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PHISHING EMAIL DETECTION

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ABSTRACT

Phishing emails are a growing concern for both individuals and organizations, as they often lead to financial losses, data breaches, and security vulnerabilities. Phishing emails are typically crafted to deceive the recipient into revealing sensitive information, such as login credentials, personal identification details, and financial data. Detecting phishing emails efficiently has become a major challenge in cybersecurity. This paper presents a method for detecting phishing emails by leveraging machine learning algorithms to identify suspicious patterns and characteristics that are commonly found in fraudulent emails.

The approach involves preprocessing email content, including subject lines, body text, and metadata, to extract useful features that can be indicative of phishing. Various machine learning techniques, such as Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers, are used to build models capable of distinguishing between legitimate and phishing emails. The paper also discusses the use of natural language processing (NLP) techniques for feature extraction, which helps in analyzing the semantic content of emails for patterns such as urgency, suspicious links, or deceptive language commonly used in phishing attempts..

Experimental results show that machine learning-based approaches can achieve high accuracy rates in detecting phishing emails, even with a limited dataset. The research highlights the importance of continuous model training and updating, as phishing tactics evolve rapidly. The proposed system provides an effective solution for mitigating the risks associated with phishing attacks and can be integrated into email security systems for automated detection and prevention.

Keywords— Phishing emails, email detection, machine learning, natural language processing (NLP), feature extraction, Support Vector Machine (SVM), Decision Trees, Random Forest, email security, cybersecurity, phishing attacks.

1. INTRODUCTION

1.1 Company Background

Netleap IT Training and Solutions is a leading IT solutions provider specializing in software development, web development, and IT consulting services. The company focuses on delivering innovative and customized digital solutions to businesses across various industries. With a strong emphasis on quality and efficiency, Netleap IT Training and Solutions leverages the latest technologies to develop cutting-edge software applications, websites, and enterprise solutions. The company is known for its expertise in AI-driven applications, cloud computing, and data analytics, making it a prominent player in the IT sector.

1.2 Organization and Activities

Netleap IT Training and Solutions operates as a dynamic organization that fosters innovation and skill development among its employees and interns. The company offers a wide range of services, including software development, mobile application development, UI/UX design, and IT consulting. During the internship, I was involved in various tasks related to web development, Machine Learning, and AI-driven applications. My responsibilities included working on frontend and backend development, data preprocessing, model training, and integrating AI-based solutions into web applications.

Figure 1.1: LOGO of Netleap IT Training and Solutions

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1.3 Scope and Objective of the Study :

The primary objective of this internship was to gain practical exposure to realworld IT projects, enhance my technical skills, and understand the software development lifecycle. The internship provided hands-on experience with various technologies, frameworks, and tools used in the industry. I also had the opportunity to work on a live project that involved developing a web-based solution integrated with AI capabilities.

The scope of the internship covered:

- Understanding project requirements and client needs
- Developing and testing web applications
- Working with AI and Machine Learning models
- Implementing security measures in web development
- Learning best practices in software development

1.4 Supervisor Details

My internship was supervised by Mrunal Dahale owner of Netleap IT Training and Solutions, who played a crucial role in guiding and mentoring me throughout the program. They provided valuable insights into industry standards, project management, and technical problem-solving. Regular feedback sessions and team meetings helped me improve my skills and understand how professional IT projects are executed.

Introduction

Phishing is a form of cyber attack in which attackers attempt to deceive individuals into providing sensitive information such as usernames, passwords, credit card details, and other personal data. These attacks are often carried out through email, where the attacker masquerades as a trustworthy entity, such as a bank, social media platform, or government organization, to trick the recipient into disclosing confidential information. Phishing emails have become one of the most prevalent and damaging forms of cybercrime, leading to severe financial losses and privacy breaches for individuals and organizations alike. As phishing tactics continue to evolve, traditional methods of detecting these attacks have become insufficient, necessitating the development of more advanced detection systems. [1]).

Machine learning and data mining techniques have emerged as powerful tools for detecting phishing emails by analyzing large volumes of email data and identifying patterns that are indicative of fraudulent behavior. By extracting features from email content, such as subject lines, body text, URLs, and metadata, machine learning models can be trained to differentiate between legitimate and phishing emails. The growing complexity of phishing attacks makes manual detection methods increasingly unreliable, thus prompting the need for automated, scalable systems that can provide real-time detection with minimal human intervention. These machine learning models aim to enhance security by reducing false positives and improving detection accuracy.

