knn

August 5, 2025

0.0.1 Importing Required Libraries

[2]:
```
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
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score
from sklearn.impute import SimpleImputer
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import matthews_corrcoef
```

0.0.2 Loading dataset

[3]:
```
df = pd.read_csv('spambase.csv')
```

0.0.3 Basic info

[4]:
```
print("Dataset Info:\n", df.info())
print("\nFirst 5 rows:\n", df.head())
print("\nMissing Values:\n", df.isnull().sum())
```

```
<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
Dataset Info:
 None

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]

Missing Values:
 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
```

0.0.4 Handling missing values

[5]:
```
imputer = SimpleImputer(strategy='mean')
df_imputed = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
```

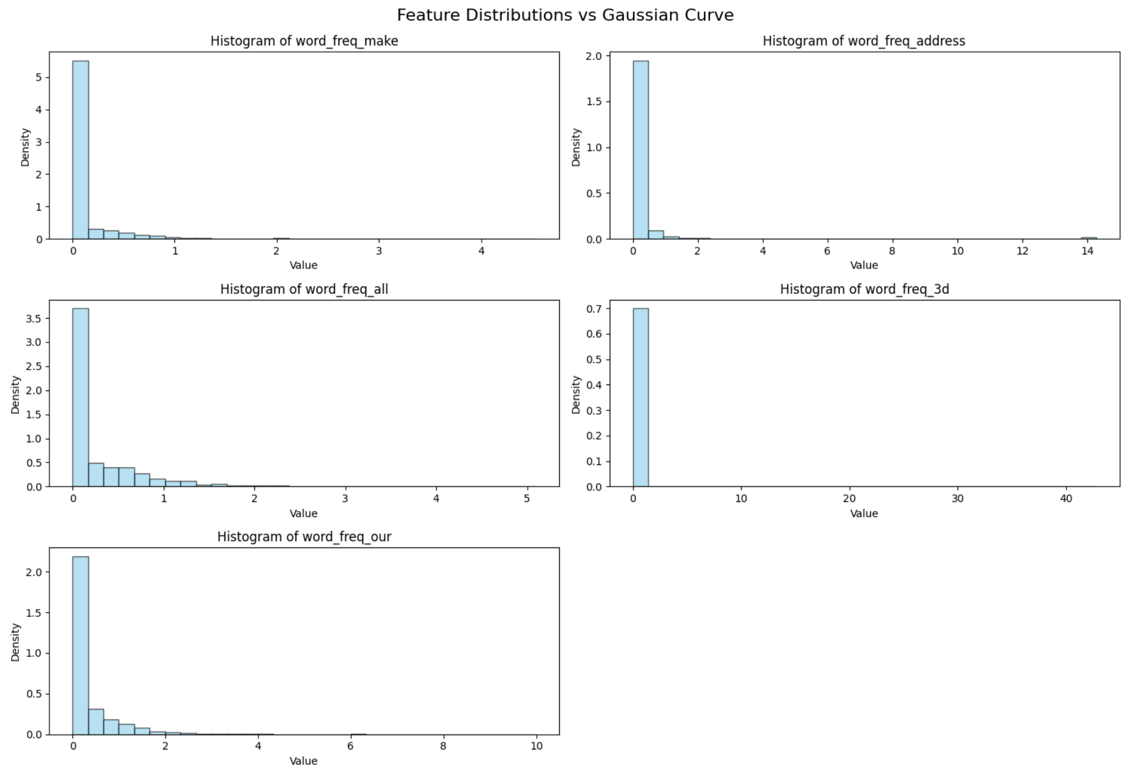
0.0.5 Splitting of feature and target

[6]:
```
X = df_imputed.drop('class', axis=1)
y = df_imputed['class']
```

0.0.6 Checking Distribution

[7]:
```
X = df.drop('class', axis=1)  # Assuming 'class' is the target

# Choose a few features to visualize
sample_features = X.columns[:5]  # First 5 features

# Plot histograms with Gaussian curve overlay
plt.figure(figsize=(15, 10))
for i, feature in enumerate(sample_features):
    plt.subplot(3, 2, i + 1)
    data = X[feature]

    # Plot histogram
    count, bins, ignored = plt.hist(data, bins=30, density=True, alpha=0.6,␣
↪color='skyblue', edgecolor='black')

    # Plot normal distribution curve
```

```
    '''mu, std = data.mean(), data.std()
    xmin, xmax = plt.xlim()
    x = np.linspace(xmin, xmax, 100)
    p = 1 / (std * np.sqrt(2 * np.pi)) * np.exp(-(x - mu)**2 / (2 * std**2))
    plt.plot(x, p, 'r', linewidth=2)'''

    plt.title(f'Histogram of {feature}')
    plt.xlabel('Value')
    plt.ylabel('Density')

plt.tight_layout()
plt.suptitle('Feature Distributions vs Gaussian Curve', fontsize=16, y=1.02)
plt.show()
```



