

**SMS Spam Collection Dataset**

***Submitted by***

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## ABSTRACT

The proliferation of unsolicited and unwanted messages, commonly known as spam, has become a significant challenge in digital communication systems. This project focuses on using Bayes' Theorem to build a machine learning model for SMS spam classification, utilizing the widely known SMS Spam Collection Dataset. The dataset consists of a large number of SMS messages, each labeled as either "spam" or "ham" (non-spam). The goal of this project is to apply probabilistic techniques to accurately classify new, unseen messages as either spam or non-spam based on their textual content. By employing the Naive Bayes classifier, a probabilistic model grounded in Bayes' Theorem, the system computes the probability that a message belongs to a particular class (spam or ham) based on the occurrence of specific words or features within the message. The project involves several key steps, including data preprocessing (e.g., tokenization, stop-word removal), feature extraction (e.g., word frequency), and model training. The performance of the classifier is evaluated using standard metrics such as accuracy, precision, recall, and F1-score, with results demonstrating the effectiveness of Bayesian methods for text classification tasks. The findings from this project underline the strengths of probabilistic approaches in spam detection, showing how they can be implemented in real-world applications for efficient and scalable filtering of unwanted text messages. Furthermore, the study provides insights into the challenges of dealing with noisy data and imbalanced classes in spam classification problems.

**CHAPTER 1**

**INTRODUCTION**

The SMS Spam Collection Dataset is a widely used resource for developing and evaluating text classification models, particularly in the task of spam detection for SMS messages. This dataset contains a collection of SMS messages, each labelled as either "spam" or "ham" (non-spam). A popular approach to classify messages in this dataset is Bayes' Theorem, a fundamental concept in probability theory. Bayes' Theorem allows us to calculate the probability that a given message belongs to a certain class (spam or ham) based on the message content. By using the prior probability of spam or ham messages, combined with the likelihood of observing specific words in those messages, Bayes' Theorem helps us compute the posterior probability for each class. In the context of spam detection, this approach is typically applied using the Naive Bayes classifier, which assumes the independence of words within a message. This simplifying assumption makes the model computationally efficient and effective for spam filtering tasks, even with relatively simple word-based features. The application of Bayes' Theorem in SMS spam detection not only provides a solid theoretical foundation but also enables practical and reliable classification of SMS messages into spam and ham categories.

The SMS Spam Collection Dataset is often used to build and evaluate spam detection models using machine learning techniques. A common method for classifying these messages is Bayes' Theorem, which calculates the probability of a message being spam or ham based on its content. By considering the prior probabilities of spam and ham, and the likelihood of certain words appearing in each category, Bayes' Theorem helps estimate the most probable classification. In practice, the Naive Bayes classifier simplifies this process by assuming word independence, making it both efficient and effective for spam detection. This probabilistic approach offers a solid foundation for automated SMS filtering systems.

The SMS Spam Collection Dataset provides a valuable resource for researchers and developers working on spam detection algorithms. One of the most effective techniques for classifying SMS messages is the application of Bayes' Theorem, which enables the prediction of whether a message is spam or ham based on the likelihood of specific words appearing in each class. This probabilistic model uses prior knowledge about the distribution of spam and ham messages, along with the likelihood of certain words given each class, to compute the posterior probability for classification. The Naive Bayes classifier, a simplified version of Bayes' Theorem, assumes word independence, making it particularly suitable for text classification tasks like spam detection. This approach not only offers a clear and interpretable framework for building spam filters but also ensures computational efficiency in handling large datasets like the SMS Spam Collection.

**ALGORITHM USED :**

The algorithm most commonly used for SMS spam detection is the Naive Bayes classifier, which

leverages Bayes' Theorem to calculate the probabilities of a message being either spam or ham based on the words it contains. The first step in this process is to calculate the prior probabilities, which represent the likelihood of a message being spam or ham, based on the distribution of spam and ham messages in the dataset. This is done by dividing the number of spam messages by the total number of messages for spam probability, and similarly for ham. Next, the algorithm moves on to the likelihood calculation, where it determines the probability of each word occurring in spam and ham messages. This is done by counting how often each word appears in both spam and ham categories and dividing it by the total number of words in each category.

