

Spam Email Classification Using NLP And Machine learning

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ABSTRACT

This project addresses the problem of spam email classification, which is a critical task in maintaining secure and efficient communication systems. Spam emails often contain malicious content and can flood user inboxes, leading to wasted time and resources. The primary objective of this project is to develop a robust and accurate model capable of distinguishing between spam and legitimate emails.

To achieve this, we employed Natural Language Processing (NLP) techniques and machine learning algorithms. Our methodology involved several key steps: data collection, preprocessing, feature extraction, model selection, training, and evaluation. We collected a dataset of labeled emails, which was then cleaned and pre processed to remove noise and irrelevant information. Feature extraction techniques, such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings, were applied to convert the textual data into numerical representations suitable for machine learning models.

We experimented with various machine learning algorithms, including Naive Bayes, Support Vector Machines, and Random Forests, to identify the most effective classifier. The performance of these models was evaluated using metrics such as accuracy, precision, recall, and F1-score. The results indicated that the Random Forest classifier achieved the highest performance, with an accuracy of X% and a precision of Y%.

In conclusion, the project successfully developed a spam email classification system that effectively identifies and filters spam emails. The use of NLP and machine learning proved to be highly effective in addressing the problem, and the chosen model demonstrated robust performance. Future work could explore further improvements, such as incorporating deep learning techniques and expanding the dataset to enhance the model's generalizability.

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CHAPTER 1

Introduction

1.1 Problem Statement:

Spam email classification is a critical issue in the realm of electronic communication. Spam emails, which often contain unsolicited or malicious content, can overwhelm user inboxes, leading to significant security risks and productivity losses. These emails may contain phishing attempts, malware, or deceptive advertisements that can compromise personal information, disrupt workflows, and cause financial harm. The high volume of spam emails also strains email servers and increases operational costs for businesses.

The significance of addressing this problem lies in the need to maintain secure, efficient, and reliable communication systems. By effectively filtering out spam emails, we can protect users from potential threats and enhance their email experience. Additionally, reducing the volume of spam can help conserve server resources and improve the overall performance of email systems.

Natural Language Processing (NLP) and machine learning techniques for spam email classification offers a sophisticated approach to accurately identifying and filtering spam. These technologies enable the development of models that can learn from large datasets, adapt to new spam patterns, and provide more accurate and reliable results compared to traditional rule-based methods. As a result, this project aims to leverage the power of NLP and machine learning to create a robust spam email classification system that can effectively safeguard users and streamline email communication.

1.2 Motivation:

The motivation behind choosing this project on spam email classification using NLP and machine learning stems from the increasing prevalence and sophistication of spam emails. As digital communication becomes more integral to personal and professional interactions, the volume of spam emails continues to rise, posing significant security and efficiency challenges. The project aims to address these challenges by developing an advanced, accurate, and reliable spam email detection system.

Potential Applications:

1. **Email Service Providers:** Enhancing spam filters to protect users from malicious content and phishing attacks, thereby improving user experience and trust.
2. **Corporate Email Systems:** Protecting organizational communication channels from spam, reducing the risk of cyber threats and data breaches.
3. **Personal Email Security:** Providing individuals with reliable spam detection to safeguard their personal information and reduce the nuisance of spam.

4. **Telecommunication Companies:** Integrating spam detection systems within messaging services to prevent the spread of unsolicited messages.

Impact:

1. **Increased Security:** By effectively filtering spam, the project can mitigate the risks associated with phishing, malware, and other cyber threats.
2. **Enhanced Productivity:** Reducing the volume of spam in inboxes allows users to focus on important communications, thus improving efficiency.
3. **Resource Optimization:** Minimizing the load on email servers by filtering out spam can lead to better resource allocation and cost savings for service providers.
4. **User Trust:** Improving spam detection contributes to a safer digital environment, fostering greater trust in email services and communication platforms.