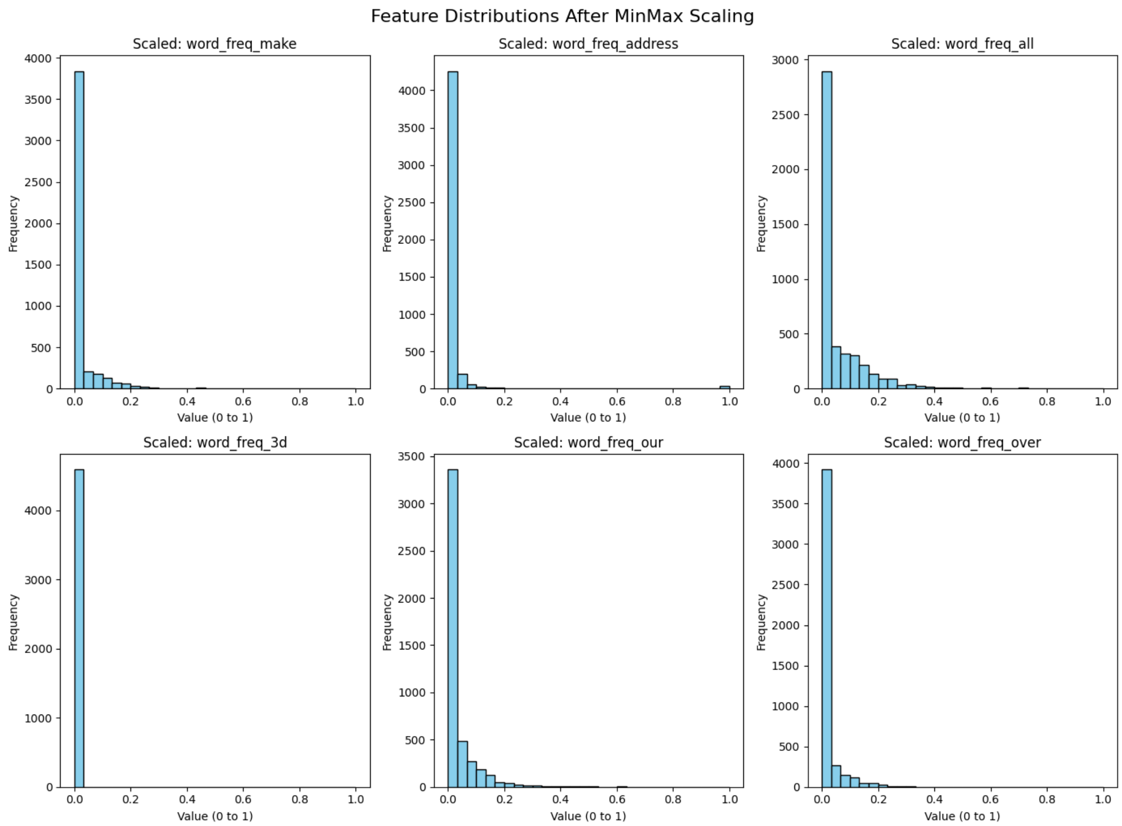
0.0.7 Applying min max scaling

[8]:
```
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
```

##Plots

0.0.8 Histogram

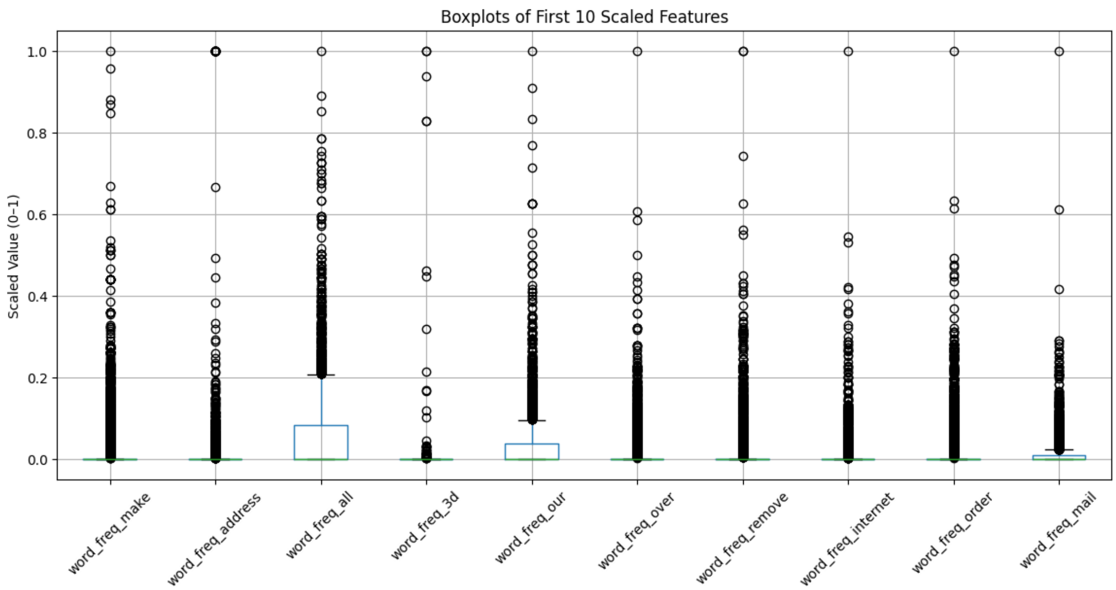
[9]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(14, 10))
for i in range(6):  # first 6 features as an example
    plt.subplot(2, 3, i + 1)
    plt.hist(X_scaled[:, i], bins=30, color='skyblue', edgecolor='black')
    plt.title(f'Scaled: {X.columns[i]}')
    plt.xlabel('Value (0 to 1)')
    plt.ylabel('Frequency')
plt.tight_layout()
plt.suptitle('Feature Distributions After MinMax Scaling', fontsize=16, y=1.02)
plt.show()
```



0.0.9 Boxplot

[10]:
```
import pandas as pd

