Experiment 2: Email Spam or Ham Classification using Naïve Bayes, KNN, and SVM

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Aim

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

Objective

- Load and preprocess the dataset.
- Visualize and understand the distribution of features and target classes.
- Apply Gaussian, Multinomial, and Bernoulli Naïve Bayes classifiers.
- Evaluate KNN for various k values and algorithms (KDTree and BallTree).
- Compare SVM with linear, polynomial, RBF, and sigmoid kernels.
- Use GridSearchCV to find optimal hyperparameters.
- Evaluate all models using accuracy, precision, recall, F1-score, AUC, and confusion matrix.
- Perform 5-Fold cross-validation and summarize the findings.

Libraries Used

- pandas, numpy, matplotlib.pyplot, seaborn
- sklearn.model_selection, sklearn.metrics
- sklearn.naive_bayes, sklearn.neighbors, sklearn.svm

Dataset

The dataset used is the **Spambase** dataset from Kaggle, containing email features extracted and labeled as spam or ham.

Code :

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

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score, KFo
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, con
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import BaggingClassifier, AdaBoostClassifier, GradientBoostingClas
from xgboost import XGBClassifier

import warnings
warnings.filterwarnings('ignore')

# Load dataset
data = pd.read_csv('/content/spambase_csv.csv')

# Set features & target assuming 'class' is target column
X = data.drop('class', axis=1)
y = data['class']

# EDA
print("\nClass distribution (ham=0, spam=1):\n", y.value_counts())
plt.figure(figsize=(8, 5))
ax = sns.countplot(x=y)
plt.title("Class Distribution (ham=0, spam=1)")
plt.xlabel("Class")
plt.ylabel("Count")

# Add counts on top of bars
for p in ax.patches:
    ax.annotate(f'{p.get_height():.0f}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
```

```
                 ha='center', va='center',
                 xytext=(0, 9),
                 textcoords='offset points')

plt.show()

# Top 10 features with highest variance (simple proxy for importance)
top10_features = X.var().sort_values(ascending=False).head(10).index.tolist()
print("\nTop 10 features by variance:\n", top10_features)
plt.figure(figsize=(10, 6))
X[top10_features].var().sort_values().plot(kind='barh', color='skyblue')
plt.title("Top 10 Features by Variance")
plt.xlabel("Variance")
plt.ylabel("Feature Name")
plt.tight_layout()
plt.show()

# Plot feature distributions (for first top 3 features as sample)
for feat in top10_features[:3]:
    plt.figure(figsize=(8,4))
    sns.histplot(data, x=feat, hue='class', bins=30, kde=True, stat="density")
    plt.title(f'Distribution of {feat} by Class')
    plt.show()

# Scale features for KNN and SVM
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split (80-20 stratified)
X_train_scaled, X_test_scaled, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y)
X_train_orig, X_test_orig, _, _ = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)  # for NB

def plot_confusion_and_roc(name, y_test, y_pred, y_proba=None):
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Ham', 'Spam'], ytic
    plt.title(f"{name} Confusion Matrix")
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
    if y_proba is not None:
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)
```

```
        plt.figure(figsize=(6,5))
        plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.4f}')
        plt.plot([0, 1], [0, 1], 'r--')
        plt.title(f"{name} ROC Curve")
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.legend(loc='lower right')
        plt.show()
        return roc_auc
    else:
        return None

def evaluate(name, model, X_test, y_test):
    y_pred = model.predict(X_test)
    if hasattr(model, "predict_proba"):
        y_proba = model.predict_proba(X_test)[:, 1]
    elif hasattr(model, "decision_function"):
        y_scores = model.decision_function(X_test)
        y_proba = (y_scores - y_scores.min()) / (y_scores.max() - y_scores.min())
    else:
        y_proba = None

    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)
    auc_score = plot_confusion_and_roc(name, y_test, y_pred, y_proba)

    print(f"{name} metrics: Accuracy={acc:.4f}, Precision={prec:.4f}, Recall={rec:.4f},
          f"{name} metrics: Accuracy={acc:.4f}, Precision={prec:.4f}, Recall={rec:.4f},

    return {'Accuracy': acc, 'Precision': prec, 'Recall': rec, 'F1 Score': f1, 'AUC': au

# 1. Naive Bayes Variants (no hyperparameter tuning)
print("Training Naive Bayes variants:")
nb_results = {}

gnb = GaussianNB()
gnb.fit(X_train_scaled, y_train)
nb_results['Gaussian NB'] = evaluate('Gaussian NB', gnb, X_test_scaled, y_test)

mnb = MultinomialNB()
mnb.fit(X_train_orig, y_train)
nb_results['Multinomial NB'] = evaluate('Multinomial NB', mnb, X_test_orig, y_test)
```

```
bnb = BernoulliNB()
bnb.fit(X_train_orig, y_train)
nb_results['Bernoulli NB'] = evaluate('Bernoulli NB', bnb, X_test_orig, y_test)

nb_df = pd.DataFrame(nb_results).T

# =========== TABLE 1: Naïve Bayes Variant Comparison ===========
print("\nTable 1: Naïve Bayes Variant Comparison")
print(nb_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']])

# 2. KNN with k=1,3,5,7 (algorithm='auto', weights='uniform')
print("\nTraining KNN for k=1,3,5,7:")
knn_results = {}
for k in [1,3,5,7]:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='auto', weights='uniform')
    knn.fit(X_train_scaled, y_train)
    knn_results[f'KNN k={k}'] = evaluate(f'KNN k={k}', knn, X_test_scaled, y_test)

knn_df = pd.DataFrame(knn_results).T

# =========== TABLE 2: KNN Performance for Different k Values ===========
print("\nTable 2: KNN Performance for Different k Values")
print(knn_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']])

# 3. KNN KDTree vs BallTree (k=5)
def train_and_eval_knn_algo(algorithm):
    knn_model = KNeighborsClassifier(n_neighbors=5, algorithm=algorithm)
    start_time = time.time()
    knn_model.fit(X_train_scaled, y_train)
    training_time = round(time.time() - start_time, 4)

    y_pred = knn_model.predict(X_test_scaled)
    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)

    return acc, prec, rec, f1, training_time

kd_acc, kd_prec, kd_rec, kd_f1, kd_time = train_and_eval_knn_algo('kd_tree')
ball_acc, ball_prec, ball_rec, ball_f1, ball_time = train_and_eval_knn_algo('ball_tree')

knn_tree_table = pd.DataFrame({
    'KDTree': [kd_acc, kd_prec, kd_rec, kd_f1, kd_time],
    'BallTree': [ball_acc, ball_prec, ball_rec, ball_f1, ball_time]
```