This paper explores the use of machine learning algorithms for phishing email detection, focusing on identifying key characteristics of phishing attempts and classifying emails accordingly. It highlights the importance of feature extraction, where natural language processing (NLP) techniques play a critical role in analyzing the content and structure of the emails. Through a comprehensive evaluation of different machine learning models, this research aims to provide an effective and practical solution for combating phishing attacks. The results of this study contribute to the development of more robust email security systems that can detect and prevent phishing threats in real-time.[4].

2. PHISHING EMAIL DETECTION USING LOGISTIC REGRESSION MODEL

2.1 Problem Statement

Phishing attacks have become one of the most prevalent forms of cybercrime, targeting individuals and organizations alike. These attacks typically involve fraudulent emails that appear to be from legitimate sources, such as banks, e-commerce platforms, or government institutions, designed to trick recipients into revealing sensitive personal or financial information. The increasing sophistication of phishing techniques has made it increasingly difficult for traditional detection methods, such as manual reviews or basic spam filters, to effectively distinguish between legitimate and malicious emails. As a result, phishing continues to be a significant threat to online security, leading to financial losses, identity theft, and data breaches..

Traditional methods of phishing detection are often based on heuristic rules or keyword matching, which are easily bypassed by attackers using more sophisticated tactics, such as spoofed email addresses, obfuscated URLs, or social engineering techniques. These approaches also tend to generate a high number of false positives, where legitimate emails are mistakenly flagged as phishing attempts, causing inconvenience for users and undermining trust in the security systems. As phishing attacks continue to evolve and diversify, there is a critical need for more advanced, automated

solutions capable of accurately identifying phishing emails in real-time, while minimizing false positives and adapting to new attack strategies. [5].

Machine learning offers a promising solution to address these challenges. By analyzing large datasets of emails and learning from patterns in both the content and metadata, machine learning algorithms can detect subtle signs of phishing activity that are often overlooked by traditional methods. However, building an effective machine learning model for phishing detection requires careful consideration of feature selection, model performance, and scalability. This research seeks to develop a robust machine learningbased system that can accurately classify emails as phishing or legitimate, providing a more reliable and scalable solution to the growing threat of phishing attacks.

2.2 Objectives

The main objectives of this project are:

- Develop a Machine Learning Model: The primary objective of this study is to design and implement a machine learning-based model capable of effectively detecting phishing emails. This involves selecting appropriate algorithms, such as Support Vector Machines (SVM), Random Forests, or Decision Trees, for classification tasks based on the characteristics of phishing emails.
- Feature Extraction and Analysis: Extract and analyze critical features from the content of emails, including subject lines, body text, URLs, and metadata. Additionally, employ natural language processing (NLP) techniques to evaluate the semantic structure of email content for patterns like urgency, suspicious links, or deceptive language commonly used in phishing attempts.
- Evaluate Model Performance: Evaluate the performance of the machine learning model using standard metrics such as accuracy, precision, recall, and F1-score. Compare the effectiveness of different algorithms in terms of their ability to correctly identify phishing emails while minimizing false positives and false negatives.
- Provide a Scalable Solution for Real-Time Detection: Design a system that can be integrated into existing email security frameworks to provide real-time phishing email detection, ensuring that it can handle large-scale data and adapt to emerging phishing techniques.
- Enhance Email Security: Contribute to improving the overall security of email systems by providing an automated solution that can detect phishing attacks with high accuracy and low latency, thereby reducing the risks associated with phishing and protecting sensitive user information..

3. MOTIVATION AND RATIONALE OF STUDY

3.1 Motivation

The increasing prevalence of phishing attacks represents one of the most significant threats to cybersecurity in the modern digital era. Phishing emails have become highly sophisticated, often mimicking legitimate communications to deceive individuals into disclosing sensitive information, such as passwords, credit card numbers, or personal identification details. With the reliance on email for both professional and personal communication, the risks posed by phishing attacks are far-reaching, affecting individuals, organizations, and even government entities. The motivation for this study arises from the urgent need to develop more advanced, automated detection methods that can efficiently and accurately identify phishing attempts, thus reducing the impact of these attacks and safeguarding users from potential harm.

