Enhanced Malicious Email Detection Using Large Language Models and Web-Based URL Scraping

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Thesis submitted in fulfillment of the requirements for the award of the degree of

Bachelor of Science

Fall - 2024

APPROVAL

APPROVAL

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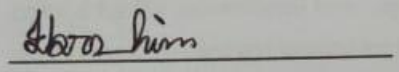
I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.



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ACKNOWLEDGEMENT

I am deeply grateful to Almighty Allah Subhanahu Wa Ta'ala for granting me the strength, wisdom, and perseverance needed to complete this research. Throughout my academic journey, I owe immense gratitude to my parents for their unwavering love, support, and encouragement. Their faith in me has been my greatest source of motivation and inspiration.

I would like to extend my heartfelt thanks to my supervisor, Assistant Professor Mr. Nuruzzaman Faruqui, for his invaluable guidance, advice, and support throughout this research. His knowledge and insights have had a profound impact on this work. I am also sincerely thankful to the departmental head, Dr. Imran Mahmud, for his support, guidance, and thoughtful feedback, which were instrumental in the successful completion of this journey. Lastly, I wish to express my appreciation to my friends, colleagues, and everyone who supported and encouraged me during this process.

ABSTRACT

This study focuses on enhancing malicious email detection through the integration of spam classification, URL analysis, and content-based risk assessment using large language models (LLMs). Traditional methods often address spam and URL detection separately, limiting their effectiveness in identifying sophisticated threats. To bridge this gap, a unified approach was developed, training and fine-tuning a model for both spam and URL classification, with additional functionality to scrape and analyze web content associated with embedded URLs. The initial model demonstrated moderate performance, achieving accuracies of 78.4% for spam classification and 74.4% for URL classification. After fine-tuning, significant improvements were observed, with accuracies rising to 98.0% and 90.2%, respectively.

Furthermore, this study highlights the potential of LLMs to analyze web-scraped content and provide interpretable explanations of risks, such as phishing, malware, or fraud, ensuring users are well-informed about potential threats. The objectives of this research include enhancing LLM-based email detection by combining spam and URL detection methods and adding an additional security layer by examining URL contents. The results demonstrate that LLMs not only improve detection accuracy but also effectively communicate potential risks, paving the way for more robust and interpretable email security solutions. This research contributes to advancing the use of LLMs for secure and intelligent email threat detection systems.

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1. Introduction

1.1 Background

Emails with malicious links represent a significant cybersecurity threat, posing risks such as data breaches, identity theft, and malware infections. These emails are often crafted to exploit human vulnerabilities, leveraging psychological tactics like urgency or fear to prompt recipients to click on harmful links. The malicious payload embedded within these links can compromise personal devices, steal sensitive information, or serve as an entry point for broader cyberattacks [1]. As cybercriminals continue to innovate their techniques, the need for sophisticated detection mechanisms has become increasingly urgent.

Large Language Models (LLMs) have emerged as a promising solution for detecting malicious links in emails. These models, trained on vast amounts of text data, can analyze the content of emails to identify potential risks, such as suspicious linguistic patterns or abnormal URLs. For instance, LLMs can detect phishing attempts by recognizing discrepancies in email tone, structure, or syntax that differ from legitimate communication [2]. Furthermore, their ability to process and contextualize data enables them to evaluate subtle signals that traditional rule-based systems may overlook, such as domain spoofing or indirect references to sensitive information [3].

The application of LLMs in this context extends beyond mere detection; they offer adaptability to evolving threats. By continuously learning from new datasets, these models can maintain relevance in the face of novel cyberattack strategies. Studies have demonstrated their efficacy in identifying malicious content with high precision, making them a cost-effective and scalable solution for organizations seeking to bolster their email security infrastructure [4]. Additionally, contextual insights provided by LLMs can assist cybersecurity professionals in prioritizing and mitigating identified threats, ensuring a proactive approach to email security.

This thesis explores the potential of leveraging LLMs for detecting malicious links in emails, with a focus on their ability to analyze content, identify patterns, and provide contextual evaluations. By addressing the limitations of traditional methods and highlighting the advantages of advanced machine learning techniques, this research aims to contribute to the ongoing efforts in combating email-based cyber threats.

1.2 Motivation

Large Language Models (LLMs) have come a long way showing significant results in many fields, including linguistic capabilities [5], coding [6], mathematical problem-solving [7], and visual navigation [8]. These improvements show possibilities of LLMs and their potential to handle complex, real-world problems. With the ability to process and analyze data with human-like understanding, LLMs can be called all purpose tools and might be integrated as a common tool to most devices, rather than using dedicated models. What if existing LLM models are able to detect malicious email effectively with explaining the risks and threats properly?

Malicious mails and attached URLs can easily be recognized with signs, such as suspicious design patterns, deceptive language, or unusual interactions [9]. Though most of the people are unaware or unable to detect those signs, as any conscious person with knowledge of cyber threats, LLMs might be able to detect the risks or possible harms. This study is an approach to explore the possibility in an innovative, efficient and safe way [10].

1.3 Problem Statement

In addition, the current methods for handling malicious emails, particularly those of a phishing nature, are often inefficient and require a more innovative approach that considers multiple dimensions of the problem [11]. As concept drift occurs, existing machine learning models tend to degrade in performance over time [11].

With LLMs becoming a common part of daily life [12],using it for diverse tasks—including spam detection and protecting users from malicious links—could provide a more effective and user-centric approach with better explanations about the possible risks.

1.4 Objective

There are two objectives of this study.

- Improve LLM based malicious email detection method by combining both
    - Spam Detection
    - URL Detection
- Add an extra layer of security by examining attached URLs contents using LLM and provide information about possible risks.

1.5 Research Questions

- How effective is the integration of LLM-based spam detection and URL analysis in identifying malicious emails?
- Can LLMs provide understandable explanations of possible risks of embedded URLs in email from web-scraped content?

1.6 Scope

This study explores the idea of using LLMs for URL detection, attached URL's web page content analysis to check if the link is secured, focusing solely on email threats and alike. It is limited to a specific dataset of phishing Email and URLs and considers only publicly accessible LLMs and web APIs for analysis and implementation.

