_true, y_proba, multi_class='ovr',␣
↪average='weighted')
            ll = log_loss(y_true, y_proba)

            print(f"\n ROC-AUC Score    : {auc_score:.4f}")
            print(f" Log Loss         : {ll:.4f}")
        except:
            print(" ROC-AUC/Log Loss not available for this output.")

    # Optional: Plot Confusion Matrix
    plt.figure(figsize=(6, 5))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(f'{name} - Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.tight_layout()
    plt.show()

# --- Step 8: Print evaluations ---
for name in models:
    evaluate_model(name, y_test, preds[name], probas[name])
```

```
Performance of MultinomialNB Model:
Accuracy          : 0.7362
```

```
 Precision (Wgt)  : 0.7345
 Recall    (Wgt)  : 0.7362
 F1 Score  (Wgt)  : 0.7351

 Confusion Matrix:
[[444 114]
 [129 234]]

 Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.80      0.79       558
           1       0.67      0.64      0.66       363

    accuracy                           0.74       921
   macro avg       0.72      0.72      0.72       921
weighted avg       0.73      0.74      0.74       921

 ROC-AUC/Log Loss not available for this output.
```

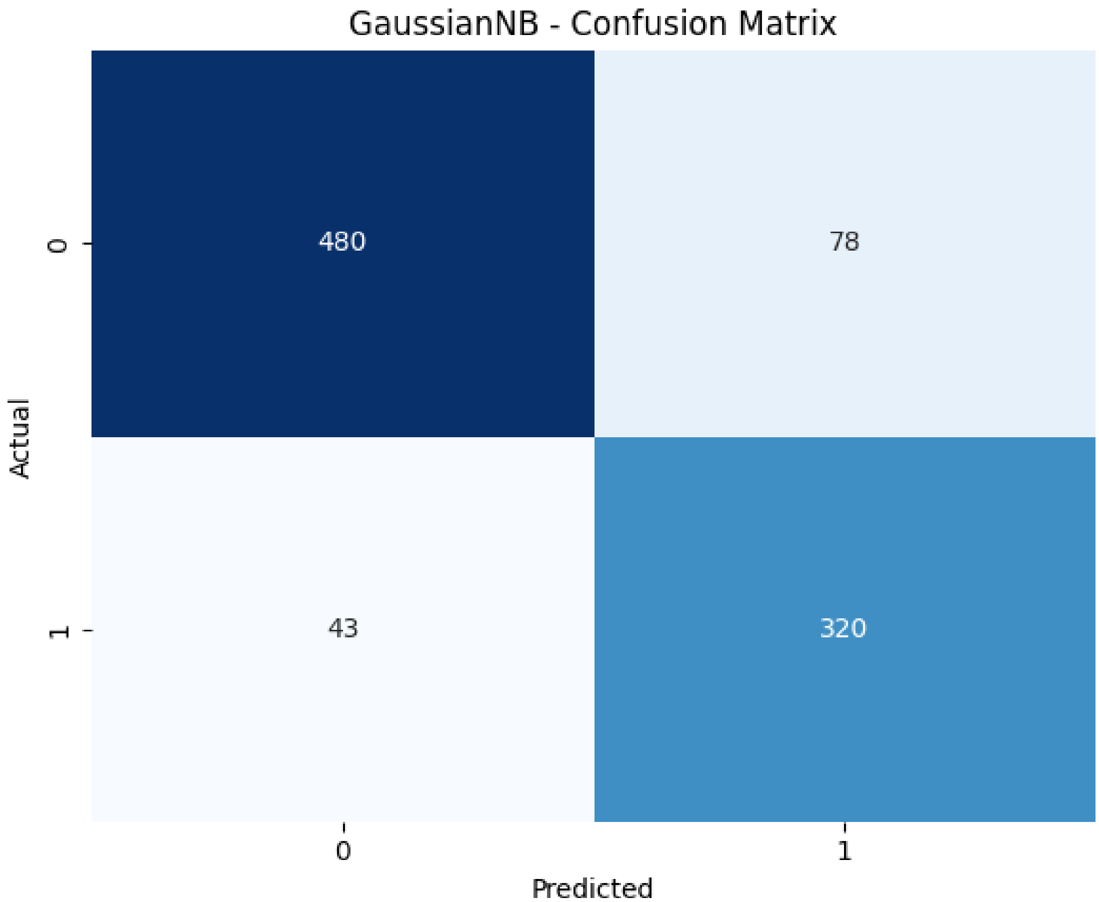


```
 Performance of BernoulliNB Model:
 Accuracy         : 0.7970
 Precision (Wgt)  : 0.7999
 Recall    (Wgt)  : 0.7970
 F1 Score  (Wgt)  : 0.7979

 Confusion Matrix:
[[453 105]
 [ 82 281]]

 Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.81      0.83       558
           1       0.73      0.77      0.75       363

    accuracy                           0.80       921
   macro avg       0.79      0.79      0.79       921
weighted avg       0.80      0.80      0.80       921

