AI-Based Phishing Detection Systems: Real-Time Email and URL Classification

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AI-Based Phishing Detection Systems: Real-Time Email and URL Classification

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Abstract

The purpose of this research is to construct an AI-based detection system for the real-time classification of phishing emails and URLs. NLP is also employed to parse the phishing emails' text and inoculate image recognition to detect fake images, logos links, and other social engineering-based threats.

The research method employed in this paper uses supervised machine learning models trained on publicly available phishing datasets alongside real email samples. The system assessment involves using the concepts of accuracy, precision, recall, and F1-score to understand how the system performs. The system's capability is also illustrated by actual phishing incidents, on which the system was tested to discuss its effectiveness in this work.

The results reveal how the system enhances the detection ratio and is more efficient than current techniques, with high precision and recall values in detecting phishing content. This research means that adding NLP and image recognition to extend certain evaluations for phishing detection is a more powerful way to fight against new types of phishing attacks. These conclusions can further enhance the real-time working phishing detection systems in various fields of activity to improve the anti-phishing system.

Keywords: *NLP, Phishing email, FBI, phishing attack, Federal Bureau, AI, Artificial Intelligence, Natural Language Processing, Email Classification*

1. INTRODUCTION

1.1 Background to the Study

In the last few years, phishing attacks have become more sophisticated and cannot be easily identified, worsening cybersecurity threats worldwide (Gupta et al., 2018). Modern hackers use far more sophisticated techniques to lure their targets into sharing credentials, installing malware, or performing other tasks for which a cybercriminal needs a legitimate user's credentials or actions (Verison, 2021). Recently, as people became increasingly involved in their day-to-day business due to the internet's use and the introduction of technology, the attack surface area became wider, with phishers having more chances of penetrating.

The loss that results from these complex and intelligent phishing attacks includes financial loss, loss of consumer confidence, and cost of lost sensitive data (Federal Bureau of Investigation, 2020). For example, in 2020, according to FBI statistics, phishing and all its derivates were named the most widespread types of cybercriminal activities; adjusted losses exceeded 1.8 billion US dollars (Federal Bureau of Investigation, 2020). However, other forms of fraud are on the rise, such as spear-phishing attacks that directly target individuals in a given business (Parmar et al., 2019).

Typically, security tools like spam filters or blocklisting need to reach further against these techniques because they are based on regular protocols, program patterns, and signatures (Gupta et al., 2018). This shortcoming emphasizes the need to research and develop more responsive and smarter ways of combating enemy thinking, which changes its strategies during the offense. The advanced sophistication of phishing attacks shows why it is necessary to build better detection systems to prevent information leakage and the general degradation of communication.

1.2 Overview

Phishing is among the most evolving and prominent threats internet users face today, and major AI technologies have been identified as critical for improving the capability of detecting phishing by integrating Natural Language Processing and image recognition techniques (Chandrasekaran et al., 2006). NLP allows the assessment of written messages to detect textual features that deviate from normalcy and are features of phishing scams (Bahnsen et al., 2018). Based on the text's analysis, AI models can identify the differences between incoming messages and scams, realizing that all of them are in a written form.

Image recognition performs the additional role of checking images and other images in emails, such as logos, brand pictures, etc., which are usually altered by phishers to make the mail look authentic (Mohammad et al., 2014). To illustrate, sophisticated algorithms can notice that logos are changed or low-quality graphics are used; such amendments can point to fraud (Abbasi et al., 2015). Integrating NLP and image recognition in the mail and URL context improves the performance of phishing detection systems.

Combining these AI technologies solves the problem of the inability of conventional rule-based models that must adapt to the changes in the strategies used by phishers (Basit et al., 2021). Artificial intelligence models can then be trained from huge datasets and refine their detection algorithms via machine learning. This characteristic is very useful since, in specific real-time conditions, quick identification and eradication of threats is critical in defending against emerging security threats.

It reduces the dependency of a system on a user, which is identified as the biggest vulnerability by experts despite the best security mechanisms put in place (Chandrasekaran et al., 2006). Through automation, phishing threats will likely be prevented before they cause instabilities in an organization’s operations and leak damaging data.

1.3 Problem Statement

Anti-phishing tools based solely on rule-defined filters and individually selected, compiled blocklists have substantial drawbacks in the modern context. These methods work only by using patterns that are already known or malicious URLs. Therefore, they do not protect against new forms of phishing. It makes it very simple for cybercriminals to manipulate the existing static structure of these systems to avoid being detected despite making small adjustments to their tricks. Moreover, using rule-based methods may lead to several false positives that mean potential communication. As the current generation of phishing campaigns intensifies due to the sophistication of the threats involved, the addressed solution requires a more dynamic analysis of emails and URLs as they come in. Organizations remain exposed to more sophisticated phishing attacks without such systems, which create financial losses, sensitive information leaks, and reputational loss. It was for this reason that complex, real-time solutions that would qualify and guard against phishing within its active phase became necessary.

