EMAIL SPAM PREDICTION

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by

2203A52178	**S Pranav**
2203A52108	**N Nived Kumar**
2203A52165	**M Manoj Kumar**
2303A52L07	**R Srivalika**

Submitted to

DR. SANDEEP KUMAR

SCHOOL OF COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE SR UNIVERSITY, ANANTHASAGAR, WARANGAL

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SCHOOL OF COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE

CERTIFICATE

This is to certify that this project entitled "**TEXT BASED PERSONALITY PREDICTION**" is the bonafied work carried out by **Nived Kumar, Pranav, Manoj, Srivalika,** a Major Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in School of **Computer Science and Artificial Intelligence** during the academic year **2024-2025** under our guidance and Supervision.

Supervisor	**Head of the Department**
Dr. Sandeep Kumar	Dr. M. Sheshikala
Professor & Associate Dean (Data Science)	Prof & HOD (CS&AI)
SR University	SR University

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CHAPTER – 1
INTRODUCTION

Email has become an essential mode of communication in both personal and professional settings. However, the rise of spam emails—unsolicited and often harmful messages—poses significant challenges to information security, user productivity, and system performance. These emails can contain phishing links, malware attachments, or misleading advertisements, making spam detection a crucial component of modern email systems.

Traditional rule-based filtering methods are often ineffective against the constantly evolving nature of spam. As a result, machine learning and Natural Language Processing (NLP) techniques have gained popularity for their ability to automatically learn patterns and classify messages accurately. By analyzing email content, subject lines, sender information, and other metadata, machine learning models can distinguish between spam and legitimate emails with high accuracy.

This study aims to develop and evaluate a spam detection system using various machine learning algorithms, including Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression. Through data preprocessing, feature extraction techniques like TF-IDF, and model training, the system is designed to enhance email security and reduce the impact of unwanted messages on users.

Spam detection traditionally relied on rule-based filters that used predefined keyword lists or blacklists to block known spam sources. However, these systems often fail to account for new types of spam or adapt to changing tactics used by spammers. With the ever-evolving nature of spam emails, these methods have become less effective, prompting the need for more sophisticated approaches. Machine learning and Natural Language Processing (NLP) have emerged as powerful tools to address this challenge, as they can learn patterns in data and improve performance over time.

Machine learning-based spam detection involves the development of algorithms that can automatically classify emails into two categories: spam (unwanted) and ham (legitimate). These algorithms use features such as the email's text content, subject line, sender information, and various other metadata to make predictions. A key aspect of spam detection is feature extraction, where relevant information from the email is extracted and transformed into numerical features that can be processed by machine learning models.

Among the most commonly used machine learning techniques for spam detection are Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression. Naïve Bayes classifiers, based on probability theory, have been widely used due to their simplicity and effectiveness in handling text classification tasks. SVMs, known for their high accuracy in high-dimensional spaces, are particularly useful in distinguishing complex patterns in email content. Logistic

Regression, with its foundation in statistical analysis, has also proven to be a reliable method for binary classification tasks like spam detection.

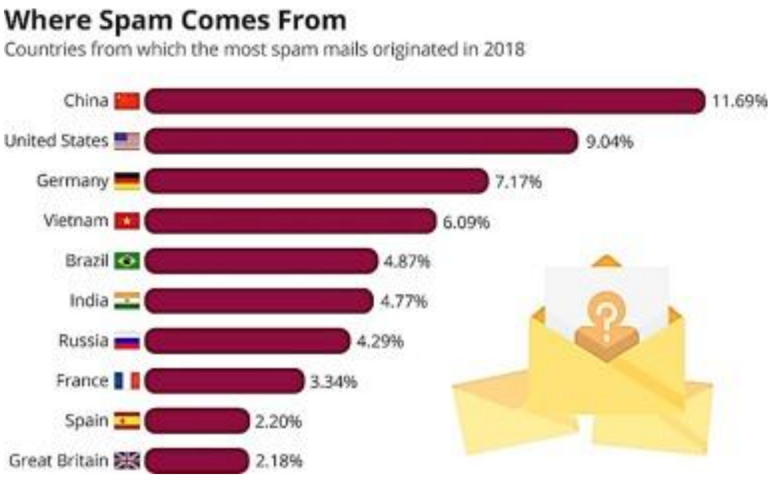
In the digital age, email has become one of the most widely used and essential means of communication for personal, academic, and professional purposes. However, with the increase in email usage, there has also been a significant rise in unsolicited and potentially harmful emails, commonly known as **spam**. Spam emails not only consume bandwidth and storage space but also pose serious security risks, such as phishing attacks, malware distribution, and identity theft. As a result, **email spam detection** has become a crucial area of research and development in the fields of **cybersecurity**, **natural language processing (NLP)**, and **machine learning**.

