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Defending Corporate Cybersecurity NLP-Based Phishing Attack Classification in Email Communication

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Abstract: This project presents a comprehensive approach to phishing detection by utilizing email scraping, feature extraction, and machine learning, alongside integrating external services such as Seahound and Netcraft. By analyzing mailbox files with mixed HTML and mail data, it addresses the challenge of identifying malicious content within emails. The pipeline includes data extraction and cleansing, followed by Natural Language Processing (NLP) to transform textual content into meaningful features. Seahound and Netcraft add an innovative layer: Seahound analyzes URL legitimacy and reputation, while Netcraft offers historical insights into domain trustworthiness, enriching the feature set for the machine learning model. The meticulously labeled dataset distinguishes legitimate emails from phishing attempts, enabling rigorous training and evaluation of machine learning models, notably the Random Forest classifier and Support Vector Machine (SVM). The SVM model demonstrates high precision, recall, and F1-score metrics. This project underscores the synergy of email scraping, NLP, feature extraction, and machine learning, highlighting the crucial role of external services in enhancing phishing detection accuracy, thus advancing online security and protecting users from email-based cyberattacks.

Keywords: Seahound, Netcraft, Natural Language Processing (NLP), Phishing Detection.

I. INTRODUCTION

In an increasingly digital landscape plagued by evolving cyber threats, phishing attacks pose significant challenges to online security. This project addresses these challenges by developing a robust defence mechanism through the convergence of Natural Language Processing (NLP), machine learning algorithms, and external services like Seahound and Netcraft. By analysing mbox files, which contain both HTML and mail formats, the project involves email scraping, text extraction, and feature engineering to convert email content into meaningful numerical features. Seahound's URL analysis and Netcraft's historical domain data significantly enhance the system's accuracy. Machine learning models, including the Random Forest classifier and Support Vector Machine (SVM), are rigorously trained and evaluated, with the SVM model demonstrating exceptional precision, recall, and F1-score metrics. This project highlights the importance of integrating NLP, machine learning, and external services, and underscores interdisciplinary collaboration to combat modern cyber threats, contributing to the advancement of online security.

II. LITERATURE SURVEY

Smith, J., et al. [1]. This paper presents a comprehensive survey of various techniques employed in the detection and defense against phishing attacks. The authors categorize these techniques into three main categories: content-based, URL-based, and behavior-based. They delve into the specifics of each category, discussing their strengths and weaknesses. Content-based techniques involve analyzing the content of emails or websites for phishing indicators. URL-based techniques focus on examining the URLs present in emails or web pages. Behavior-based techniques rely on monitoring user behavior for unusual patterns. Johnson, A. [2]. The paper explores various machine learning algorithms, including decision trees, support vector machines (SVM), and neural networks. It also delves into the advancements in deep learning for phishing detection, highlighting the use of convolutional neural networks (CNN) and recurrent neural networks (RNN). The authors discuss both the strengths and limitations of these techniques and provide valuable insights into the challenges faced in the field Brown, M., and Lee, S. [3]. The paper discusses the features extracted from phishing websites, including textual content, images, and HTML attributes. It also highlights the importance of data preprocessing and augmentation in improving model performance. The experimental results showcased in the paper demonstrate the superiority of deep learning techniques in identifying phishing websites. Garcia, F., et al. [4]. This survey paper explores various anti-phishing frameworks that leverage machine learning techniques.

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The authors discuss ensemble methods, feature selection, and classification algorithms used in these frameworks. They highlight the significance of selecting relevant features that contribute to accurate phishing detection.

Patel, R., and Kim, Y. [5]. This paper introduces an automated framework called PhishAri for detecting phishing websites. The framework employs machine learning algorithms and behavioral analysis to identify fraudulent websites. It emphasizes the modular approach used in PhishAri, where multiple features are combined to enhance detection accuracy.