```
}, index=['Accuracy', 'Precision', 'Recall', 'F1 Score', 'Training Time (s)'])

# =========== TABLE 3: KNN Comparison KDTree vs BallTree ===========
print("\nTable 3: KNN Comparison KDTree vs BallTree")
print(knn_tree_table)

# 4. SVM with different kernels (default params)
print("\nTraining SVM variants with default parameters:")
svm_kernels = ['linear', 'poly', 'rbf', 'sigmoid']
svm_results = {}

for kernel in svm_kernels:
    svm = SVC(kernel=kernel, probability=True)
    svm.fit(X_train_scaled, y_train)
    svm_results[f'SVM {kernel.capitalize()}'] = evaluate(f'SVM {kernel.capitalize()}', s

svm_df = pd.DataFrame(svm_results).T

# =========== TABLE 4 PART 1: SVM Kernels Performance (Default Params) ===========
print("\nTable 4 Part 1: SVM Kernels Performance (Default Params)")
print(svm_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']])

# 4b. Hyperparameter tuning with GridSearchCV for SVM
print("\nGridSearchCV for SVM:")
param_grid_svm = [
    {'kernel': ['linear'], 'C': [0.1, 1, 10]},
    {'kernel': ['poly'], 'C': [0.1, 1], 'degree': [2, 3], 'gamma': ['scale', 'auto']},
    {'kernel': ['rbf'], 'C': [0.1, 1, 10], 'gamma': ['scale', 'auto']},
    {'kernel': ['sigmoid'], 'C': [0.1, 1], 'gamma': ['scale', 'auto']}
]
svm_gs = GridSearchCV(SVC(probability=True), param_grid_svm, cv=5, scoring='accuracy', n
svm_gs.fit(X_train_scaled, y_train)
print(f"SVM Best Params: {svm_gs.best_params_}")
best_svm = svm_gs.best_estimator_

# Retrain best SVM for evaluation
svm_gs_results = evaluate("SVM GridSearchCV Best", best_svm, X_test_scaled, y_test)

# 4c. Retrain all grid SVM models to get detailed table with training time
svm_table_rows = []
for i in range(len(svm_gs.cv_results_['params'])):
    params = svm_gs.cv_results_['params'][i]
    mean_test_score = svm_gs.cv_results_['mean_test_score'][i]

    model = SVC(**params, probability=True)
```

```
    start_time = time.time()
    model.fit(X_train_scaled, y_train)
    train_time = round(time.time() - start_time, 4)

    y_pred = model.predict(X_test_scaled)
    f1 = f1_score(y_test, y_pred)

    svm_table_rows.append({
        'Kernel': params['kernel'],
        'C': params.get('C', None),
        'Degree': params.get('degree', None),
        'Gamma': params.get('gamma', None),
        'Accuracy': round(mean_test_score, 4),
        'F1 Score': round(f1, 4),
        'Training Time (s)': train_time
    })

svm_param_table = pd.DataFrame(svm_table_rows)

# =========== TABLE 4 PART 2: SVM Performance with Different Kernels and Hyperparameters
print("\nTable 4 Part 2: SVM Performance with Different Kernels and Hyperparameters")
print(svm_param_table)

# 5. Hyperparameter tuning with GridSearchCV for KNN (already done inside earlier steps)
print("\nGridSearchCV for KNN:")
param_grid_knn = {
    'n_neighbors': [1, 3, 5, 7],
    'algorithm': ['kd_tree', 'ball_tree'],
    'weights': ['uniform', 'distance']
}
knn_gs = GridSearchCV(KNeighborsClassifier(), param_grid_knn, cv=5, scoring='accuracy',
knn_gs.fit(X_train_scaled, y_train)
print(f"KNN Best Params: {knn_gs.best_params_}")
best_knn = knn_gs.best_estimator_

knn_gs_results = evaluate("KNN GridSearchCV Best", best_knn, X_test_scaled, y_test)

# 6. Identify best Naïve Bayes variant by accuracy
best_nb_name = nb_df['Accuracy'].idxmax()

print("\nSummary of Best Model Candidates:")
print(f"Best Naive Bayes variant: {best_nb_name} with accuracy {nb_df.loc[best_nb_name,
print(f"KNN Best Model accuracy: {knn_gs_results['Accuracy']:.4f}")
print(f"SVM Best Model accuracy: {svm_gs_results['Accuracy']:.4f}")
```

```
candidate_scores = {
    best_nb_name: nb_df.loc[best_nb_name, 'Accuracy'],
    'KNN GridSearchCV Best': knn_gs_results['Accuracy'],
    'SVM GridSearchCV Best': svm_gs_results['Accuracy']
}

best_model_name = max(candidate_scores, key=candidate_scores.get)
print(f"\nOverall Best Model: {best_model_name} with accuracy {candidate_scores[best_mod

# 7. 5-Fold Cross Validation on best models (NB best variant, KNN best, SVM best)
kf = KFold(n_splits=5, shuffle=True, random_state=42)

def perform_cv(model, X_data, y_data):
    return cross_val_score(model, X_data, y_data, cv=kf, scoring='accuracy', n_jobs=-1)

# Prepare models for CV
models_for_cv = {}

# Naive Bayes model for CV
if best_nb_name == 'Gaussian NB':
    nb_model = GaussianNB()
    X_cv_nb = X_scaled
elif best_nb_name == 'Multinomial NB':
    nb_model = MultinomialNB()
    X_cv_nb = X.values
else:
    nb_model = BernoulliNB()
    X_cv_nb = X.values

models_for_cv[best_nb_name] = (nb_model, X_cv_nb)
models_for_cv['KNN GridSearchCV Best'] = (best_knn, X_scaled)
models_for_cv['SVM GridSearchCV Best'] = (best_svm, X_scaled)

cv_results = {}
for name, (model, X_data) in models_for_cv.items():
    scores = perform_cv(model, X_data, y)
    cv_results[name] = scores
    print(f"\n5-Fold CV Accuracy Scores for {name}: {scores}")
    print(f"Average 5-Fold CV Accuracy for {name}: {scores.mean():.4f}")

