Spam Detection using Machine Learning and Natural Language Processing

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Computer Science and
Engineering

By

VATHUMALLI SRI GANESH

REG. 38110623

&

VATTIKUTI MANIDEEP SITARAM

REG. 38110624

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY

JEPPIAAR NAGAR, RAJIV GANDHI SALAI,

CHENNAI – 600119, TAMILNADU.

MAY 2022

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

(Established under Section 3 of UGC Act, 1956)

JEPPIAAR NAGAR, RAJIV GANDHI SALAI

CHENNAI– 600119

www.sathyabama.ac.in

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **VATHUMALLI SRI GANESH (Reg. No: 38110623) & VATTIKUTI MANIDEEP SITARAM** who carried out the project entitled "**Spam Detection using Machine Learning and Natural language processing**" under my supervision from December 2021 to May 2022.

Internal Guide

Dr. S. Prince Mary M.E., Ph.D.

Head of the Department

Dr. S.VIGNESHWARI, M.E., Ph.D.,

Dr. L.LAKSHMANAN, M.E., Ph.D.,

Submitted for Viva-voce Examination held on

Internal Examiner **External Examiner**

DECLARATION

We, **Vathumalli Sri Ganesh, Vattikuti Manideep Sitaram** hereby declare that the project report entitled "**Spam Detection using Machine Learning and Natural Language Processing"** done by us under the guidance of **Dr. S. Prince Mary M.E., Ph.D.** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering Degree in Computer Science and Engineering.

Date: **V. Sri Ganesh**

V. Manideep Sitaram

Place: Signature of the Candidate

ACKNOWLEDGEMENT

We are pleased to acknowledge our sincere thanks to the **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. We are grateful to them.

we convey our thanks to **Dr. T. Sasikala M.E., Ph.D., Dean,** School of Computing**, Dr. S. Vigneshwari, M.E., Ph.D. and Dr. L. Lakshmanan, M.E., Ph.D., Heads of the Department** of **Computer Science and Engineering** for providing us necessary support and details at the right time during the progressive reviews.

we would like to express our sincere and deep sense of gratitude to our Project Guide **Dr. S. Prince Mary M.E., Ph.D.,** for her valuable guidance, suggestions, and constant encouragement that paved way for the successful completion of our project work.

we wish to express our thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

Abstract

Nowadays communication plays a major role in everything be it professional or personal. Email communication service is being used extensively because of its free use services, low-cost operations, accessibility, and popularity. Emails have one major security flaw that is anyone can send an email to anyone just by getting their unique user id. This security flaw is being exploited by some businesses and ill-motivated persons for advertising, phishing, malicious purposes, and finally fraud. This produces a kind of email category called SPAM.

Spam refers to any email that contains an advertisement, unrelated and frequent emails. These emails are increasing day by day in numbers. Studies show that around 55 percent of all emails are some kind of spam. A lot of effort is being put into this by service providers. Spam is evolving by changing the obvious markers of detection. Moreover, the spam detection of service providers can never be aggressive with classification because it may cause potential information loss to incase of a misclassification.

To tackle this problem we present a new and efficient method to detect spam using machine learning and natural language processing. A tool that can detect and classify spam. In addition to that, it also provides information regarding the text provided in a quick view format for user convenience.

TABLE OF CONTENTS

List of Figures

List of Tables

1. Introduction

Today, Spam has become a major problem in communication over internet. It has been accounted that around 55% of all emails are reported as spam and the number has been growing steadily. Spam which is also known as unsolicited bulk email has led to the increasing use of email as email provides the perfect ways to send the unwanted advertisement or junk newsgroup posting at no cost for the sender. This chances has been extensively exploited by irresponsible organizations and resulting to clutter the mail boxes of millions of people all around the world.

Spam has been a major concern given the offensive content of messages, spam is a waste of time. End user is at risk of deleting legitimate mail by mistake. Moreover, spam also impacted the economical which led some countries to adopt legislation.

Text classification is used to determine the path of incoming mail/message either into inbox or straight to spam folder. It is the process of assigning categories to text according to its content. It is used to organized, structures and categorize text. It can be done either manually or automatically. Machine learning automatically classifies the text in a much faster way than manual technique. Machine learning uses pre-labelled text to learn the different associations between pieces of text and it output. It used feature extraction to transform each text to numerical representation in form of vector which represents the frequency of word in predefined dictionary.

Text classification is important to structure the unstructured and messy nature of text such as documents and spam messages in a cost-effective way. Machine learning can make more accurate precisions in real-time and help to improve the manual slow process to much better and faster analysing big data. It is important especially to a company to analyse text data, help inform business decisions and even automate business processes.

In this project, machine learning techniques are used to detect the spam message of a mail. Machine learning is where computers can learn to do something

without the need to explicitly program them for the task.

It uses data and produce a program to perform a task such as classification. Compared to knowledge engineering, machine learning techniques require messages that have been successfully pre-classified. The pre-classified messages make the training dataset which will be used to fit the learning algorithm to the model in machine learning studio.

A combination of algorithms are used to learn the classification rules from messages. These algorithms are used for classification of objects of different classes. These algorithms are provided with pre labelled data and an unknown text. After learning from the prelabelled data each of these algorithms predict which class the unknown text may belong to and the category predicted by majority is considered as final.

2. Literature Review

2.1 Introduction

This chapter discusses about the literature review for machine learning classifier that being used in previous researches and projects. It is not about information gathering but it summarize the prior research that related to this project. It involves the process of searching, reading, analysing, summarising and evaluating the reading materials based on the project.

A lot of research has been done on spam detection using machine learning. But due to the evolvement of spam and development of various technologies the proposed methods are not dependable. Natural language processing is one of the lesser known fields in machine learning and it reflects here with comparatively less work present.

2.2 Related work

Spam classification is a problem that is neither new nor simple. A lot of research has been done and several effective methods have been proposed.

i. M. RAZA, N. D. Jayasinghe, and M. M. A. Muslam have analyzed various techniques for spam classification and concluded that naïve Bayes and support vector machines have higher accuracy than the rest, around 91% consistently [1].

ii. S. Gadde, A. Lakshmanarao, and S. Satyanarayana in their paper on spam detection concluded that the LSTM system resulted in higher accuracy of 98%[2].

iii. P. Sethi, V. Bhandari, and B. Kohli concluded that machine learning algorithms perform differently depending on the presence of different attributes [3].

iv. H. Karamollaoglu, İ. A. Dogru, and M. Dorterler performed spam classification on Turkish messages and emails using both naïve Bayes classification algorithms and support vector machines and concluded that the accuracies of both models measured around 90% [4].

v. P. Navaney, G. Dubey, and A. Rana compared the efficiency of the SVM,

naïve Bayes, and entropy method and the SVM had the highest accuracy (97.5%) compared to the other two models [5].

vi. S. Nandhini and J. Marseline K.S in their paper on the best model for spam detection it is concluded that random forest algorithm beats others in accuracy and KNN in building time [6].

vii. S. O. Olatunji concluded in her paper that while SVM outperforms ELM in terms of accuracy, the ELM beats the SVM in terms of speed [7].

viii. M. Gupta, A. Bakliwal, S. Agarwal, and P. Mehndiratta studied classical machine learning classifiers and concluded that convolutional neural network outperforms the classical machine learning methods by a small margin but take more time for classification [8].

ix. N. Kumar, S. Sonowal, and Nishant, in their paper, published that naïve Bayes algorithm is best but has class conditional limitations [9].

x. T. Toma, S. Hassan, and M. Arifuzzaman studied various types of naïve Bayes algorithms and proved that the multinomial naïve Bayes classification algorithm has better accuracy than the rest with an accuracy of 98% [10].

F. Hossain, M. N. Uddin, and R. K. Halder in their study concluded that machine learning models outperform deep learning models when it comes to spam classification and ensemble models outperform individual models in terms of accuracy and precision [11].

2.3 Summary

From various studies, we can take that for various types of data various models performs better. Naïve Bayes, random forest, SVM, logistic regression are some of the most used algorithms in spam detection and classification.

3. Objectives and Scope

3.1 Problem Statement

Spammers are in continuous war with Email service providers. Email service providers implement various spam filtering methods to retain their users, and spammers are continuously changing patterns, using various embedding tricks to get through filtering. These filters can never be too aggressive because a slight misclassification may lead to important information loss for consumer. A rigid filtering method with additional reinforcements is needed to tackle this problem.