Spam emails are usually sent in bulk by automated systems with deceptive subject lines and content, aiming to trick recipients into clicking malicious links or disclosing sensitive information. These messages can severely disrupt communication channels, reduce user productivity, and compromise organizational security. Traditional rule-based or keyword-based filters are often unable to keep up with the evolving tactics of spammers, leading to a high rate of false positives (legitimate emails marked as spam) and false negatives (spam emails allowed into the inbox). To address these challenges, intelligent and adaptive systems powered by machine learning have emerged as a promising solution.

Machine learning techniques allow spam filters to **learn patterns** from large datasets of labeled emails and make accurate predictions on new, unseen messages. These models can capture complex language patterns, analyze metadata, and continuously improve over time as more data is introduced. Among the most commonly used algorithms in spam detection are **Naïve Bayes**, **Support Vector Machines (SVMs)**, **Logistic Regression**, **Random Forest**, and **deep learning approaches** such as Recurrent Neural Networks (RNNs). Each algorithm has its strengths, with Naïve Bayes.

NEED OF THE PROJECT

DATA WHERE SPAM EMAIL OCCURS:



1. Escalating Volume of Spam Emails

Spam emails constitute a significant portion of global email traffic, with estimates suggesting that they account for over 50% of all emails sent daily. This overwhelming volume not only clutters inboxes but also strains email servers and network resources, leading to decreased efficiency and increased operational costs. Implementing an effective spam detection system is crucial to mitigate these issues and ensure seamless communication.

2. Security Threats and Cybercrime Prevention

Spam emails are often vectors for malicious activities, including phishing attacks, malware distribution, and ransomware campaigns. By deceiving recipients into clicking harmful links or downloading infected attachments, these emails can compromise sensitive information and disrupt organizational operations. Advanced spam detection mechanisms are essential to identify and block such threats proactively, thereby safeguarding users and systems.

3. Enhancing User Productivity and Experience

The constant influx of spam emails can overwhelm users, making it challenging to identify and respond to legitimate messages promptly. This not only hampers productivity but also increases the likelihood of missing critical communications. By filtering out unwanted emails, spam detection systems streamline inbox management, allowing users to focus on pertinent tasks and communications.

4. Preserving Organizational Reputation and Trust

Organizations that fail to implement robust spam filters risk having their email domains blacklisted, which can severely impact their ability to communicate with clients and partners. Moreover, if employees inadvertently respond to phishing emails, it can lead to data breaches and erode stakeholder trust. A reliable spam detection system is vital to maintain an organization's credibility and ensure secure communications.

5. Adaptation to Evolving Spam Techniques

Spammers continually refine their tactics to bypass traditional filters, employing techniques such as obfuscation, use of images instead of text, and mimicking legitimate email formats. Modern spam detection projects must leverage machine learning and artificial intelligence to adapt to these evolving strategies, ensuring sustained effectiveness in identifying and blocking spam.

6. Compliance with Regulatory Standards

Data protection regulations, such as the General Data Protection Regulation (GDPR), mandate organizations to implement measures that protect personal data from unauthorized access and breaches. Effective spam detection systems play a crucial role in compliance by preventing phishing attacks and unauthorized data collection through spam emails.

