

# SMS Spam Classifier using Naive Bayes

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# 1 Introduction

With the rapid growth of digital communication, especially via mobile messaging, identifying and filtering out spam messages has become a crucial task. This project applies the Naive Bayes algorithm to detect spam in SMS messages with high accuracy and efficiency. It culminates in a lightweight, interactive web-based tool that allows end users to test their own messages for spam detection. The full project, including code and documentation, is available on my GitHub: [github.com/rabiulhassandev/ML-SMS-Spam-Detector.git](https://github.com/rabiulhassandev/ML-SMS-Spam-Detector.git).

## 2 Mathematical Foundations

### 2.1 Bayes' Theorem

Naive Bayes is built on Bayes' Theorem, which describes the probability of a class  $C$  given some data  $X$ :

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)}$$

In this context:

- $P(C|X)$  is the posterior probability of class  $C$  (spam or ham) given the text  $X$
- $P(X|C)$  is the likelihood of observing text  $X$  given class  $C$
- $P(C)$  is the prior probability of class  $C$
- $P(X)$  is the prior probability of text  $X$

### 2.2 Multinomial Naive Bayes

This variant of Naive Bayes is especially suited for text classification where input features represent frequencies of words. For each message, the model calculates:

$$P(C) \prod_{i=1}^n P(x_i|C)$$

Where  $x_i$  represents word occurrences in a message. Laplace smoothing is used to avoid zero probabilities.

### 2.3 Strengths and Weaknesses

- **Advantages:** Fast training, scalable, simple to implement, works well with text data.
- **Limitations:** Assumes feature independence, which may not hold true in natural language.

## 3 Real-World Applications

### 3.1 Common Use Cases

- Spam detection in SMS and email systems
- News categorization
- Sentiment analysis of customer reviews
- Topic classification in blogs or forums

### 3.2 Dataset Description

This project uses the publicly available **SMS Spam Collection Dataset** from UCI Machine Learning Repository. It includes:

- 5,572 total SMS messages
- 4,825 labeled as **ham** (non-spam)
- 747 labeled as **spam**

### 3.3 Label Distribution

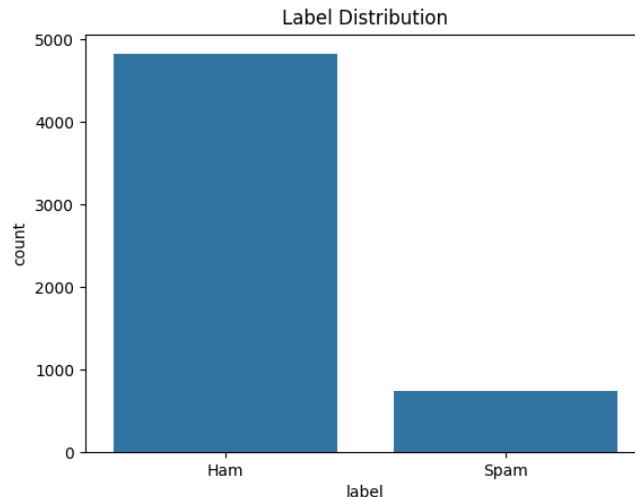


Figure 1: Label distribution showing class imbalance

## 4 Implementation

### 4.1 Tools and Libraries

- Python and Flask for backend and web app
- `scikit-learn` for machine learning
- Pandas, Matplotlib, Seaborn for data processing and visualization

## 4.2 Pipeline Overview

1. Load and clean the dataset
2. Convert labels to binary form (0 for ham, 1 for spam)
3. Split the data into training and test sets
4. Vectorize messages using `CountVectorizer`
5. Train the Naive Bayes classifier
6. Evaluate with classification metrics
7. Build a Flask-based web UI for real-time testing

## 4.3 Sample Code

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(messages)
model = MultinomialNB()
model.fit(X_train, y_train)
```

## 5 Model Evaluation

### 5.1 Performance Report

	precision	recall	f1-score	support
0	0.96	1.00	0.98	966
1	1.00	0.74	0.85	149
accuracy			0.97	1115
macro avg	0.98	0.87	0.92	1115
weighted avg	0.97	0.97	0.96	1115

### 5.2 Accuracy

$$\text{Accuracy} = 96.6\%$$

This demonstrates excellent performance, particularly in identifying ham messages. The slightly lower recall for spam is expected due to class imbalance.

## 6 Web Interface

The deployed Flask web application allows users to:

- Explore summary statistics and charts
- View the classification report
- Enter their own SMS message and receive instant spam/ham prediction

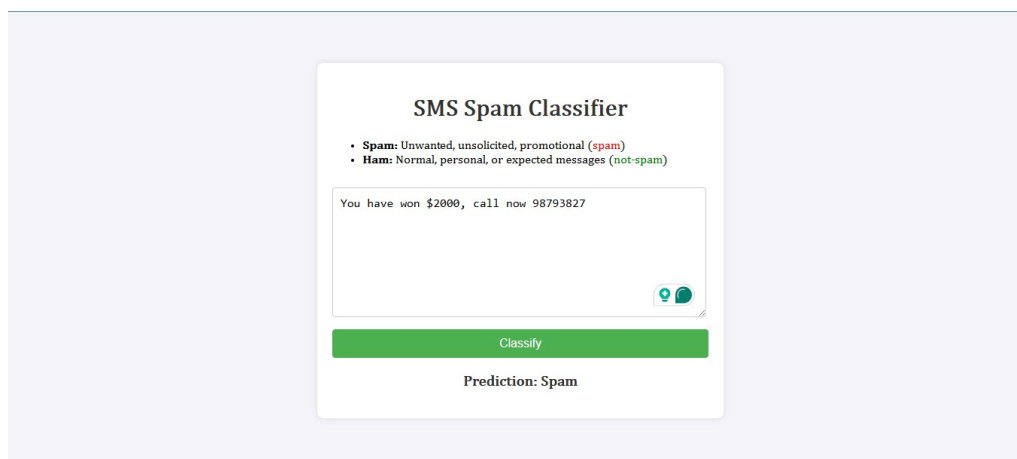


Figure 2: Web Interface Screenshot

## 7 Conclusion

This project successfully implements and deploys a machine learning solution for spam classification using Naive Bayes. It showcases how a classic algorithm, combined with modern tools like Flask and scikit-learn, can deliver a powerful real-world application. The classifier achieved over 96% accuracy and is capable of real-time spam detection through a browser.

For complete source code and documentation, visit my GitHub repository:  
<https://github.com/rabiulhassandev/ML-SMS-Spam-Detector.git>