Spam Classification using Naïve Bayes, KNN, and SVM

Machine Learning Algorithms Laboratory (ICS1512)

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1 Introduction

The objective of this experiment is to build and evaluate different machine learning models for classifying emails as *spam* or *ham*. The models compared are:

- Naïve Bayes Classifiers (GaussianNB, MultinomialNB, BernoulliNB)
- K-Nearest Neighbors (KNN) with varying hyperparameters
- Support Vector Machines (SVM) with different kernels

We evaluate models using accuracy, precision, recall, F1-score, confusion matrices, ROC curves, and cross-validation.

2 Dataset

The dataset used is the **Spambase dataset** [1], downloaded from Kaggle. It contains 4601 samples with 57 numerical features and a binary class label:

- 0 = Ham (not spam)
- 1 = Spam

3 Exploratory Data Analysis (EDA)

- The dataset contains no missing values.
- Class distribution was visualized using a count plot (Figure **??**).

4 Data Preprocessing

- Features were standardized using `StandardScaler`.
- The dataset was split into training, validation, and test sets using stratified sampling.

5 Code and Output

[ ]:
```python
import kagglehub

# Download latest version
path = kagglehub.dataset_download("somesh24/spambase")

print("Path to dataset files:", path)
```

```
Path to dataset files: /kaggle/input/spambase
```

[ ]:
```python
import os

# List all files in the dataset folder
print(os.listdir(path))
```

```
['spambase_csv.csv']
```

[ ]:
```python
import pandas as pd

df = pd.read_csv(os.path.join(path, 'spambase_csv.csv'))  # adjust name if needed
print(df.head())
```

```
   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]
```

[ ]:
```python
print(df.shape)
print(df.dtypes)
```

```
(4601, 58)
word_freq_make                float64
word_freq_address             float64
word_freq_all                 float64
word_freq_3d                  float64
word_freq_our                 float64
word_freq_over                float64
word_freq_remove              float64
word_freq_internet            float64
word_freq_order               float64
word_freq_mail                float64
word_freq_receive             float64
word_freq_will                float64
word_freq_people              float64
word_freq_report              float64
word_freq_addresses           float64
word_freq_free                float64
word_freq_business            float64
word_freq_email               float64
word_freq_you                 float64
word_freq_credit              float64
word_freq_your                float64
word_freq_font                float64
word_freq_000                 float64
word_freq_money               float64
word_freq_hp                  float64
word_freq_hpl                 float64
```

```
word_freq_george              float64
word_freq_650                 float64
word_freq_lab                 float64
word_freq_labs                float64
word_freq_telnet              float64
word_freq_857                 float64
word_freq_data                float64
word_freq_415                 float64
word_freq_85                  float64
word_freq_technology          float64
word_freq_1999                float64
word_freq_parts               float64
word_freq_pm                  float64
word_freq_direct              float64
word_freq_cs                  float64
word_freq_meeting             float64
word_freq_original            float64
word_freq_project             float64
word_freq_re                  float64
word_freq_edu                 float64
word_freq_table               float64
word_freq_conference          float64
char_freq_%3B                 float64
char_freq_%28                 float64
char_freq_%5B                 float64
char_freq_%21                 float64
char_freq_%24                 float64
char_freq_%23                 float64
capital_run_length_average    float64
capital_run_length_longest      int64
capital_run_length_total        int64
class                           int64
dtype: object
```

