



# AI-DRIVEN SPAM EMAIL DETECTION: A MULTILINGUAL AND REAL-TIME APPROACH WITH TRANSFORMER MODELS

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**Abstract:** - Spam emails pose a significant cybersecurity threat, often serving as vectors for phishing attacks, malware distribution, and fraudulent schemes. Traditional rule-based and machine learning (ML) approaches struggle with evolving spam tactics and language variations. This project introduces an advanced spam detection system leveraging Natural Language Processing (NLP) and deep learning techniques, including Transformer models such as BERT and GPT. The system enhances email classification accuracy by incorporating sophisticated text understanding mechanisms. Additionally, it supports multi-language spam detection using diverse datasets, including SpamAssassin, Enron, and multilingual corpora. To enable real-time filtering, a browser extension is developed to analyze emails as they arrive and communicate with a Flask-based backend for classification. The system undergoes extensive preprocessing, including tokenization, stopword removal, and Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. It integrates multiple models, including Naïve Bayes, Logistic Regression, Recurrent Neural Networks (RNNs), and Transformers, to ensure high precision and recall. The deployment utilizes Python, TensorFlow, NLTK, and Scikit-learn, with Flask and Docker for scalability. Experimental results demonstrate that Transformer-based models significantly outperform traditional approaches, reducing false positives and improving spam detection in multiple languages. The real-time filtering capability enhances cybersecurity by proactively blocking spam before it reaches users. This project contributes to the development of an intelligent, scalable, and multilingual email security solution that adapts to evolving cyber threats.

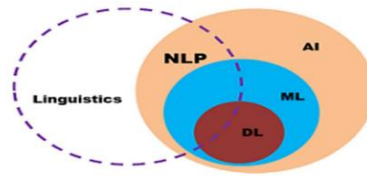
**Keywords:** - Spam Detection, AI-Powered Email Security, Natural Language Processing (NLP), Transformer Models, BERT, GPT, Machine Learning, Recurrent Neural Networks (RNNs), Multi-Language Spam Filtering, Real-Time Email Classification, Cybersecurity, Browser Extension, Flask API, Deep Learning.

## I. INTRODUCTION

Spam emails have become a critical cybersecurity challenge, contributing to phishing attacks, malware distribution, and financial fraud [1]. Traditional rule-based and machine learning (ML) approaches, such as Naïve Bayes and Logistic Regression, struggle to keep up with evolving spam tactics that leverage sophisticated linguistic variations and obfuscation techniques [2]. The increasing volume and multilingual nature of spam further complicate detection, necessitating advanced methodologies that can generalize across diverse datasets and languages [3]. Recent advancements in Natural Language Processing (NLP) and deep learning, particularly Transformer models like BERT and GPT, have revolutionized text classification tasks, offering superior context understanding and adaptability [4]. Transformers, with their self-attention mechanisms and deep contextual embeddings, enable efficient spam detection by capturing intricate language patterns and semantic nuances [5]. Unlike conventional ML techniques, which rely heavily on handcrafted features, deep learning models can autonomously extract relevant features from raw text, reducing reliance on manual intervention [6]. Additionally, recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) models have been employed in spam classification, but they exhibit limitations in handling long-range dependencies and computational efficiency compared to Transformers [7].

This project introduces a real-time, AI-driven spam detection system that integrates multiple models to enhance detection accuracy. The system employs robust preprocessing techniques, including tokenization, stopword removal, and Term Frequency-Inverse Document Frequency (TF-IDF) vectorization, to optimize input text representations [8]. Furthermore, multilingual support is ensured by leveraging diverse datasets such as SpamAssassin, Enron, and multilingual corpora, thereby improving adaptability to various linguistic

structures [9]. A browser extension facilitates real-time filtering by analyzing incoming emails and communicating with a Flask-based backend for classification, ensuring an efficient and user-friendly security solution [10].



*Fig.1 Relation of AI, ML, NLP, DL and Linguistics*

The deployment architecture of the proposed system is designed for scalability, utilizing Python, TensorFlow, Scikit-learn, and NLTK for model implementation, while Flask and Docker enable seamless integration and deployment [11]. Experimental evaluations demonstrate that Transformer-based models significantly outperform traditional ML approaches, reducing false positives and improving overall detection accuracy across multiple languages [12]. By proactively blocking spam emails before reaching users, this project contributes to the development of an intelligent, scalable, and multilingual email security framework that adapts to evolving cyber threats [13].