 ROC-AUC/Log Loss not available for this output.
```




```
Performance of GaussianNB Model:
Accuracy         : 0.8686
Precision (Wgt)  : 0.8729
Recall    (Wgt)  : 0.8686
F1 Score  (Wgt)  : 0.8695

Confusion Matrix:
[[480  78]
 [ 43 320]]

Classification Report:
             precision    recall  f1-score   support

           0       0.92      0.86      0.89       558
           1       0.80      0.88      0.84       363

    accuracy                           0.87       921
   macro avg       0.86      0.87      0.86       921
```

```
weighted avg       0.87      0.87      0.87       921

 ROC-AUC/Log Loss not available for this output.
```




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

     # Define models
     models = {
         "MultinomialNB": MultinomialNB(),
         "BernoulliNB": BernoulliNB(),
         "GaussianNB":GaussianNB()
     }

     # Perform 5-fold cross-validation
     for name, model in models.items():
         print(f"\n=== 5-Fold Cross-Validation for {name} ===")
         scores = cross_val_score(model, X, y, cv=5, scoring='accuracy')
```

```
    print("Accuracy scores for each fold:", scores)
    print("Mean Accuracy:", np.mean(scores))
    print("Standard Deviation:", np.std(scores))
```

```
=== 5-Fold Cross-Validation for MultinomialNB ===
Accuracy scores for each fold: [0.70792617 0.71521739 0.71630435 0.77282609
0.57826087]
Mean Accuracy: 0.6981069725723458
Standard Deviation: 0.06429053108970888

=== 5-Fold Cross-Validation for BernoulliNB ===
Accuracy scores for each fold: [0.81976113 0.82391304 0.83369565 0.85108696
0.74456522]
Mean Accuracy: 0.8146043997545203
Standard Deviation: 0.036644733973513026

=== 5-Fold Cross-Validation for GaussianNB ===
Accuracy scores for each fold: [0.87513572 0.88152174 0.88804348 0.90108696
0.7673913 ]
Mean Accuracy: 0.8626358400604259
Standard Deviation: 0.04839107821153015
```

KNN

[ ]:
```
import time

# ---------------------------------------
# 8. Evaluate specific k values with metrics + training time
# ---------------------------------------
k_values = [1, 3, 5, 7]
results = {}

for k in k_values:
    print(f"\n[INFO] Evaluating KNN with k={k}")

    knn_model = KNeighborsClassifier(
        n_neighbors=k,
        weights=best_params.get('weights', 'uniform'),
        p=best_params.get('p', 2)
    )

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

    # Predictions
```

```python
    y_pred_k = knn_model.predict(X_test)

    # Metrics
    acc = accuracy_score(y_test, y_pred_k)
    prec = precision_score(y_test, y_pred_k, average='macro')
    rec = recall_score(y_test, y_pred_k, average='macro')
    f1 = f1_score(y_test, y_pred_k, average='macro')

    # Print metrics
    print(f"Accuracy: {acc:.4f}")
    print(f"Precision (macro): {prec:.4f}")
    print(f"Recall (macro): {rec:.4f}")
    print(f"F1 Score (macro): {f1:.4f}")
    print(f"Training Time: {train_time:.4f} seconds")

    # Save results
    results[k] = {
        "Accuracy": acc,
        "Precision_macro": prec,
        "Recall_macro": rec,
        "F1_macro": f1,
        "Train_Time_sec": train_time
    }

# ---------------------------------------
# 9. Summary Table
# ---------------------------------------
results_df = pd.DataFrame(results).T
print("\nKNN (specific k values) Performance Summary:\n", results_df)
```

```
[INFO] Evaluating KNN with k=1
Accuracy: 0.7926
Precision (macro): 0.7840
Recall (macro): 0.7783
F1 Score (macro): 0.7808
Training Time: 0.0097 seconds

[INFO] Evaluating KNN with k=3
Accuracy: 0.7872
Precision (macro): 0.7791
Recall (macro): 0.7705
F1 Score (macro): 0.7739
Training Time: 0.0039 seconds

[INFO] Evaluating KNN with k=5
Accuracy: 0.7861
Precision (macro): 0.7768
```

```
Recall (macro): 0.7725
F1 Score (macro): 0.7744
Training Time: 0.0044 seconds

[INFO] Evaluating KNN with k=7
Accuracy: 0.7807
Precision (macro): 0.7722
Recall (macro): 0.7632
F1 Score (macro): 0.7668
Training Time: 0.0036 seconds

KNN (specific k values) Performance Summary:
    Accuracy  Precision_macro  Recall_macro  F1_macro  Train_Time_sec
1  0.792617         0.784012      0.778311  0.780781        0.009732
3  0.787188         0.779064      0.770461  0.773935        0.003870
5  0.786102         0.776757      0.772453  0.774372        0.004364
7  0.780673         0.772231      0.763159  0.766752        0.003601
```