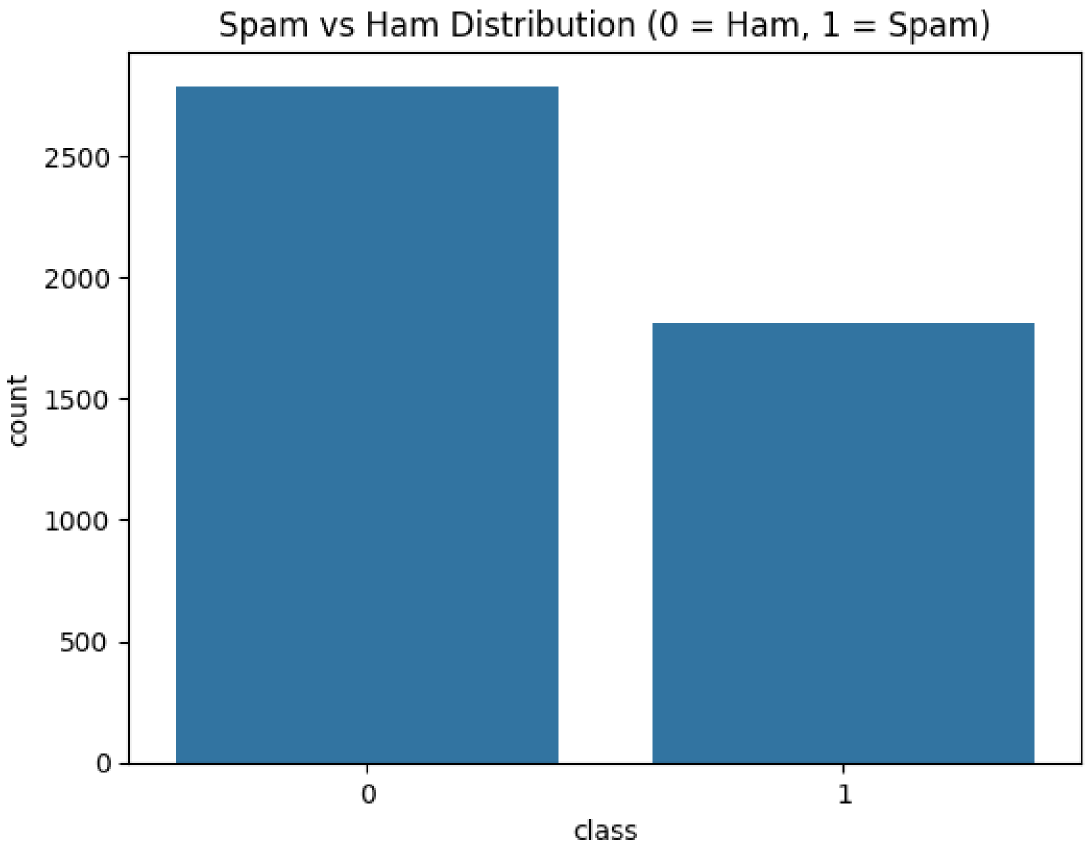
##2. EDA

Split features and label

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

Visualize Class Balance

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

sns.countplot(x=y)
plt.title("Spam vs Ham Distribution (0 = Ham, 1 = Spam)")
plt.show()
```



Check for Missing Values

[ ]:
```
print(X.isnull().sum().sum())  # Should be 0
```

0

##3. Scale the Features

[ ]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

5.1 4. Splitting (Train, Valid, Test)

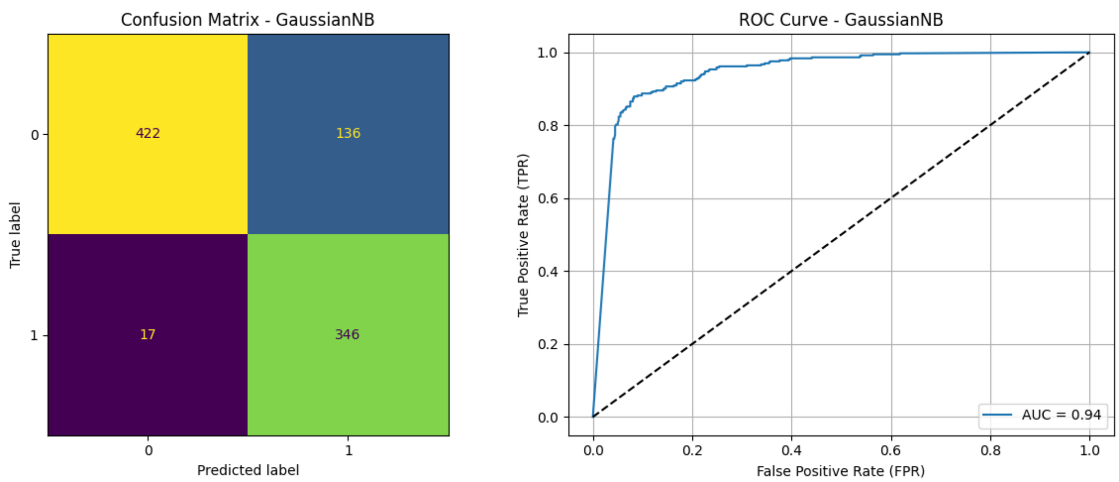
[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪stratify=y, random_state=42)
```

