CSCE 5290.003 (13149)

Natural Language Processing

Spam Email Detection with Text Classification and Sentiment Analysis

Using Machine Learning Random Forest

SPAM Email Detection with Sentiment Analysis

Project Title and Team Members

Project Group **- 5**

Project Title **- Spam Email Detection with Sentiment Analysis**

Team Members:

- **Danda Reethika Reddy - 11608030**
- **Surya Sai Raj Lakkoju - 11610081**
- **Ashesh Pinisetti - 11649062**
- **Mohammad Khaja Moinuddin - 11603687**

1. Goals and Objectives:

- **Motivation:**
  The reason behind getting motivated about this project is that in the current existing machine learning models we see there are models that can detect whether the emails are spam or not, but not about analyzing the sentiment of the email content.Here we analyze how the spam emails were detected using the Text classification techniques and then we will be implementing the sentimental analysis techniques to find out the sentiment of the email content(positive,neutral or negative).The main motive of using sentiment analysis is to improve the accuracy and effectiveness of spam detection by analyzing sentiment of email content.By adding sentiment analysis we can get more additional insights like understanding emotional tone and attitude expressed in the content.Here we will be using a random forest Machine learning model which will be trained with the dataset to analyze the accuracy.

- **Significance:**
  The main significance of our project is to identify and classify the spam emails. Identifying the spam emails will help users in not getting involved in any type of fraud. The users will have a basic understanding of what type of the context present in the email.

Importance for spam mails to be filtered is, as it can contain malicious content that can spread viruses and cyber attacks.To overcome these types of attacks, spam mails filtering is necessary.

After identification of spam emails,Based on the content present in the mail we are identifying the sentiment of context using the vadersentiment.

- **Objective:**
  The primary objective of spam email detection with sentiment analysis is to identify and filter out unwanted emails from the inbox of an email account. This involves using machine learning algorithms to automatically detect and categorize emails as spam or not.

  Sentiment analysis, on the other hand, involves analyzing the language used in a piece of text to determine the underlying emotional tone or sentiment. In the context of email filtering, sentiment analysis can be used to determine whether an email is trying to manipulate or deceive the recipient, such as through the use of overly positive or negative language.

  By combining spam email detection with sentiment analysis, it is possible to create a more effective email filtering system that can identify and block unwanted emails that may be attempting to manipulate or deceive the recipient. This can help improve the user's email experience by reducing the amount of unwanted or malicious emails that they receive, and also enhance their security and privacy online.

- **Features:**
  Here are some common features we are using in spam email detection:

  Content Analysis: Spam emails often contain certain patterns or phrases that can be identified and used as indicators of spam. These include things like suspicious keywords, unusual formatting, and overuse of capital letters or exclamation points.

  Blacklists and Whitelists: These are lists of known good and bad email addresses, domains, and IP addresses. Emails from whitelisted sources are allowed to pass through, while those from blacklisted sources are blocked or flagged as spam.

Reputation Analysis: The reputation of an email sender can be evaluated based on factors such as how often their emails are marked as spam, the types of content they send, and the quality of their email infrastructure.

URL Analysis: Links in spam emails often lead to fraudulent or malicious websites. URL analysis can be used to identify these links and block or flag emails that contain them.

Sentiment Analysis: Here we are using the vader sentiment library to classify the sentiment of the text into positive,negative or neutral.

2 Related work :

2.1 Sentiment analysis using unlabeled dataset.

Sentiment analysis is the process of classifying whether a block of text is positive, negative,or,neutral.Usually,sentiment analysis view it as text classification problem but it needs labeled data to train the model.But most of the times we will get the unlabeled data,which is to be done manually.So every time to label the data manually takes time and it is hard.In this the author found the best techniques to label the dataset automatically by avoiding manual labeling.In this lexicon labeling and k-mean labeling are compared and lexicon labeling gave the better results.They used TF-IDF for feature extraction, to train Naïve Bayes and Support vector machine (SVM) classifiers.

2.2 A Comprehensive Review on Email Spam Classification using Machine Learning Algorithms

Email spam classification is a well-studied problem in the field of natural language processing (NLP). In the paper[2], the authors provide a comprehensive review of the existing work in email spam classification using machine learning algorithms. The authors compare the strengths and weaknesses of various machine learning algorithms and discuss the features that can be extracted from emails for classification. The article identifies some of the challenges in email spam classification, such as the imbalance between spam and non-spam emails, and the need for feature selection to avoid overfitting. To address these challenges, some researchers have proposed hybrid approaches that combine multiple machine learning algorithms or use feature selection techniques like Principal Component Analysis (PCA). They have primarily focused on analyzing the content and metadata of emails for classification, while sentiment analysis can help identify the sentiment of the email content and potentially improve classification accuracy.

2.3 An email classification model based on rough set theory

In this paper[3], the authors presented a novel email classification model based on rough set theory. They proposed a three-stage process for email classification, which involves data preprocessing, feature extraction, and classification. In the feature extraction, they used rough set theory to identify the most relevant features for email classification. This involves reducing the feature space by identifying the essential attributes that are most discriminatory for the classification task. Finally, in the classification stage, the authors used a decision tree algorithm to classify the email data into spam or non-spam categories. The key contribution of the paper is the application of rough set theory to the problem of email classification, which allows for the identification of the most relevant features for classification, thus reducing the dimensionality of the feature space and improving classification accuracy. The paper demonstrates the effectiveness of their proposed model in email classification and highlights the potential of rough set theory as a useful tool in the field of email classification.

2.4 Sentiment Analysis for Fake News Detection by Means of Neural Networks

The authors proposed a two-stage approach for fake news detection, which involves sentiment analysis and classification using neural networks. In the first stage, they performed sentiment analysis on the news articles to extract sentiment-related features such as positive or negative sentiment, emotion, and opinion. In the second stage, they used a neural network model to classify the news articles as fake or real based on the sentiment-related features. By incorporating sentiment-related features into the classification process, the authors had aimed to improve the accuracy of fake news detection. The experimental results show that the proposed approach achieves high accuracy in detecting fake news, outperforming some of the existing methods. The article presents a promising approach to fake news detection that combines sentiment analysis and neural networks.

2.5 Spam email classification and sentiment analysis based on semantic similarity methods

Now-a-days electronic email is widely used for communication purposes.So classifying the spam and non-spam email is necessary for security purposes.There are many NLP techniques to do this but these cannot handle unbalanced classes and have lower efficiency due to irrelevant feature extraction. So in paper[4] the author used sentiment analysis- based semantic FE and hybrid FS techniques to increase the efficiency. In this technique, it will measure the polarity of the text and then the spam detection will be done.The TF-IDF, Information gain and gini-index is used.This analysis is showing that gini index and SVM classifier shows the higher performance of 95.17%.

2.6 Novel email spam detection method using sentiment analysis and personality recognization.

Different techniques were developed for detecting spam emails in recent days.In this paper[6] the author focused on specific machine learning algorithms-content based filters.These filters will understand the content of the emails to classify them as spam or non-spam.Filters include such as heuristic filtering,learning-based filtering and filtering by compression.The author compared different techniques like rule-based system,IP blacklist,Heuristic-based filters , bayesian-network based filters white list and DNS black-holes.After comparison concluded that bayesian-network based filters are most effective and accurate.Author demonstrated that even there are many techniques implemented ,bayesian methods of text classification are still useful.

2.7 Phishing Email Detection Using Improved RCNN Model With Multilevel Vectors and Attention Mechanism.

The fast growth of Internet technology has drastically altered the experience of online users, while security concerns are becoming increasingly overpowering. In the current state, new threats have the potential to seriously harm consumers systems as well as steal their money and personal information (PII). Among these concerns, phishing stands out as a prominent criminal activity that employs social engineering and technology to steal a victim's identification data and account information. According to an Anti-Phishing Working Group (APWG) report, the number of phishing attacks have increased significantly by 46% during the first quarters of 2018 when compared to the final quarters of 2017. To identify these attacks many MNC companies came up with a solution of finding such phishing emails and providing one layer of security by eliminating them to steal the customers PII using Deep Learning models. In this there are different DL models used in finding such phishing or spam or cyber attacking emails. In these models some of the highly used models are RCNN, BI-LSTM etc. These models extract the features from the emails and in-turn learn themselves by understanding the context of what kind of emails these are based on tagging those emails as SPAM/JUNK.

2.8 Efficient spam and phishing emails filtering based on deep learning

The number of emails is increasing quickly because they are the primary, quick, and affordable form of communication in all industries. As a result, the demand for more precise spam filters has increased. To have a reliable and secure email filter, it is essential to be able to quickly identify spam emails. A specific type of social network attacking technique is phishing. Phishing aims to deceive victims by providing sensitive information, including identification and financial details. Emails with malicious attachments or redirected URLs are frequent forms of phishing attacks. To avoid such types of cyber-attacks, Google, Yahoo and Microsoft some of the famous internet email service providers have implemented some of the deep learning techniques where these neural networks extract the features and train themselves using the training data and run the same simulations on the testing data. These types of models are called supervised models. There are different types of supervised and unsupervised models.

