# TIJER || ISSN 2349-9249 || © March 2023 Volume 10, Issue 3 || www.tijer.org SMS SPAM DETECTION USING MACHINE LEARNING

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ABSTRACT: In recent years, there has been considerable interest among people to use short message service (SMS) as one of the essential and straightforward communications services on mobile devices. The increased popularity of this service also increased the number of mobile devices attacks such as SMS spam messages. SMS spam messages constitute a real problem to mobile subscribers. this worries telecommunication service providers as it disturbs their customers and causes them to lose business. to enhanced SMS spam filtering performance by combining two of data mining task association and classification. FP-growth in association is utilized for mining frequent pattern on SMS and Naive Bayes Classifier is used to classify whether SMS is spam or ham. Training data was using SMS spam collection from previous research. The result of using collaboration of Naive Bayes and FP-Growth performs the highest average accuracy of 98, 506% and 0,025% better than without using FP-Growth for dataset SMS Spam Collection v.1, and improves the precision score; thus, the classification result is more accurate

Keywords: Spam, Machine Learning, Naïve Bayes Algorithm, SMS (Short Message Service), Vectorizer.

**Introduction:** SMS is a text-based communication media that allows mobile phone users to share a short text (usually it is well beyond 160 characters in 7-bit). Along with the widespread use and popularity as the most important communications media, there are plenty of those who use it for commercial purposes such as advertising media and even fraud. The reduced SMS rate is one of the causes of increasing SMS spam as well, as in China, the SMS tariff is well under than \$ 0.001. Moreover, based on the Korea Information

Security (KISA), this amount exceeds the email spam. For instance, mobile users in the US gains 1.1 billion SMS spams, and Chinese users receives 8,29 billion SMS spams weekly.

There is a solution that could be performed to solve the above problems. It is by filtering SMS based on the text classification. There are some popular text classifications techniques, including decision trees, Naive Bayes, rule induction, neural network, nearest neighbours, and Support Vector Machine. Nevertheless, this SMS classification is different from the classification on a regular document text or e-mail due to the very short text (160 7-bit characters maximum), plenty of abbreviated texts, and tend to be informal text in SMS.

# Literature Survey:

[1] SMS (Short Message Service) is still the primary choice as a communication medium even though nowadays mobile phone is growing with a variety of communication media messenger applications.

[2] In the modern world where digitization is everywhere, SMS has become one of the most vital forms of communications, unlike other chatting-based messaging systems like Facebook, WhatsApp etc., SMS does not require active internet connection at all.

[3] Despite the fact that in many parts of the world, versatile informing channel is right now viewed as "spotless" and trusted, on the complexity ongoing reports obviously show that the volume of cell phone spam is drastically expanding step by step.

[4] Due to its convenient, economical, fast, and easy to use nature Electronic mail is a vital revolution taking place over traditional communication systems. A main obstruction in electronic communications is the vast publicizing of unwanted, harmful emails known as spam emails. Lots of time of client is being wasted for sorting approaching mail and erasing undesirable correspondence, so there is a need for spam detection so that its outcomes can be reduced. The main aim is to development of suitable filters that can appropriately detect those emails and results in a high-performance rate.

[5] Over recent years, as the popularity of mobile phone devices has increased, Short Message Service (SMS) has grown into a multi-billion dollars industry. At the same time, reduction in the cost of messaging services has resulted in growth in unsolicited commercial advertisements (spams) being sent to mobile phones. In parts of Asia, up to 30% of text messages were spam in 2012. Lack of real databases for SMS spams, short length of messages and limited features, and their informal language are the factors that may cause the established email filtering algorithms to underperform in their classification. In this project, a database of real SMS Spams from UCI Machine Learning repository is used, and after pre-processing and feature extraction, different machine learning techniques are applied to the database. Finally, the results are compared and the best algorithm for spam filtering for text messaging is introduced. Final simulation results using 10-fold cross validation shows the best classifier in this work reduces the overall error rate of best model in original paper citing this dataset by more than half.

[6] In the recent advanced society the online social networking sites like Twitter, Facebook, LinkedIn are very popular. Twitter, an online Social Networking site, is one of the most visited sites. Lot of users communicates with each other using Twitter. The rapidly growing social network Twitter has been infiltrated by large amount of spam. As Twitter spam is not similar to traditional spam, such as email and blog spam, conventional spam filtering methods are not appropriate and effective to detect it. Thus, many researchers have proposed schemes to detect spammers

[7] Spam involves sending someone unwanted messages. Currently the internet is the biggest platform to get some information, also social media is going to be very popular nowadays. Because of that, many spammers will try to mislead users by sending lots of spam messages. And because of spam messages, there are lots of problems, fraud occurs. So we want to filter messages into spam or ham. To classify the messages as spam or not spam we are using machine learning (the multinomial naïve Bayes classifier algorithm) and Count Vectorizer provided by Scikit-learn library in python programming. First, we collect the datasets and convert them into numerical data (matrix) by Count Vectorizer and then we apply the naïve Bayes algorithm on datasets for classification purposes

[8] presents detection of Spam and ham messages using various supervised machine learning algorithms like naïve Bayes Algorithm, support vector machines algorithm, and the maximum entropy algorithm and compares their performance in filtering the Ham and Spam messages. As people indulge more in Web-based activities, and with rising sharing of private – data by companies, SMS spam is very common. SMS spam filter inherits much functionality from E-mail Spam Filtering. Comparing the performance of various supervised learning algorithms, we find the support vector machine algorithm gives us the most accurate result.

