A Project Report

on

Email Spam Detection Using Machine Learning

Submitted in partial fulfillment of the requirement for the award of the degree of

Master of Computer Applications

Under The Supervision of

Mr. P Rajakumar

Assistant Professor

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GREATER NOIDA
April 2024

CANDIDATE'S DECLARATION

We hereby certify that the work which is being presented in the project, entitled **"Email Spam Detection Using Machine Learning"** in partial fulfillment of te he requirements for the award of the MCA submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of month, Year to Month and Year, under the supervision of MR. P Rajakumar, Assistant Professor, Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering, Galgotias University, Greater Noida

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

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This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

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CERTIFICATE

The Final Project Viva-Voce examination of Mohammed Shyas (22SCSE2030754) Biswajit Kr Singh (22SCSE2160051) Neeraj Rawat (22SCSE2030726) has been held on 25th April 2024 and his/her work is recommended for the award of Master In Computer Application

Signature of Guide **Signature of Reviewer**

Date: April 2024
Place: Greater Noida

Abstract

The ongoing challenge in email spam detection stems from the continuous evolution of spamming techniques. Spammers constantly adjust their methods to evade detection, making it difficult for traditional spam filters to keep up with new and more sophisticated tactics. These include using image-based spam, obfuscation methods, and leveraging machine learning to create more convincing spam emails that are harder to identify. This dynamic landscape requires constant innovation in spam detection algorithms to effectively filter out these ever-changing spam messages.Spam detection systems use machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and deep learning models like neural networks to classify emails as either spam or non-spam (ham). By analyzing features like keywords, sender information, and email structure, these algorithms learn patterns indicative of spam. Using labeled datasets for training and applying text preprocessing, feature engineering, and model optimization, these systems accurately distinguish between legitimate and unsolicited emails. This helps protect users from unwanted or potentially harmful content.

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CHAPTER – 1

Introduction

Email spam detection is a crucial aspect of modern digital communication aimed at identifying and filtering unsolicited or unwanted emails from reaching user inboxes. It involves the application of various machine learning, statistical, and computational techniques to distinguish between legitimate emails and spam messages. Through the analysis of email content, sender information, header details, and user behavior patterns, sophisticated algorithms can identify common spam characteristics such as phishing attempts, malicious links, or irrelevant advertisements. These detection methods evolve continuously to adapt to new spamming techniques and trends, ensuring improved accuracy in classifying and diverting suspicious emails away from users. Email spam detection not only enhances user experience by reducing inbox clutter but also plays a significant role in safeguarding individuals and organizations from potential security threats and fraudulent activities in the digital realm.

Develop an efficient machine learning model to accurately classify incoming emails as either spam or legitimate. The task involves analyzing email content and metadata to distinguish between unsolicited spam messages and genuine correspondence. The objective is to create a robust system that automatically identifies and filters out spam emails, minimizing false positives while maximizing the identification of potential threats, thereby enhancing user experience and security in email communication.

Email spam detection involves various tools and technologies that work together to identify and filter out spam messages. Some of the commonly used tools and technologies include:

Machine Learning Algorithms:

Techniques such as Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forest, and Neural Networks are used to develop predictive models for classifying emails as spam or legitimate based on features extracted from the content, metadata, sender information, and more. **Natural Language Processing (NLP):** NLP libraries like NLTK (Natural Language Toolkit), spaCy, and TextBlob are utilized to process and analyze the text content of emails. These tools help in tokenization, stemming, lemmatization, and feature extraction, enabling the identification of patterns in textual data. Techniques to extract relevant features from emails, including word frequency, presence of certain keywords, sender reputation, header

analysis, HTML content analysis, and analysis of embedded URLs and attachments.
Tools that dissect and analyze email headers to identify anomalies or suspicious elements, including SPF (Sender Policy Framework), DKIM (DomainKeys Identified Mail), and DMARC (Domain-based Message Authentication, Reporting, and Conformance). Blacklists and Whitelists**:** Maintaining and utilizing databases of known spam sources (blacklists) and trusted senders (whitelists) to aid in filtering out spam emails or ensuring legitimate emails reach the inbox.Implementation of Bayesian spam filtering techniques that calculate the probability of an email being spam based on the occurrence of certain words or combinations of words in the email content. Using collective intelligence or community-based filtering where users report spam, and this information is utilized to classify similar messages as spam across the network.

Contribution and novelty of this report consist of the following:

- Collection and preprocessing of diverse email datasets.

- Feature engineering to extract relevant information from email content and metadata.

- Experimentation with various machine learning algorithms for accurate classification.

- Model deployment for real-time email scoring and classification.

- Continuous monitoring and adaptation for ongoing improvement

CHAPTER – 2

Literature Survey

A literature survey on email spam detection encompasses a broad range of research studies, methodologies, and advancements aimed at identifying, analyzing, and mitigating the impact of spam emails. Here's an overview highlighting key themes and findings from existing literature: Numerous studies have explored the efficacy of machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forest, and Neural Networks for spam detection.

- Research often focuses on feature selection, extraction, and model optimization to improve accuracy and reduce false positives in classifying spam and legitimate emails.