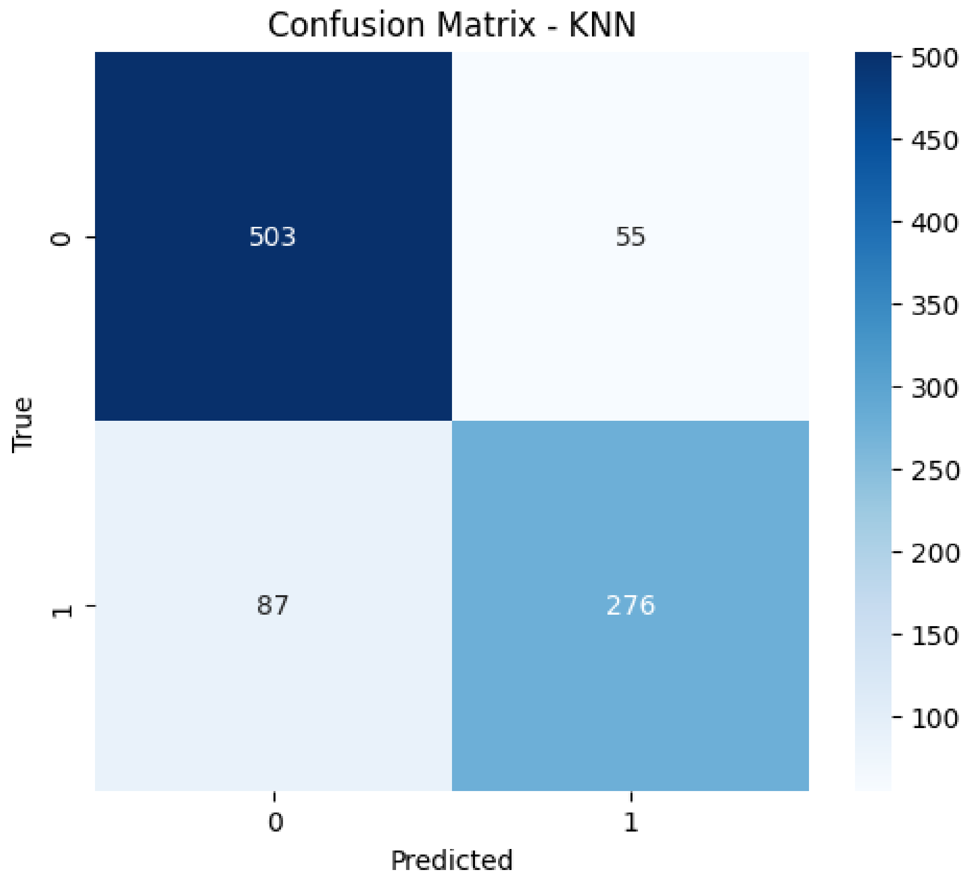
[ ]:

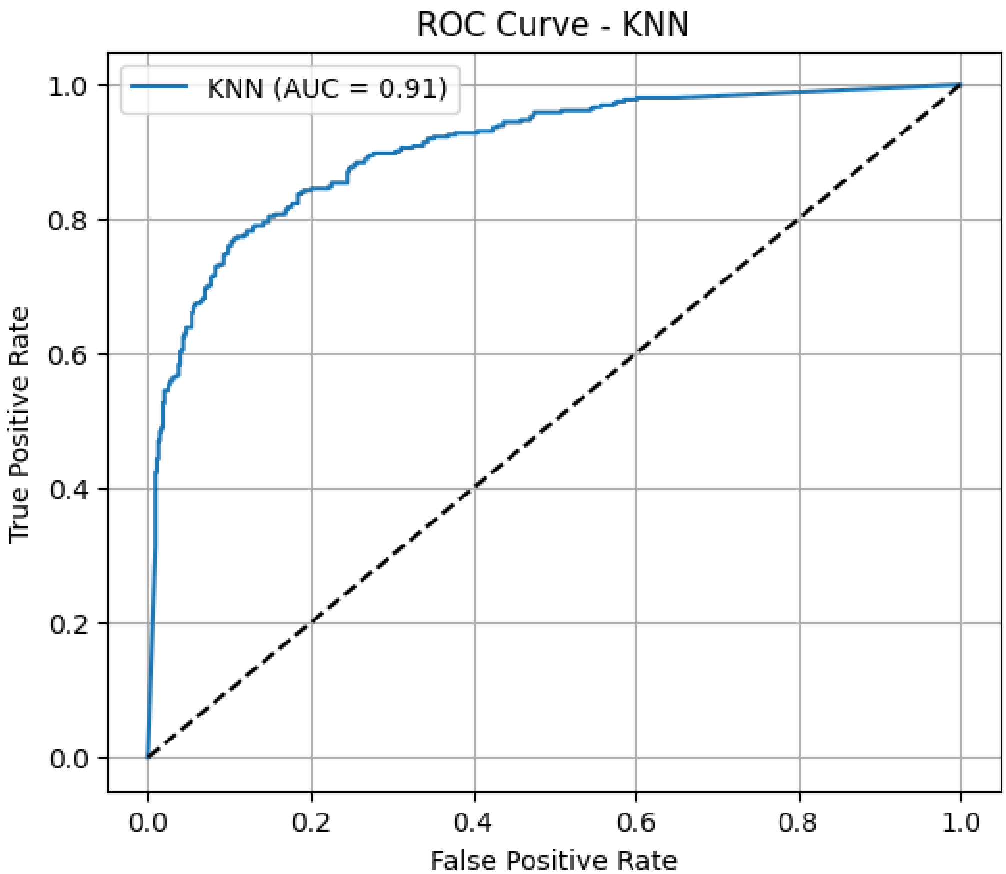
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
 ↪cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, confusion_matrix,
    classification_report, matthews_corrcoef, roc_auc_score, roc_curve
)
from scipy.stats import randint

