Phishing Detection Using Rule-Based Approaches: Email and URL Filtering Techniques

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The enclosed project documentation constitutes the culminating requirement for the Master of Science degree in Software Engineering

APPROVAL

This thesis/project/internship titled "**Phishing Detection Using Rule-Based Approaches: Email and URL Filtering Techniques**", submitted by **Md. Arnob Bhuyain, ID: 0242310005343001** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Masters of Science in Software Engineering and approval as to its style and contents.

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I formally declare that this thesis has been conducted under the supervision of **Assistant Professor Dr. Md. Fazla Elahe** from the **Department of Software Engineering at Daffodil International University.** I further attest that neither this thesis, nor any portion thereof, has been previously submitted by any party for the conferral of any degree.

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Abstract

Phishing, a well-known name in the field of cybersecurity. It is one of the most dangerous cyber-attacks in recent it or online. Phishing can be done using various techniques. Almost every few days, there are new techniques evolving to perform phishing attacks. By successfully making a phishing attack, an attacker can steal sensitive user information. This thesis proposes a rule-based detection system that analyzes email content and metadata such as subject lines, body text, URLs, and sender domains to identify phishing attempts. Using a carefully selected dataset of both authentic and phishing emails, a score system based on several rules was used to categorize emails. Accuracy, precision, recall, and F1-score were used to assess the system's performance following preprocessing and the application of detection rules. The results demonstrate that a rule-based strategy provides a simple and understandable way to detect phishing attempts, especially in settings with low resources. This rule-based approach to detecting phishing emails is lightweight, and it does not require large training data or complex interfaces. It can be easily integrated into email filtering systems for early phishing prevention.

CHAPTER 1
INTRODUCTION

1.1 Introduction

Emails are one of the most widely utilized communication tools in the modern digital world worldwide. But because of its accessibility and popularity, it has also become a frequent target for cybercriminals, especially those who use phishing assaults. Phishing is a tactic used by attackers to pose as trustworthy or reputable businesses in an attempt to fool victims into disclosing passwords, bank account information, or personal information. These assaults frequently appear as emails that appear legitimate but are actually loaded with malicious files, dubious links, or social engineering material.

New methods are being developed by attackers to carry out phishing attacks. Conventional phishing detection systems often fail to detect these types of attacks. Although a lot of research and studies have been conducted on this subject, the majority of them employ AI-driven methods and machine learning to identify phishing. In addition to requiring a sizable training dataset, this type of research may also necessitate significant computational resources. Rule-based detection, on the other hand, provides a computational resource that is lighter and less demanding, making it potentially simpler to set up and manage.

By examining several important elements, including email subject lines, body content, sender email address, and URLs in the body, this study aims to use a rule-based method for identifying phishing emails. In order to identify phishing attempts via emails, this study intends to provide a workable system by using predetermined rules to flag anomalous patterns.

1.2 Motivation

Phishing attack methods are becoming more sophisticated every day and typically get past conventional filters, posing a major security concern. Since complex machine learning models necessitate big training datasets and expensive processing resources, many businesses lack the infrastructure to implement them, particularly in low-resource situations. This encourages us to develop a straightforward, useful, and efficient rule-based system that can identify phishing emails by looking for odd metadata and context patterns. These systems work well for making decisions, are simpler to set up, and use less processing power. The goal of this study is to determine how a rule-based strategy can be a useful and highly successful defense against phishing attacks.

1.3 Research Objective

- To design and implement a rule-based phishing email detection system that analyzes analyze email content such as subject, body, sender, and URLs to identify phishing attempts.

- To develop a scoring mechanism with predefined rules that can classify emails as phishing or legitimate without depending on machine learning models.

- To find the efficiency of the proposed method by using performance matrixes such as accuracy, precision, recall, and F1-score.

1.4 Research Gap

- Lack of lightweight detection system: Most of the existing phishing email detection filters rely on machine learning models, which can be resource-intensive and require large training datasets.

- Less use of custom rule-based approaches: There is a lot of research found exploring machine-learning models to detect phishing email, but very less research focuses purely on role-based approaches to detect phishing, especially in academic or low-resource settings.

1.5 Dissertation Chapters and Structure

- Chapter 1 – Introduction: Provide a general overview of the research, including motivation, objectives, and identified research gaps.