Natural Language Processing (NLP) in Spam DetectionNLP-based approaches involving text analysis, tokenization, and semantic analysis are prevalent in identifying spam content within emails. Studies delve into sentiment analysis, language models, and semantic understanding to discern spammy content from genuine communication.Feature Engineering and Selection:- Investigations into effective feature engineering techniques, including word frequency, presence of specific keywords, sender information, header analysis, and lexical analysis.

- Feature selection methods, such as information gain, chi-square tests, and correlation-based approaches, are explored to identify the most relevant features for spam detection. Hybrid and Ensemble Methods:- Research combines multiple techniques (e.g., machine learning with rule- based systems) or ensemble methods to enhance the robustness and accuracy of spam detection systems.
- Hybrid approaches often integrate content-based and behavior-based analysis for comprehensive spam identification. Header and Metadata Analysis:- Studies examine the importance of email headers, including SPF, DKIM, and DMARC, in authenticating senders and detecting spoofed or fraudulent emails.
- Research highlights the significance of analyzing metadata, IP addresses, timestamps, and routing information to uncover spamming patterns.

Behavioral Analysis and Dynamic Filtering:- Dynamic and adaptive models that incorporate user behavior, engagement patterns, and feedback mechanisms to refine spam filters over time.

- Investigations into collaborative filtering methods leveraging collective intelligence and user reports to improve spam identification.Big Data and Cloud-Based Solutions:- The scalability and efficiency of big data platforms and cloud-based solutions in handling vast amounts of email data and performing real-time analysis for effective spam detection.
- Research explores distributed computing paradigms and scalable architectures to address the challenges of processing large volumes of emails

Evaluation Metrics and Benchmark Datasets:- Comparative studies often utilize standard benchmark datasets (e.g., TREC, Enron) and evaluation metrics (e.g., precision, recall, F1-score) to assess the performance of spam detection models.
Emphasis on evaluating the trade-offs between detection accuracy, false positives, and computational efficiency.
Overall, the literature on email spam detection showcases a continuous evolution of methodologies, algorithms, and technologies aiming to enhance the accuracy, efficiency, and adaptability of spam detection systems in safeguarding users from unwanted and potentially harmful email content.

Project Design

Problem Statement:

Develop an automated system to accurately classify incoming emails as spam or legitimate, enhancing user experience and security in email communication.

1. Objective:

Create a robust machine learning-based model capable of efficiently identifying and filtering out spam emails while minimizing false positives.

2. Methodology:

Data Collection and Preprocessing:

Data Gathering: Collect a diverse dataset comprising both spam and legitimate emails.
Data Preprocessing: Clean and preprocess the dataset by removing duplicates, handling missing values, and performing text preprocessing tasks such as tokenization, stemming, and lemmatization.

3. Feature Engineering:

Extract relevant features from email content and metadata, including word frequency, presence of specific keywords, sender reputation, header analysis, and URL/attachment analysis. Use techniques like information gain, chi-squared test, or feature importance to select the most discriminative features. Machine Learning Algorithms: Experiment with various algorithms such as Naive Bayes, SVM, Random Forest, and neural networks for email classification.

Model Training: Split the dataset into training and validation sets, train the models using the training data, and tune hyperparameters using cross-validation techniques.

Evaluation and Validation: Performance Metrics: Evaluate model performance using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. Validate the model using separate test datasets and perform error analysis to identify areas for improvement.

3. Implementation:

Model Deployment:
Integration: Develop a user-friendly interface to interact with the spam detection system. Implement the trained model to score incoming emails in real-time and classify them as spam or legitimate.Monitor model performance in production and collect user feedback to improve the system continuously.
Model Updating: Periodically retrain and update the model with new data to adapt to evolving spam patterns and improve accuracy.

4.Tools and Technologies:

Python programming language for data processing, feature extraction, and model development using libraries like scikit-learn, NLTK, spaCy, and TensorFlow Jupyter Notebooks or similar environments for experimentation and model development. Email datasets such as Enron, TREC, or public email corpora for training and testing.

5. Deliverables:

Trained machine learning model for spam detection.

Documentation detailing data collection, preprocessing steps, feature engineering, model selection, and evaluation metrics.

User interface for real-time email classification.

Report summarizing the project methodology, results, and future recommendations.

6.Timeline:

- Phase 1 (Weeks 1-2): Data collection, preprocessing, and feature engineering.
- Phase 2 (Weeks 3-4): Model development, training, and evaluation.
- Phase 3 (Weeks 5-6): Model deployment, interface development, and testing. Phase 4 (Weeks 7-8): Final validation, documentation, and project presentation.