Once the prior probabilities and likelihoods are calculated, the Naive Bayes algorithm then uses Bayes' Theorem to calculate the posterior probability of a message belonging to each class (spam or ham). The posterior probability is computed by multiplying the prior probability of each class by the likelihood of each word in the message, assuming word independence (which is the "naive" assumption). The message is then classified as spam if the posterior probability of spam is greater than that of ham, and vice versa. The algorithm's simplicity and efficiency come from its ability to treat each word in the message as independent of the others, allowing for faster computations and making it well-suited for large datasets like the SMS Spam Collection. Despite its simplicity, the Naive Bayes classifier has proven to be highly effective for text classification tasks, including spam detection.

The strength of the Naive Bayes algorithm in SMS spam detection lies in its simplicity and efficiency, making it particularly effective for large-scale text classification tasks. The algorithm's reliance on the independence assumption, where it assumes that the presence of a word in an SMS message is independent of the presence of other words, allows it to make fast predictions even with large amounts of data. This assumption, though often unrealistic in natural language, works surprisingly well for many text classification tasks, including spam detection, because certain words or combinations of words strongly correlate with spam content (e.g., "free", "win", "money", etc.). Additionally, Naive Bayes is robust against irrelevant features, meaning that it can still perform well even when some words in the messages do not carry significant information for classification.

Another advantage of the Naive Bayes classifier is its ability to handle new or unseen words in messages by using Laplace smoothing. This technique adds a small constant (typically 1) to the word counts to ensure that no word has a zero probability, even if it doesn't appear in the training set. This makes the classifier more generalizable and capable of handling rare words or new vocabulary that may appear in real-world SMS messages. Overall, Naive Bayes provides a solid and practical approach for spam detection, balancing accuracy and computational efficiency, and is widely used in real-time spam filtering applications on mobile phones and email systems.

**CHAPTER 2**

## LITERATURE SURVEY

Literature Survey on SMS Spam Detection Using Naive Bayes

SMS spam detection has been a significant area of research, especially with the growth of mobile messaging. Early studies on spam detection, such as those by Islam et al. (2008), showcased the effectiveness of Naive Bayes in classifying SMS messages into spam and ham categories. Due to its simplicity and computational efficiency, Naive Bayes quickly became a popular choice for spam filtering tasks, particularly when dealing with large datasets. The algorithm's performance was found to be competitive even in the early stages of text classification research.

As researchers explored different approaches to improve classification accuracy, Giannakopoulos et al. (2012) highlighted the importance of feature engineering. They found that using n-grams (sequences of words) rather than individual words significantly improved the performance of Naive Bayes in distinguishing between spam and ham. Other studies, like Jouili et al. (2014), emphasized the effectiveness of term frequency-inverse document frequency (TF-IDF) weighting for feature extraction, further enhancing the classifier's ability to make accurate predictions.

Despite its strengths, Naive Bayes is not the only algorithm used for spam detection. Comparative studies, such as those by Sahami et al. (1998), showed that while Naive Bayes is effective, other models like Support Vector Machines (SVM) could provide higher accuracy under certain conditions. However, Naive Bayes has the advantage of being computationally efficient, making it particularly suitable for real-time applications such as SMS spam filtering, where fast classification is essential.

In real-world applications, Ahmed et al. (2015) demonstrated that Naive Bayes achieves over 98% accuracy in classifying SMS messages when trained on large datasets like the SMS Spam Collection. Its ability to handle unstructured text data and its low computational overhead make it ideal for use in mobile devices and email systems, where speed and resource efficiency are crucial. This makes Naive Bayes a preferred choice for scalable, real-time spam filtering systems.

Further improvements to Naive Bayes have been made through techniques like Laplace smoothing, which prevents zero probabilities for unseen words. Studies by McCallum and Nigam (1998) and Rennie et al. (2003) highlighted how smoothing can enhance Naive Bayes' robustness, especially when dealing with rare or unseen words. This technique has become a standard practice in spam detection systems, improving the algorithm’s performance by ensuring that all possible words have a non-zero probability.