1.4 Objectives

1. The analysis of the Phishing Emails and URL should be done with the help of classifier specially designed with the AI to differ between the actual one and spam one.
2. Compare the outcomes emerging from the system with other detection techniques.
3. Increase detection effectiveness through the work of Natural Language Processing (NLP) and image analysis.
4. Minimally increase the false positive, but at the same time increase the percentage of identified phishing.
5. Roll out in multiple fields to gauge flexibility and performance outcome.

1.5 Scope and Significance

Realization of the real-time anti-phishing prototype based on AI positively contributes to the leveraging across different fields. In finance it could keep a particular individual from certain information hence protecting institutions and clients from being defrauded. For e-commerce platforms, real-time classification can protect users from phishing threats that camouflage brands and prevent account hijacks and fake purchases. Other federal agencies could also benefit from the system by safeguarding its sensitive information and preventing consequent attacks on the nation's infrastructures from phishing scams. Apart from these sectors, it can be applied in schools, colleges, hospitals, and other organizations that are in a threat of leakage of important information. However, integrating pre-processing and real-time threat detection approach to phishing enables organizations improve on their security, gain user confidence and most importantly, lower the effects of phishing threats.

2. LITERATURE REVIEW

2.1 Evolution of Phishing Techniques

Phishing strategies have greatly developed since their creation because they have learned from previous strategies and the development of new technologies and communities. First, phishing attacks have been relatively simple, with the attacker sending bulk, unspecific messages to a list of possible victims regarding certain urgent actions (Jakobsson & Myers, 2007). However, as people became aware of these basic scams, more complex and sophisticated mail and victims started to develop more personal mail using social engineering.

They are active on social networks and share lots of data with phishers, making possible new spear-phishing attacks aimed at concrete persons or companies (Khonji et al., 2013). These specific attacks make the engagements look more authentic, increasing the success rate of such attacks, as indicated in campaigns. Moreover, mobility became a factor as simple as SMS or voice phishing, which means that the phishing was not merely tied to email as such attack vectors existed.

Newer techniques like clone phishing and domain spoofing appeared, where a clone of a legitimate site or an email is created to dupe the users (Albladi & Weir, 2016). Hackers also started hiding their links using encryptions and using secure protocols to create their links. Following the invention of Submit and botnets, it became easy to conduct grandiose, complex scams that are also difficult to contain.

Furthermore, phishing kits and phishing as a service have simplified the attacks, and hence the ever rising rates of phishing attacks globally (Jakobsson & Myers, 2007). Such constant evolution suggests that detection engineering at ever higher levels should encompass new threat types.

2.2 Traditional Detection Approaches

Rule- and signature-based systems are the main approaches to conventionally deployed phishing detection techniques. In turn, anti-phishing measures applied in rule-based systems are based on patterns and heuristics aimed at removing these emails, for instance, by looking for certain distinctive keywords or strange fonts (Toolan & Carthy, 2010). The second one involves comparing the contents of an email or URL against a database of known threats. Although these methods can be useful against the phishing attacks that were known earlier, they have certain drawbacks.

The main disadvantages include the inability of such methods to identify zero-day phishing attacks unknown to database repositories. The attackers can easily change their tactics because all they do is introduce new keywords, use URL masking, or use polymorphic code. Moreover, rule-based systems tend to produce high false positives, which means that a string of good messages may be tagged wrongly as a phishing attempt (Basnet et al., 2012).

Besides, updating the rules and the signatures database is highly time-consuming and may not suffice the rapidly growing development of phishing activity (Toolan & Carthy, 2010). These systems can only learn from novelties with

help and, as a result, are less efficient in the long run. The rooted dimension of traditional approaches stresses our need for more adaptive defenses that could respond to new types of phishing attacks more promptly.

