



## Email Spam Detection Using Machine Learning

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### Abstract

Email spam classification is a critical task in today's digital world, where the amount of spam emails has increased dramatically. In this project, we propose to use machine learning (ML) and natural language processing (NLP) techniques to classify email messages as either spam or legitimate. The project aims to develop an efficient spam classifier that can accurately identify and filter spam emails from legitimate ones. The dataset used in this project will consist of a large number of email messages with their corresponding labels (spam/ham). We will use NLP techniques such as tokenization, stop word removal, stemming, and feature extraction to preprocess the text data and extract relevant features. We will evaluate several ML algorithms such as Naive Bayes, Support Vector Machines (SVMs), and Random Forests to determine the best model for spam classification. We will also perform hyper parameter tuning to optimize the model's performance. The accuracy of the classifier will be measured using evaluation metrics such as precision, recall, and F1-score. The project's outcomes will include a spam classifier model that can be integrated into an email system to automatically filter spam emails, improving email security and productivity. Additionally, the project will contribute to the advancement of NLP and ML techniques for email spam classification.

**Keywords-** Ham/spam, Natural Language Processing, Machine Learning, Online Platform, Email.

### INTRODUCTION

Email spam has become a significant problem in today's digital age, posing challenges for individuals, businesses, and organizations alike. Spam emails are unsolicited messages that flood inboxes, wasting valuable time and resources while potentially exposing users to malicious content or scams. To combat this issue, machine learning techniques have emerged as powerful tools for email spam detection.

The objective of email spam detection is to accurately classify incoming emails as either legitimate (ham) or spam. Traditional rule-based approaches have limited effectiveness due to the constantly evolving nature of spam. Machine learning offers a more dynamic and adaptable approach by leveraging patterns and features extracted from large email datasets.

Machine learning algorithms can learn from labeled email datasets to build models capable of recognizing patterns indicative of spam. These models can then be used to automatically classify new, unseen emails. By analyzing various email attributes such as sender information, subject line, content, and embedded URLs, machine learning algorithms can identify spam characteristics and make accurate predictions.

There are several machine learning techniques commonly employed for email spam detection. These include Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, and Neural Networks. These algorithms can be trained on labeled datasets, allowing them to learn the underlying patterns and relationships between spam and non-spam emails. The success of email spam detection using machine learning heavily relies on the quality and diversity of the training data. A comprehensive dataset that covers a wide range of spam types and legitimate emails is essential for training robust models. Additionally, feature engineering plays a crucial role in identifying relevant attributes and extracting meaningful information from email data. The benefits of using machine learning for email spam detection are

numerous. It enables efficient filtering and separation of legitimate emails from spam, reducing the time and effort spent by users in manually sorting through their inbox. Moreover, machine learning models can adapt to evolving spam techniques, continuously improving their accuracy over time.

In this email spam detection approach, machine learning not only enhances email security but also contributes to overall productivity and user experience. By accurately identifying and filtering spam, individuals and organizations can focus on important emails and mitigate potential risks associated with malicious content. In conclusion, email spam detection using machine learning offers a promising solution to the pervasive problem of unwanted and harmful emails. By leveraging pattern recognition and predictive models, machine learning algorithms can effectively distinguish spam from legitimate emails, enhancing email security and user experience. The continuous evolution and improvement of machine learning techniques ensure that email spam detection remains a dynamic and efficient defense against the ever-growing threat of spam.

In today's digital age, email is one of the most widely used communication mediums, and spam emails have become a significant problem for both individuals and organizations. Email spam filters are essential in managing and prioritizing emails in our inboxes. Machine learning (ML) and natural language processing (NLP) techniques can be used to develop effective email spam classifiers that can automatically identify and filter spam emails. In this project, we aim to develop an ML and NLP-based email spam classification system to accurately classify emails as spam or non-spam. The system's performance will be evaluated based on various metrics such as accuracy, precision, recall, and F1 score. The development of an accurate and efficient email spam classification system has potential to significantly improve email management and reduce the risk of fraudulent activities.

Email is one of the most popular communication methods, but unfortunately, it is also a common target for spam messages. Spam emails not only waste time but can also contain malicious links or attachments that can harm computer systems. As the volume of emails continues to grow, it has become challenging to identify and classify spam emails manually. Therefore, the development of machine learning (ML) and natural language processing (NLP) techniques has opened up new avenues for automated email spam classification. In this project, we aim to use ML and NLP techniques to classify emails as spam or legitimate, based on their content and other relevant features. The project involves building a model to analyze the text of emails and determine whether they are spam or legitimate. This study has the potential to provide a valuable solution to the problem of email spam and help users to manage their emails more effectively.