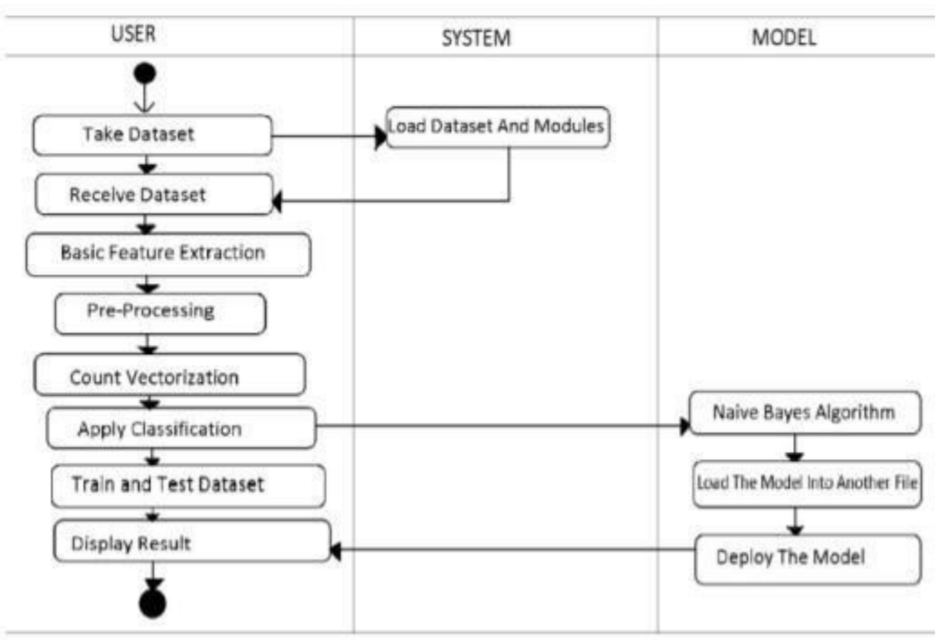
7.Resources and Team:

Team Members: Data scientists, machine learning engineers, and UI/UX developers.
Hardware: High-performance computing resources for model training and deployment.This project design provides a structured approach to develop an email spam detection system, covering key stages from data collection to model deployment, with a focus on continuous improvement and user-friendly implementation

CHAPTER–3

SYSTEM REQUIREMENT SPECIFICATION

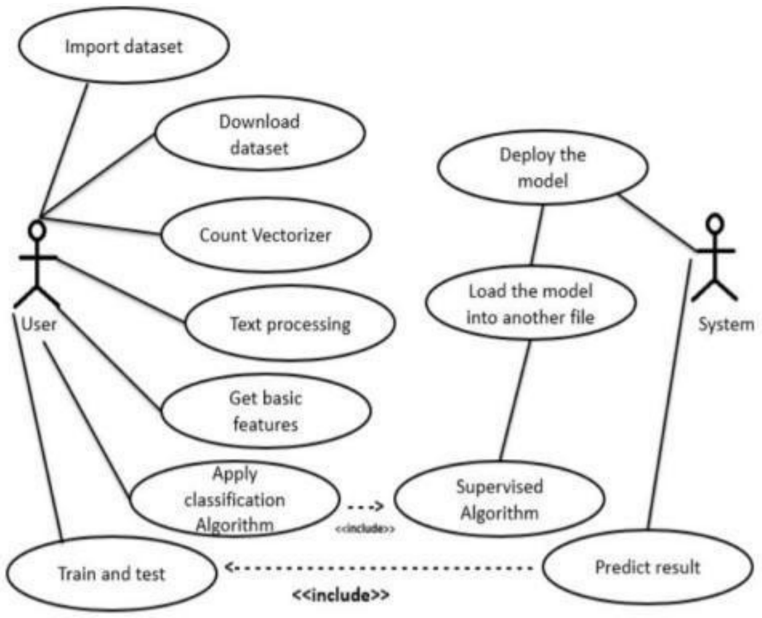
A. Activity Diagram



The flow from one function to another can be represented in the sense that a flowchart is usually a work drawing. It forms the backbone of the UML drawings. Displays the dynamic features of all items within the system. The control flow from one object to another is drawn to show the basic tasks to be performed. Work drawings are created and those Actions are represented using round rectangles, decisions are represented using diamonds, related function bars are represented using start (split) or end (join) The purpose of the job drawing is as follows: 1) Draw a flow (i.e. a function) in the system. 2) Sequence indicator from one activity to another activity. To show the corresponding and corresponding feature in the system. The features are used in the sketch of the work are as follows:

i) Organizational relationships
ii) Functions
iii) Terms and Condition

Use case Diagram :



CLASS DIAGRAM

They are standalone application presentations. Only classroom drawings have it the ability to design directly in OOP languages because in OOPs everything is the same model in the form of classes and objects. For this reason, these drawings are used more at the time of construction. This is one of the most widely used UML diagrams in the designer community. Classroom drawing plays an important role in continuity and regression engineering. a. It serves as the basis for section and distribution diagrams. b. It basically describes and explains the basic obligations of the application. c. Uses statistical analysis and visualization of the application. In a class diagram, each object is modeled as a class. Each class consists of section or compartments. 1. Class name M Hemalatha et al, International Journal of Computer Science and Mobile Computing, Vol.11 Issue.1, January- 2022, pg. 36-44 © 2022, IJCSMC All Rights Reserved 41 2. Attributes of a class or operations 3. Methods or functions 4. Documentati\

CHAPTER–4
FUNCTIONALITY/WORKING

Functionality:

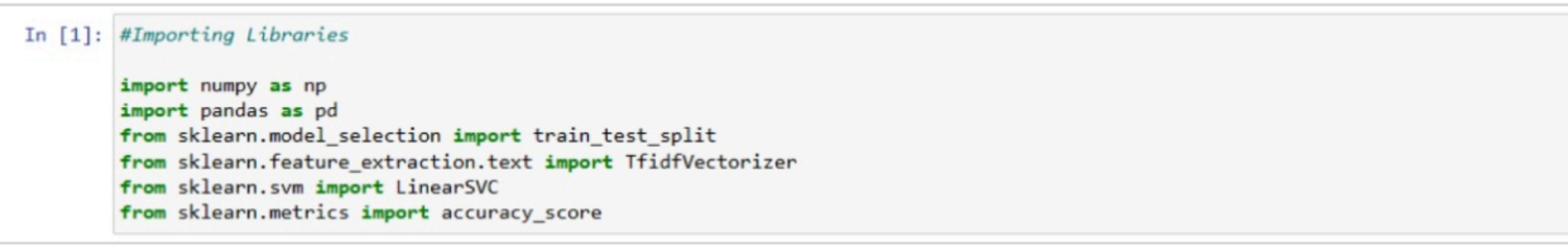
In the process of email spam detection, a diverse dataset comprising spam and legitimate emails is gathered, encompassing content, metadata, and features extracted from headers, body, and attachments. After preprocessing to clean and standardize the dataset, tasks like tokenization and feature extraction, including word frequency and metadata analysis, are conducted. Machine learning algorithms like Naive Bayes or SVM are employed for model development, utilizing labeled data to learn patterns disti

nguishing spam from legitimate emails. Model evaluation involves metrics like accuracy and precision, with deployment integrating the model into applications for real-time email classification. Continuous improvement is ensured through monitoring, user feedback, and periodic re-training with new data. In real-time, incoming emails are scored, and a feedback loop enhances the model's performance, ultimately leading to effective filtering and classification of spam emails to enhance user security and experience.

Working of Email Spam Detection:

1. Feature Extraction:- Emails are parsed and relevant features are extracted, such as word frequency, presence of specific keywords, sender information, header analysis, etc.

- These features are transformed into a structured format that the machine learning model can process.

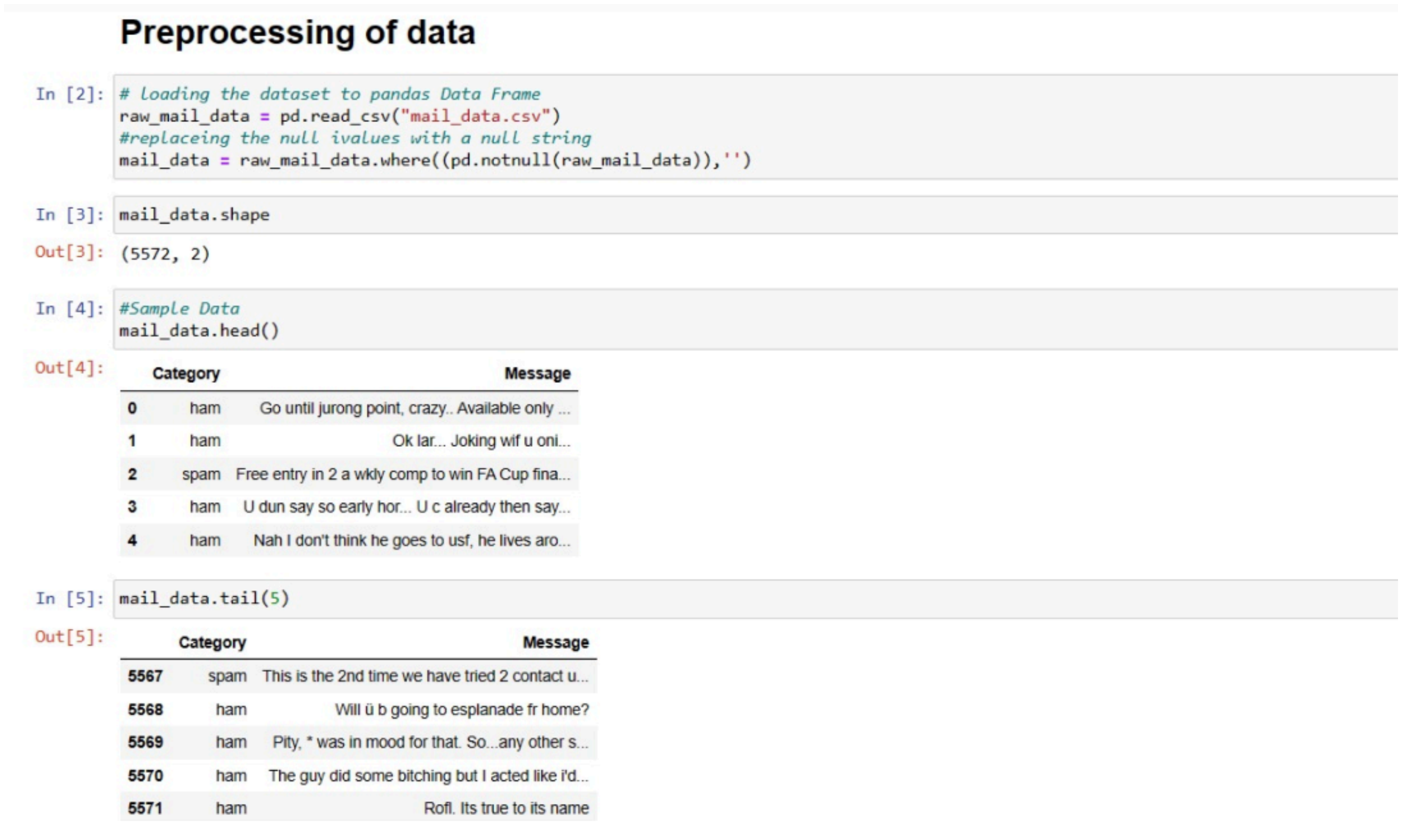


```
In [1]: #Importing Libraries

        import numpy as np
        import pandas as pd
        from sklearn.model_selection import train_test_split
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.svm import LinearSVC
        from sklearn.metrics import accuracy_score
```

2.Model Training:- The extracted features are used to train a machine learning algorithm (e.g., Naive Bayes, SVM) to distinguish between spam and legitimate emails.