- Chapter 2 – Literature Review: Reviews related to research papers which work to detect phishing emails, highlight strengths, weaknesses and limitations.

- Chapter 3 – Methodology: Describe the framework, dataset collection and filtering process, custom rule creation, implement logic.

- Chapter 4 – Results and Discussion: Showing results of experiments such as accuracy, precision, recall, and F1-score, along with a discussion of findings.

- Chapter 5 – Conclusion and Future Work: Summarize the outcome of the research, like contribution, limitation and outline future improvements.

CHAPTER-2
LITERATURE REVIEW

2.1 Literature Review

Cybercriminals can use a variety of popular attack techniques to make the internet dangerous. Phishing is among the most popular techniques at their disposal. Because an attacker can use this technique to steal sensitive or private information from a victim, it poses a serious risk to a business. This attack may result in significant financial losses, which could have disastrous repercussions. Organizations can identify this threat using a variety of methods. This research uses rule-based techniques on emails and URLs to assist enterprises in identifying phishing attacks. [3] Le and Nguyen, "Phishing Detection System Using Rule-Based Classification", discussed the potential of rule-based approaches in helping organizations detect phishing attacks with minimal computational overhead.

There are many different types of phishing assaults. Phishing assaults come in various forms, including URL-based phishing, email phishing, spear phishing, and smashing & vishing. [4] Rani and Gupta, "Rule-Based Approach for Phishing Website Detection Using URL Features" explored different phishing techniques including URL manipulation, highlighting how URL characteristics play a vital role in phishing classification.

Email phishing is an attack vector in which criminals send phony emails purporting to be from reputable companies in an attempt to fool recipients into opening harmful attachments or clicking on links or URLs or downloading malware. Here, hackers create fake links or viruses and send them out over email in an effort to get victims' sensitive and private information. Spear Phishing: This kind of attack is a little different from email phishing in that the attacker targets individuals or organizations using private conversations. The attacker gathers information on the target by using several social media sites or databases that have been leaked. [2] Kumar and Indrani, "Frequent Rule Reduction for Phishing URL Classification Using Fuzzy Deep Neural Network Model" emphasized targeted phishing variations and how attackers personalize content using external data sources.

Sending phony text messages with malicious URLs or phony links is one way to carry out a smashing attack. However, in order to obtain sensitive information, attackers conduct phone calls in which they pretend to be victims and contact customer service. [11] Tan and Wang, "Rule-Based Phishing Detection Using Machine Learning and Heuristic Rules" mentioned the blending of phishing vectors such as SMS and voice phishing and the challenges associated with detecting them.

URL-Based Phishing: The attacker deceives the user into clicking or inputting sensitive or personal information, such as financial information, by fabricating a website that is nearly identical to authentic ones. The majority of these URLs have extra subdomains or misspellings; for instance, an attacker might make a URL like https://g00gle.com. You would initially believe that this was a valid URL, but if you look closely, you'll see that it was spelled as 00 rather than the correct Google spelling. Because it was their website rather than the official Google site, the attacker can simply obtain the credentials if a victim attempts to log in using them on these URLs. [6] Zhang et al., "Rule-Based Phishing Detection Approach Using URL and HTML Features" identified that URL features such as misspellings and subdomain usage are key indicators of phishing websites.

A phishing attack has the potential to seriously harm a person or an organization. It may be the cause of monetary losses and damage to an organization's or individual's reputation. Data breaches, fines, and the potential loss of a company's customers' trust are all possible outcomes for businesses. Over the years, there have been numerous instances where phishing attacks have caused businesses to lose the faith of their clients and incur financial losses. Regaining the trust of customers in an organization that fails to prevent phishing assaults is extremely difficult after it has been lost. [9] Liao and Wu, "Phishing Detection Using Heuristic and Rule-Based Methods", reported that phishing results in not only data loss but long-term reputational damage, and recovery is resource-intensive and complex.

A massive phishing campaign that attacked American banks between 2007 and 2009 included Wells Fargo and Bank of America, two of the most well-known banks at the time. A bank employee was duped into entering their credentials on a phony website by an Egyptian attacker who sent them a phony banking email. They transferred more than 1.5 million dollars abroad after stealing them, according to the results of an inquiry. The FBI and Egyptian officials were able to track down and apprehend more than 100 participants in that cybercrime in 2009. [13] Zhang and Liu, "Phishing Detection Using Rule-Based and Machine Learning Models: A Comparative Study" highlighted real-world case studies including phishing attacks on financial institutions to demonstrate the importance of effective detection systems.