# ---------------------------------------
# 1. Prepare data
# ---------------------------------------
X = df.drop("class", axis=1)
y = df["class"]

# Train/validation/test split
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
)

# ---------------------------------------
```

```python
# 2. RandomizedSearchCV for best k
# ---------------------------------------
param_dist = {
    'n_neighbors': randint(1, 30),
    'weights': ['uniform', 'distance'],
    'p': [1, 2]  # Manhattan (1) or Euclidean (2)
}

knn = KNeighborsClassifier()
random_search = RandomizedSearchCV(
    knn, param_distributions=param_dist, n_iter=20,
    cv=5, scoring='accuracy', random_state=42, n_jobs=-1
)
random_search.fit(X_train, y_train)

best_params = random_search.best_params_
print("Best Parameters from Random Search:", best_params)

# ---------------------------------------
# 3. Train final KNN model with best params
# ---------------------------------------
best_knn = KNeighborsClassifier(**best_params)
best_knn.fit(X_train, y_train)

# Predictions
y_pred = best_knn.predict(X_test)
y_proba = best_knn.predict_proba(X_test)[:, 1] if len(np.unique(y)) == 2 else None

# ---------------------------------------
# 4. Evaluation Metrics
# ---------------------------------------
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision (macro):", precision_score(y_test, y_pred, average='macro'))
print("Recall (macro):", recall_score(y_test, y_pred, average='macro'))
print("F1 Score (macro):", f1_score(y_test, y_pred, average='macro'))
print("Matthews Corrcoef:", matthews_corrcoef(y_test, y_pred))

if y_proba is not None:
    print("ROC AUC:", roc_auc_score(y_test, y_proba))

# ---------------------------------------
# 5. Confusion Matrix Heatmap
# ---------------------------------------
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
```

```python
            xticklabels=best_knn.classes_,
            yticklabels=best_knn.classes_)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix - KNN")
plt.show()

# ---------------------------------------
# 6. ROC Curve (Binary Only)
# ---------------------------------------
if y_proba is not None:
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    plt.figure(figsize=(6, 5))
    plt.plot(fpr, tpr, label=f"KNN (AUC = {roc_auc_score(y_test, y_proba):.2f})")
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curve - KNN")
    plt.legend()
    plt.grid()
    plt.show()

# ---------------------------------------
# 7. Cross-Validation
# ---------------------------------------
cv_scores = cross_val_score(best_knn, X, y, cv=5, scoring='accuracy')
print("\nCross-Validation Accuracy Scores:", cv_scores)
print("Mean CV Accuracy:", np.mean(cv_scores))
```

```
Best Parameters from Random Search: {'n_neighbors': 11, 'p': 1, 'weights':
'distance'}

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.90      0.88       558
           1       0.83      0.76      0.80       363

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

Accuracy: 0.8458197611292074
Precision (macro): 0.8431896154436991
Recall (macro): 0.8308821351343345
F1 Score (macro): 0.8358478346002068
Matthews Corrcoef: 0.6739593836840387
ROC AUC: 0.9050746961304147
```


Confusion Matrix - KNN
503
55
87
276
True
Predicted
0
1
0
1
500
450
400
350
300
250
200
150
100




```
Cross-Validation Accuracy Scores: [0.7795874  0.81630435 0.8576087  0.85217391
0.7326087 ]
Mean CV Accuracy: 0.8076566114336968
```

[ ]:
```
import time
from sklearn.neighbors import KNeighborsClassifier

# ---------------------------------------
# Compare KD-Tree vs Ball Tree
# ---------------------------------------
algorithms = ["kd_tree", "ball_tree"]
results = {}

for algo in algorithms:
    print(f"\n[INFO] Evaluating KNN with algorithm = {algo}")

    knn_model = KNeighborsClassifier(
        n_neighbors=best_params.get("n_neighbors", 5),
```

```python
        weights=best_params.get("weights", "uniform"),
        p=best_params.get("p", 2),
        algorithm=algo
    )

    # Training time
    start_time = time.time()
    knn_model.fit(X_train, y_train)
    train_time = time.time() - start_time

