Spam Detection with Naive Bayes

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Abstract—**Spam detection is an important task in the current digital age, especially in the areas of natural language processing and privacy security, as unwanted messages can disrupt digital communication.This research uses a machine learning-based method to classify SMS messages as either SPAM or HAM (legitimate messages). A data set called SMS Spam Collection will be used, which includes over 5,500 labeled messages .Naive Bayes a machine learning algorithm will be used to detect spam messages. Naive Bayes is renowned for its simplicity, fast training capabilities and text classification performance. Through data pre-processing, feature extraction and possibility based modeling, the Naive Bayes will be trained and learn to effectively distinguish between Spam and non-spam (HAM) messages.The test results show that the model achieves high accuracy and precision with unseen data, proving the suitability of the Naive Bayes algorithm for spam detection.**

Index Terms—**component, formatting, style, styling, insert.**

I. INTRODUCTION

In the current era, email communication has become a fast, cost-effective and effective medium that has become important for everyone from individual users to corporate organizations.While email plays a very important role in information exchange, it also has some negative aspects. One of the biggest problems is spam email, which sends unnecessary, confusing and sometimes privacy critical harmful messages to users. [1]

Research has shown that an normal email user receives 40 to 50 emails per day, of which about 60 to 70 percent may be spam.In this situation, it becomes difficult to manually sort out spam emails, and these spam emails are often used by hackers to spread malware, hack accounts or create unnecessary traffic on the network. [1].To overcome this challenge, automated and intelligent solutions are needed, for which machine learning-based approach have been considered an effective way.

Previously, blocking messages from certain email IDs or domains was the solution, but now those strategies have become ineffective.Because, spammers are continuously changing their strategies and developing new techniques to send spam messages and act legitimate. We need automated solution and Machine learning-based methods are an effective way to solve this problem. [2]

Among machine learning algorithms, Naive Bayes classifier is a very popular and effective algorithm for detecting spam

.It works on the basis of probability and it can be trained very quickly. For it's simplicity fast training process, it is very effective for even larger dataset [1] [2].

In this paper, we demonstrate an efficient model for spam SMS detection using the Naive Bayes classifier. A standard dataset (downloaded from Kaggle) is used where SMS messages are labelled as either Spam or Ham. After preprocessing, feature extraction and training, the model's performance will be evaluated through accuracy, precision,recall and F-score.
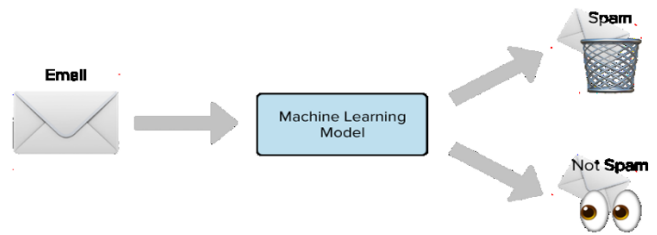

Fig. 1. Classification into Spam and non-spam [2]

This image in fig:1 illustrates the process of a simple spam recognition.An input email is first analyzed by a machine learning model. The model determines whether the message is spam or Ham based on the trained data.If the email is marked as spam, it is sent directly to the spam folder.On the other hand, if the email is not a spam, then it is considered as ham or valid and important and is brought to the user's attention.

II. BACKGROUND AND RELATED WORK

Email spam is a long-standing problem that wastes time and sometimes resources by sending users annoying messages and unwanted information through their email systems.Initially, spam recognition mainly used by fixed rules and blacklists, but these techniques can be easily avoided by spammers [1].

Naive Bayes algorithm has been used for a long time in email spam filtering.Harisinghaney et al. (2014) conducted an analysis of Naïve Bayes and KNN. They showed that, even without data pre-processing, the Naïve Bayes provides very good result with the accuracy of 87 percent. Another research conducted by Mohamad and Selamat (2015). they applied a

hybrid method of TF-IDF and Rough Set Theory in their study and get effective accuracy in results. [3] [4]

Apart from Naive Bayes, other studies have attempted to improve spam recognition using other algorithms such as Support Vector Machine (SVM), Extreme Learning Machine (ELM) Decision Tree and Artificial Neural Network. For example, Feng et al. (2016) proposed a hybrid SVM-NB model. Their hybrid model was tested on the Chinese spam email dataset. The result showed that it performed better than either using single SVM or Naive Bayes. [5]