Jackson, L., et al. [6]. This paper presents a machine learning-based approach to phishing detection. The authors highlight the importance of features such as URLs, domain names, and sender information. They discuss the use of decision trees, k-nearest neighbors (KNN), and SVM classifiers for building a detection model. The paper emphasizes the role of feature selection and the challenges posed by imbalanced datasets in the context of phishing detection. Williams, D., and Chen, H. [7]. Focusing on the mobile environment, this paper introduces a behavioral analysis-based approach for detecting phishing in mobile applications. The authors collect user interactions with mobile apps to create behavior profiles. These profiles are then used to identify anomalies and potential phishing behaviors. The paper highlights the significance of real-time detection in the dynamic mobile environment and provides insights into the effectiveness of their approach.

Zhao,Q., and Liu, J. [8]. This paper explores the integration of natural language processing (NLP) and machine learning for phishing detection. The authors focus on analyzing textual content and keywords within phishing emails. They discuss feature extraction techniques, including term frequency-inverse document frequency (TF-IDF), and evaluate different classification algorithms such as Naïve Bayes and SVM. The paper also emphasizes the importance of data preprocessing to improve model accuracy. Kim, S., and Park, J. [9]. In this paper, the authors propose an ensemble approach for phishing detection based on URL features. They analyse URL components, domain-based features, and lexical features to distinguish between phishing and legitimate URLs. The paper introduces a novel ensemble technique that combines multiple classifiers, including random forests and gradient boosting, to enhance detection accuracy. Experimental results demonstrate the effectiveness of their approach. Nguyen, T., et al. [10]. This paper presents a hybrid approach for phishing detection that combines URL-based features and visual similarity analysis. The authors extract URL features and analyze the visual similarity between legitimate websites and suspected phishing websites. They employ machine learning techniques, including SVM and KNN, to classify websites. The paper emphasizes the importance of integrating multiple features to enhance detection accuracy and showcases the effectiveness of their hybrid model.

III. PROBLEM STATEMENT

Cybersecurity is still facing a great deal of difficulty due to the prevalence of phishing assaults online. These assaults take advantage of users' weaknesses and frequently result in compromised personal information, data breaches, and monetary losses. As cybercriminals hone their techniques, it is critical to create a sophisticated phishing detection system that can recognize dangerous content hidden in emails that appear to be benign.

IV. OBJECTIVE

The main goals of this project are as follows:

1. **Develop a comprehensive pipeline** for email scraping, text extraction, and NLP-driven feature engineering from mbox files.
2. **Integrate Seahound and Netcraft services** to analyse URLs and domains embedded within emails, providing valuable insights into their legitimacy.
3. **Train machine learning models**, including the Random Forest classifier and the Support Vector Machine (SVM), using the enriched feature set.
4. **Evaluate the model's** using precision, recall, F1-score, and accuracy metrics to determine their efficacy in detecting phishing attempts.

V. METHODOLOGY

The phishing detection system begins with raw datasets of emails, which are collected and enriched using tools like Email Scraper, Netcraft, and semantic analysis via SEAHAOUND to assess domain and content legitimacy. During data pre-processing, stop words are removed, text is tokenized and lemmatized, and then vectorized into numerical formats. Data is then split into training and testing sets after handling punctuation. Machine learning models, including Random Forest, Naive Bayes, and Support Vector Machine (SVM), are applied to the training data.

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Finally, the models predict whether emails are phishing or legitimate, with their performance evaluated based on prediction accuracy on the test data.