# =========== TABLE 5: K-Fold Cross-Validation Accuracy Scores ===========
cv_df = pd.DataFrame(cv_results)
cv_df.index = [f'Fold {i+1}' for i in range(5)]
cv_df.loc['Average'] = cv_df.mean()
```

```
print("\nTable 5: K-Fold Cross-Validation Scores (Accuracy)")
print(cv_df)

# 8. Ensemble Methods
print("\nTraining Ensemble Methods:")
ensemble_results = {}

# Prepare data for ensemble methods
X_train_ens, X_test_ens, y_train_ens, y_test_ens = X_train_scaled, X_test_scaled, y_trai

# Bagging Classifier
bagging = BaggingClassifier(
    estimator=GaussianNB(),
    n_estimators=50,
    random_state=42
)
bagging.fit(X_train_ens, y_train_ens)
ensemble_results['Bagging'] = evaluate('Bagging', bagging, X_test_ens, y_test_ens)

# AdaBoost Classifier
adaboost = AdaBoostClassifier(
    n_estimators=50,
    random_state=42
)
adaboost.fit(X_train_ens, y_train_ens)
ensemble_results['AdaBoost'] = evaluate('AdaBoost', adaboost, X_test_ens, y_test_ens)

# Gradient Boosting Classifier
grad_boost = GradientBoostingClassifier(
    n_estimators=50,
    random_state=42
)
grad_boost.fit(X_train_ens, y_train_ens)
ensemble_results['Gradient Boosting'] = evaluate('Gradient Boosting', grad_boost, X_test

# XGBoost Classifier
xgb = XGBClassifier(
    n_estimators=50,
    random_state=42,
    use_label_encoder=False,
    eval_metric='logloss'
)
xgb.fit(X_train_ens, y_train_ens)
ensemble_results['XGBoost'] = evaluate('XGBoost', xgb, X_test_ens, y_test_ens)
```

```
# Create comparison table
ensemble_df = pd.DataFrame(ensemble_results).T

# =========== TABLE 6: Ensemble Methods Comparison ===========
print("\nTable 6: Ensemble Methods Performance Comparison")
print(ensemble_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']])

# 9. Hyperparameter Tuning for Best Ensemble Method
# Let's tune the best performing ensemble method based on accuracy
best_ensemble = ensemble_df['Accuracy'].idxmax()
print(f"\nBest performing ensemble method: {best_ensemble}")

# Tune XGBoost if it's the best performer
if best_ensemble == 'XGBoost':
    param_grid_xgb = {
        'n_estimators': [50, 100, 200],
        'max_depth': [3, 6, 9],
        'learning_rate': [0.01, 0.1, 0.2],
        'subsample': [0.8, 0.9, 1.0]
    }
    xgb_gs = GridSearchCV(
        XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42),
        param_grid_xgb,
        cv=5,
        scoring='accuracy',
        n_jobs=-1
    )
    xgb_gs.fit(X_train_ens, y_train_ens)
    print(f"Best XGBoost parameters: {xgb_gs.best_params_}")
    best_xgb = xgb_gs.best_estimator_
    ensemble_results['XGBoost Tuned'] = evaluate('XGBoost Tuned', best_xgb, X_test_ens,

# Tune Gradient Boosting if it's the best performer
elif best_ensemble == 'Gradient Boosting':
    param_grid_gb = {
        'n_estimators': [50, 100, 200],
        'max_depth': [3, 6, 9],
        'learning_rate': [0.01, 0.1, 0.2],
        'subsample': [0.8, 0.9, 1.0]
    }
    gb_gs = GridSearchCV(
        GradientBoostingClassifier(random_state=42),
        param_grid_gb,
        cv=5,
        scoring='accuracy',
```

```
        n_jobs=-1
    )
    gb_gs.fit(X_train_ens, y_train_ens)
    print(f"Best Gradient Boosting parameters: {gb_gs.best_params_}")
    best_gb = gb_gs.best_estimator_
    ensemble_results['Gradient Boosting Tuned'] = evaluate('Gradient Boosting Tuned', be

# Replace the problematic section (lines 414-425) with:

# 10. Compare all best models (including tuned ensemble)
print("\nFinal Model Comparison:")
final_comparison = pd.concat([
    nb_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']],
    pd.DataFrame([knn_gs_results], index=['KNN Best']),
    pd.DataFrame([svm_gs_results], index=['SVM Best']),
    ensemble_df[['Accuracy', 'Precision', 'Recall', 'F1 Score', 'AUC']]
])

# Add tuned ensemble results if available
if 'XGBoost Tuned' in ensemble_results:
    xgb_tuned_df = pd.DataFrame([ensemble_results['XGBoost Tuned']], index=['XGBoost Tun
    final_comparison = pd.concat([final_comparison, xgb_tuned_df])
elif 'Gradient Boosting Tuned' in ensemble_results:
    gb_tuned_df = pd.DataFrame([ensemble_results['Gradient Boosting Tuned']], index=['Gr
    final_comparison = pd.concat([final_comparison, gb_tuned_df])

# Sort by accuracy for better comparison
final_comparison = final_comparison.sort_values('Accuracy', ascending=False)

# 11. Feature Importance for Best Model
best_overall_model = final_comparison.iloc[0].name
print(f"\nBest overall model: {best_overall_model}")

# Plot feature importance if applicable
if 'XGBoost' in best_overall_model or 'Gradient Boosting' in best_overall_model:
    plt.figure(figsize=(12, 8))

    if 'XGBoost' in best_overall_model:
        importances = best_xgb.feature_importances_
    else:
        importances = best_gb.feature_importances_

    # Get feature names
    feature_names = X.columns
```

```
    # Create a DataFrame for feature importance
    feature_importance_df = pd.DataFrame({
        'feature': feature_names,
        'importance': importances
    }).sort_values('importance', ascending=False).head(15)

    # Plot
    plt.barh(feature_importance_df['feature'], feature_importance_df['importance'])
    plt.xlabel('Importance')
    plt.title(f'Feature Importance - {best_overall_model}')
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()