In 2011, a phishing assault was launched against RSA Security, a cybersecurity company based in the United States. An employee of that company opened a malicious Excel attachment in a phishing email that was supplied by an attacker, and then clicked on the file. By clicking on that file, the employee unintentionally activated the virus, which was distributed through phishing emails. The malware took advantage of security flaws to steal authentication tokens and private information. [7] Sorokin and Smirnov, "Phishing Detection Based on Classification Algorithms and Rule-Based Models" mentioned the RSA breach as an example of advanced phishing exploiting document attachments and internal weaknesses.

The organization was so severely impacted by this incident that they had to replace millions of authentication tokens, which came at a cost of over $66 million, and raise concerns about the security of two-factor authentication. The biggest retailer in the United States experienced a significant data breach in 2013 due to a phishing attack on its HVAC vendor. The attacker is able to enter the target payment system without authorization and takes over 70 million personal records and 40 million credit and debit card details. The target of this data leak incurred litigation totaling about $292 million. [14] Al-Azzawi and Hashim, "A Hybrid Rule-Based System for Phishing URL Detection Using URL Feature Analysis" discussed the consequences of phishing breaches, including legal, financial, and reputational costs.

A Lithuanian hacker sent phony invoices to Google and Facebook employees between 2013 and 2015. Before learning of the theft in 2017, this company transferred more than $100 million without anyone knowing about it. This extensive phishing attempt revealed flaws in the vendor payment process and email security. The assailant was later arrested. [12] Ma and Li, "A Rule-Based Approach to Detecting Phishing Websites Using Semantic Analysis of URLs," discussed the importance of securing vendor communication and invoice processing systems to prevent social engineering attacks.

In 2022, an SMS phishing attempt was launched against TWILLO, a cloud communication company based in the United States. The hacker tricked the employee into disclosing their login credentials by sending them a phony message. About 125 consumers were impacted by this incident, which penetrated TWILLO's internal infrastructure. The financial damage was not disclosed by the company; this attack also raises questions regarding the security of cloud services. [8] Vasudevan and Chawla, "Rule-Based Framework for Detecting Phishing URLs Using String Matching and Heuristic Rules" emphasized the evolving nature of phishing and its impact on cloud-based platforms.

