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SPAM VS HAM EMAIL CLASSIFIER

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Department : Computer Engineering

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INTRODUCTION

- Email is a widely used communication medium, but spam emails and sms have become a major threat.
- Spam includes phishing links, malware, financial scams, and harmful URLs.
- Nearly half of daily global email traffic is spam, requiring strong filtering systems.
- Traditional rule-based filters rely on keywords and blacklists but fail against evolving attacks.
- Machine learning adapts better by learning patterns from historical email and sms data.
- This study focuses on ML-based text classification models using TF-IDF features.
- Four commonly used algorithms are evaluated: Naïve Bayes, Logistic Regression, KNN, and Random Forest.

PROBLEM

- Users receive a large number of unwanted and harmful emails every day.
- These spam messages often contain scams, fake offers, phishing links, or malware.
- Traditional rule-based filters fail because attackers keep changing the way spam looks.
- Keyword-based systems cannot detect new or modified spam patterns.
- Many safe emails get marked as spam, and many spam emails enter the inbox.
- There is a need for a machine-learning model that can learn from data and classify emails accurately.

OBJECTIVE

- To build a system that automatically identifies spam emails and sms.
- To protect users from scams, phishing links, and unwanted messages using NLP.
- To clean and analyze email text using machine learning.
- To compare different ML models and choose the most accurate one.
- To provide a simple Streamlit interface for real-time spam detection.

ML MODELS FOR CLASSIFICATION

Naïve Bayes

- From the study by Sultana & Thashina, we found that NB is widely used in early spam filters due to its simplicity and fast computation.
- The paper shows NB performs well when spam contains repetitive keywords like “free,” “win,” “urgent.”

Logistic Regression

- Alsuwit et al. (2024) report that Logistic Regression is one of the most reliable linear models for large-scale spam detection.
- Their findings indicate that LR works particularly well with TF-IDF features and high-dimensional datasets.

k-Nearest Neighbors (k-NN)

- The review by Tusher et al. (2024) discusses the use of k-NN in earlier spam detection research.
- Their analysis shows that while k-NN is simple and intuitive, its performance drops in high-dimensional text spaces because distance metrics become less meaningful.

ML MODELS FOR CLASSIFICATION

Random Forest

- According to Speiser et al. (2019) and the comparative work by Alsuwit et al. (2024), Random Forest provides better generalization than a single decision tree.
- These studies emphasize that RF reduces overfitting through bagging and random feature selection, making it effective for text classification.

TF-IDF & Feature Extraction

- Shafi'i et al. (2018) and Hegde (2021) highlight preprocessing methods such as tokenization, stopword removal, and stemming as essential for improving spam detection accuracy.
- Their work supports TF-IDF as the most widely used and effective technique for converting text into discriminative numerical features.

DATASET AND TOOLS

Dataset

- **Kaggle** : Email Spam vs Ham Dataset
- Contains labelled messages: spam or ham

- Used for training, testing, and evaluating the ML models (80% - train , 20% test)

- The dataset contains 20k + email rows with 3 main columns:

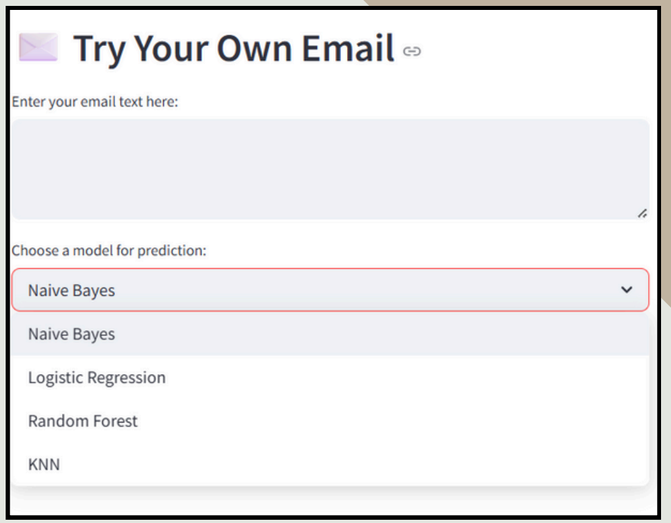
1. label → indicates whether the text is spam or ham
2. text → the actual email/message content
3. type → the text is email or SMS.