In addition, Naive Bayes has been used in another study with the combination of Particle Swarm Optimization (PSO) for better results. Idris et al. (2015), in their research, obtained the accuracy of spam detection up to 83.20 percent with combination of PSO and the negative selection algorithm. [6]

III. MACHINE LEARNING

Machine learning is a cutting-edge technology of our modern world of time. Machine Learning is a method that gives computer systems or a machine the ability to learn automatically through data analysis. Machine Learning is a branch of artificial intelligence (AI) where machines learn from experience and are able to make future decisions without following any specific rules like human. In general programming, specific instructions are given for each step, where machine learning models learn by identifying hidden patterns like human and making future decisions. Machine Learning includes various algorithms and statistical models like Linear regression, decision-tree, neural networks and etc. Currently, machine learning technology is being widely used in many fields including healthcare, banking, cybersecurity, robotics,language processing and etc. It is considered to be one of the driving forces of our industrial revolution [7].

A. Supervised learning

Supervised learning is a type of machine learning where each input data has a specified output. The model learns based on this input-output pair and is able to predict the relevant output after receiving new input.The most common phases of supervised learning include classification, such as email spam or ham, and regression, such as predicting future sales. The effectiveness of this method depends on the quantity and quality of the training data set.It has been successfully used in healthcare, financial institutions, and e-commerce sectors. [8] [9]

B. Unsupervised learning

Unsupervised learning is a type of machine learning method where the input data is not labeled or does not have output. In this method, the algorithm basically analyzes the structural features of the data to find patterns or hidden relationships. Clustering, Association Rule Learning and Dimensionality Reduction are the type of Unsupervised learning. These are mainly used for data exploration, segmentation, and social network analysis. [8] [9]

C. Reinforcement learning

Reinforcement learning is another type of machine learning method in which an agent interacts with its environment and is rewarded or punished according to the results. The goal of this learning method is to develop policies by maximizing rewards. The method is very popular in gaming, robotic control, and autonomous driving. The Reinforcement Learning helps to build models for adaptive decision making in different environments. It is a kind of long-term learning process where the agent analyzes all the feedback from past experiences and execute future decisions. [7]

IV. DATASET

The SMS Spam Collection dataset is download from kaggle.com. The dataset is a collection of 5,574 SMS messages. Each messages are represented as a single line in the file. Each line contains two fields, the first field (v1) is a label indicating whether the message is ham (legitimate) or spam, and the second field (v2) contains the raw text of the message. The dataset is provided in a plain text format, which making it easy and straight-forward to load and process for machine learning tasks. There are no missing values in the dataset which is very efficient for data pre-processing and feature extraction.
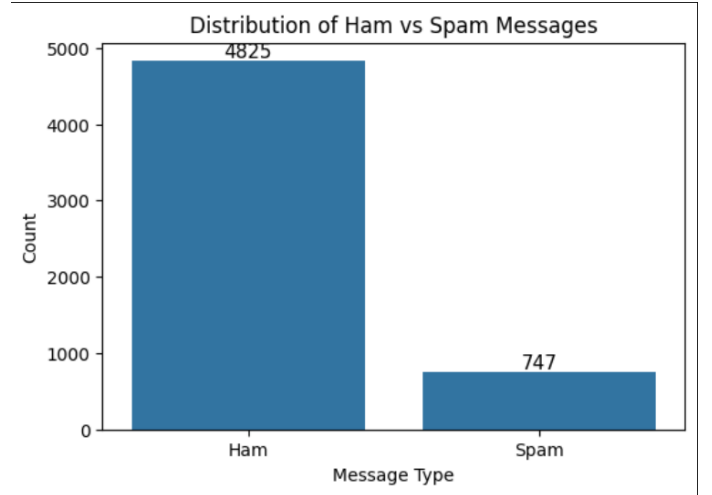

Fig. 2. Classes of The Dataset

V. NAIVE BAYES

The Naive Bayes algorithm is a machine learning classification method that works based on the Baye's theorem. The main feature of this algorithm is that it assumes each feature as independent and for that it is called Naive. It is very popular and effective and widely used in text classification, such as spam detection. Because, it can be trained very quickly and efficiently using less data. Naive Bayes performance is also very good in some cases, even when the features are dependent on each other. One of the biggest advantages of Naive Bayes is that it works very fast in both training and result, which makes it very useful and efficient for large datasets. It can also perform well on noisy data. Its practical

applications include email filtering, document categorization, and sentiment analysis. But it has limitations also, such as the results can be less reliable when features depend heavily on each other. Additionally, continuous features require special transformations such as Gaussian Naive Bayes, yet Naive Bayes is being used as a popular classifier due to its simplicity, scalability, and excellent performance. [10] [5]

A. Types of Naive Bayes Classifiers

There are different variants of the Naive Bayes algorithm that are suitable for different types of data.