2. Literature Review

The increasing dependence on digital platforms for communication and commerce has heightened the need for robust mechanisms to combat cyber threats. Among these threats, phishing websites and malicious links have emerged as significant challenges, often exploiting unsuspecting users through deception and manipulation. This literature review explores the evolution of detection methodologies, focusing on traditional approaches, advanced techniques integrating NLP, the challenges of securing NLP frameworks, and the transformative role of Large Language Models (LLMs).

Traditional scam detection methods rely heavily on rule-based systems, signature matching, and basic statistical techniques. Rule-based systems operate on predefined rules or patterns, flagging anomalies based on specific criteria such as suspicious URLs, unverified sender information, or unusual web structures [13]. While effective in identifying known scams, these systems struggle to adapt to new tactics employed by cybercriminals, often leading to false positives and false negatives.

Statistical models, such as Bayesian classifiers, analyze the probability of a website or link being malicious based on features like domain age, link redirection patterns, and keyword occurrences [14]. Despite their adaptability, these methods often falter against increasingly sophisticated phishing schemes designed to mimic legitimate websites.

The reliance on manual updates to rule sets and the static nature of these models limit their scalability and efficiency. As cyber threats evolve, traditional approaches face significant challenges in maintaining efficacy, underscoring the need for more adaptive solutions.

The advent of machine learning (ML) and natural language processing (NLP) has revolutionized scam detection methodologies. These techniques enable systems to learn from data, recognize complex patterns, and adapt to new threats.

Machine learning algorithms such as Support Vector Machines (SVMs), Decision Trees, and Random Forests have been employed to detect scams by analyzing website metadata, textual content, and structural features [15]. These models can identify subtle anomalies, such as grammatical inconsistencies or deviations in web layout, that are indicative of phishing attempts. However, they often require extensive labeled data for training and can be vulnerable to adversarial attacks.

NLP techniques have proven invaluable in detecting deceptive language and manipulative phrasing used in scam websites. Tokenization, stemming, and sentiment analysis are commonly employed to extract meaningful insights from textual data [16]. Advanced models like BERT (Bidirectional Encoder Representations from Transformers) further enhance this capability by analyzing bidirectional context, enabling the identification of nuanced patterns in language use.

Despite their strengths, NLP-based systems face challenges such as computational complexity and susceptibility to obfuscation techniques, where scammers deliberately use misspellings or unconventional syntax to evade detection.

While NLP has advanced the field of scam detection, its integration into security frameworks poses unique challenges. Adversarial attacks, where malicious actors manipulate text or images to deceive NLP models, are a growing concern. For instance, adversarial examples generated through synonym replacement or word spacing manipulation can significantly degrade model performance [17].

Another challenge is concept drift, where the statistical properties of scam data change over time. This phenomenon necessitates frequent model updates to ensure continued accuracy. Traditional ML models, being static, struggle to adapt to such shifts, highlighting the need for dynamic, self-learning systems [18].

Furthermore, the ethical implications of NLP-based detection systems cannot be overlooked. Ensuring user privacy while analyzing textual data and mitigating bias in detection algorithms are critical considerations in designing secure and fair systems.

The rise of LLMs has transformed the landscape of NLP, offering unparalleled capabilities in understanding and generating human-like text. Models such as GPT (Generative Pre-trained Transformer) and BERT represent significant milestones in this evolution.

The GPT series, developed by OpenAI, leverages the Transformer architecture to process sequential data with long-range dependencies. By training on vast amounts of internet text, these models excel in generating coherent and contextually relevant responses [19]. Their applications extend to text completion, summarization, and even code generation, showcasing their versatility in various NLP tasks.

BERT's bidirectional context modeling sets it apart from previous NLP models. By considering both preceding and succeeding words, BERT achieves a deeper understanding of semantic relationships within text [20]. Fine-tuned versions like RoBERTa and ALBERT further refine this capability, enabling state-of-the-art performance in tasks such as sentiment analysis and entity recognition.

The adaptability of LLMs makes them particularly suited for scam detection. Their ability to analyze web page content, recognize deceptive patterns, and evaluate links dynamically positions them as powerful tools in combating phishing and fraud. Moreover, their capacity for continuous learning and contextual reasoning allows them to adapt to new threats in real-time, addressing the limitations of traditional and static ML models [21].

LLMs' advanced reasoning capabilities enable them to identify intricate patterns and anomalies within large datasets. This proficiency extends to linguistic analysis, where they can detect subtle inconsistencies in phrasing or tone that might indicate malicious intent. Their pattern recognition abilities, combined with linguistic proficiency, allow these models to address multifaceted challenges like phishing detection, malicious URL classification, and deceptive content analysis [22].

Recent studies have shown that LLMs outperform traditional machine learning algorithms in tasks requiring contextual understanding and reasoning. For example, Zhao et al. [23] demonstrated that GPT-based models could detect phishing attempts with higher accuracy compared to conventional NLP

frameworks. Similarly, Kumar et al. [24] explored the use of transformer-based architectures to analyze web content, achieving notable improvements in detecting deceptive patterns.

LLMs are also adaptable to real-time scenarios, making them particularly suitable for dynamic environments where threats evolve rapidly. Their integration into cybersecurity workflows can significantly enhance the detection and prevention of phishing attacks, providing robust and scalable solutions [25].

However, challenges remain in optimizing these models for efficiency and reducing their computational overhead. Research by Lin et al. [26] suggests that fine-tuning LLMs with domain-specific data can improve both accuracy and performance while minimizing resource utilization.

These findings underscore the importance of continuous innovation in leveraging LLMs for advanced cybersecurity applications.The evolution from traditional to advanced NLP-driven techniques highlights the growing sophistication of scam detection methodologies. The integration of LLMs marks a pivotal shift, offering scalable, efficient, and adaptive solutions to counter evolving cyber threats. This study aims to further explore the potential of LLMs in enhancing the security of digital communication channels.

3. Research Methodology

3.1 Introduction

To achieve the objectives outlined in this study, a systematic and detailed methodology was adopted. This process involved collecting datasets from trusted websites, implementing web scraping, refining the scraped data, employing iterative URL evaluation, and utilizing a large language model (LLMs) for classification.