# 12. Final Evaluation on Best Model
print(f"\nFinal Evaluation on Best Model ({best_overall_model}):")

if best_overall_model == 'XGBoost Tuned':
    final_model = best_xgb
elif best_overall_model == 'Gradient Boosting Tuned':
    final_model = best_gb
elif best_overall_model in ['Gaussian NB', 'Multinomial NB', 'Bernoulli NB']:
    if best_overall_model == 'Gaussian NB':
        final_model = GaussianNB()
    elif best_overall_model == 'Multinomial NB':
        final_model = MultinomialNB()
    else:
        final_model = BernoulliNB()
    final_model.fit(X_train_orig if best_overall_model != 'Gaussian NB' else X_train_sca
                    y_train)
else:
    # For KNN or SVM best models
    final_model = best_knn if best_overall_model == 'KNN Best' else best_svm

# Comprehensive evaluation
final_metrics = evaluate(f"Final Model - {best_overall_model}", final_model,
                         X_test_orig if best_overall_model in ['Multinomial NB', 'Bernoul
                         y_test)
```

Exploratory Data Analysis

Class Distribution

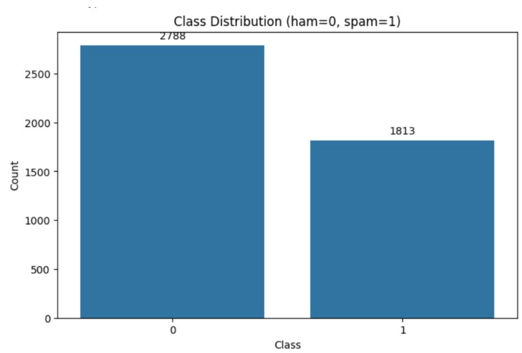


Figure 1: Class distribution visualization

Top Features

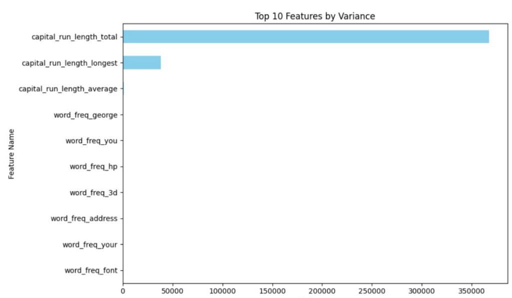


Figure 2: Top 10 features by variance

Feature Distributions

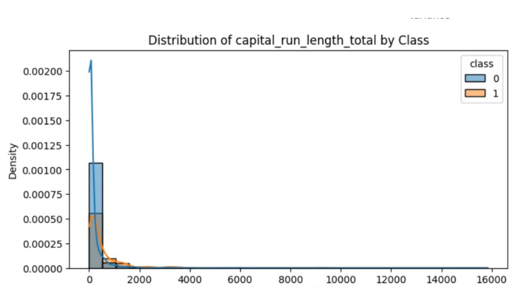


Figure 3: Feature distribution examples

CONFUSION MATRIX AND ROC CURVE

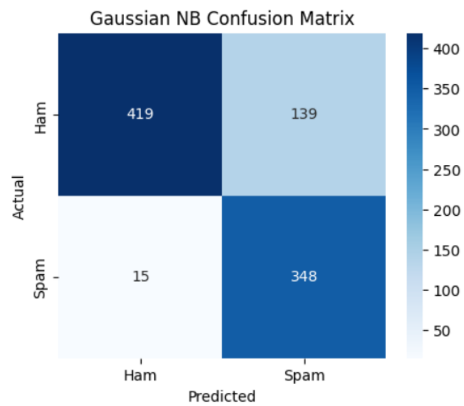