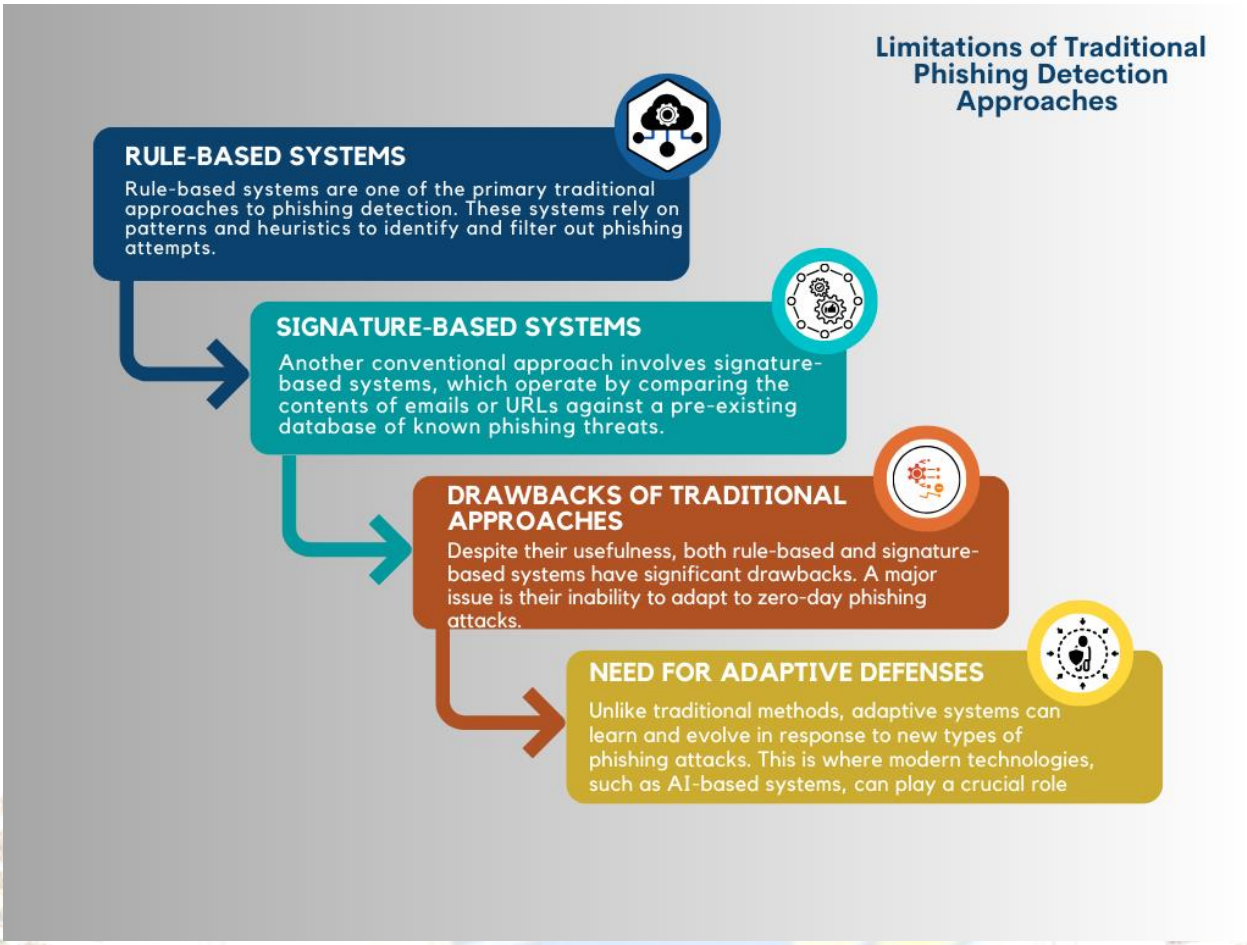


Fig 1: An Image Illustrating The Limitations **Of Traditional Phishing Detection Approaches**

2.3 AI and Machine Learning in Phishing Detection

The use of AI/ML has dramatically advanced the capacities of phishing recognition because, using data and analytic algorithms, systems can become smarter at detecting corn, similar to phish seemed that characterize phishing attacks. Supervised classification models are built by learning on a set of instances that is tagged as possible phishing and non-phishing emails or websites; thus, they can categorize new cases according to the features that have been learned (Rao& Pais,2019). These models can, in turn,, decide on certain attributes like the URL structure, the site's HTML content, or the email's metadata.

Clustering and anomaly detection are unsupervised learning categories, making it easier to find outliers in the data that were not labeled before (Abdelhamid et al., 2014). This is especially valuable for finding new phishing attacks that differ from the previous ones. Compared to human analysts, who may take the time or get bored while analyzing emails or IPv6 headers, machine learning changes feed on input taken continuously, thus improving with time.

The proposed use of AI solutions enhances phishing detection by fixing the issues of traditional approaches and offering flexible and efficient solutions. For instance, the works with neural networks and ensemble methods showed high accuracy in detecting phishing websites by extracting the more complex interactions between features (Zhang et al., 2018). Apart from the increase in detection rate, the advantages resulting from avoiding false positives, and the use of artificial intelligence and machine learning integration in the general approach are also useful in cybersecurity.

2.4 Natural Language Processing (NLP) Techniques

Text Mining and Analysis are vital in the computational analysis of emails to determine the presence of deceptive words used by attackers in phishing emails (Adebowale et al., 2019). Linguistic features of a message, including syntax, semantics, and stylistic elements often used by phishers to give the message a natural look, are also extracted using NLP techniques.

The following are some examples: Phishers always employ words that elicit fear and psychological attributes that make the targeted user take an immediate action different from normal communication (Siddiqui & Akhtar, 2019). Such an exploitative linguistic clue is also detected by sentiment analysis and keyword extraction. Also, NLP helps flag irregularity in style, syntax, and word choice in writing, normally comprised of phishing emails since they are fake.