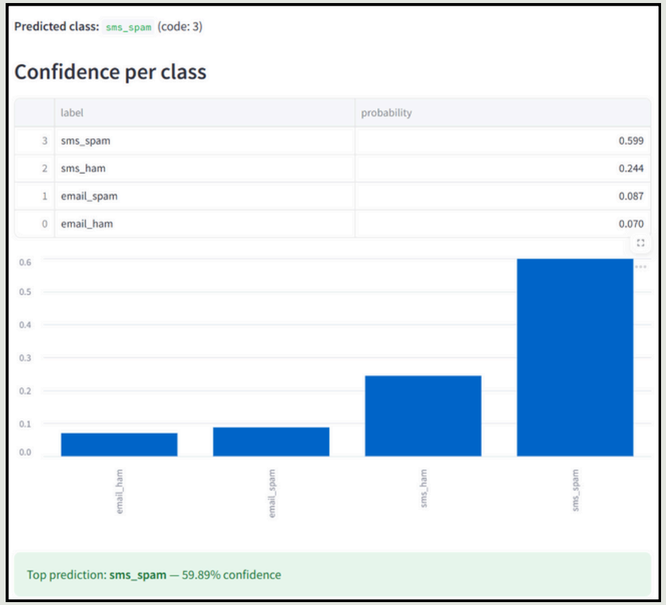
Technologies

- **Python** : main programming language
- **Streamlit** : for building the interactive web app
- **scikit-learn** : machine learning algorithms & metrics
- **Pandas / NumPy :** data handling and processing
- **Matplotlib / Seaborn** : for visualizations
- **sklearn ,re and String** for preprocessing
- **TF-IDF (Sklearn) :** for converting text into numerical features
- **NLTK:** For detecting phishing links and domain,etc.
- **Joblib** : to save and load trained models

KEY FEATURES

- Automatic spam vs ham classification for both ham and spam using machine learning.
- Clean and preprocess email and sms text using TF-IDF–based feature extraction and NLP based preprocessing.
- Supports multiple ML models: Naïve Bayes, Logistic Regression, Random Forest, and KNN.
- User can select the model they want to test or use for prediction.
- Real-time 4 way classification and prediction through an easy and interactive Streamlit interface.
- Visual performance comparison using confusion matrices .





METHODOLOGY

- The system starts by using the Kaggle Spam vs Ham dataset (combined) as the labelled source for email messages.

- The text is cleaned using preprocessing steps such as :
  1.Lowercasing
  2. Removal of digits
  3. Removing punctuation
  4. Tokenization on whitespace
  5. Removing English stop words
  6. Rejoining tokens

- Label encoding

- The cleaned messages are then transformed into numerical vectors using a 3000-feature TF-IDF representation.

NLP:

- Lemmatizes words to their base form. (running –> run)
- Adds security features (URLs, suspicious domains, phishing keywords, all-caps, exclamations)
- Helps the model detect spam/ham patterns more accurately

- These features are used to train multiple models including Naïve Bayes, Logistic Regression, Random Forest, and KNN.

- Finally, the models are evaluated using accuracy, precision, recall, F1-score, and ROC curves to identify the best-performing classifier for deployment.

PRE-PROCESSING RESULTS

Cleaning Text Data...

Sample Cleaned Text (First 5 Rows)

	text	clean_text
0	WINNER!!! You have won $1000 cash!!! Click here NOW... .	winner won cash click
1	Hey, r u coming 2day? :) meeting @ 5pm!!	hey r u coming day meeting pm
2	URGENT!! Your account will be BLOCKED. Visit http://xyz.com/secure	urgent account blocked visit httpxyzcomsecure
3	FREE entry in 2 a wkly draw!! Txt WIN to 80085!!!?	free entry wkly draw txt win
4	Hello John, Your invoice #INV-9987 is due on 12/09/24.	hello john invoice inv

✅ Text cleaning complete!