3.2 Objectives

The objectives of this project are

i. To create a ensemble algorithm for classification of spam with highest possible accuracy.
ii. To study on how to use machine learning for spam detection.
iii. To study how natural language processing techniques can be implemented in spam detection.
iv. To provide user with insights of the given text leveraging the created algorithm and NLP.

3.3 Project Scope

This project needs a coordinated scope of work.

i. Combine existing machine learning algorithms to form a better ensemble algorithm.
ii. Clean, processing and make use of the dataset for training and testing the model created.
iii. Analyse the texts and extract entities for presentation.

3.4 Limitations

This Project has certain limitations.

i. This can only predict and classify spam but not block it.
ii. Analysis can be tricky for some alphanumeric messages and it may struggle with entity detection.
iii. Since the data is reasonably large it may take a few seconds to classify and anlayse the message.

4. Experimentation and Methods

4.1 Introduction

This chapter will explain the specific details on the methodology being used to develop this project. Methodology is an important role as a guide for this project to make sure it is in the right path and working as well as plan. There is different type of methodology used in order to do spam detection and filtering. So, it is important to choose the right and suitable methodology thus it is necessary to understand the application functionality itself.

4.2 System Architecture

The application overview has been presented below and it gives a basic structure of the application.

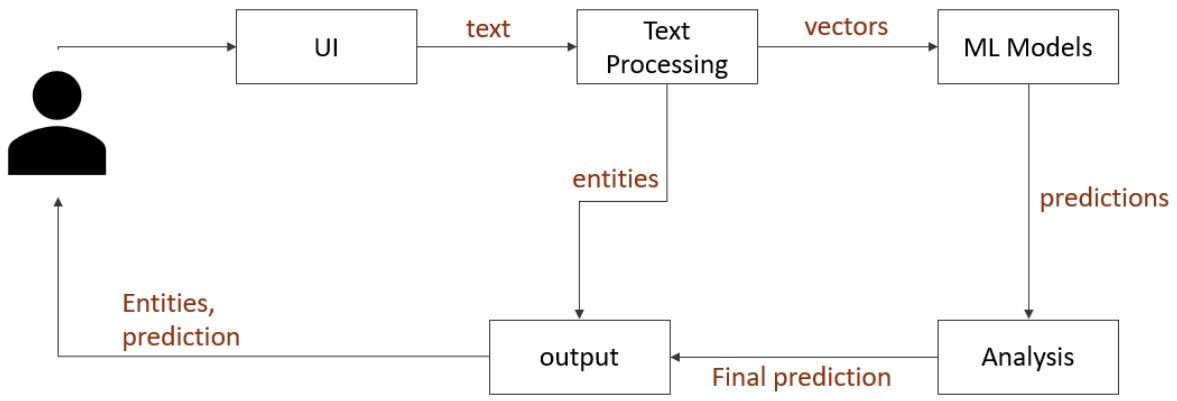


fig no. 4.1 Architecture

The UI, Text processing and ML Models are the three important modules of this project. Each Module's explanation has been given in the later sections of this chapter.

A more complicated and detailed view of architecture is presented in the workflow section.

4.3 Modules and Explanation

The Application consists of three modules.

i. UI
ii. Machine Learning
iii. Data Processing

I. UI Module

a. This Module contains all the functions related to UI(user interface).
b. The user interface of this application is designed using Streamlit library from python based packages.
c. The user inputs are acquired using the functions of this library and forwarded to data processing module for processing and conversion.
d. Finally the output from ML module is sent to this module and from this module to user in visual form.

II. Machine Learning Module

a. This module is the main module of all three modules.
b. This modules performs everything related to machine learning and results analysis.
c. Some main functions of this module are

i. Training machine learning models.
ii. Testing the model
iii. Determining the respective parameter values for each model.
iv. Key-word extraction.
v. Final output calculation

d. The output from this module is forwarded to UI for providing visual response to user

III. Data Processing Module

a. The raw data undergoes several modifications in this module for further process.
b. Some of the main functions of this module includes

i. Data cleaning
ii. Data merging of datasets
iii. Text Processing using NLP
iv. Conversion of text data into numerical data(feature vectors).
v. Splitting of data.

c. All the data processing is done using Pandas and NumPy libraries.
d. Text processing and text conversion is done using NLTK and scikit-learn libraries.

4.4 Requirements

Hardware Requirements

PC/Laptop

Ram – 8 Gig

Storage – 100-200 Mb

Software Requirements

OS – Windows 7 and above

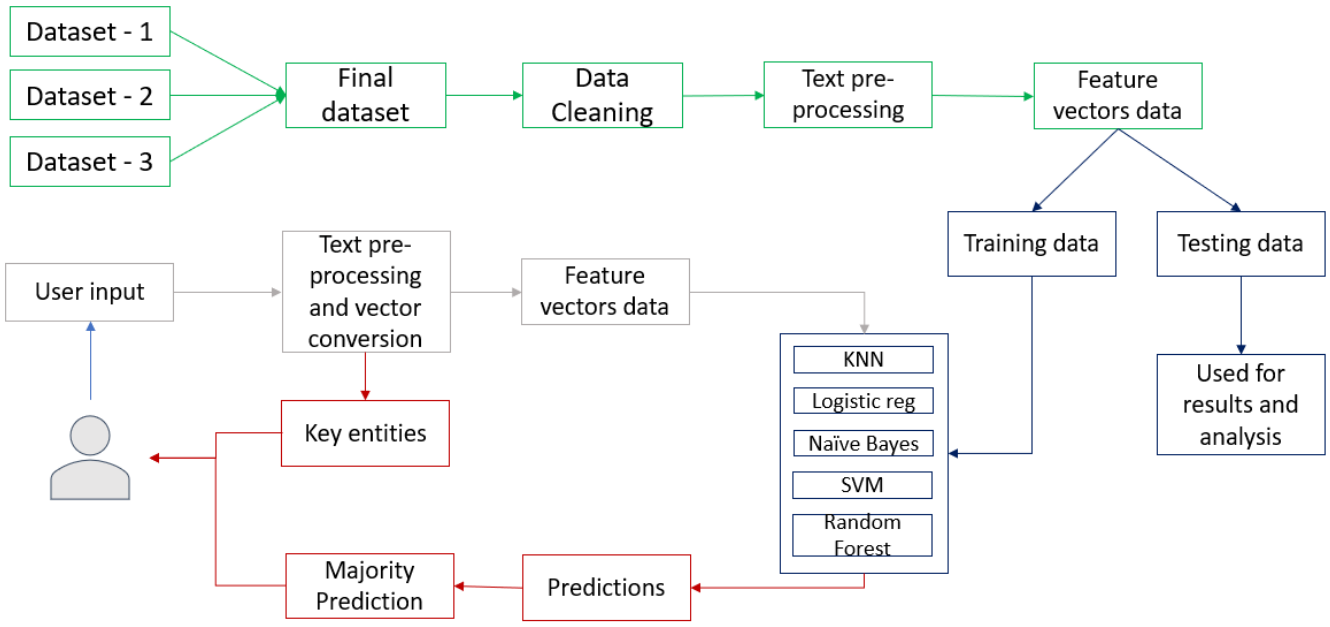
Code Editor – Pycharm, VS Code, Built in IDE

Anaconda environment with packages nltk, numpy, pandas, sklearn, tkinter, nltk data.

Supported browser such as chrome, firefox, opera etc..

4.5 WorkFlow

fig no. 4.2 Workflow



In the above architecture, the objects depicted in Green belong to a module called Data Processing. It includes several functions related to data processing, natural Language Processing. The objects depicted in Blue belong to the Machine Learning module. It is where everything related to ML is embedded. The red objects represent final results and outputs.

4.5.1 Data Collection and Description

- Data plays an important role when it comes to prediction and classification, the more the data the more the accuracy will be.
- The data used in this project is completely open-source and has been taken from various resources like Kaggle and UCI
- For the purpose of accuracy and diversity in data multiple datasets are taken.
  2 datasets containing approximately over 12000 mails and their labels are used for training and testing the application.
- 6000 spam mails are taken for generalisation of data and to increase the accuracy.

Data Description

Dataset : enronSpamSubset.

Source : Kaggle

Description : this dataset is part of a larger dataset called enron. This dataset contains a set of spam and non-spam emails with 0 for non spam and 1 for spam in label attribute.