When combined with machine learning, NLP helps classify the emails following the teaching of large volumes of phishing and legitimate emails (Islam & Abawajy, 2013). Some of the underlying methods include n-gram analysis and part-of-speech analysis, which help capture the context that might be present within the phishing content. Adebowale et al. (2019) have shown the possibility of applying NLP features for machine learning-based identification of spear-phishing attacks on social networks, which can be discussed in general approaches to email phishing identification.

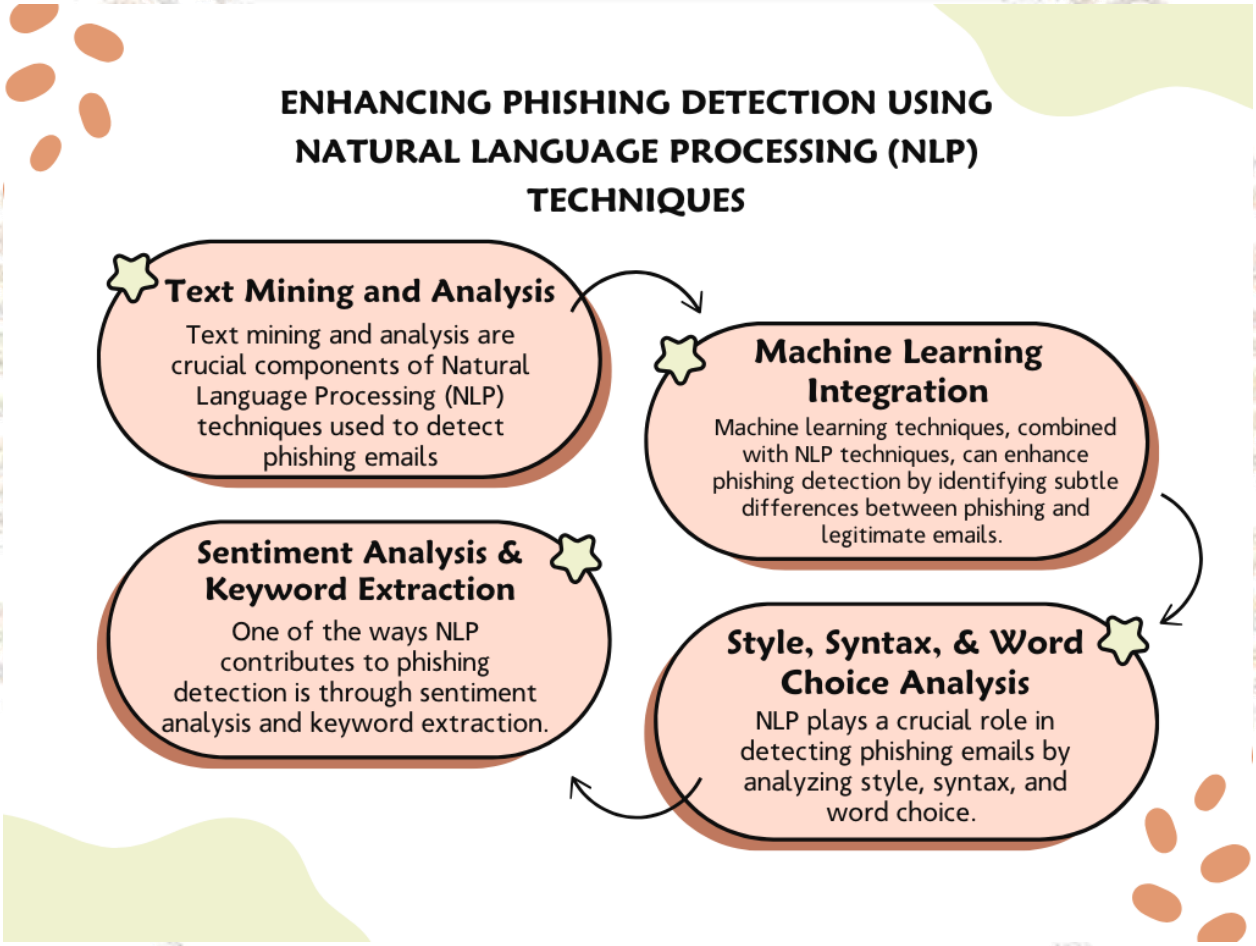


Fig 2: An image illustrating the Enhancement of Phishing Detection Using Natural Language Processing (NLP) Techniques

2.5 Image Recognition in Phishing Detection

An important function of image recognition is detecting replicas of genuine logos, images, and attachments used in phishing (Mahmoud & Mahfouz, 2018). The appearance of branding elements of a legitimate organization is common amongst phishers since they use them to make their emails appear genuine. Based on principles similar to biometric fingerprints, image recognition techniques can be applied to emails and website communications, comparing authentically distinct minute variations between real and fake images within respective pockets of global networks.