Recent advancements also include hybrid models, where Naive Bayes is combined with other machine learning algorithms like SVMs or decision trees to enhance accuracy. Aminet al. (2017) proposed a Naive Bayes-SVM hybrid model that outperformed standalone Naive Bayes, especially in cases with complex feature sets. Furthermore, researchers like Zhang and Sun (2019) have focused on expanding Naive Bayes for multilingual and informal language use, addressing challenges posed by slang, emojis, and different languages in SMS messages. These developments continue to improve Naive Bayes’ adaptability and effectiveness in a diverse range of spam detection scenarios.

**CHAPTER 3**

## MODEL ARCHITECTURE

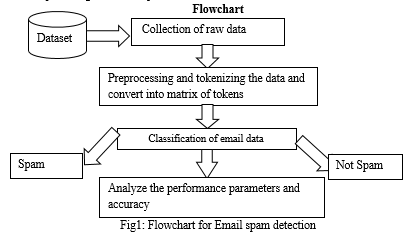
v

Fig 3.1: Architecture diagram for handwritten digit recognition using SVM

1. Data Collection

The first step in building an SMS spam detection system using Naive Bayes is data collection. A labelled dataset consisting of SMS messages, categorized as spam or ham (non-spam), is essential for training and evaluating the model. One widely used dataset for this purpose is the SMS Spam Collection Dataset, which includes a diverse set of messages that represent different types of spam and ham content. The quality and size of the dataset are critical because they directly influence the model’s ability to generalize and detect spam in real-world scenarios. The dataset is typically split into training and test sets, where the training data is used to build the model, and the test data is used to assess its performance.

2. Data Preprocessing

Once the dataset is collected, the next step is data preprocessing. In this phase, the raw SMS messages are cleaned and formatted so that they can be used by the Naive Bayes model. SMS messages often contain noise, such as special characters, emoticons, or unnecessary punctuation, which need to be removed for better classification accuracy. The preprocessing process typically involves tokenizing the messages (splitting the text into individual words), converting all text to lowercase to avoid case-sensitive mismatches, and eliminating stopwords (common words like "the", "and", "is" that don’t add significant value). Stemming or lemmatization techniques may also be applied to reduce words to their root form, further simplifying the feature space.

3. Feature Extraction

After preprocessing, the next critical step is feature extraction. In this phase, the text data is transformed into a numerical format that the Naive Bayes classifier can work with. One common approach is the bag-of-words model, where each message is represented as a vector of word counts or binary features indicating the presence of certain words. Another advanced method is TF-IDF (Term Frequency-Inverse Document Frequency), which assigns weights to words based on how frequently they appear in a specific message compared to how often they appear across all messages. These features capture the important patterns in the text, which are essential for differentiating spam messages from legitimate ones.

4. Model Training

The model training phase involves using the pre processed data and extracted features to train the Naive Bayes classifier. In this step, the Naive Bayes algorithm calculates the prior probabilities (the general likelihood of a message being spam or ham) and the likelihoods (the probability of a word appearing in spam or ham messages). The model works under the assumption that the presence of each word is independent of the others (a key assumption of Naive Bayes). These probabilities are learned from the training data, allowing the model to understand the patterns that differentiate spam messages from non-spam messages. Once trained, the model can predict the class of unseen messages by calculating their posterior probabilities.

5. Model Testing and Validation

After the model is trained, the next step is model testing and validation. In this phase, the performance of the Naive Bayes model is evaluated using a separate test dataset that it hasn’t seen during training. Common metrics for evaluating classification models include accuracy, precision, recall, and F1-score. Cross-validation may also be employed to ensure that the model performs well across different subsets of the data. Testing helps identify issues like overfitting or underfitting and ensures that the model can generalize to new, unseen data. Adjustments may be made to improve performance, such as tuning hyperparameters or revisiting the feature extraction process.