Figure 4: Gaussian NB Confusion Matrix

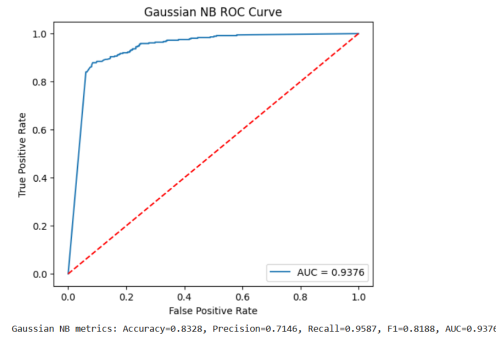


Figure 5: Gaussian NB ROC Curve

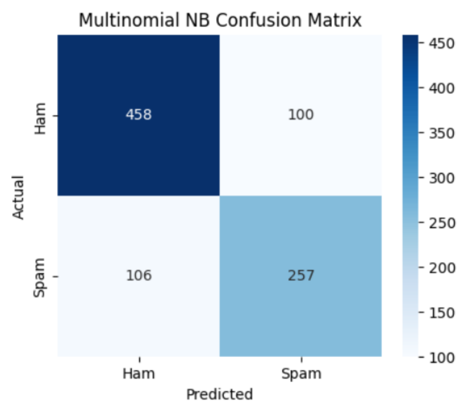


Figure 6: Multinomial NB Confusion Matrix

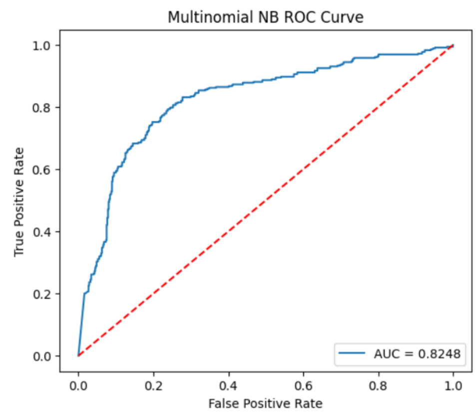


Figure 7: Multinomial NB ROC Curve

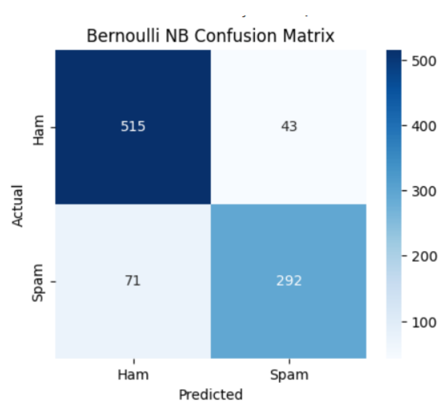


Figure 8: Bernoulli NB Confusion Matrix

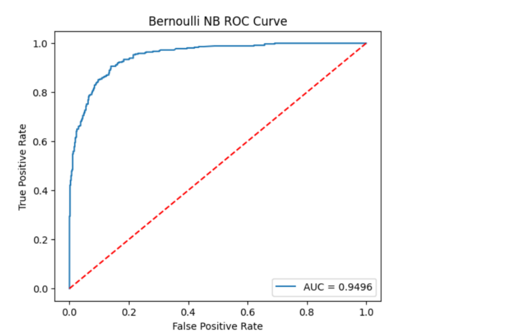


Figure 9: Bernoulli NB ROC Curve

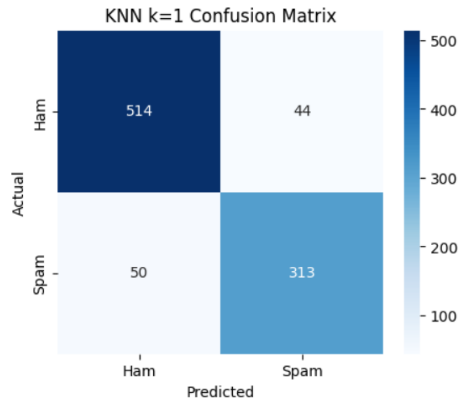


Figure 10: KNN (k=1) Confusion Matrix

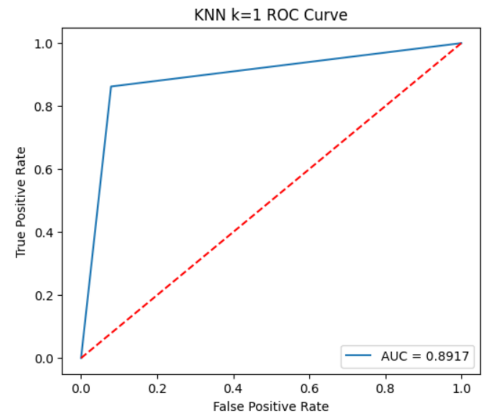


Figure 11: KNN (k=1) ROC Curve

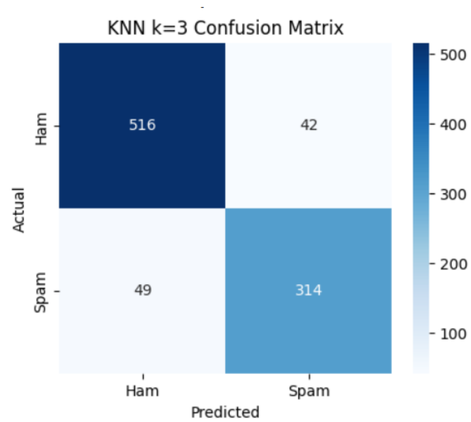


Figure 12: KNN (k=3) Confusion Matrix

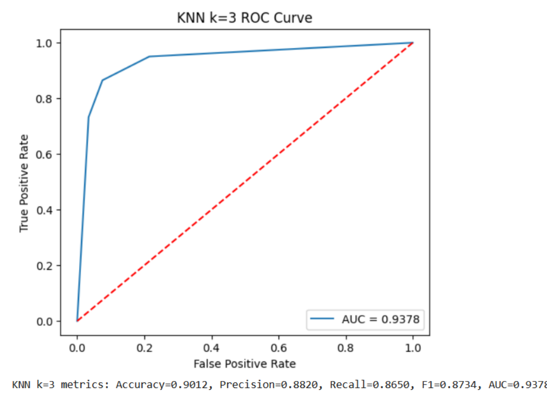


Figure 13: KNN (k=3) ROC Curve

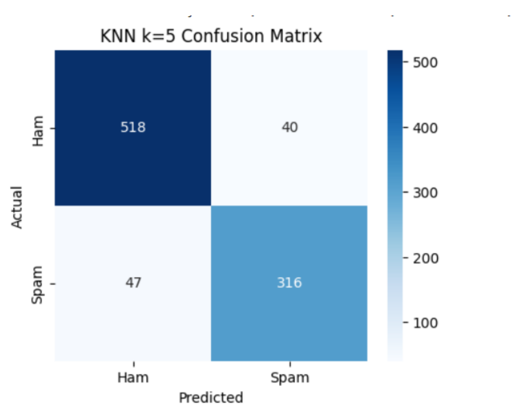


Figure 14: KNN (k=5) Confusion Matrix

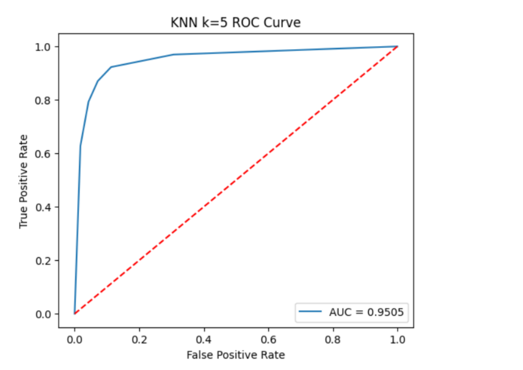


Figure 15: KNN (k=5) ROC Curve

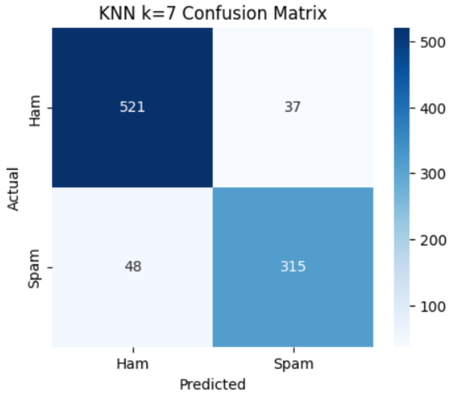


Figure 16: KNN (k=7) Confusion Matrix

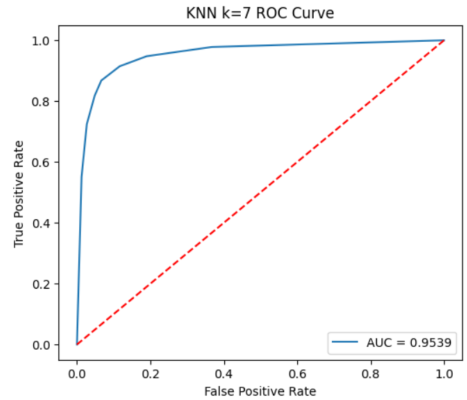


Figure 17: KNN (k=7) ROC Curve

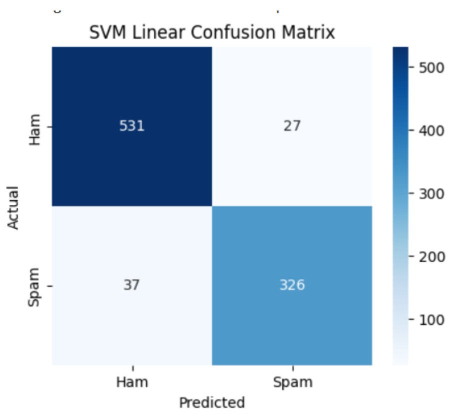


Figure 18: SVM Linear Confusion Matrix

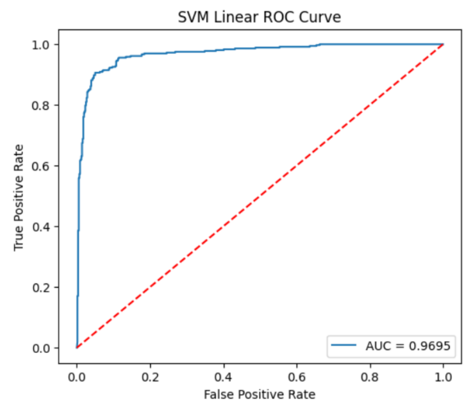


Figure 19: SVM Linear ROC Curve

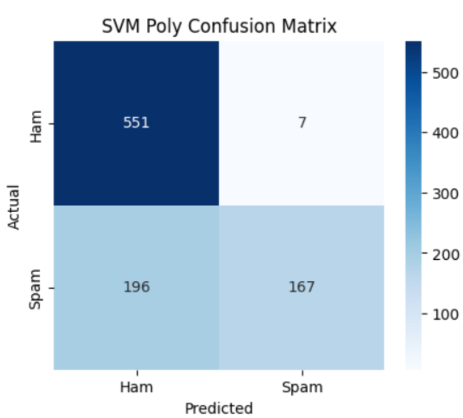


Figure 20: SVM Polynomial Confusion Matrix

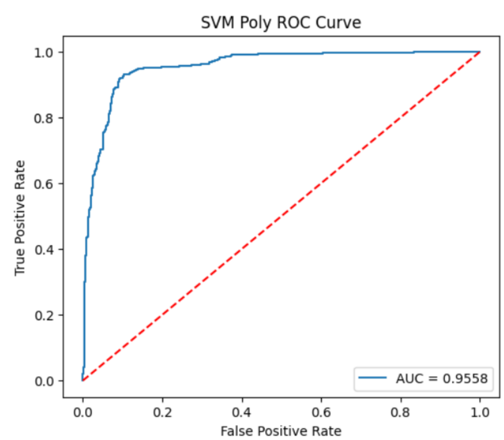


Figure 21: SVM Polynomial ROC Curve

