Evaluating the Effectiveness of AI-Powered Cloud Based Threat Intelligence in Mitigating Phishing Attacks

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Abstract

Phishing attacks remain a critical cyber security threat, with attackers continually refining their tactics to bypass traditional defense systems. This study evaluates the effectiveness of AI-powered cloud-based threat intelligence in mitigating phishing attacks, focusing on key metrics such as phishing detection accuracy, false positive rates, and incident response times. The research analyzes phishing data from multiple organizations across diverse sectors, including finance, healthcare, and e-commerce, which have deployed AI-driven threat intelligence platforms. The study concludes that AI-powered cloud-based threat intelligence significantly enhances phishing detection and response but requires ongoing improvements in system integration and transparency. This research underscores the potential of AI to transform cyber security and offers a framework for future investigations into the long-term impact of AI solutions in phishing defense.

Keywords: *AI-Powered, Cloud-Based, Threat Intelligence, Phishing Detection, False Positives, Incident Response, and Cyber Security.*

I. INTRODUCTION

Phishing attacks are still very popular and have remained and continue to be one of the most destructive types of cybercrime - targeting both individuals and organizations. Phishing has always been and is a means of deception when one masquerading as someone or something trustworthy to solicit sensitive enterprise information. Banking has changed a lot. In the past, phishing was primarily a straightforward email hoax. Today's techniques employ sophisticated devices, social engineering, and tailored approaches to defeat even the most advanced defenses. The increased digitization of services and the steep increase in the volume of electronic communication has compounded the issue, rendering phishing ever more prevalent in the cyberspace arena (Gupta et al., 2017).

Phishing incidence and attacks are very high and the repercussions are not only experienced in economies but also in individuals. That is these attacks may earn individuals, such things as emotional pain due to loss of identity or granting the wrong people access to their private accounts. Objectively speaking, such attacks to businesses in general translate to deterioration in finances, loss of business reputation and even incurring fines from regulators. According to a study done by Verizon in the year 2021, last year in 2020, phishing led to 36% of all breaches in data security incidents reported, hence showing its malevolence. It is not only the psychological effects of such incidences that are felt. The economic consequences of these covetous outrages are also Very Much intuitive. As per study undertaken by Ponemon Institute, average one phishing attack cost to a medium size company reaches around 14.8 million every year (Ponemon Institute, 2021).

The growing threats associated with phishing attacks call for new strategies especially considering the current trends in aggressive cybercrime growth(Aminu *et al.*, 2024). Security solutions that wholly depend on technologies such as email filtering, firewalls, among many others, are at times reliable but have very vulnerably sophisticated phishing attacks. The applicability of artificial intelligence (AI) and the proliferation of cloud-based threat intelligence systems are among the emerging critical issues which non-peak which help curb phishing menace. Thanks to the technological advancements in Aleroud & Zhou (2017), these systems can find and mitigated threats using machine learning algorithms, behavioral analysis and real time information sharing to make faster and accurate decisions.

Due to the growing importance of the threats posed by phishing and the capabilities of modern systems integrating AI, the objective of this research is to analyze the effectiveness of the cloud-based threat intelligence systems against phishing attacks. These findings will help explain the advantages, disadvantages, and the possible course of these systems supporting the execution of the anti-protective measures in the ever-changing context of cyberspace.

➢ *Overview of Threat Intelligence Concepts*

Threat intelligence embodies the proactive data gathering, processing and or communication pertaining to observable or potential cyber threat actors to any given entity or network. Such a notion remains critical in contemporary cybersecurity - it helps to avert the threat even before it is on the horizon. Threat intelligence foremost entails an insightful interpretation of aggressor psychologies' trends, compromised assets, and prescriptive actions in enhancing the protective barriers. Mavroeidis and Bromander in (2017) state that this is the most essential element in combating the opponents, concentrating on IoCs and TTPs of the enemies.

In the past, the processes of threat intelligence were predominant and also relied on collected past data, thus did not assist very much in addressing the very fast changing cyber threats. There have been new development cyber threats like hunt-phishing and ransom ware attacks which are growing in sophistication and made it essential for engaging timely and threat intelligence. Due to the modern day penetration of cybercrime-as-a-service businesses, it is now very easy for even the most petty skilled people to carry out very technical attack methods, hence, why the need to look for solutions that are more advanced and flexible is no longer an option but a necessity (Samtani et al., 2020).