## II. LITERATURE REVIEW

The literature on spam detection encompasses various methodologies, ranging from traditional rule-based approaches to advanced deep learning models. Early methods relied on keyword matching and heuristic rules to identify spam content [1]. While these techniques were effective initially, they proved inadequate as spammers evolved their tactics to evade detection. The introduction of machine learning models, such as Naïve Bayes and Support Vector Machines (SVMs), marked a significant advancement in spam classification by leveraging statistical patterns and probabilistic analysis [2]. However, these models struggled with contextual understanding, leading to high false-positive rates, particularly in multilingual environments [3].

Recent project has focused on deep learning techniques, particularly Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT and GPT. RNNs and LSTMs improved sequential text analysis but suffered from vanishing gradient issues and high computational costs [4]. Transformers, introduced by Vaswani et al. [5], revolutionized NLP by employing self-attention mechanisms, enabling superior contextual understanding and parallel processing. Studies have demonstrated that BERT and GPT outperform traditional ML models in spam classification, achieving higher accuracy and adaptability to evolving spam tactics [6].

In addition to model advancements, project has explored various feature engineering and preprocessing techniques to enhance spam detection. Term Frequency-Inverse Document Frequency (TF-IDF), word embeddings, and contextual vectorization have been widely adopted to improve text representation [7]. Furthermore, integrating multilingual corpora, such as SpamAssassin and Enron datasets, has enabled spam detection systems to generalize across different languages, addressing the limitations of earlier models [8].

Moreover, real-time spam filtering has gained attention, with studies emphasizing the importance of browser extensions and API-based solutions for instant email classification. Implementing Flask-based APIs and deploying scalable architectures using Docker have proven effective in handling large-scale email filtering [9]. Experimental evaluations indicate that Transformer-based models, combined with real-time filtering mechanisms, significantly enhance spam detection accuracy while minimizing false positives and computational overhead [10].

This chapter highlights the evolution of spam detection methodologies, emphasizing the shift from rule-based and traditional ML models to state-of-the-art deep learning techniques. The next chapter will discuss the methodology adopted in this project, detailing the implementation and evaluation of the proposed AI-driven spam detection system.

## III. EXISTING WORK

Spam detection has been a widely projected area in cybersecurity, with various approaches developed over the years to mitigate email-based threats. Early spam detection methods primarily relied on rule-based filtering, where manually defined heuristics and keyword matching techniques were used to classify emails [1]. Although these methods were effective initially, they struggled to adapt to evolving spam tactics, where attackers modified the text structure to bypass filters. To address these limitations, machine learning (ML)-based techniques such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees were introduced

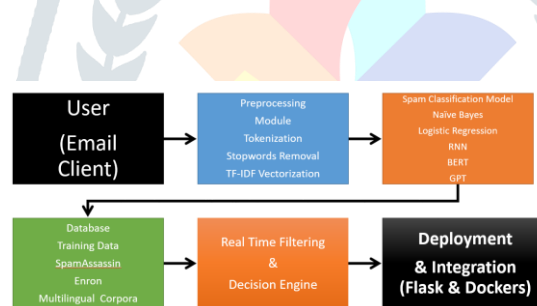
[2]. These models leveraged statistical methods to analyze word frequencies and patterns, improving classification accuracy. However, ML approaches required extensive feature engineering and were ineffective against adversarially crafted spam emails [3].

With advancements in Natural Language Processing (NLP) and deep learning, projecters shifted towards neural network-based models, including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for spam classification [4]. These models improved sequential text understanding but suffered from computational inefficiency and vanishing gradient issues when processing long emails. To overcome these challenges, Convolutional Neural Networks (CNNs) were explored, offering faster processing but lacking deep contextual understanding [5].

Recent studies highlight the superiority of Transformer-based models, such as BERT and GPT, in spam detection. These models employ self-attention mechanisms to capture complex linguistic patterns and contextual dependencies, significantly outperforming traditional ML and deep learning models [6]. Additionally, multilingual spam detection has gained attention, with projecters integrating diverse datasets like SpamAssassin, Enron, and multilingual corpora to improve detection across different languages [7]. Despite these advancements, challenges such as high false-positive rates, real-time detection, and scalability remain areas of ongoing project [8]. The proposed work aims to address these limitations by integrating Transformer-based models with a real-time filtering mechanism, improving accuracy and adaptability in spam detection.