TF-IDF WORKING

$$TFIDF(T,D) = TF(T,D) \times IDF(T)$$

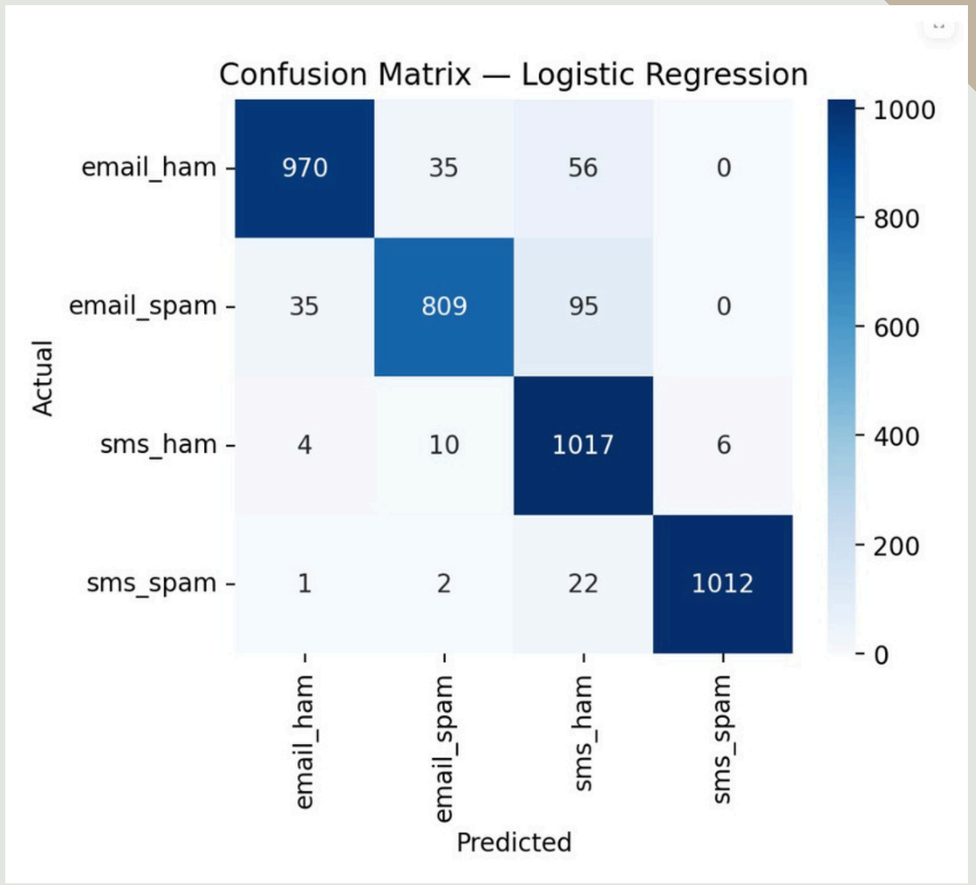
	text	tf	idf
0	Eddard Stark is a king in the north.	1	3
1	A king but one king : kings are everywhere.	2	3
2	Hodor was different : he was not a king .	1	3
3	But the North could not change without him.	0	3

	king	was	the	not	a		he	one	north	kings	is	in	him	everywhere	A	different	could	change	but	are	Stark	North	Hodor	Eddard
0	0.333333	0.0	0.5	0.0	0.5	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0
1	0.666667	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0
2	0.333333	2.0	0.0	0.5	0.5	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
3	0.000000	0.0	0.5	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0