2.9 Sentiment Analysis for Fake News Detection by Means of Neural Networks

Public opinion research can offer us vital information. Many uses may be found for the analysis of sentiment on social media platforms like Twitter and Facebook, which has grown to be a potent tool for discovering what consumers think. Yet, the difficulties in natural language processing are impeding sentiment analysis's effectiveness and accuracy. Last, a few years, deep learning models have improved a lot in answering the problems related to NLP. In this publication we are discussing the most recent research using deep learning to address issues with sentiment analysis, like sentiment polarity. Models that use term frequency-inverse document frequency (TF-IDF) and word embedding techniques have been applied on a series of datasets. Here the sentiment analysis is mainly focused on the words which are tokenized. The tokenized words are finally segregated into two different categories: positive and negative. In positive categories the words which are not related to violence, threatening kind of words. Based on these categories, the sentiment analysis will be done on the content passed to the model. Automatic sentiment analysis (SA) is an issue that is becoming a more popular research area. Despite the importance of SA and the variety of applications that it currently has, there are several difficulties with natural language processing that must be overcome. Using deep learning models like CNN, RNN, and DNN to automatically classify the context.

2.10 Twitter Sentiment Analysis Using Natural Language Toolkit and VADER Sentiment

This paper discusses a study that uses a tool called VADER to analyze the sentiment of tweets. Sentiment analysis is a way to determine if a piece of text is positive, negative, or neutral in tone. The process is first collect Twitter data, then data preprocessing, and analyze the sentiment using VADER. VADER will then quickly analyze the sentiment of the text, taking into account different factors like word order and degree modifiers. In this study, it was used to classify tweets as positive, negative, neutral, or compound (a mix of sentiments). The researchers also developed a scoring system to categorize tweets into classes, such as, high positive, positive, neutral, negative, and high negative. The results of the study showed that most tweets in the dataset expressed negative or neutral opinions about the presidential election. The researchers concluded that VADER is an effective tool for sentiment analysis using Twitter data, as it can quickly classify large amounts of data. However, there were some limitations in the study, such as using a general lexicon (a set of words and their meanings) to categorize a specific data. In the future, the researchers plan to improve the system by using larger volumes of data, a more specific lexicon, and a corpus (a collection of written or spoken texts) for training the data to achieve better results.

2.11 A SURVEY OF OPINION MINING AND SENTIMENT ANALYSIS

This paper discusses the growing field of opinion mining and sentiment analysis, which is the study of people's opinions, emotions, and attitudes towards various topics. The increasing use of social media and online platforms has created a large number of public opinions that individuals and organizations can use for decision-making purposes. Businesses often want to know consumers' opinions about their products and services. However, accurately summarizing the information within them is challenging due to the vast amount of sites and the human biases that come into play when analyzing textual information. One example provided in the paper involves analyzing a review segment on the iPhone, with the goal being to extract various opinions expressed within the review. This can help in understanding the structure of unstructured text and provide a unified framework for future research in this field.

2.12 Spam Email Detection Using Deep Learning Technique

This paper uses BERT-based model for the task of automatically detecting spam emails. Different natural language processing (NLP) techniques, are employed to accomplish this task. The authors follow a standard NLP approach, consisting of five main phases those are, data collection, data pre-processing, feature extraction, model training, and model evaluation. Two open-source datasets are used, one from the UCI machine learning repository and the other one from Kaggle. Both datasets contain email texts and corresponding labels.

The authors split the training data into 70% for training and 30% for validation. Then they apply cross-validation, specifically using an 8-fold technique, to improve accuracy of the results. The performance of the models is compared using two evaluation metrics, those are, accuracy and F1 score. The BERT-based transformer model performs best, after achieving an accuracy of 98.67% and an F1 score of 98.66%. Another BiLSTM model using Keras word embeddings was also used, but it achieved slightly lower results, with a 96.43% accuracy and a 96% F1 score. The authors suggest that the performance could be further improved by using a larger input sequence, but they were limited by their GPU memory resources. The spam detection task can potentially be applied to other languages, such as Arabic.

2.13 Sentiment analysis based on deep learning: A comparative study

This paper uses BERT-based model for the task of automatically detecting spam emails. Different natural language processing (NLP) techniques, are employed to accomplish this task. The authors follow a standard NLP approach, consisting of five main phases those are, data collection, data pre-processing, feature extraction, model training, and model evaluation. Two open-source datasets are used, one from the UCI machine learning repository and the other one from Kaggle. Both datasets contain email texts and corresponding labels.

The authors split the training data into 70% for training and 30% for validation. Then they apply cross-validation, specifically using an 8-fold technique, to improve accuracy of the results. The performance of the models is compared using two evaluation metrics, those are, accuracy and F1 score. The BERT-based transformer model performs best, after achieving an accuracy of 98.67% and an F1 score of 98.66%. Another BiLSTM model using Keras word embeddings was also used, but it achieved slightly lower results, with a 96.43% accuracy and a 96% F1 score. The authors suggest that the performance could be further improved by using a larger input sequence, but they were limited by their GPU memory resources. The spam detection task can potentially be applied to other languages, such as Arabic.

3. Dataset

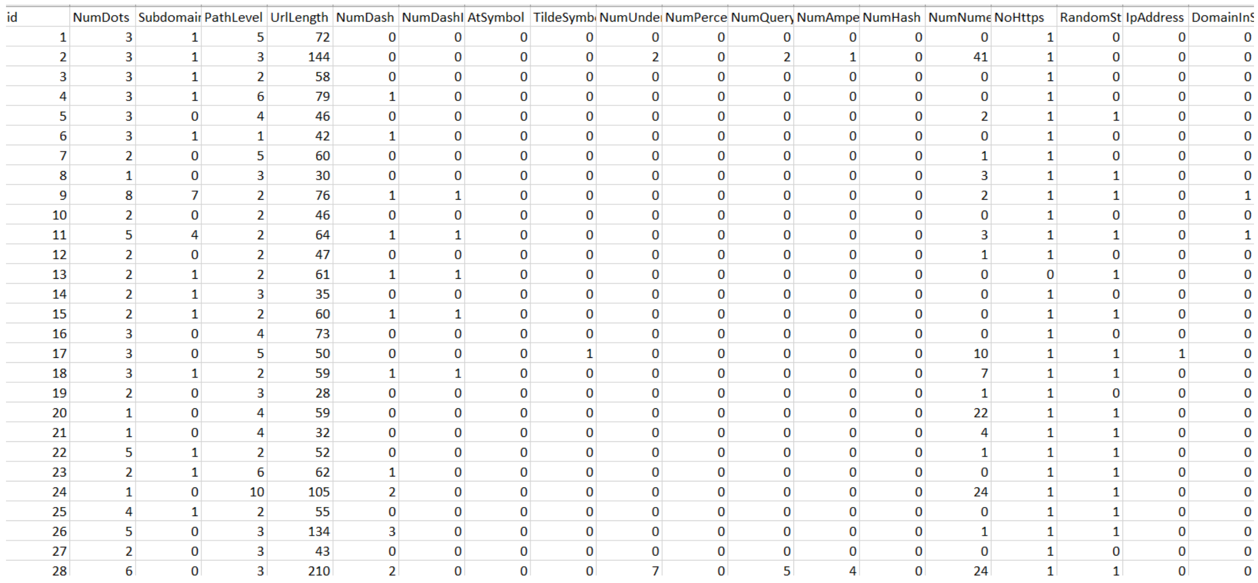
The dataset contains 48 features extracted from 10,000 web pages, consisting of 5,000 phishing webpages and 5,000 legitimate webpages. The webpages were downloaded from January to May 2015 and from May to June 2017.
The dataset's primary purpose is to be used for machine learning-based phishing detection, where the features can be used to train and evaluate machine learning models that can classify a given webpage as either a phishing webpage or a legitimate web page.
Each of the 10,000 web pages in the dataset is labeled as either a phishing webpage or a legitimate webpage. This means that the dataset is a supervised learning dataset, where the machine learning model can learn from the labeled examples to make predictions on new, unlabeled web pages.
Overall, this dataset is a valuable resource for anyone interested in developing and evaluating machine learning models for phishing detection, as it provides a large set of features extracted from webpages and labels indicating whether each webpage is a phishing or legitimate webpage.

Here are some high-level description about the features in the dataset :

- NumDots: The number of dots (.) in the URL.
- SubdomainLevel: The number of levels in the subdomain.
- PathLevel: The number of levels in the URL path.
- UrlLength: The length of the URL.
- AtSymbol: Whether the URL contains an @ symbol.
- RightClickDisabled: Whether right-clicking is disabled on the webpage.
- PopUpWindow: Whether the webpage contains a pop-up window.
- SubmitInfoToEmail: Whether the webpage submits information to an email address.