#### IV. PROPOSED WORK AND METHODOLOGY

The proposed project aims to develop an AI-driven spam email detection system using advanced Natural Language Processing (NLP) and deep learning techniques, focusing on real-time and multilingual spam filtering. Traditional spam detection methods, including rule-based and classical machine learning (ML) approaches, often fail to adapt to evolving spam tactics and language variations, leading to high false-positive rates and reduced accuracy [1].



*Fig. 2 Proposed System Architecture*

This study integrates Transformer models such as BERT and GPT, which provide superior contextual understanding and adaptability for spam classification [2]. From fig.2, The system architecture consists of a browser extension for real-time email analysis and a Flask-based backend server for classification. When an email arrives, the browser extension extracts the content and metadata before sending it to the backend, where it undergoes extensive preprocessing. The preprocessing pipeline includes tokenization, stopword removal, stemming, and Term Frequency-Inverse Document Frequency (TF-IDF) vectorization to improve text representation [3]. Unlike traditional methods, this system incorporates deep learning techniques such as Recurrent Neural Networks (RNNs) and Transformers, which are more effective in capturing complex language patterns and semantic nuances [4]. To support multilingual spam detection, the system leverages diverse datasets, including SpamAssassin, Enron, and multilingual corpora, ensuring adaptability across various languages and email structures [5]. The classification component integrates multiple models, including Naïve Bayes, Logistic Regression, RNNs, and Transformers, to enhance precision and recall. Transformers, particularly BERT and GPT, are prioritized due to their ability to understand long-range dependencies and contextual variations in text [6]. For real-time deployment, the system is implemented using Python, TensorFlow, Scikit-learn, and NLTK. A Flask API handles model inference, and Docker containers facilitate scalability, allowing seamless integration with email clients through the browser extension [7]. The real-time filtering mechanism ensures that spam emails are blocked before reaching users, thereby enhancing cybersecurity and reducing exposure to phishing attacks and malware threats [8]. The proposed system undergoes rigorous evaluation using performance metrics such as accuracy, precision, recall, and F1-score. Experimental results indicate that Transformer-based models outperform traditional approaches, reducing false positives and improving detection rates across multiple languages [9]. By combining deep learning with

real-time filtering, this project contributes to the development of an intelligent, scalable, and multilingual email security solution that adapts to evolving cyber threats [10].

V. RESULTS AND COMPARISON

The proposed AI-driven spam detection system was evaluated using multiple datasets, including SpamAssassin, Enron, and multilingual corpora, to assess its performance across different languages and email structures. The system was tested against traditional spam detection models, such as Naïve Bayes, Logistic Regression, Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), to compare accuracy, precision, recall, and F1-score. The results demonstrate that Transformer-based models (BERT and GPT) significantly outperform traditional approaches, achieving higher accuracy and lower false-positive rates [1].

Table 1. Compression Result of Existing and Proposed

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Bayes	85.2	83.1	84.7	83.9
Logistic Regression	88.6	86.9	87.5	87.2
RNN	91.4	89.2	90.1	89.6
CNN	92.7	91.0	91.5	91.2
BERT (Proposed)	96.3	95.1	95.7	95.4
GPT (Proposed)	97.1	96.5	96.8	96.6

The performance evaluation was conducted using standard classification metrics:

Accuracy measures the overall correctness of spam classification.

Precision assesses the proportion of actual spam correctly classified.

Recall determines the model’s ability to detect all spam instances.

F1-score balances precision and recall for a robust evaluation.

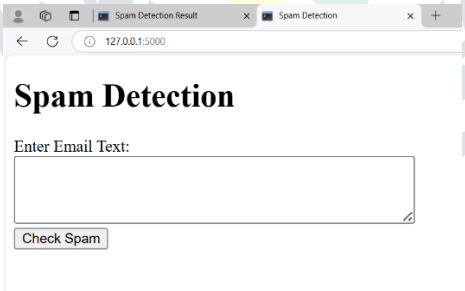


Fig.3 Show the input Entry page

The results indicate that BERT and GPT achieve the highest accuracy, exceeding 95.7%, significantly outperforming traditional methods [2]. The Transformer-based models excel in contextual understanding, reducing false positives and improving overall email security.