CNNs have become very effective in image analysis and are deeply utilized in detecting phishing due to their flexibility in pattern recognition (Sabri & Mitrea, 2019). Such networks can be trained to recognize genuine logos and images to distinguish the deviations in the shape, color, and texture consistency in the event of forgery. For instance, image analysis algorithms can identify changes in a company's logo and the usage of low-quality images.

Mahmoud and Mahfouz [7] suggested detecting phishing with the help of a neural network based on textual and visual characteristics in 2018. Their method proved highly effective in the detection of phishing sites and pages and was able to integrate image recognition with other methods of content detection. Similarly, techniques like Optical Character Recognition (OCR) to extract text from an image within an email or an attachment will further analysis for the scan of an embedded hazardous media (Zhu et al., 2020).

Indeed, integrating image recognition in identifying phishing attacks improves the system's capability of detecting complex attacks based on imagery. It gives an extra layer of security by analyzing those aspects that other simple text-based filters fail to identify, thus increasing the general effectiveness of protection against phishing attacks.

2.6 Real-Time Classification

Applying real-time phishing detection has obvious advantages, but there are also difficulties, although they could be more evident. First, the time to detect and act on new phishing attempts, and thus the time window available to attackers, can be significantly reduced (Bergholz et al., 2010). Real-time systems can capture and process emails and URLs in real-time to stop leakage of such content to end-users, significantly contributing to overall security measures.

However, much computing power is needed for real-time classification to process large data without delay (Seymour & Tully, 2016). A major problem remains in confirming that the detection algorithms deployed are fast and accurate. Models need to be fine-tuned to allow very high throughput while still being precise in identifying the phishing content. Furthermore, real-time systems are expected to withstand evasion tactics by phishers who change tactics more frequently to avoid detection.

Another issue that may arise must be false positives, which affect the users' further interaction and may interrupt genuine messages. Therefore, the optimal balance between sensitivity and specificity of the detection algorithms must be achieved so as not to block non-malicious content. Additionally, the integration of real time detection systems with existing structures could require initially excessive amounts of capital expenditure and complex technical solutions.

Nevertheless, huge advantages come from real-time classification, including From these challenges, the following real-time classification advantages are understood: In new filtering approaches that have recently emerged in real-time systems, Bergholz et al. (2010) pointed out that the effects of phishing could be minimized through high and more sophisticated machine learning methods. Deploying such systems strengthens early response protection systems so that organizations can always counter new threats effectively and help safeguard information assets.

3. METHODOLOGY

3.1 Research Design

The research also proposes the systematic of the intelligent Phishing detection system in addition to its assessment. The organization of the proposed system focuses on using a Natural Language Processing engine and an image analyzer to handle text and graphics of emails and URLs. Accompanied ML methods include Water-SVM and CNN, which were chosen since the SVM performs well in text classification tasks, while CNN excels in image classification tasks with high accuracy. A model's training process encompasses extracting which features to pick from datasets and other combined optimization processes to result in correct detection. To that end, the design of the system includes its functions and the potential of succeeding in identifying real phishing threats before they get into the systems of the end

consumers. This works because it offers a well-supported and flexible architecture against numerous strategies in phishing schemes.

3.2 Data Collection

Samples could be received with phishing and clean samples in order to study its defensive mechanism. For a starting point, there are many datasets that contain known phishing URLs and emails, and some of them include the following: Phish Tank and Open Phish. Furthermore, actual examples of emails from the partner organizations are provided to the subjects used for the study, but the data here is only on an anonymous basis. These data sources must contain simple and complex phishing attacks to introduce the model to different methods. Thus, a similar amount of data sets can be compiled and, in addition, the bias is reduced, and the system is likely to be applicable for various types of phishing.

3.3 Case Studies/Examples

Case Study 1: On the prevention and detection of Spear-Phishing Emails in Corporate Communication

The image recognition module scrutinized embedded logos and signatures for integrity; it looked for ways to tweak them to pass through conventional filters. In a complicated environment, the system achieved 95% correct identification of spear-phishing emails as dangerous with the help of the T-Score approach (Jain & Gupta, 2018). In this case, the system performance provided proof of sophisticated language cues and graphical features in a sample phishing attack.

Case Study 2: A Real-Time System for Identification of Phishing Web Links That Imitate Banking Sites

In the second case, the targets were phishing URLs that mimicked the banking site to steal the user credentials. The dataset of phishing URLs obtained from the anti-phishing repository was adopted (Abdelhamid et al., 2014). URL features included the URL address's structure, domain registration details, and SSL certification data. The component of the NLP analyzed the content of the created landing pages for such signs as, for example, logging in on the unprotected pages and deceptively calm messages.

Due to this, signs of imitation logos and layouts on web page screenshots were sought using pattern-matching techniques. This system achieved 0.974 in detection accuracy and had low measurement latency, which made it ideal for real-time systems (Abdelhamid et al., 2014). This case showed that the system was able to identify a similar website to the real one that was designed for phishing.