Composition :

Unique values : 9687

Spam values : 5000

Non-spam values : 4687

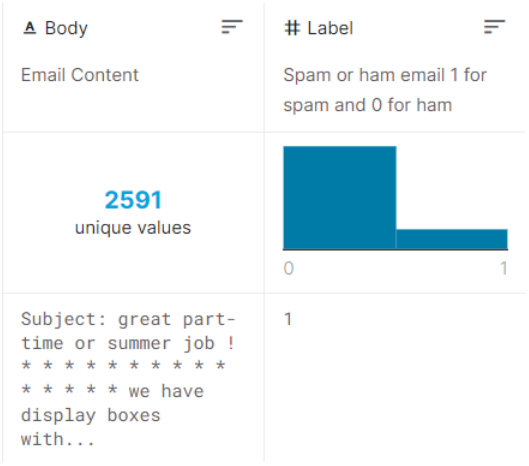


fig no. 4.3 enron spam

Dataset : **lingspam.**

Source : Kaggle

Description : This dataset is part of a larger dataset called Enron1 which contains emails classified as spam or ham(not-spam).

Composition :

Unique values : 2591

Spam values : 419

Non-spam values : 2172

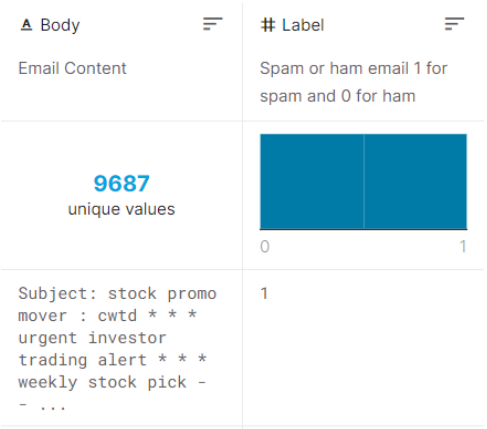


fig no. 4.4 lingspam

4.5.2 Data Processing

4.5.2.1 Overall data processing

It consists of two main tasks

- **Dataset cleaning**

  It includes tasks such as removal of outliers, null value removal, removal of unwanted features from data.

- **Dataset Merging**

  After data cleaning, the datasets are merged to form a single dataset containing only two features(text, label).

  Data cleaning, Data Merging these procedures are completely done using Pandas library.

4.5.2.2 Textual data processing

- **Tag removal**

  Removing all kinds of tags and unknown characters from text using regular expressions through Regex library.

- **Sentencing, tokenization**

  Breaking down the text(email/SMS) into sentences and then into tokens(words).

  This process is done using NLTK pre-processing library of python.

- **Stop word removal**

  Stop words such as of , a ,be , … are removed using stopwords NLTK library of python.

- **Lemmatization**

  Words are converted into their base forms using lemmatization and pos-tagging

  This process gives key-words through entity extraction.

  This process is done using chunking in regex and NLTK lemmatization.

- **Sentence formation**

  The lemmatized tokens are combined to form a sentence.

  This sentence is essentially a sentence converted into its base form and removing stop words.

  Then all the sentences are combined to form a text.

- While the overall data processing is done only to datasets, the textual processing is done to both training data, testing data and also user input data.

4.5.2.3 Feature Vector Formation

- The texts are converted into feature vectors(numerical data) using the words present in all the texts combined
- This process is done using countvectorization of **NLTK** library.
- The feature vectors can be formed using two language models Bag of Words and Term Frequency-inverse Document Frequency.

4.5.2.3.1 Bag of Words

Bag of words is a language model used mainly in text classification. A bag of words represents the text in a numerical form.

The two things required for Bag of Words are

- A vocabulary of words known to us.
- A way to measure the presence of words.

Ex: a few lines from the book “A Tale of Two Cities” by Charles Dickens.

“ It was the best of times,

it was the worst of times,

it was the age of wisdom,

it was the age of foolishness, ”

The unique words here (ignoring case and punctuation) are:

[“it”, “was”, “the”, “best”, “of”, “times”, “worst”,“age”, “wisdom”, “foolishness”]

The next step is scoring words present in every document.

After scoring the four lines from the above stanza can be represented in vector form as

“It was the best of times“ = [1, 1, 1, 1, 1, 1, 0, 0, 0, 0]

"it was the worst of times" = [1, 1, 1, 0, 1, 1, 1, 0, 0, 0]

"it was the age of wisdom" = [1, 1, 1, 0, 1, 0, 0, 1, 1, 0]

"it was the age of foolishness"= [1, 1, 1, 0, 1, 0, 0, 1, 0, 1]

This is the main process behind the bag of words but in reality the vocabulary even from a couple of documents is very large and words repeating frequently and important in nature are taken and remaining are removed during the text processing stage.

4.5.2.3.2 Term Frequency-inverse document frequency

Term frequency-inverse document frequency of a word is a measurement of the importance of a word. It compares the repentance of words to the collection of documentsand calculates the score.

Terminology for the below formulae:

t – term(word)

d – document(set of words)

N – count of documents

The TF-IDF process consists of various activities listed below.

i) **Term Frequency**

The count of appearance of a particular word in a document is called term frequency

$$\boldsymbol{tf(t, d) = count\ of\ t\ in\ d / number\ of\ words\ in\ d}$$

ii) **Document Frequency**

Document frequency is the count of documents the word was detected in. We consider one instance of a word and it doesn't matter if the word is present multiple times.

$$\boldsymbol{df(t) = occurrence\ of\ t\ in\ documents}$$

iii) **Inverse Document Frequency**

- IDF is the inverse of document frequency.
- It measures the importance of a term t considering the information it contributes. Every term is considered equally important but certain terms such as (are, if, a, be, that, ..) provide little information about the document. The inverse document frequency factor reduces the importance of words/terms that has highe recurrence and increases the importance of words/terms that are rare.

$$\boldsymbol{idf(t) = N/df}$$

Finally, the TF-IDF can be calculated by combining the term frequency and inverse document frequency.

$$\boldsymbol{tf\_idf(t, d) = tf(t, d) * \log(N/(df + 1))}$$

the process can be explained using the following example:

"**Document 1 It is going to rain today.**
Document 2 Today I am not going outside.
Document 3 I am going to watch the season premiere."

The Bag of words of the above sentences is

[going:3, to:2, today:2, i:2, am:2, it:1, is:1, rain:1]

Then finding the term frequency

table no. 4.1 Term frequency

Words	IDF Value
Going	log(3/3)
To	log(3/2)
Today	log(3/2)
I	log(3/2)
Am	log(3/2)
It	log(3/1)
Is	log(3/1)
rain	log(3/1)

Then finding the inverse document frequency

table no. 4.2 inverse document frequency

Words	Document1	Document2	Document3
Going	0.16	0.16	0.12
To	0.16	0	0.12
Today	0.16	0.16	0
I	0	0.16	0.12
Am	0	0.16	0.12
It	0.16	0	0
Is	0.16	0	0
rain	0.16	0	0

Applying the final equation the values of tf-idf becomes

Words/ documents	going	to	Today	i	am	if	it	rain
Document1	0	0.07	0.07	0	0	0.17	0.17	0.17
Document2	0	0	0.07	0.07	0.07	0	0	0
Document3	0	0.05	0	0.05	0.05	0	0	0

table no. 4.3 TF-IDF

Using the above two language models the complete data has been converted into two kinds of vectors and stored into a csv type file for easy access and minimal processing.

4.5.3 Data Splitting

The data splitting is done to create two kinds of data Training data and testing data. Training data is used to train the machine learning models and testing data is used to test the models and analyse results. 80% of total data is selected as testing data and remaining data is testing data.

4.5.4 Machine Learning

4.5.4.1 Introduction

Machine Learning is process in which the computer performs certain tasks without giving instructions. In this case the models takes the training data and train on them.
Then depending on the trained data any new unknown data will be processed based on the ruled derived from the trained data.

After completing the countvectorization and TF-IDF stages in the workflow the data is converted into vector form(numerical form) which is used for training and testing models.

For our study various machine learning models are compared to determine which method is more suitable for this task. The models used for the study include Logistic Regression, Naïve Bayes, Random Forest Classifier, K Nearest Neighbors, and Support Vector Machine Classifier and a proposed model which was created using an ensemble approach.

4.5.4.2 Algorithms

a combination of 5 algorithms are used for the classifications.

4.5.4.2.1 Naïve Bayes Classifier

A naïve Bayes classifier is a supervised probabilistic machine learning model that is used for classification tasks. The main principle behind this model is the Bayes theorem.

Bayes Theorem:
Naive Bayes is a classification technique that is based on Bayes' Theorem with an assumption that all the features that predict the target value are independent of each other. It calculates the probability of each class and then picks the one with the highest probability.