# Convert scaled array back to DataFrame for easier plotting
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
```

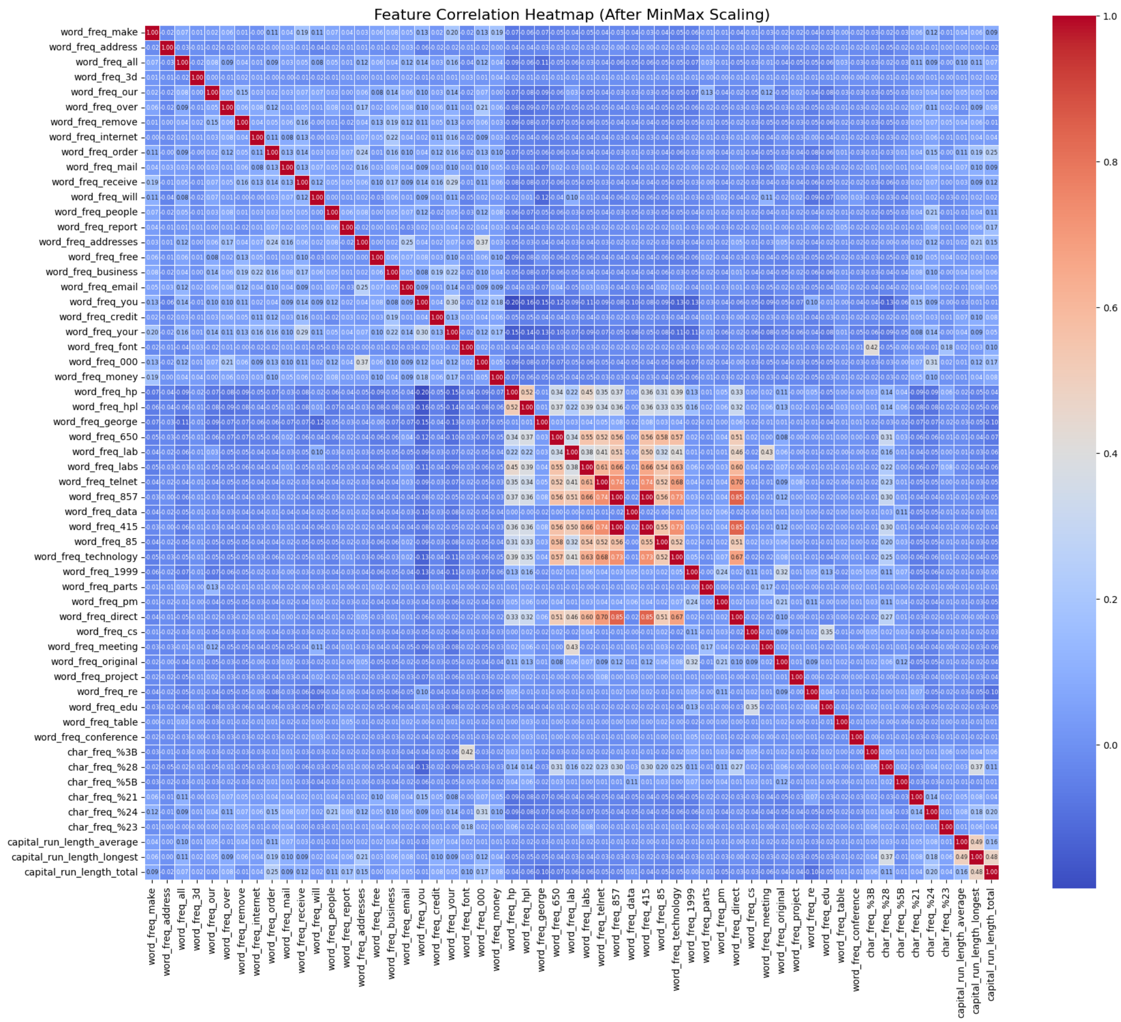
```
plt.figure(figsize=(14, 6))
X_scaled_df.iloc[:, :10].boxplot(rot=45)
plt.title('Boxplots of First 10 Scaled Features')
plt.ylabel('Scaled Value (0-1)')
plt.grid(True)
plt.show()
```



0.0.10 Correlation HeatMap

[11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Assuming X_scaled_df is your scaled DataFrame
corr_matrix = X_scaled_df.corr()

plt.figure(figsize=(18, 15))  # Bigger figure
sns.heatmap(
    corr_matrix,
    cmap='coolwarm',
    square=True,
    annot=True,             # Show values inside squares
    fmt=".2f",              # Format to 2 decimal places
    linewidths=0.5,         # Thin grid lines
    annot_kws={"size": 6}   # Smaller font size
)
```

```
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.title("Feature Correlation Heatmap (After MinMax Scaling)", fontsize=16)
plt.tight_layout()
plt.show()
```



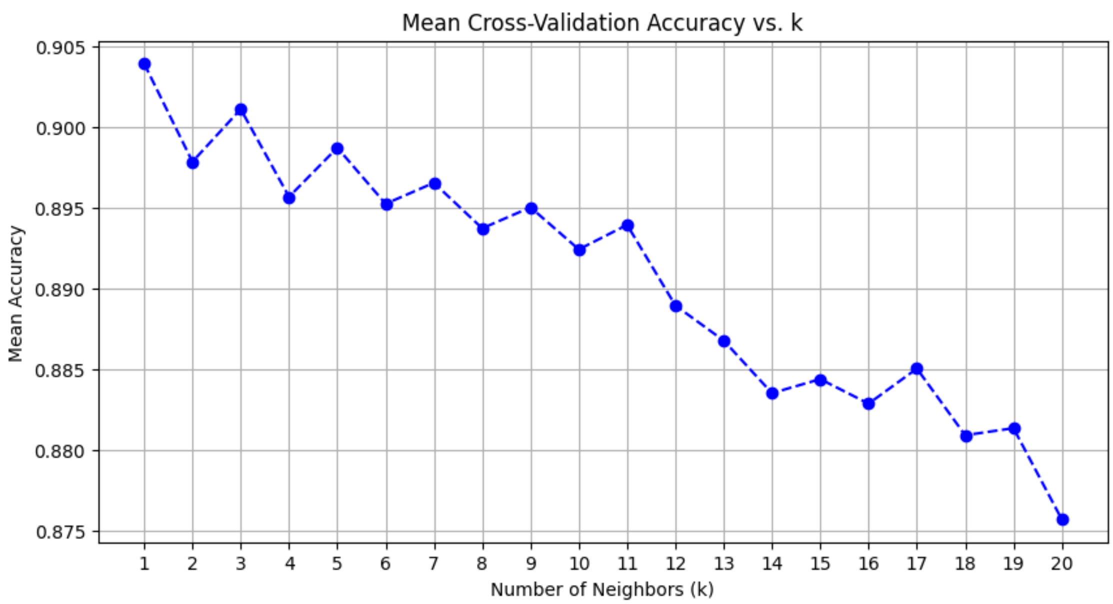
0.0.11 Choosing best k value using k-fold cross validation