CHAPTER-3

METHODOLOGY

3.1 Methodological Framework

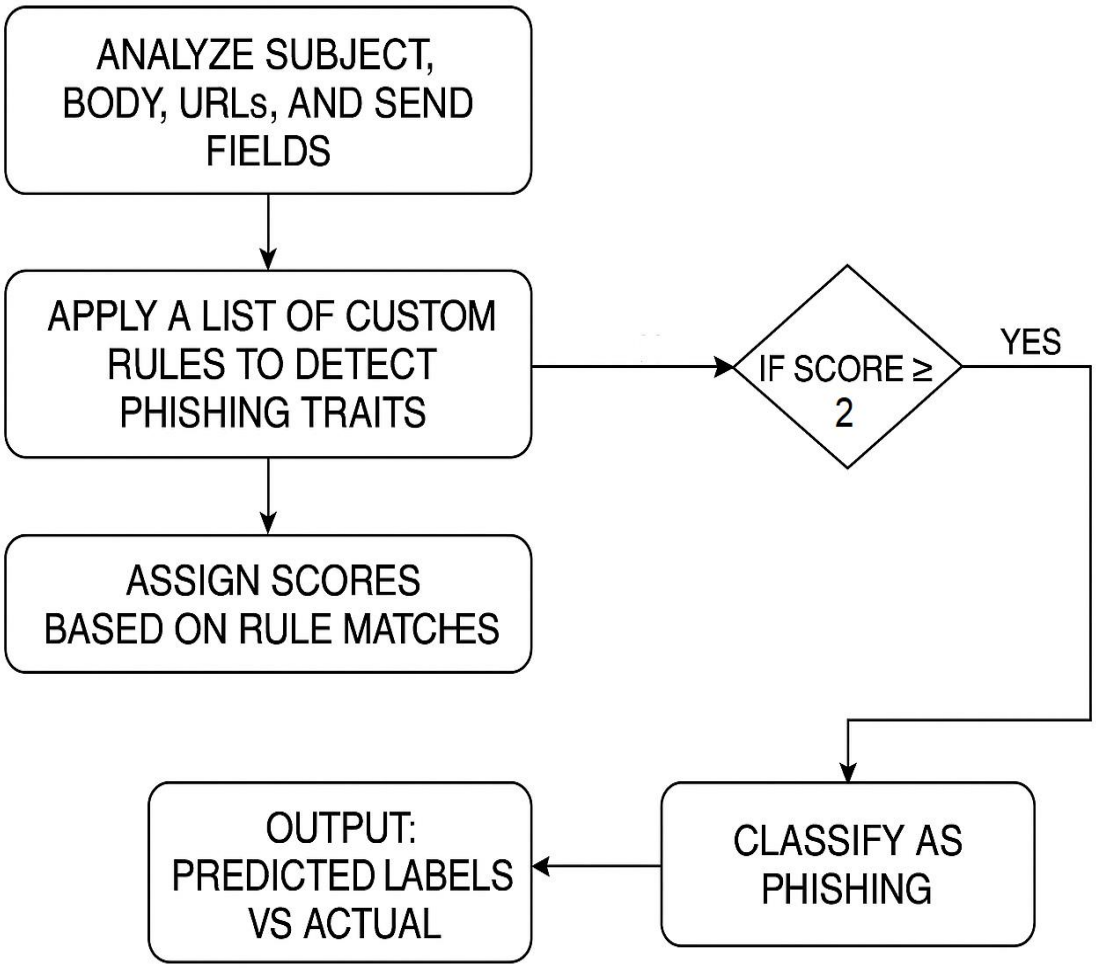

Figure 1: Phishing Detection Workflow Flowchart

By examining particular characteristics taken from email data, this study aims to develop a unique rule-based method for identifying phishing emails. Data collection and filtering are the first steps in the overall framework, which is then followed by data preparation, feature extraction, rule implementation, and outcome evaluation.

In order to start our investigation, we first gather publicly accessible and reliable datasets that include both authentic and phishing emails. Phishing emails are labeled as 1 in this dataset, while legal emails are flagged as label 0.

The dataset is then cleaned so that it can be used for our research. In order to find frequently used patterns linked to phishing efforts, we have cleaned this dataset and extracted specific aspects from the email text and metadata, such as the subject line, body, URLs, and sender information.

We classified emails as either legitimate or phishing by applying established rules to this extracted feature. These predefined rules are designed to detect phishing indications, including strange sender addresses, excessive link usage, and suspicious keywords. Following the application of rules for email classification, a result is produced.

3.2 Dataset Acquisition and Description

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	sender	receiver	date	subject	body	label	urls						
2	"Hu, Sylvi	"Acevedo	Fri, 29 Jun	FW: June :	User ID:	0	['http://web.bna.com', 'http://pubs.bna.com/ip/BNA/dlr.nsf/id/a0a4j						
3	"Webb, Ja	"Lambie, (	Fri, 29 Jun	NGX failov		0	[]						
4	"Symms, M	"Thomas,	Fri, 29 Jun	RE: Intran	Rika r	0	['http://eastpower.dev.corp.enron.com/summary/pjmsummary.asp',						
5	"Thorne, J	"Grass, Jo	Fri, 29 Jun	FW: ENA U	John/Ger	0	[]						
6	"Williams	"Nemec, (	Fri, 29 Jun	New Mast	Gerald	0	[]						
7	"Thorne, J	"Hodge, J	Fri, 29 Jun	FW: ENA U	FYI.	0	[]						
8	"Brennan,	"Dushinsk	Fri, 29 Jun	PG&E GT-I	PG&E GT-	0	[]						
9	"Shah, Kal	"Taylor, M	Fri, 29 Jun	Internet A	Mark -- I	0	[]						
10	"Shah, Kal	"Taylor, M	Fri, 29 Jun	FW: Interr	oops.	0	[]						
11	"Gimble, I	"Weldon,	Fri, 29 Jun	FMPA Oil	Mark and	0	[]						
12	"Newgard	"Fastow, A	Fri, 29 Jun	Smith Gra	Please	0	[]						
13	"Solis, Me	"Garberdi	Fri, 29 Jun	2001 15:24	Per Eric	0	[]						
14	"Thorn, Te	"Hayslett,	Fri, 29 Jun	SABIC	Rod-	0	[]						
15	"Edison, D	"Buy, Rick	Fri, 29 Jun	FW: Marin		0	[]						
16	"Barkowsl	"Farmer, I	Fri, 29 Jun	RE: EPGT	Daren -	0	[]						
17	"Kozadinc	"Johnson,	Sun, 01 Ju	RE: Surpri	Hi,	0	['http://home.enron.com/sites/', 'http://community.zuniversity.com/						
18	KTracey11	"Baughma	Sun, 01 Ju	Fwd: Truly		0	['http://www.patriotichouse.com', 'http://www.patriotichouse.com']						
19	"Johnson,	"Barrow, (	Sun, 01 Ju	Policy Nar	Attached	0	[]						
20	"Owen, Di	"Johnson,	Mon, 02 Ju	RE: LRCI tr		0	[]						