Naive Bayes classifier assumes that the features we use to predict the target are independent and do not affect each other. Though the independence assumption is never correct in real-world data, but often works well in practice. so that it is called “Naive” [14].

$$P(A \mid B)=(P(B \mid A)P(A))/P(B)$$

P(A|B) is the probability of hypothesis A given the data B. This is called the posterior probability.
P(B|A) is the probability of data B given that hypothesis A was true.
P(A) is the probability of hypothesis A being true (regardless of the data). This is called the prior probability of A.
P(B) is the probability of the data (regardless of the hypothesis) [15].

Naïve Bayes classifiers are mostly used for text classification. The limitation of the Naïve Bayes model is that it treats every word in a text as independent and is equal in importance but every word cannot be treated equally important because articles and nouns are not the same when it comes to language. But due to its classification efficiency, this model is used in combination with other language processing techniques.

4.5.4.2.2 Random Forest Classifier

Random Forest classifier is a supervised ensemble algorithm. A random forest consists of multiple random decision trees. Two types of randomnesses are built into the trees. First, each tree is built on a random sample from the original data. Second, at each tree node, a subset of features is randomly selected to generate the best split [16].

Decision Tree:

The decision tree is a classification algorithm based completely on features. The tree repeatedly splits the data on a feature with the best information gain. This process continues until the information gained remains constant. Then the unknown data is evaluated feature by feature until categorized. Tree pruning techniques are used for improving accuracy and reducing the overfitting of data.

Several decision trees are created on subsets of data the result that was given by the majority of trees is considered as the final result. The number of trees to be created is determined based on accuracy and other metrics through iterative methods. Random forest classifiers are mainly used on condition-based data but it works for text if the text is

converted into numerical form.

4.5.4.2.3 Logistic Regression

Logistic Regression is a “Supervised machine learning” algorithm that can be used to model the probability of a certain class or event. It is used when the data is linearly separable and the outcome is binary or dichotomous [17]. The probabilities are calculated using a sigmoid function.

For example, let us take a problem where data has n features.
We need to fit a line for the given data and this line can be represented by the equation

$$z=b_0+b_1 x_1+b_2 x_2+b_3 x_3….+b_n x_n$$

here z = odds
generally, odds are calculated as

$$odds=p(event\ occurring)/p(event\ not\ occurring)$$

Sigmoid Function:
A sigmoid function is a special form of logistic function hence the name logistic regression. The logarithm of odds is calculated and fed into the sigmoid function to get continuous probability ranging from 0 to 1.

The logarithm of odds can be calculated by

$$log(odds)=dot(features,coefficients)+intercept$$

and these log_odds are used in the sigmoid function to get probability.

$$h(z)=1/(1+e^{(-z)})$$

The output of the sigmoid function is an integer in the range 0 to 1 which is used to determine which class the sample belongs to. Generally, 0.5 is considered as the limit below which it is considered a NO, and 0.5 or higher will be considered a YES. But the border can be adjusted based on the requirement.

4.5.4.2.4 K-Nearest Neighbors

KNN is a classification algorithm. It comes under supervised algorithms. All the data points are assumed to be in an n-dimensional space. And then based on neighbors the category of current data is determined based on the majority.
Euclidian distance is used to determine the distance between points.

The distance between 2 points is calculated as

$$d=\sqrt{([(x2-x1)]^2+[(y2-y1)]^2}$$

The distances between the unknown point and all the others are calculated. Depending on the K provided k closest neighbors are determined. The category to which the majority of the neighbors belong is selected as the unknown data category.

If the data contains up to 3 features then the plot can be visualized. It is fairly slow compared to other distance-based algorithms such as SVM as it needs to determine the distance to all points to get the closest neighbors to the given point.

4.5.4.2.5 Support Vector Machines(SVM)

It is a machine learning algorithm for classification. Decision boundaries are drawn between various categories and based on which side the point falls to the boundary the category is determined.

Support Vectors:

The vectors closer to boundaries are called support vectors/planes. If there are n categories then there will be n+1 support vectors. Instead of points, these are called vectors because they are assumed to be starting from the origin.The distance between the support vectors is called margin. We want our margin to be as wide as possible because it yields better results.

There are three types of boundaries used by SVM to create boundaries.
Linear: used if the data is linearly separable.
Poly: used if data is not separable. It creates any data into 3-dimensional data.
Radial: this is the default kernel used in SVM. It converts any data into infinite-dimensional data.

If the data is 2-dimensional then the boundaries are lines. If the data is 3-dimensional then the boundaries are planes. If the data categories are more than 3 then boundaries are called hyperplanes.

An SVM mainly depends on the decision boundaries for predictions. It doesn't compare the data to all other data to get the prediction due to this SVM's tend to be quick with predictions.

4.5.5 Experimentation

The process goes like data collection and processing then natural language processing and then vectorization then machine learning.The data is collected, cleaned, and then subjected to natural language processing techniques specified in section IV. Then the cleaned data is converted into vectors using Bag of Words and TF-IDF methods which goes like...

The Data is split into Training data and Testing Data in an 80-20 split ratio. The training and testing data is converted into Bag-of-Words vectors and TF-IDF vectors.

There are several metrics to evaluate the models but accuracy is considered for comparing BoW and TF-IDF models. Accuracy is generally used to determine the efficiency of a model.

Accuracy:
"Accuracy is the number of correctly predicted data points out of all the data points".

Naïve Bayes Classification algorithm:

Two models, one for Bow and one for TF-IDF are created and trained using respective training vectors and training labels. Then the respective testing vectors and labels are used to get the score for the model.

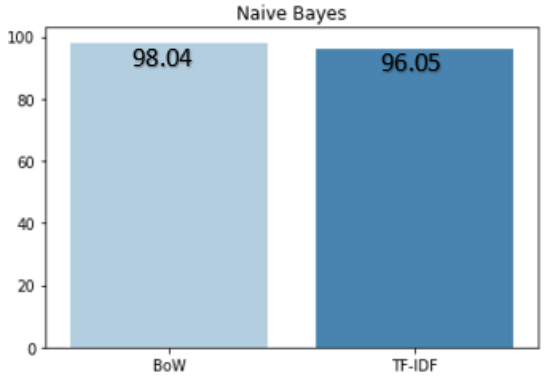


fig no. 4.5 naïve Bayes

The scores for Bag-of-Words and TF-IDF are visualized.

The scores for the Bow model and TF-IDF models are 98.04 and 96.05 respectively for using the naïve bayes model.

Logistic Regression:

Two models are created following the same procedure used for naïve Bayes models and then tested the results obtained are visualized below.

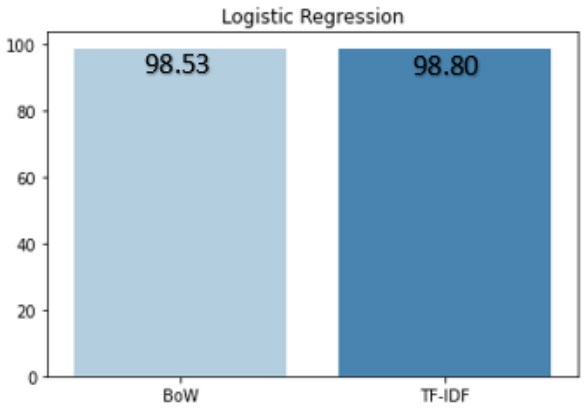


fig no. 4.6 Logistic Regression (Bow vs TF-IDF)

The scores for BoW and TF-IDF models are 98.53 and 98.80 respectively.

K-Nearest Neighbors:

Similar to the above models the models are created and trained using respective vectors and labels. But in addition to the data, the number of neighbors to be considered should also be provided.

Using Iterative Method K =3 (no of Neighbors) provided the best results for the BoW model and K = 9 provided the best results for the TF-IDF model.

Using the K values the scores for BOW and TF-IDF are vis

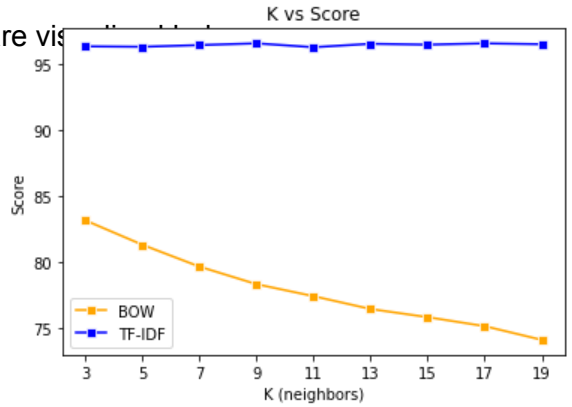


fig no. 4.7 Neighbors vs Accuracy

Taking K=3 and K=9 for Bow and TF-IDF

respectively the scores are calculated and are presented below.