- IframeOrFrame: Whether the webpage contains an iframe or frame.
- MissingTitle: Whether the webpage is missing a title.
- ImagesOnlyInForm: Whether the webpage contains only images in a form.
- SubdomainLevelRT: The number of levels in the subdomain in the redirected URL.
- UrlLengthRT: The length of the redirected URL.
- PctExtResourceUrlsRT: The percentage of external resources in the redirected URL.
- ExtMetaScriptLinkRT: Whether the redirected URL contains external meta, script or link tags.
- CLASS_LABEL: A binary label indicating whether the URL is a phishing email or not.

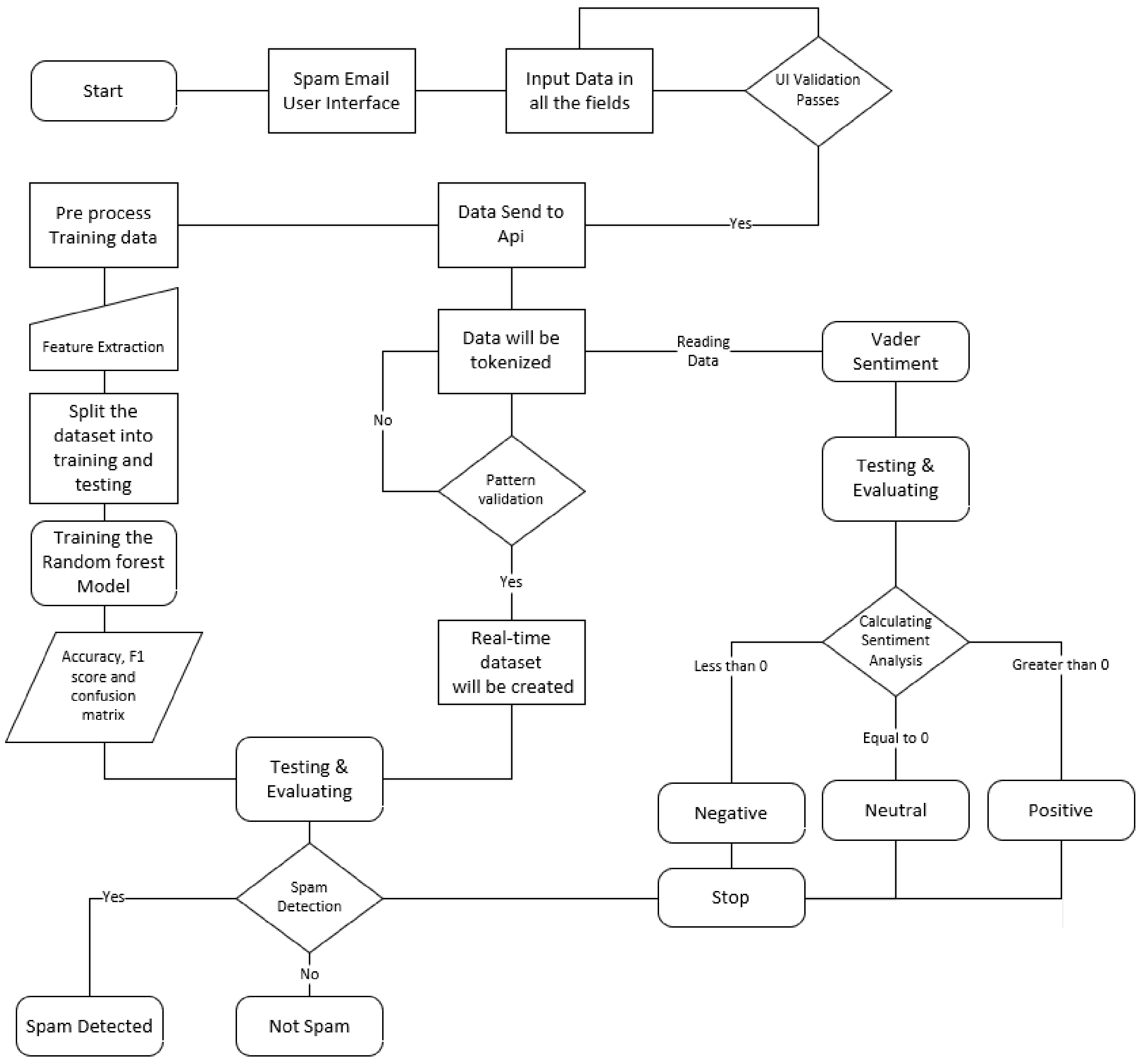
Sample view of our dataset is :



id	NumDots	Subdomair	PathLevel	UrlLength	NumDash	NumDashI	AtSymbol	TildeSymb	NumUnder	NumPerce	NumQuery	NumAmpe	NumHash	NumNume	NoHttps	RandomSt	IpAddress	DomainIn
1	3	1	5	72	0	0	0	0	0	0	0	0	0	0	1	0	0	0
2	3	1	3	144	0	0	0	0	2	0	2	1	0	41	1	0	0	0
3	3	1	2	58	0	0	0	0	0	0	0	0	0	0	1	0	0	0
4	3	1	6	79	1	0	0	0	0	0	0	0	0	0	1	0	0	0
5	3	0	4	46	0	0	0	0	0	0	0	0	0	2	1	1	0	0
6	3	1	1	42	1	0	0	0	0	0	0	0	0	0	1	0	0	0
7	2	0	5	60	0	0	0	0	0	0	0	0	0	1	1	0	0	0
8	1	0	3	30	0	0	0	0	0	0	0	0	0	3	1	1	0	0
9	8	7	2	76	1	1	0	0	0	0	0	0	0	2	1	1	0	1
10	2	0	2	46	0	0	0	0	0	0	0	0	0	0	1	0	0	0
11	5	4	2	64	1	1	0	0	0	0	0	0	0	3	1	1	0	1
12	2	0	2	47	0	0	0	0	0	0	0	0	0	1	1	0	0	0
13	2	1	2	61	1	1	0	0	0	0	0	0	0	0	0	1	0	0
14	2	1	3	35	0	0	0	0	0	0	0	0	0	0	1	0	0	0
15	2	1	2	60	1	1	0	0	0	0	0	0	0	0	1	1	0	0
16	3	0	4	73	0	0	0	0	0	0	0	0	0	0	1	0	0	0
17	3	0	5	50	0	0	0	1	0	0	0	0	0	10	1	1	1	0
18	3	1	2	59	1	1	0	0	0	0	0	0	0	7	1	1	0	0
19	2	0	3	28	0	0	0	0	0	0	0	0	0	1	1	0	0	0
20	1	0	4	59	0	0	0	0	0	0	0	0	0	22	1	1	0	0
21	1	0	4	32	0	0	0	0	0	0	0	0	0	4	1	1	0	0
22	5	1	2	52	0	0	0	0	0	0	0	0	0	1	1	1	0	0
23	2	1	6	62	1	0	0	0	0	0	0	0	0	0	1	1	0	0
24	1	0	10	105	2	0	0	0	0	0	0	0	0	24	1	1	0	0
25	4	1	2	55	0	0	0	0	0	0	0	0	0	0	1	1	0	0
26	5	0	3	134	3	0	0	0	0	0	0	0	0	1	1	1	0	0
27	2	0	3	43	0	0	0	0	0	0	0	0	0	0	1	0	0	0
28	6	0	3	210	2	0	0	0	7	0	5	4	0	24	1	1	0	0

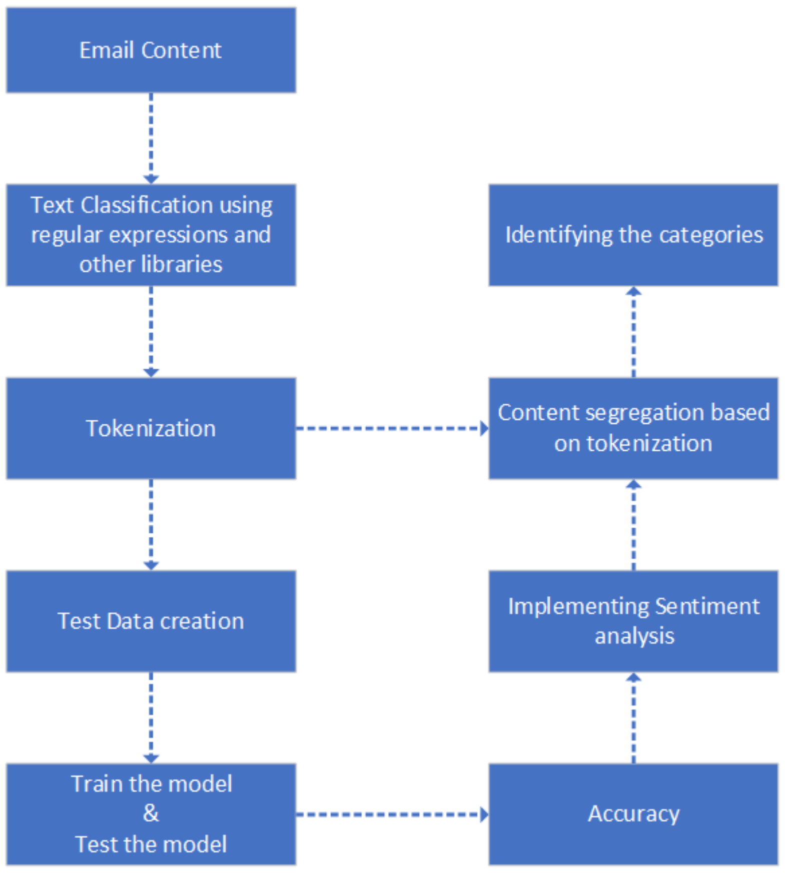
4. Model :

Architecture diagram :



Initially data is sent to API through user interface and this data is tokenized and pattern validation is done after tokenization.During this process real-time dataset is created and trained by random forest algorithm which will give accuracy scores and then the data(email) is classified as spam or not spam. Tokenized data is given to the vader sentiment and sentiment analysis is calculated according to the compound value generated.