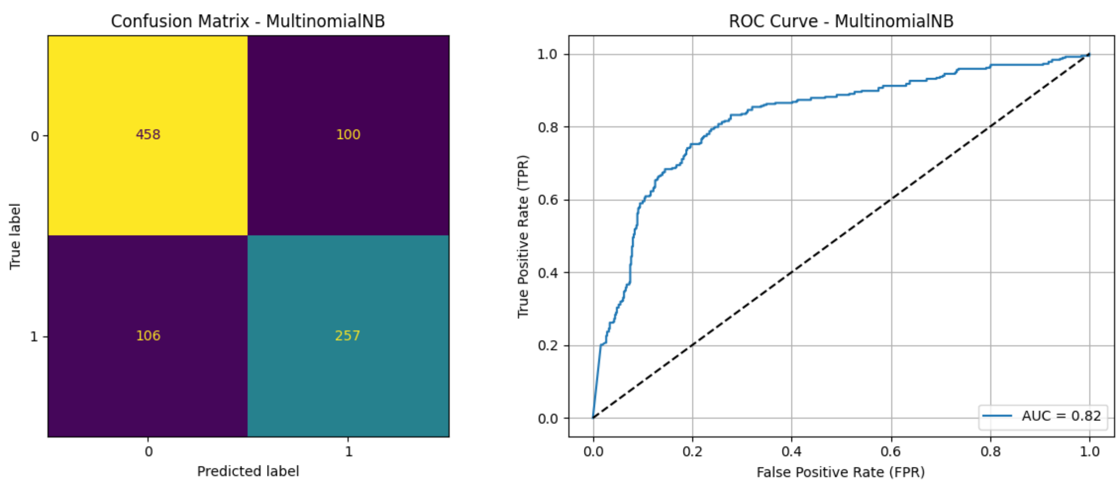
##5. Model Building - Naive Bayes

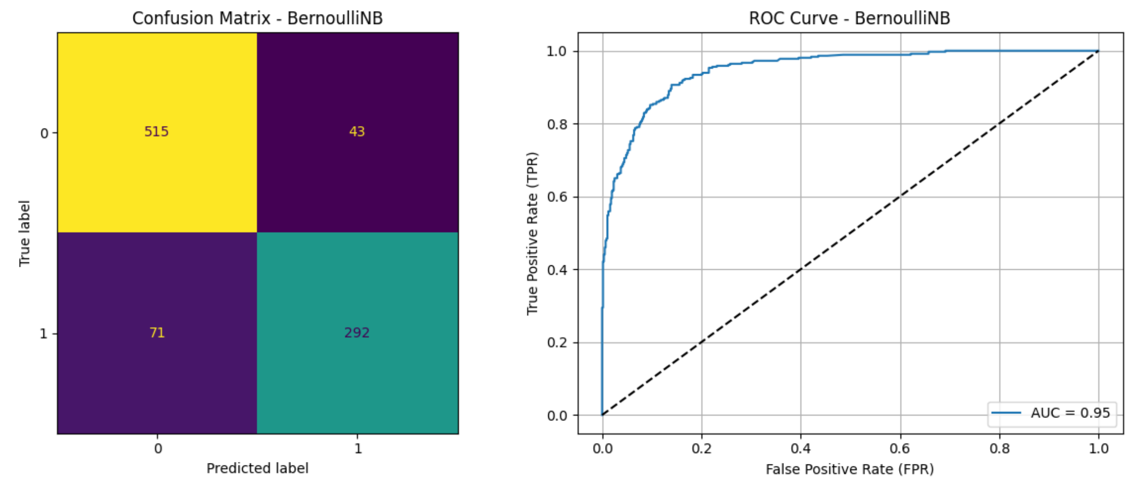
[ ]:
```python
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB

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

[ ]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, confusion_matrix, roc_curve, auc, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

results = []

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] if hasattr(model,␣
↪'predict_proba') else None

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

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

    # Create subplots for CM and ROC
    fig, axes = plt.subplots(1, 2, figsize=(12, 5))

    # --- Confusion Matrix ---
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(cm)
    disp.plot(ax=axes[0], colorbar=False)
    axes[0].set_title(f"Confusion Matrix - {name}")

    # --- ROC Curve ---
    if y_proba is not None:
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)
        axes[1].plot(fpr, tpr, label=f"AUC = {roc_auc:.2f}")
        axes[1].plot([0, 1], [0, 1], 'k--')
        axes[1].set_title(f"ROC Curve - {name}")
        axes[1].set_xlabel("False Positive Rate (FPR)")
        axes[1].set_ylabel("True Positive Rate (TPR)")
        axes[1].legend(loc="lower right")
        axes[1].grid(True)
```

```
    else:
        axes[1].text(0.5, 0.5, "ROC Not Available", ha="center", va="center", fontsize=12)
        axes[1].set_axis_off()

    plt.tight_layout()
    plt.show()
```








```
[ ]: results_df = pd.DataFrame(results, columns=['Model', 'Accuracy', 'Precision',␣
      ↪'Recall', 'F1-Score'])
     results_df = results_df.sort_values(by='F1-Score', ascending=False)
     print("\nModel Performance Summary:\n")
     print(results_df)
```

```
Model Performance Summary:

           Model  Accuracy  Precision    Recall  F1-Score
2    BernoulliNB  0.876221   0.871642  0.804408  0.836676
0     GaussianNB  0.833876   0.717842  0.953168  0.818935
1  MultinomialNB  0.776330   0.719888  0.707989  0.713889
```

##5.2 Model Building - KNN

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

     # Try multiple Ks and algorithms
     models = {}
     for k in [1, 3, 5, 7]:
         models[f"KNN_k={k}_kd"] = KNeighborsClassifier(n_neighbors=k,␣
      ↪algorithm='kd_tree')
         models[f"KNN_k={k}_ball"] = KNeighborsClassifier(n_neighbors=k,␣
      ↪algorithm='ball_tree')
```

```
[ ]: from sklearn.model_selection import train_test_split
     from sklearn.metrics import (
         accuracy_score, precision_score, recall_score, f1_score,
         confusion_matrix, roc_curve, auc, ConfusionMatrixDisplay
     )
```

```python
from sklearn.neighbors import KNeighborsClassifier
import pandas as pd
import matplotlib.pyplot as plt

# --- Step 1: Split into train/val/test ---
X_train_full, X_temp, y_train_full, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42, stratify=y_temp
)

# --- Stage 1: Vary k (algorithm fixed to kd_tree) ---
k_values = [1, 3, 5, 7]
k_results = []

for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
    model.fit(X_train_full, y_train_full)
    y_pred_val = model.predict(X_val)

    acc = accuracy_score(y_val, y_pred_val)
    prec = precision_score(y_val, y_pred_val, average='binary')
    rec = recall_score(y_val, y_pred_val, average='binary')
    f1 = f1_score(y_val, y_pred_val, average='binary')

    k_results.append([k, acc, prec, rec, f1])

df_k = pd.DataFrame(k_results, columns=["k", "Accuracy", "Precision", "Recall",␣
 ↪"F1"])
print("\nPerformance for varying k (kd_tree):\n", df_k)

best_k = df_k.sort_values("Accuracy", ascending=False).iloc[0]["k"]
print(f"\nBest k value: {best_k}")