    # Predictions
    y_pred_algo = knn_model.predict(X_test)

    # Metrics
    acc = accuracy_score(y_test, y_pred_algo)
    prec = precision_score(y_test, y_pred_algo, average="macro")
    rec = recall_score(y_test, y_pred_algo, average="macro")
    f1 = f1_score(y_test, y_pred_algo, average="macro")

    # Print
    print(f"Accuracy: {acc:.4f}")
    print(f"Precision (macro): {prec:.4f}")
    print(f"Recall (macro): {rec:.4f}")
    print(f"F1 Score (macro): {f1:.4f}")
    print(f"Training Time: {train_time:.4f} seconds")

    # Save results
    results[algo] = {
        "Accuracy": acc,
        "Precision_macro": prec,
        "Recall_macro": rec,
        "F1_macro": f1,
        "Train_Time_sec": train_time
    }

# ---------------------------------------
# Summary Table
# ---------------------------------------
results_df = pd.DataFrame(results).T
print("\nKNN Algorithm Comparison (KD-Tree vs Ball Tree):\n", results_df)
```

```
[INFO] Evaluating KNN with algorithm = kd_tree
Accuracy: 0.7861
Precision (macro): 0.7768
Recall (macro): 0.7725
F1 Score (macro): 0.7744
Training Time: 0.0355 seconds
```

```
[INFO] Evaluating KNN with algorithm = ball_tree
Accuracy: 0.7861
Precision (macro): 0.7768
Recall (macro): 0.7725
F1 Score (macro): 0.7744
Training Time: 0.0269 seconds

KNN Algorithm Comparison (KD-Tree vs Ball Tree):
            Accuracy  Precision_macro  Recall_macro  F1_macro  Train_Time_sec
kd_tree    0.786102         0.776757      0.772453  0.774372        0.035519
ball_tree  0.786102         0.776757      0.772453  0.774372        0.026863
```

[ ]:

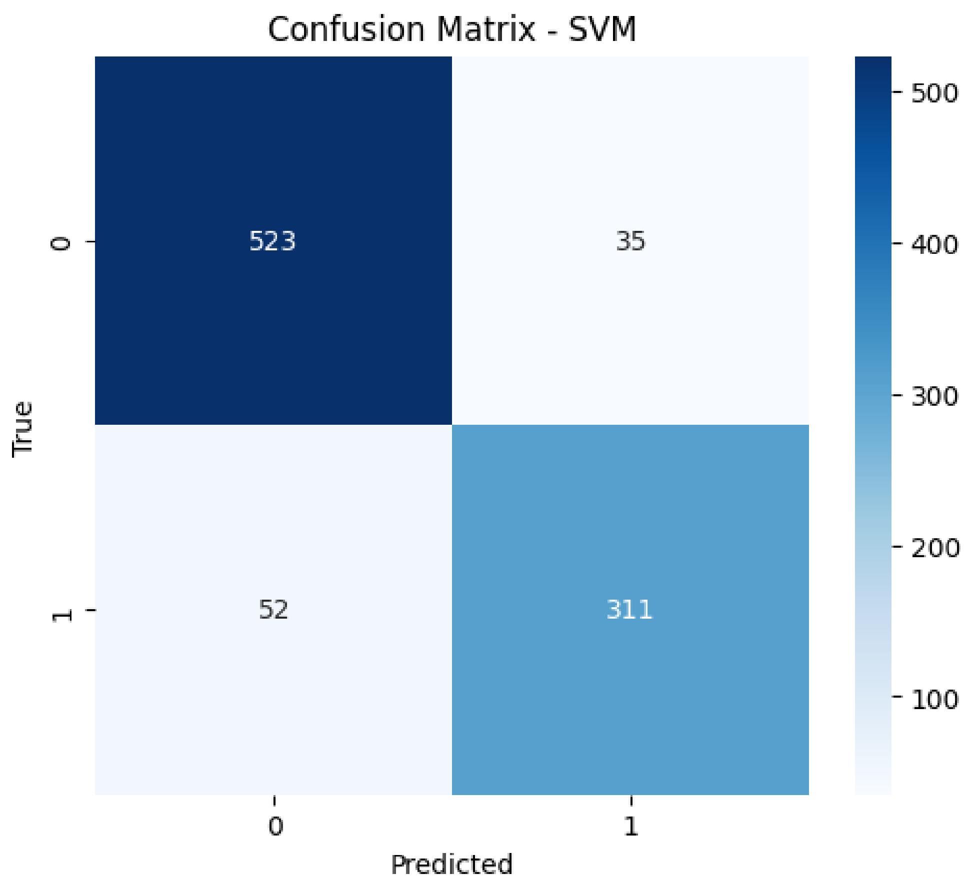
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
 ↪cross_val_score
from sklearn.svm import SVC
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, confusion_matrix,
    classification_report, matthews_corrcoef, roc_auc_score, roc_curve
)
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from scipy.stats import uniform

# ---------------------------------------
# 1. Prepare Data
# ---------------------------------------
X = df.drop("class", axis=1)
y = df["class"]

# Train/Validation/Test split
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
)

# ---------------------------------------
# 2. RandomizedSearchCV for SVM (with scaling)
# ---------------------------------------
svm_pipeline = Pipeline([
```