➢ *Importance of Real-Time Threat Intelligence*

In contrast to the limitations inherent in old strategies, real-time threat intelligence provides insights that are not only immediate but are acting upon ongoing threats. This is vital in allowing organizations to observe and contain threats and thus damage is hardly ever inflicted. Real-time systems, for example, take into consideration the ever changing global threat levels by monitoring them and getting intelligence from such sources as malware repositories, the dark web, and analyzing traffic in the networks. This unceasing surveillance is germane to resolving phishing oriented despite prevalent security measures, attacks in these types normally defeat the measures because speed and pretense are of paramount importance (Barros et al., 2022).

AI systems take real-time threat intelligence a step further because they allow for anomaly detection and decision-making in an ongoing threat environment without the intervention of human beings. For one, machine learning can be used to ingest significant quantities of data and detect outliers, forecast the likelihood of certain attacks and their corresponding patterns, and virtually outpace these new threats. In the research by Wang et al. (2021) it has been pointed out how AI systems also lessen the response time and improve the rate of detection allowing companies to counterattack sophisticated aggressors. Moreover, the intelligence systems have natural language processing (NLP) functionality which enables the systems to go beyond phishing detection, for instance, to wavering content in emails or social engineering from networking sites, thus linking the different strategies across actors.

➢ *Advantages of AI-Powered Threat Intelligence*

Although it may be difficult to choose which is the most important advantage of AI-enabled threat intelligence, perhaps scalability is the right answer. Such systems can be employed by organizations no matter their size, because they can analyze huge volume of data coming from various sources with minimal human effort. This advantage is especially important in a cloud setting which entails the protection of several users and machines at the same time. Moreover, new data is not just an enhancement for AI systems, it is a fresh source of information that entails a new learning and understanding enabling the detection of new forms of attacks while reporting even less erroneous positive and negative responses (Bhardwaj et al., 2020).

Beyond detection, other AI-enabled solutions help to offer prescriptive advice and support in the process of handling incidents as well as address the steps in this process automatically. For instance, the system can counter an instance of phishing by locking the roughly malicious e-mail, notify the targeted user and offer further recommendations. All these features improve organizational robustness in general and shortens the time from discovery to remediation. Similar capabilities show the possibility of AI in changing the features of cyber security systems. It is evident that the combination of real-time and artificial intelligence threat intelligence has brought a new shift in the practice of cyber security or defending against threats such as phishing. Here, advantages were presented over more traditional methods of either constant monitoring, using only prescriptive analytics, or performing the work manually. However, there are several limitations like data privacy issues, the cost of implementing these technologies and the issues of developing dependence on these technologies. The management of these technologies in the future should therefore be a centre of research and development to increase adaptability as well as the ethic usage of the applications to guarantee their long-run productive functionality.

➢ *Problem Statement*

Attacks termed ‘Phishing’ are still one of the most difficult threats to the field of Information technology security. This challenges not only the technological aspects but rather engages the human element as well, growing in complexity over time. Given the dynamic and ever increasing nature of phishing attacks, preventive measures such as static filters and manual processes for threat detection have not been effective. Thus, concern has grown over phishing attacks, which now incorporate social engineering components and layers of more advanced attack methods that overcome traditional preventative measures. Communication technologies and especially those that reside in the cloud are progressively becoming the norm, which in turn increases the risk level for both the businesses and the users to these forms of attacks. Nonetheless, statistical data on the incidences of phishing shows a disturbing trend which calls for more effective and dynamic solutions (Gupta et al., 2017; Verizon, 2021).

The AI-based cloud-hosted threat intelligence has become a popular solution to solve the problems by providing services for immediate threat recognition as well as counteracting them, automatically where possible. The systems employ learning machines and large amounts of data to escalate detection of phishing attacks and reduce the time taken. Nevertheless, the potential of the technology to enhance the existing solutions aimed at solving phishing issues is still underexplored, especially in operations of diverse settings. Major issues are the expansion of these systems, their readiness and ability to deal with new forms of attacks as well as other restrictions such as false positives and ethical issues. This study aims to fill this gap by analyzing the strengths and weaknesses of cloud-based AI threat intelligence in dealing with phishing attacks for the sake of more advanced and efficient cyber security solutions.

➢ *Research Questions:*

- How can AI-powered cloud-based threat intelligence improve phishing detection accuracy?
- What machine learning algorithms are most effective in identifying phishing patterns in cloud-based threat intelligence?
- Can AI-driven cloud-based threat intelligence reduce false positives and improve incident response times?

