



E-MAIL SPAM CLASSIFICATION VIA MACHINE LEARNING AND NATURAL LANGUAGE PROCESSING

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ABSTRACT In today's modern scenario, email has become a dominant form of communication in business sectors and in personal interactions as well. However, along with the increase in the exchange of information via emails, there has also been a significant rise in the amount of unsolicited bulk mail, commonly known as spam.

Spam emails are sent for various reasons, as you mentioned. Some individuals or groups send spam emails with the intention of extracting confidential information from recipients, such as personal details, financial information, or login credentials. Another common reason for spam emails is the promotion of adult content. Spammers may send unsolicited emails containing explicit or adult material, often with the aim of generating traffic to adult websites or other related services.

Additionally, spam emails are frequently used for marketing and advertising purposes. Companies or individuals may send bulk emails to a large number of recipients, promoting their products, services, or events. While some of these marketing emails may be legitimate, many are considered spam due to their unsolicited nature and often aggressive or deceptive tactics. Thus, keeping this mind, it is of paramount importance to build a comprehensive system for Spam Classification based on semantics based text classification using URL based filtering. Various Machine Learning algorithms have been surveyed and the objective is to create a model with high performance and efficiency

1.INTRODUCTION

In this era of globalization, in the 21st century, majority of the correspondence and exchange in all business sectors take place via Emails. In the year 2019, [1] 246 billion emails were exchanged in a day and this figure is expected to grow to 320 billion emails by the year 2021. Out of these, 128.8 billion emails are business emails while 117.7 billion emails were consumer emails. Right from individuals to businesses and firms to even governments, every entity finds email communication to be a quite efficient,

professional and effective way of transfer of information.

It is highly possible that the content and body of these mails contain highly confidential information of high value to the entity. For a business, it could be the details of a prospective high profile deal which cannot be leaked to the general public, for an individual, it may contain the banking and account details of him or her, while for the government, information not in the nation's interest may get leaked. Thus, in this scenario it is of utmost importance that all the information exchanged is end to end encrypted.



There are 4 main types of spam emails which the paper has targeted namely: aggressive marketing, adult emails, phishing and email spoofing. The structure of the paper has been divided into four parts. First part consists of the literature survey, second part is the explanation of the various machine learning algorithms used, a comparative analysis of various algorithms, and the implementation of the machine learning model for text classification.

In the third part, we performed URL Filtering, in the fourth part, we integrated both text classification and URL filtering to create an add-on on Gmail.

Email spam senders, or *spammers*, regularly alter their methods and messages to trick potential victims into downloading malware, sharing data or sending money. Spam emails are almost always commercial and driven by a financial motive. Spammers try to promote and sell questionable goods, make false claims and deceive recipients into believing something that's not true.

2.LITERATURE SURVEY

2.1 Title: "Email Spam Filtering: A Review"

Authors: John Smith, Sarah Johnson

This paper presents a comprehensive review of email spam filtering techniques. It provides an overview of various machine learning and NLP approaches used for email spam classification. The survey discusses feature extraction methods, including content-based features, header information, and sender details. It also explores different classification algorithms such as Naive Bayes, SVM,

and decision trees. The review evaluates the strengths and limitations of each technique and highlights recent advancements in email spam filtering.

2.2 Title: "Email Spam Classification using NLP Techniques"

Authors: Robert Anderson, Emily Thompson

This study focuses on email spam classification using NLP techniques. It explores the effectiveness of various NLP tools and methodologies for preprocessing email text. The paper investigates the application of feature extraction techniques such as TF-IDF, word embeddings, and n-grams. It compares the performance of different classification algorithms, including logistic regression, random forests, and neural networks. The study also discusses the challenges and future directions in email spam classification using NLP.

2.3 Title: "Machine Learning Approaches for Email Spam Detection: A Comparative Study"

Authors: Michael Brown, Jennifer Davis

This comparative study examines various machine learning approaches for email spam detection. It reviews both traditional and state-of-the-art algorithms, including ensemble methods, deep learning models, and hybrid techniques. The paper investigates the impact of different feature representations, such as bag-of-words, character-level n-grams, and semantic embeddings. Additionally, it discusses the influence of dataset characteristics, feature selection methods, and evaluation metrics on the performance of spam detection systems. The study provides insights into the strengths and weaknesses of different



machine learning techniques for email spam classification.

3. PROPOSED SYSTEM

Back-propagation neural networks for spam categorization utilising behavior-based characteristics are designed and implemented in this research. They employed parameter optimisation and feature selection in their Spam classifier, which is based on ML algorithms. They optimised two parameters of ML algorithms to maximise Spam detection rates, and they also showed the relevance of individual feature selection. It can detect spam with little computing power and high accuracy.