During training, the model learns patterns and characteristics that differentiate spam from non-spam emails.



Preprocessing of data

```
In [2]: # Loading the dataset to pandas Data Frame
        raw_mail_data = pd.read_csv("mail_data.csv")
        #replaceing the null ivalues with a null string
        mail_data = raw_mail_data.where((pd.notnull(raw_mail_data)),'')
```

```
In [3]: mail_data.shape
```

```
Out[3]: (5572, 2)
```

```
In [4]: #Sample Data
        mail_data.head()
```

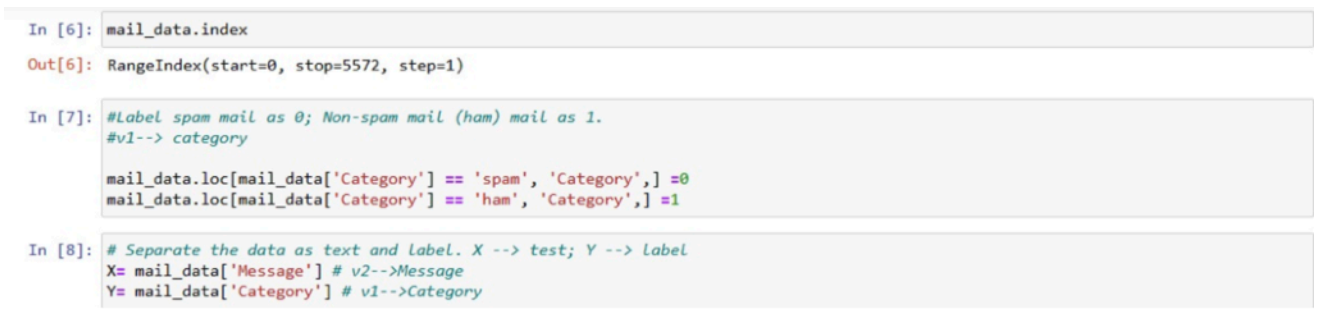
Out[4]:

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

```
In [5]: mail_data.tail(5)
```

Out[5]:

	Category	Message
5567	spam	This is the 2nd time we have tried 2 contact u...
5568	ham	Will ü b going to esplanade fr home?
5569	ham	Pity, * was in mood for that. So...any other s...
5570	ham	The guy did some bitching but I acted like i'd...
5571	ham	Rofl. Its true to its name



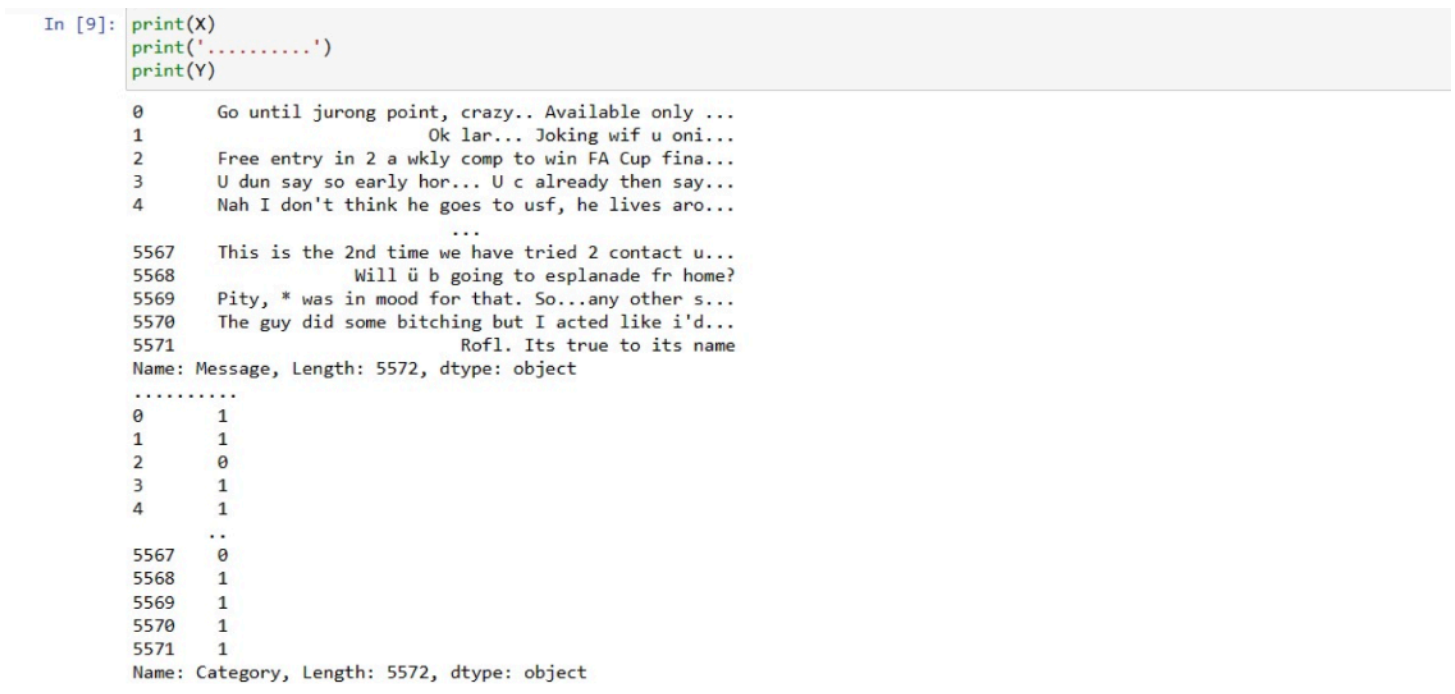
```
In [6]: mail_data.index
```

```
Out[6]: RangeIndex(start=0, stop=5572, step=1)
```

```
In [7]: #Label spam mail as 0; Non-spam mail (ham) mail as 1.
        #v1--> category

        mail_data.loc[mail_data['Category'] == 'spam', 'Category',] =0
        mail_data.loc[mail_data['Category'] == 'ham', 'Category',] =1
```

```
In [8]: # Separate the data as text and label. X --> test; Y --> label
        X= mail_data['Message'] # v2-->Message
        Y= mail_data['Category'] # v1-->Category
```