III. APPLICATIONS

1. Gmail's AI-Powered Spam Filtering

Google has significantly enhanced Gmail's spam detection capabilities by integrating artificial intelligence and neural networks. These advancements have enabled Gmail to filter out 99.9% of spam emails, reducing the spam rate to 0.1% and the false-positive rate to 0.05%. The system adapts to individual user preferences, ensuring a personalized and secure email experience. WIRED+1WIRED+1

2. Spam Titan's Impact on Organizations

Spam Titan, an email security solution, has been instrumental for various organizations in combating spam. For instance, Huron Valley Steel faced a crippling amount of spam that disrupted their communication. Implementing Spam Titan effectively eliminated the spam deluge, restoring efficient communication channels. Similarly, a credit union reported immediate improvements in blocking spam, enhancing its overall email security. SpamTitan Email Security

3. Deep Quarantine: Advanced Spam Detection

Deep Quarantine (DQ) is a cloud-based technology designed to detect and quarantine potential spam messages. By applying convolutional neural networks to email headers, DQ can identify spam campaigns early and hold suspicious emails in a quarantine folder for further analysis. This approach enhances the reliability of spam detection systems and protects users from emerging threats. arXiv

4. Holmes: Semantic-Based Anomalous Email Detector

Holmes is an efficient and lightweight semantic-based engine for detecting anomalous emails. Unlike traditional signature-based approaches, Holmes converts email event logs into sentences using word embeddings and identifies abnormalities that deviate from historical baselines. This method has proven effective in detecting concealed malicious emails that traditional filters might miss. arXiv

5. Spam-T5: Leveraging Large Language Models

Spam-T5 is a model that benchmarks large language models for few-shot email spam detection. By comparing models like BERT, Sentence Transformers, and Seq2Seq, Spam-T5 demonstrates superior performance, especially in scenarios with limited training data. This adaptability makes it uniquely suited for spam detection tasks requiring frequent updates. arXiv

CHAPTER-2

LITERTURE REVIEW

S.NO	AUTHOR NAME AND YEAR OF PUBLICATION	METHODOLOGY	RESULTS	DATASET NAME	LIMITATIONS
1	Ghazala Nasreen , Muhammad Murad Khan , Muhammad Younus(2024)	GWO-BERT, LSTM, MACHINE LEARNING ALGORITHMS	ACCURACY:99.14% PRECISION:99.89% RECALL : 94.73% F-SCORE: 97.29%	LING SPAM DATASET	IT CANNOT APPLY ON BIG EMAIL SPAM DETECTION.
2	Salman A. Khan, Kashif Iqbal , Nazeeruddin Mohammad(2022)	BERT, LSTM, FUZZY-LOGIC	ACCURACY: 0.97 PRECISION: 0.98 RECALL: 0.98	ENRON, LINGSPAM DATASETS	THE PURPOSED FUZZY-LOGIC BASED PERFORMANCE TESTED ONLY LIMITED NO OF MODELS AND DATASETS.
3	Isra'a AbdulNabi, Qussai Yaseen(2024)	DEEP LEARNING MODELS , AND BI-LSTM MODEL	BI-LSTM : ACCURACY-96.43%, F1-SCORE-96%, BERT MODEL: ACCURACY: 98.67% F1-SCORE: 98.66%	Spambase data set from the UCI machine learning repository.	MODEL PERFOMANCE NOT UP TO THE MARK BECAUSE THEY USED **RESTRICTED GPU** MEMOREY.
4	Cherry A.Ezzat, Abdullah M.Alkadri(2025)	AraBERT model	ACCURACY:0.9986% PRECISION:0.9986% F1-SCORE:0.9986 RECALL: 0.9987 Epochs: 6	Kaddouraa et al. dataset type of Modern standard Arabic(MSA)	This AraBERT model is applied to a smaller Arabic social media dataset.
5	Subba Reddy Borra, Muppaneni Yukthika, Murari Bhargavi(2024)	AdaBoost, SVM models	**ADABOOST:** ACCURACY-89.72% PRECISION-81.74% RECALL- 79.72% F1-SCORE- 79.72% **SVM:** ACCURACY:76% PRECISION:50.4% RECALL:49.54% F1-SCORE:48%	UCI dataset, CSDMC dataset	THIS ML MODELS REQUIRED HIGH QUALITY DATA FOR BETTER RESULTS.
6	NIKHIL KUMAR, SANKET SONOWAL, NISHANT(2022)	MACHINE LEARNING MODELS LIKE NAVIE BAYES, SVM, RANDOM FOREST	**ACCURACY:** **NAVIES BAYES-** 0.98% **SVM** – 0.92% **RANDOM FORWEST**- 0.92%	KAGGLE SPAM DATASET	NAIVE BAYES ALGORITHM WORKS ACCURATE BUT THE ACCURACY IS NOT TRUE BECAUSE IT CLASSIFIES EMAILS INCORRECTLY. AND LIMITED DATASET.
7	SAMIRA.DOUZI, FEDA A. ALSHAHWAN, M. LEMOUDDEN(2020)	SVM , KNN, LOGISTIC REGRESSION	**LOGISTIC REGRESSION** **ACCURACY- 0.96%** **PRESICION- 0.96%** **RECALL- 0.99%** **F1 SCORE- 0.98%**	LING SPAM DATASET, ENRON DATASET	TAKEN MORE TIME TO CONVERT TF-IDF TO ASSIGN TO EACH MESSAGE DUAL