## LITERATURE SURVEY

- Almeida, T. A., Gómez, H. F., & Yamakami, A. (2010). Contributions to the study of SMS spam filtering: New collection and results. *Journal of Machine Learning Research*, 11, 3611-3628.

This study focuses on SMS spam filtering but provides insights into feature selection and classification algorithms applicable to email spam detection using machine learning.

- Carreras, X., & Marquez, L. (2001). Boosting trees for anti-spam email filtering. In *Proceedings of the Conference on Recent Advances in Natural Language Processing* (pp. 9-15).

The authors propose a boosting-based approach for email spam filtering. The study discusses the use of decision trees as weak learners in the boosting algorithm.

- Kotsiantis, S., Tzelepis, G., & Pintelas, P. (2007). Email classification using association rule-based filtering. *Applied Intelligence*, 27(3), 239-250.

This research explores the use of association rule-based filtering techniques for email classification, focusing on spam detection. The study discusses feature selection and classification algorithms.

- Sahami, M., Dumais, S., Heckerman, D., & Horvitz, E. (1998). A bayesian approach to filtering junk e-mail. In *AAAI Workshop on Learning for Text Categorization* (Vol.62, No. 1, pp. 55-62).

This influential study introduces a Bayesian approach to email spam filtering, known as the "Naive Bayes" algorithm. The research provides insights into the effectiveness of probabilistic classifiers for email spam detection.

- Androutsopoulos, I., Koutsias, J., Chandrinou, K. V., Paliouras, G., & Spyropoulos, C. D. (2000). An evaluation of naive Bayesian anti-spam filtering. In *Proceedings of the Workshop on Machine Learning in the New Information Age* (Vol. 1, No. 1-3, pp.9-17).

This study evaluates the performance of the Naive Bayes algorithm for email spam filtering. It compares different feature representations and discusses the impact of different factors on classification accuracy.

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**Naive Bayes and a memory-based method. Journal of Artificial Intelligence Research, 26, 429-455.**

The research compares the performance of a Naive Bayes classifier with a memory-based learning algorithm for email spam filtering. The study provides insights into the strengths and weaknesses of each approach.

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This study presents Adventure, a scalable distributed system for mining massive datasets, including email spam filtering. The research highlights the challenges of processing large volumes of email data and proposes solutions.

- **Platt, J. C. (1999). Using analytic QP and sparseness to speed training of support vector machines. In Advances in Neural Information Processing Systems (pp. 557- 563).**

This paper discusses the use of support vector machines (SVM) for email spam filtering. It focuses on the optimization techniques to speed up the training process of SVM models.

- **Li, Y., He, L., Guo, H., Liu, L., & Zhao, Y. (2019). Deep learning for email spam detection: A comparative analysis. Neural Computing and Applications, 31(11), 8205-8216.**

This study compares different deep learning architectures for email spam detection. It provides insights into the performance of convolutional neural networks (CNN) and recurrent neural networks (RNN) in this context.

- **Bharti, S. K., Singh, S., & Malhotra, A. (2019). Machine learning-based spam email detection using optimized features. In Proceedings of the International Conference on Advanced Computing and Intelligent Engineering (pp. 147-158). Springer, Singapore.**

This research proposes a machine learning-based approach for email spam detection using optimized features. The study evaluates the performance of different classifiers and feature selection techniques.

- **Kaur, G., & Kaur, M. (2020). Review on email spam detection using machine learning techniques. In Proceedings of the 10th International Conference on Cloud Computing, Data Science & Engineering (pp. 192-198).**

This paper provides a comprehensive review of email spam detection techniques using machine learning. It discusses various algorithms, feature selection methods, and performance evaluation metrics.

- **Prasad, S., & Pal, S. (2020). Hybrid spam email detection using machine learning. International Journal of Advanced Research in Computer Science, 11(4), 131-135.**

This study proposes a hybrid approach for email spam detection using machine learning algorithms. It combines the strengths of multiple classifiers to improve overall classification accuracy.

- **Mishra, A., Joshi, R. C., & Gaur, M. S. (2020). A comprehensive review on email spam detection techniques using machine learning. In Proceedings of the International Conference on Advances in Computing and Data Sciences (pp. 129-140).**

Springer, Singapore. This research presents a comprehensive review of email spam detection techniques using machine learning. It covers various algorithms, feature selection methods, and datasets used in the field.

