

# Spam Classifier ML Project

## Project Overview

A machine learning-based spam SMS classifier that distinguishes between spam and ham (non-spam) messages using the Multinomial Naive Bayes algorithm. This project demonstrates fundamental natural language processing (NLP) techniques and machine learning implementation for text classification.

## Features

- **Text Preprocessing:** Automatic data cleaning and transformation
- **Machine Learning Model:** Multinomial Naive Bayes classifier
- **Feature Extraction:** Count Vectorization for text-to-numeric conversion
- **Performance Evaluation:** Accuracy scoring and prediction capabilities
- **Real-time Prediction:** Classify new messages instantly

## Installation & Setup

### Prerequisites

- Python 3.7+
- Google Colab or local Python environment
- Required libraries: pandas, scikit-learn

### Installation Steps

#### 1. Upload the dataset:

```
python
```

```
from google.colab import files
```

```
uploaded = files.upload()
```

#### 2. Install required packages (if not already installed):

```
python
```

```
!pip install pandas scikit-learn
```

## Dataset Information

- **Source:** SMS Spam Collection Dataset
- **Size:** 5,574 messages
- **Classes:**
  - Ham (legitimate): 4,827 messages

- Spam: 747 messages
- **Features:** Message text and label

## Project Structure

```
text
spam-classifier/
|--- spam.csv          # Dataset file
|--- spam_classifier.ipynb # Main project file
|--- README.md         # Documentation
```

## Implementation

### 1. Data Loading & Exploration

```
python
```

```
import pandas as pd
df = pd.read_csv("spam.csv")
df.head()
```

### 2. Data Preprocessing

- Check for missing values: `df.isnull().sum()`
- Convert labels to numerical values:

```
python
```

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

### 3. Train-Test Split

```
python
```

```
from sklearn.model_selection import train_test_split
X = df['message']      # Features
y = df['label_num']    # Target
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

### 4. Feature Extraction

```
python
```

```
from sklearn.feature_extraction.text import CountVectorizer  
  
cv = CountVectorizer()  
  
X_train_cv = cv.fit_transform(X_train)  
  
X_test_cv = cv.transform(X_test)
```

## 5. Model Training

python

```
from sklearn.naive_bayes import MultinomialNB  
  
model = MultinomialNB()  
  
model.fit(X_train_cv, y_train)
```

## 6. Model Evaluation

python

```
from sklearn.metrics import accuracy_score  
  
y_pred = model.predict(X_test_cv)  
  
accuracy = accuracy_score(y_test, y_pred)  
  
print(f"Model Accuracy: {accuracy:.2%}")
```

## Usage

### Making Predictions

python

```
# Test with new message  
  
message = ["Congratulations! You won a free iPhone"]  
  
message_cv = cv.transform(message)  
  
prediction = model.predict(message_cv)
```

*# Convert prediction back to label*

```
result = "spam" if prediction[0] == 1 else "ham"  
  
print(f"The message is classified as: {result}")
```

### Example Predictions

python

```
test_messages = [
```

```
"Hey, are we still meeting tomorrow?",  
"FREE entry to win £1000 prize! Text NOW!",  
"Your package will arrive today at 3 PM"  
]
```

```
for msg in test_messages:
```

```
    msg_cv = cv.transform([msg])  
  
    pred = model.predict(msg_cv)[0]  
  
    label = "spam" if pred == 1 else "ham"  
  
    print(f"Message: {msg}")  
  
    print(f"Classification: {label}\n")
```

## Model Performance

- **Algorithm:** Multinomial Naive Bayes
- **Accuracy:** Typically achieves 98%+ accuracy
- **Training Time:** Fast training (seconds)
- **Prediction Time:** Real-time classification

## Key Components

### 1. CountVectorizer

- Converts text documents to matrix of token counts
- Handles preprocessing internally (lowercasing, tokenization)
- Creates vocabulary from training data

### 2. Multinomial Naive Bayes

- Particularly suited for discrete features (word counts)
- Efficient for text classification
- Handles multiple classes naturally

### 3. Train-Test Split

- 80% training data, 20% testing data
- Random state for reproducibility
- Stratified sampling maintains class distribution

## Results

The model achieves high accuracy in distinguishing between spam and ham messages. Example output:

text

Model Accuracy: 98.47%

Message: "Congratulations! You won a free iPhone" → Classification: spam

Message: "Hey, are we still meeting tomorrow?" → Classification: ham

## Extending the Project

### Additional Features

#### 1. TF-IDF Vectorization:

python

```
from sklearn.feature_extraction.text import TfidfVectorizer  
tfidf = TfidfVectorizer()
```

#### 2. Multiple Algorithms:

python

```
from sklearn.svm import SVC  
from sklearn.ensemble import RandomForestClassifier
```

#### 3. Enhanced Evaluation:

python

```
from sklearn.metrics import classification_report, confusion_matrix
```

## Web Interface (Future Enhancement)

python

```
from flask import Flask, request, render_template  
import joblib
```

```
app = Flask(__name__)
```

```
model = joblib.load('spam_model.pkl')
```

```
@app.route('/')
```

```
def home():
```

```
return render_template('index.html')

@app.route('/predict', methods=['POST'])

def predict():

    message = request.form['message']

    # Prediction logic here

    return render_template('result.html', prediction=prediction)
```

## Troubleshooting

### Common Issues

1. **File Upload Error:** Ensure spam.csv is in the correct directory
2. **Shape Mismatch:** Always use transform() not fit\_transform() on test data
3. **Memory Issues:** Reduce dataset size or use sparse matrices

## Solutions

### python

```
# Check data dimensions

print(f"Training shape: {X_train_cv.shape}")

print(f"Test shape: {X_test_cv.shape}")

# Verify label distribution

print(df['label'].value_counts())
```

## Future Improvements

- Implement TF-IDF vectorization
- Add multiple machine learning algorithms
- Create web interface with Flask
- Deploy as REST API
- Add model persistence with joblib
- Implement cross-validation
- Add hyperparameter tuning
- Include more comprehensive evaluation metrics

## **Dependencies**

python

pandas>=1.3.0

scikit-learn>=1.0.0

## **Contributing**

1. Fork the repository
2. Create a feature branch
3. Commit your changes
4. Push to the branch
5. Create a Pull Request.

## **Contact**

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