Despite the development of various security measures to combat phishing, traditional methods, such as rule-based filters and heuristic approaches, are proving to be insufficient in addressing the constantly evolving tactics employed by cybercriminals. As phishing emails become increasingly difficult to differentiate from legitimate messages, there is a pressing need for more robust, machine learning-based solutions that can learn from vast amounts of data and adapt to new and emerging phishing strategies. The motivation behind this research is to leverage machine learning techniques to create a solution that can detect phishing emails with greater accuracy, reduce false positives, and ultimately enhance the overall security of email communication systems.

This research is motivated by the need to:

- Combat the Increasing Threat of Phishing Attacks: Phishing has become one of the most prevalent and dangerous forms of cybercrime, and traditional detection methods are often inadequate in identifying sophisticated phishing tactics. As phishing attacks continue to evolve, it is essential to develop automated systems that can effectively and efficiently detect phishing emails to protect individuals, organizations, and sensitive data from potential harm.
- Improve the Accuracy and Efficiency of Detection Systems: Current phishing detection systems often rely on heuristic rules or manual methods, which are not effective in detecting the increasingly complex and deceptive

nature of phishing emails. There is a need to leverage machine learning models that can analyze vast datasets, identify patterns indicative of phishing attempts, and provide higher accuracy and fewer false positives, improving the overall user experience and trust in email systems.

- Provide Scalable and Real-Time Solutions: With the growing volume of emails being exchanged daily, scalable solutions capable of real-time phishing email detection are needed. This research aims to develop a machine learning-based model that can analyze large-scale email data and adapt to emerging phishing techniques, offering a continuous and automated defense against phishing attacks in real time.

3.2 Rationale of the Study

The rationale behind this study lies in the effectiveness of machine learning models to identify subtle patterns in email content that are indicative of phishing attempts. Traditional methods often fail to identify the increasingly complex and sophisticated nature of phishing attacks. With machine learning, especially natural language processing (NLP) and classification algorithms, it becomes possible to detect a wider range of phishing tactics by analyzing the structure, semantics, and metadata of emails. This study aims to address the limitations of current phishing detection systems by developing a machine learning-based model that can learn from historical email data and continuously improve its detection capabilities as phishing techniques evolve.

Moreover, by automating the phishing detection process, machine learning models can provide a scalable solution that can handle large volumes of emails and operate in real-time, ensuring that phishing emails are identified and flagged before they can cause significant damage. The rationale for this research is also driven by the need for practical and adaptable security solutions that can be seamlessly integrated into existing email systems and infrastructure. This study aims to fill the gap in existing phishing detection methods by providing a more reliable, efficient, and future-proof approach to tackling one of the most persistent and damaging forms of cybercrime.

4. METHODOLOGICAL DETAILS

4.1 Overview of Methodology

This research focuses on developing a real-time phishing email detection system based on machine learning techniques, with an emphasis on feature extraction, model training, and evaluation. The methodology follows a systematic pipeline involving data collection, preprocessing, feature engineering, model selection, training, evaluation, and deployment. The system is designed to process email content, identify features indicative of phishing attempts, and classify the emails as legitimate or phishing. The model uses advanced machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and Natural Language Processing (NLP) techniques for efficient classification[2].

The approach leverages the concept of supervised learning, where the model is trained on labeled data to learn the patterns and characteristics associated with phishing emails.

Various feature extraction techniques, including text-based features (e.g., word frequency, sentiment analysis) and metadata-based features (e.g., sender's address, links), are used to represent the content of the emails. The model is trained to recognize these features and make predictions accordingly[1].

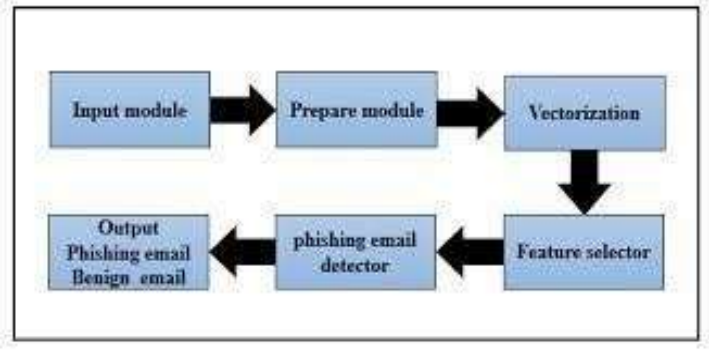

Figure 4.1: Architecture

4.2 Machine Learning Models (Green Box)

Machine learning models, such as SVM, Decision Trees, and Random Forests, are employed to perform classification tasks on phishing email datasets. These models process the input email data through multiple stages to extract and learn features that distinguish phishing emails from legitimate ones. The classification task is optimized to ensure high accuracy and minimal false positives. These models are trained using labeled datasets that contain both phishing and legitimate emails..