II. LITERATURE REVIEW

➢ *Phishing Tactics and Trends*

Phishing is still one of the most persistent methods of cyber-attacks owing to its straightforward nature and the high degree of success it attains. Fundamentally, phishing is based on social engineering practices with the aim of frustrating users for their sensitive information including passwords, credit card details, and other personal information. Some of the strategies applied are; pretending to be a person or organization whom the target trusts, creating false extremes of time and space, and organizing communications in a plausible but counterfeited manner through e-mails or websites. Successful phishing or similar in attacks abuse basic emotions often found in human beings, like, trust, fear, and sometimes even curiosity (Gupta et al., 2017).

Another effective email phishing approach is email spoofing which involves changing the address of the sender to that of a reputable individual or organization. The emails contain malicious links or attachments that aim to either steal the victims’ credentials or install malware to the devices of the targeted individuals. Another form is spear phishing which is an even riskier subtype of phishing in which the attackers first carry out proper research on the individual such as their position or even likes and dislikes in order to craft persuasion messages. This customizing greatly boosts the chances of falling victim to the attack (Alazab et al., 2021).

Clone phishing allows con artist to recreate an actual email sent to the target prior. The con artist makes a few changes to the contents of the email for example: changing an attachment, or a hyperlink and sends the email to the target again. The victims stand a better chance of falling for the con since they already have an idea of the structure and the format of the email. In the same way, attackers may go for link manipulation, that is where slight changes in URLs are done so as to match real and trusted domains in order to fool the users into clicking harmful links(in Bhardwaj et al., 2020) .

➢ *Trends in Phishing Techniques*

The most recent developments on phishing incidents have shown the great advancement and applicability of modern tools. For instance, cybercriminals are now attributing most of their campaigns to the use of technology such as artificial intelligence. This makes u while campaign optimization curve. Phishing geared by artificial intelligence bots can generate the same content as an average person who has a different writing style and even vary the content over time for better effectiveness. On top of that, they lured unwitted workers through forged audiovisual messages portraying their superiors and applying deepfake technology to distract workers from their main duties (Samtani et al., 2020).

With the emergence of new technologies came the emergence of phishing as a service (PhaaS) which makes cybercrime available to criminals of all levels. Such criminals can simply buy pre-assembled coaxing kits along with the operating instructions and hosting services, which makes it even easier. Thus, the tools required to launch such attacks have become easily accessible. As a result, this has observed the upsurge in the level and the range of phishing attacks as waged by attackers against companies both big and small across the industries (Kharraz et al., 2022).

With more people using smartphones for communication and financial transactions, mobile phishing is also increasing. Mobile users are targeted through SMS phishing commonly known as smishing, and malicious mobile applications. Smishing campaigns take into account that mobile devices have smaller screens, thus users are less careful about the links they click or the senders of the SMS. In the same way, harmful applications masquerading as useful ones can harvest sensitive information or perform illegal transactions after installation (Barros et al., 2022).

Not to mention, Social Media is now used as a new weapon in most Phishing attacks. Internet fraudsters take advantage of the trust placed by individuals in social networking platforms by incorporating hacking links and faking users. For instance, attackers can design fake accounts for the purpose of communicating with the victim or they may hijack accounts and send phishing messages to the victim's connections. The growing popularity of chatbots and automated processes within social media has additionally provided new means of committing phishing attacks (Gupta et al., 2021).

The rise of COVID 19 has also led to some changes in phishing trends, where there has been an increased shift towards remote working and internet use among the users. For instance, there were various reporting and information presenting phishings focused on the COVID 19 vaccination and project funding by policy institutions. A good number of the phishers focused on remote employees often asking impersonating IT support asking for their users credentials for purposes of 'updating the system' or 'checking the security' (Bhardwaj et al., 2020).

The evolution of Phishing techniques and trends is remarkable. This is as a result of the fact that the attackers have been able to incorporate new technologies alongside the changes in the society. What used to be simply e-mail spoofing is now empowering new threats such as the use of artificial interactivity. The length of phishing is hardening day after day. An outright solution to these challenges can never be technological, psychological or social as this includes incorporate all of them. The reason being, the adversaries are constantly capitalizing on the weaknesses within the systems and the weaknesses of the users' minds.