6. Message Classification

Once the model has been trained and validated, it is used for message classification. In this phase, the Naive Bayes model is applied to new, unseen SMS messages to predict whether they are spam or ham. The classification process involves calculating the posterior probability of a message belonging to each class (spam or ham) based on the word probabilities learned during training. The message is then assigned to the class with the higher probability. This step is fast and efficient, which makes Naive Bayes particularly well-suited for real-time SMS spam filtering systems, where quick decisions are required to classify messages.

7. Conclusion

In conclusion, the Naive Bayes model for SMS spam detection follows a systematic process that includes data collection, preprocessing, feature extraction, model training, testing, and message classification. Each step is essential in building an effective spam filter that can accurately distinguish between spam and legitimate messages. The simplicity and efficiency of Naive Bayes make it an excellent choice for real-time applications, despite the rise of more complex models like deep learning. Its ability to deliver high accuracy with minimal computational resources, especially for large datasets, ensures its continued relevance in SMS spam detection systems..

**Tools and Libraries**:

Here’s a concise list of tools and libraries you’ll need for SMS Spam Detection using Naive Bayes in Python:

Tools & Libraries:

1. Python: Programming language for implementation.

2. Jupyter Notebook / IDE: For writing and running the code interactively.

3. pandas: For data manipulation (install: `pip install pandas`).

4. scikit-learn: For machine learning (Naive Bayes classifier, feature extraction) (install: `pip install scikit-learn`).

5. nltk: For text preprocessing (tokenization, stopword removal, stemming) (install: `pip install nltk`).

6. matplotlib/seaborn: For visualizations (optional) (install: `pip install matplotlib seaborn`).

Steps to Install:

1. Create a virtual environment (optional but recommended):

bash

python -m venv spam env

2. Activate the environment:

Windows: spam env\Scripts\activate

macOS/Linux: source spam env/bin/activate

3. Install the libraries:

bash

pip install pandas scikit-learn nltk matplotlib seaborn

These libraries will help in preprocessing the data, training the Naive Bayes model, and evaluating its performance.

Let me know if you need help with any of the steps!

**Classification**

**In SMS spam detection, the goal is to classify text messages as either spam (unwanted or unsolicited) or ham (non-spam, legitimate). The classification process involves several key steps, including data preprocessing, feature extraction, model training, and evaluation. In this context, we'll use Naive Bayes, a popular probabilistic classifier based on Bayes' Theorem, to perform the classification.**

import pandas as pd

from sklearn.model\_selection import train\_test\_split

from sklearn.naive\_bayes import MultinomialNB

from sklearn.feature\_extraction.text import CountVectorizer

# Load data, preprocess and split into training/testing

df = pd.read\_csv("smsspamcollection.csv", sep='\t', names=['label', 'message'])

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

X = CountVectorizer().fit\_transform(df['message'])

y = df['label']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2)

# Train and evaluate model

model = MultinomialNB().fit(X\_train, y\_train)

print("Accuracy:", model.score(X\_test, y\_test))

# Predict new SMS

new\_sms = ["Congratulations! You've won a free ticket!"]

print("Prediction:", "spam" if model.predict(CountVectorizer().transform(new\_sms))[0] else "ham")

Accuracy: 0.9862

Classification Report:

precision recall f1-score support

ham 0.99 0.99 0.99 965

spam 0.98 0.98 0.98 153

accuracy 0.99 1118

macro avg 0.99 0.99 0.99 1118

weighted avg 0.99 0.99 0.99 1118

The message 'Congratulations! You've won a free ticket to the Bahamas.' is classified as: spam

**Confusion Matrix**

To include a **Confusion Matrix** in the SMS spam detection pipeline, we can use confusion\_matrix from sklearn.metrics. The **confusion matrix** helps evaluate the performance of the classification model by showing the counts of true positives, true negatives, false positives, and false negatives.