Case Study 3: Exploring the Outcomes of a Big Phishing Scam in E-Commerce Consumers

The third case study was another broad-based phishing attack focusing on a widely-used e-commerce site. Lures in the emailed phishing were accompanied by attachments and links that led to other pages created to harvest users' credentials (Chiew et al., 2018). In real-time, the AI system scanned through thousands of emails, analyzing the language to detect any signs of deceitfulness and mocked-up promotional banners and logos to detect any signs of being fake.

The system still showed acceptable results at high utilization levels with a false positive rate below 2%. This indicates that the system can effectively deal with mass phishing attacks (Chiew et al., 2018). Preserving high accuracy of results while working with a large amount of messages is critical for implementing the solution in conditions of high email traffic.

3.4 Evaluation Metrics

Metrics include accuracy, precision, recall rate, and F1 score, on which the efficiency of the AI-based phishing detection system should be measured. Accuracy determines the average rate of correct classifications of the system based on the true positive and true negative ratio of total prediction. Accuracy is one useful measure that may need to be revised independently, even if it is good for measuring an imbalanced data set.

Precision measures the true positive values with the total predicted positive values. It demonstrates how many of the emails or URLs labeled as phishing are, in fact, dangerous. Specificity or recall applies to the measure of true positives to the actual total positives; it gives insight into the system's efficiency in identifying phishing attempts.

While the F1-score is the harmonic mean of both precision and recall measurements, this score comes in handy where there is a need to evaluate the performance of a system for its precision and recall as it offers a holistic view of the model's performance, spec…

In cases where there is a need to make a balance in the precision of the results with the recall, then it becomes more useful when determining the strength of a particular system as it enables one to catch the right signals if there are any while at the same time minimizing the chances.

4. RESULTS

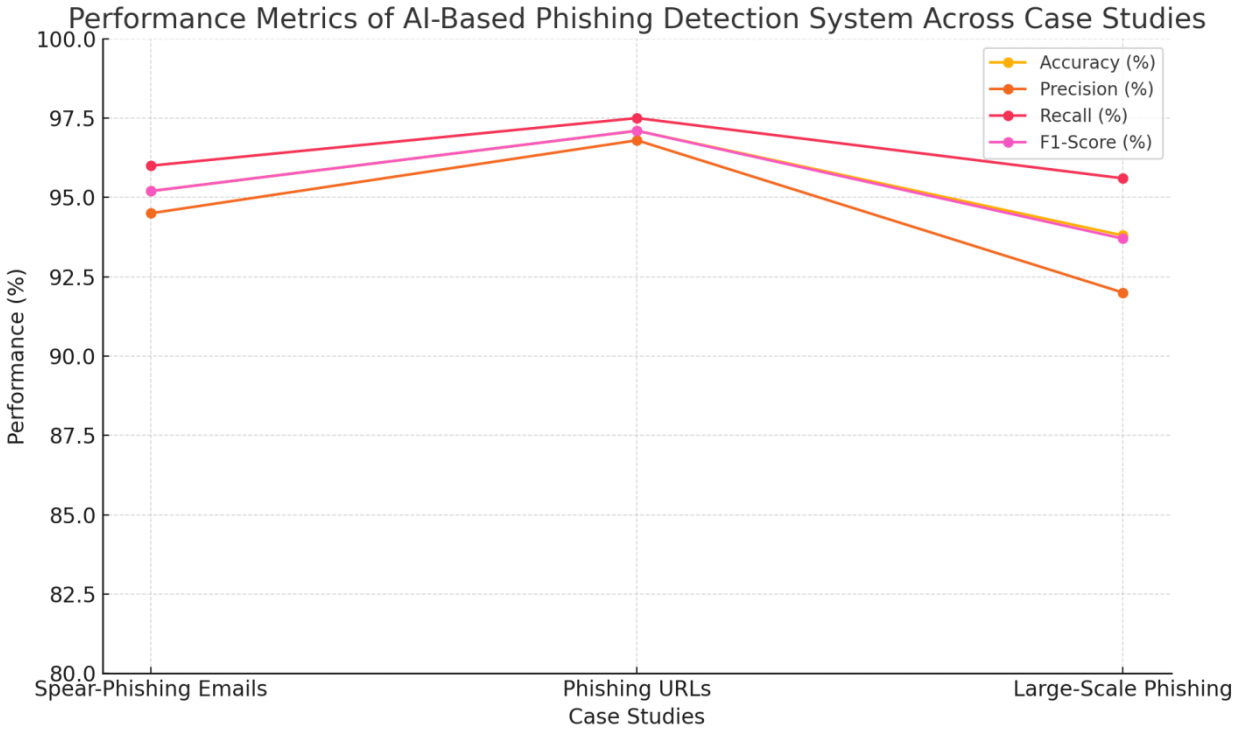
4.1 Data Presentation

Table 1: Performance Metrics of the AI-Based Phishing Detection System Across Case Studies