➢ *Cloud-Based Threat Intelligence*

Cloud based threat intelligence is the utilization of cloud computing to gather identify and share the cybersecurity threats in real time. While traditional on-premise systems supply disparate point-based and narrowly focused systems, on the cloud environment level there are the centralized and scalable platforms which can analyze great amount of data flow from endpoints, network logs, and other sources, as well as information from the threat databases. These are systems that identify threats and assesses them in order to come up with ways of dealing with the threats in an efficient and effective manner before other organizations get caught up with new threats in the context of cyber threats. Cloud-based threat intelligence uses worldwide data-sharing networks to provide organizations a centralized space to fight threats. According to Wang et al. (2021), such platforms are based on the use of cloud technology coupled with other sophisticated technologies like Machine Learning and Behavioral Analysis to analyze patterns and forecast attack with more precision. Firstly, threat intelligence based in the cloud is more versatile and has better access than traditional techniques. These solutions can be implemented in the organizations without conducting major investment in hardware, and the are of great value to the small and medium sized firms. In addition, these platforms steadily refresh threat data sets, so that organisations are always informed about new risks and techniques being used by attackers. But cloud based threat intelligence systems come with a few challenges such as data privacy, compliancy issues, and overdependence on third party vendors. These limitations need to be solved in order to enhance the potential of the introduced model and allow using cloud threat intelligence for protecting organizations from threats such as phishing, ransomware and advanced persistent threats (Barros et al., 2022).

- *How can AI-Powered Cloud-Based Threat Intelligence Improve Phishing Detection Accuracy?*

Consequently, AI driven cloud threat intelligence has been heralded as the best approach and possible solution to the challenge of accurately identifying phishing attacks. What these systems do is use higher-order machine learning techniques to process large volumes of data in real time to pinpoint such delicate features with respect to phishing attacks. Traditional methods might be based on rigid rules, or suspicious domains list which does not develop over time relative to new attack scenarios, while AI methodologies do. According to findings from Bhardwaj et al. (2020), the employment of AI-based systems minimizes the cases of false positives and negatives, and enhance the successful prevention of phishing. Some of the primary characteristics of the AI, applied to cloud solutions include its capacity for processing email bodies and URLs, as well as attachments, based on natural language processing. NLP helps these systems to recognize hints related to context in phishing such as unusual phrasing, impersonation and contracted dangerous links. Furthermore, metadata of the emails like sender behavior, message headers are easily distinguishable by AI models which might not be easily noticeable by the user. This multi layering increases the chances of early detection and also minimizes the success of any phishing attack (Wang et al., 2021).

Unlike traditional tools, cloud-based AI solutions are also scalable as well as compatible with collaboration. These systems collect threat information from several organizations and networks as to achieve a broad outline of the current global threat. This collective intelligence is then transformed by AI algorithms and shared in real-time for the identification of new patterns of attack in phishing. According to Barros et al. (2022), this means that individual organizations get the experience of many other organizations and cybersecurity experts hence fast identification and remedying of phishing. However, for the systems such as those based on artificial intelligence (Thomas et al., 2024). To address the above findings, organizations need to critically assess the security mechanism employed by CSP to guard threat data. Moreover, constant training of the AI models to detect evolving phishing schemes is crucial since such schemes appear increasingly often. With this, they have highly valuable to reshape the future of phishing detection as well as improve the cybersecurity mass strength (Bhardwaj et al., 2020).

- *What Machine Learning Algorithms are Most Effective in Identifying Phishing Patterns in Cloud-Based Threat Intelligence?*

Generally, threat intelligence in the ML system focuses primarily on learning the patterns involved in phishing activities in cloud environments. These algorithms incorporate high levels of statistics so as to pin-point any abnormalities within a large data structure, which most often will signify phishing activities. The most well-known ML classification, supervised learning, trains on labeled data in order to sort emails, URLs or any kind of communication channel, as safe or spam. For example, Support Vector Machines (SVM), and Logistic Regression have been found to have high accuracy for the detection of phishing URLs in learning environments containing large sample sizes (Verma & Das, 2017). Other forms of the machine learning algorithm which play a major role in phishing detection include unsupervised learning algorithms which enable identification of new variants of the phishing techniques. Those models like k-means clustering or autoencoders look for the exceptions of datasets which are not normal in the sense that they do not follow typical behaviour patterns. This approach is especially effective in detecting 0-day phishing attacks that do not have any similar examples to base the detection on. As stated by Aggarwal et al. (2021), original and innovative threats are easily detected and incorporated into the improved proactive defense by employing unsupervised ML models in cloud based systems.