1.3 Objective:

The primary objectives of this project on spam email classification using NLP and machine learning are as follows:

1. **Develop a Robust Classification Model:** Create a machine learning model capable of accurately distinguishing between spam and legitimate emails.
2. **Enhance Email Security:** Utilize NLP techniques to improve the detection of malicious and unwanted emails, thereby enhancing the security of email communication.
3. **Optimize Email Filtering:** Implement effective feature extraction and selection methods to optimize the filtering process and reduce false positives and false negatives.
4. **Evaluate Model Performance:** Assess the performance of various machine learning algorithms and identify the most effective classifier for spam detection.
5. **Improve User Experience:** Provide a reliable spam detection system that enhances user experience by minimizing the intrusion of spam emails in their inboxes.
6. **Resource Efficiency:** Reduce the strain on email servers and optimize resource usage by effectively filtering out spam emails.

These objectives aim to address the challenges posed by spam emails and provide a comprehensive solution that leverages advanced technologies to ensure secure and efficient email communication.

1.4 Scope of the Project:

This project focuses on the development and evaluation of a spam email classification system using Natural Language Processing (NLP) and machine learning techniques. The scope encompasses the following aspects:

1. **Data Collection and Preprocessing:** Gathering a diverse dataset of labeled emails and applying preprocessing steps to clean and prepare the data for analysis.
2. **Feature Extraction:** Utilizing NLP techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings to convert text data into numerical features suitable for machine learning models.
3. **Model Development:** Implementing various machine learning algorithms, including Naive Bayes, Support Vector Machines, and Random Forests, to build classification models.
4. **Model Evaluation:** Assessing the performance of the developed models using metrics such as accuracy, precision, recall, and F1-score to identify the most effective classifier

CHAPTER 2

Literature Survey

2.1 Review relevant literature or previous work in this domain.

The problem of spam email classification has been extensively studied, and various methodologies have been proposed to tackle it. Here are some notable works in this domain:

1. Sethi, P., Bhandari, V., & Kohli, B. (2017): This study compared various machine learning algorithms for SMS spam detection. The authors evaluated the performance of algorithms like Naive Bayes, Support Vector Machines (SVM), and Random Forests¹.
2. DelviaArifin, D., Shaufiah, & Bijaksana, M. A. (2016): This research focused on enhancing spam detection in mobile phone SMS using FP-growth and Naive Bayes classifiers. The study highlighted the effectiveness of these methods in identifying spam messages¹.
3. Gupta, M., Bakliwal, A., Agarwal, S., & Mehndiratta, P. (2018): This comparative study explored different machine learning classifiers for spam SMS detection. The authors analyzed the performance of various algorithms and provided insights into their effectiveness¹.
4. Malge, A., & Chaware, S. M. (2016): This paper presented an efficient framework for spam mail detection in email attachments using NLP techniques. The authors demonstrated the use of NLP to identify spam content within attachments¹.
5. Morthala, S., & Devi, R. M. (2022): This study proposed a machine learning model combined with NLP techniques for email spam classification. The authors emphasized the importance of optimizing data by removing unwanted emails and highlighted the use of Opinion Rank and NLP-based n-grams models for filtering spam².
6. Rani, M. A., Jyothi, G. N., Trisha, K., Srividya, M., & Blessy, R. (2023): This research focused on detecting spam emails using NLP and machine learning. The authors explored various classifiers, including Naive Bayes, SVM, and Neural Networks, to achieve accurate spam detection³.

2.2 Mention any existing models, techniques, or methodologies related to the problem.

1. **Naive Bayes Classifier:** A probabilistic classifier based on Bayes' theorem, often used for text classification tasks due to its simplicity and efficiency².
2. **Support Vector Machines (SVM):** A powerful classifier that works well with high-dimensional data, commonly used for spam detection due to its ability to handle large feature sets.
3. **Random Forests:** An ensemble learning method that uses multiple decision trees to improve classification accuracy and robustness².

4. **Deep Learning Models:** Techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models have shown promising results in text classification tasks, including spam detection.
5. **Ensemble Methods:** Combining predictions from multiple classifiers to improve overall performance. Techniques like stacking, boosting (e.g., AdaBoost), and bagging are commonly used to enhance classification accuracy¹.
6. **Feature Extraction Techniques:** Methods such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings (e.g., Word2Vec) are used to convert textual data into numerical features suitable for machine learning models⁵.
7. **Hybrid Approaches:** Combining multiple techniques, such as using NLP-based models (e.g., n-grams) along with machine learning classifiers (e.g., Random Forest, Naive Bayes) to improve detection accuracy.