Workflow Diagram :

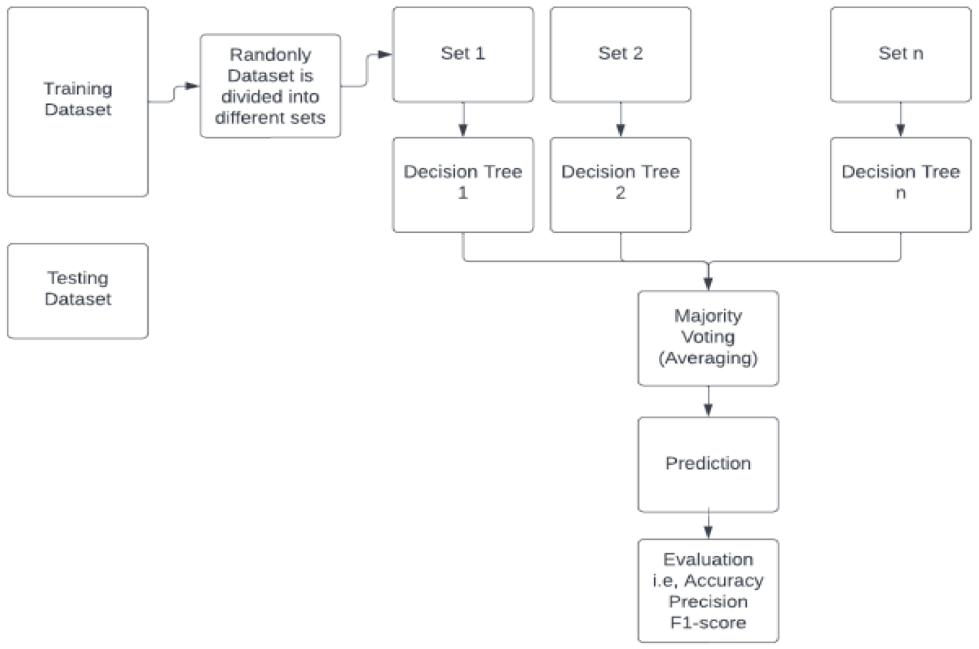

Email Content
Text Classification using regular expressions and other libraries
Tokenization
Test Data creation
Train the model & Test the model
Accuracy
Implementing Sentiment analysis
Content segregation based on tokenization
Identifying the categories

Here initially content from the UI(email content) is extracted and text classification is done based on regular expressions.Then the tokenization is done using the beautify method.During the process of creating the tokens a test dataset is created and using this dataset the model is evaluated.We used random forest algorithm and printed the accuracy scores(confusion matrix).later this is passed to vadersentiment libraries where sentiment analysis is performed.This will return the sentiment of the text that is passed(positive or negative).

5. Implementation :

In order to train our model we used the random forest algorithm.

Random forest Algorithm :


Training Dataset
Randonly Dataset is divided into different sets
Set 1
Set 2
Set n
Decision Tree 1
Decision Tree 2
Decision Tree n
Testing Dataset
Majority Voting (Averaging)
Prediction
Evaluation i.e, Accuracy Precision F1-score

Random Forest is a supervised machine learning algorithm which can be used for both the Classification and Regression problems. This produces good results even without hyper-parameter tuning. In this Algorithm, the training dataset is divided randomly into n different datasets i.e, set 1, set 2,....., set n. For each set, a decision tree is constructed. Then majority voting i.e, average of the results of all decision trees is done. Then, the predictions are done. Then the output is evaluated using measures like Accuracy, Precision and F1-score.

Pseudocode:

```
rfc = RandomForestClassifier(criterion='entropy', max_features='sqrt', max_samples=0.5,
min_samples_split=80) rfc.fit(X_train, y_train) y_pred = rfc.predict(X_val)
print(classification_report(y_val, y_pred, zero_division=0))
```

The hyperparameters used here are:

● criterion - is set to ‘entropy’ to calculate information gain, which determines the effectiveness of split.

● max_featues - this decides the maximum number of features that can be considered to split. We cannot assign all the features because it will not give an efficient decision tree. So, here we set it to sqrt i.e, square root of total number of features.

● max_samples - this defines what percentage of dataset to be included in an individual tree.

● min_samples_split - this determines the minimum number of observations to be considered for each split.

VaderSentiment:

vaderSentiment is a Python library for sentiment analysis, developed by C.J. Hutto. It is a rule-based sentiment analysis tool which uses a lexicon of words and their intensity scores to determine the sentiment of a text.

vaderSentiment uses a set of heuristics to determine the sentiment of a text. For example, it considers the capitalization of words, the presence of exclamation marks or question marks, and the use of emoticons or emojis. It also takes into account negations and modifiers, such as "not" or "very".

The library is easy to use and comes with pre-trained English language sentiment analysis models. It also allows for customization of the lexicon and rules, allowing for greater flexibility in analysis.

how it works:

vaderSentiment works by using a lexicon of words and their intensity scores, combined with a set of heuristics and grammar rules, to determine the sentiment of a text. The library uses these lexical features to calculate the sentiment of a text by computing the sentiment intensity score. The sentiment intensity score is a metric that ranges from -1 (most negative) to +1 (most positive), with a score of 0 indicating a neutral sentiment.

The following factors when determining the sentiment of a sentence:

1. The use of uppercase letters, which can indicate emphasis or intensity.

2. The presence of exclamation marks or question marks can indicate strong emotions.

3. The use of negations, such as "not" or "no", can reverse the polarity of a sentence.

4. The use of modifiers, such as "very" or "extremely", can increase the sentiment's intensity.

vaderSentiment returns a sentiment classification label based on the score. The labels range from "very negative" to "very positive", with a "neutral" label for scores close to 0.

Process :

Initially the data received from the front end(UI) will undergo a tokenization process which is done by the beautify method.

```
def beautify(text):
    import nltk
    nltk.download('stopwords')
    from nltk.corpus import stopwords
    token_list = {}
    tokens = [t for t in text.split()]
    clean_tokens = tokens[:]
    sr = stopwords.words('english')
    for token in tokens:
        if token in stopwords.words('english'):
            clean_tokens.remove(token)
    freq = nltk.FreqDist(clean_tokens)
    for key, val in freq.items():
        token_list[key] = val
    return token_list
```

Pattern validation will be done for those tokenizers.

```
emailpattern = r'\b[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\.[A-Z|a-z]{2,}\b'

nohttps = r'/^[a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+\.[a-zA-Z]{2,}$/'

urlpattern = r'^https?://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'

nohttpspattern = r'^http://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'

httpspattern = r'^https://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'

dotpattern = r'\.'

ippattern=r'^(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\\.(?:25[0-5]|2[0-4][0-9]|[01]?[
0-9][0-9]?)\\.(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\\.(?:25[0-5]|2[0-4][0-9]|[01]?[
0-9][0-9]?)$'

dashurlpattern = r'/\(\([a-z_-]*\.[a-z_-]*\)\|\([a-z_]*\.[a-z_-]*\.[a-z_-]*\)\)/'

numpattern = r'[0-9]'

stringpattern = r'[a-zA-z]'

sensitivepattern = r'(.)\1{9,}'

hostnamepattern = r'^https?://([\w.-]+)'

hostpathpattern = r'^https?://[\w.-]+(/.*)'

querypattern = r'(?<=\?)\S+'    # r'^https?://[\w.-]+(/.*)\?(\S+)'

subdomainpattern = r'(?<=://)([\w.-]+)\.'
```

A dataset is created during the pattern validation.This dataset is passed to a random forest model.