[12]:
```
# Step 1: 5-Fold Stratified CV Setup
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Step 2: Try different k values
k_range = range(1, 21)
mean_accuracies = []
```

```python
print("Cross-Validation Accuracies for Different k:")
print("-" * 45)

for k in k_range:
    model = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(model, X_scaled, y, cv=cv, scoring='accuracy')
    mean_accuracies.append(scores.mean())

    print(f"k = {k:2d} -> Fold Accuracies: {np.round(scores, 4)} -> Mean␣
 ↪Accuracy: {scores.mean():.4f}")

# Step 3: Plot Mean Accuracy vs. k
plt.figure(figsize=(10, 5))
plt.plot(k_range, mean_accuracies, marker='o', linestyle='--', color='blue')
plt.title('Mean Cross-Validation Accuracy vs. k')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Mean Accuracy')
plt.xticks(k_range)
plt.grid(True)
plt.show()

# Step 4: Best k
best_k = k_range[np.argmax(mean_accuracies)]
print(f"\n Best k based on mean CV accuracy: {best_k}")
```

```
Cross-Validation Accuracies for Different k:
---------------------------------------------
k =  1 -> Fold Accuracies: [0.9034 0.9076 0.9152 0.9    0.8935] -> Mean
Accuracy: 0.9039
k =  2 -> Fold Accuracies: [0.8914 0.8924 0.9076 0.8989 0.8989] -> Mean
Accuracy: 0.8978
k =  3 -> Fold Accuracies: [0.8947 0.8989 0.9087 0.9087 0.8946] -> Mean
Accuracy: 0.9011
k =  4 -> Fold Accuracies: [0.8947 0.8902 0.9022 0.9043 0.887 ] -> Mean
Accuracy: 0.8957
k =  5 -> Fold Accuracies: [0.8969 0.8946 0.9011 0.9054 0.8957] -> Mean
Accuracy: 0.8987
k =  6 -> Fold Accuracies: [0.9001 0.8902 0.8967 0.9011 0.888 ] -> Mean
Accuracy: 0.8952
k =  7 -> Fold Accuracies: [0.899  0.8978 0.8989 0.8946 0.8924] -> Mean
Accuracy: 0.8965
k =  8 -> Fold Accuracies: [0.8914 0.8891 0.9033 0.8946 0.8902] -> Mean
Accuracy: 0.8937
k =  9 -> Fold Accuracies: [0.8936 0.8913 0.9065 0.8978 0.8859] -> Mean
Accuracy: 0.8950
k = 10 -> Fold Accuracies: [0.8947 0.888  0.9033 0.888  0.888 ] -> Mean
Accuracy: 0.8924
```

```
k = 11 -> Fold Accuracies: [0.8958 0.8924 0.9054 0.8957 0.8804] -> Mean
Accuracy: 0.8939
k = 12 -> Fold Accuracies: [0.8925 0.8826 0.8967 0.8924 0.8804] -> Mean
Accuracy: 0.8889
k = 13 -> Fold Accuracies: [0.8893 0.8826 0.8957 0.8935 0.8728] -> Mean
Accuracy: 0.8868
k = 14 -> Fold Accuracies: [0.8914 0.8783 0.8859 0.8891 0.8728] -> Mean
Accuracy: 0.8835
k = 15 -> Fold Accuracies: [0.8882 0.8826 0.8946 0.8913 0.8652] -> Mean
Accuracy: 0.8844
k = 16 -> Fold Accuracies: [0.8849 0.8793 0.8891 0.887  0.8739] -> Mean
Accuracy: 0.8829
k = 17 -> Fold Accuracies: [0.8893 0.887  0.8902 0.8946 0.8641] -> Mean
Accuracy: 0.8850
k = 18 -> Fold Accuracies: [0.886  0.8826 0.8902 0.8826 0.863 ] -> Mean
Accuracy: 0.8809
k = 19 -> Fold Accuracies: [0.8795 0.8837 0.8935 0.8902 0.8598] -> Mean
Accuracy: 0.8813
k = 20 -> Fold Accuracies: [0.8773 0.8761 0.8902 0.8837 0.8511] -> Mean
Accuracy: 0.8757
```




```
Best k based on mean CV accuracy: 1
```