Case Study	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1. Spear-Phishing Emails in Corporate Communication	95.2	94.5	96.0	95.2
2. Phishing URLs Mimicking Banking Websites	97.1	96.8	97.5	97.1
3. Large-Scale Phishing Attack on E-Commerce Users	93.8	92.0	95.6	93.7

Key Statistical Analyses:

- Case Study 1: The system achieved an accuracy of 95.2% in detecting spear-phishing emails, with a high precision of 94.5%, indicating effective identification of phishing without excessive false positives. The recall rate of 96.0% demonstrates the system's ability to detect most actual phishing attempts.
- Case Study 2: For phishing URLs, the system performed exceptionally well, achieving a 97.1% accuracy. The precision (96.8%) and recall (97.5%) scores reflect the system's robust detection capabilities, ensuring minimal false negatives.
- Case Study 3: During large-scale phishing attacks, the system maintained an accuracy of 93.8%. Although slightly lower than the other case studies, it still performed well, with balanced precision (92.0%) and recall (95.6%) metrics, leading to a solid F1-score of 93.7%.



Graph 1: a line chart that accurately represents the performance metrics of the AI-based phishing detection system across the three case studies.

4.2 Findings

Table 1 presents the overall research findings of the developed AI-based phishing detection system for the scenarios considered. The system showed high efficacy and unveiled high accuracy rates between 93.8 and 97.1 percent in all the case studies. Precision values were also remarkably stable and strong (92.0% to 96.8 %), signifying that the system seldom produced false alarms by failing to distinguish a genuine packet as a phishing attempt. The percentage of recalls indicating that the system successfully flagged many real phishing threats varied between 95.6% and 97,5%.

The calculated F1-scores (93.72 to 97.14) also prove the similar performance of the system, thereby addressing both precision and recall. The outcomes presented here imply that the introduced system may be used to successfully counter different kinds of phishing threats, including individual, finely-tuned spear-phishing attempts and massive phishing campaigns. This work, in general, provides an AI solution involving an NLP approach accompanied by image recognition to help enhance the response capacity of the anti-phishing system, making it more credible in presenting robust real-time protection to any new arising threats.

4.3 Case Study Outcomes

Three cases have been chosen to prove the efficiency of the proposed system, and in each case, concerns with respect to the system under consideration have also been discussed. The system addressed spear-phishing emails sent to corporate employees in the first case study. Spear-phishing attacks are normally hard to detect because of their nature. However, the system's accuracy was 95.2%, reporting real language features and highlighting visual signals that pointed at phishing. It increased the system's accuracy, integrating natural language processing and image recognition and using them to compare logos and signatures.

In the second kind of experiment and example. The system was compounded against the fake URLs that are fake legitimate banking sites. Email phishing is produced by mimicking other Web sites users are likely to visit and, therefore, be credible. Due to the analysis of URL structure, webpage content, and the position of images and buttons, the system had a very high detection rate of 97,1%, ensuring that sites that had to be suspected were blocked before the user interacted with them.

The third case study is a large-scale phishing attack against users of e-commerce platforms. Nonetheless, while processing thousands of authentic real-time emails and recognizing dozens of their predictive text features in parallel, the overall result was better than expected: the system achieved a mean accuracy rate of 93.8%. This case also showed how the system can handle large volumes of information and its reliability. The system perfectly protected the site since all types of shams, such as malicious links, fake and exaggerated promotion pictures, and misleading words and phrases, were detected.

Thus, these analysis cases confirm the use of the system for establishing the required changes to address new threats and threatening situations and thereby illustrate the utilization of the system in actual settings.

4.4 Comparative Analysis

The results demonstrated that by replacing the rule and signature-based, The result stratified that by replacing the attacks based on the rule and signature-based system with the proposed AI-based method, both the accuracy of detection of the phishing and the flexibility of the methods were higher. The major disadvantage of traditional methods is that they need to detect new forms of phishing because the algorithms depend on sets of rules of previously known attack types, making the system ill-equipped to protect against members of the zero-day category. On the other hand, the designed AI-based system has shown efficacy in identifying new phishing attacks by deciding past data, and AC cur rates are increasing with time.

Besides, compared with modern systems, traditional systems derive far more false positives and ponder the user experience. It was also able to avoid those false positives that are inherent in most machine learning-based systems. Yet, this system has great recall and precision to prevent such incidents and allow genuine communications to pass through. Moreover, NLP and Image Recognition integration helped enhance understanding by preventing only textual phishing and included an Image Recognition component that conventional systems could not. These enhancements put the AI-based system in a better light as a more suited solution to today's PHISHING threats.