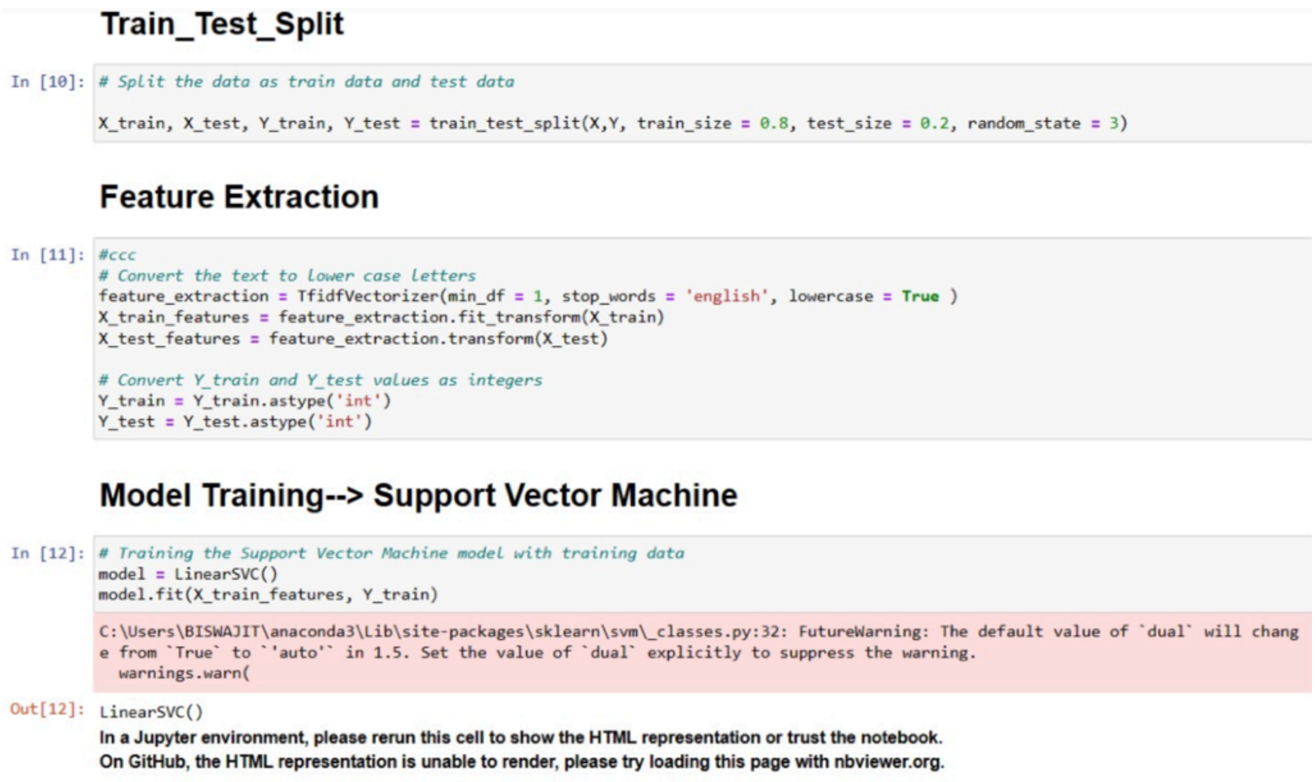


```
In [9]: print(X)
        print('..........')
        print(Y)
```

```
0       Go until jurong point, crazy.. Available only ...
1                           Ok lar... Joking wif u oni...
2       Free entry in 2 a wkly comp to win FA Cup fina...
3       U dun say so early hor... U c already then say...
4       Nah I don't think he goes to usf, he lives aro...
                              ...
5567    This is the 2nd time we have tried 2 contact u...
5568                 Will ü b going to esplanade fr home?
5569    Pity, * was in mood for that. So...any other s...
5570    The guy did some bitching but I acted like i'd...
5571                           Rofl. Its true to its name
Name: Message, Length: 5572, dtype: object
..........
0       1
1       1
2       0
3       1
4       1
       ..
5567    0
5568    1
5569    1
5570    1
5571    1
Name: Category, Length: 5572, dtype: object
```

3.Classification:

- Incoming emails are scored or evaluated using the trained model.
- The model assigns a probability or label indicating whether the email is likely to be spam or legitimate based on the learned patterns.