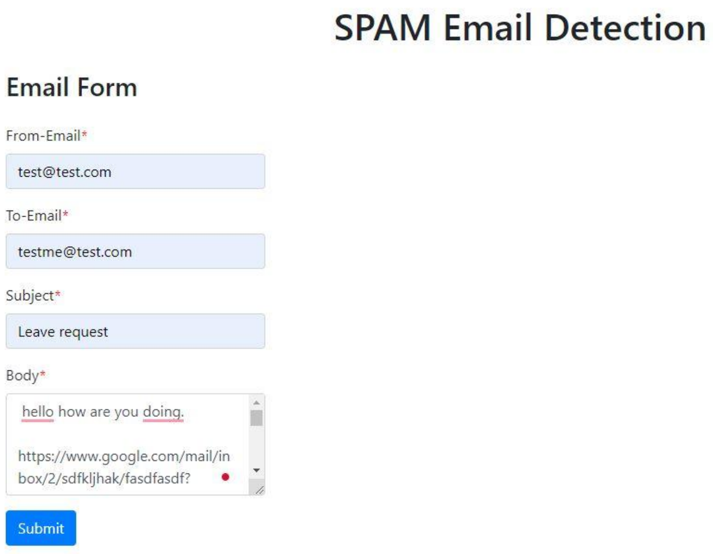
Sentiment analysis is done by using vader sentiment.while the data text is given and submitted through UI the compound value is calculated.if compound value is greater than 0 then sentiment of the text is positive otherwise negative.

```
analyzer = SentimentIntensityAnalyzer()

sentiment = analyzer.polarity_scores(input_val)

print("Sentiment Analysis: if the Compound result is in -, then the sentiment is negative and if there is only 0 then it is positive")

print(sentiment)

# adding the sentiment of the input

if sentiment['compound'] < 0:

   sentiment_result = "Negative"

elif sentiment['compound'] > 0:

   sentiment_result = "Positive"

else:

   sentiment_result = "Neutral"
```

6.Analysis of data:

Preprocessing of data:

Step 1 : Email content i.e The message present in the email is extracted and then text classification is done based on the regular expressions and some other libraries.



SPAM Email Detection

Email Form

From-Email*

test@test.com

To-Email*

testme@test.com

Subject*

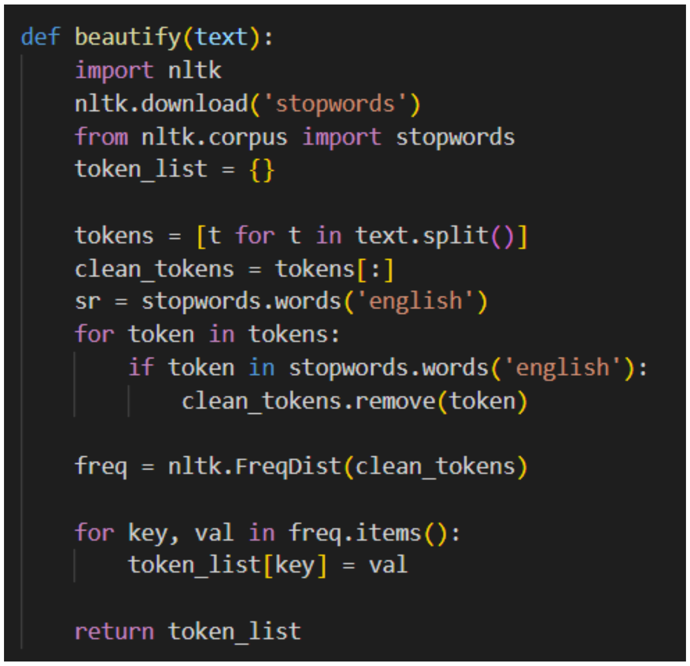
Leave request

Body*

hello how are you doing.

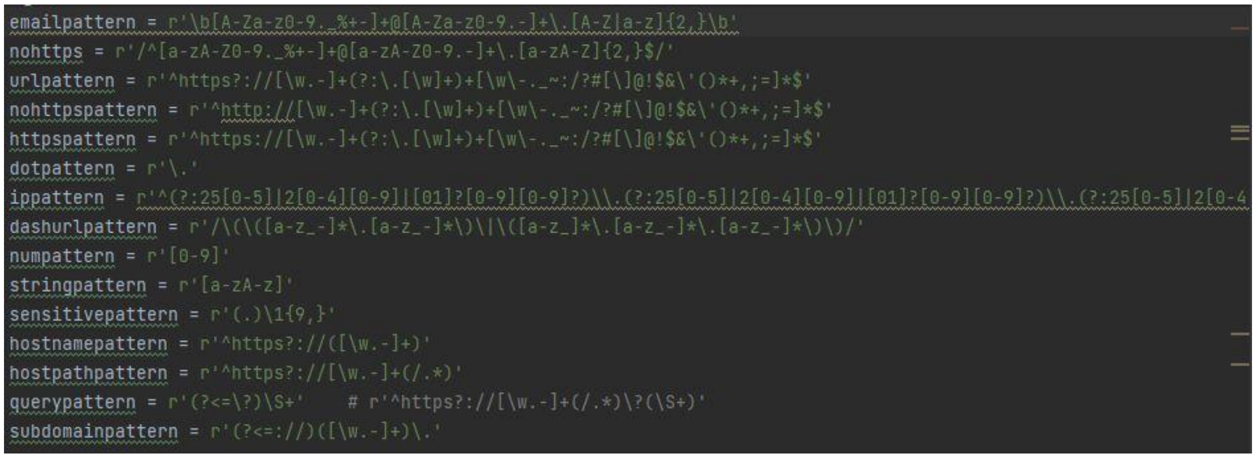
https://www.google.com/mail/inbox/2/sdfkljhak/fasdfasdf?

Step 2 : The classified data is sent into the tokenization process. This process is done by using the beautify method.



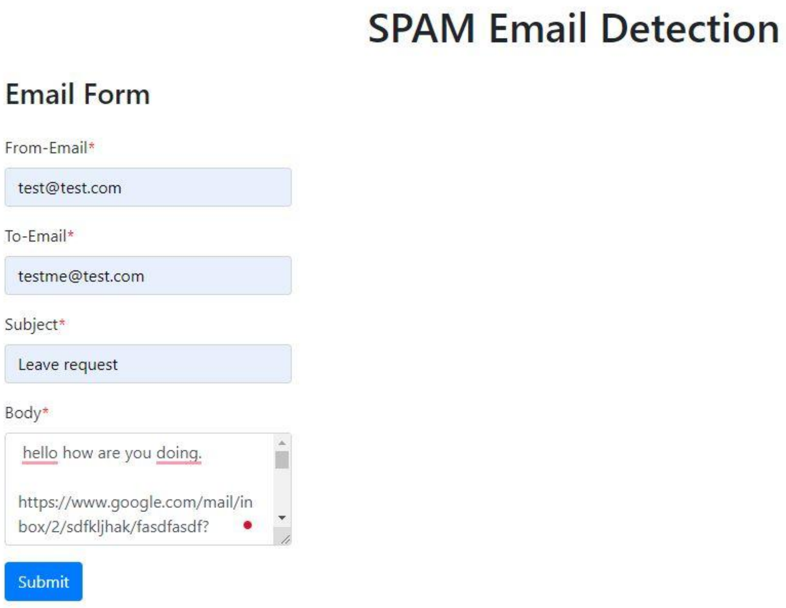
```
def beautify(text):
    import nltk
    nltk.download('stopwords')
    from nltk.corpus import stopwords
    token_list = {}

    tokens = [t for t in text.split()]
    clean_tokens = tokens[:]
    sr = stopwords.words('english')
    for token in tokens:
        if token in stopwords.words('english'):
            clean_tokens.remove(token)

    freq = nltk.FreqDist(clean_tokens)

    for key, val in freq.items():
        token_list[key] = val

    return token_list
```

Step 3 : After the tokenization,pattern validation is done by using below patterns.



```
emailpattern = r'\b[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\.[A-Z|a-z]{2,}\b'
nohttps = r'/^[a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+\.[a-zA-Z]{2,}$/'
urlpattern = r'^https?://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'
nohttpspattern = r'^http://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'
httpspattern = r'^https://[\w.-]+(?:\.[\w]+)+[\w\-._~:/?#[\]@!$&\'()*+,;=]*$'
dotpattern = r'\.'
ippattern = r'^(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\\.(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\\.(?:25[0-5]|2[0-4
dashurlpattern = r'/\(\([a-z_-]*\.[a-z_-]*\)\|\([a-z_]*\.[a-z_-]*\.[a-z_-]*\)\)/'
numpattern = r'[0-9]'
stringpattern = r'[a-zA-z]'
sensitivepattern = r'(.)\1{9,}'
hostnamepattern = r'^https?://([\w.-]+)'
hostpathpattern = r'^https?://[\w.-]+(/.*)'
querypattern = r'(?<=\?)\S+'    # r'^https?://[\w.-]+(/.*)\?(\S+)'
subdomainpattern = r'(?<=://)([\w.-]+)\.'
```

Step 4 : For the frontend data that we are passing initially, a test dataset is created in the backend while validating the patterns.