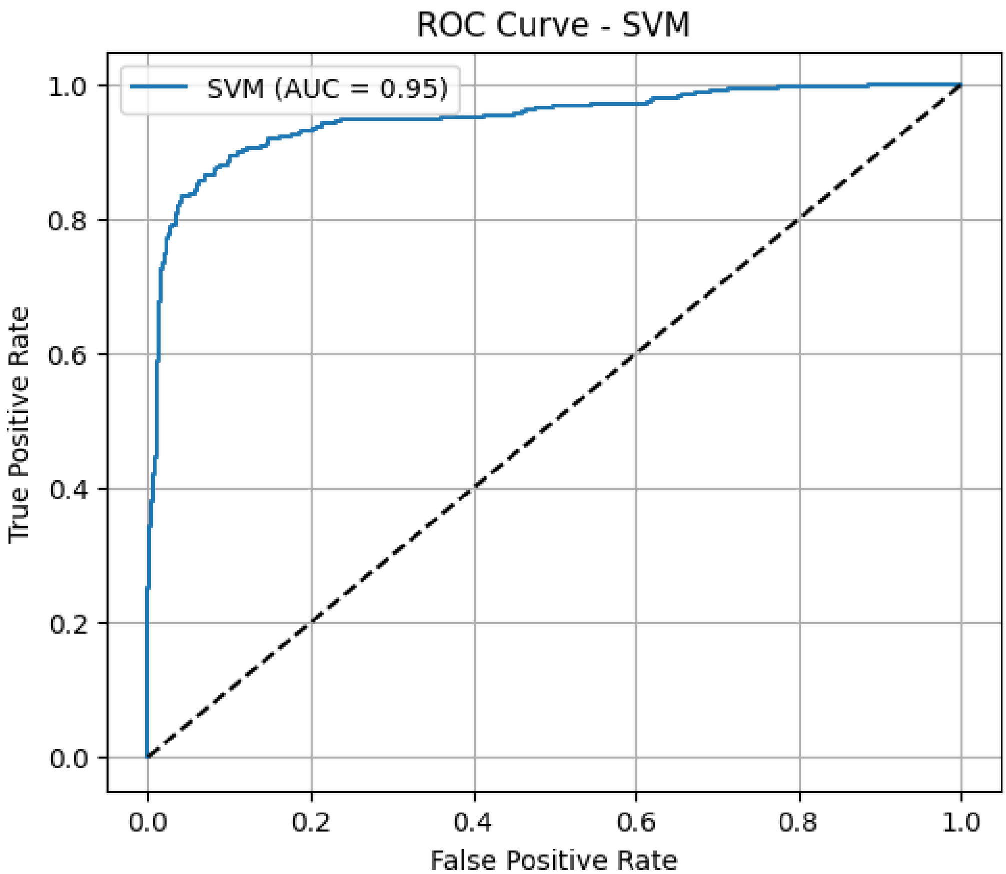
```
    ('scaler', StandardScaler()),
    ('svc', SVC())  # No probability=True here for speed
])

param_dist = {
    'svc__C': uniform(0.1, 5),                    # Regularization parameter
    'svc__kernel': ['linear', 'poly', 'rbf'],    # Kept poly
    'svc__degree': [2, 3],                        # Reduced poly degrees
    'svc__gamma': ['scale', 'auto', 0.1, 1]      # Kernel coefficient
}

random_search = RandomizedSearchCV(
    svm_pipeline, param_distributions=param_dist, n_iter=10,  # fewer iterations
    cv=3, scoring='accuracy', random_state=42, n_jobs=-1      # fewer folds
)
print("[INFO] Starting RandomizedSearchCV...")
random_search.fit(X_train, y_train)
best_params = random_search.best_params_
print("[INFO] Best Parameters from Random Search:", best_params)

# ---------------------------------------
# 3. Train Final SVM Model with probability=True
# ---------------------------------------
final_svm_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(
        C=best_params['svc__C'],
        kernel=best_params['svc__kernel'],
        degree=best_params['svc__degree'],
        gamma=best_params['svc__gamma'],
        probability=True  # Only here for ROC curve
    ))
])

print("[INFO] Training final SVM model...")
final_svm_pipeline.fit(X_train, y_train)

# Predictions
y_pred = final_svm_pipeline.predict(X_test)
y_proba = final_svm_pipeline.predict_proba(X_test)[:, 1] if len(np.unique(y)) == 2␣
 ↪else None

# ---------------------------------------
# 4. Evaluation Metrics
# ---------------------------------------
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```python
print("Precision (macro):", precision_score(y_test, y_pred, average='macro'))
print("Recall (macro):", recall_score(y_test, y_pred, average='macro'))
print("F1 Score (macro):", f1_score(y_test, y_pred, average='macro'))
print("Matthews Corrcoef:", matthews_corrcoef(y_test, y_pred))

if y_proba is not None:
    print("ROC AUC:", roc_auc_score(y_test, y_proba))

# ---------------------------------------
# 5. Confusion Matrix Heatmap
# ---------------------------------------
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=final_svm_pipeline.named_steps['svc'].classes_,
            yticklabels=final_svm_pipeline.named_steps['svc'].classes_)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix - SVM")
plt.show()

# ---------------------------------------
# 6. ROC Curve (Binary Only)
# ---------------------------------------
if y_proba is not None:
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    plt.figure(figsize=(6, 5))
    plt.plot(fpr, tpr, label=f"SVM (AUC = {roc_auc_score(y_test, y_proba):.2f})")
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curve - SVM")
    plt.legend()
    plt.grid()
    plt.show()

# ---------------------------------------
# 7. Cross-Validation
# ---------------------------------------
print("[INFO] Performing cross-validation...")
cv_scores = cross_val_score(final_svm_pipeline, X, y, cv=5, scoring='accuracy')
print("\nCross-Validation Accuracy Scores:", cv_scores)
print("Mean CV Accuracy:", np.mean(cv_scores))
```

```
[INFO] Starting RandomizedSearchCV. . .
[INFO] Best Parameters from Random Search: {'svc__C':
np.float64(1.9727005942368125), 'svc__degree': 2, 'svc__gamma': 0.1,
'svc__kernel': 'rbf'}
```

```
[INFO] Training final SVM model. . .

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.94      0.92       558
           1       0.90      0.86      0.88       363

    accuracy                           0.91       921
   macro avg       0.90      0.90      0.90       921
weighted avg       0.91      0.91      0.91       921

Accuracy: 0.9055374592833876
Precision (macro): 0.9042045740135712
Recall (macro): 0.8970126484789241
F1 Score (macro): 0.900252335064117
Matthews Corrcoef: 0.8011849435839974
ROC AUC: 0.9495295081805347
```






```
[INFO] Performing cross-validation. . .

Cross-Validation Accuracy Scores: [0.8946797  0.90108696 0.90869565 0.93043478
0.81195652]
Mean CV Accuracy: 0.889370721805221
```