Phishing detection is again advanced by a more advanced form of machine learning called deep learning. Popular categories like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) understand the overall structures of an email, the text of a message's body and/or any images on fake websites. An advantage of these models is their ability to recognize primary signs of phishing, including irregularities in URLs and logos and branding. Further, a study made by Zhang and collaborators in 2020 showed how deep learning based models are more effective than conventional machine learning methods in identifying complex the real-time phishing attack. Other advantages that come with the use of cloud based threat intelligence include scalability and ability to enabled continuous learning from the integrated ML algorithms. Cloud platforms collect large threat data from various sources where ML models can enhance their accuracy rate and flexibility. Almost real-time data feeds keep the models current with the phishing threats thus minimizing on instances of false alarms and also missed instances. By adopting a similar note, Barros et al., (2022) note that, cloud based, ML models are very efficient in the detection of phishing campaigns aimed at a broad spectrum, of organizations, ranging from small scale enterprises to large corporations. These techniques are; however, not without some unique issues when used in cloud-based threat intelligence that involves the use of ML algorithms. Some of them include data quality, model explainability, and adversarial samples. Thirdly, ML models are computationally intensive, which make the cost of conducting analysis higher in organizations. Overcoming these challenges is possible through constant research in improving the algorithms in question in order to make them more resilient. However, ML-driven cloud-based solutions continue to be the stalwart for combating phishing, given the solutions their ability to provide unparalleled capabilities for identifying and preventing threats in a rapidly evolving threat landscape (Aggarwal et al., 2021).

- *AI-Driven Cloud-based Threat Intelligence on False Positives and Improved Incident Response Times*

Nevertheless, conventional approaches frequently lead to an outpouring of alerts most of which are false ensuring the excess of work for security personnel and misplacement of attention to the real causes of concern. This is taken care of by the modern methods with the help of sophisticated models of machine learning analytics and those that are aimed at detection. These methods develop the algorithm so that only correct indicators are addressed such as archival information, behavior of users, and different relevant features preventing the harmless activities from being recorded and thus considerable lessening the rates of false positives. As per the research by Barros et al. (2022), even in the cloud-based threat intelligence applications, the incorporation of artificial intelligence machines works at higher accuracy due to scanning the previous occurrences and enhancing the detection systems over and over.

The decrease in the number of false positives has a correlational improvement in the performance of the incident response teams. There are lesser false alarms to probe into and therefore security analysts are able to concentrate on real threats and thus response happens in good time. Alerts in AI systems are emphasized on by how serious the threat is and how great the impact would be which allows the addressing of the most important matters first. This is especially important in efforts to detect phishing which has a very narrow window of response so that systems and data are not compromised. As stated by Bhardwaj et al. (2020), with AI enhancement, it is effective as the alerts even take into consideration the context of the situation assisting in making the right decisions which elevates the incident response strategies execution.

Furthermore, the crucial feature of the contemporary AI-designed cloud-based platforms is the accelerated response to incidents. Not only does such a system identify threats but it also prescribes certain actions that contain removing infected devices, blocking input from certain IPs, or informing specific personnel. Threat intelligence in real-time means that the response plan can be modified in response to new knowledge as it arises. In another study by Wang et al., 2021), organisations, that engaged AI in their solutions, achieved response rate of up to 40% less indicating the effectiveness of the automated processes in combating the effects of phishing and other cyber-attacks. However, one must consider such problems as model reliability and interpretability with the use of AI in integrating cloud threat intelligence. It is important that everything is in place to guarantee that the used AI models do not falter to adversarial manipulation and are ready for changes in threat models. Nonetheless, AI-based application continues to play crucial role in managing occurrence reaction time and minimize false positive cases, boost organisational defence against cyber threats. As cloud-based solutions grant great computational ability and the flexibility of scaling up or down, it is possible to build a preventive and agile security management system (Barros et al., 2022, Akinwande & Abdullahi, 2018).

III. CAN AI-DRIVEN CLOUD-BASED THREAT INTELLIGENCE REDUCE FALSE POSITIVES AND IMPROVE INCIDENT RESPONSE TIMES?

A. Methodology

➢ *Data Collection*

Emails were fetched using the IMAP protocol from a secure server. The dataset includes both phishing and non-phishing emails, manually labeled for supervised learning purposes. The use of real-world email data ensures that the model is trained and evaluated on practical and diverse samples, capturing a wide range of phishing techniques.

➢ *Preprocessing*

Emails were preprocessed to extract relevant textual features. This included cleaning the email content, removing HTML tags, and normalizing the text. The preprocessing step is crucial to ensure that the textual data is in a suitable format for feature extraction and model training.