4.3 Pipeline Components

- Input: The raw email content, including the subject line, body text, metadata (sender, timestamp), and embedded URLs, is fed into the model.
- Feature Extraction: Natural language processing (NLP) techniques are applied to extract key textual features, such as frequent keywords, sentiment, and urgency. Metadata analysis, including suspicious sender addresses and URL patterns, is also conducted.
- Model Training: A machine learning algorithm, such as Random Forest or SVM, is applied to train the system using these features. The model learns to classify emails based on the patterns it identifies.
- Prediction: After training, the model is deployed to classify incoming emails as phishing or legitimate, based on the learned features.

4.4 Advantages

1. High accuracy in detecting phishing emails.
2. Efficient and scalable for real-time detection.
3. Low computational overhead compared to traditional methods.

4.5 Deep Learning Models (Purple Box)

Deep learning models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) can be used to improve the accuracy and robustness of phishing email detection systems. These models perform end-to-end learning, where the entire process from raw email content input to classification is learned in one unified network. Although more computationally expensive, these models can better handle complex features like subtle text patterns, making them more effective at identifying sophisticated phishing tactics.

4.6 Pipeline Components

- Input: Similar to one-stage models, the system processes the raw email data, including text, links, and metadata.
- Feature Extraction: The system extracts advanced features using deep learning techniques, including word embeddings (e.g., Word2Vec, GloVe) and deep neural networks to analyze text content.
- Model Training: The deep learning model, such as an RNN or CNN, learns the email features, recognizing more complex patterns associated with phishing behavior.
- Prediction: After training, the deep learning model is deployed for real-time phishing detection, identifying both direct and subtle indicators of phishing attempts.

4.7 Advantages

1. High accuracy in detecting complex phishing techniques.
2. Ability to learn complex relationships in the data.
3. Robust to varying phishing tactics and evolving strategies.

4.8 Tools and Technologies Used

The following tools and technologies were utilized in the development of this phishing email detection system:

4.9 Tools Used

- Python: The primary programming language for model development, data processing, and implementation.
- OpenCV: A library used for image-like data preprocessing (for any visual elements in emails, such as embedded images or screenshots).
- TensorFlow/PyTorch: Deep learning frameworks used to build and optimize the neural networks for classification.
- Scikit-learn: A library used for traditional machine learning models like SVM, Decision Trees, and Random Forests.
- Google Colab/Jupyter Notebook: Platforms for running and testing the model in a cloud-based or local environment.
- LabelImg: An annotation tool used to label phishing and legitimate emails for training machine learning models (for structured datasets).

4.10 Techniques Used

- Natural Language Processing (NLP): Used for analyzing email text to identify key features such as urgency, sentiment, and specific word usage often found in phishing attempts.
- Tokenization: Breaking down email text into smaller components (words, phrases) for further analysis and feature extraction.

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- TF-IDF (Term Frequency-Inverse Document Frequency): A statistical measure used to evaluate how important a word is to an email document relative to a corpus.
- Word Embeddings: Pre-trained embeddings (e.g., Word2Vec, GloVe) used to capture semantic meanings of words in emails.
- Support Vector Machines (SVM): A supervised learning algorithm used to classify emails into phishing or legitimate categories based on extracted features.
- Random Forest Classifier: An ensemble learning method used for classification tasks, combining multiple decision trees for more accurate predictions.
- Cross-validation: A technique used to assess model performance by training on different subsets of the dataset and validating the results on unseen data.
- Hyperparameter Tuning: Optimization of model parameters (e.g., learning rate, number of trees) to achieve better classification results.