SPAM Email Detection

Email Form

From-Email*

test@test.com

To-Email*

testme@test.com

Subject*

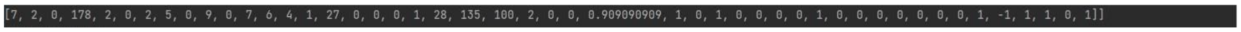
Leave request

Body*

hello how are you doing.

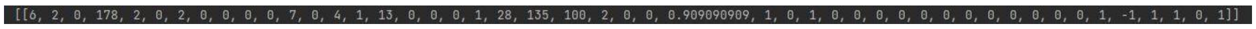
https://www.google.com/mail/inbox/2/sdfkljhak/fasdfasdf?

Spam detected :



```
[7, 2, 0, 178, 2, 0, 2, 5, 0, 9, 0, 7, 6, 4, 1, 27, 0, 0, 0, 1, 28, 135, 100, 2, 0, 0, 0.909090909, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, -1, 1, 1, 0, 1]]
```

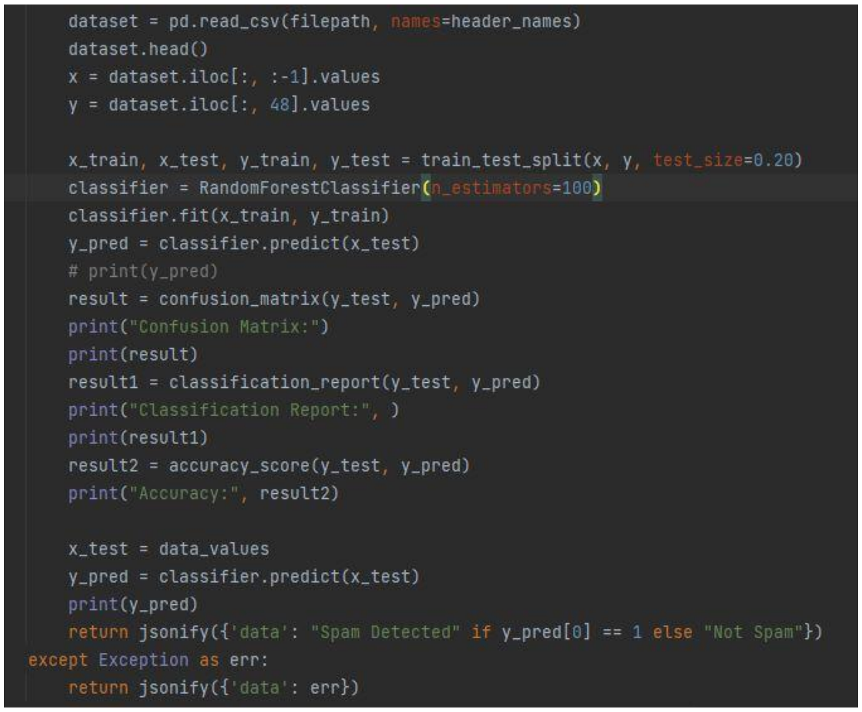
Not spam :



```
[[6, 2, 0, 178, 2, 0, 2, 0, 0, 0, 0, 7, 0, 4, 1, 13, 0, 0, 0, 1, 28, 135, 100, 2, 0, 0, 0.909090909, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, -1, 1, 1, 0, 1]]
```

Data distribution:

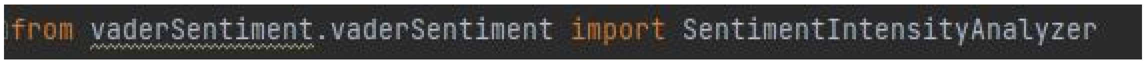
Step 5 : This testing dataset is passed to our model (random forest). As our training model is trained it will predict whether the email is spam or not.



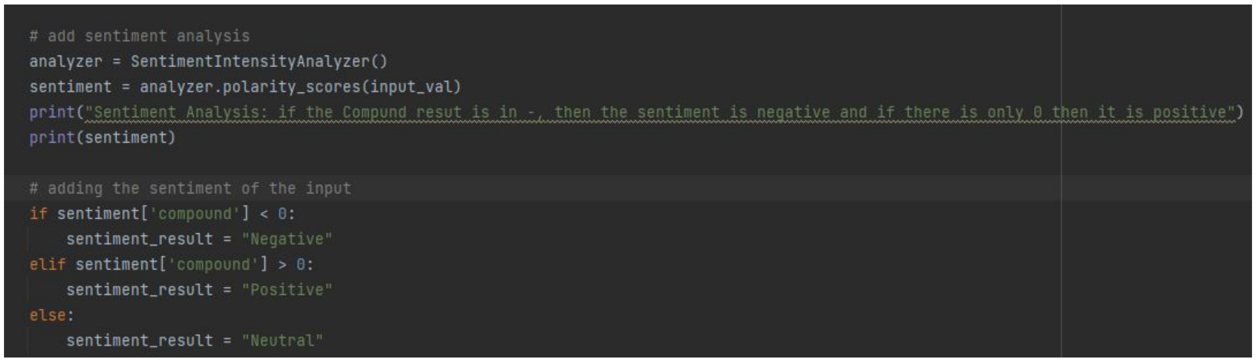
```
    dataset = pd.read_csv(filepath, names=header_names)
    dataset.head()
    x = dataset.iloc[:, :-1].values
    y = dataset.iloc[:, 48].values

    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20)
    classifier = RandomForestClassifier(n_estimators=100)
    classifier.fit(x_train, y_train)
    y_pred = classifier.predict(x_test)
    # print(y_pred)
    result = confusion_matrix(y_test, y_pred)
    print("Confusion Matrix:")
    print(result)
    result1 = classification_report(y_test, y_pred)
    print("Classification Report:", )
    print(result1)
    result2 = accuracy_score(y_test, y_pred)
    print("Accuracy:", result2)

    x_test = data_values
    y_pred = classifier.predict(x_test)
    print(y_pred)
    return jsonify({'data': "Spam Detected" if y_pred[0] == 1 else "Not Spam"})
except Exception as err:
    return jsonify({'data': err})
```

Step 6 : After passing the dataset to the model, it will predict and give us the accuracy results. Here we used confusion matrix, classification report and accuracy_score as our evaluation metrics.

Step 7 : After running the spam analysis, we are importing the vadersentiment package so that the text is passed through libraries in vadersentiment to process the sentiment analysis and finally will return the sentiment of the context which is extracted from the UI and predict the final report (positive or negative or neutral).

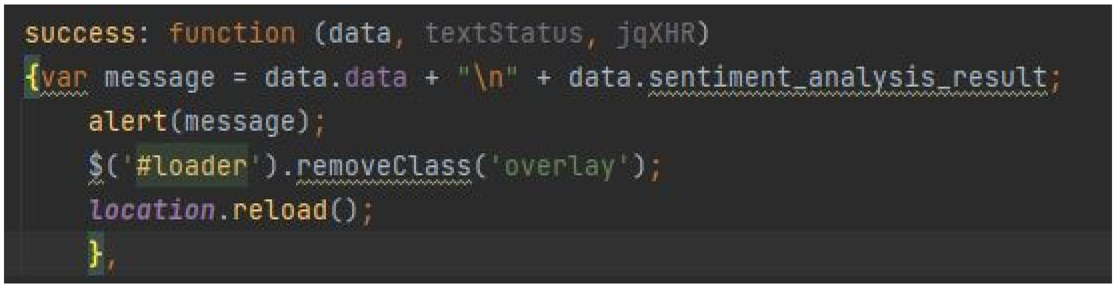


```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
```



```python
# add sentiment analysis
analyzer = SentimentIntensityAnalyzer()
sentiment = analyzer.polarity_scores(input_val)
print("Sentiment Analysis: if the Compund resut is in -, then the sentiment is negative and if there is only 0 then it is positive")
print(sentiment)

# adding the sentiment of the input
if sentiment['compound'] < 0:
    sentiment_result = "Negative"
elif sentiment['compound'] > 0:
    sentiment_result = "Positive"
else:
    sentiment_result = "Neutral"
```

Here the sentiment of the context is calculated.If compound value is less than 0 then it is negative, greater than 0 is positive and 0 is neutral.



```javascript
success: function (data, textStatus, jqXHR)
{var message = data.data + "\n" + data.sentiment_analysis_result;
    alert(message);
    $('#loader').removeClass('overlay');
    location.reload();
    },
```

passing the data of spam detection and sentiment analysis in pop up.

Evaluation Methods:

1. Confusion matrix: A confusion matrix is a table that summarizes the results of predictions. It tells us how many samples the model has correctly predicted and how many it has missed. There are four possible outcomes, those are:
   True Positives (TP): A true positive is when the model correctly captures a sample as the positive class.
   False Positives (FP): A false positive is when the model incorrectly identifies a sample as the positive class.
   True Negatives (TN): A true negative is when the model correctly identifies a sample as the negative class.
   False Negatives (FN): A false negative is when the model incorrectly identifies a sample as the negative class.