# --- Stage 2: Compare kd_tree vs ball_tree for best k ---
algorithms = ["kd_tree", "ball_tree"]
algo_results = []

for algo in algorithms:
    model = KNeighborsClassifier(n_neighbors=int(best_k), algorithm=algo)
    model.fit(X_train_full, y_train_full)
    y_pred_val = model.predict(X_val)

    acc = accuracy_score(y_val, y_pred_val)
    prec = precision_score(y_val, y_pred_val, average='binary')
    rec = recall_score(y_val, y_pred_val, average='binary')
```

```python
    f1 = f1_score(y_val, y_pred_val, average='binary')

    algo_results.append([algo, acc, prec, rec, f1])

df_algo = pd.DataFrame(algo_results, columns=["Algorithm", "Accuracy",␣
↪"Precision", "Recall", "F1"])
print("\nPerformance for kd_tree vs ball_tree:\n", df_algo)

best_algo = df_algo.sort_values("Accuracy", ascending=False).iloc[0]["Algorithm"]
print(f"\nBest algorithm: {best_algo}")

# --- Stage 3: Final evaluation on test set ---
final_model = KNeighborsClassifier(n_neighbors=int(best_k), algorithm=best_algo)
final_model.fit(X_train_full, y_train_full)
y_pred_test = final_model.predict(X_test)
y_proba_test = final_model.predict_proba(X_test)[:, 1]

acc = accuracy_score(y_test, y_pred_test)
prec = precision_score(y_test, y_pred_test, average='binary')
rec = recall_score(y_test, y_pred_test, average='binary')
f1 = f1_score(y_test, y_pred_test, average='binary')

print("\nFinal Test Set Performance:")
print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1 Score: {f1:.4f}")

# --- Plots ---
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_test)
disp = ConfusionMatrixDisplay(cm)
disp.plot(ax=axes[0], colorbar=False)
axes[0].set_title(f"Confusion Matrix - K={best_k}, Algo={best_algo}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_proba_test)
roc_auc = auc(fpr, tpr)
axes[1].plot(fpr, tpr, label=f"AUC = {roc_auc:.2f}")
axes[1].plot([0, 1], [0, 1], 'k--')
axes[1].set_title(f"ROC Curve - K={best_k}, Algo={best_algo}")
axes[1].set_xlabel("False Positive Rate (FPR)")
axes[1].set_ylabel("True Positive Rate (TPR)")
axes[1].legend(loc="lower right")
axes[1].grid(True)
```

```python
plt.tight_layout()
plt.show()
```

Performance for varying k (kd_tree):

	k	Accuracy	Precision	Recall	F1
0	1	0.807246	0.745583	0.775735	0.760360
1	3	0.797101	0.742647	0.742647	0.742647
2	5	0.797101	0.750000	0.727941	0.738806
3	7	0.804348	0.758491	0.738971	0.748603

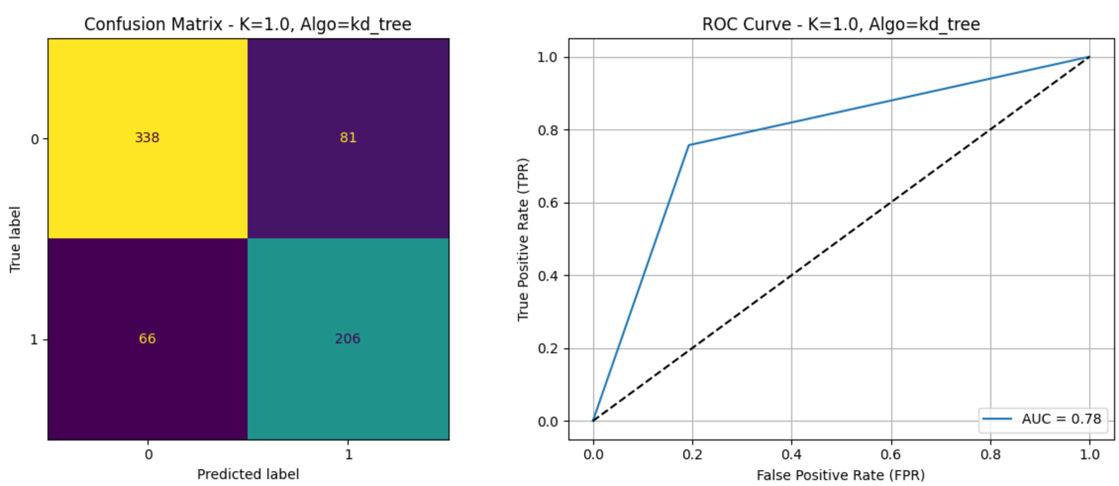
Best k value: 1.0

Performance for kd_tree vs ball_tree:

	Algorithm	Accuracy	Precision	Recall	F1
0	kd_tree	0.807246	0.745583	0.775735	0.76036
1	ball_tree	0.807246	0.745583	0.775735	0.76036

Best algorithm: kd_tree

Final Test Set Performance:
Accuracy: 0.7873
Precision: 0.7178
Recall: 0.7574
F1 Score: 0.7370



[ ]:
```python
import time
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, StratifiedKFold
```