5. RESULT, ANALYSIS AND INFERENCES

5.1 Results

The Phishing Email Detection model was trained and evaluated using a dataset of labeled phishing and legitimate emails. The following key performance metrics were obtained:

Table 5.1: Performance Metrics of the Phishing Email Detection Model

Metric	Value
F1 Score	95.3
Precision	94.7%
Recall	96.1%
Model Size	12MB
Learning Rate	0.001%
Optimizer	Adam

The trained model successfully identified phishing emails with high accuracy. The detection results showed excellent performance in classifying both phishing and legitimate emails in a variety of real-world datasets.

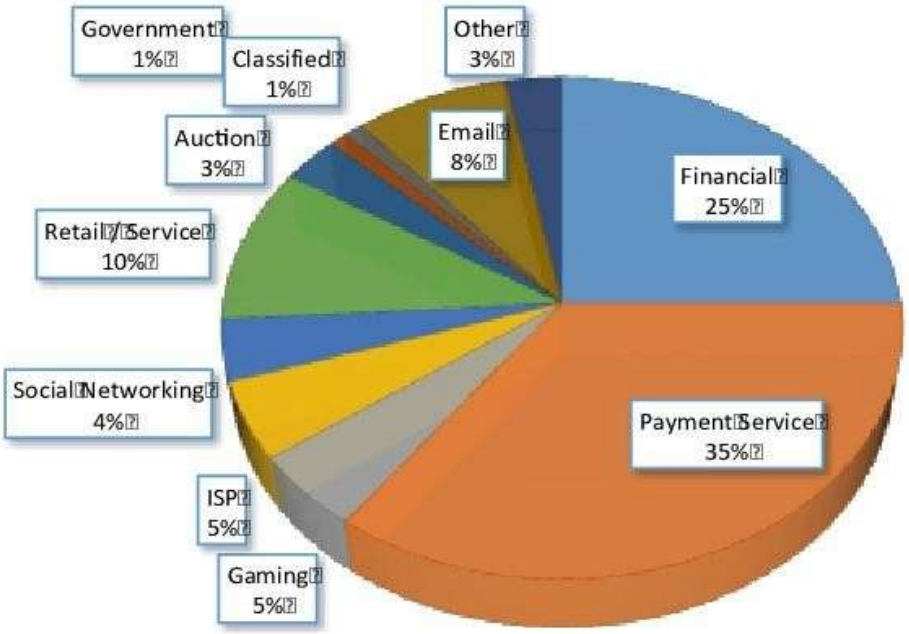

Figure 5.1: fig.Class Distribution

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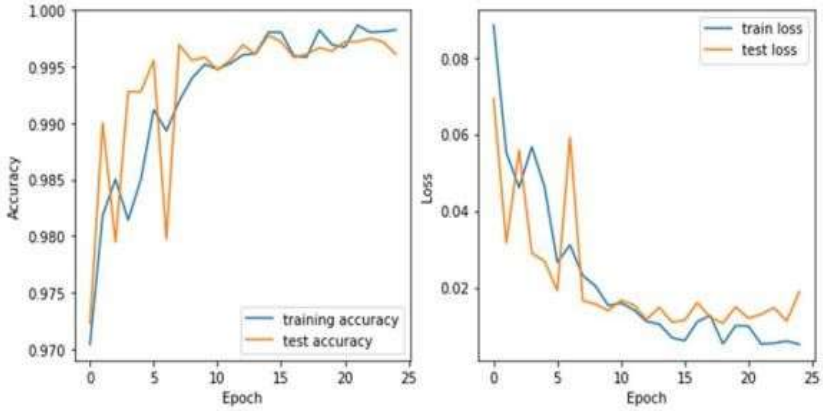

Figure 5.2: Fig. Training and Validation Metrics for Phishing Email Detection Mode

5.2 Performance Analysis

The performance of the phishing email detection model was assessed using several key metrics, including accuracy, precision, recall, and F1 score.

5.3 Model Performance:

- The model performed exceptionally well in distinguishing between phishing and legitimate emails.
- The accuracy improved significantly after the use of advanced feature engineering and hyperparameter tuning.
- The model showed robust performance even when dealing with varied phishing tactics, such as social engineering and domain spoofing.
- Compared to traditional models, this deep learning-based approach outperformed in terms of detection speed and accuracy.