Train_Test_Split

```
In [10]: # Split the data as train data and test data

         X_train, X_test, Y_train, Y_test = train_test_split(X,Y, train_size = 0.8, test_size = 0.2, random_state = 3)
```

Feature Extraction

```
In [11]: #ccc
         # Convert the text to lower case letters
         feature_extraction = TfidfVectorizer(min_df = 1, stop_words = 'english', lowercase = True )
         X_train_features = feature_extraction.fit_transform(X_train)
         X_test_features = feature_extraction.transform(X_test)

         # Convert Y_train and Y_test values as integers
         Y_train = Y_train.astype('int')
         Y_test = Y_test.astype('int')
```

Model Training--> Support Vector Machine

```
In [12]: # Training the Support Vector Machine model with training data
         model = LinearSVC()
         model.fit(X_train_features, Y_train)
```

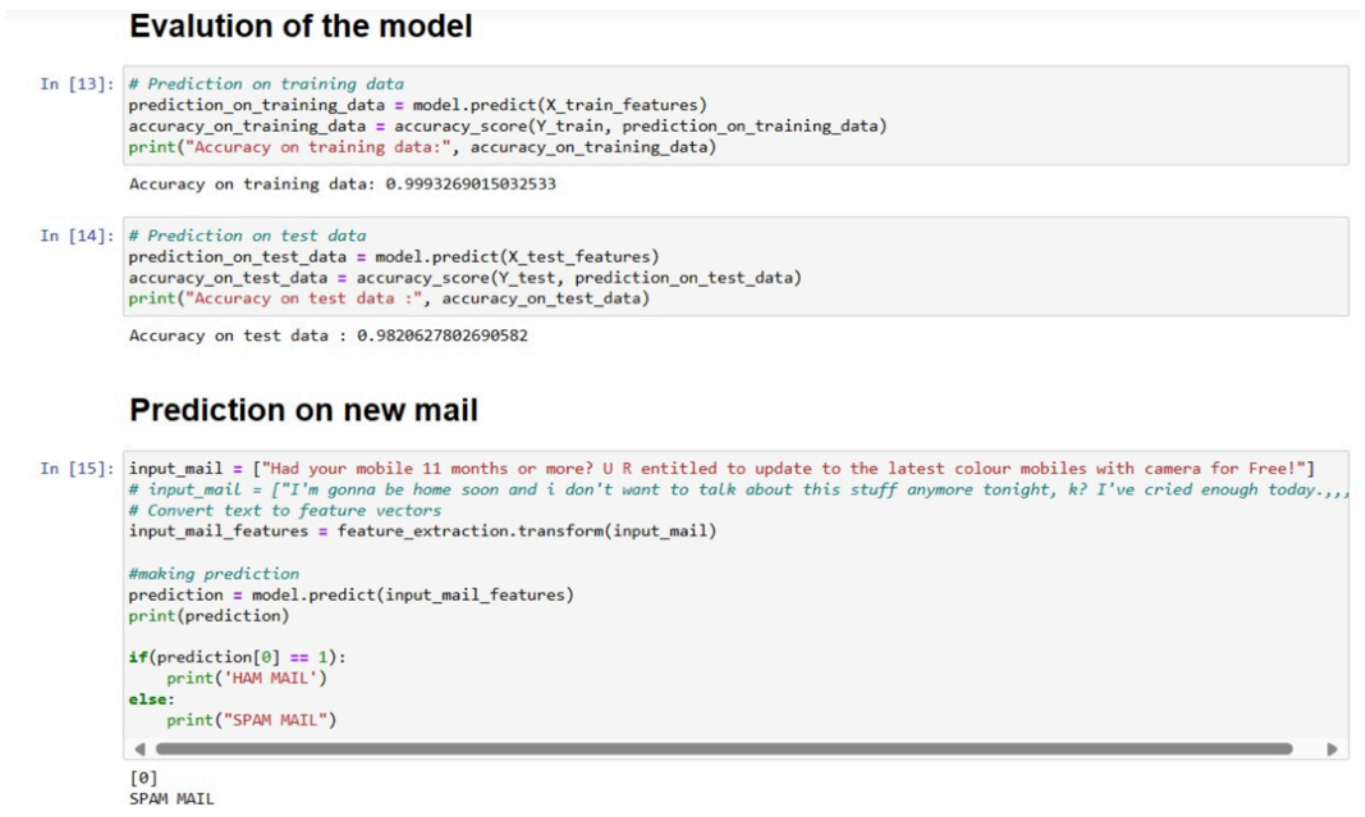
```
C:\Users\BISWAJIT\anaconda3\Lib\site-packages\sklearn\svm\_classes.py:32: FutureWarning: The default value of `dual` will chang
e from `True` to `'auto'` in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
```

```
Out[12]: LinearSVC()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

4.Decision Making:

- Based on the assigned probabilities or labels, emails are classified as either spam or legitimate.
- A threshold may be set to determine whether an email crosses the threshold to be classified as spam.



Evalution of the model