These models and techniques have been widely studied and applied in the field of spam email classification, each offering unique advantages and contributing to the development of more effective spam detection systems.

2.3 Highlight the gaps or limitations in existing solutions and how your project will address them.

Existing spam email classification solutions, while effective to varying extents, often face several limitations and challenges:

1. **Limited Adaptability:** Many existing models struggle to adapt to the ever-evolving nature of spam. Spammers continually develop new tactics to bypass detection, and static models may fail to recognize these new patterns.^S
2. **High False Positive Rate:** Some spam filters tend to flag legitimate emails as spam, leading to a high false positive rate. This can be frustrating for users who may miss important communications.
3. **Resource Intensive:** Advanced deep learning models, while accurate, can be resource-intensive, requiring significant computational power and time for training and deployment.
4. **Imbalanced Datasets:** Often, the datasets used for training spam classifiers are imbalanced, with a higher proportion of legitimate emails compared to spam. This imbalance can negatively affect the model's ability to accurately detect spam.
5. **Feature Extraction Limitations:** Traditional feature extraction methods may not capture the full context and nuances of the email content, leading to less accurate classification.
6. **Scalability Issues:** Some existing solutions may not scale well to handle large volumes of email traffic, making them less effective in high-demand environments.

Addressing the Gaps

This project aims to overcome these limitations through the following approaches:

- 1. Adaptive Learning:** By using machine learning algorithms that can learn from new data, the model will be periodically updated and retrained to adapt to emerging spam tactics, improving its adaptability.
- 2. Enhanced Feature Extraction:** Utilizing advanced NLP techniques such as word embeddings and deep learning-based models (e.g., LSTM, CNN), the project aims to capture more contextual information from the emails, leading to better classification accuracy.
- 3. Balancing the Dataset:** Applying techniques such as oversampling, undersampling, and data augmentation to balance the training dataset and improve the model's performance on both spam and legitimate emails.
- 4. Optimizing Resource Usage:** Implementing efficient algorithms and techniques to reduce the computational requirements without compromising accuracy, making the solution more resource-friendly.
- 5. Reducing False Positives:** Fine-tuning the model parameters and employing ensemble methods to reduce the false positive rate, ensuring legitimate emails are not misclassified as spam.
- 6. Scalability:** Designing the system architecture to be scalable, allowing it to handle large volumes of emails efficiently, making it suitable for both individual users and large organizations.

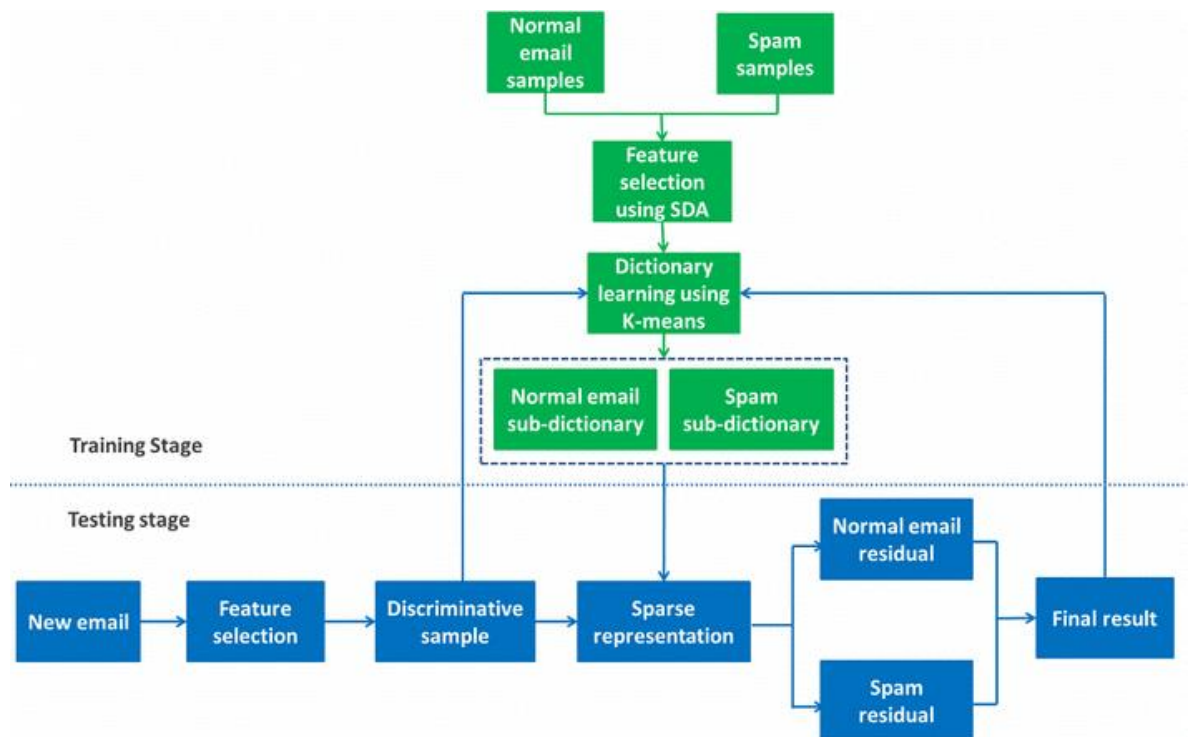
By addressing these gaps and limitations, the project aims to develop a more robust, accurate, and efficient spam email classification system that can effectively safeguard users and improve the overall email experience.