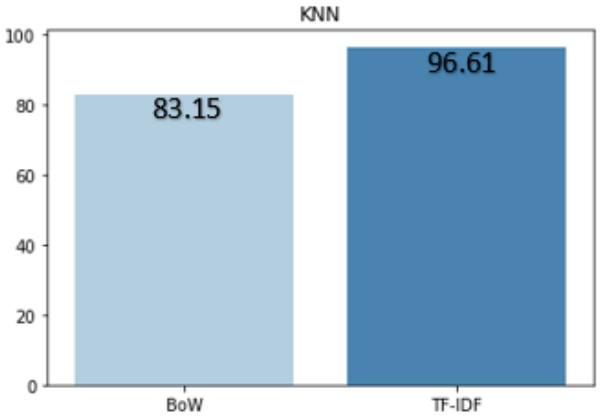


fig no. 4.8 KNN (Bow vs TF-IDF)

Random Forest:

Similar to previous algorithms two models are created and trained using respective training vectors and training labels. But the number of trees to be used for forest has to be provided.

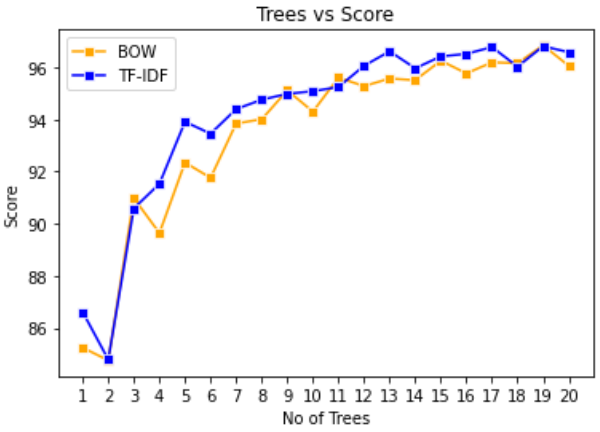
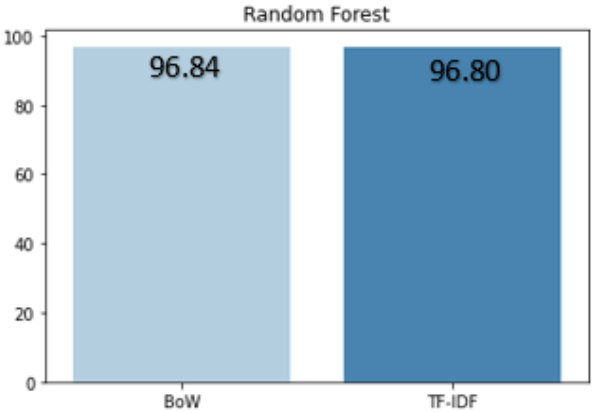


fig no. 4.9 Random Forest (trees vs score)

Using the Iterative method best value for the number of trees is determined. From the results, it is clear that 19 estimators provide the best score for both the BoW and TF-IDF models. The no of tress and scores for both models are visualized.

The scores for BoW and TF-IDF models are visualized.



(fig no. 4.10 Random Forest(bow vs tfidf)

Support Vector Machines (SVM):

Finally, two SVM models, one for BoW and one for TF-IDF are created and then trained using respective training vectors and labels. Then tested using testing vectors and labels.

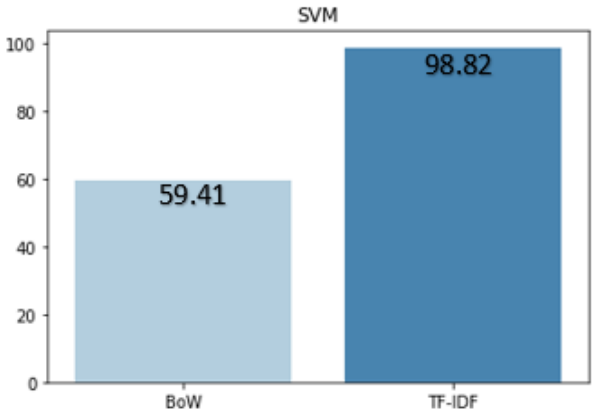


fig no. 4.11 SVM(Bow vs TF_IDF)

The scores for BoW and TF-IDF models are 59.41 and 98.82 respectively.

Proposed Model:

In our proposed system we combine all the models and make them into one. It takes an unknown point and feeds it into every model to get predictions. Then it takes these predictions, finds the category which was predicted by the majority of the models, and finalizes it.

To determine which model is effective we used three metrics Accuracy, Precision, and F1score. In the earlier system, we used only the F1 Score because we were not determining which model is best but which language model is best suited for classification.

4.5.6 User Interface(UI)

interface (UI) is an important component in this application. The user only interacts with the interface.

The UI of this project has been constructed with the help of an open source library called streamlit. The complete information and API reference sheet can be obtained from here

4.5.7 Working Procedure

The working procedure includes the internal working and the data flow of application.

i. After running the application some procedures are automated.
    1. Reading data from file
    2. Cleaning the texts
    3. Processing
    4. Splitting the data
    5. Intialising and training the models
ii. The user just needs to provide some data to classify in the area provided.
iii. The provided data undergoes several procedures after submission.
    1. Textual Processing
    2. Feature Vector conversion
    3. Entity extraction
iv. The created vectors are provided to trained models to get predictions.
v. After getting predictions the category predicted by majority will be selected.
vi. The accuracies of that prediction will be calculated
vii. The accuracies and entities extracted from the step 3 will be provided to user.

Every time the user gives something new the procedure from step 2 will be repeated.

5. Results and Discussion

5.1 Language Model Selection

While selecting the best language model the data has been converted into both types of vectors and then the models been tested for to determine the best model for classifying spam.

The results from individual models are presented in the experimentation section under methodology. Now comparing the results from the models.

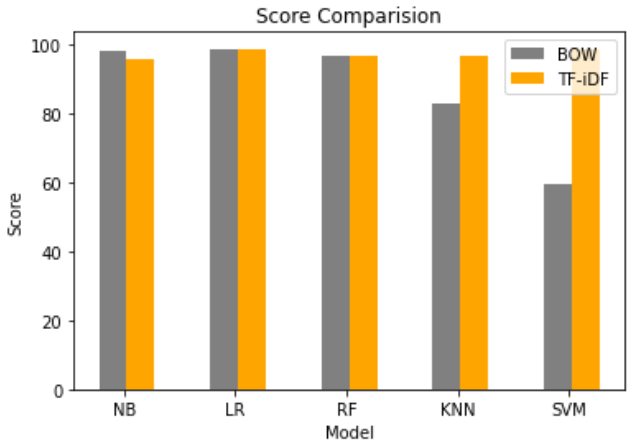


fig no. 5.1 Bow vs TF-IDF (Cumulative)

From the figure it is clear that TF-IDF proves to be better than BoW in every model tested. Hence TF-IDF has been selected as the primary language model for textual data conversion in feature vector formation.

5.2 Proposed Model results

To determine which model is effective we used three metrics Accuracy, Precision, and F1score.

The resulted values for the proposed model are

Accuracy – 99.0

Precision – 98.5

F1 Score – 98.6

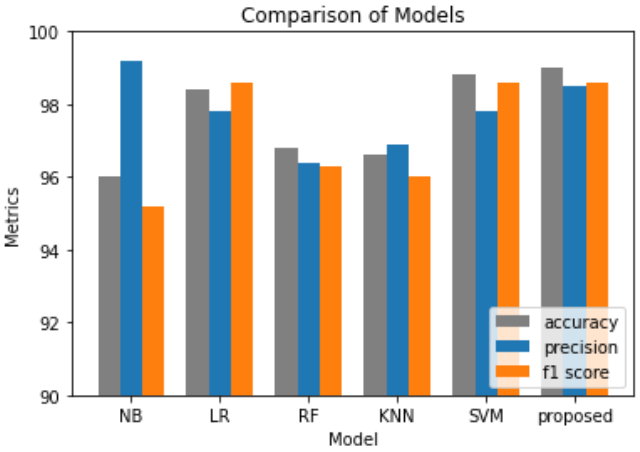
5.3 Comparison

The results from the proposed model has been compared with all the models individually in tabular form to illustrate the differences clearly.