RESULTS

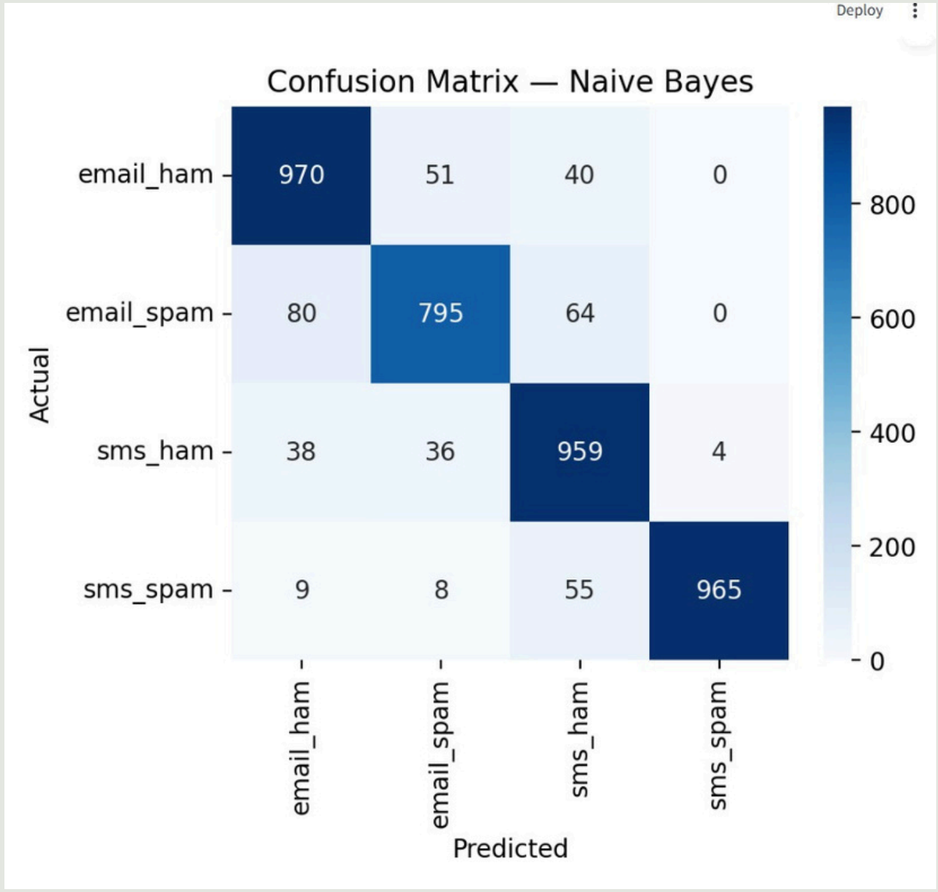
Logistic Regression

- Logistic Regression achieved the highest accuracy among all models.
- It performed strongly across precision, recall, and F1-score.
- It produced very few false negatives and kept false positives low.
- TF-IDF features helped it form clear and stable decision boundaries.
- Overall, it proved to be the most reliable model for spam detection.