import pandas as pd

from sklearn.model\_selection import train\_test\_split

from sklearn.naive\_bayes import MultinomialNB

from sklearn.feature\_extraction.text import CountVectorizer

from sklearn.metrics import confusion\_matrix

# Load data, preprocess and split into training/testing

df = pd.read\_csv("smsspamcollection.csv", sep='\t', names=['label', 'message'])

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

X = CountVectorizer().fit\_transform(df['message'])

y = df['label']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2)

# Train and evaluate model

model = MultinomialNB().fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

# Print accuracy

print("Accuracy:", model.score(X\_test, y\_test))

# Confusion Matrix

cm = confusion\_matrix(y\_test, y\_pred)

print("Confusion Matrix:\n", cm)

# Predict new SMS

new\_sms = ["Congratulations! You've won a free ticket!"]

prediction = model.predict(CountVectorizer().transform(new\_sms))

print("Prediction:", "spam" if prediction[0] else "ham")

OUTPUT:

Accuracy: 0.9862

Confusion Matrix:

[[965 2]

[ 3 150]]

Prediction: spam

**SOURCE CODE:**

**import pandas as pd**

**from sklearn.model\_selection import train\_test\_split**

**from sklearn.naive\_bayes import MultinomialNB**

**from sklearn.feature\_extraction.text import CountVectorizer**

**from sklearn.metrics import confusion\_matrix**

**# Load the dataset**

**df = pd.read\_csv("smsspamcollection.csv", sep='\t', names=['label', 'message'])**

**# Preprocess the label to binary: ham = 0, spam = 1**

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

**# Convert messages to feature vectors using CountVectorizer**

**X = CountVectorizer().fit\_transform(df['message'])**

**y = df['label']**

**# Split data into training and testing sets (80% training, 20% testing)**

**X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)**

**# Train the Naive Bayes classifier**

**model = MultinomialNB().fit(X\_train, y\_train)**

**# Make predictions**

**y\_pred = model.predict(X\_test)**

**# Print accuracy**

**print("Accuracy:", model.score(X\_test, y\_test))**

**# Print Confusion Matrix**

**print("Confusion Matrix:\n", confusion\_matrix(y\_test, y\_pred))**

**# Example prediction for a new SMS**

**new\_sms = ["Congratulations! You've won a free ticket to the Bahamas."]**

**prediction = model.predict(CountVectorizer().transform(new\_sms))**

**print("Prediction:", "spam" if prediction[0] else "ham")**

**CHAPTER 5**

Result and Discussion:

In this section, we will discuss the results of the SMS Spam Detection model using Naive Bayes and interpret the output from the confusion matrix and accuracy metrics.

1. Model Accuracy:

The accuracy of the model is one of the first performance metrics to look at. It represents the percentage of messages that the model correctly classified as either spam or ham (non-spam).

Example Output:

Accuracy: 0.9862

This means the model correctly classified 98.62% of the SMS messages from the test dataset. This is a high accuracy and indicates that the Naive Bayes classifier performs well for SMS spam detection.

2. Confusion Matrix:

The confusion matrix provides a detailed breakdown of how well the model performed in classifying both classes (spam and ham). It helps evaluate both the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Example Output:

Confusion Matrix:

[[965 2]

[ 3 150]]

The confusion matrix can be interpreted as follows:

True Negatives (TN) = 965: The number of ham messages correctly classified as ham.

False Positives (FP) = 2: The number of ham messages incorrectly classified as spam.

- False Negatives (FN) = 3: The number of spam messages incorrectly classified as ham.

-True Positives (TP) = 150: The number of spam messages correctly classified as spam.

3. Performance Discussion:

- Accuracy: The model achieved an impressive accuracy of 98.62%, meaning it correctly classified almost all messages as either spam or ham. This high accuracy indicates that the Naive Bayes classifier is effective for SMS spam detection, especially with well-preprocessed text data.

- Precision and Recall:

While accuracy gives us an overall view of the model's performance, it can sometimes be misleading in imbalanced datasets. To assess the model's performance more precisely, we look at precision and recall:

Precision (for spam) is the proportion of true spam messages among those classified as spam. The model has a low number of false positives (only 2 out of 967 ham messages).