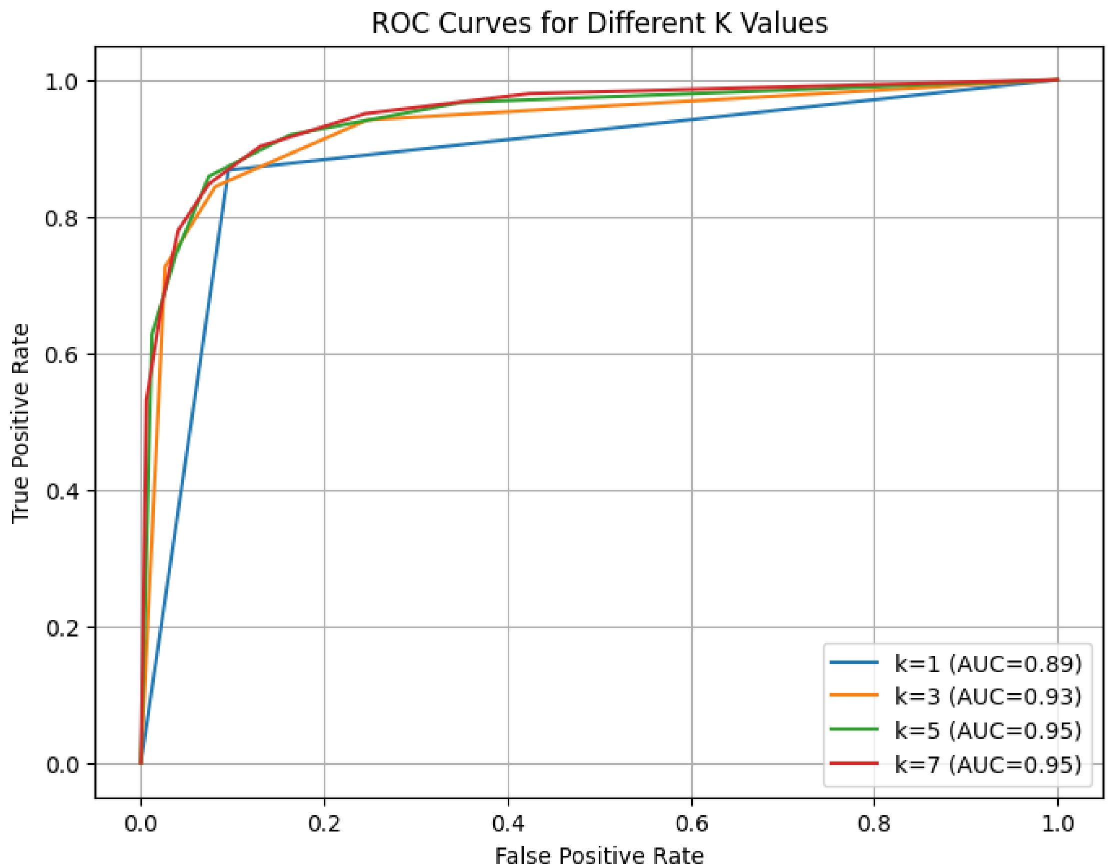
0.0.12 Model Training and Evaluation

[21]:
```python
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    f1_score, confusion_matrix, roc_curve, auc,
    classification_report
)

# Split the data again (or reuse your earlier split)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.3, stratify=y, random_state=42
)

# Store results
knn_results = []

# Plot setup for ROC
plt.figure(figsize=(8, 6))

# Loop through different k values
for k in [1, 3, 5, 7]:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1]

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, zero_division=0)
    rec = recall_score(y_test, y_pred, zero_division=0)
    f1 = f1_score(y_test, y_pred, zero_division=0)
    mcc = matthews_corrcoef(y_test, y_pred)

    fpr, tpr, _ = roc_curve(y_test, y_prob)
    roc_auc = auc(fpr, tpr)

    # Plot ROC
    plt.plot(fpr, tpr, label=f'k={k} (AUC={roc_auc:.2f})')

    print(f"\n  KNN Evaluation for k = {k}")
    print(f"Accuracy : {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall    : {rec:.4f}")
    print(f"F1 Score : {f1:.4f}")
    print(f"MCC       : {mcc:.4f}")
    print("\nClassification Report:")
```

```python
    print(classification_report(y_test, y_pred, zero_division=0))

    knn_results.append({
        'k': k,
        'Accuracy': acc,
        'Precision': prec,
        'Recall': rec,
        'F1 Score': f1,
        'MCC': mcc,
        'AUC': roc_auc
    })

# Final ROC Curve Plot
plt.title("ROC Curves for Different K Values")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.grid(True)
plt.legend()
plt.show()

# Comparison Table
knn_df = pd.DataFrame(knn_results)
print("\n Comparison Table:")
print(knn_df)
```

```
 KNN Evaluation for k = 1
Accuracy : 0.8899
Precision: 0.8551
Recall   : 0.8676
F1 Score : 0.8613
MCC      : 0.7701

Classification Report:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.91       837
         1.0       0.86      0.87      0.86       544

    accuracy                           0.89      1381
   macro avg       0.88      0.89      0.89      1381
weighted avg       0.89      0.89      0.89      1381


 KNN Evaluation for k = 3
Accuracy : 0.8892
Precision: 0.8710
Recall   : 0.8438
```

```
F1 Score : 0.8571
MCC      : 0.7670

Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.92      0.91       837
         1.0       0.87      0.84      0.86       544

    accuracy                           0.89      1381
   macro avg       0.89      0.88      0.88      1381
weighted avg       0.89      0.89      0.89      1381


 KNN Evaluation for k = 5
Accuracy : 0.8993
Precision: 0.8828
Recall   : 0.8585
F1 Score : 0.8705
MCC      : 0.7884

Classification Report:
              precision    recall  f1-score   support

         0.0       0.91      0.93      0.92       837
         1.0       0.88      0.86      0.87       544

    accuracy                           0.90      1381
   macro avg       0.90      0.89      0.89      1381
weighted avg       0.90      0.90      0.90      1381


 KNN Evaluation for k = 7
Accuracy : 0.8950
Precision: 0.8815
Recall   : 0.8474
F1 Score : 0.8641
MCC      : 0.7790

Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.93      0.91       837
         1.0       0.88      0.85      0.86       544

    accuracy                           0.90      1381
   macro avg       0.89      0.89      0.89      1381
weighted avg       0.89      0.90      0.89      1381
```