			SVM **ACCURACY-0.96** **PERCISION- 0.95%** **RECALL- 0.99%** **F1 SCORE-0.97%** **KNN** **ACCURACY-0.97%** **PRECISION-0.97%** **RECALL-0.99%** **F1 SCORE- 0.97%**		REPERESENTATION VECTORS.
8	M.A.NIVEDHA, S.RAJA(2022)	RANDOM FOREST APPORACH, NLP TECHNIQUES	ACCURACY- 97.72% PRECISION- 98.64% SENSITIVITY- 98.36%	THE SHORT MESSAGE SERVICE SPAM COLLECTION DATASET	LOW ACCURACY BECAUASE OF LESS DATASET FOR BETTER FEATURES AND CLASSIFICATION SYSTREMS.
9	Sultan ZAVRAK, Seyhmus YILMAZ(2022)	HIERARCHICAL ATTENTION HYBRID DEEP LEARNING METHOD(CNN)	ACCURACY: TR-0.99% GS-0.95% SA-0.955% EN- 0.958% LS- 0.980%	DATASETS: TR(TREC 2007), GENSPAM(GS), SPAMASSASSIN(SA), ENRON(EN), LING SPAM(LS)	PERFORMED VERY WELL THAN BERT, LSTM MODELS. BUT TAKE MORE TIME TO RUN FOR EPOCHS FOR BETTER RESULTS
10	Yuliya Kontsewayaa , Evgeniy Antonova, Alexey Artamonov(2020)	KNN, Naive Bayes, Decision tree, Random forest, SVM, Logistic regression	ACCURACY KNN-0.90% DECISION- 0.94 NAVIES BAYES- 0.99% SVM- 0.98% RANDOM FOREST- 0.84% LOGISITIC REGERESSION- 0.99 %	LING SPAM DATASET	LOGISITIC REGRESSION GOT BETTER RESULTS USED DATASET CONTAINS BINARY CLASSIFICATION DIRECTLY 0'S AND 1'S.

Research Gaps

- Spammers continue to change their tricks - like putting spam in images or copying legitimate messages - and this makes it difficult for spam filters.

- Most datasets are imbalanced with an abundance of normal emails rather than spam emails, so the system gets confused and misses spam emails.

- Many spam filters don't work in real time because they're too slow, so we need systems that are faster and smarter.

Objectives

- CNN will analyze the text of the email for common spam indicators, such as common phrases or word combinations often used by spammers.
- LSTM will analyze the flow of the message, given that messages that mask hidden spam may be longer than a sentence.
- Random Forest will take different characteristics of each email (who sent it, subject, content, etc) and leverage those features into better decisions.
- All of the models will be combined (voting, stacking) through ensemble methods to improve accuracy of the system.
- The system will be real-time so that spam is blocked immediately while also enabling real messages to be sent/received.
- The system of multiple models will enable it to adapt to spam techniques as they evolve and keep inboxes clean and safe.

CHAPTER – 3

PROPOSED WORK

The proposed work aims to develop an advanced email spam detection system that combines machine learning and deep learning models to effectively classify emails as spam or legitimate (ham). The system will focus on improving the accuracy, efficiency, and adaptability of spam detection, ensuring it can handle evolving spam techniques and large-scale email datasets. The approach will involve multiple stages, including data collection, preprocessing, feature extraction, model training, and real-time deployment.

1. Data Collection and Preprocessing

The first step is to collect a large, diverse dataset of labeled emails, including both spam and legitimate emails. This dataset will be pre-processed to remove irrelevant information such as special characters, stop words, and punctuation. Tokenization, lemmatization, and stemming techniques will be applied to transform text into a format suitable for machine learning models.