Metric Model	Accuracy	Precision	F1 Score
Naïve Bayes	96.0	99.2	95.2
Logistic Regression	98.4	97.8	98.6
Random forest	96.8	96.4	96.3
KNN	96.6	96.9	96.0
SVM	98.8	97.8	98.6
Proposed model	**99.0**	**98.5**	**98.6**

Table no. 5.1 Models and results

The color RED indicates that the value is lower than the proposed model and GREEN indicates equal or higher.



Here we can observe that our proposed model outperforms almost every other model in every metric. Only one model(naïve Bayes) has slightly higher accuracy than our model but it is considerably lagging in other metrics.

The results are visually presented below for easier understanding and comparison.

fig no. 5.2 Comparision of Models

From the above comparison barchart we can clearly see that all models individually are not as efficient as the proposed method.

5.4 Summary

There are two main tasks in the project implementation. Language model selection for completing the textual processing phase and proposed model creation using the individual algorithms. These two tasks require comparison from other models and select of various parameters for better efficiency.

During the language model selection phase two models, Bag of Words and TF-IDF are compared to select the best model and from the results obtained it is evident that TF-IDF performs better.

During the proposed model design various algorithms are tested with different parameters to get best parameters. Models are merged to form a ensemble algorithm and the results obtained are presented and compared above. It is clear from the results that the proposed model outperforms others in almost every metric derived.

6. Conclusion and Future Scope

6.1 Conclusion

From the results obtained we can conclude that an ensemble machine learning model is more effective in detection and classification of spam than any individual algorithms. We can also conclude that TF-IDF (term frequency inverse document frequency) language model is more effective than Bag of words model in classification of spam when combined with several algorithms. And finally we can say that spam detection can get better if machine learning algorithms are combined and tuned to needs.

6.2 Future work

There are numerous appilcations to machine learning and natural language processing and when combined they can solve some of the most troubling problems concerned with texts. This application can be scaled to intake text in bulk so that classification can be done more affectively in some public sites.

Other contexts such as negative, phishing, malicious, etc,. can be used to train the model to filter things such as public comments in various social sites. This application can be converted to online type of machine learning system and can be easily updated with latest trends of spam and other mails so that the system can adapt to new types of spam emails and texts.

References

[1] S. H. a. M. A. T. Toma, "An Analysis of Supervised Machine Learning Algorithms for Spam Email Detection," in International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), 2021.

[2] S. Nandhini and J. Marseline K.S., "Performance Evaluation of Machine Learning Algorithms for Email Spam Detection," in International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), 2020.

[3] A. L. a. S. S. S. Gadde, "SMS Spam Detection using Machine Learning and Deep Learning Techniques," in 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021, 2021.

[4] V. B. a. B. K. P. Sethi, "SMS spam detection and comparison of various machine learning algorithms," in International Conference on Computing and Communication Technologies for Smart Nation (IC3TSN), 2017.

[5] G. D. a. A. R. P. Navaney, "SMS Spam Filtering Using Supervised Machine Learning Algorithms," in 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2018.

[6] S. O. Olatunji, "Extreme Learning Machines and Support Vector Machines models for email spam detection," in IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), 2017.

[7] S. S. a. N. N. Kumar, "Email Spam Detection Using Machine Learning Algorithms," in Second International Conference on Inventive Research in Computing Applications (CIRCA), 2020.

[8] R. Madan, "medium.com," [Online]. Available: https://medium.com/analytics-vidhya/tf-idf-term-frequency-technique-easiest-explanation-for-text-classification-in-nlp-with-code-8ca3912e58c3.

[9] N. D. J. a. M. M. A. M. M. RAZA, "A Comprehensive Review on Email Spam Classification using Machine Learning Algorithms," in International Conference on Information Networking (ICOIN), 2021, 2021.

[10] A. B. S. A. a. P. M. M. Gupta, "A Comparative Study of Spam SMS Detection Using Machine Learning Classifiers," in Eleventh International Conference on Contemporary Computing (IC3), 2018.

[11] M. M. J. Fattahi, "SpaML: a Bimodal Ensemble Learning Spam Detector based on NLP Techniques," in IEEE 5th International Conference on Cryptography, Security and

Privacy (CSP), 2021, 2021.

[12] Harika, "Analytics Vidhya," [Online]. Available: https://www.analyticsvidhya.com/blog/2021/07/an-introduction-to-logistic-regression/.

[13] İ. A. D. a. M. D. H. Karamollaoglu, "Detection of Spam E-mails with Machine Learning Methods," in Innovations in Intelligent Systems and Applications Conference (ASYU), 2018.

[14] M. N. U. a. R. K. H. F. Hossain, "Analysis of Optimized Machine Learning and Deep Learning Techniques for Spam Detection," in IEEE International IoT, Electronics and Mechatronics Conference (IEMTRONICS), 2021.

[15] H. Deng, "Towards Data Science," [Online]. Available: https://towardsdatascience.com/random-forest-3a55c3aca46d.

[16] j. Brownlee, "machinelearningmastery," 2017. [Online]. Available: machinelearningmastery.com/gentle-introduction-bag-words-model.

[17] d. AI, "deepai," [Online]. Available: deepai.org/machine-learning-glossary-and-terms/accuracy-error-rate.

Appendices

A. Source code

1. Module – Data Processing

```
import re
from nltk.tokenize import sent_tokenize,word_tokenize
from nltk import pos_tag
from nltk.corpus import wordnet as wn
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from collections import defaultdict
import spacy

tag_map = defaultdict(lambda : wn.NOUN)
tag_map['J'] = wn.ADJ
tag_map['V'] = wn.VERB
tag_map['R'] = wn.ADV
lemmatizer=WordNetLemmatizer()
stop_words=set(stopwords.words('english'))

nlp=spacy.load('en_core_web_sm')

def process_sentence(sentence):
    nouns = list()
    base_words = list()
    final_words = list()
    words_2 = word_tokenize(sentence)
    sentence = re.sub(r'[^ \w\s]', '', sentence)
    sentence = re.sub(r'_', ' ', sentence)
    words = word_tokenize(sentence)
    pos_tagged_words = pos_tag(words)

    for token, tag in pos_tagged_words:

base_words.append(lemmatizer.lemmatize(token,tag_map[tag[0]]))
    for word in base_words:
        if word not in stop_words:
            final_words.append(word)
    sym = ' '
    sent = sym.join(final_words)
    pos_tagged_sent = pos_tag(words_2)
    for token, tag in pos_tagged_sent:
        if tag == 'NN' and len(token)>1:
            nouns.append(token)
    return sent, nouns

def clean(email):
    email = email.lower()
    sentences = sent_tokenize(email)
    total_nouns = list()
    string = ""
    for sent in sentences:
        sentence, nouns = process_sentence(sent)
```

```
        string += " " + sentence
        total_nouns += nouns
    return string, nouns


def ents(text):
    doc = nlp(text)
    expls = dict()
    if doc.ents:
        for ent in doc.ents:
            labels = list(expls.keys())
            label = ent.label_
            word = ent.text
            if label in labels:
                words = expls[label]
                words.append(word)
                expls[label] = words
            else:
                expls[label] = [word]
        return expls
    else:
        return 'no'
```

2. Module – Machine Learning

```
from sklearn.feature_extraction.text import
CountVectorizer,TfidfVectorizer
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
import pandas as pd

class model:
    def __init__(self):
        self.df = pd.read_csv('Cleaned_Data.csv')
        self.df['Email'] = self.df.Email.apply(lambda email:
np.str_(email))
        self.Data = self.df.Email
        self.Labels = self.df.Label
        self.training_data, self.testing_data,
self.training_labels, self.testing_labels =
train_test_split(self.Data,self.Labels,random_state=10)
        self.training_data_list = self.training_data.to_list()
        self.vectorizer = TfidfVectorizer()
        self.training_vectors =
self.vectorizer.fit_transform(self.training_data_list)
        self.model_nb = MultinomialNB()
        self.model_svm = SVC(probability=True)
        self.model_lr = LogisticRegression()
        self.model_knn = KNeighborsClassifier(n_neighbors=9)
        self.model_rf = RandomForestClassifier(n_estimators=19)
```

```
        self.model_nb.fit(self.training_vectors,
self.training_labels)
        self.model_lr.fit(self.training_vectors,
self.training_labels)
        self.model_rf.fit(self.training_vectors,
self.training_labels)
        self.model_knn.fit(self.training_vectors,
self.training_labels)
        self.model_svm.fit(self.training_vectors,
self.training_labels)
    def get_prediction(self,vector):
        pred_nb=self.model_nb.predict(vector)[0]
        pred_lr=self.model_lr.predict(vector)[0]
        pred_rf=self.model_rf.predict(vector)[0]
        pred_svm=self.model_svm.predict(vector)[0]
        pred_knn=self.model_knn.predict(vector)[0]
        preds=[pred_nb,pred_lr,pred_rf,pred_svm,pred_knn]
        spam_counts=preds.count(1)
        if spam_counts>=3:
            return 'Spam'
        return 'Non-Spam'
    def get_probabilities(self,vector):
        prob_nb=self.model_nb.predict_proba(vector)[0]*100
        prob_lr = self.model_lr.predict_proba(vector)[0] * 100
        prob_rf = self.model_rf.predict_proba(vector)[0] * 100
        prob_knn = self.model_knn.predict_proba(vector)[0] * 100
        prob_svm = self.model_svm.predict_proba(vector)[0] * 100
        return [prob_nb,prob_lr,prob_rf,prob_knn,prob_svm]

    def get_vector(self,text):
        return self.vectorizer.transform([text])
```