**Problem Statement:** Short Message Service (SMS) is one of the well-known communication services in which a message sends electronically. The lessening in the cost of SMS benefits by telecom organizations has prompted the expanded utilization of SMS. This ascent pulled in assailants, which have brought about SMS Spam problem. Spam messages include advertisements, free services, promotions, awards, etc. People are using the ubiquity of mobile phone devices is expanding day by day as they give a vast variety of services by reducing the cost of services. Short Message Service (SMS) is one of the broadly utilized communication service. In any case, this has prompted an expansion in mobile phones attacks like SMS Spam. In this problem, preliminary results are mentioned or explained herein based on Singapore based publicly available datasets. This problem is further expanded using multiple background datasets.

**Proposed System:**Several techniques have been suggested to combat spam. To automatically detect spam, researchers have implemented data mining algorithms to make spam detection a classification issue. Data mining has many types but, in this research, spamming extraction from tweets by using deep learning and machine learning. Machine learning uses two main techniques: Supervised learning allows you to collect data or produce a data output from a previous ML deployment. Unsupervised learning finds the hidden pattern or data grouping without the requirement for human intercession.

**Feasibility Algorithm:**Comparison of algorithm aims to get the algorithm that is considered the fastest and accurate to make a prediction of a problem. Result of comparison of Naive Bayes and K-Nearest Neighbor algorithm can be concluded that Naive Bayes algorithm yield 98.03% accuracy and K-Nearest Neighbor algorithm yield 88.52% accuracy.

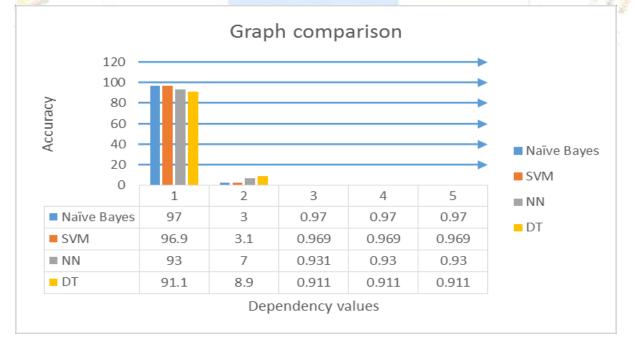
Naive Bayes is better classifier than decision tree and k-NN with the accuracy percentage 98.03% and the accuracy rate for decision tree was 96.86% and for K- NN, it was 88.52% which is much lower than Naive Bayes accuracy value.

S.L.NO	Algorithm	Accuracy
1	Naïve Bayes	98.03%
2	K-NN	88.52%
3	Decision Tree	96.86%
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Method/ Parmeter	Decision Tree	Naïve Bayesian	KNN
Understandibility	Simple to understand and generate	Easy to Understand and build	Easy to understand
Data Type	Numerical and categorical	Numerical and categorical	Numerical and categorical
Determinstic/ Non deterministic	Deterministic	Non Deterministic	Non Deterministic
Effectiveness on	Large data	Huge data	Large data
Applicable	Pattern Recognition, Sequence Recognition, Financial Applications	Text Classification, Spam Filtering	Text Classification Decision Making

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**Algorithm:** The Naive Bayes classification algorithm is a probabilistic classifier. It is based on probability models that incorporate strong independence assumptions. The independence assumptions often do not have an impact on reality. Therefore, they are considered as naive. Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable

**Naive Bayes Classifier:** Naive Bayes classifiers belong to the probabilistic classifiers and are highly scalable, requiring several parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers. This system uses a hybrid approach using both rule-based systems and automatic systems in order to achieve higher accuracy of sentiment calculation. 'TextBlob' library has been used for processing text data. It provides an API for natural language processing (NLP) tasks.

## Algorithm:

Consider a training data set D consists of documents which belong to different classes say class A and B.
 Prior probability of both classes A and B is calculated as shown Class A=number of objects of class A / total number of objects. Class B=number of objects of class B / total number of objects.

3. Now calculate the total number of word frequencies of both classes A and B i.e., ni na = the total number of word frequencies of class A. nb =the total number of word frequency of class B.