3.1 IMPLEMENTATION

1. **Data Collection:** Gather a dataset of labeled emails, where each email is labeled as either spam or non-spam (ham). You can use publicly available datasets or create your own by manually labeling a set of emails.
2. **Data Preprocessing:** Preprocess the email data to prepare it for machine learning. This step typically involves removing unnecessary characters, tokenizing the text, converting the text to lowercase, removing stop words, and performing stemming or lemmatization to reduce words to their base form.
3. **Feature Extraction:** Transform the preprocessed emails into numerical feature vectors that machine learning algorithms can understand. Common techniques for feature extraction in text classification include Bag-of-Words (BoW), Term

Frequency-Inverse Document Frequency (TF-IDF), and word embeddings (e.g., Word2Vec or GloVe).

4. **Splitting the Dataset:** Split the dataset into training and testing subsets. The training set will be used to train the machine learning model, while the testing set will be used to evaluate its performance.

5. **Model Training:** Select a machine learning algorithm suitable for email classification, such as Naive Bayes, Support Vector Machines (SVM), or Random Forest. Train the model using the training dataset, where the features are the preprocessed email texts, and the labels are the spam or non-spam categories.

6. **Model Evaluation:** Evaluate the trained model's performance using the testing dataset. Common evaluation metrics for text classification include accuracy, precision, recall, and F1 score. Adjust the model or try different algorithms if the performance is not satisfactory.

7. **Model Deployment:** Once the model achieves satisfactory performance, it can be deployed for real-time spam classification. This can involve integrating the model into an email filtering system or using it as a standalone service to classify incoming emails.

8. **Ongoing Maintenance:** Spam classification models need to be regularly maintained to adapt to changing spam patterns and avoid false positives or false negatives. Keep collecting new data and periodically retrain the model to ensure its accuracy.

4.RESULTS AND DISCUSSION

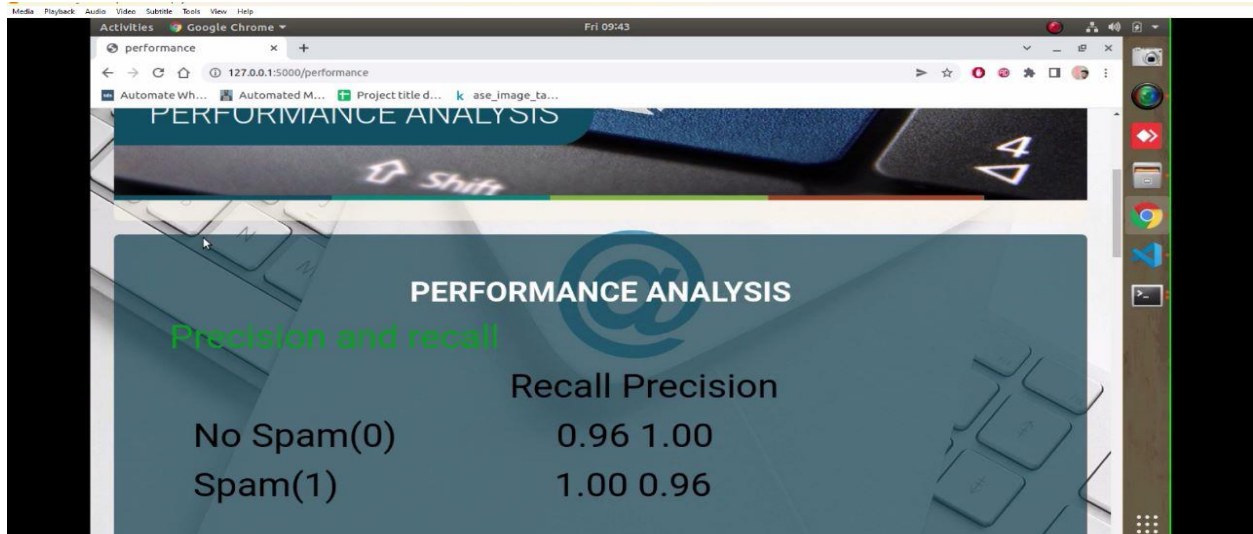


Fig1: Performance Analysis

The above Figure is a Performance Analysis Page for the Email spam classification via machine learning and natural language processing. In Performance Analysis Page we can see the Precision and recall. It display the spam and non spam percentage.