3. Module – User interface

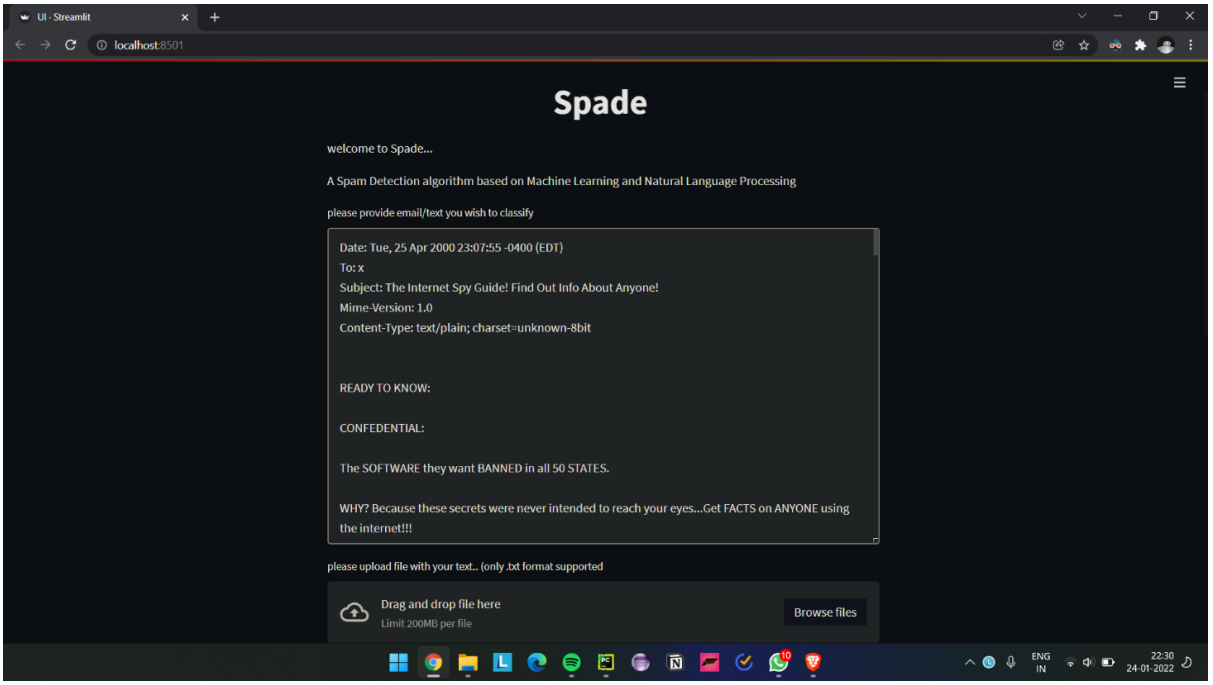
```
import time
from ML import model
import streamlit as st
from DP import *
import matplotlib.pyplot as plt
import seaborn as sns
inputs=[0,1]
@st.cache()
def create_model():
    mode=model()
    return mode
col1,col2,col3,col4,col5=st.columns(5)
with col3:
    st.title("Spade")
st.write('welcome to Spade...')
st.write('A Spam Detection algorithm based on Machine Learning
and Natural Language Processing')
text=st.text_area('please provide email/text you wish to
classify',height=400,placeholder='type/paste more than 50
characters here')
```

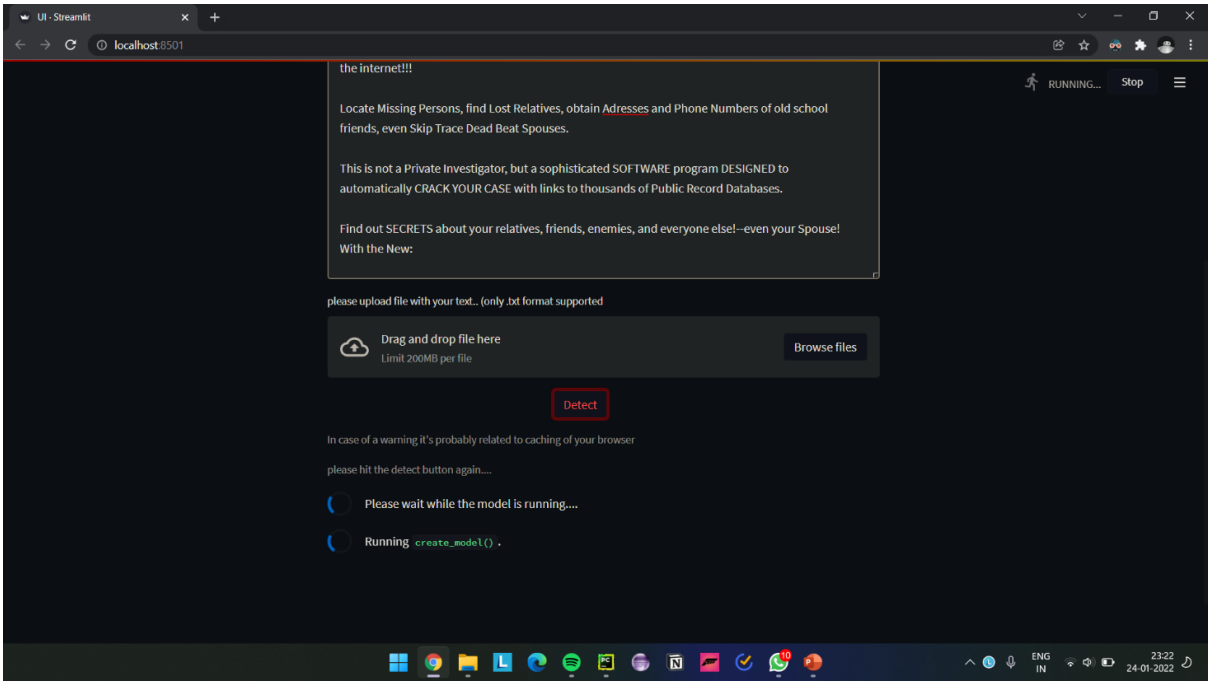
```
file=st.file_uploader("please upload file with your text.. (only
.txt format supported")

if len(text)>20:
    inputs[0]=1
if file is None:
    inputs[1]=0
if inputs.count(1)>1:
    st.error('multiple inputs given please select only one
option')
else:
    if inputs[0]==1:
        e=text
        given_email = e
    if inputs[1]==1:
        bytes_data = file.getvalue()

        given_email = bytes_data
predictions=[]
probs=[]
col1,col2,col3,col4,col5=st.columns(5)
with col3:
    clean_button = st.button('Detect')
st.caption("In case of a warning it's probably related to
caching of your browser")
st.caption("please hit the detect button again....")

if clean_button:
    if inputs.count(0)>1:
        st.error('No input given please try after giving the
input')
    else:
        with st.spinner('Please wait while the model is
running....'):
            mode = create_model()
        given_email,n=clean(given_email)
        vector = mode.get_vector(given_email)
        predictions.append(mode.get_prediction(vector))
        probs.append(mode.get_probabilities(vector))
        col1, col2, col3 = st.columns(3)
        with col2:
            st.header(f"{predictions[0]}")
        probs_pos = [i[1] for i in probs[0]]
        probs_neg = [i[0] for i in probs[0]]
        if predictions[0] == 'Spam':
            # st.caption(str(probs_pos))
            plot_values = probs_pos
        else:
            # st.caption(str(probs_neg))
            plot_values = probs_neg
        plot_values=[int(i) for i in plot_values]
        st.header(f'These are the results obtained from the
models')
        col1, col2 = st.columns([2, 3])
        with col1:
            st.subheader('predicted Accuracies of models')
```