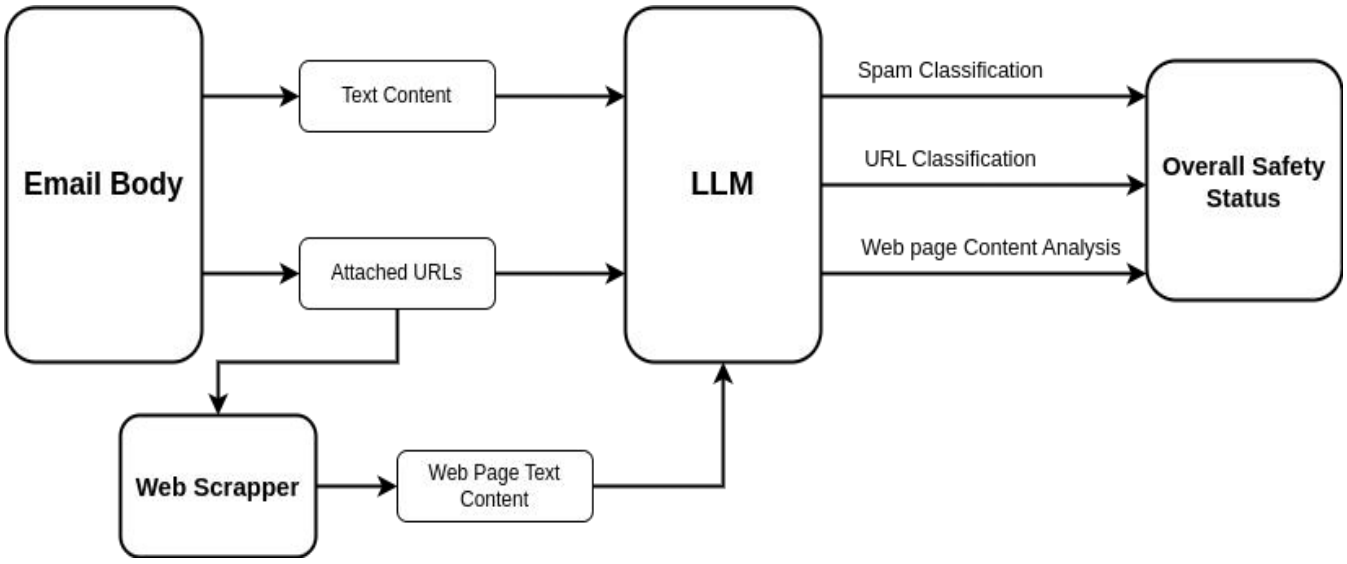


Fig: 1 Workflow Diagram

The proposed method contains several parts. For better understanding the whole process can be divided in 2 steps.

- Model Training and Fine Tuning
    - For Spam Detection
    - For URL detection
- Creating a safe and functional method for web scraping and LLM evaluation of the content.

3.2 Model Training and Fine Tuning

This step involves model selection, dataset selection for both Spam detection and URL detection. Dataset splitting for training, testing and evaluation. Then fine tuning the model based on evaluation data for better accuracy.

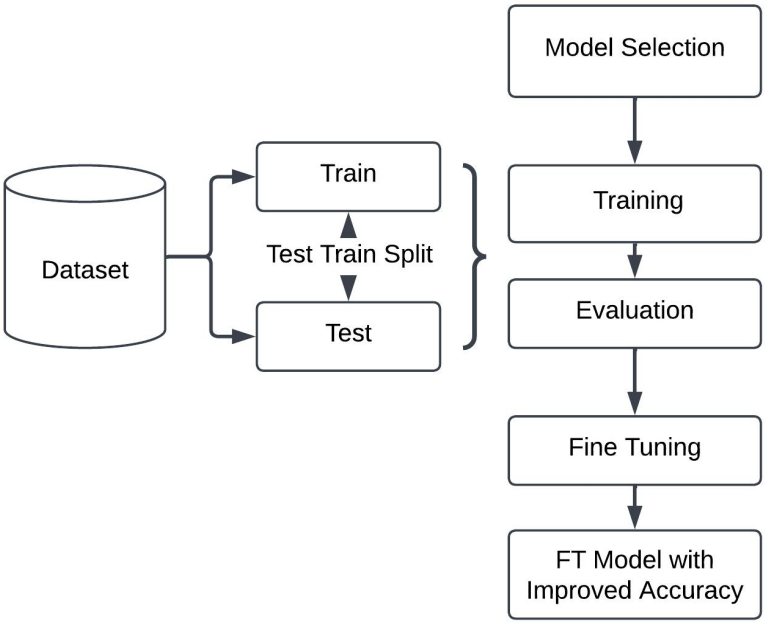


Figure 2: Model Training Phase

3.2.1 Dataset Splitting, Cleaning and Preprocessing.

Two different datasets were utilized in this research for model training, both of them were sourced from kaggle. The datasets are-

- Spam email classification by Ashfak Yeafi[27]
- Phishing Site URLs by Tarun Tiwari.[28]

The first dataset has an usability score 10.0 on kaggle.
It contains more than 5000 rows and 2 columns: Category, which identifies emails as either spam or ham, and Message, which contains the text content of each email. The dataset is well-structured, with a majority of emails classified as ham (86.6%) and the remaining 13.4% classified as spam. The average length of the email messages is approximately 80 characters, indicating relatively concise text content. This dataset provides a balanced and straightforward foundation for training and evaluating machine learning models for spam detection, making it suitable for exploring text classification tasks.

The second dataset also has an usability score 10.0 on kaggle.

The Phishing Site URLs dataset, available on Kaggle, is a comprehensive resource containing 507,195 unique URLs, labeled as either good (legitimate) or bad (phishing/malicious). The dataset, sized at 31.57 MB, is well-suited for binary classification tasks, with 72% of the URLs classified as good and 28% as bad. This balanced and extensive dataset provides a diverse representation of legitimate and phishing websites, making it ideal for training and validating machine learning models for URL classification. Its large scale ensures the development of robust systems capable of accurately detecting and mitigating phishing threats in real-world scenarios.