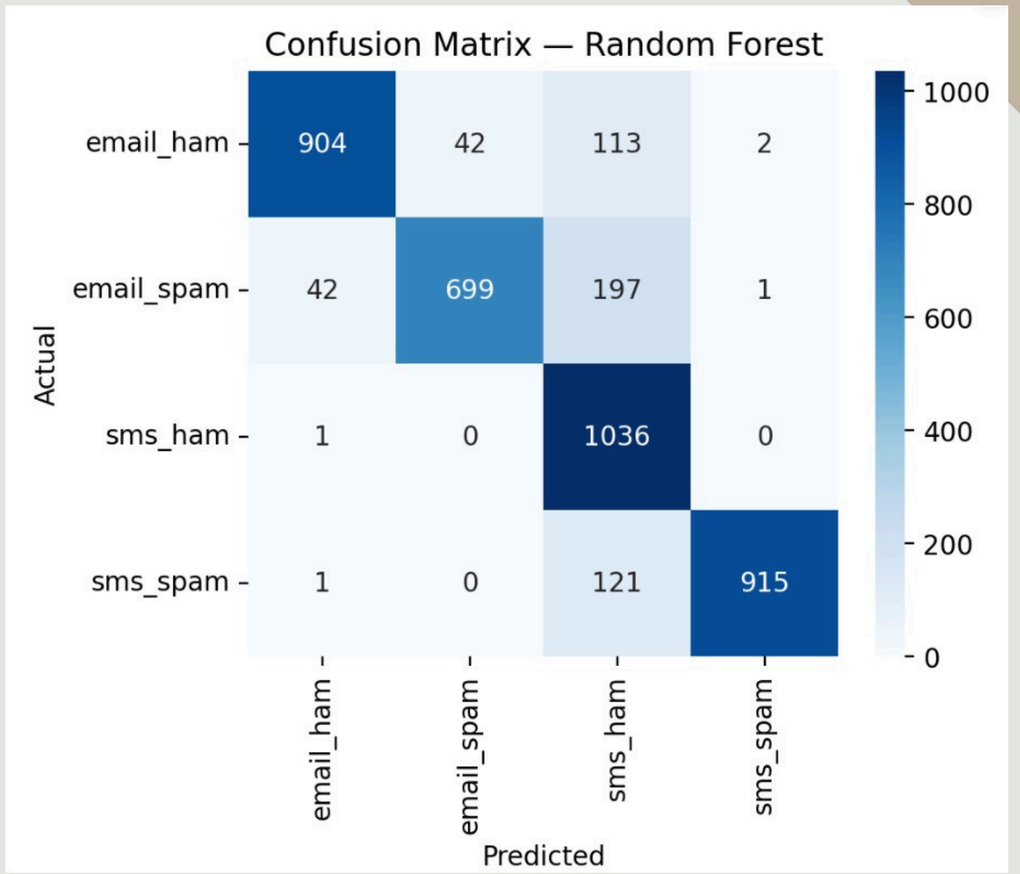
Naive Bayes

- Showed strong overall accuracy with very high recall for spam emails.
- Confusion matrix indicated a moderate number of false negatives but relatively low false positives.
- Performed well on large, sparse TF-IDF features due to its probabilistic nature.
- Very fast training and prediction, making it efficient for real-time filtering.
- Slightly struggled with emails containing mixed or informal language.



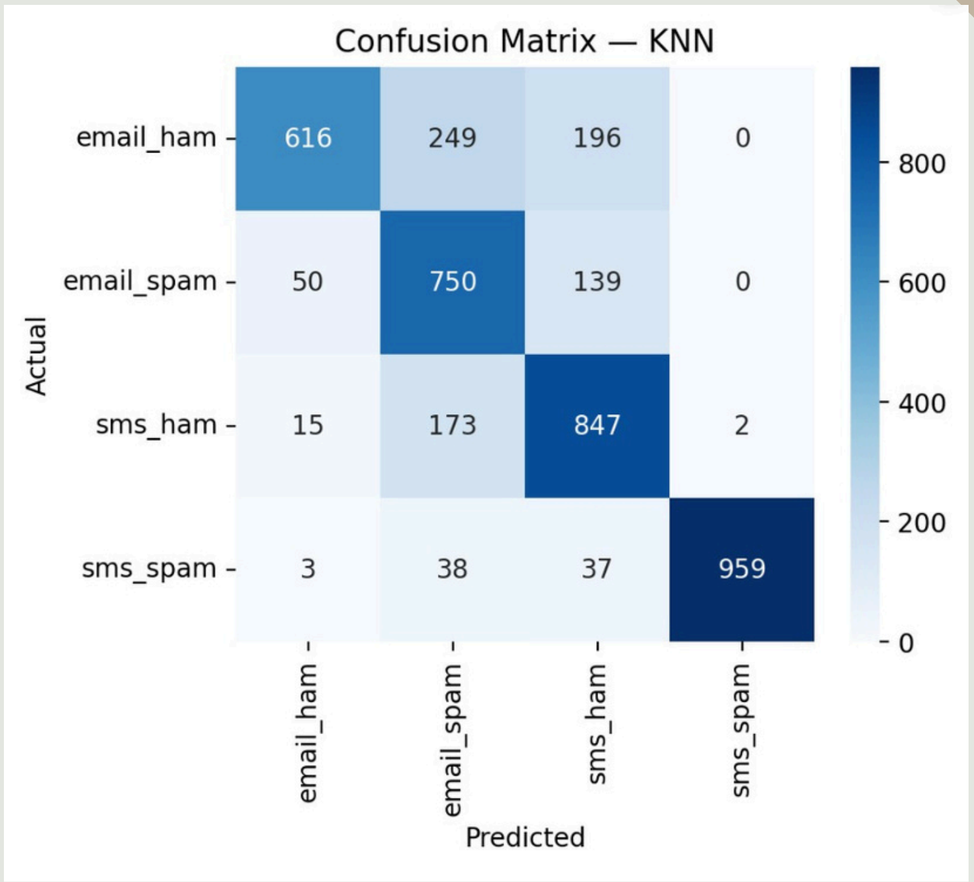
Random Forest

- Delivered strong accuracy with particularly high recall for spam messages.
- Confusion matrix revealed more false positives than Logistic Regression, showing slight over-flagging of spam.
- Benefited from ensemble voting, capturing nonlinear patterns in the dataset.
- Performed reliably but required more computational resources than linear models.
- Showed robustness to noise and uneven feature distributions.