Here is an example of a confusion matrix:

	Predicted Negative	Predicted Positive
Actual Negative	TN	FP
Actual Positive	FN	TP

2. **Classification Report:** A classification report is a summary of the performance of a classification model on a dataset. It typically includes metrics such as precision, recall, F1 score for each class label. A classification report provides a detailed evaluation of the model's performance.

3. **Accuracy:** This is the most straightforward evaluation method that measures how many predictions made by the model are correct. It is calculated by dividing the number of correct predictions by the total number of predictions.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

4. **Precision and Recall:** These evaluation metrics are used to evaluate the performance of classification tasks. Precision measures how many of the positive predictions made by the model are correct, while recall measures how many of the actual positives in the dataset the model has identified correctly.

Precision = TP / (TP + FP)

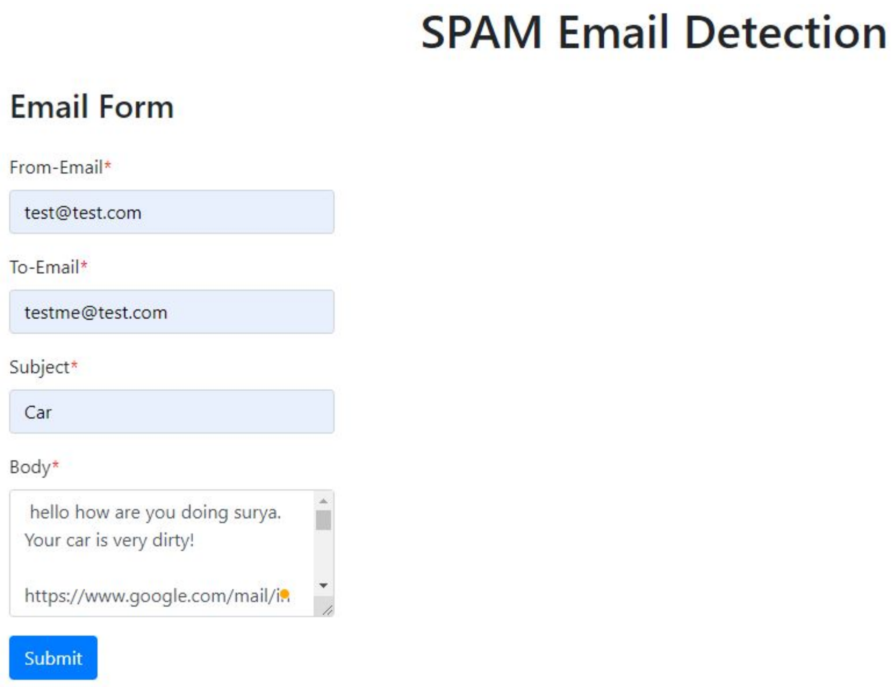
Recall = TP / (TP + FN)

5. **F1 Score:** The F1 score is the harmonic mean of precision and recall. It is a commonly used evaluation metric for classification tasks that balances precision and recall.

F1 Score = 2 * ((Precision * Recall) / (Precision + Recall))

7. Analysis and preliminary results:

Spam detected :


SPAM Email Detection

Email Form

From-Email*

test@test.com

To-Email*

testme@test.com

Subject*

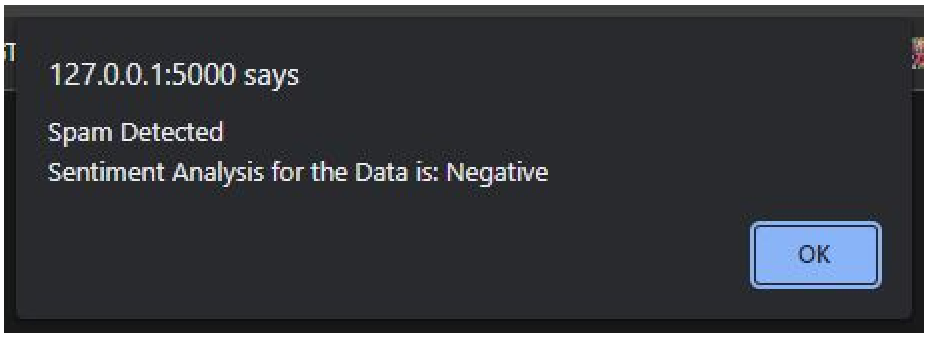
Car

Body*

hello how are you doing surya.
Your car is very dirty!

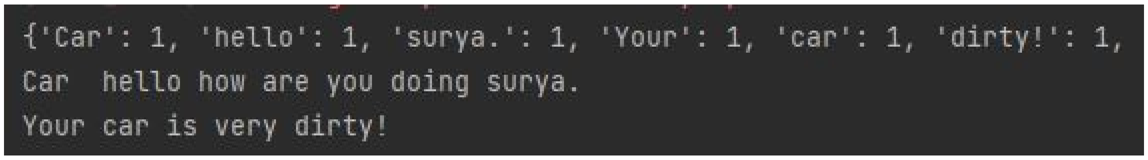
https://www.google.com/mail/i

Here the above message is passed and clicked on submit.Then the pop-up is shown as below:

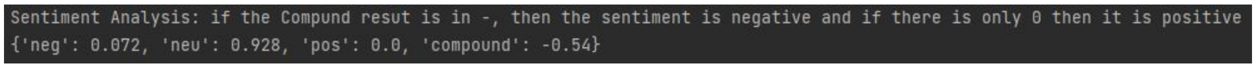

127.0.0.1:5000 says

Spam Detected
Sentiment Analysis for the Data is: Negative

It is displaying the spam is detected along with the sentiment analysis of that data.As it is spam the sentiment for the data is negative.

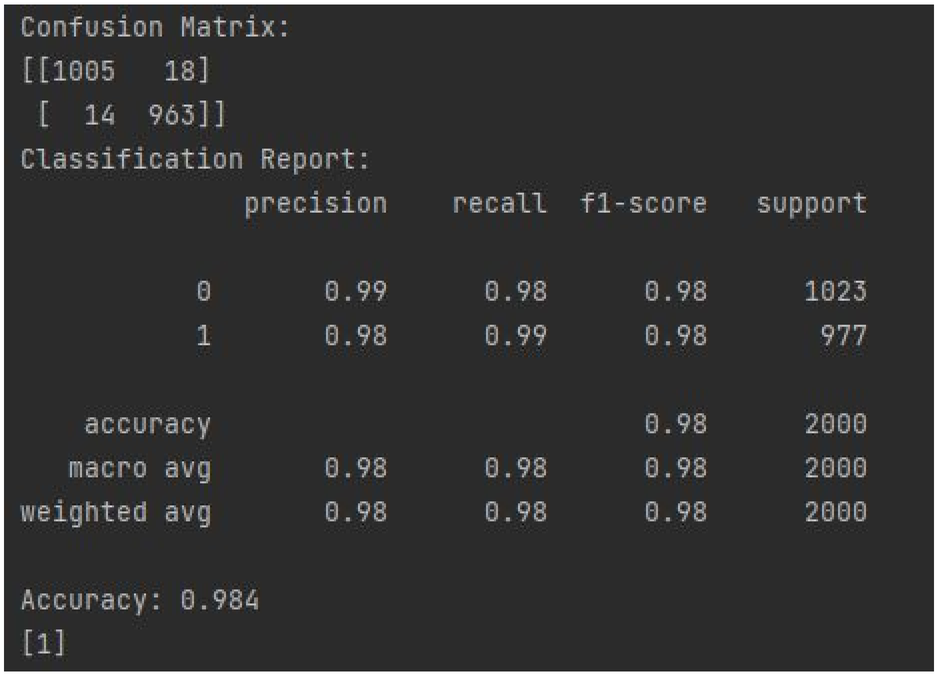

```
{'Car': 1, 'hello': 1, 'surya.': 1, 'Your': 1, 'car': 1, 'dirty!': 1,
Car  hello how are you doing surya.
Your car is very dirty!
```

Here in the above image we can observe the word ‘dirty’ which has a negative meaning.



```
Sentiment Analysis: if the Compund resut is in -, then the sentiment is negative and if there is only 0 then it is positive
{'neg': 0.072, 'neu': 0.928, 'pos': 0.0, 'compound': -0.54}
```

For above passed spam text,the compound value is calculated.As the compound value is negative the sentiment of the text is classified as negative.