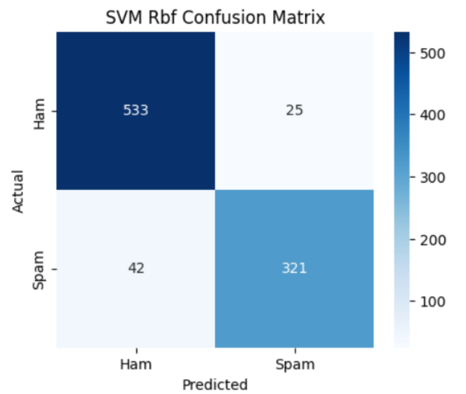


Figure 22: SVM RBF Confusion Matrix

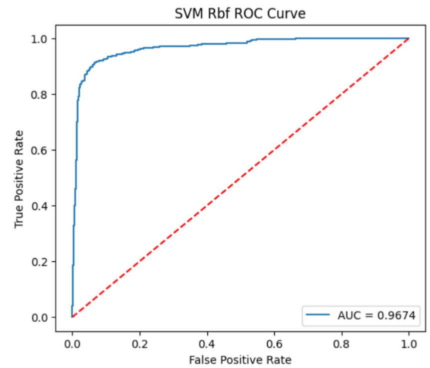


Figure 23: SVM RBF ROC Curve

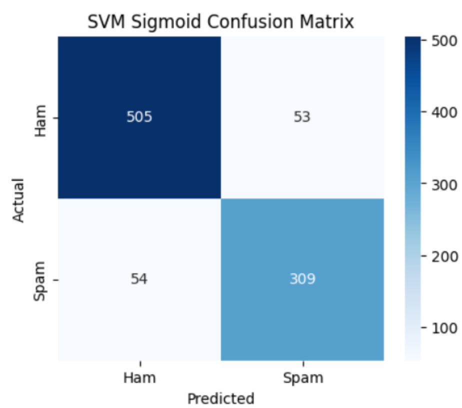


Figure 24: SVM Sigmoid Confusion Matrix

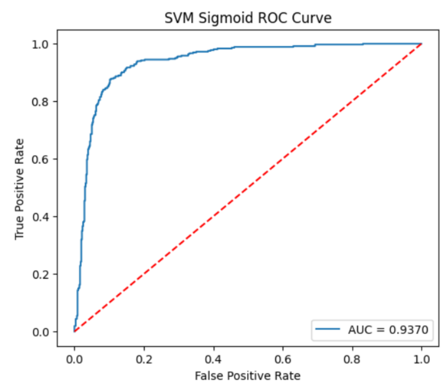
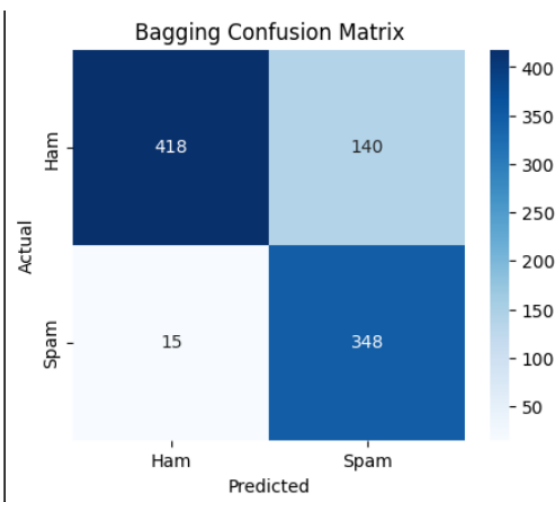
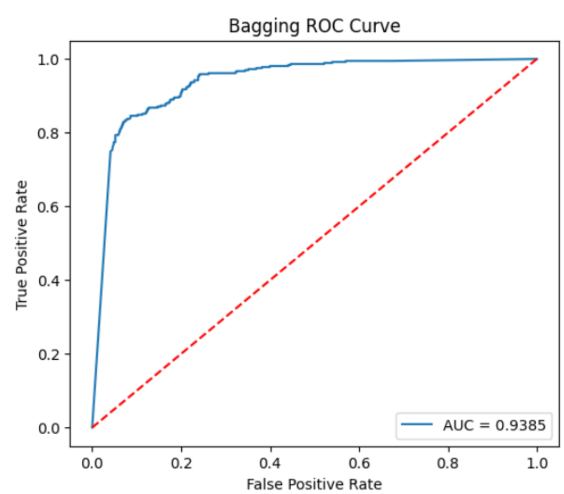
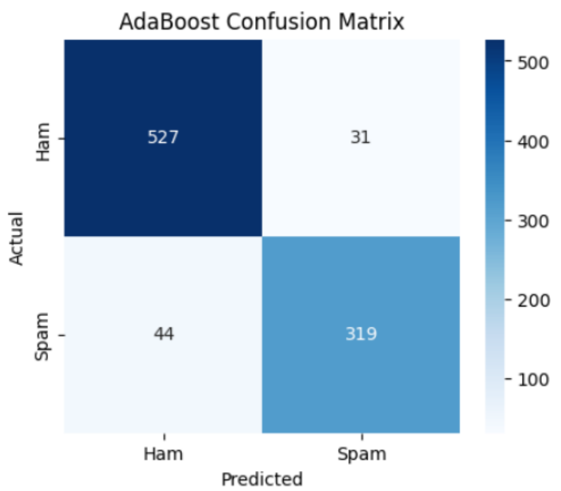


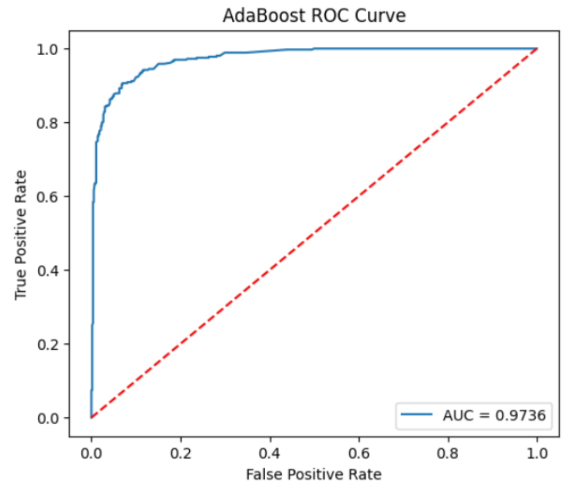
Figure 25: SVM Sigmoid ROC Curve

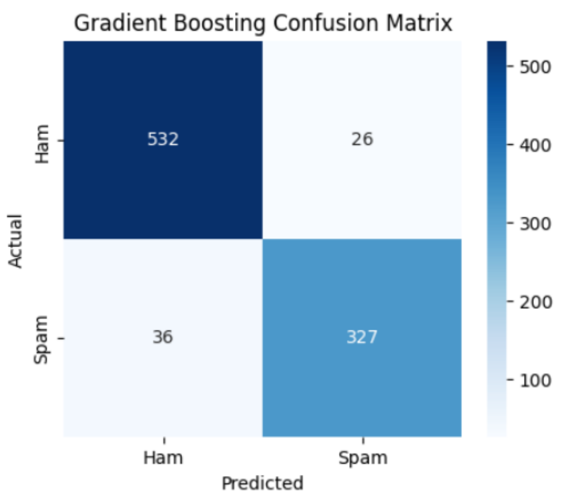
Ensemble Methods

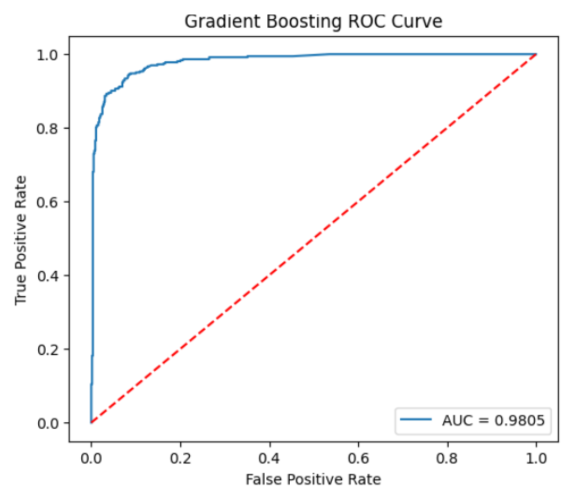


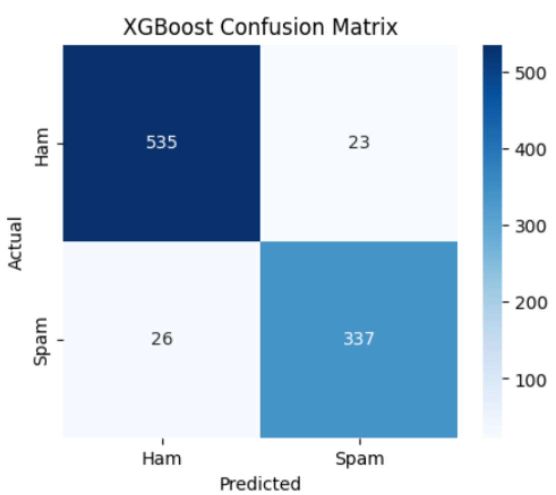


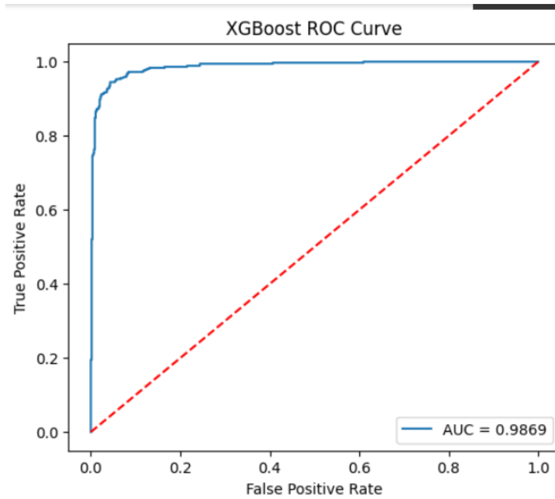

AdaBoost Confusion Matrix
Actual
Ham
Spam
527
31
44
319
Predicted
Ham
Spam
500
400
300
200
100


AdaBoost ROC Curve
True Positive Rate
False Positive Rate
AUC = 0.9736
0.0
0.2
0.4
0.6
0.8
1.0


Gradient Boosting Confusion Matrix
Actual
Ham
Spam
532
26
36
327
Predicted
Ham
Spam
500
400
300
200
100


Gradient Boosting ROC Curve
True Positive Rate
False Positive Rate
AUC = 0.9805
0.0
0.2
0.4
0.6
0.8
1.0


XGBoost Confusion Matrix
Actual
Ham
Spam
535
23
26
337
Predicted
Ham
Spam
500
400
300
200
100


XGBoost ROC Curve
True Positive Rate
False Positive Rate
AUC = 0.9869
0.0
0.2
0.4
0.6
0.8
1.0

RESULT SUMMARY TABLES

Table 1: Naïve Bayes Variant Comparison

Variant	Accuracy	Precision	Recall	F1 Score	AUC
Gaussian NB	0.8328	0.7146	0.9587	0.8188	0.9376