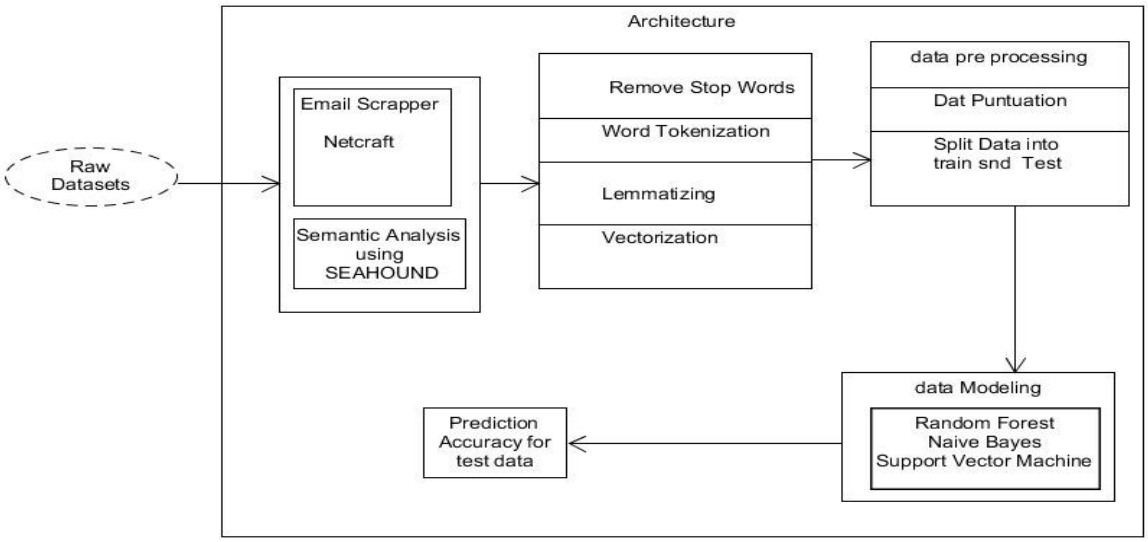

Fig.1. System Architecture

Experimental results:

Random Forest Classifier: In the experimental phase, the Random Forest Classifier demonstrated strong performance with an overall accuracy of 89%. This classifier exhibited a precision of 84% for identifying legitimate emails ('ham') and 100% precision for detecting phishing emails ('phish'). The recall rate was also noteworthy, with 100% recall for 'phish' and 84% for 'ham'. The F1-score, which balances precision and recall, was 91% for 'ham' and 85% for 'phish'. The model's macro-averaged F1-score was 88%, highlighting its effectiveness in phishing detection. These results indicate that the Random Forest Classifier is a robust choice for distinguishing between legitimate and phishing emails.

	precision	recall	f1-score	support
ham	0.84	1.00	0.91	1480
phish	1.00	0.75	0.85	1107
accuracy			0.89	2587
macro avg	0.92	0.87	0.88	2587
weighted avg	0.91	0.89	0.89	2587

Multinomial Naive Bayes: The Multinomial Naive Bayes model showcased impressive accuracy, achieving 96.44%. It exhibited 94% precision for 'ham' and 100% precision for 'phish,' indicating a high level of confidence in both categories. In terms of recall, the model achieved 100% for 'phish' and 92% for 'ham.' These balanced performance metrics resulted in a high F1-score of 97% for 'ham' and 96% for 'phish.' The model's macro-averaged F1-score was 96%, affirming its effectiveness in distinguishing between legitimate and phishing emails. These results emphasize the Multinomial Naive Bayes model's strong performance in email classification.