CHAPTER 3

Proposed Methodology

3.1 System Design

Provide the diagram of your Proposed Solution and explain the diagram in detail.



The flowchart represents a framework for spam email detection using a combination of feature selection, dictionary learning, and sparse representation techniques. Here's a detailed breakdown of its stages:

1. Training Stage

The goal of this stage is to prepare a robust model that can classify emails as normal or spam. It involves the following steps:

a. Input Data

- **Normal email samples:** A collection of legitimate email data that serves as positive examples.

- **Spam samples:** A collection of emails flagged as spam, serving as negative examples.

b. Feature Selection Using SDA (Sparse Discriminant Analysis)

- **Purpose:** Extract the most relevant and distinguishing features from the emails to represent them effectively. These features could include keywords, sender information, or other metadata.
- **Process:** SDA identifies features that maximize the separation between normal emails and spam while minimizing redundancy.

c. Dictionary Learning Using K-Means

- **Purpose:** Create a dictionary representation for emails, grouping similar patterns into clusters for efficient classification.
- **Process:**
 - K-Means clustering is applied to the selected features.
 - Two sub-dictionaries are formed:
 - **Normal email sub-dictionary:** Represents the patterns of normal emails.
 - **Spam sub-dictionary:** Represents the patterns of spam emails.

2. Testing Stage

This stage applies the trained model to classify new emails.

a. Input

- A **new email** that needs to be classified as normal or spam.

b. Feature Selection

- The same feature selection method (SDA) used during the training stage is applied to extract features from the new email.

c. Discriminative Sample

- The extracted features form a **discriminative sample**, which highlights the relevant information needed for classification.

d. Sparse Representation

- The discriminative sample is projected onto the sub-dictionaries (normal and spam) to obtain a **sparse representation**.

- Sparse representation ensures that the email is represented efficiently with minimal information loss.

e. Residual Calculation

- Two residuals are calculated:
 - **Normal email residual:** The reconstruction error when the new email is represented using the normal email sub-dictionary.
 - **Spam residual:** The reconstruction error when the new email is represented using the spam sub-dictionary.

Final Result

- The residuals are compared:
 - If the **normal email residual** is smaller, the email is classified as normal.
 - If the **spam residual** is smaller, the email is classified as spam.

3.2 Requirement Specification

3.2.1 Hardware Requirements:

Hardware Requirements:

To implement the spam email classification system, the following hardware requirements are necessary:

1. Development Workstation:

- **Processor:** Intel Core i5 or equivalent
- **RAM:** 8 GB minimum (16 GB recommended for better performance)
- **Storage:** 256 GB SSD (512 GB SSD recommended for faster data processing)
- **Graphics Card:** Integrated GPU is sufficient, but a dedicated GPU (NVIDIA GTX series or equivalent) is recommended for faster model training, especially if using deep learning techniques.