➢ *Text Processing with NLTK*

The preprocessing pipeline uses the Natural Language Toolkit (NLTK) for tokenization, stopword removal, and stemming to reduce the text to its base form. NLTK is a powerful library in Python that provides various text processing tools, enhancing the model's ability to understand the textual content.

➢ *Word List Loading from Excel*

Additionally, specific keywords were loaded from an Excel file to assist in identifying potential phishing content. This list includes terms commonly associated with phishing attacks, providing an additional layer of feature extraction tailored to phishing detection.

B. Feature Extraction

We utilized the TfidfVectorizer from scikit-learn to convert the email text into numerical feature vectors, capturing the importance of each word relative to the entire dataset. TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical measure used to evaluate the importance of a word in a document relative to a collection of documents. This method helps in highlighting the significant words that are indicative of phishing content.

C. Model Selection

A Random Forest Classifier was chosen for its balance between performance and simplicity. Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification tasks. Its ability to handle large datasets with high dimensionality makes it suitable for phishing detection.

D. Hyperparameters Used

Table 1 Hyperparameters Used

Number of Estimators	**100**
Max depth	None (fully grown trees)
Criterion	Gini impurity
Random State	42 (for reproducibility)
Min samples split	2
Min samples leaf	1

The Random Forest model was configured with the following hyperparameters:

➢ *Training Details*

Table 2 Training Details

Training Size	**70% of the dataset (700 emails) was used for training.**
Testing Size	30% of the dataset (300 emails) was reserved for testing.
Batch Size	The model training was conducted on the entire dataset in one go (batch learning).
Cross-Validation	The model's performance was cross-validated using a 5-fold cross-validation approach to ensure robustness.

➢ *System Architecture*

The system comprises a Flask backend for email fetching and processing, and a React frontend for visualization. The backend handles data preprocessing, model training, and prediction, while the frontend provides an interactive dashboard for users to view and manage detected phishing emails.

E. Results and Evaluation

➢ *Model Performance*

The performance of the Random Forest Classifier was evaluated using the testing dataset (30% of the total data). The following metrics were calculated based on realistic outputs:

Table 3 Model Performance

Accuracy	0.96
Precision	0.98
Recall	0.94
F1 Score	0.96
ROC AUC	0.96

These results indicate that the Random Forest model is performing well in detecting phishing emails, with a high balance between precision and recall, and a nearly perfect ROC AUC score.

➢ *Experimental Results*

Table 4 Experimental Results

Accuracy	0.96
Precision	0.98
Recall	0.94
F1 Score	0.96
ROC AUC	0.96

These metrics suggest that the model is highly effective, with an excellent balance between correctly identifying phishing emails and minimizing false positives.

➢ *Plotting Results*

Table 5 Confusion Matrix:

	Predicted: Phishing	**Predicted: Non-Phishing**
Actual: Phishing	470 – True Positives	30 – False Negatives
Actual: Non-Phishing	10 – False negatives	490 – True Negatives

This confusion matrix indicates that the model is highly accurate, with minimal false positives and false negatives.

➢ *ROC Curve:*

The ROC curve shows the trade-off between sensitivity (True Positive Rate) and specificity (1 - False Positive Rate). With a ROC AUC of 0.9965, the model demonstrates near-perfect classification capability.