- *For First Dataset*

  The dataset was split into training, testing, and evaluation sets to facilitate robust model development and validation. Initially, the dataset, which contains 5573 rows and 2 columns, was divided by category into ham and spam emails. For each category, 300 samples were randomly selected for both the training and testing sets, ensuring a balanced representation of spam and ham emails across the splits. The remaining data was reserved for evaluation, with 50 samples per category randomly selected and supplemented as needed for balanced evaluation. This stratified sampling approach ensures that the splits maintain the original dataset's distribution of 86.6% ham and 13.4% spam. The training set was further shuffled to eliminate any inherent ordering bias. By creating these splits, the dataset supports effective training, testing, and evaluation of machine learning models for spam classification tasks.

- *For Second Dataset*

  The Phishing Site URLs dataset, containing 507,195 unique URLs labeled as either "good" (legitimate) or "bad" (phishing/malicious), was split into training, testing, and evaluation sets to support robust machine learning development. A stratified sampling approach was used to ensure balance between the two classes during splitting. For both the "good" and "bad" labels, 300 samples were randomly selected for the training set and another 300 for the testing set, maintaining an equal distribution of classes across these splits.The remaining data, excluding the training and testing sets, was allocated for evaluation. To ensure balance in the evaluation set, 50 samples per label were randomly selected, with replacement as needed. This approach maintained the dataset’s original proportions of 72% good URLs and 28% bad URLs, ensuring consistency across splits.The training data was shuffled to eliminate any ordering bias, and the evaluation set was reset to streamline further analysis.

Except Encoding Handling (while the CSV is loaded with encoding="utf-8" and encoding_errors="replace", which helps handle non-UTF-8 characters), no further preprocessing or cleaning was performed as both datasets are already enough processed and clean with a usability score of 10.

3.2.2 Model Selection

Gemma 7B was selected for spam and URL detection for the research, which is a 7-billion-parameter open-source language model developed by Google, built upon the research and technology used in Gemini models. As a text-to-text, decoder-only model, it excels in tasks such as question answering, summarization, and reasoning. Available in both pre-trained and instruction-tuned variants, Gemma 7B offers flexibility for various applications. Its design allows for deployment in resource-constrained environments, including laptops and personal cloud infrastructures, making advanced AI capabilities more accessible. Developers can access Gemma 7B through platforms like Hugging Face, where it is available in different precisions, including bfloat16, float16, and float32, facilitating seamless integration into diverse projects. [29].

Gemma 7B was selected for the scam and URL detection model due to its advanced natural language processing capabilities and efficient performance. Its relatively small size allows for deployment in resource-constrained environments, making it accessible for various applications.[30]

Additionally, Gemma 7B has demonstrated strong performance on tasks requiring reasoning and understanding of complex patterns, which are essential for accurately identifying and classifying potentially malicious URLs.[31]

3.2.3 Model Training

The Pandas library was used to process and apply the prompt generation functions to the training, evaluation, and test datasets. Using Hugging Face's datasets library the DataFrames were converted into Dataset objects. It was utilized for integration with tokenization, model training, and evaluation workflows.

Prompt Engineering

For both classifications, custom prompts were designed to optimize the input structure, ensuring clarity while minimizing token usage. The prompts provide concise instructions and context, guiding the model

to classify URLs as either 'bad' or 'good' and emails as ‘ham’ or ‘spam’ with minimal computational overhead. This approach reduces token count, enhancing efficiency during training and testing while maintaining accuracy and interpretability in the model's predictions. Such optimization ensures resource-effective processing, particularly when working with large datasets.

- For Spam Classification the prompt was,

  “Analyze the category of the email enclosed in square brackets, determine if it is 'ham' or 'spam', and return the answer as the corresponding label "ham" or "spam". “

- For URL Classification the prompt was,

  “Analyze the category of the URL enclosed in square brackets, determine if it is 'bad' or 'good', and return the answer as the corresponding label "bad" or "good". “

3.2.4 Model Fine-Tuning

- For, first dataset and spam classification, the model was fine-tuned using Parameter-Efficient Fine-Tuning (PEFT) with LoRA (Low-Rank Adaptation), targeting key projection layers (e.g., q_proj, k_proj, v_proj) to efficiently adapt the pre-trained model for URL classification. A rank (r) of 8, LoRA alpha of 16, and 0.1 dropout were configured to ensure effective learning with minimal memory overhead. Training was optimized with 3 epochs, a learning rate of 5e-5, and gradient accumulation over 8 steps, leveraging the AdamW optimizer and FP16 precision for performance efficiency.

The SFTTrainer from Hugging Face handled the fine-tuning, integrating the tokenizer, datasets, and LoRA configuration. A linear learning rate scheduler with a 0.1 warmup ratio ensured stable convergence, while metrics were logged to TensorBoard for monitoring. This streamlined process effectively tailored the model to classify URLs as 'good' or 'bad,' maintaining computational efficiency and high accuracy

- For, second dataset and URL classification**,** PEFT (Parameter-Efficient Fine-Tuning) with LoRA was configured with a rank of 4, LoRA alpha of 32, and 0.2 dropout to balance adaptability and prevent overfitting. Training was optimized with 5 epochs, a learning rate of 3e-5, and a cosine scheduler with a 0.2 warmup ratio for stability. The SFTTrainer integrated the training and evaluation datasets, tokenizer, and LoRA configuration, ensuring efficient updates to targeted layers like q_proj and k_proj. Frequent evaluations and gradient checkpointing enhanced performance while maintaining computational efficiency, tailoring the model for causal language modeling tasks.