[ ]:

```
import time
import pandas as pd
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# ---------------------------------------------------
# Define kernels to evaluate
# ---------------------------------------------------
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
results = {}
```

```python
# Different hyperparameter grids depending on kernel
param_grids = {
    'linear': {
        'svc__C': [0.1, 1, 10, 100]
    },
    'poly': {
        'svc__C': [0.1, 1, 10],
        'svc__degree': [2, 3, 4],
        'svc__gamma': ['scale', 'auto']
    },
    'rbf': {
        'svc__C': [0.1, 1, 10],
        'svc__gamma': ['scale', 'auto']
    },
    'sigmoid': {
        'svc__C': [0.1, 1, 10],
        'svc__gamma': ['scale', 'auto']
    }
}

# ----------------------------------------------------
# Loop over kernels
# ----------------------------------------------------
for kernel in kernels:
    print(f"\n[INFO] Evaluating kernel: {kernel}")

    # Pipeline
    pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('svc', SVC(kernel=kernel, probability=True))
    ])

    # GridSearchCV
    grid = GridSearchCV(
        pipeline,
        param_grid=param_grids[kernel],
        cv=5,
        scoring='accuracy',
        n_jobs=-1
    )

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

```python
    # Predictions with best estimator
    best_model = grid.best_estimator_
    y_pred = best_model.predict(X_test)

    # Metrics
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='macro')
    rec = recall_score(y_test, y_pred, average='macro')
    f1 = f1_score(y_test, y_pred, average='macro')

    print(f"Best Params: {grid.best_params_}")
    print(f"Accuracy: {acc:.4f}")
    print(f"Precision (macro): {prec:.4f}")
    print(f"Recall (macro): {rec:.4f}")
    print(f"F1 Score (macro): {f1:.4f}")
    print(f"Training Time: {train_time:.2f} seconds")

    # Save results
    results[kernel] = {
        "Best_Params": grid.best_params_,
        "Accuracy": acc,
        "Precision": prec,
        "Recall": rec,
        "F1_macro": f1,
        "Train_Time_sec": train_time
    }

# -----------------------------------------------------
# Summary Table
# -----------------------------------------------------
results_df = pd.DataFrame(results).T
print("\nKernel-wise Performance Summary:\n", results_df)
```

```
[INFO] Evaluating kernel: linear
Best Params: {'svc__C': 10}
Accuracy: 0.8936
Precision (macro): 0.8917
Recall (macro): 0.8843
F1 Score (macro): 0.8876
Training Time: 92.70 seconds