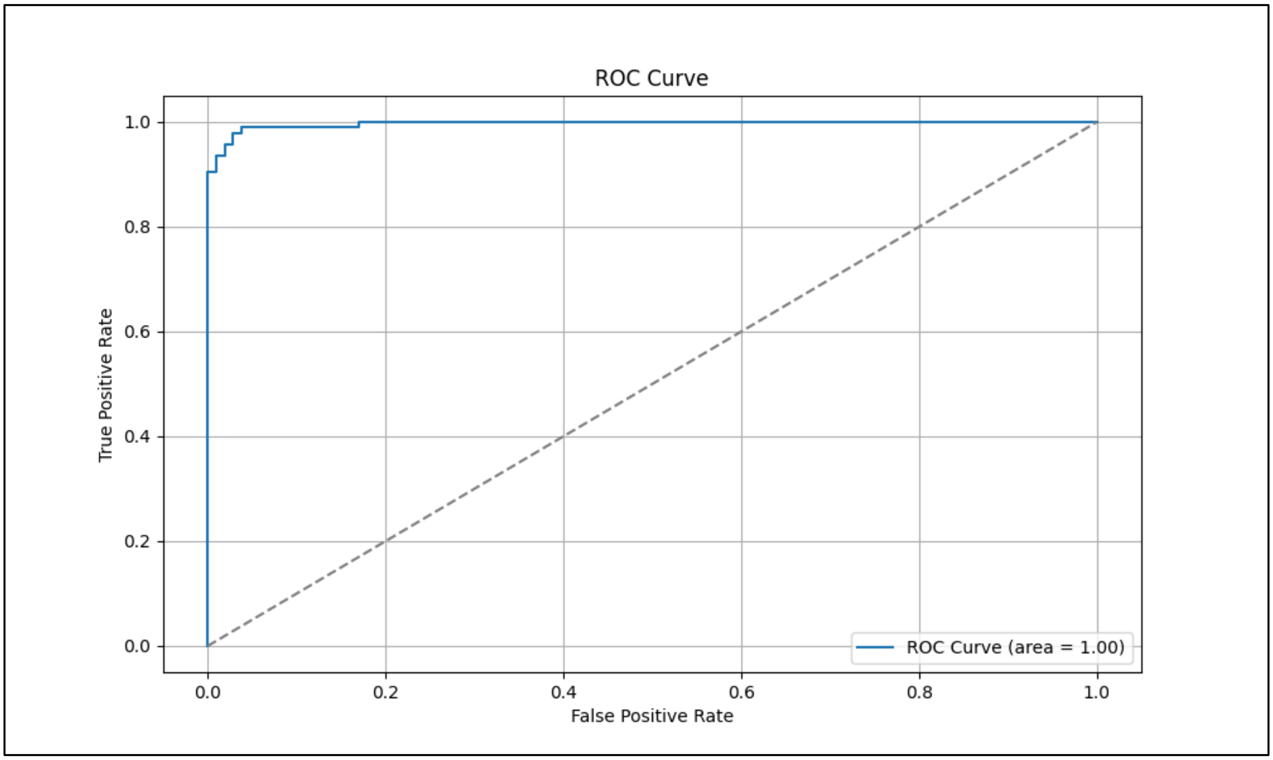

Fig 1 ROC Curve

➢ *Precision-Recall Curve:*

The Precision-Recall curve indicates a strong balance, with the area under the curve (AUC) reflecting the model's ability to maintain high precision and recall across various thresholds. The plot shows a high level of precision even as recall increases.