Figure 2: Table view of dataset

The dataset that was chosen for this study was obtained from a trusted public source on KAGGLE, titled "Phishing email dataset Nazario_5 and TREC07". This dataset has emails from two sources: the NAZARIO phishing corpus and the TREC07 legitimate email corpus.

The NAZARIO phishing corpus is a collection of real-world phishing emails which was collected by JOSE NAZARIO, a well-known cybersecurity researcher. These phishing emails were collected from spam traps and honeypots. This phishing email is considered to be relevant and mostly used as a benchmark to detect phishing.
In contrast, the TREC07 corpus has a collection of legitimate, also known as ham emails developed for the Text Retrieval Conference (TREC) spam track.

The dataset we have used is Nazario_5.csv, which contains both legitimate and phishing datasets combined from the KIGGLE dataset. It has a balanced mix of phishing and legitimate emails, each labeled with a binary value:

- 1 for phishing emails
- 0 for legitimate (ham) emails

3.3 Data Filtering and Label Selection

The original dataset file, Nazario_5.csv, has a huge number of email records with varying formats and labeling inconsistencies. Many rows either do not have proper data or missing critical information or lack a proper classification label. To get quality data, a filtering process was applied and removed rows which did not have proper data or some missing information.

After the filtering process, a total of 2664 email records were retained, categorized as follows:

1,407 phishing emails (label = 1)

1,257 legitimate emails (label = 0)

Each email entry in the dataset has several fields which have proper data available on the raw for further analysis. It includes the column "sender", which has information about the sender's email address, "receiver", which has information about the recipient's email address, "date" has timestamp about when the email was sent, "subject" has subject line of the email, "body" has email body content, "urls" a list of urls found in emails, "label" which has two different values 1 denote emails as phishing and 0 denotes legitimate emails. This filtering and label selecting was very important to ensure integrity and accuracy for rule-based detection approach.

3.4 Model Description

This proposed model is a rule-based phishing email detection system designed to identify legitimate or phishing emails based on predefined patterns. It analyses fields such as email subject, body, and URLs using predefined keyword-based and structural rules. As it is a score-based detection system, anytime rules find any matching keyword, it adds a score. If we find multiple suspicious keywords, then the score will be 2, and it will count as phishing. Along with that, this rule-based system also analyzes any special character or encoding in emails. If found, then it will count as phishing as well.

The system is implemented in python using pythons built into library pandas. Custom rules are applied through user-defined functions which analyze multiple features for unusual keywords or patterns.

Main keywords to look in this model are:

Subject Keywords	verify, urgent, alert, suspended, payment, reset, wallet, invoice, account, security, password, blocked, netflix, metamask, warning, shutdown
Body Keywords	click here, reset password, update info, login to your account, verify your wallet, unauthorized access, your account will be suspended, limited access, payment confirmation, account locked, password change, security update, verify your account
Suspicious Domains	.ru, .cn, .xyz, .top, .ml, .tk
Dangerous File Extensions	.exe, .php, .scr, .bat, .zip, .jar
Special Character Patterns	Ã, , Ã,, Â, â, ã, º, µ
Base64-Like Pattern	Ends with =, ==

CHAPTER-4

Result and Discussion

4.1 Accuracy

Accuracy is a metric that is primarily utilized as the primary evaluation metric for evaluating the performance of a suggested model system. We also assessed a rule-based phishing detection system's accuracy for our investigation. It will show the percentage of all predictions that were accurate.