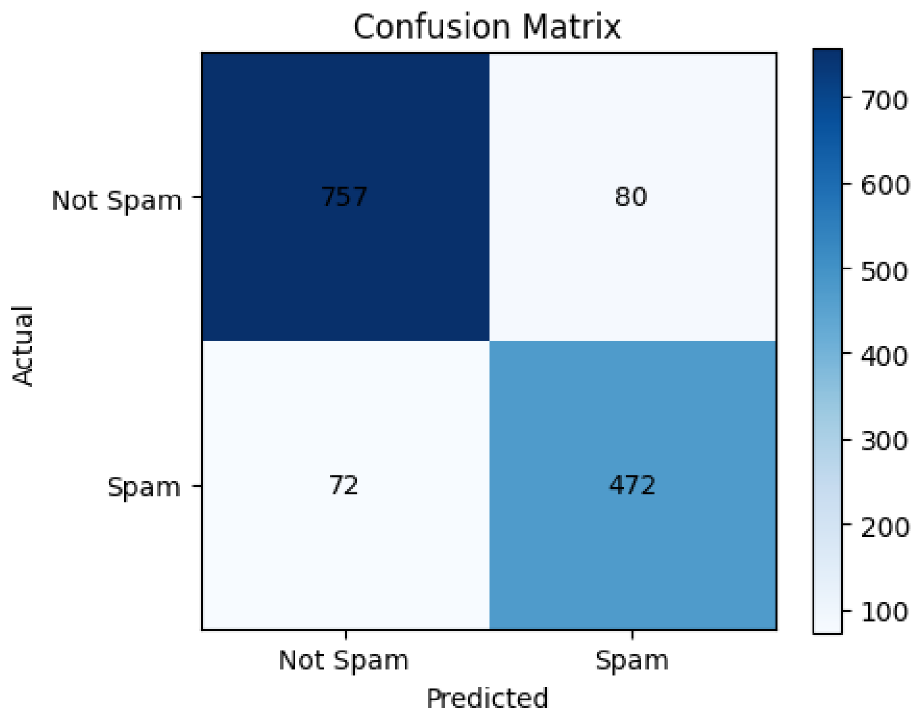



```
 Comparison Table:
   k  Accuracy  Precision    Recall  F1 Score       MCC       AUC
0  1  0.889935   0.855072  0.867647  0.861314  0.770142  0.886034
1  3  0.889211   0.870968  0.843750  0.857143  0.766959  0.931442
2  5  0.899348   0.882798  0.858456  0.870457  0.788392  0.945145
3  7  0.895004   0.881453  0.847426  0.864105  0.779014  0.950240
```

[15]:

```
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5, 4))
plt.imshow(conf_matrix, cmap='Blues')
plt.title('Confusion Matrix')
plt.colorbar()
plt.xticks([0, 1], ['Not Spam', 'Spam'])
plt.yticks([0, 1], ['Not Spam', 'Spam'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
for i in range(2):
```

```
    for j in range(2):
        plt.text(j, i, conf_matrix[i, j], ha='center', va='center',␣
 ↪color='black')
plt.tight_layout()
plt.show()
```



0.0.13 KD Tree and Ball Tree

[17]:
```
# Use KDTree
model_kd = KNeighborsClassifier(n_neighbors=best_k, algorithm='kd_tree')
model_kd.fit(X_train, y_train)

# Use BallTree
model_ball = KNeighborsClassifier(n_neighbors=best_k, algorithm='ball_tree')
model_ball.fit(X_train, y_train)
```

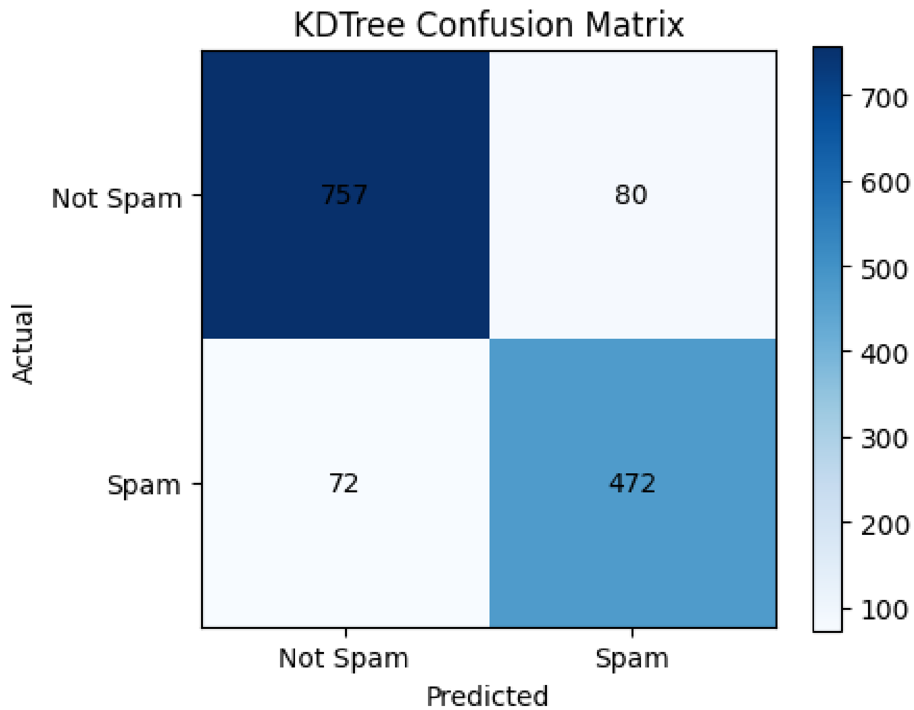
[17]: KNeighborsClassifier(algorithm='ball_tree', n_neighbors=1)