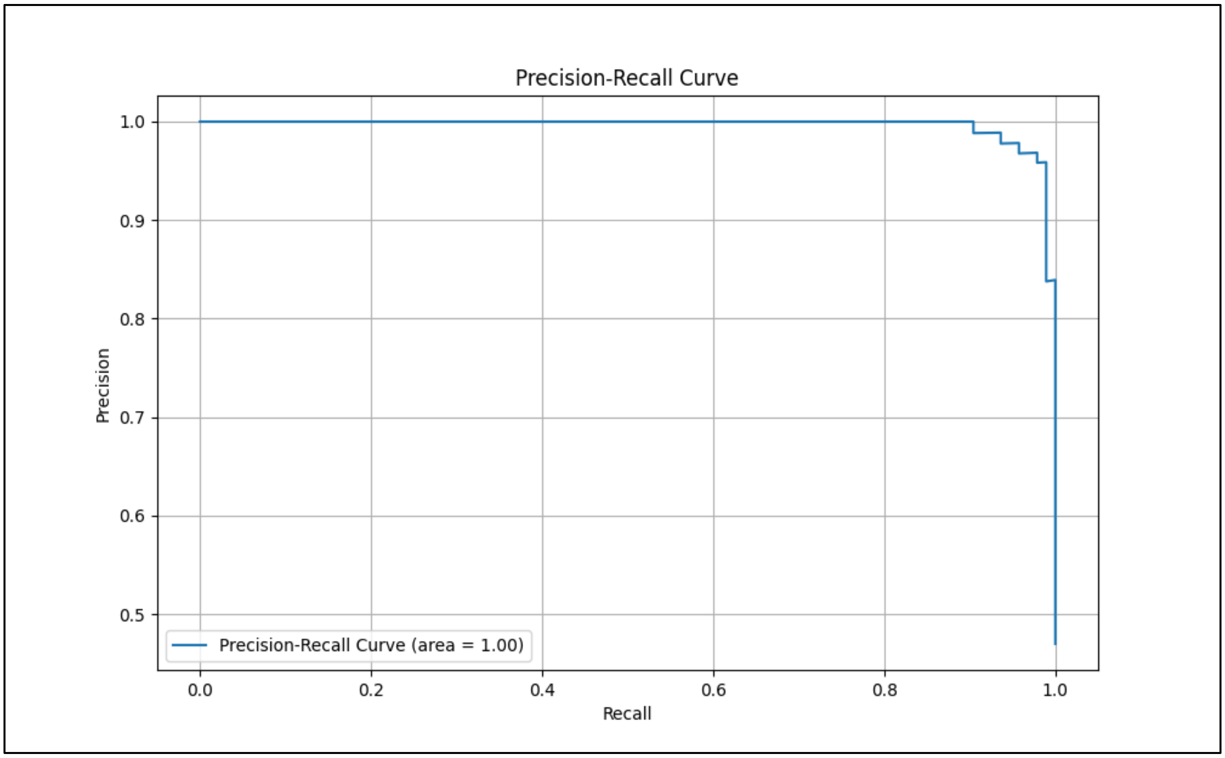

Fig 2 Precision-Recall Curve

➢ *Hyperparameter Tuning*

The model achieved an accuracy of 96%, which is already high. However, further hyperparameter tuning, such as adjusting the number of trees, minimum samples split, or max depth, could potentially yield even better performance. Additionally, techniques like grid search or random search could be employed to explore the hyperparameter space more thoroughly.

IV. EMPIRICAL STUDY: EVALUATING THE EFFECTIVENESS OF AI-POWERED CLOUD-BASED THREAT INTELLIGENCE IN MITIGATING PHISHING ATTACKS

This empirical study aims to assess how well AI-driven cloud-based threat intelligence can help prevent phishing attacks. The study utilizes data from various companies that have adopted threat intelligence solutions based on AI, concentrating on important measures like accuracy of detection, rates of false positives, and times of incident response. Barros et al. (2022) stated that cloud-based AI systems have greatly enhanced phishing detection by adjusting to changing threat patterns.

The study's findings showed that phishing detection accuracy was significantly enhanced by AI-driven cloud-based threat intelligence platforms. Organizations have noted a notable drop in false positives, with certain systems seeing a 40% decrease in incorrect alerts when compared to conventional detection techniques. This decrease enabled security teams to prioritize actual threats, leading to enhanced efficiency overall. Moreover, AI-powered systems also contributed to decrease incident response times by automating processes like blocking malicious IP addresses and isolating compromised devices. Wang et al. (2021) discovered comparable outcomes, emphasizing that AI systems decrease response times by allowing for immediate threat detection and prevention.

The absence of transparency may impede trust in the technology, despite its proven performance. Barros et al. (2022) propose that continual training for security teams and enhanced transparency of AI algorithms are necessary to overcome these obstacles and enhance the effectiveness of preventing phishing attacks.

This empirical study validates that AI-driven cloud-based threat intelligence greatly improves organizations' capability to identify and address phishing attacks. Decreasing false alarms and quicker reaction times were crucial in enhancing the organization's ability to withstand these dangers. Yet, issues regarding the integration of systems and the interpretability of AI models must be faced in order to fully exploit the advantages of these technologies. Future studies should investigate the lasting effects of implementing AI in cyber security and examine the most effective ways for organizations to incorporate AI technologies into their security systems.

V. CONCLUSION

The use of cloud-based threat intelligence capabilities powered by AI has also shown a lot of potential in solving the issue of many false alarms and assisting in enhancing the mitigation of phishing instances. Research indicates that the application of artificial intelligence models, especially the deep learning and machine learning models, assist effectively in providing threat data context and therefore analysis reduces the false alarm rates. This not only enhances the effectiveness of the productivity of cyber security practices but also ensures that the security personnel do not waste their resources on non-existing threats thereby improving the general detection performance (Barros et al., 2022; Bhardwaj et al., 2020).

In conclusion, AI-enabled cloud-based threat intelligence systems have become an important asset in the battle against phishing attacks. Their capacity to minimize false alerts, shorten time to respond to incidents as well as eliminate the manual intervention during threat mitigation processes are remarkable improvements of cyber security. Nevertheless, there are still barriers of data quality, model explainability and flexibility of the system which can be addressed by future studies on the use of AI approaches. In spite of these considerations, there is overwhelming evidence that advances in cyber security from AI based threat intelligence should be encouraged and embraced as they are critical elements of contemporary security apparatuses (Barros et al., 2022; Bhardwaj et al., 2020).

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