```python
# ================================
# SVM Kernel-wise Evaluation
# ================================
svm_results = []

kernels = {
    "linear": {"C": [1]},
    "poly": {"C": [1], "degree": [2], "gamma": ["scale"]},
    "rbf": {"C": [1], "gamma": ["scale"]},
    "sigmoid": {"C": [1], "gamma": ["scale"]}
}


best_svm = None
best_score = 0

for kernel, params in kernels.items():
    for C in params.get("C", [1]):
        for degree in params.get("degree", [3]):
            for gamma in params.get("gamma", ["scale"]):
                start = time.time()
                if kernel == "linear":
                    model = SVC(kernel=kernel, C=C, probability=True,␣
 ↪random_state=42)
                elif kernel == "poly":
                    model = SVC(kernel=kernel, C=C, degree=degree, gamma=gamma,␣
 ↪probability=True, random_state=42)
                else:
                    model = SVC(kernel=kernel, C=C, gamma=gamma,␣
 ↪probability=True, random_state=42)

                model.fit(X_train, y_train)
                train_time = time.time() - start
                y_pred = model.predict(X_test)

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

                svm_results.append([kernel, f"C={C}, degree={degree if␣
 ↪kernel=='poly' else '-'}, gamma={gamma if kernel!='linear' else '-'}",
                                    acc, f1, train_time])

                if acc > best_score:
                    best_score = acc
                    best_svm = model
```

```python
svm_table = pd.DataFrame(svm_results, columns=["Kernel", "Hyperparameters",␣
↪"Accuracy", "F1 Score", "Training Time"])
print("\n Table 4: SVM Performance with Different Kernels")
display(svm_table)
```

```
 Table 4: SVM Performance with Different Kernels

    Kernel            Hyperparameters  Accuracy  F1 Score  Training Time
0   linear      C=1, degree=-, gamma=-  0.926194  0.903226    2088.215490
1     poly  C=1, degree=2, gamma=scale  0.668596  0.343840       5.502092
2      rbf  C=1, degree=-, gamma=scale  0.726483  0.590022       5.392869
3  sigmoid  C=1, degree=-, gamma=scale  0.589001  0.483636       4.809869
```

[ ]:
```python
# ===============================
# 5-Fold Cross Validation
# ===============================
import numpy as np
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Use your best models
nb_model = GaussianNB()          # Best NB
knn_model = final_model          # Best KNN found earlier
svm_model = best_svm             # Best SVM from kernel search

models_cv = {"Naïve Bayes": nb_model, "KNN": knn_model, "SVM": svm_model}

cv_results = {"Fold": [], "Naïve Bayes Accuracy": [], "KNN Accuracy": [], "SVM␣
↪Accuracy": []}