[INFO] Evaluating kernel: poly
Best Params: {'svc__C': 1, 'svc__degree': 3, 'svc__gamma': 'scale'}
Accuracy: 0.8914
Precision (macro): 0.8927
Recall (macro): 0.8786
F1 Score (macro): 0.8844
```

```
Training Time: 87.48 seconds

[INFO] Evaluating kernel: rbf
Best Params: {'svc__C': 1, 'svc__gamma': 'scale'}
Accuracy: 0.9023
Precision (macro): 0.9029
Recall (macro): 0.8914
F1 Score (macro): 0.8963
Training Time: 22.48 seconds

[INFO] Evaluating kernel: sigmoid
Best Params: {'svc__C': 1, 'svc__gamma': 'auto'}
Accuracy: 0.8893
Precision (macro): 0.8888
Recall (macro): 0.8778
F1 Score (macro): 0.8825
Training Time: 24.82 seconds

Kernel-wise Performance Summary:
                                                Best_Params  Accuracy  \
linear                                     {'svc__C': 10}  0.893594
poly     {'svc__C': 1, 'svc__degree': 3, 'svc__gamma': . . .   0.891422
rbf                   {'svc__C': 1, 'svc__gamma': 'scale'}   0.90228
sigmoid                {'svc__C': 1, 'svc__gamma': 'auto'}  0.889251

        Precision    Recall  F1_macro Train_Time_sec
linear   0.891682  0.884268  0.887581      92.696532
poly     0.892708  0.878625    0.8844      87.483815
rbf      0.902865  0.891436   0.89631      22.484255
sigmoid  0.888826  0.877796  0.882484      24.823553
```

Results Tables

Metric	Gaussian NB	Multinomial NB	Bernoulli NB
Accuracy	0.8686	0.7362	0.7970
Precision	0.8729	0.7345	0.7999
Recall	0.8686	0.7362	0.7970
F1 Score	0.8695	0.7351	0.7979

k	Accuracy	Precision	Recall	F1 Score
1	0.7926	0.7840	0.7783	0.7808
3	0.7872	0.7791	0.7705	0.7739
5	0.7861	0.7768	0.7725	0.7744
7	0.7807	0.7722	0.7632	0.7668

Metric	KDTree	BallTree
Accuracy	0.7861	0.7861
Precision	0.7768	0.7768
Recall	0.7725	0.7725
F1 Score	0.7744	0.7744
Training Time (s)	0.0355	0.0269

Kernel	Hyperparameters	Accuracy	F1 Score	Training Time (s)
Linear	C = 10	0.8936	0.8876	92.70
Polynomial	C = 1, degree = 3, gamma = scale	0.8914	0.8844	87.48
RBF	C = 1, gamma = scale	0.9023	0.8963	22.48
Sigmoid	C = 1, gamma = auto	0.8893	0.8825	24.82

Fold	Naïve Bayes Accuracy	KNN Accuracy	SVM Accuracy
Fold 1	0.7079	0.7796	0.8947
Fold 2	0.7152	0.8163	0.9011
Fold 3	0.7163	0.8576	0.9087
Fold 4	0.7728	0.8522	0.9304
Fold 5	0.5783	0.7326	0.8120
Average	0.6981	0.8077	0.8894

4. Observations

- **Naïve Bayes:** GaussianNB achieved the highest accuracy (86.8%) among NB variants, while MultinomialNB underperformed (73.6%). BernoulliNB gave moderate results (79.7%).
- **KNN:** Performance decreased slightly with increasing k. The best accuracy (79.3%) was observed at $k = 1$, but overall stability was seen around $k = 3$–5. KDTree and BallTree gave identical accuracies, with BallTree being faster.
- **SVM:** RBF kernel outperformed all others with accuracy 90.2% and F1 score 0.896. Linear and Polynomial kernels performed comparably (≈89%), while Sigmoid kernel was the weakest (88.9%).**Cross-validation:**$SVMconsistentlyachievedthebestaverageaccuracy(88.9\%), followedbyKNN(80$

- Training time varied significantly: Linear/Polynomial kernels were computationally expensive (≈90s), whereas RBF and Sigmoid were much faster (≈20–25s).

5. Conclusion

From the experimental results, it can be concluded that:

- Naïve Bayes is lightweight but less accurate compared to KNN and SVM for spam classification.
- KNN showed decent performance but was sensitive to k and slower for larger datasets.
- SVM with RBF kernel provided the best trade-off between accuracy and computational efficiency, making it the most effective model for this task.

- Cross-validation confirmed that SVM consistently generalizes better across folds.
- Overall, SVM (RBF kernel) is recommended for robust spam vs ham classification in real-world scenarios.

6. Learning Outcomes

1. Understood the implementation of Naïve Bayes, KNN, and SVM for classification tasks.
2. Gained hands-on experience in evaluating models using accuracy, precision, recall, and F1-score.
3. Learned the impact of hyperparameters (k in KNN, kernels in SVM) on model performance.
4. Analyzed performance using K-Fold cross-validation for robust comparison.
5. Developed skills to interpret results through performance tables and confusion matrices.