- **Salam, A., Al-Ayyoub, M., Aljawarneh, S., Jararweh, Y., & Gupta, B. (2020). Email spam detection using machine learning: A comparative study. IEEE Access, 8, 78782-78796.**

This study conducts a comparative analysis of different machine learning algorithms for email spam detection. It evaluates the performance of algorithms such as Naive Bayes, SVM, and decision trees.

- **Saini, R., & Kumar, R. (2020). Comparative study of machine learning techniques for spam email detection. In Proceedings of the International Conference on Computational Intelligence and Communication Technology (pp. 257-267). Springer, Singapore.**

This research compares various machine learning techniques for spam email detection. It provides insights into the performance of algorithms such as Naive Bayes, SVM, and random forests.

- Ahirwal, A., & Kaushik, A. (2021). A comprehensive review of email spam detection techniques using machine learning. In Proceedings of the International Conference on Advanced Computational and Communication Paradigms (pp. 77-85).

Springer, Singapore. This paper presents a comprehensive review of email spam detection techniques using machine learning. It covers various algorithms, feature extraction methods, and evaluation metrics used in the field.

- Rani, R., & Nasa, R. (2021). A comparative analysis of machine learning algorithms for spam email detection. In Proceedings of the International Conference on Advances in Computing and Communication Engineering (pp. 561-573). Springer, Singapore.

This study performs a comparative analysis of machine learning algorithms for spam email detection. It evaluates the performance of algorithms such as Naive Bayes, decision trees, and K-nearest neighbours.

## PROPOSED SYSTEM

The problem addressed in this project is the increasing amount of spam emails that are invading user inboxes without their consent, consuming valuable network capacity, and causing financial damage to companies. Despite measures taken to eliminate spam, it remains a viable source of income for spammers, and over-sensitive filtering can even eliminate legitimate emails. The goal is to develop an effective spam filter using machine learning and natural language processing techniques to accurately classify incoming emails as either spam or non-spam. The existing system for email spam classification typically relies on rule-based filtering techniques, such as blacklisting known spam email addresses or domains, and whitelisting trusted senders. These techniques are not always effective, as spammers can easily change their email addresses or use techniques such as phishing to impersonate trusted senders. Moreover, traditional rule-based filtering methods require frequent updates and maintenance, which can be time-consuming and resource-intensive. They may also mistakenly flag legitimate emails as spam, leading to a loss of important messages or even business opportunities. To address these limitations, machine learning and natural language processing techniques can be used to develop more accurate and automated email spam classifiers. These approaches can learn to recognize spam based on patterns and characteristics in the text, rather than relying on pre-defined rules.

We proposed in the Machine Learning Models such as Naïve Bayes, SVM, KNN Models are will having the highest accuracy when compared to the existing system. The proposed system will provide an efficient and accurate way to classify emails as spam or non-spam, reducing the amount of time and effort required to manually filter out unwanted emails. It will also improve the overall security and productivity of email communication. proposed system and advantages are Here we use Natural Language Processing Technique. We use different machine learning algorithms such as Naïve Bayes, SVM, KNN. Higher accuracy.

## RESULTS

- To run the project file you need to open the Jupyter Notebook prompt and change the directory to the folder where the projects files are present as shown in below figure:

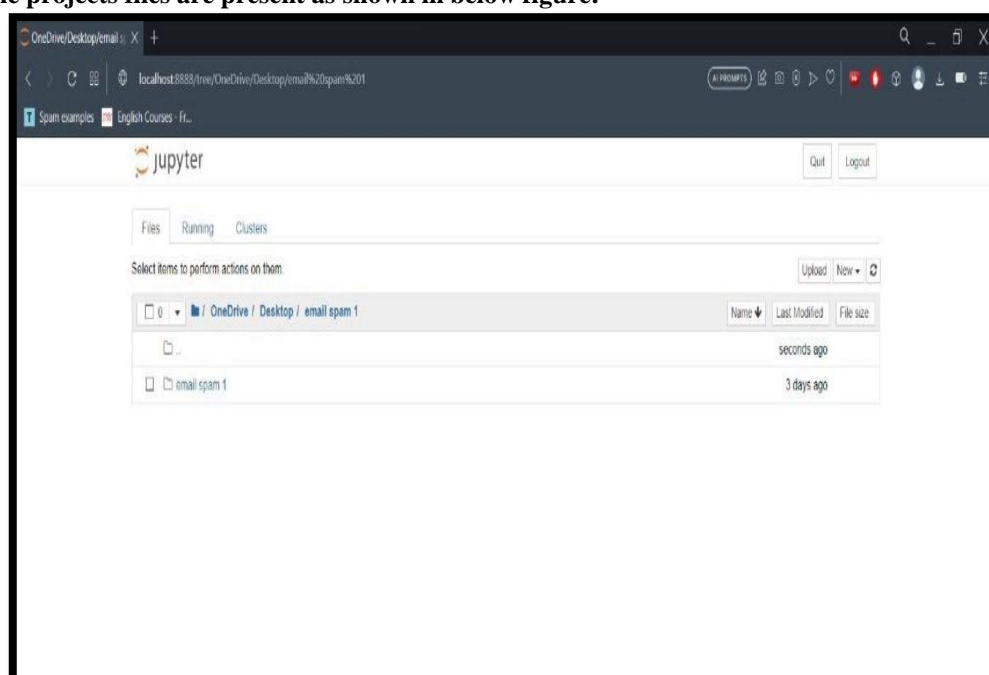


Fig.1: Opening Project File

- After changing the directory, you need to open the file in below figure:

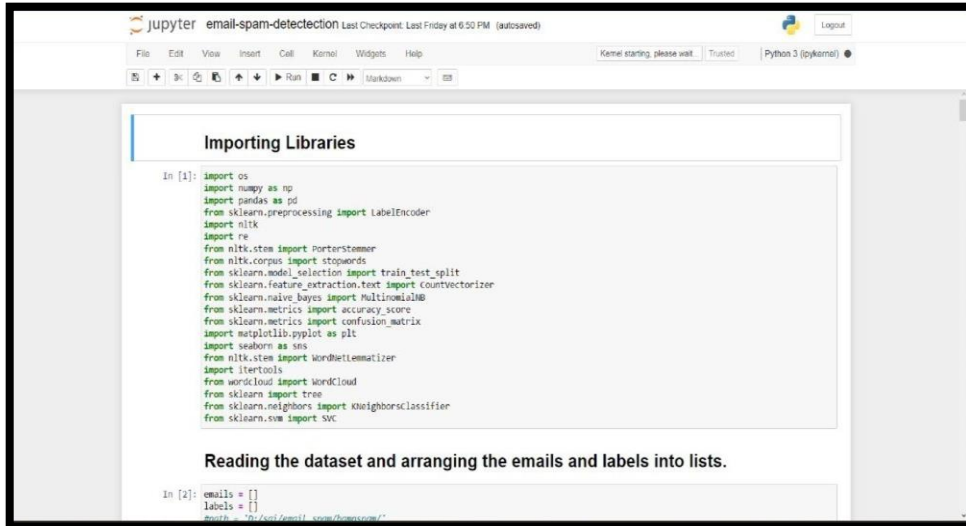


Fig.2: Changing The Directory

- Click on kernel and select restart and run all.