1) Multinomial Naive Bayes: Multi-Nominal Naive Bayes Classifier is the most used for SMS or email spam detection , which is very effective for determining things like word count or word density in a SMS or an email. It assumes that each feature, such as the number of words in a document, follows a multi-nominal distribution. This model can efficiently model the density of each word in a SPAM versus a normal HAM message, making it successfully used for spam filtering. Multi-nominal Naive Bayes is particularly suitable for document classification, especially in natural language processing applications such as email filtering and spam recognition. [11] [12].

2) Bernoulli Naive Bayes: Another important type is the Bernoulli Naive Bayes, which is used for binary features such as whether a word is present or absent in a message. Multi-nominal models, which look at the density of words, are associated only by considering the presence or absence of the word. The Bernoulli Naive Bayes model, where the number of times a word appears is not important, but whether the word is present or absent is sufficient. Although it is not widely used in spam filtering, it is very useful in cases where yes or no type features are used [12].

3) Gaussian Naive Bayes: The third type is Gaussian Naive Bayes, which is designed for continuous data. It assumes that each feature follows a Gaussian normal distribution and is commonly used in classification where the input values are numbers, such as temperature, age, birthday.This model is not widely used in spam detection because spam data is usually discrete, but it is very useful in cases where numerical input needs to be analyzed [13].

In this study, the Multinomial Naive Bayes model was selected from among the three Naive Bayes classifiers because it is the most effective and widely used in text-based SPAM identification. Our dataset is an SMS spam collection consisting mainly of message words, where the presence and density of different words in each message is important.Multi-nominal Naive Bayes works by taking into account the density or term frequency of the word, so it is very suitable for solving such problems. On the other hand, the Bernoulli Naive Bayes model works only based on the presence or absence of words and the Gaussian model is suitable for continuous or numerical input, which is not applicable to this project. The model is the best choice for our spam filtering system, which provides fast training, high reliability and simple implementation.

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

Fig. 3. Naive Bayes Theory

B. Mathematical Foundation and Basic Principle

Mathematically, it determines the probability using the probability of each class using Bayes' Theorem: formula shown in fig:3, where C is the class and X is the feature vector extracted from the SMS contentes. The Naive Bayes classifier assumes that the features of the SMS x1,x3,x3......... in X are independent [5].

C. Bayes' Theorem Applied to Spam Classification

$$P(\text{Spam}|\text{Clues}) = \frac{P(\text{Clues}|\text{Spam}) \times P(\text{Spam})}{P(\text{Clues})}$$

Fig. 4. Bayes Theorem Simplified for Spam Detection

The picture in fig:4 shows again Bayes' Theorem simplified for spam classification. It helps calculate the probability that an SMS is SPAM or HAM based on the clues (words) it contains.

P(Spam—Clues) : The probability of SMS is Spam, if the sms contains certain word or feature.

P(Clues—Spam) : It means how often these words show up in spam SMS. For example, how often the word "Free" exist in Spam Sms.

P(Spam) : How many SMS are Spam in total.

P(Clues) : How often do the words show up in the SMS (SPAM or HAM).

After the calculation, the model picks the class (SPAM or HAM) with the higher probability and marks the message as that type.