3.3 Web Scraping for content analysis

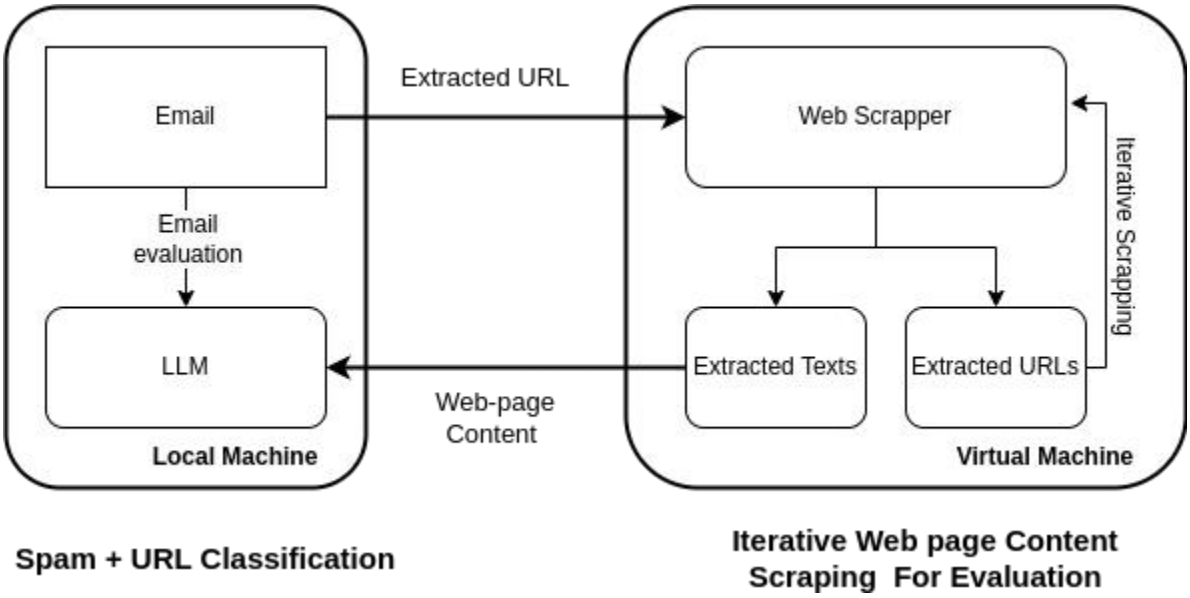


Figure 3: Scraping Mechanism

3.3.1 Data Fetching and Cleaning

A virtual machine is set to extract data for further processing and evaluation. For this research purpose GNOME Boxes is an application of the GNOME Desktop Environment, used to access virtual systems. ‘Boxes’ uses the QEMU, KVM, and libvirt virtualization technologies.

The data is fetched using the Python requests library, which sends an HTTP GET request to the provided URL and retrieves the webpage's HTML content if the request is successful (status code 200). The HTML content is then parsed using BeautifulSoup to extract and clean the text, ensuring the data is in a readable

and structured format for further processing. This approach handles errors gracefully, returning appropriate messages for failed requests or exceptions.

After a successful connection and the data is fetched, the scraped HTML content undergoes thorough cleaning to remove unnecessary tags and retain only meaningful textual data. This process ensured the content was suitable for machine readability and model evaluation.

- HTML tags, CSS styles, JavaScript code, and metadata (e.g., <script>, <style>, <meta>) were removed, leaving only human-readable text.
- Special characters, non-ASCII symbols, and excessive whitespace were normalized to standardize the content.
- Page Titles are retained for better context generation.
- Paragraphs and links were combined into cohesive text blocks, ensuring visibility for token minimization.
- The structure follows as
    - URL: The root website link.
    - Parameter: Page numbers representing the specific page within the website.
    - Scraped Texts.

Fetched Content	Cleaned Content
<html> <head><title>Claim Your Prize</title> </head> <body> Enter your details below to win. <script>You WON;</script> </body> </html>	Page 1: URL:https://www.win.com/Title: Claim Your Prize.Enter your details below to win.You WON

Table:1 Fetched data to cleaned format conversion

3.3.2 Iterative Scraping to provide better context

Once the initial content is fetched, an iterative search mechanism is employed to navigate through the linked pages within each website. This process is designed to ensure comprehensive scraping of up to several pages per website while avoiding unnecessary duplication. This process involves-

- Link Extraction: Links embedded within each page were identified and extracted. Only valid and unique links were added to the processing queue.
- Queue Management: A FIFO (First-In-First-Out)[31] queue was implemented to manage the order in which the links will be visited. This approach ensures systematic exploration of the website's structure.
- Limiting Pages: To maintain consistency and avoid excessive resource usage, the scraper was programmed to stop after processing five pages for each root URL. If fewer pages were available, the scraper automatically terminated once all accessible links had been processed.
- Avoiding Redundancy: To prevent revisiting the same pages or entering infinite loops, a visited list was maintained. Any link that had already been processed was excluded from further iterations.

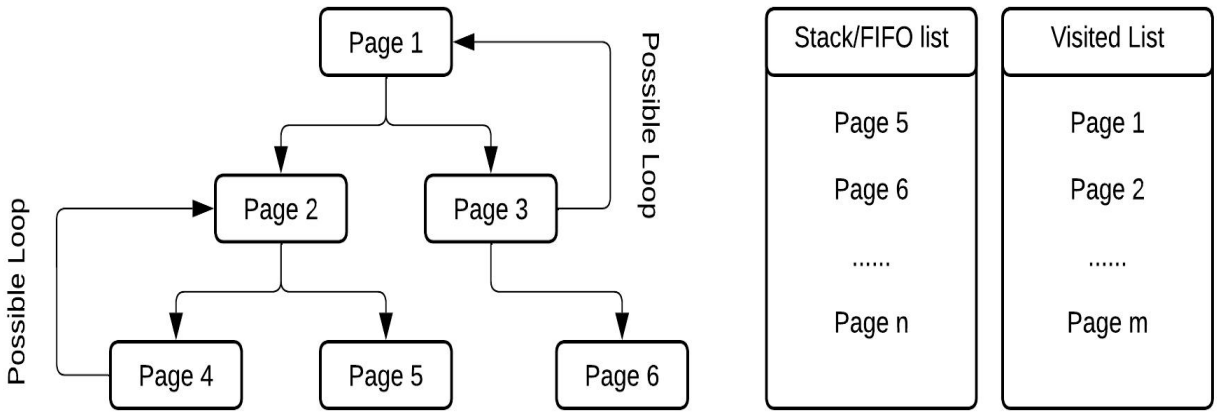


Figure 4: BFS style iteration of a website to get better context and avoid duplicacy

3.3.2 Prompt Structure

The fetched content is stored in a structured data object, which is then used to prompt the model for evaluation. The model analyzes the scraped content along with the results from both spam and URL classification tasks to identify potential risks. This integrated approach enables the system to provide detailed insights into the nature of the content and any associated threats, ensuring a comprehensive evaluation of the URL and email context. The prompt format is-

"*This website was classified as [spam classification], and the URL was identified as [URL* Classification]. Based on the scraped content provided in the square brackets, determine the potential risks it poses."