In the context of phishing detection:

- Accuracy indicates how successfully the system distinguishes between authentic and phishing emails.
- A greater accuracy indicates that the suggested model is dependable and trustworthy in practical situations.
- From a security standpoint, even little decreases in accuracy can result in legitimate emails being blocked or fraudulent emails evading filters.

Accuracy Formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where:

- **TP** = True Positives (phishing correctly predicted as phishing)
- **TN** = True Negatives (legitimate correctly predicted as legitimate)
- **FP** = False Positives (legitimate wrongly predicted as phishing)
- **FN** = False Negatives (phishing wrongly predicted as legitimate)

Now on our study we have:

- TP = 1407
- TN = 1257

- FP = 143
- FN = 156

$$\text{Accuracy} = \frac{1407 + 1257}{1407 + 1257 + 143 + 156} = \frac{2664}{2963} \approx 0.899$$

Final Accuracy:
≈ 89.9% (approximately 90%)

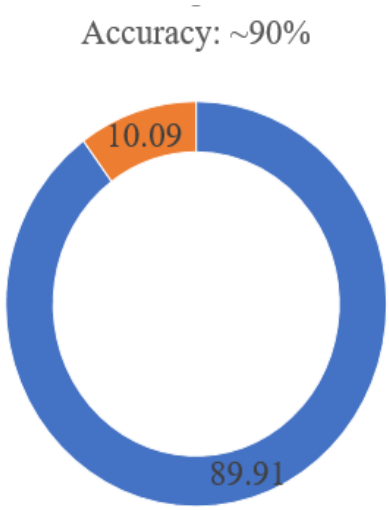

Figure 3: PIE chart of Accuracy

4.2 Confusion Matrix

A Confusion Matrix shows how many predictions were correct and how many predictions were incorrect. Below is a figure showing the consumption matrix for this study.