VI. METHODOLOGY

A. Required Libraries and Tools

This figure in fig:5 shows the Python libraries that are imported for implementing the Naive Bayes model to classify spam SMS.This Section includes libraries for data manipulation (pandas, numpy), text processing (re, string), and visualization (matplotlib, seaborn). For machine learning, scikit-learn provides modules for model training MultinomialNB, for feature extraction TfidfVectorizer, data splitting traintestsplit, cross-validation, and performance evaluation using metrics like accuracy, confusion matrix, and classification report.

```
# Data manipulation and analysis
import pandas as pd
import numpy as np

# Text processing and regex
import re
import string

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

Fig. 5.   Required Libraries and Tools

B. Data Preprocessing

Before training the model, the raw text data should be converted into a form that is suitable for machine learning. This step basically involves text cleaning and extracting relevant features, and converting each message into a vector of numbers.

1) Tokenization and Lowercasing: The text data is divided into tokens and all characters are converted to lowercase. This task is done automatically by scikit-learn's TfidfVectorizer tool, which automatically tokenizes the input text and converts all words to lowercase.This also eliminates the confusion of the same word having multiple forms and improves the model's performance.

2) Punctuation and unwanted charracter Removal: Using TfidfVectorizer and Python's RE (regular expression) library, The unnecessary or unwanted symbols and characters have been removed, such as commas, dots, slashes, special symbols, etc., whose presence is not productive to contribute to text classification and it makes more accurately distinguish between spam and ham messages.

3) STOP words Removal: Another step is STOP words removal . The data pre-process includes this technique using a list of commonly used words such as I,me, my, you, are, was, the, and, or no, etc.. These words do not provide any useful information for spam detection. So they are stored in a set and filtered out during the training.

C. Feature Engineering

For the proper functioning of the spam detection model, it is not enough to just clean the text data. Selecting and transforming relevant features is very important. In this project, mainly two types of features have been extracted and the features are text-based features and mathematical features (Message length).

1) Construction of Feature Matrix: First, a Bag of Words (BoW) features is extracted from the text. Then it is stored in a variable named Xbow. This matrix is then converted into a sparse format using csrmatrix(). It is helpful to handle large datasets. After that the length of each message was calculated and also reshaped into a column vector using reshape(-1, 1). This column was also converted into a sparse format.Both the BoW vectors and message length feature were combined using

the hstack() function to form a final feature matrix named Xcombined, which will be later used for model training and evaluation.

```
# Convert BoW list to sparse matrix
X_bow_matrix = csr_matrix(X_bow)

# Reshape message length and convert to sparse
length_col = df['length'].values.reshape(-1, 1)
length_sparse = csr_matrix(length_col)

# Combine BoW vectors with message length
X_combined = hstack([X_bow_matrix, length_sparse])
```

Fig. 6.   Combining Text Features and Message Length for Model Input

2) Vectorization Method Used: The text messages is then transformed into numbers using the vectorizer (TfidfVectorizer) earlier in the notebook. The output was saved in a variable called Xbow, which will be later used to build the final feature matrix.

D. Model Training and Validation

After preparing the final feature matrix, the dataset is now split into training and testing subsets with 80:20 ratio. This allowed the model to be trained on a 80 percent of the data. And 20 percent of the data is stored and will be used to evaluate model performance.The stratify=y parameter was used to ensure that both the training and testing sets have the balanced class distribution (Ham And Spam SMS).

1) Model Selection and Hyperparameter Tuning: The Multinomial Naive Bayes classifier was chosen for this task because it is efficient and effective in handling discrete features such as word counts. To find the best smoothing parameter (alpha), a grid search with 5-fold cross-validation was performed using GridSearchCV.

```
# Define model and parameter grid
model = MultinomialNB()
param_grid = {'alpha': [0.01, 0.1, 0.5, 1.0, 2.0]}