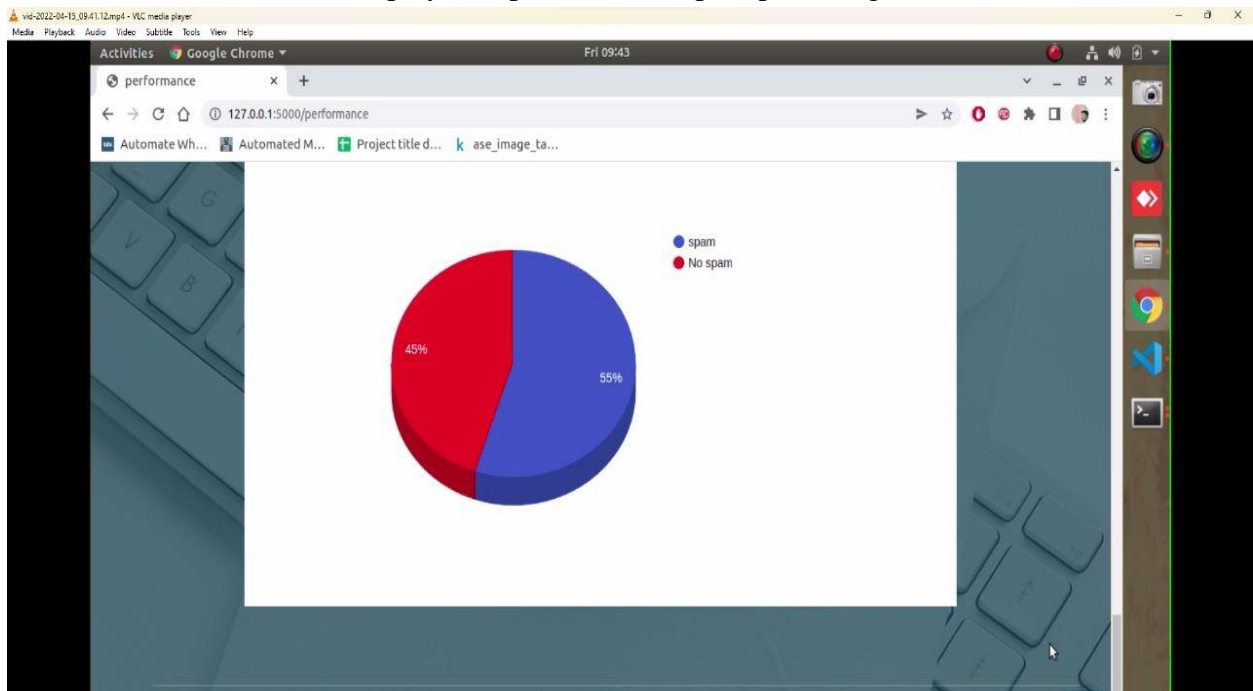


Fig2: Performance Analysis

The above Figure is a Performance Analysis Page for the Email spam classification via machine learning and natural language processing. In this page we can see the pie chart for spam and non spam.