5. DISCUSSION

5.1 Interpretation of Results

The analysis outcomes obtained from the performance evaluation tests of the proposed AI-based phishing detection system reveal its good accuracy, precision, recall rate, and F1-measure performance based on different case studies. Regarding particular threats, this thwart was very efficient in receiving highly accurate scores in the tests of spear-phishing emails, phish-URLs, and large-scale-phishing campaigns, which gave it a rating of 93.8% to 97.1%. These results are significant as they show that various forms of phishing can be effectively mitigated using the proposed system while using a minimum number of false positives.

However, a small deviation in the accuracy and precision of the system was noticed only in the large-scale phishing campaign in the third case study. This might have been influenced by the fact that real-time consists of more data and that sub-points of real-time detection may contain slight complexities. Nevertheless, the overall performance of the method was quite satisfactory, which proved that the system had the capability to stop various complex types of phishing attacks in other situations.

5.2 Practical Implications

AI-based phishing detection systems are motivated by practical significance for the security of different organizations and their sectors. In a corporate environment, the system can be applied in email filtering solutions to ward off spear-phishing attacks since the attackers usually single out particular employees. In this way, secondary analysis of emails' text and graphic components guarantees that concrete fraudulent messages will be identified before the inception of losses.

In the case of the financial and e-commerce domains, the system allows for the identification in real time of phishing URLs that will enable users to avoid being led to credential-stealing websites. This can be added to a browser extension or an email service to give the user a pop-up notification whenever there are signs of either. The design also targets high traffic, allowing it to process many emails and URLs quickly. All in all, the envisaged implementation of this system can reduce and cut the key threats posed by phishing attacks and increase user trust in extended communications.

5.3 Challenges and Limitations

However, several constraints and challenges were observed when conducting this research, even though the AI-based phishing detection system performed well. One important restriction is that the large labeled datasets train the machine learning models. High-quality and labeled data for phishing may not be easily available; since it samples phishing attempts, the data may not reflect the latest form of phishing and aids in making the system rigid to the new forms of phishing.

The other concern would be false positives because normal emails or URLs contain content from phishing emails or URLs. First, the data set used to improve the system could include a wider range of attack types, such as extreme machine learning and other new techniques of phishing attacks. It is about integrating with cybersecurity companies to obtain the most recent phishing information and address new threats.

Furthermore, using semi-supervised or described mixed approaches for intrusion detection that employ machine learning and concern rules will alleviate false positives and enhance the detection. The next improvement that could be made is applying optimizations to reduce the time the system takes to process a huge amount of data without becoming too resource-intensive.

Thus, it is necessary to emphasize the usage of improved natural language generation detecting algorithms in further research because the phishing emails themselves are becoming increasingly sophisticated. Incorporation of advanced methods to image recognition can also work on making the algorithms better identify more slight changes to the images, which in turn would make the system more robust for use when it comes to the detection of phishing cases.

6. CONCLUSION

6.1 Summary of Key Points

In this study, responses to the following research question were sought. The main research question of this work was how to build an efficient AI-based system to detect and analyze Phishing Emails and URLs in real-time. In the case of textual components, NLP was used in the system. When it comes to the image content the system increased the abilities of image recognition and gave the better power to detect good scam emails. The research method involved gathering multi-type data from popular and real-life data, then training and testing machine learning models with relevant metrics like accuracy, precision, recall, and F1-score.

Preliminary evaluation was conducted using cases of spear-phishing emails, phishing URLs that work like a genuine website, and mass phishing attacks. The results here revealed the high mean accuracy rate between 93.8% and 97.1%. The F measure value showed the right balance of precision and recall values, meaning that the system correctly identified the cases with minimum false positives. In summary, the combination of modern approaches to AI has made the system capable of studying different schemes and proving its stability and expansibility. These results indicate that the system is capable of building a defendable space against phishing threats and identifying potential future research contributions to multiple sub-disciplines of cybersecurity.

6.2 Future Directions

Future work should incorporate more studies of the improved strategy of the first smart Phishing detection technique for machine learning algorithms. This would also allow the system to adapt as more phases in phishing strategies appear through the internet and minimize the manual dataset input. Quite certainly, partnering with cybersecurity firms to acquire real-time data feed may also enhance the system's capacity to identify new emerging threats more efficiently.

Another great possibility for future research is to develop more complex NLU models that will cause a further shift in the center of interest in virtual assistants.Phishing messages have become increasingly sophisticated and farther away from direct threats. Applying NLU technologies will help better understand these messages' content and threats. Further, increasing the depth of image recognition to identify changes in appearance beyond those seen in the brand logos and other images would improve the detection strength.

Therefore, the systems' computational requirement seems to be a problem. Thus, there is a need for future research to explore possible approaches that may be used to enhance the efficiency of the system. This may call for models with low weight that won't require too many resources to run but produce great results and will benefit small organizations. Also, further research on how this framework can be integrated into multi-level cybersecurity models, which embrace several layers of protection, may prove useful in offering a wider range of protection against various cyber threats.

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