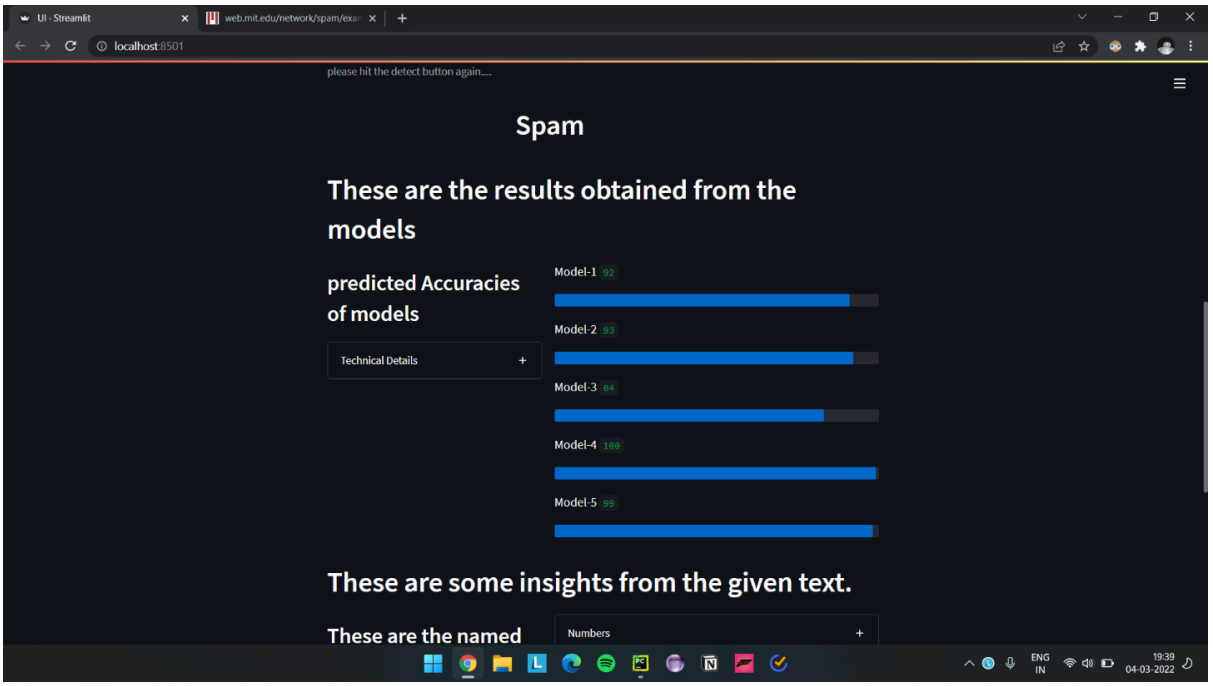
```
            with st.expander('Technical Details'):
                st.write('Model-1 : Naive Bayes')
                st.write('Model-2 : Random Forest')
                st.write('Model-3 : Logistic Regression')
                st.write('Model-4 : K-Nearest Neighbors')
                st.write('Model-5 : Support Vector Machines')
        with col2:
            st.write('Model-1', plot_values[0])
            bar1 = st.progress(0)
            for i in range(plot_values[0]):
                time.sleep(0.01)
                bar1.progress(i)
            st.write('Model-2', plot_values[1])
            bar2 = st.progress(0)
            for i in range(plot_values[1]):
                time.sleep(0.01)
                bar2.progress(i)
            st.write('Model-3', plot_values[2])
            bar3 = st.progress(0)
            for i in range(plot_values[2]):
                time.sleep(0.01)
                bar3.progress(i)
            st.write('Model-4', plot_values[3])
            bar4 = st.progress(0)
            for i in range(plot_values[3]):
                time.sleep(0.01)
                bar4.progress(i)
            st.write('Model-5', plot_values[4])
            bar5 = st.progress(0)
            for i in range(plot_values[4]):
                time.sleep(0.01)
                bar5.progress(i)
        st.header('These are some insights from the given
text.')
        entities=ents(text)
        col1,col2=st.columns([2,3])
        with col1:
            st.subheader('These are the named entities extracted
from the text')
            st.write('please expand each category to view the
entities')
            st.write('a small description has been included with
entities for user understanding')
        with col2:
            if entities=='no':
                st.subheader('No Named Entities found.')
            else:
                renames = {'CARDINAL': 'Numbers', 'TIME':
'Time', 'ORG': 'Companies/Organizations', 'GPE': 'Locations',
                           'PERSON': 'People', 'MONEY': 'Money',
'FAC': 'Factories'}
                for i in renames.keys():
                    with st.expander(renames[i]):
                        st.caption(spacy.explain(i))
                        values = list(set(entities[i]))
                        strin = ',  '.join(values)
```

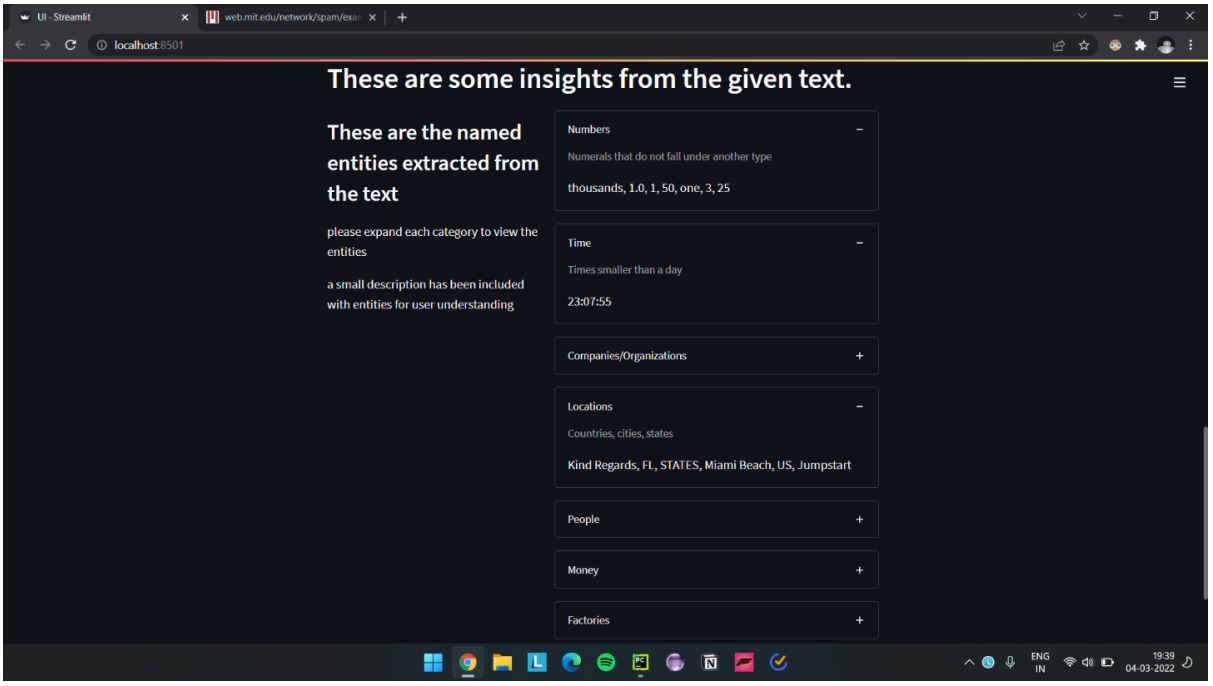
`st.write(strin)`

B. Screenshots






UI - Streamlit
web.mit.edu/network/spam/exa
localhost:8501
please hit the detect button again....
Spam
These are the results obtained from the models
predicted Accuracies of models
Technical Details
Model-1 92
Model-2 93
Model-3 84
Model-4 100
Model-5 99
These are some insights from the given text.
These are the named
Numbers
ENG IN
19:39
04-03-2022


UI - Streamlit
web.mit.edu/network/spam/exa
localhost:8501
These are some insights from the given text.
These are the named entities extracted from the text
please expand each category to view the entities
a small description has been included with entities for user understanding
Numbers
Numerals that do not fall under another type
thousands, 1.0, 1, 50, one, 3, 25
Time
Times smaller than a day
23:07:55
Companies/Organizations
Locations
Countries, cities, states
Kind Regards, FL, STATES, Miami Beach, US, Jumpstart
People
Money
Factories
ENG IN
19:39
04-03-2022