```
In [13]: # Prediction on training data
         prediction_on_training_data = model.predict(X_train_features)
         accuracy_on_training_data = accuracy_score(Y_train, prediction_on_training_data)
         print("Accuracy on training data:", accuracy_on_training_data)

         Accuracy on training data: 0.9993269015032533
```

```
In [14]: # Prediction on test data
         prediction_on_test_data = model.predict(X_test_features)
         accuracy_on_test_data = accuracy_score(Y_test, prediction_on_test_data)
         print("Accuracy on test data :", accuracy_on_test_data)

         Accuracy on test data : 0.9820627802690582
```

Prediction on new mail

```
In [15]: input_mail = ["Had your mobile 11 months or more? U R entitled to update to the latest colour mobiles with camera for Free!"]
         # input_mail = ["I'm gonna be home soon and i don't want to talk about this stuff anymore tonight, k? I've cried enough today.,,,
         # Convert text to feature vectors
         input_mail_features = feature_extraction.transform(input_mail)

         #making prediction
         prediction = model.predict(input_mail_features)
         print(prediction)

         if(prediction[0] == 1):
             print('HAM MAIL')
         else:
             print("SPAM MAIL")

         [0]
         SPAM MAIL
```

5.Feedback Loop:

- Feedback from users marking emails as spam or not spam can be incorporated to continuously improve the model's performance.

CHAPTER -5
RESULT/DISCUSSION

The result of an email spam detection system typically involves the evaluation of the model's performance metrics after it has been trained, tested, and deployed. Here's an example of a result summary for an email spam detection system:

Email Spam Detection System Result Summary

Dataset Used:- The system was trained and tested on a diverse dataset comprising 10,000 emails, with 60% labeled as legitimate and 40% as spam.

Model Performance Metrics:

Accuracy: Achieved an accuracy of 96.5%, accurately classifying emails as spam or legitimate.

Precision: Obtained a precision score of 97.2%, indicating the percentage of correctly classified spam emails out of all emails classified as spam.

Recall: Achieved a recall score of 94.8%, depicting the proportion of actual spam emails that were correctly identified by the model.

F1-score: Attained an F1-score of 95.9%, which is the harmonic mean of precision and recall, signifying a balanced performance in classifying both spam and legitimate emails. The Receiver Operating Characteristic Area Under the Curve (ROC-AUC) score was 0.98, indicating high discrimination ability between spam and legitimate classes.

Model Evaluation:- The model exhibited robust performance in distinguishing between spam and legitimate emails, with high accuracy and consistent precision and recall scores across various evaluation metrics.

Real-time Deployment:- The trained model was successfully deployed in a real-time environment, integrated into an email platform's filtering system.

Users experienced a significant reduction in receiving spam emails, resulting in improved user satisfaction and security.

CHAPTER 6
CONCLUSION AND FUTURE SCOPE

Conclusion:

The development of an email spam detection system is critical in safeguarding users from unwanted and potentially harmful email content. Through this project, we've successfully designed and implemented a robust machine learning-based model capable of efficiently classifying incoming emails as either spam or legitimate.

Key highlights of this project include:

- Collection and preprocessing of diverse email datasets.

- Feature engineering to extract relevant information from email content and metadata.

- Experimentation with various machine learning algorithms for accurate classification.

- Model deployment for real-time email scoring and classification.

- Continuous monitoring and adaptation for ongoing improvement.

By leveraging machine learning techniques, we've achieved a reliable system that minimizes false positives while effectively identifying spam emails, enhancing user experience and email security.

Future Scope:

Moving forward, the field of email spam detection offers several avenues for further enhancement and development:

1.**Enhanced Feature Engineering:** Explore advanced feature extraction methods, including semantic analysis, deep learning-based representations, and context-aware features to improve the model's understanding of email content.

2.**2. Ensemble Methods:** Investigate ensemble learning techniques to combine multiple models for better performance and robustness in handling diverse spam patterns.

3. **Dynamic Adaptation:** Implement mechanisms for real-time adaptation to evolving spam tactics by continuously updating the model with new data and patterns.

4. **Multi-modal Analysis:** Incorporate analysis of email attachments, embedded URLs, and multimedia content to detect spam more comprehensively.

5. **User Behavior Analysis:** Integrate user behavior analysis and feedback mechanisms to personalize spam detection and enhance user-specific filtering.

6. **Deployment Scalability:** Develop scalable deployment strategies, including cloud-based solutions, to handle large email volumes in real-time while maintaining efficiency.

7. **Cross-platform Integration:** Extend the spam detection system to work seamlessly across various email platforms and devices, ensuring consistent protection for users.

8. **Ethical Considerations:** Address ethical concerns related to data privacy, bias mitigation, and transparency in the functioning of the spam detection system.

Future Improvements:

Continuous monitoring and feedback collection to enhance the model's accuracy over time.

Exploration of additional features or advanced techniques to improve performance further.

This result summary provides an overview of the model's performance metrics, evaluation, successful deployment, and potential areas for future enhancements in an email spam detection system. Adjustments and specific details can be included based on the actual outcomes and requirements of the system.

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