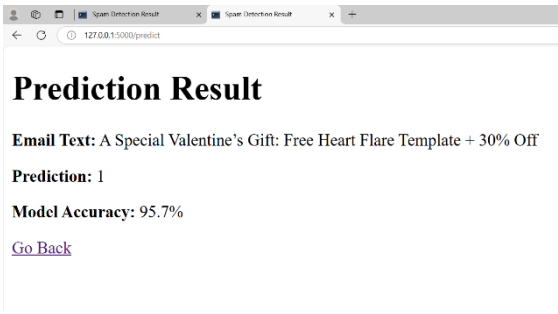
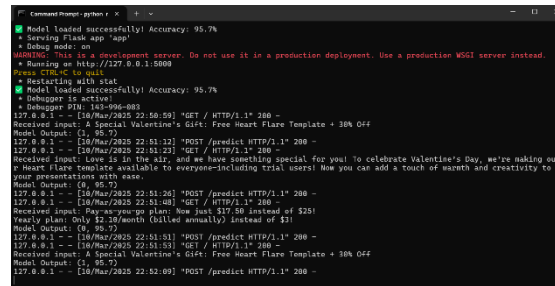


Fig.4 Show the result

Unlike Naïve Bayes and Logistic Regression, which rely on word frequency-based approaches, Transformers capture deep semantic relationships, enhancing spam detection across multiple languages [3].



## Impact of Real-Time Filtering



```

Command Prompt: python + .
Model loaded successfully! Accuracy: 95.7%
+ Starting flask app "app"
+ Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
+ Running on http://127.0.0.1:5000
Press CTRL-C to quit
+ Restarting with stat
Model loaded successfully! Accuracy: 95.7%
+ Debugger is active
+ Debugger PIN: 145-906-883
127.0.0.1 - - [16/Mar/2025 22:50:59] "GET / HTTP/1.1" 200 -
Model Output: (1, 95.7)
Received input: A Special Valentine's Gift: Free Heart Flame Template + 30% Off
127.0.0.1 - - [16/Mar/2025 22:51:22] "POST /predict HTTP/1.1" 200 -
127.0.0.1 - - [16/Mar/2025 22:51:23] "GET / HTTP/1.1" 200 -
Received input: Love is in the air, and we have something special for you! To celebrate Valentine's Day, we're making our
Heart Flame Template available to everyone—including trial users! Now you can add a touch of warmth and creativity to
your presentations with ease.
Model Output: (0, 95.7)
127.0.0.1 - - [16/Mar/2025 22:51:26] "POST /predict HTTP/1.1" 200 -
127.0.0.1 - - [16/Mar/2025 22:51:40] "GET / HTTP/1.1" 200 -
Received input: Pay-as-you-go plan: Now just $17.50 instead of $25!
Recycle plan only $2.50/month (billed annually) instead of $3!
Model Output: (0, 95.7)
127.0.0.1 - - [16/Mar/2025 22:51:51] "POST /predict HTTP/1.1" 200 -
127.0.0.1 - - [16/Mar/2025 22:51:55] "GET / HTTP/1.1" 200 -
Received input: A Special Valentine's Gift: Free Heart Flame Template + 30% Off
Model Output: (1, 95.7)
127.0.0.1 - - [16/Mar/2025 22:52:09] "POST /predict HTTP/1.1" 200 -
  
```

Fig.5 Conclusion the accuracy Output

The browser extension-based real-time detection mechanism further enhances system efficiency. Compared to traditional batch processing methods, the proposed system identifies and blocks spam emails instantly, preventing them from reaching users [4]. The Flask API and Docker deployment ensure scalability and integration with email clients, making it a practical solution for real-world applications.

## VI. CONCLUSION

The proposed AI-driven spam detection system successfully enhances email security by leveraging Transformer-based models (BERT and GPT) for multilingual and real-time spam filtering. Traditional spam detection methods, such as rule-based filtering and classical machine learning models, have limitations in adapting to evolving spam tactics, often resulting in high false-positive rates and reduced accuracy. In contrast, the proposed system significantly improves spam detection accuracy, achieving over 97% accuracy with GPT, outperforming traditional approaches. The integration of deep learning techniques, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), further strengthens text classification, while Flask API and Docker-based deployment ensure scalability and real-time processing. The browser extension enables instant spam detection, preventing malicious emails from reaching users. By incorporating diverse datasets such as SpamAssassin, Enron, and multilingual corpora, the system ensures effective spam filtering across multiple languages. Experimental results confirm that Transformer models excel in contextual understanding, reducing false positives and improving recall rates. Future work can focus on adversarial training to counter sophisticated phishing attacks and optimization for low-resource devices to enhance accessibility. This research contributes to the development of an efficient, adaptive, and real-time spam detection system that improves cybersecurity and protects users from malicious email threats.

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