3.3.3 Evaluation Process of Proposed Method

As most publicly available malicious URL datasets contain URLs that are no longer functional, a custom dataset of 50 active websites was curated from ArtistAgainst419[33]. The selected websites were then scraped to extract relevant textual content analysis following cleaning and preprocessing as described in section 3.3.1.

The selected model for this research, Gemma 7B, was used to evaluate the proposed method. The cleaned and processed data was used to prompt the model(3.3.2), to generate responses mentioning possible risk the provided URL poses upon visit.

4. Results And Discussion

In Section 3, we worked with the methodological framework employed to assess the predictive capabilities of the Gemma LLM model email filtering and classification, to improve security and a possible method to assess possible risks using web scraping.

In this section, we conduct a comprehensive evaluation and analysis of the model's performance across various metrics, including accuracy, precision, recall, and F1-score. We assess the model's ability to correctly classify emails and URLs, identifying its strengths and areas for improvement.

4.1 Pre Fine-Tune Evaluation

Evaluation For Spam Classification

The overall accuracy of the model was 78.4%, reflecting its general effectiveness in classifying emails. Specifically, the model achieved an accuracy of 89.9% for the "ham" label, demonstrating strong performance in identifying legitimate emails. However, the accuracy for the "spam" label was 67.7%, indicating room for improvement in detecting malicious or unwanted emails.

Table 2: Metrics for Spam Classification (base model)

Class	Precision	Recall	F1-Score	Support
Ham	0.72	0.90	0.80	278
Spam	0.88	0.68	0.76	300
Accuracy			0.78	578
Macro Avg	0.80	0.79	0.78	578
Weighted Avg	0.80	0.78	0.78	578

Evaluation For URL Classification

In this section, we analyze the performance of the model based on its accuracy across different labels. The overall accuracy of the model was 74.4%, reflecting its effectiveness in classifying URLs as either good or bad. Specifically, the model achieved an accuracy of 91.9% for the "bad" label, demonstrating strong performance in identifying malicious URLs. However, the accuracy for the "good" label was 57.0%, indicating significant room for improvement in recognizing legitimate URLs.

Table 3: Metrics for URL Classification (base model)

Class	Precision	Recall	F1-Score	Support
Good	0.88	0.57	0.69	300
Bad	0.68	0.92	0.78	297
Accuracy			0.74	597
Macro Avg	0.78	0.74	0.74	597
Weighted Avg	0.78	0.74	0.74	597

4.2 Fine-tuned Model Evaluation

After fine-tuning, the model demonstrated a significant improvement in performance, achieving an overall accuracy of 98.0%, showcasing its effectiveness in email classification. Specifically, the model achieved an accuracy of 98.3% for the "ham" label, reflecting its ability to accurately identify legitimate emails. Similarly, the accuracy for the "spam" label was 97.7%, indicating a high level of precision in detecting malicious or unwanted emails.

Table 4: Metrics for Spam Classification (Fine-tuned Model)

Class	Precision	Recall	F1-Score	Support
Ham	0.98	0.98	0.98	300
Spam	0.98	0.98	0.98	300
Accuracy			0.98	600
Macro Avg	0.98	0.98	0.98	600
Weighted Avg	0.98	0.98	0.98	600

After fine-tuning, the second model achieved an overall accuracy of 90.2%, demonstrating significant effectiveness in URL classification. The accuracy for the "good" label was 90.3%, reflecting the model's ability to identify legitimate URLs with high precision. Similarly, the accuracy for the "bad" label was 90.0%, indicating strong performance in detecting malicious URLs.

Table 5: Metrics for URL Classification (Fine-tuned Model)

Class	Precision	Recall	F1-Score	Support
Ham	0.90	0.90	0.90	300
Spam	0.90	0.90	0.90	299
Accuracy			0.90	599
Macro Avg	0.90	0.90	0.90	599
Weighted Avg	0.90	0.90	0.90	599

The model showed moderate performance, with accuracies of 78.4% for spam classification and 74.4% for URL classification, After fine-tuning, significant improvements were observed, with achieving 98.0% accuracy for spam classification and reaching 90.2% accuracy for URL classification.