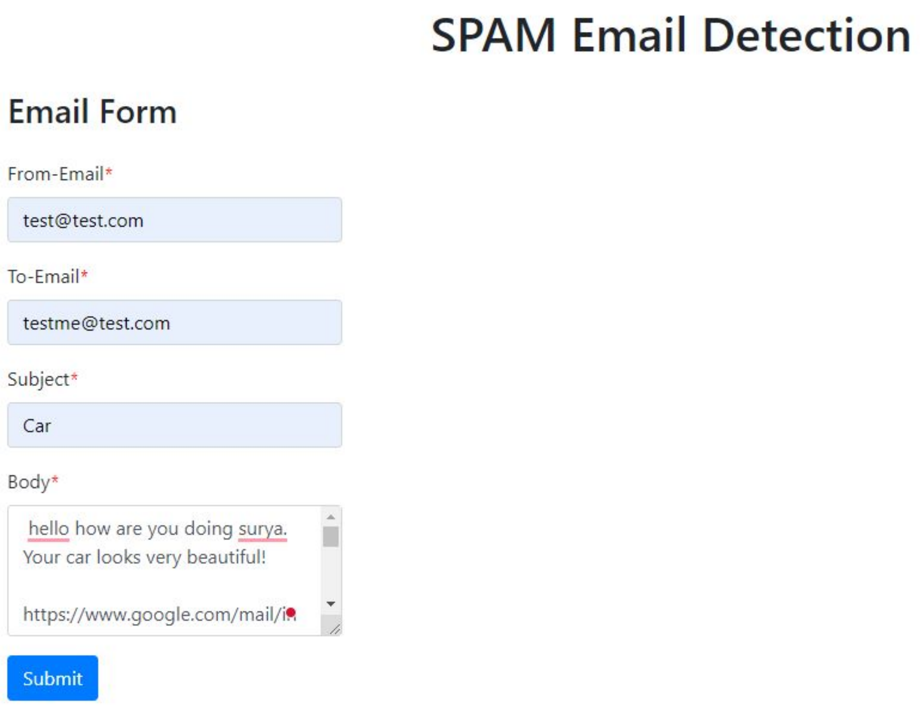


```
Confusion Matrix:
[[1005   18]
 [  14  963]]
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.98      0.98      1023
           1       0.98      0.99      0.98       977

    accuracy                           0.98      2000
   macro avg       0.98      0.98      0.98      2000
weighted avg       0.98      0.98      0.98      2000

Accuracy: 0.984
[1]
```

Confusion matrix and accuracy scores are calculated.

Not spam :

The below text is passed and clicked on submit.



SPAM Email Detection

Email Form

From-Email*

test@test.com

To-Email*

testme@test.com

Subject*

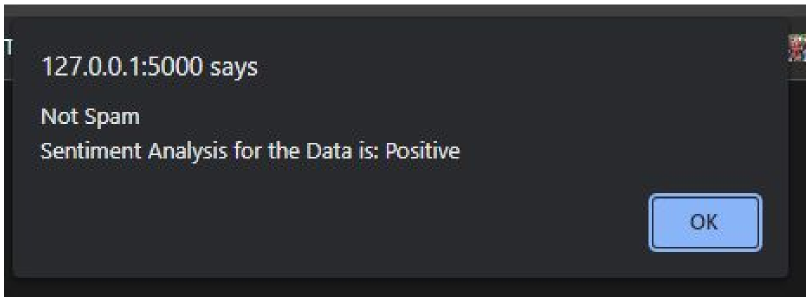
Car

Body*

hello how are you doing surya.
Your car looks very beautiful!

https://www.google.com/mail/i

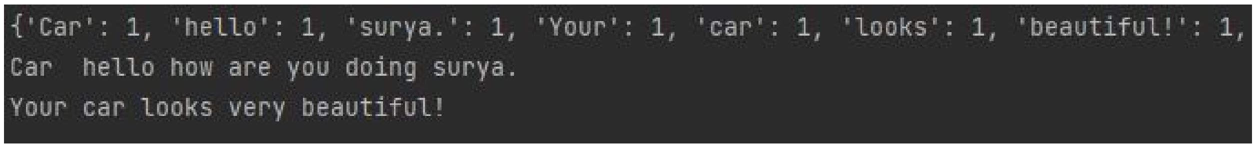
The text is classified as not spam and sentiment analysis is positive.



127.0.0.1:5000 says

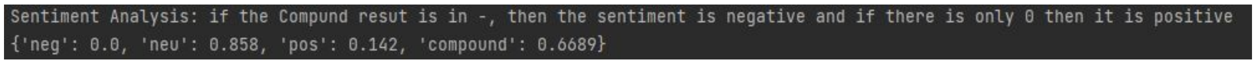
Not Spam
Sentiment Analysis for the Data is: Positive

Here you may observe that the word dirty in spam text is replaced with beautiful.

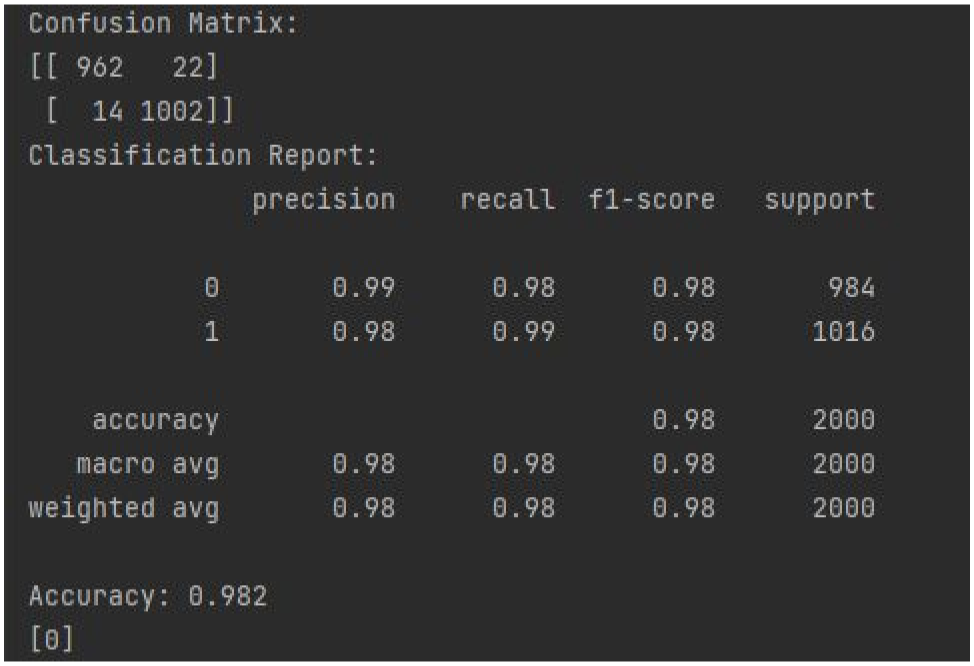


```
{'Car': 1, 'hello': 1, 'surya.': 1, 'Your': 1, 'car': 1, 'looks': 1, 'beautiful!': 1,
Car  hello how are you doing surya.
Your car looks very beautiful!
```

Here compound value is positive so sentiment is classified as positive.



```
Sentiment Analysis: if the Compund resut is in -, then the sentiment is negative and if there is only 0 then it is positive
{'neg': 0.0, 'neu': 0.858, 'pos': 0.142, 'compound': 0.6689}
```



```
Confusion Matrix:
[[ 962   22]
 [  14 1002]]
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.98      0.98       984
           1       0.98      0.99      0.98      1016

    accuracy                           0.98      2000
   macro avg       0.98      0.98      0.98      2000
weighted avg       0.98      0.98      0.98      2000

Accuracy: 0.982
[0]
```

Confusion matrix and accuracy scores are calculated and printed.

8. References:

Dataset : https://www.kaggle.com/datasets/shashwatwork/phishing-dataset-for-machine-learning?select=Phishing_Legitimate_full.csv

Vadersentiment : https://github.com/cjhutto/vaderSentiment

[2.1] https://ieeexplore.ieee.org/abstract/document/9004372/

[2.2] https://ieeexplore-ieee-org.libproxy.library.unt.edu/document/9334020

[2.3] https://ieeexplore.ieee.org/abstract/document/1505383

[2.4] https://link.springer.com/chapter/10.1007/978-3-030-50423-6_49

[2.5]https://www.inderscienceonline.com/doi/abs/10.1504/IJCSE.2023.129147?journalCode=ijcse

[2.6]https://academic.oup.com/jigpal/article-abstract/28/1/83/5680435

[2.7]https://ieeexplore.ieee.org/abstract/document/8701426

[2.8]https://www.sciencedirect.com/science/article/abs/pii/S1389128622000469

[2.9]https://link.springer.com/chapter/10.1007/978-3-030-50423-6_49

[2.10]https://www.iaeng.org/publication/IMECS2019/IMECS2019_pp12-16.pdf

[2.11]https://link.springer.com/chapter/10.1007/978-1-4614-3223-4_13?source=post_page---------------------------

[2.12]https://www.sciencedirect.com/science/article/pii/S1877050921007493

[2.13]https://www.mdpi.com/2079-9292/9/3/483

9. Git Repository URL: https://github.com/surya5a72/csce5290_NLP

Demo Video Google drive link (vedio) : https://drive.google.com/file/d/1KI0hgJ2HQZ5M0zJZ2vF4fnSVrNYWgmVy/view?usp=sharing

PPT presentation :
https://drive.google.com/file/d/1oN1QTBa5jedZBvS4vXhakLrncHUWc_dj/view?usp=share_link