2. Feature Extraction

To capture meaningful information from the email content, various feature extraction techniques will be used. These include **TF-IDF (Term Frequency-Inverse Document Frequency)**, **Bag of Words (BoW)**, and pre-trained word embeddings like **Word2Vec** or **Fast Text**. Additionally, metadata such as email headers, sender information, and subject lines will be incorporated to provide contextual insights into the email's legitimacy.

3. Model Selection and Training

Several machine learning and deep learning models will be employed to classify emails. These models include:

- **BERT (Bidirectional Encoder Representations from Transformers):** BERT will be fine-tuned on the email dataset to understand the contextual relationships within the email text, making it suitable for detecting more sophisticated spam, such as phishing and fraud.
- **Convolutional Neural Networks (CNN):** CNNs will be used to detect local patterns and phrases that are indicative of spam, such as promotional language or suspicious content.
- **Long Short-Term Memory (LSTM):** LSTMs will be applied to capture sequential dependencies within email content, especially for detecting subtle spam patterns that occur over longer email bodies.
- **Random Forest:** As an ensemble model, Random Forest will be used to classify emails based on various features, including the extracted content and metadata, improving the robustness and accuracy of the system.
- **Naïve Bayes:** This probabilistic model will be included for its simplicity and efficiency in text classification tasks, particularly for initial filtering.
-

4. Ensemble Methods

To enhance the overall performance of the spam detection system, ensemble methods such as **voting classifiers** or **stacking** will be employed. These methods combine the strengths of different models by taking a weighted or majority vote from their predictions, which improves accuracy and robustness.

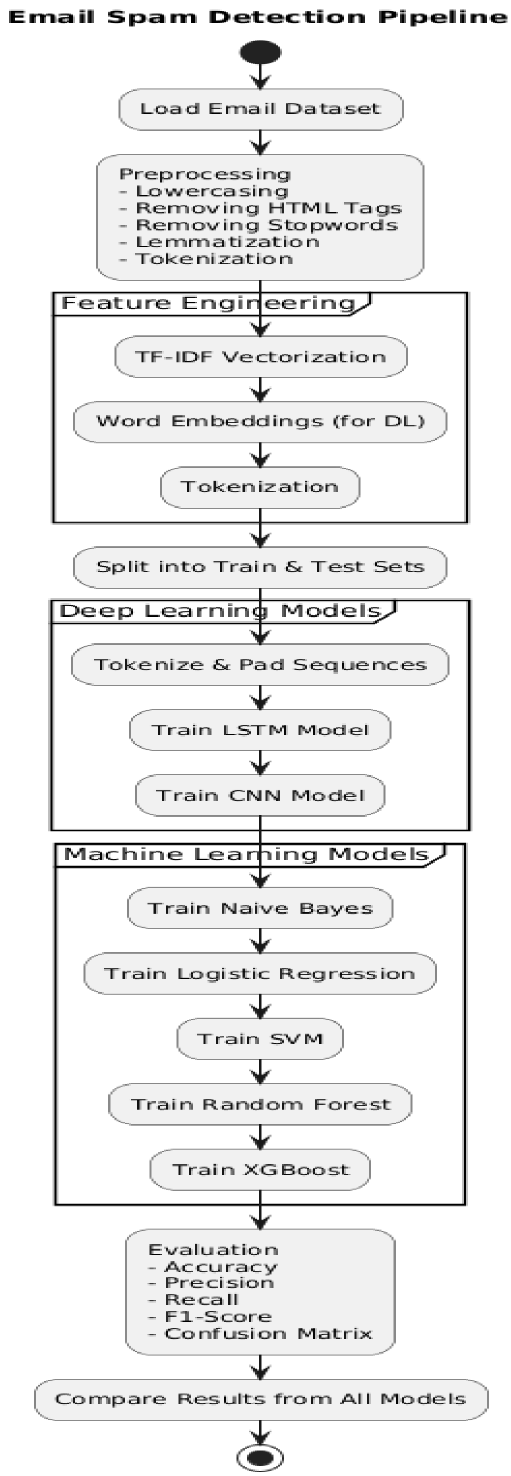
5. Model Evaluation

The models will be evaluated based on key metrics such as **accuracy**, **precision**, **recall**, **F1-score**, and **AUC-ROC**. These metrics will help assess the system's ability to correctly classify spam and ham emails while minimizing false positives (legitimate emails marked as spam) and false negatives (spam emails not detected).