# Use GridSearchCV to find best alpha
grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)
```

Fig. 7.   Model Selection and Hyperparameter Tuning

2) Best Model Selection and Saving: The best-performing model and corresponding alpha value were extracted from the grid search results. Both the model and the vectorizer were then saved using joblib for future use.

E. Cross-Validation Results Visualization

The graph in fig :8, describes how the model's cross-validation accuracy changes when different values of the smoothing parameter alpha changes in the Naive Bayes classifier. The blue line represents the average accuracy across five validation folds for every alpha value: 0.01, 0.1, 0.5, 1.0, and 2.0.
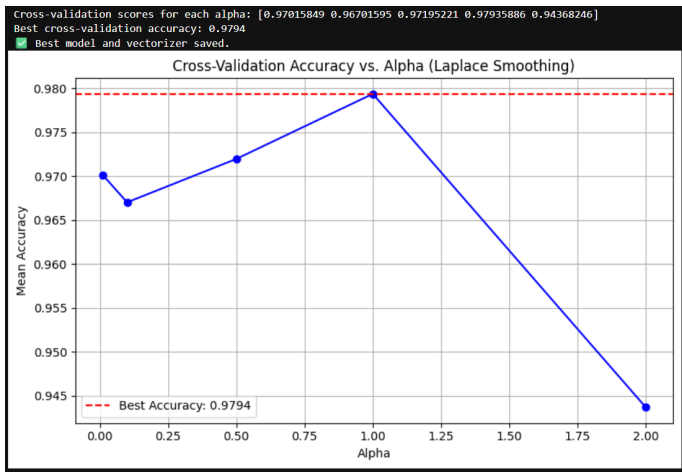
Fig. 8. Cross-Validation Accuracy vs. Alpha

From the fig:8, we can see:

Accuracy was stable between alpha values 0.01 and 1.0.

The best performance was reached at alpha = 1.0, where the model reached n accuracy of 97.94

At alpha = 2.0, the accuracy dropped significantly at 94 percent, showing that too much smoothing harms the model's ability to learn useful patterns.

The red dashed line indicates the best accuracy, helping visualize which alpa gained the best result.

This analysis helped in selecting the most suitable value of alpha (1.0) for choosing the final model.

F. Test Results

After selecting the best model using cross-validation, its performance was evaluated on the unseen 20 percent test data. The results demonstrate that the model generalizes well and is now capable of accurately identifying spam messages. The key performance metrics are as follows:

Fig. 9. Test Result

Accuracy: 97.76 percent – it means that the model correctly predicted nearly 98 out of every 100 messages.

Precision: 93.66 percent– it means that when the model predicted a message as spam or ham , it was correct 94 percent of the time.

Recall: 89.26 percent – it implies the model successfully recognized about 89 percent of spam messages.

F1 Score: 91.41 percent – a balance between precision and recall, representing the model's overall effectiveness.

These scores implies that the spam classifier is highly accurate, with a strong balance between detecting spam and avoiding false positives.

G. Confusion Matrix For Test Data

The confusion matrix in the figure:10 shows how well the model performed on the test data by comparing the actual labels with the predicted labels.
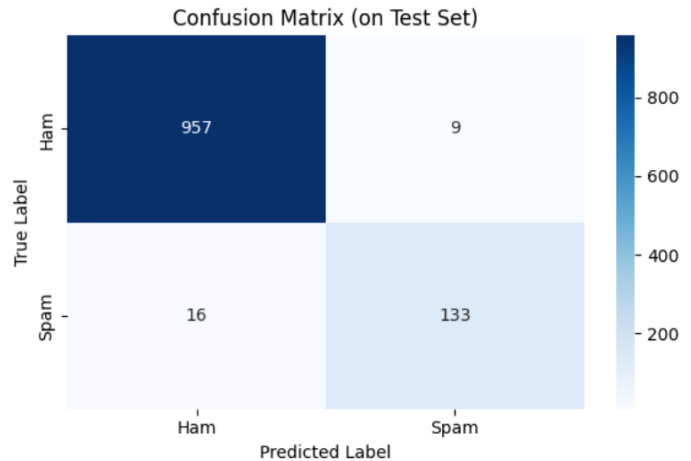

Fig. 10. Confusion Matrix For Test Data

957 messages were correctly predicted as ham .

133 messages were correctly predicted as spam.

9 ham messages were wrongly predicted as spam (false positives).

16 spam messages were wrongly predicted as ham (false negatives).

This implies that the model is very good at identifying both spam and ham messages. But like other classifiers, it made a few small mistakes. Overall, the amount of correct predictions is much higher than the incorrect ones.It is showing that the model prediction is highly accurate

VII. CONCLUSION

In this project, a spam detection system was developed with a machine learning based approach using the Multinomial Naive Bayes. The dataset was preprocessed by several aspects to make suitable for training like cleaning the text, removing stop words, and extracting useful features like word frequency and message length. These features were then combined to train the model.

To improve the model's performance,cross-validation is used where different values of the smoothing parameter (alpha) were tested then the best alpha value was selected, and the final model achieved high accuracy on the test data.

The results showed that the model can now effectively identify spam messages, with good accuracy, precision, recall, and F1 score. The confusion matrix represents that most messages were classified correctly as SPAM or HAM. Overall, the model is simple and fast which makes it very suitable and well performing for spam detection.

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