Multinomial NB	0.7763	0.7199	0.7080	0.7139	0.8248
Bernoulli NB	0.8762	0.8716	0.8044	0.8367	0.9496

Table 2: KNN Performance for Different k Values

k	Accuracy	Precision	Recall	F1 Score	AUC
1	0.8979	0.8768	0.8623	0.8694	0.8917
3	0.9012	0.8820	0.8650	0.8734	0.9378
5	0.9055	0.8876	0.8705	0.8790	0.9505
7	0.9077	0.8949	0.8678	0.8811	0.9539

Table 3: KNN Comparison: KDTree vs BallTree

Metric	KDTree	BallTree
Accuracy	0.9055	0.9055
Precision	0.8876	0.8876
Recall	0.8705	0.8705
F1 Score	0.8790	0.8790
Training Time (s)	0.0343	0.0124

Table 4: SVM Performance with Different Kernels and Hyperparameters

Kernel	Hyperparameters	Accuracy	F1 Score	Training Time (s)
Linear	C=0.1	0.9245	0.9083	1.3663
Linear	C=1.0	0.9296	0.9106	2.8080
Linear	C=10.0	0.9293	0.9063	14.2990
Poly	C=0.1, degree=2, gamma=scale	0.7101	0.4990	4.6430
Poly	C=0.1, degree=2, gamma=auto	0.7122	0.5081	4.7247
Poly	C=0.1, degree=3, gamma=scale	0.6845	0.3921	3.5441
Poly	C=0.1, degree=3, gamma=auto	0.6859	0.3956	4.5605
Poly	C=1.0, degree=2, gamma=scale	0.8334	0.7718	2.7677
Poly	C=1.0, degree=2, gamma=auto	0.8348	0.7805	2.7534
Poly	C=1.0, degree=3, gamma=scale	0.7663	0.6220	3.3830
Poly	C=1.0, degree=3, gamma=auto	0.7685	0.6422	3.9291
RBF	C=0.1, gamma=scale	0.9062	0.8835	2.7757
RBF	C=0.1, gamma=auto	0.9054	0.8851	2.8310
RBF	C=1.0, gamma=scale	0.9340	0.9055	1.8260
RBF	C=1.0, gamma=auto	0.9340	0.9055	2.8488
RBF	C=10.0, gamma=scale	0.9332	0.9001	1.7754