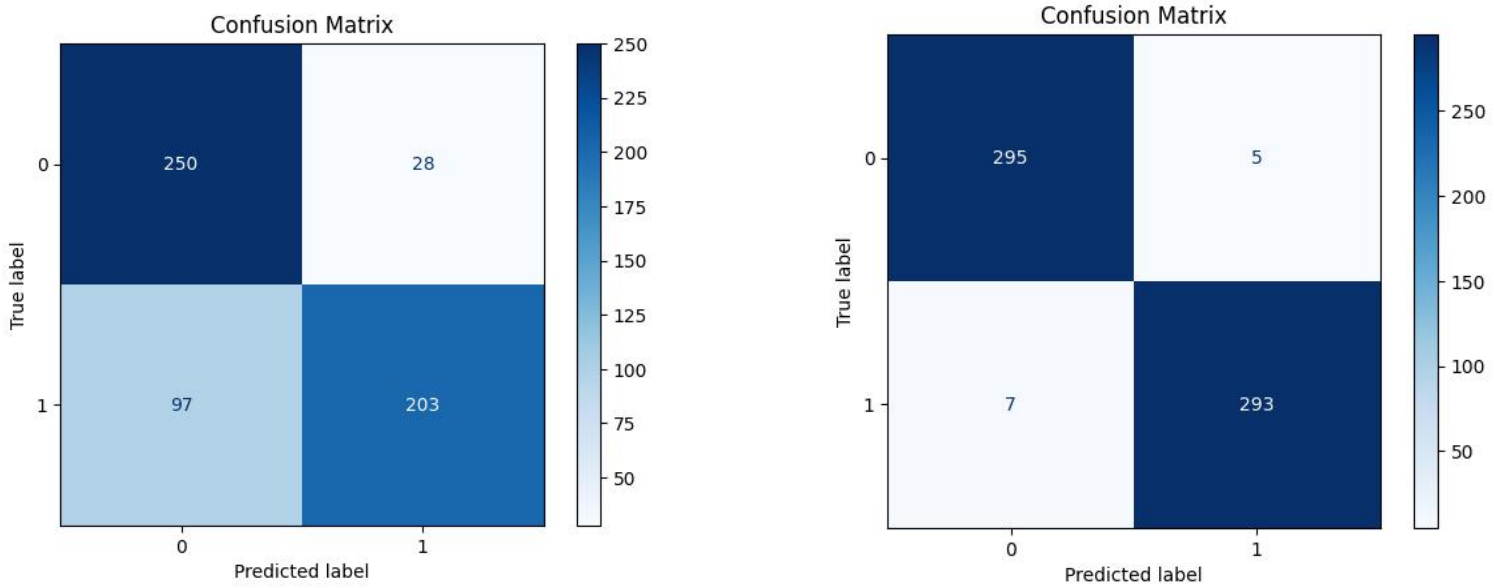
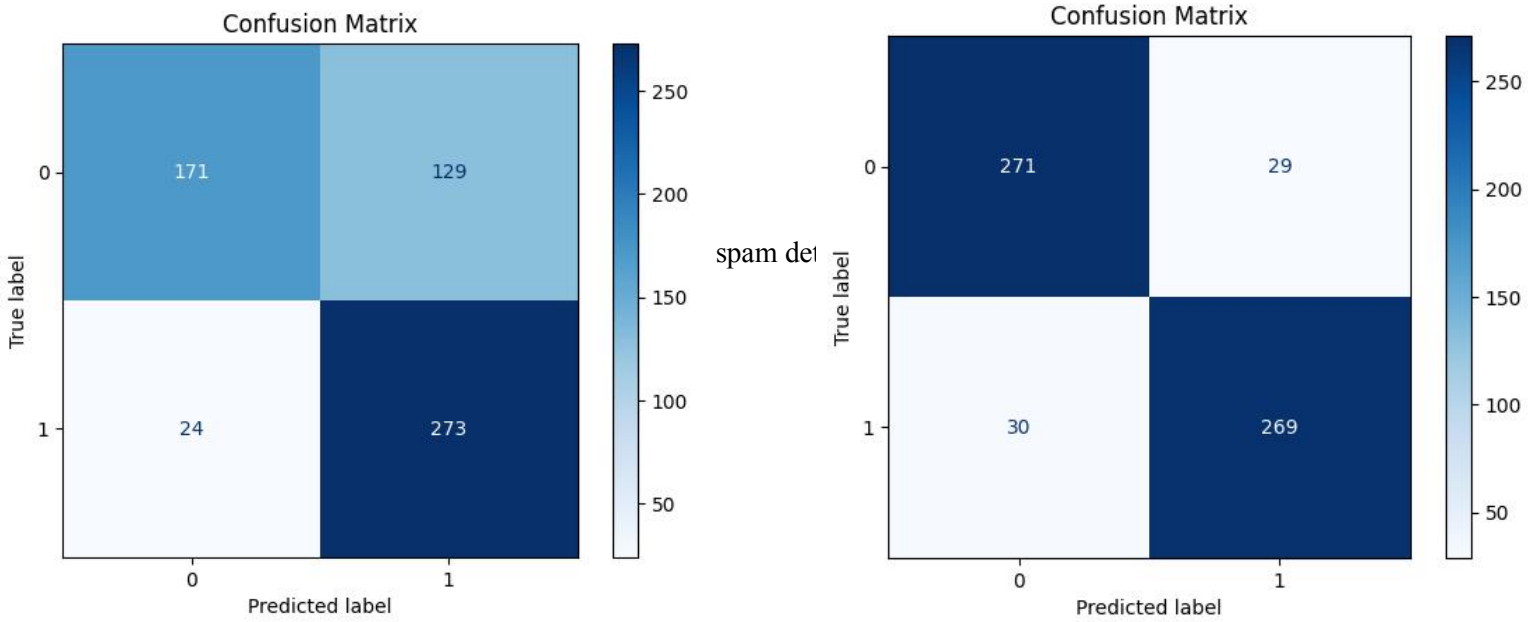