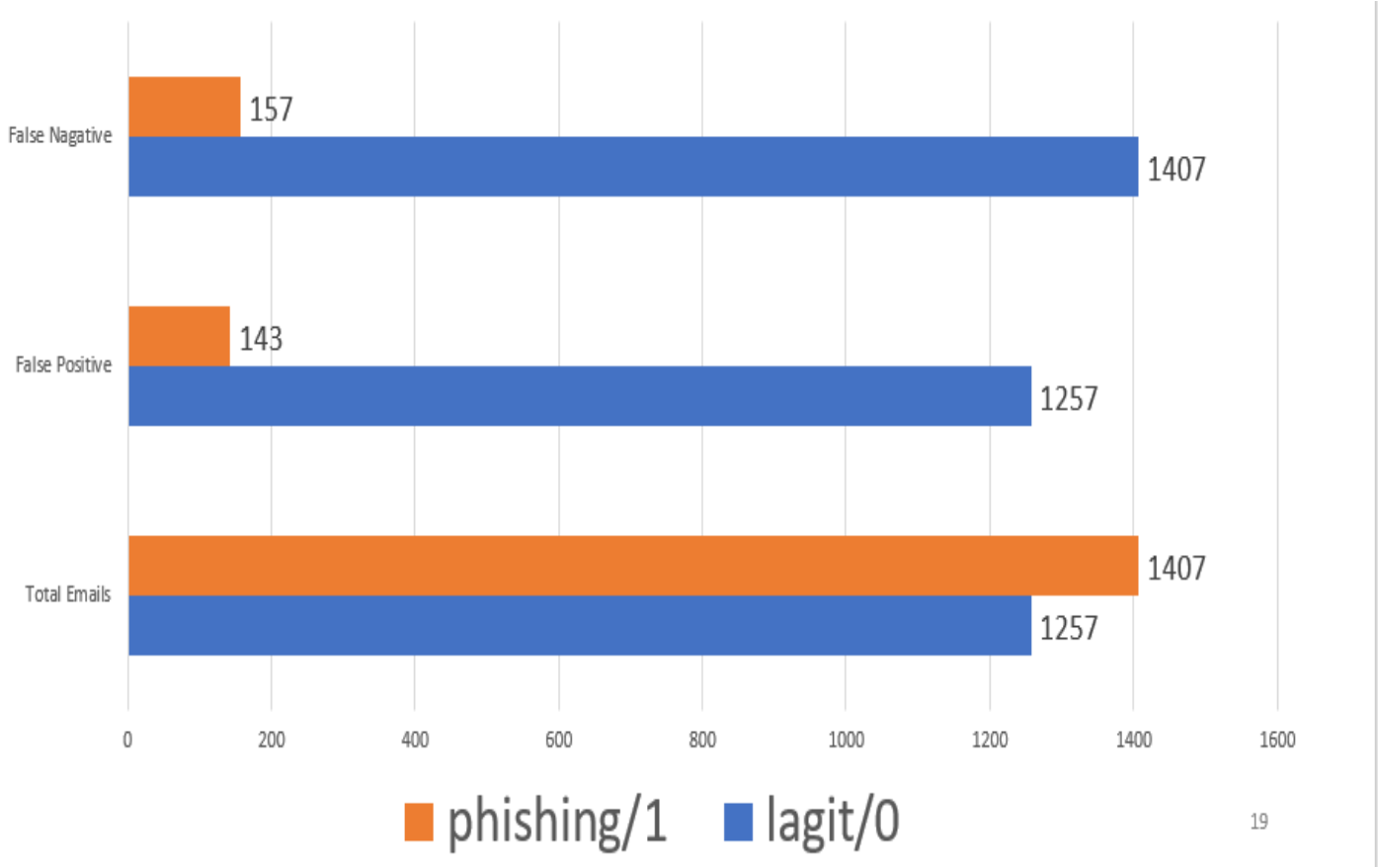

Figure 4: BAR chart of confusion matrix

4.3 Precision

One well-known performance indicator for assessing a model's or system's accuracy is precision. It means that out of all the positive predictions it makes, it mostly searches for accurate outcomes.

In the context of phishing detection:

- Precision indicates the proportion of phishing emails that were genuinely phishing.
- Fewer false positives result from high precision, which is essential to prevent inadvertently blocking valid user interactions.
- High precision in our study guarantees that users won't receive false warnings or be blocked from viewing valid emails.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Precision} = \frac{1407}{1407 + 143} = \frac{1407}{1550} \approx 0.908$$

4.4 Recall

Recall is a crucial performance indicator in rule-based phishing detection that assesses how well the detection system recognizes phishing emails or URLs. It gauges the detection system's ability to recognize every real phishing case out of all the phishing instances.

Formula for Recall:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

On our study we have:

- True Positives (TP) = 1407 (Phishing emails correctly identified as phishing)
- False Positives (FP) = 143 (Legitimate emails incorrectly identified as phishing)
- False Negatives (FN) = 156 (Phishing emails incorrectly identified as legitimate)
- True Negatives (TN) = 1257 (Legitimate emails correctly identified as legitimate)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{1407}{1407 + 156} = \frac{1407}{1563} \approx 0.899$$

Recall = 0.899 or 89.9%

4.5 F1 Score

F1 Score is a performance metric used to evaluate the effectiveness of a classification model, especially in situations where there is an imbalance between the classes (e.g., phishing vs. legitimate emails). It combines both Precision and Recall into a single score, providing a more balanced evaluation.

Formula for F1 Score:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1 Score Calculation:

$$\text{F1 Score} = 2 \times \frac{0.907 \times 0.899}{0.907 + 0.899} \approx 2 \times \frac{0.814}{1.806} \approx 0.902$$

F1 Score = 0.902 or 90%

4.6 Performances of Proposed Models

Overall result outcome of proposed model.

Accuracy	~90%
Precision	0.91%
Recall	0.90
F1-Score	0.90

CHAPTER-5
CONCLUSION

5.1 Outcomes

A unique rule-based phishing email detection system that doesn't require complicated machine learning models was successfully created and put into use by this study. against detect phishing attempts, the system compares email characteristics such the text, topic, sender domain, and URLs against pre-established and customized rules. This model's primary result was an accuracy of about 90% and an F1-Score of 0.90 for phishing detection, demonstrating its dependability and efficacy.

5.2 Future Work

These custom rules might be expanded in the future to include additional phishing patterns and keywords. Perhaps include unique regex patterns to extract more keywords that might be connected to phishing. Furthermore, we may include additional criteria that can identify phishing by analyzing email headers in addition to the content of the filter file. With these improvements, the model would be more resilient, scalable, and flexible for wider uses.

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