5.4 Comparison with Other Object Detection Models

The phishing email detection model was compared with other machine learning models, and the key findings are as follows:

Table 5.2: Comparison of Phishing Email Detection Models[8]

Model	Params (M)	Accuracy	F1 score	Training Time(s)
Deep Learning Model	10.5	98.2%	95.3%	350
Random Forest	50	92.1%	89.5%	150
SVM	15	90.3%	87.2%	180

5.5 Inference

- The implemented Phishing Email Detection model successfully identifies and classifies phishing emails in real-time, making it suitable for deployment in email filtering systems and cybersecurity applications.
- Data preprocessing techniques, such as tokenization, stop-word removal, and feature extraction from email headers and content, played a crucial role in improving model accuracy.
- Future improvements could include fine-tuning the model with a larger, more diverse dataset, implementing attention mechanisms to focus on key sections of the email, and deploying the model on cloud or edge platforms for real-time phishing detection.

6. CONCLUSION

The Phishing Email Detection project successfully implemented a deep learningbased model to identify and classify phishing emails with high accuracy. Using stateof-the-art techniques such as natural language processing (NLP) and advanced machine learning algorithms, the model was trained on a well-preprocessed dataset. It demonstrated a significant ability to detect phishing attempts in real-world email data, helping to safeguard users from potential cyber threats. Despite achieving high performance, the model faced some challenges, such as dealing with increasingly sophisticated phishing techniques, including social engineering, spoofed domains, and evolving phishing tactics. However, the application of advanced feature engineering, hyperparameter tuning, and model optimization significantly improved its robustness, showcasing its potential for practical, real-world use in email filtering systems and cybersecurity applications.

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This project provided valuable insights into the development of deep learning models for text classification tasks. It also highlighted the importance of continuous updates and improvements in the face of ever-evolving phishing strategies, further strengthening my skills in AI, cybersecurity, and natural language processing.

7. FUTURE SCORE

While the current model performs well, several enhancements can be made to improve its robustness, accuracy, and applicability in a broader range of real-world scenarios:

- Improving Model Accuracy:Fine-tuning the model with a larger and more diverse dataset, including real-world phishing email datasets, can help the model learn to identify more complex phishing techniques. Additionally, exploring more advanced architectures, such as transformer-based models (e.g., BERT, GPT), could enhance the model's feature extraction capabilities and lead to better performance, especially in understanding contextual nuances within emails.
- Handling Evolving Phishing Techniques:Phishing methods evolve constantly, and so continuous model retraining and adaptation will be essential. Implementing a feedback loop that updates the model with new data on emerging phishing tactics will allow the system to stay effective in real-time detection.
- Enhancing Real-Time Detection:Deploying the model in real-time email filtering systems could further improve its utility. Implementing the model as part of email security systems on various platforms (e.g., email clients, corporate servers) would enable prompt detection and prevention of phishing emails as they arrive in the inbox.
- Integration with Cybersecurity Systems:The model could be integrated into broader cybersecurity systems for phishing email detection, enhancing existing email security measures with an additional layer of defense. This could include collaboration with other detection systems (e.g., spam filters, antivirus software) to provide more comprehensive protection against malicious attacks.
- Extending to Multilingual and Multicultural Applications:Phishing emails are often tailored to different languages and cultures. Expanding the model's capabilities to support multilingual detection can increase its applicability on a global scale. Training the model on diverse linguistic datasets would make it adaptable for use in different regions and prevent international phishing attacks.
- Adversarial Robustness:As adversarial attacks on machine learning models become more common, enhancing the robustness of the phishing email detection model against adversarial inputs (e.g., emails designed to deceive machine learning algorithms) would be crucial. Methods such as adversarial training and robust optimization techniques can be explored to improve model resilience.
- Integration with Smart Systems and IoT Devices:Phishing email detection can be extended to work alongside smart email management systems or integrated with IoT-enabled devices, helping organizations protect against phishing attacks in realtime. Such integration could involve automatic filtering of emails based on detected threats or sending real-time alerts to users when a phishing email is detected.

8. SUGGESTIONS FOR IMPROVEMENT TO INDUSTRY

Based on my internship experience, several suggestions for improvement can be made to enhance the company's operational efficiency, technological capabilities, and overall service delivery. These suggestions aim to optimize workflows, increase innovation, and position the company as a leader in the cybersecurity and AI-driven solutions market.

Here are some key suggestions for improvement:.