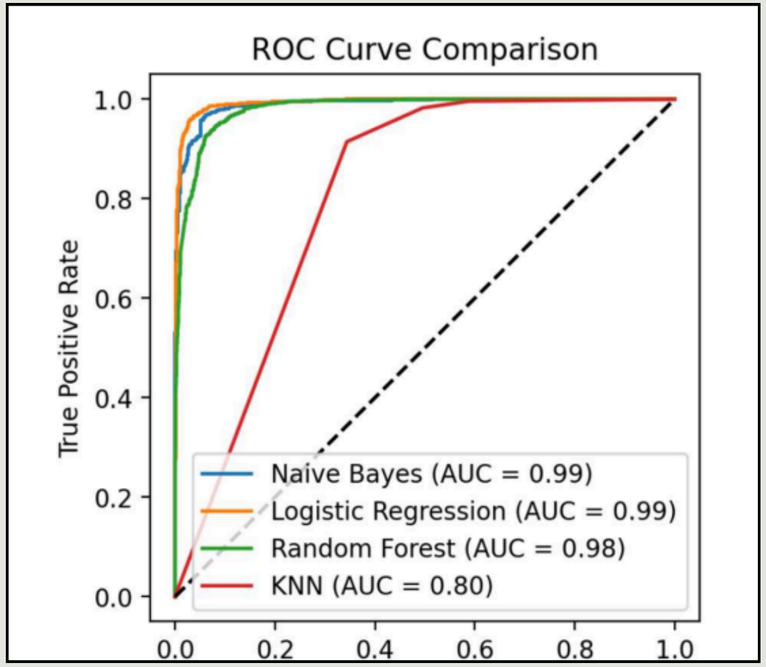


K-Nearest Neighbors (k-NN)

- Showed the weakest performance among all models on the heatmap, with many false positives.
- Struggled with high-dimensional TF-IDF vectors, leading to poor separation between classes.
- Predictions were slow due to distance calculations during inference.
- Performed inconsistently on sparse data, misclassifying many legitimate emails as spam.
- Served as a useful baseline but not suitable for production-level spam filtering.



- **Logistic Regression:** achieved the highest accuracy and F1-score is (0.934) with an AUC of 0.99, showing excellent discrimination between spam and ham.
- **Naïve Bayes:** also performed strongly, with accuracy (0.905) and AUC (0.99), indicating high reliability across all evaluations.
- **Random Forest:** reached accuracy (0.875) and AUC (0.98), handling high-dimensional text well but slightly below the linear models.
- **KNN:** had the lowest accuracy (0.778) and AUC (0.80), confirming its weaker ability to separate classes in complex textual data.



Model performance

	Model	Accuracy	Precision	Recall	F1 Score
0	Naive Bayes	0.905500	0.908000	0.905500	0.905900
1	Logistic Regression	0.934700	0.938500	0.934700	0.934900
2	Random Forest	0.872400	0.899200	0.872400	0.875100
3	KNN	0.778600	0.808300	0.778600	0.780200

Overall

Logistic Regression proves to be the most reliable and effective model for spam detection.

FUTURE SCOPE

- Improve accuracy using hybrid/ensemble models combining NB, LR, and RF.
- Apply feature selection methods (Chi-square, Mutual Information) to reduce noise and speed up training.
- Automatic integration in the user’s email and sms app

CONCLUSION

The system accurately classifies both emails and SMS messages into spam and ham categories using NLP, TF-IDF, and engineered security features. Logistic Regression and Random Forest gave the best overall performance. The project proves that a well-designed ML pipeline can reliably detect spam across multiple communication channels without needing deep learning.

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Thank You

For your attention