SMS Spam Detection Using Machine Learning

1. Project Title

SMS Spam Detection Using Machine Learning

2. Introduction

- Spam messages are unsolicited or potentially harmful SMS texts that interfere with normal communication and consume valuable user time.
- These messages often include deceptive content, advertisements, or malicious links, posing risks to both user privacy and security.
- Automatically detecting and filtering out such spam is essential for enhancing the overall user experience and maintaining a secure messaging environment.
- This project focuses on developing a machine learning model capable of accurately classifying SMS messages into two categories: "spam" (unwanted messages) and "ham" (legitimate, non-spam messages).
- By leveraging natural language processing and predictive algorithms, the model aims to streamline communication and protect users from digital nuisances and threats.

3. Dataset Description

- The dataset contains approximately 5,500 SMS messages.
- Each message is labeled as **spam** or **ham**.
- Data source: SMS Spam Collection Dataset from UCI
- The dataset has two columns:
  - label : 'spam' or 'ham'
  - message : the text content of the SMS

In [1]:

```
# Import necessary libraries import pandas as pd import
matplotlib.pyplot as plt import seaborn as sns from
sklearn.model_selection import train_test_split from
sklearn.feature_extraction.text import CountVectorizer from
sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification

# Load the dataset
url = "https://raw.githubusercontent.com/justmarkham/pycon-2016-tutorial/mas
df = pd.read_table(url, header=None, names=['label', 'message'])

# Show first few rows df.head()
```

Out [1]:

	Label	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

4. Data Preprocessing

- Clean and prepare text data for the model.
- Converting labels (spam / ham) to binary values (1/0).
- Spliting data into training and testing sets.
- Vectorizing text messages using **CountVectorizer** to convert text into numeric feature vectors.

In [2]:

```
# Convert labels to numbers: ham=0, spam=1
df['label_num'] = df.label.map({'ham': 0, 'spam': 1})

# Check distribution of classes df['label'].value_counts()
```

Out[2]:

```
label
ham     4825
spam     747
Name: count, dtype: int64
```

In [3]:

```
# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    df['message'], df['label_num'], test_size=0.2, random_state=42)

print(f"Training messages: {len(X_train)}") print(f"Testing
messages: {len(X_test)}")
```

Out [3]:

```
Training messages: 4457
Testing messages: 1115
```

In [4]:

```
# Convert text messages to numbers (vectorization) vectorizer
= CountVectorizer()

# Learn vocabulary from training data and transform training data
X_train_vec = vectorizer.fit_transform(X_train)

# Transform test data (using the same vocabulary)
X_test_vec = vectorizer.transform(X_test)
```

5. Model Selection

- I used the **Multinomial Naive Bayes** algorithm, which is effective for text classification problems.
- Chosen for its simplicity, speed, and good performance on spam detection.

In [5]:

```
# Create the Naive Bayes model model
= MultinomialNB()
```

6. Training the Model

- Training the Naive Bayes model using the vectorized training data.

In [6]:

```
# Train the model on training data model.fit(X_train_vec,
y_train)
```

Out[6]:

```
▼ MultinomialNB
MultinomialNB()
```

7. Model Evaluation

- Predict labels for the test data.
- Evaluate model using:
  - Accuracy score
  - Confusion matrix
  - Classification report (precision, recall, f1-score)
- This will also visualize the confusion matrix for a better understanding.

In [7]:

```
# Predict labels for test messages y_pred
= model.predict(X_test_vec)

# Check accuracy
print("Accuracy:", accuracy_score(y_test, y_pred))
```