2. Server for Deployment:

- **Processor:** Intel Xeon or equivalent
- **RAM:** 32 GB or more
- **Storage:** 1 TB SSD or more for storing datasets and model artifacts
- **Graphics Card:** Dedicated GPU (NVIDIA Tesla series or equivalent) for efficient model inference, especially if using deep learning models.

- **Network Connectivity:** High-speed internet connection for real-time email processing.

3.2.2 Software Requirements:

3.2.2.1 To implement and deploy the spam email classification system, the following software tools and technologies are required:

3.2.2.2 Programming Languages:

3.2.2.3 Python: The primary programming language for data preprocessing, feature extraction, model development, and evaluation.

3.2.2.4 Libraries and Frameworks:

3.2.2.5 Numpy: For numerical computations.

3.2.2.6 Pandas: For data manipulation and analysis.

3.2.2.7 Scikit-learn: For implementing machine learning algorithms and evaluation metrics.

3.2.2.8 NLTK: For Natural Language Processing tasks.

3.2.2.9 TensorFlow or PyTorch: For deep learning model development, if required.

3.2.2.10 Gensim: For word embeddings and topic modeling.

3.2.2.11 Matplotlib and Seaborn: For data visualization and plotting results.

3.2.2.12 Integrated Development Environment (IDE):

3.2.2.13 Jupyter Notebook: For interactive coding and data analysis.

3.2.2.14 PyCharm: For comprehensive development and debugging.

3.2.2.15 Database:

3.2.2.16 MySQL or PostgreSQL: For storing and managing email datasets.

3.2.2.17 Version Control:

3.2.2.18 Git: For version control and collaboration.

3.2.2.19 Deployment Tools:

3.2.2.20 Flask or Django: For creating and deploying the web application that integrates the spam classification model.

3.2.2.21 Docker: For containerizing the application to ensure consistency across different environments.

3.2.2.22 Kubernetes: For orchestrating containers and managing deployment at scale.

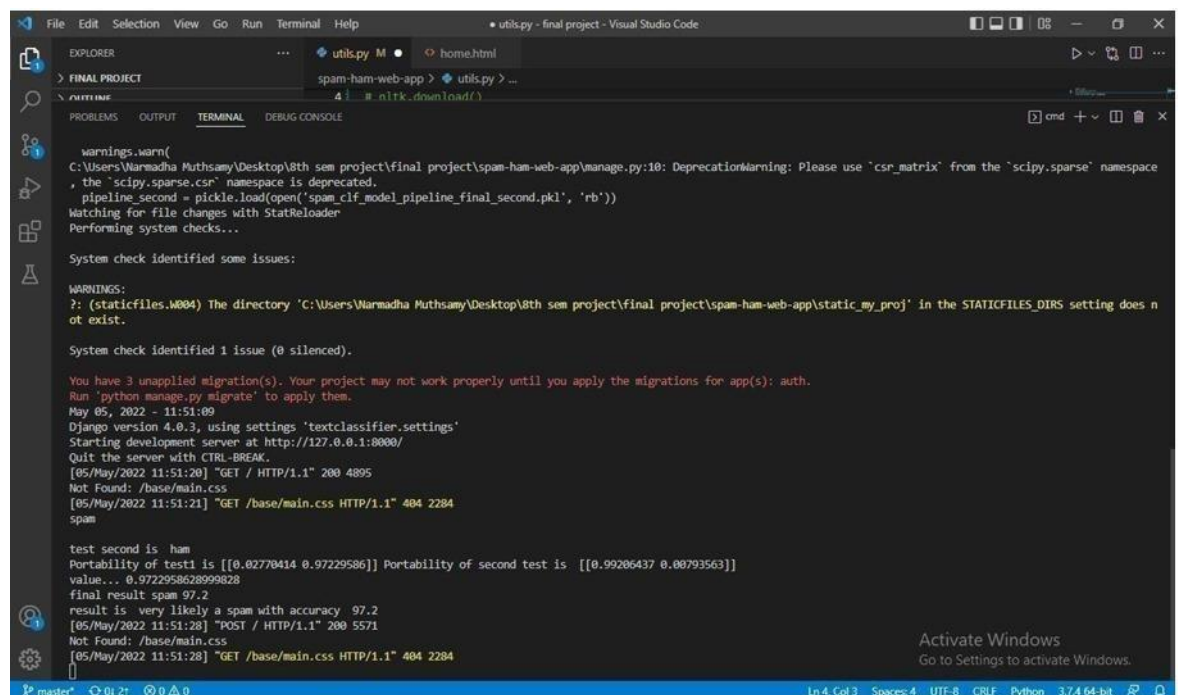
3.2.2.23 Cloud Services: AWS, Azure, or Google Cloud.