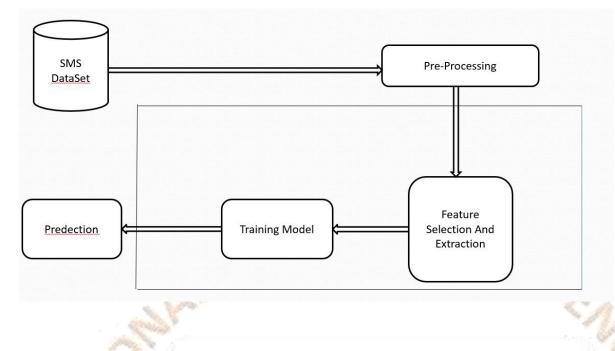
4. Calculate the conditional probability of keyword occurrence for given class P(word1 / class A) = wordcount / ni(A) P(word1 / class B) = wordcount / ni(B) P(word2 / class A) = wordcount / ni(A) P(word2 / class B) = wordcount / ni (B) . . . . . P(word n / class B) = wordcount / ni (B)

5. Uniform distributions are to be performed in order to avoid zero frequency problems.

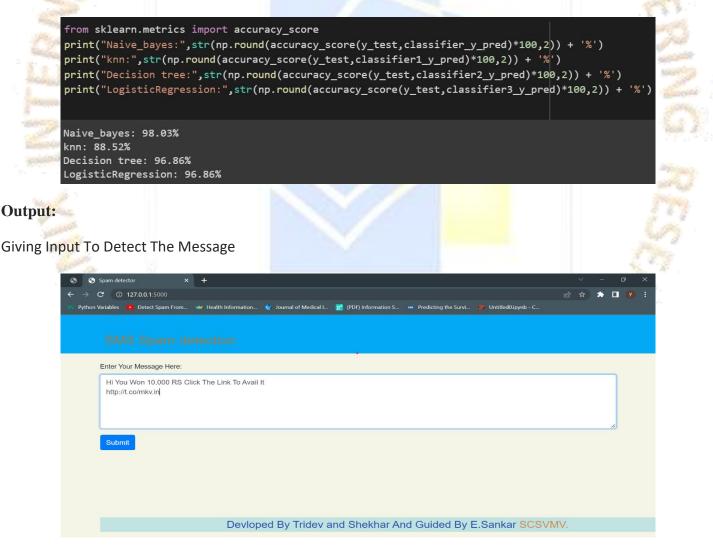
6. Now a new document M is classified based on calculating the probability for both classes A and B P (M/W).
a) Find P(A / W) = P(A) \* P(word1/class A)\* P(word2/ class A).....\* P(word n / class A). b) Find P(B / W) = P(B) \* P(word1/class B)\*P(word2/ class B)......\* P(word n / class B).

7. After calculating probability for both classes A and B the class with higher probability is the one the new document M assigned.

**System Architecture:** 

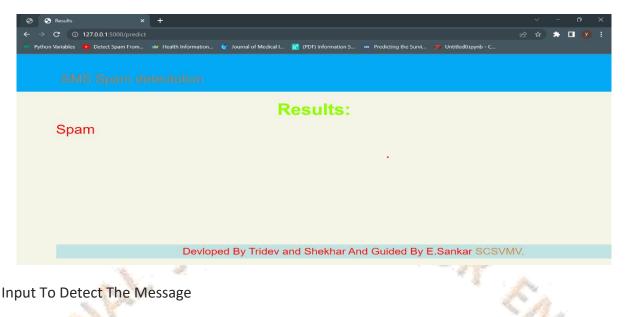


**Result:**From the results we can clearly see that Naïve Bayes performs clearly in classifying the reviews as OR or CB followed by Random Forest classifier and KNN is averagely performing by giving only 88.52% accuracy. Thus, we can conclude that Naïve Bayes is a clear winner in detecting fake reviews.



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Given Message Is Detected As A Spam



# Giving Input To Detect The Message

Not a Spam (It is a Ham)

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# **Results:**

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**Conclusion:** From the above discussion and experimentation authors have concluded that Machine Learning algorithms can play a vital role in identifying SPAM SMS. The accuracy obtained in this work is more than 95% in both the cases. The aims and objectives of the project, which achieved throughout the course, defined at the very first stage of the process. To collect all the information, the research work involved a careful study on the different filtering algorithms and existing anti-spam tools. These large-scale research papers and existing software programs are one of the sources of inspiration behind this project work. The whole project was divided into several iterations. Each iteration was completed by completing four phases: inception, where the idea of work was identified; elaboration, where architecture of the part of the system is designed; construction, where existing code is implemented; transition, where the developed part of the project is validated. However, there are still some parts that can be improved: for example, adding additional filtering techniques or changing aspects of the existing ones. The changes such as incrementing or decrementing the number of interesting words of the message and reorganizing the formula for calculating interesting rate can be done later.

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