6. Real-Time Deployment

Once trained and evaluated, the spam detection system will be deployed for real-time email filtering. The system will integrate with popular email platforms such as Gmail, Outlook, and Yahoo Mail, processing incoming emails instantly to identify and filter out spam. The system will also be capable of continuously learning from new data to adapt to evolving spam tactics.

FLOWCHART


Email Spam Detection Pipeline
Load Email Dataset
Preprocessing
- Lowercasing
- Removing HTML Tags
- Removing Stopwords
- Lemmatization
- Tokenization
Feature Engineering
TF-IDF Vectorization
Word Embeddings (for DL)
Tokenization
Split into Train & Test Sets
Deep Learning Models
Tokenize & Pad Sequences
Train LSTM Model
Train CNN Model
Machine Learning Models
Train Naive Bayes
Train Logistic Regression
Train SVM
Train Random Forest
Train XGBoost
Evaluation
- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix
Compare Results from All Models

RESULTS

CONFIGURATION OF LAPTOP:

OS : Windows 11 Home

Brand: HP

Hard Disk Size : 512 GB

CPU Model : Core i5

RAM Memory : 16 GB

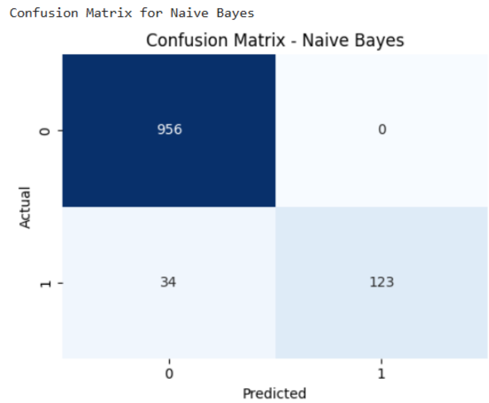
MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
LOGISTIC REGRESSION	0.696	0.96	1.00	0.98
LINEAR SVM	0.98	0.98	0.99	0.99
NAVIE BAYES	0.97	0.97	1.00	0.98
RANDOM FOREST	0.89	0.89	1.00	0.94
XG BOOST	0.97	0.97	0.99	0.98

TABLE 1- MACHINE LEARNING MODELS

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
CNN	0.98	0.98	0.89	0.99
LSTM	0.98	0.97	0.98	0.98

TABLE 2- DEEP LEARNING MODEL

CONFUSION MATRIX:



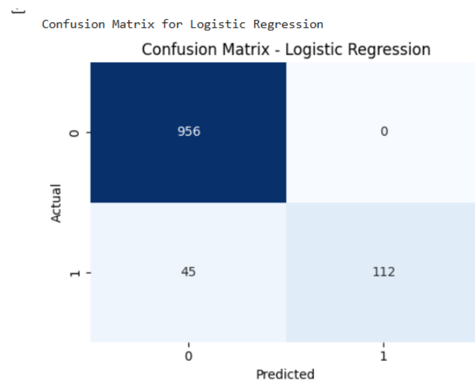
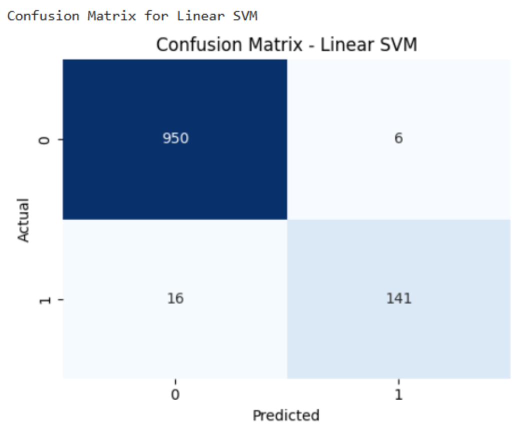