RBF	C=10.0, gamma=auto	0.9332	0.9001	1.6441
Sigmoid	C=0.1, gamma=scale	0.8910	0.8530	2.9397
Sigmoid	C=0.1, gamma=auto	0.8916	0.8547	2.9691
Sigmoid	C=1.0, gamma=scale	0.8804	0.8524	2.6172
Sigmoid	C=1.0, gamma=auto	0.8804	0.8508	2.3010

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

Fold	Naïve Bayes (Bernoulli)	KNN (k=5)	SVM (RBF)
Fold 1	0.8806	0.9034	0.9349
Fold 2	0.8902	0.9174	0.9337
Fold 3	0.8837	0.9359	0.9228
Fold 4	0.8870	0.9141	0.9359
Fold 5	0.8902	0.9152	0.9304
Average	**0.8863**	**0.9172**	**0.9315**

Table 6: Ensemble Methods Performance Comparison

Method	Accuracy	Precision	Recall	F1 Score	AUC
Bagging	0.8317	0.7131	0.9587	0.8179	0.9385
AdaBoost	0.9186	0.9114	0.8788	0.8948	0.9736
Gradient Boosting	0.9327	0.9263	0.9008	0.9134	0.9805
XGBoost	0.9468	0.9361	0.9284	0.9322	0.9869

Best performing ensemble method: XGBoost

Best XGBoost parameters: {`'learning_rate': 0.1, 'max_depth': 9, 'n_estimators': 200, 'subsample': 0.9`}

Learning Outcome (observation)

- **Best Classifier:** SVM with RBF kernel had the highest average accuracy (93.15%).
- **Best Naïve Bayes:** Bernoulli Naïve Bayes performed best among NB variants.
- **KNN Variability:** Accuracy increased with k, peaking at $k = 7$. Both KDTree and BallTree yielded same metrics but BallTree had faster training.
- **SVM Insights:** RBF and Linear kernels outperformed Poly and Sigmoid. Hyperparameter tuning further improved performance.