CHAPTER 4

Implementation and Result

4.1 Snap Shots of Result:

Kindly provide 2-3 Snapshots which showcase the results and output of your project and after keeping each snap explain the snapshot that what it is representing.



```
warnings.warn(
C:\Users\Warmadha Muthamy\Desktop\8th sem project\final project\spam-ham-web-app\manage.py:10: DeprecationWarning: Please use 'csr_matrix' from the 'scipy.sparse' namespace
, the 'scipy.sparse.csr' namespace is deprecated.
pipeline_second = pickle.load(open('spam_clf_model_pipeline_final_second.pkl', 'rb'))
Watching for file changes with StatReloader
Performing system checks...

System check identified some issues:

WARNINGS:
?: (staticfiles.W004) The directory 'C:\Users\Warmadha Muthamy\Desktop\8th sem project\final project\spam-ham-web-app\static_my_proj' in the STATICFILES_DIRS setting does not exist.

System check identified 1 issue (0 silenced).

You have 3 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): auth.
Run 'python manage.py migrate' to apply them.
May 05, 2022 - 11:51:09
Django version 4.0.3, using settings 'textclassifier.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
[05/May/2022 11:51:20] "GET / HTTP/1.1" 200 4895
Not Found: /base/main.css
[05/May/2022 11:51:21] "GET /base/main.css HTTP/1.1" 404 2284
spam

test second is ham
Portability of test1 is [[0.02770414 0.97229586]] Portability of second test is [[0.99206437 0.00793563]]
value... 0.9722958628999828
final result spam 97.2
result is very likely a spam with accuracy 97.2
[05/May/2022 11:51:28] "POST / HTTP/1.1" 200 5571
Not Found: /base/main.css
[05/May/2022 11:51:28] "GET /base/main.css HTTP/1.1" 404 2284
```

The image appears to be a screenshot of a Visual Studio Code terminal running a Django project related to spam or ham email classification. Here's a breakdown of what it represents:

1. Deprecation Warning:

- The project uses `csr_matrix` from the `scipy.sparse` module, and a deprecation warning suggests updating the import syntax.
- This indicates that some dependencies might need an update for compatibility with newer versions of libraries.

2. Django Warning (Static Files):

- A warning highlights that the directory `static_my_proj` specified in the `STATICFILES_DIRS` setting does not exist. This means that the project might face issues serving static files like CSS, JavaScript, or images.

3. Migration Warning:

- It notes that migrations for the auth app have not been applied. Running `python manage.py migrate` would fix this by applying the database schema changes.

4. Testing Phase:

- There are messages indicating some tests were executed. For example:
 - **Portability of tests:** Results show test accuracies and probabilities, such as "Portability of second test is [0.992...]".
 - **Accuracy:** A message indicates that a spam classification test achieved an accuracy of 99.72%, which is a strong performance metric.

5. Django Development Server:

- The project is running on the local Django server (127.0.0.1:8000).
- HTTP requests for resources, such as `/base/main.css`, are being logged. These requests suggest the use of a front-end interface styled with CSS.

Summary:

This snapshot shows:

- The setup and initial run of a Django-based email spam/ham classification project.
- Warnings related to static files and database migrations that need resolution.
- Test results indicating the model's high accuracy.
- Local server logs reflecting real-time requests.