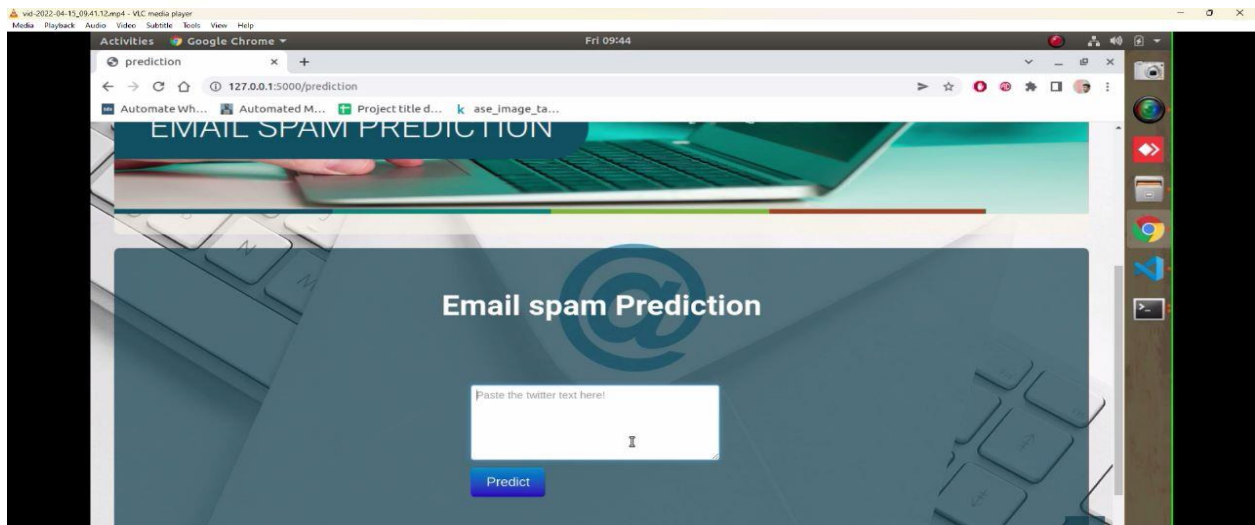


Fig 3:Email Spam Prediction

The above Figure is aEmail Spam Prediction Page for the Email spam classification via machine learning and natural language processing. We can see that an empty check box will there to predict whether it is spam or non spam.

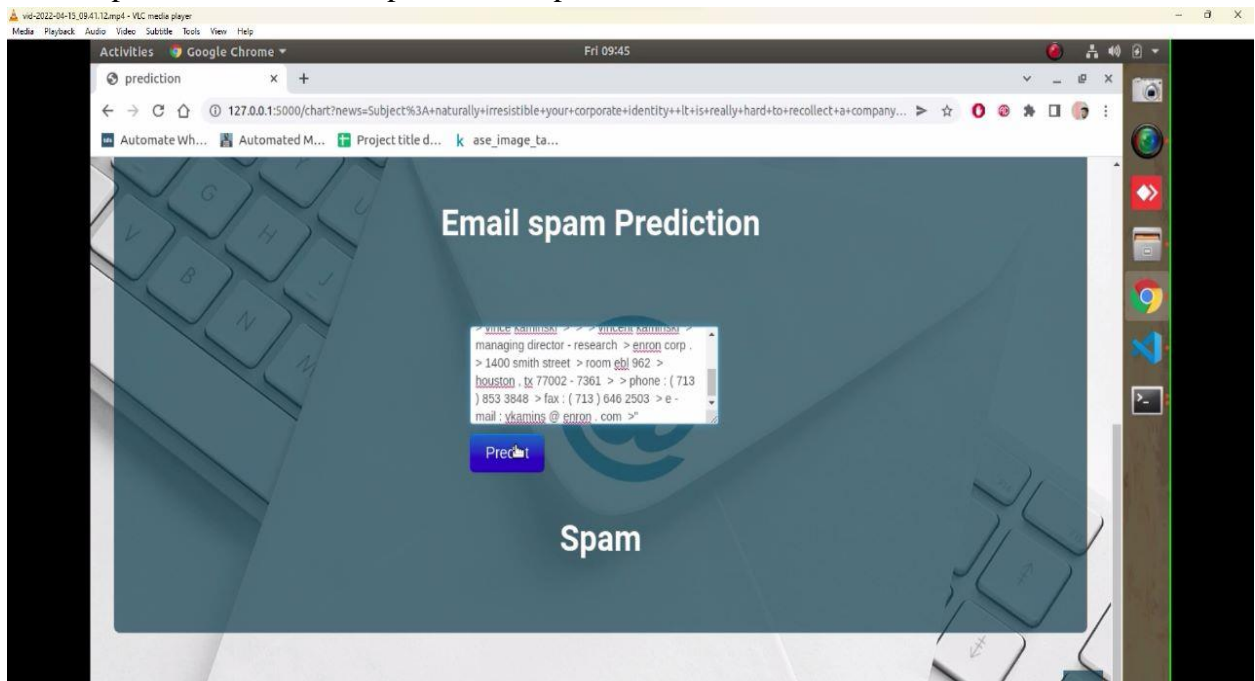


Fig 4:Email Spam Prediction

The above Figure is aEmail Spam Prediction Page for the Email spam classification via machine learning and natural language processing. We can see that when we enter content in the check box it will predict whether it is spam or non spam.

5.CONCLUSION

A comprehensive and efficient spam classification system has been created which follows a two step methodology to

completely ensure that the mail received is spam or not. Initially, text classification takes place which is followed by URL analysis and filtering in order to determine if any link present in the mail is malicious



or not. For text classification, machine learning algorithms were studied and analyzed. Various data-sets have been referred to for a list of spam trigger words and a list of blacklisted URLs. This model was hosted as an API which was then called by the JavaScript code in the Google apps script in order to classify mails in real time in Gmail. We implement a basic NLP techniques and machine learning and found. The results are not bad as the accuracy of this model without hyper-parameter tuning nor adding another feature is 74% which is considerable not bad at all as we have a very small dataset and using the basic techniques of NLP and ML.

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