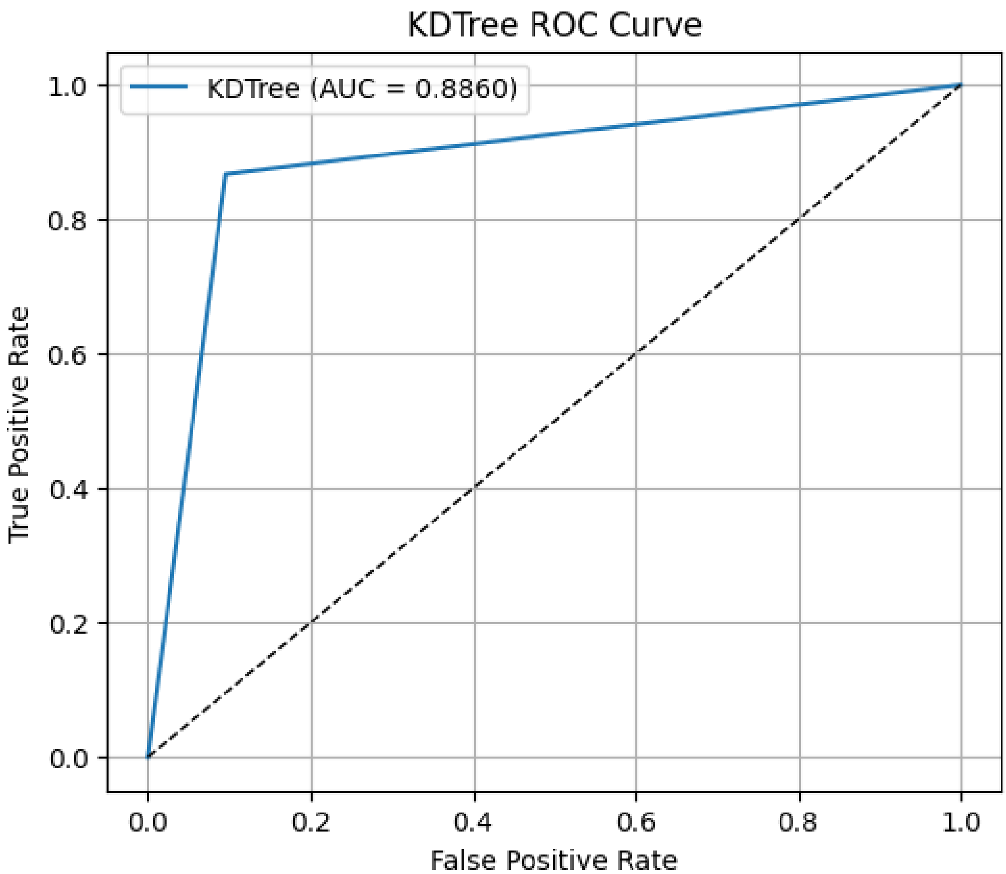
[18]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    f1_score, confusion_matrix, roc_curve, auc,
    classification_report, matthews_corrcoef
```

```
)
import matplotlib.pyplot as plt

# Helper function to evaluate a model
def evaluate_knn_model(name, model, X_train, X_test, y_train, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1]

    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)
    mcc = matthews_corrcoef(y_test, y_pred)
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    roc_auc = auc(fpr, tpr)

    print(f"\n  {name} Performance Metrics:")
    print(f"Accuracy : {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall   : {rec:.4f}")
    print(f"F1 Score : {f1:.4f}")
    print(f"MCC      : {mcc:.4f}")
    print("\nClassification Report:\n", classification_report(y_test, y_pred))

    # Confusion Matrix
    conf = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(5, 4))
    plt.imshow(conf, cmap='Blues')
    plt.title(f'{name} Confusion Matrix')
    plt.colorbar()
    plt.xticks([0, 1], ['Not Spam', 'Spam'])
    plt.yticks([0, 1], ['Not Spam', 'Spam'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    for i in range(2):
        for j in range(2):
            plt.text(j, i, conf[i, j], ha='center', va='center')
    plt.tight_layout()
    plt.show()

    # ROC Curve
    plt.figure(figsize=(6, 5))
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.4f})')
    plt.plot([0, 1], [0, 1], 'k--', linewidth=1)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

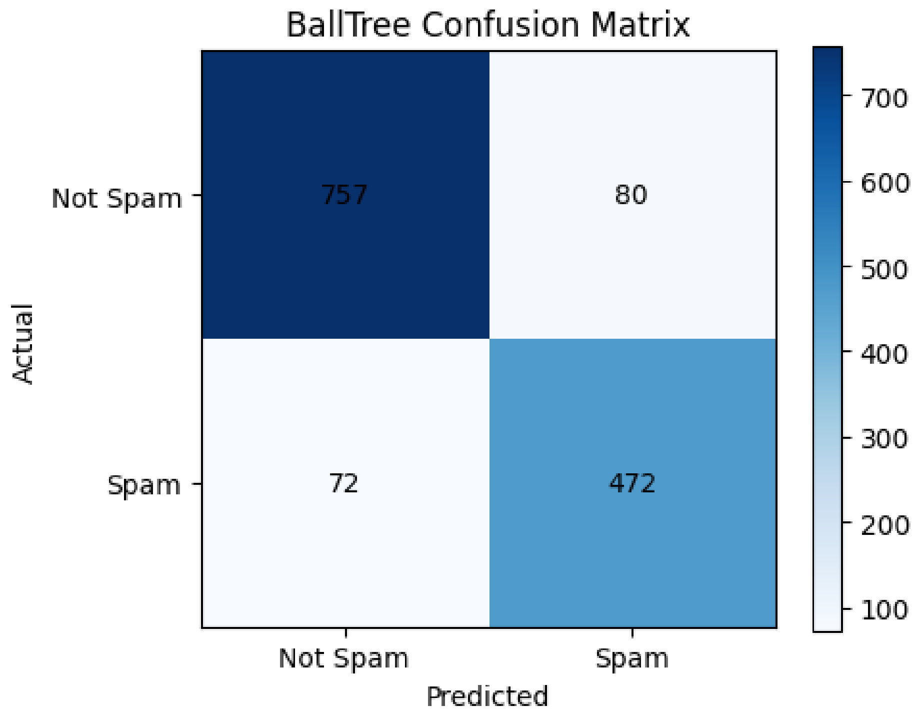
```python
    plt.title(f'{name} ROC Curve')
    plt.legend()
    plt.grid(True)
    plt.show()

# Train-test split assumed done:
# X_train, X_test, y_train, y_test already available
# best_k is selected

# Evaluate KDTree
knn_kd = KNeighborsClassifier(n_neighbors=best_k, algorithm='kd_tree')
evaluate_knn_model("KDTree", knn_kd, X_train, X_test, y_train, y_test)

# Evaluate BallTree
knn_ball = KNeighborsClassifier(n_neighbors=best_k, algorithm='ball_tree')
evaluate_knn_model("BallTree", knn_ball, X_train, X_test, y_train, y_test)
```