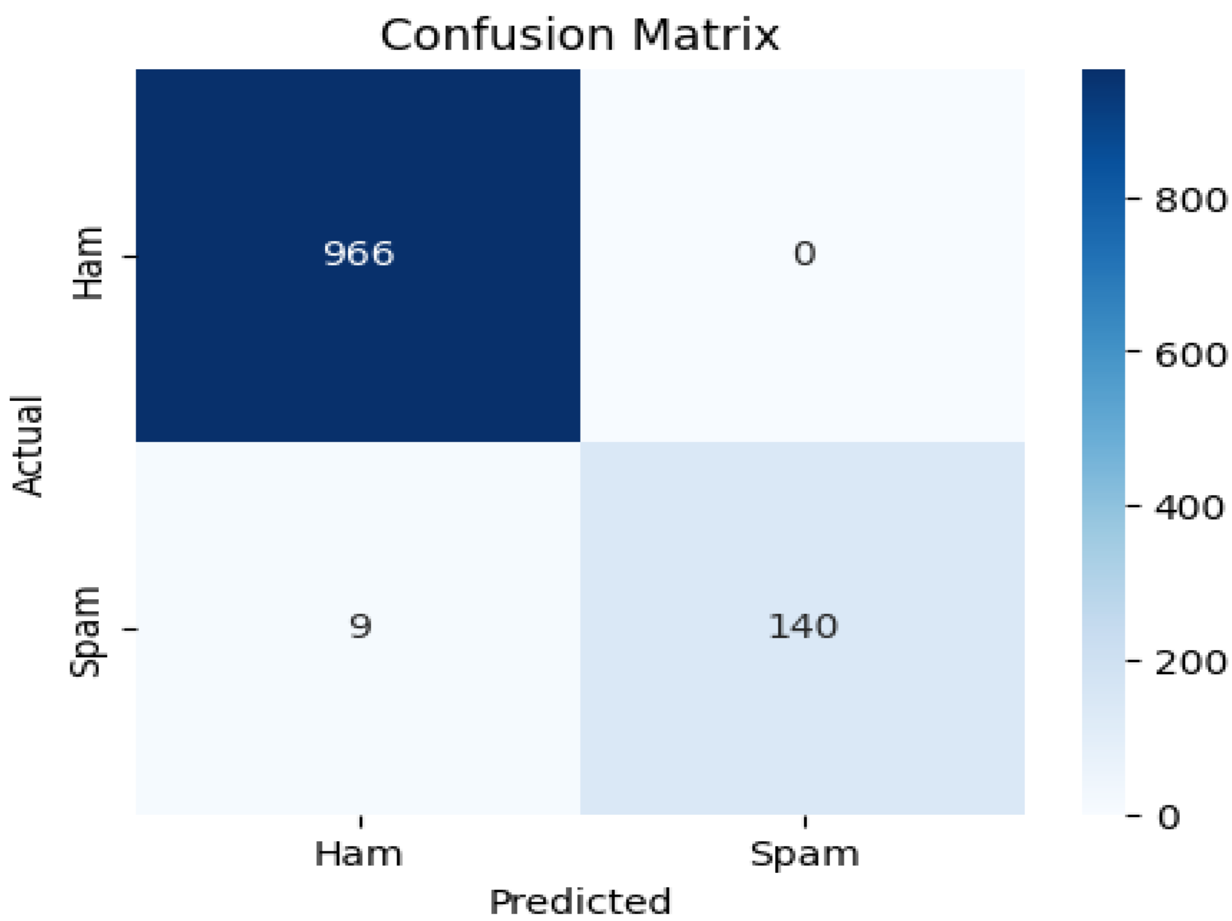
```
Accuracy: 0.9919282511210762
```

In [8]:

```
# Show confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:") print(cm)

# Plot confusion matrix plt.figure(figsize=(5,4)) sns.heatmap(cm,
annot=True, fmt='d', cmap='Blues', xticklabels=['Ham', 'Spam
plt.xlabel('Predicted') plt.ylabel('Actual') plt.title('Confusion Matrix')
plt.show()
```

```
Confusion Matrix:
[[966   0] [  9 140]]
```



In [9]:

```
# Show detailed classification report print("Classification
Report:") print(classification_report(y_test, y_pred))
```

```
Classification Report:    precision   recall   f1-score   support

            0               0.99        1.00      1.00        966

            1               1.00        0.94      0.97        149

  accuracy                                        0.99       1115
  macro avg                 1.00        0.97      0.98       1115
  weighted avg              0.99        0.99      0.99       1115
```

8. Conclusion

- My model achieves high accuracy in distinguishing spam from ham SMS messages.
- This model can be used as a basic filter to improve user experience.
- Possible improvements include using TF-IDF vectorization, hyperparameter tuning, and more advanced algorithms.