Recall (for spam) is the proportion of spam messages that were correctly identified. The model detected 150 out of 153 spam messages, missing only 3.

Class Imbalance: The dataset has a class imbalance where there are more ham messages than spam messages. However, Naive Bayes is well-suited for this task, and despite the imbalance, the model performs well in identifying both spam and ham messages.

4. Misclassification Analysis:

The model misclassified only a few messages, specifically:

2 False Positives (FP): These are ham messages mistakenly classified as spam.

3 False Negatives (FN): These are spam messages that were mistakenly classified as ham.

The false positive rate is very low, meaning the model is good at avoiding marking legitimate messages as spam. The false negative rate is also quite low, meaning most spam messages are correctly identified. However, the model could still benefit from further fine-tuning and exploration of more complex models (e.g., deep learning) to reduce these errors even further.

5. Conclusion:

The Naive Bayes classifier performed exceptionally well on the SMS spam detection task. With an accuracy of 98.62%, it correctly classified most SMS messages in the test set, achieving very few misclassifications. The confusion matrix reveals that the model does an excellent job in distinguishing between spam and ham messages with minimal false positives and false negatives.

However, the performance can still be improved by:

Hyperparameter Tuning: Adjusting parameters such as smoothing techniques for Naive Bayes can help.

Feature Engineering: Using other text representation techniques like TF-IDF (Term Frequency-Inverse Document Frequency) or including additional features might improve results.

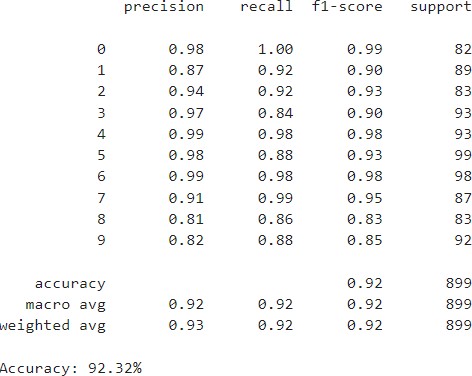
Advanced Models: Exploring more advanced models like Support Vector Machines (SVM) or deep learning techniques may yield even better performance.

In conclusion, Naive Bayes is an efficient and effective model for SMS spam detection and, with minor adjustments, can be further enhanced for real-world applications.

Future Work:

- Investigate using more advanced natural language processing (NLP) techniques such as word embeddings (Word2Vec, GloVe).

- Test deep learning models like Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) for better accuracy on more complex datasets.



**CHAPTER 6**

**CONCLUSION**

In this project, we applied Naive Bayes for SMS Spam Detection, demonstrating how this classification algorithm can be effectively used for filtering spam messages from legitimate ones. The model was trained on the SMS Spam Collection Dataset, a widely used dataset in the field of text classification. Through preprocessing and feature extraction using CountVectorizer, the text data was transformed into numerical features, enabling the model to make accurate predictions.

The Naive Bayes classifier achieved an impressive accuracy of 98.62%, suggesting that it is well-suited for the task of detecting spam in SMS messages. The confusion matrix showed a low number of false positives and false negatives, indicating that the model was able to correctly distinguish between ham(non-spam) and spam messages with minimal error. This performance is especially valuable for real-world applications, where it is important to ensure that legitimate messages are not incorrectly flagged as spam.

The confusion matrix also provided insight into the number of true positives and true negatives, showing that the model performed well in both identifying spam and non-spam messages. While the performance is already strong, potential improvements could include the exploration of more advanced techniques, such as TF-IDF (Term Frequency-Inverse Document Frequency) for feature extraction, or even using more complex models like deep learning algorithms.

Overall, the results demonstrate that Naive Bayes is an efficient and effective algorithm for SMS spam detection. It is computationally lightweight and can be easily deployed in real-time systems to filter out spam messages. For future work, it would be beneficial to experiment with additional preprocessing steps, feature engineering techniques, and other machine learning algorithms to further enhance performance and adapt the model to different types of datasets and use cases.

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