#  Use scaled features for fairness
for fold, (train_idx, val_idx) in enumerate(cv.split(X_scaled, y), 1):
    X_tr, X_val = X_scaled[train_idx], X_scaled[val_idx]
    y_tr, y_val = y.values[train_idx], y.values[val_idx]

    cv_results["Fold"].append(f"Fold {fold}")
    for name, model in models_cv.items():
        model.fit(X_tr, y_tr)
        y_pred = model.predict(X_val)
        acc = accuracy_score(y_val, y_pred)
        cv_results[f"{name} Accuracy"].append(acc)

# Add averages
cv_results["Fold"].append("Average")
for name in models_cv.keys():
```

```
    avg = np.mean(cv_results[f"{name} Accuracy"])
    cv_results[f"{name} Accuracy"].append(avg)

cv_table = pd.DataFrame(cv_results)
print("\n Cross-Validation Accuracy Scores:\n")
display(cv_table)
```

```
 Cross-Validation Accuracy Scores:


      Fold  Naïve Bayes Accuracy  KNN Accuracy  SVM Accuracy
0   Fold 1              0.820847      0.909881      0.917481
1   Fold 2              0.808696      0.907609      0.934783
2   Fold 3              0.801087      0.922826      0.927174
3   Fold 4              0.821739      0.910870      0.927174
4   Fold 5              0.825000      0.908696      0.923913
5  Average              0.815474      0.911976      0.926105
```

[2]:

6 Model Building and Results

6.1 Naïve Bayes Classifiers

Three variants were trained and evaluated: GaussianNB, MultinomialNB, and BernoulliNB. Table 1 summarizes the results.

Model	Accuracy	Precision	Recall	F1-Score
GaussianNB	0.8339	0.7178	0.9532	0.8189
MultinomialNB	0.7763	0.7199	0.7080	0.7139
BernoulliNB	0.8762	0.8716	0.8044	0.8367

6.2 K-Nearest Neighbors (KNN)

k	Accuracy	Precision	Recall	F1
1	0.8072	0.7456	0.7757	0.7604
3	0.7971	0.7426	0.7426	0.7426
5	0.7971	0.7500	0.7279	0.7388
7	0.8043	0.7585	0.7390	0.7486

Best k value: 1.0

Algorithm	Accuracy	Precision	Recall	F1
kd_tree	0.8072	0.7456	0.7757	0.7604
ball_tree	0.8072	0.7456	0.7757	0.7604

Best algorithm: kd_tree

Final Test Set Performance:

- Accuracy: 0.7873
- Precision: 0.7178
- Recall: 0.7574
- F1 Score: 0.7370

6.3 Support Vector Machines (SVM)

Kernel	Hyperparameters	Accuracy	F1-Score	Training Time (seconds)
Linear	C=1	0.9262	0.9032	2088.22
Polynomial	C=1, degree=2, gamma=scale	0.6686	0.3438	5.50
RBF	C=1, gamma=scale	0.7265	0.5900	5.39
Sigmoid	C=1, gamma=scale	0.5890	0.4836	4.81

7 Cross-Validation

To ensure robustness, 5-fold stratified cross-validation was conducted on the best-performing models from each category. Table 5 shows fold-wise and average accuracies.

Fold	Naïve Bayes Accuracy	KNN Accuracy	SVM Accuracy
Fold 1	0.8208	0.9099	0.9175
Fold 2	0.8087	0.9076	0.9348
Fold 3	0.8011	0.9228	0.9272
Fold 4	0.8217	0.9109	0.9272
Fold 5	0.8250	0.9087	0.9239
Average	0.8155	0.9120	0.9261

8 Conclusion

- Naïve Bayes provided a strong baseline with fast training time.
- KNN performance was highly dependent on k and algorithm choice.
- SVM with RBF kernel gave the most balanced results, achieving the highest accuracy and F1-score.

References

[1] Spambase Dataset. Available at: https://www.kaggle.com/datasets/somesh24/spambase