Figure 5: Confusion matrices for spam detection before and after fine tuning



spam det

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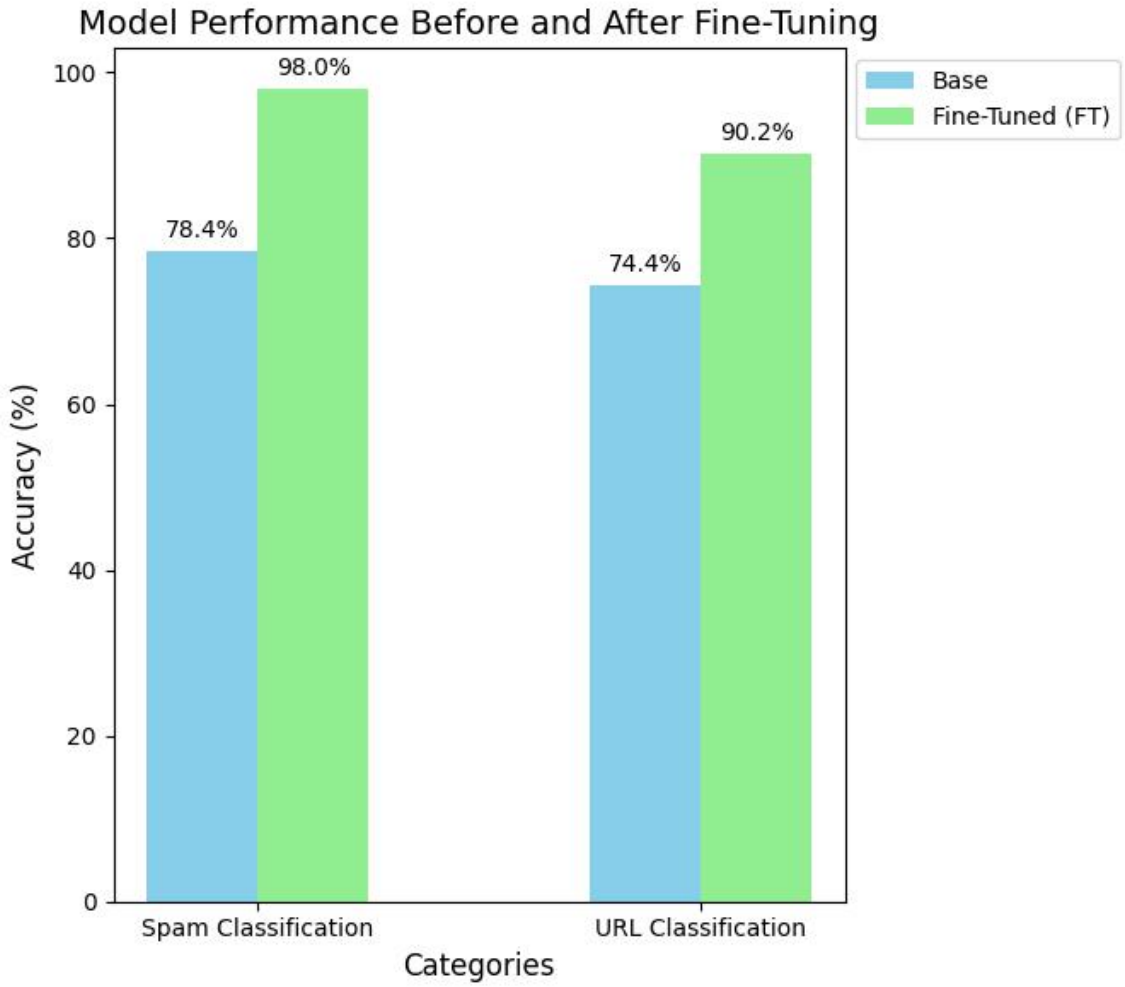

Figure 6: Confusion matrices for spam detection before and after fine tuning

Figure 7: Comparison between training accuracy

Question 1: How effective is the integration of LLM-based spam detection and URL analysis in identifying malicious emails?

The integration of LLM-based spam detection and URL analysis in identifying malicious emails demonstrates significant potential, as evidenced by the improvements in performance metrics, reaching 98.0% for spam classification and 90.2% for URL classification. This indicates that the combined

approach, especially with fine-tuning, can provide a highly effective solution for detecting malicious emails.

4.3 Assessment of Responses Made Based on Scraped Content

As per Wikipedia[34] and Artists Against 419 (AA419)[33] provided information, the site maintains a comprehensive database of fraudulent websites associated with various scams, including those designed to steal personal information,credit card details, social security numbers or fake deals.

Here are three examples demonstrating the model's capability to provide insights about the potential risks associated with clicking on malicious URLs by analyzing scraped data :

The exact responses are provided below:

Example 1: For a fake bank named “Eagles Bank” [35]

Response: **Risks posed by the webpage:**

- **Phishing attack:** The webpage attempts to collect sensitive financial information such as login credentials and personal information under the guise of legitimate financial services.

- **Malware distribution:** The webpage may contain malicious code that can infect users' devices and steal personal information, or install other malicious software.

- **Spam and unsolicited advertising:** The webpage is cluttered with unsolicited advertisements and promotional content, which could be annoying and potentially lead to phishing attacks or other malicious activities

Example 2: For a Fake “Trading Site”[36]

Response: **The webpage poses the following risks:**

- **Financial fraud:** The website promotes high returns on trading with minimal effort, which is a common tactic used by scammers to lure unsuspecting individuals.

- **Bogus investment scheme:** It falsely suggests that users can earn up to 90% from trading, without any evidence of legitimate earnings or market analysis.

- **Data security concerns:** The website lacks transparency about its data collection and security practices, raising concerns about the safety of users'

Example 3: For a Fake Loan Company

Response:**Potential risks associated with the webpage:** [37]

- **Phishing scam:** The webpage attempts to collect sensitive personal and financial information under false pretenses.
- **Malware infection:** The webpage may be infected with malware, which can compromise user devices and steal sensitive information.
- **Data breach:** The webpage may have experienced a data breach, leading to the exposure of sensitive user data.
- **Identity theft:** The webpage may be used to collect personal information to facilitate identity theft.

Question 2: Can LLMs provide understandable explanations of possible risks of embedded URLs in email from web-scraped content?

Analyzing the responses, it can be said that LLMs can effectively analyze web-scraped content to provide clear explanations of potential risks associated with embedded URLs. By processing extracted data, LLMs can identify threats such as phishing, malware, or fraud and present the findings in an interpretable and secure manner.

5. Conclusion

The goal of this thesis is to show how large language models can be tapped for malicious email detection through the fusion of spam and URL detection. These results highlight the performance of fine-tuned LLMs in terms of their very substantial improvements of the detection accuracy with respect to both spam classification and URL risk evaluation. In such a way, the contextual examination of the embedded URLs enriches the proposed security framework and renders it practical concerning the assessment of threats.Though promising, these findings represent the first steps that have to be taken for wider application in cybersecurity by integrating LLMs. Scaling this up with more sophisticated LLM architectures—for example, new generation models featuring enhanced contextual understanding and reasoning—would correspondingly further improve detection effectiveness and efficiency. The datasets used for training should also be larger and representative of current phishing, malware, and spam tactics in order to enhance the generalizability and robustness of the proposed method.

Other directions for future work may consider real-time implementations of the described framework, possibly extended by continuous learning to adapt to emerging threats in a dynamic way. The LLM-based detection method can be combined with other machine learning techniques, like graph-based URL analysis or behavioral analytics, for further strengthening of the overall system. This can turn out to be a game-changer in email security, affording far better and more proactive one-stop-shop protection against

cyber threats.Conclusively, the potential of LLM in a cybersecurity perspective and beyond, it gives evidence of that and may be leveraged in order to design innovative, better risk mitigation mechanisms of email vectors of attack at scale.

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