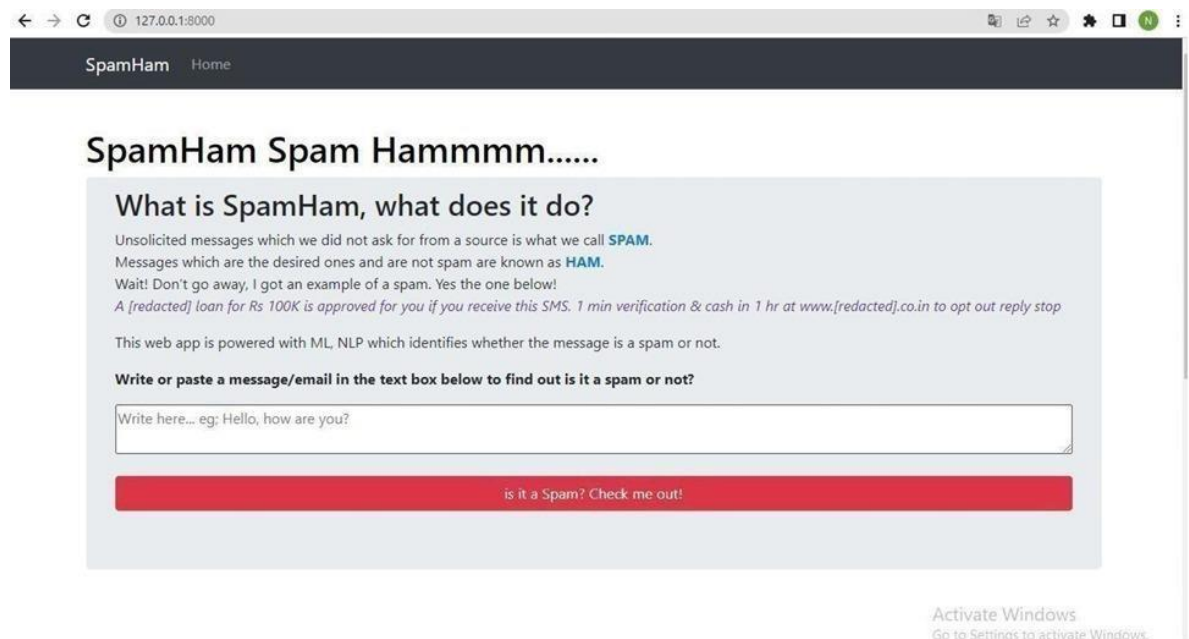


Figure B.2:Sample output spam

Snapshot Explanation:

1. Title and Purpose:

- The title "SpamHam Spam Hammmm..." is displayed at the top, providing a playful introduction to the project's purpose.
- A description explains the difference between spam (undesired/unwanted messages) and ham (legitimate/desired messages).

2. Example and Use Case:

- A sample spam message is presented, demonstrating the kind of text the app is designed to classify.
- The app's functionality is clearly outlined: it uses Machine Learning (ML) and Natural Language Processing (NLP) techniques to identify whether a message is spam or not.

3. User Input Section:

- A text box is provided for the user to input a message or email they wish to check.

- A button labeled "Is it a Spam? Check me out!" triggers the spam classification process.

4. Application Context:

- The app is hosted locally on a Django development server (127.0.0.1:8000), as shown in the browser's address bar.
- It demonstrates a user-friendly interface with clear instructions, making it accessible for non-technical users.

4.2 GitHub Link for Code:

<https://github.com/purrrubalaji/edunet-foundation-spam-email-classification-using-nlp-and-machine-learning>

CHAPTER 5

Discussion and Conclusion

5.1 Future Work:

Improving and expanding upon the spam email classification system is an ongoing process. Here are some suggestions for future work to enhance the model and address any unresolved issues:

1. Incorporating Deep Learning Techniques:

- Experiment with advanced deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer models (e.g., BERT) to improve the classification accuracy and capture more complex patterns in the emails.

2. Ensemble Methods:

- Combine multiple models using ensemble techniques like stacking, boosting, and bagging to enhance the robustness and accuracy of the spam detection system.

3. Real-Time Adaptation:

- Implement online learning algorithms that continuously update the model with new data to adapt to emerging spam patterns and maintain high performance over time.