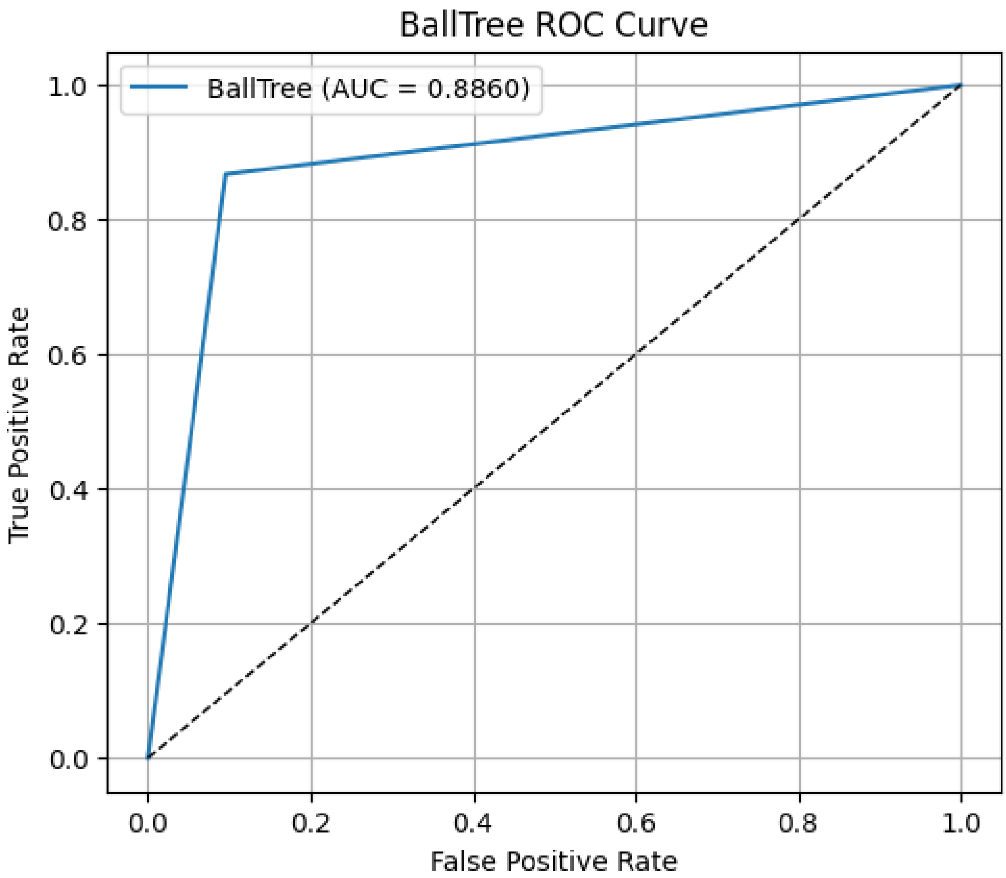
```
 KDTree Performance Metrics:
Accuracy : 0.8899
Precision: 0.8551
Recall   : 0.8676
F1 Score : 0.8613
MCC      : 0.7701

Classification Report:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.91       837
         1.0       0.86      0.87      0.86       544

    accuracy                           0.89      1381
   macro avg       0.88      0.89      0.89      1381
weighted avg       0.89      0.89      0.89      1381
```


KDTree Confusion Matrix
Not Spam
Spam
757
80
72
472
Actual
Not Spam
Spam
Predicted
700
600
500
400
300
200
100




```
 BallTree Performance Metrics:
Accuracy : 0.8899
Precision: 0.8551
Recall   : 0.8676
F1 Score : 0.8613
MCC      : 0.7701

Classification Report:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.91       837
         1.0       0.86      0.87      0.86       544

    accuracy                           0.89      1381
   macro avg       0.88      0.89      0.89      1381
weighted avg       0.89      0.89      0.89      1381
```


BallTree Confusion Matrix
Not Spam
Spam
Actual
757
80
72
472
Not Spam
Spam
Predicted
700
600
500
400
300
200
100



[26]:
```
import time

for algo in ['kd_tree', 'ball_tree', 'brute']:
    model = KNeighborsClassifier(n_neighbors=best_k, algorithm=algo)
    start = time.time()
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    duration = time.time() - start
    acc = accuracy_score(y_test, y_pred)
    print(f"{algo:10} → Accuracy: {acc:.4f}, Time: {duration:.4f} sec")
```

```
kd_tree    → Accuracy: 0.8899, Time: 0.4470 sec
ball_tree  → Accuracy: 0.8899, Time: 0.4058 sec
brute      → Accuracy: 0.8899, Time: 0.0192 sec
```