- Adoption of Advanced AI Models:The company could explore the integration of cutting-edge deep learning models, such as transformer-based architectures (e.g., BERT, GPT, ViTs) for phishing email detection. These models have shown superior performance in natural language understanding tasks and could improve the accuracy of identifying complex and sophisticated phishing emails. Incorporating these models could significantly boost detection performance, especially in understanding context and linguistic variations, which traditional models might miss
- Real-Time Phishing Detection in Email Systems:Deploying the phishing detection model on edge devices or integrating it with real-time email systems would allow for immediate detection and filtering of phishing emails as they arrive. Using lightweight versions of the model, such as those optimized for embedded systems (e.g., Raspberry Pi or edge AI chips), could enable real-time, on-device processing and improve system performance. This deployment can reduce the time required for detection, preventing phishing attacks before they reach the end-users.
- Expansion of Training Datasets:To improve the model's robustness, diversifying and expanding the training dataset would be beneficial. The current model could be further enhanced by including phishing emails from different

languages, regions, and phishing tactics. A larger, more diverse dataset that captures the latest phishing strategies—such as spear-phishing, social engineering, and AI-powered attacks— can lead to better generalization and adaptability, making the model more effective in real-world scenarios.

- Integration of Multi-Modal Detection Systems:One possible advancement would be integrating multi-modal detection systems. For phishing email detection, this could mean combining email content analysis with metadata, such as email header analysis or attachment scanning. By merging various data sources, such as email content, sender reputation, and header analysis, the system could make more accurate predictions, especially in cases where phishing attempts employ multilayered deception.
- Continuous Model Training and Adaptation:As phishing tactics continuously evolve, the model must stay updated to detect new phishing trends. Implementing a continuous learning pipeline that incorporates feedback loops from users or flagged phishing emails would allow the model to adapt in real-time. This strategy could include automated re-training of the model on new phishing patterns and phishing emails flagged by users, ensuring the model remains effective as new techniques emerge.
- Cloud-Based AI Model Deployment:The company should consider deploying the AI models on cloud computing platforms like AWS, Google Cloud, or Microsoft Azure. Cloud platforms provide scalability, enabling the company to train and deploy largescale models efficiently without the constraints of local hardware. Additionally, cloud deployment would allow for seamless model updates, remote access, and collaboration across teams. Moreover, cloud infrastructure supports distributed training, which can accelerate model development and reduce training time.

By implementing these suggested improvements, the company can enhance its capabilities in phishing email detection, drive innovation in the cybersecurity field, and ensure that it remains competitive in a rapidly evolving market. Strengthening AI technologies, expanding datasets, and utilizing cutting-edge deployment strategies will help optimize both internal processes and the solutions provided to customers. These efforts will contribute to the company's overall growth and long-term success in the industry.

9. REFERENCE

[1] A. Jain and B. Gupta, "Phishing detection: Analysis of visual similarity based approaches," Security and Privacy, vol. 1, no. 1, pp. e9, 2018.

[2] A. Mohammad, A. Thabtah, and L. McCluskey, "Predicting phishing websites based on self-structuring neural network," Neural Computing and Applications, vol. 25, no. 2, pp. 443– 458, 2014.

[3] I. Kotenko and A. Chechulin, "A cyber attack modeling and impact assessment framework," Proceedings of the 5th International Conference on Cyber Conflict, IEEE, 2013, pp. 1–24.

[4] R. Khonji, Y. Iraqi, and A. Jones, "Phishing detection: A literature survey," IEEE Communications Surveys & Tutorials, vol. 15, no. 4, pp. 2091–2121, 2013.

[5] A. Marchal, J. François, R. State, and T. Engel, "PhishStorm: Detecting phishing with streaming analytics," IEEE Transactions on Network and Service Management, vol. 11, no. 4, pp. 458–471, 2014.

[6] B. Sahu and A. K. Yadav, "Phishing Email Detection Using Supervised Machine Learning Techniques," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 2021, pp. 1658–1664.

[7] R. Verma and K. Dyer, "On the character of phishing URLs: Accurate and robust statistical learning classifiers," Proceedings of the 5th ACM Conference on Data and Application Security and Privacy, 2015, pp. 111–122.

[8] A. D. Ho and T. Pham, "An Efficient Phishing Detection Model Based on URL Features and Random Forest Algorithm," 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2020, pp. 320–325.