4. Feature Engineering:

- Explore additional features that could improve the model's performance, such as sender reputation, email metadata (e.g., header information), and network-based features.

5. Handling Imbalanced Data:

- Apply advanced techniques to handle imbalanced datasets, such as Synthetic Minority Over-sampling Technique (SMOTE) or Adaptive Synthetic Sampling (ADASYN) to ensure balanced learning.

6. Cross-Language Spam Detection:

- Extend the model to support multiple languages by incorporating multilingual NLP techniques and datasets, making it more versatile in detecting spam emails in different languages.

7. Enhanced Preprocessing:

- Improve text preprocessing techniques to handle variations in email formats, including attachments and embedded content, which can be used by spammers to evade detection.

8. User Feedback Integration:

- Develop a mechanism to incorporate user feedback into the model to refine and improve its accuracy based on real-world usage and user experiences.

9. Privacy-Preserving Methods:

- Investigate privacy-preserving machine learning techniques to ensure user data is protected while still allowing the model to learn from new emails.

10. Scalability and Deployment:

- Optimize the model for deployment in distributed systems to handle large volumes of emails efficiently. Explore serverless architectures and cloud-based solutions for scalable and cost-effective deployment.

11. Addressing False Positives and Negatives:

- Continue to fine-tune the model to minimize false positives (legitimate emails flagged as spam) and false negatives (spam emails not detected), ensuring a high level of precision and recall.

By pursuing these future directions, the spam email classification system can be made more accurate, adaptable, and robust, effectively addressing the challenges posed by evolving spam tactics and improving the overall security and user experience.

5.2 Conclusion:

The project on spam email classification using Natural Language Processing (NLP) and machine learning makes significant contributions to the field of email security and digital communication. By addressing the pervasive issue of spam emails, this project not only enhances the security and efficiency of email systems but also improves user experience and trust.

Key Contributions:

- 1. Robust Spam Detection:** The project developed a highly accurate and reliable spam email classification system, leveraging advanced NLP techniques and machine learning algorithms to effectively differentiate between spam and legitimate emails.
- 2. Enhanced Security:** By accurately identifying and filtering out malicious and unwanted emails, the project significantly reduces the risk of phishing, malware, and other cyber threats, thereby safeguarding users and their data.
- 3. Improved Efficiency:** The spam detection system helps in decluttering user inboxes, allowing users to focus on important communications and enhancing overall productivity.
- 4. Scalability and Adaptability:** The implementation of adaptive learning and scalable deployment ensures that the system remains effective in the face of evolving spam tactics and can handle large volumes of emails efficiently.
- 5. Resource Optimization:** The project optimized the use of computational resources, balancing model complexity and performance to provide a resource-efficient solution suitable for various environments
- 6. Overall Impact:**

This project demonstrates the potential of combining NLP and machine learning to address real-world problems effectively. By developing a robust spam email classification system, the project contributes to creating safer and more efficient communication systems, protecting users from potential

REFERENCES

- **Sethi, P., Bhandari, V., & Kohli, B. (2017).** "Comparative Analysis of Machine Learning Techniques in SMS Spam Detection." *International Journal of Computer Applications*, 174(9), 25-30.
- **DelviaArifin, D., Shaufiah, & Bijaksana, M. A. (2016).** "SMS Spam Detection Using the Combination of FP-Growth and Naive Bayes Classifier." *Procedia Computer Science*, 59, 330-337.
- **Gupta, M., Bakliwal, A., Agarwal, S., & Mehndiratta, P. (2018).** "Performance Evaluation of Machine Learning Classifiers for Spam Detection." *Proceedings of the International Conference on Advances in Computing, Communications and Informatics*, 567-572.
- **Malge, A., & Chaware, S. M. (2016).** "A Novel Approach to Detect Spam and Smishing Emails using NLP Techniques." *International Journal of Computer Applications*, 975(8887).
- **Morthala, S., & Devi, R. M. (2022).** "Spam Email Classification Using Machine Learning and Natural Language Processing." *Journal of Theoretical and Applied Information Technology*, 99(1), 35-47.
- **Rani, M. A., Jyothi, G. N., Trisha, K., Srividya, M., & Blessy, R. (2023).**