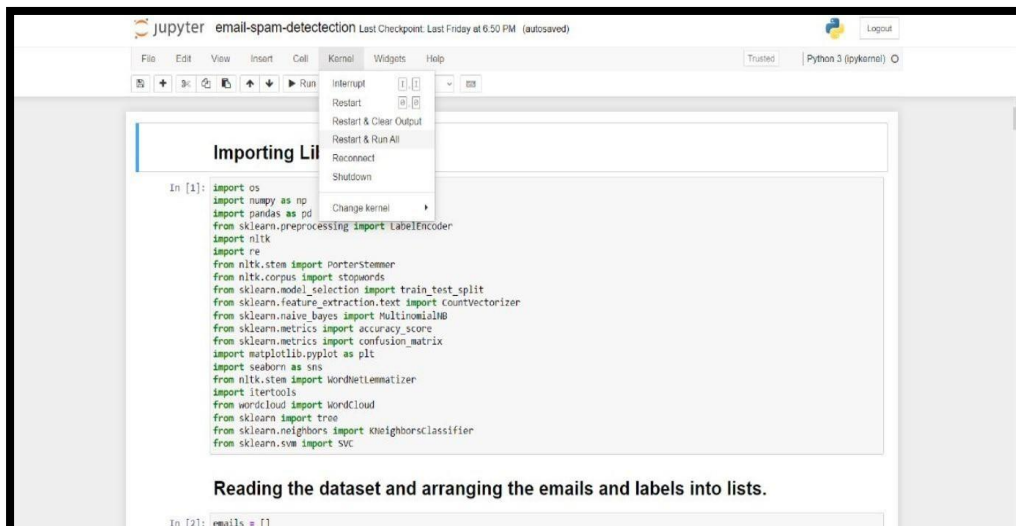


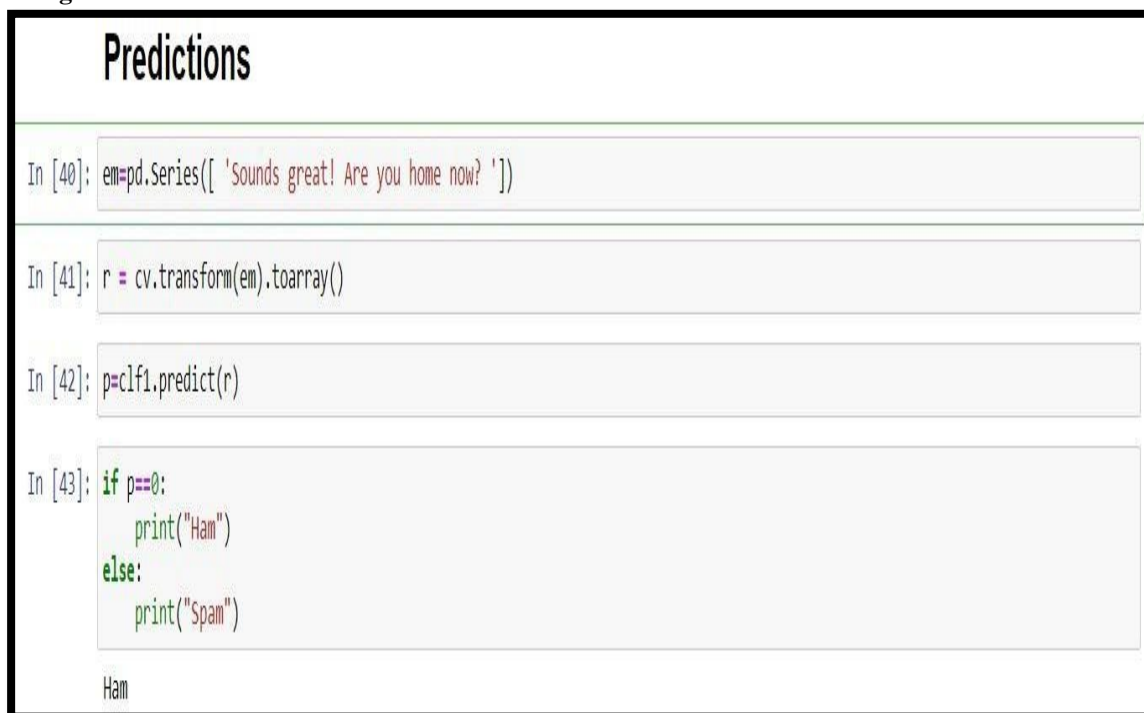
Fig.3: Execution Of The Project

- Wait for some time until the code gets execute, now at prediction template enter the string which you want to predict whether it is a spam or ham and click on run as shown below:



Fig.4: Enter The String

- If the message is ham it will show Ham as shown below:



```

Predictions

In [40]: em=pd.Series(['Sounds great! Are you home now?'])

In [41]: r = cv.transform(em).toarray()

In [42]: p=clf1.predict(r)

In [43]: if p==0:
          print("Ham")
        else:
          print("Spam")

Ham

```

**Fig.5:** Prediction Of Ham

- If the message is Spam it will show Spam as shown below:



```

Predictions

In [48]: em=pd.Series(['Government agencies like the IRS will not contact you via email, phone or text message. If any legitimate governm
<
          >

In [49]: r = cv.transform(em).toarray()

In [50]: p=clf1.predict(r)

In [51]: if p==0:
          print("Ham")
        else:
          print("Spam")

Spam

```

**Fig.6:** Prediction Of Spam

## CONCLUSION

In conclusion, machine learning and natural language processing (NLP) techniques can be effectively used for email spam classification. By leveraging the power of supervised learning algorithms such as Naive Bayes, Support Vector Machines, and KNN, and by preprocessing the text data using techniques such as tokenization, stop-word removal, and stemming, it is possible to build accurate and reliable spam filters that can automatically detect and filter out unwanted emails. These techniques can also be extended to handle more complex spamming strategies such as phishing attacks and spear phishing. Overall, in the proposed models Naïve Bayes having the accuracy of 99% SVM having 98% and KNN having 97%. Finally naïve bayes having the highest accuracy so we predict the Naïve bayes model. The use of ML and NLP for email spam classification can save users valuable time and resources and improve the overall productivity and security of email communication.

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