FIG-1 Navie Bayes

FIG-2 Logistic Regression



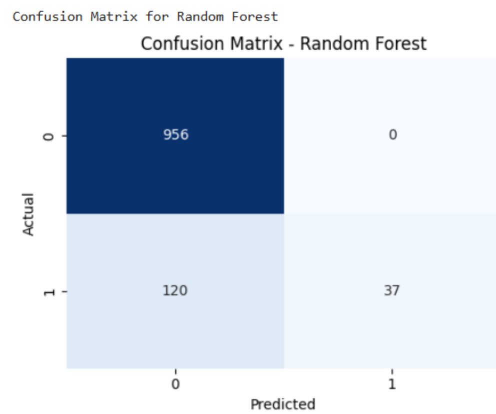


FIG-3 Linear SVM

FIG-4 Random Forest

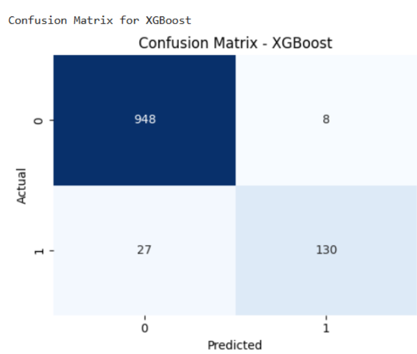


FIG-5 XGBoost

According to the performance results from **Table 1** (range of performance metrics) and Table 2 (Accuracy Score), the Linear SVM model was the best performing machine learning model. It showed the highest accuracy (0.98), precision (0.98), recall (0.99), F1, (0.99). All four metrics were strong metrics indicating the Linear SVM model was the best performing model. Essentially, the Linear SVM model accurately determined most spam and non-spam emails (high accuracy), evaluated false negatives and false positives in similar measures (high precision and recall), and finally performed quite well overall (high F1).

As evidenced by **Table 2's** performance ranges, the two other deep learning models that scored 0.98 accuracies were the CNN and LSTM. They did have differing performance metrics in other areas but also were comparable. The LSTM reached about the same recall (0.98) and precision (1.00) levels as the SVM. However, the CNN model did score slightly lower with recall (0.89), indicating the model may have resulted in not identifying a few spams (false negatives). The LSTM model, nonetheless, performed consistently well overall, although it had lower recall metrics in the range.

Clearly, Linear SVM was the best performing model for this entire task, across the range of models. This was because overall, the Linear SVM patently operated on all the metrics of accuracy, precision, recall, and F1 in such exceptional equivalency across all model results, and was therefore the better physical choice model in detecting spam and non-spam emails.

FORMULAS:

Accuracy= $$\frac{\textbf{True Positive+True Negative}}{\textbf{True Positive+True Negative+False Positive+False Negative}} \qquad \textbf{(1)}$$

Correct predictions / Total predictions. Simple but can be misleading with uneven data or different error costs.

Recall= $$\frac{True\ Positive}{True\ Positive+False\ Negative} \qquad (2)$$

Recall is a vital metric for evaluating a classification model's ability to find all the positive instances within a dataset, especially when missing positive cases is costly.

Precision = $$\frac{True\ Positive}{True\ Positive+False\ Positive} \qquad (3)$$

Precision is a vital metric for evaluating a classification model's ability to be accurate in its positive predictions, especially when incorrectly labeling negative instances as positive has significant consequences.

F1- Score = $$\frac{2*Precision*Recall}{Precision+Recall} \qquad (4)$$

The F1-score is a valuable metric that provides a balanced assessment of a classification model's performance by considering both its ability to correctly identify positive cases (Recall) and its ability to avoid incorrectly labeling negative cases as positive (Precision).

CONCLUSION

In this project, we explored Natural Language Processing (NLP) techniques to classify text messages as **Spam** or **Ham (Not Spam)** using machine learning models. By cleaning and preprocessing textual data, applying **TF-IDF vectorization**, and training multiple classification algorithms such as **Multinomial Naive Bayes**, **Logistic Regression**, **Support Vector Machines (SVM)**, and **Random Forest**, we were able to evaluate and compare the performance of each model.

Key takeaways:

- **TF-IDF** helped in converting raw text into meaningful numerical features.
- **Multinomial Naive Bayes** often performed best for text classification problems like spam detection due to its simplicity and effectiveness with word frequency.
- Evaluation metrics such as **accuracy**, **confusion matrix**, and **classification report** provided insight into each model’s strengths and weaknesses.

This project demonstrates the practical application of NLP in real-world problems like filtering unwanted messages and lays the groundwork for more advanced techniques such as **deep learning models** (e.g., LSTM, BERT) for future work.

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