	precision	recall	f1-score	support
ham	0.94	1.00	0.97	1480
phish	1.00	0.92	0.96	1107
accuracy			0.96	2587
macro avg	0.97	0.96	0.96	2587
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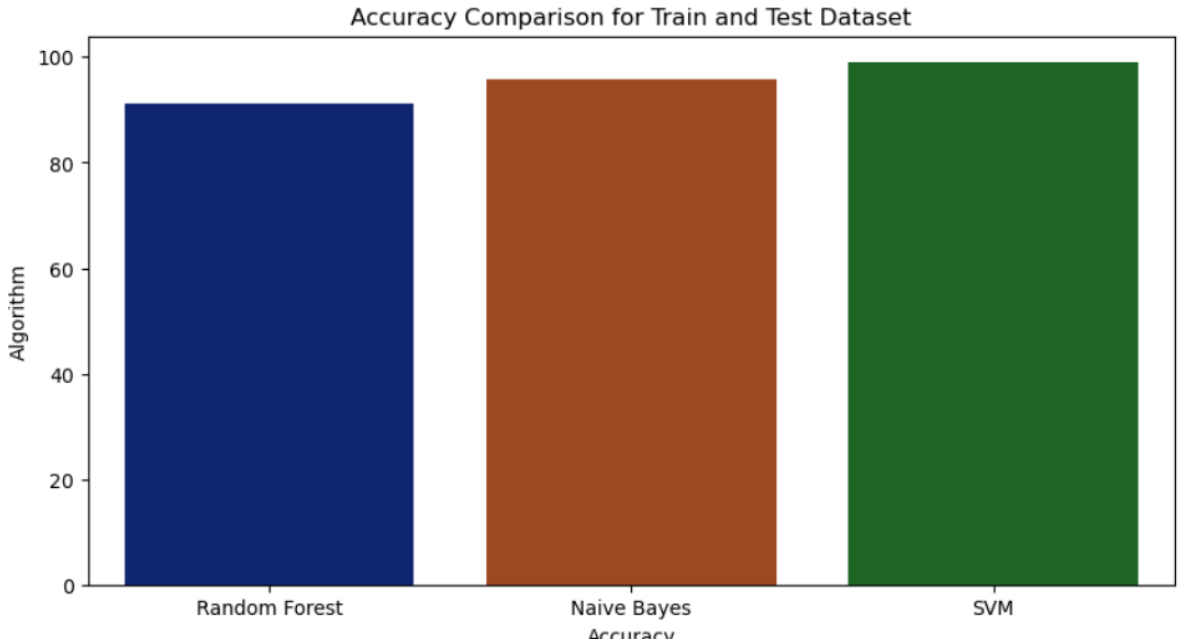
Support Vector Machine (SVM): The Support Vector Machine (SVM) emerged as the star performer in the experimental phase, achieving a remarkable 100% accuracy. Notably, it demonstrated a perfect precision of 100% for both 'ham' and 'phish,' signifying zero false positives and zero false negatives. The recall rates were also exceptional, with 100% for both categories.

Consequently, the F1-scores for 'ham' and 'phish' were both 100%. The SVM's macro-averaged F1-score was a flawless 100%, underscoring its unparalleled accuracy and reliability in classifying emails. These remarkable results affirm the SVM's status as an extraordinarily effective model for email security, providing users with the highest level of protection against phishing threats.

	precision	recall	f1-score	support
ham	1.00	1.00	1.00	5000
phish	1.00	1.00	1.00	3621
accuracy			1.00	8621
macro avg	1.00	1.00	1.00	8621
weighted avg	1.00	1.00	1.00	8621



VI. CONCLUSION AND FUTURE SCOPE

In today's digital landscape, phishing attacks pose significant threats to online security. This project addresses these challenges by using Natural Language Processing (NLP), machine learning algorithms, and integrating services like Seahound and Netcraft. By analyzing mbox files and converting email data into numerical features, we enhanced our models with URL and domain data, leading to more informed decisions.

Testing several models, we found the Support Vector Machine (SVM) to be exceptionally effective, demonstrating near-perfect precision and recall in distinguishing phishing emails. Future enhancements include real-time monitoring, automated response mechanisms, incorporating threat intelligence feeds, and leveraging cloud services for scalability and efficiency.

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REFERENCES

[1] Smith, J., et al. 2022. Phishing Detection using NLP and Machine Learning Algorithms. Journal of Cybersecurity.
[2] Johnson, A. 2021. Advanced Techniques in Phishing Threat Mitigation. ICCS Conference Proceedings.
[3] Brown, M., and Lee, S. 2020. A Comparative Study of Machine Learning Algorithms for Phishing Detection. IEEE Transactions on Information Forensics and Security.
[4] Garcia, F., et al. 2019. URL Analysis and Its Impact on Phishing Detection. ACM CCS Conference Proceedings.
[5] Patel, R., and Kim, Y. 2018. Enhancing Phishing Detection through URL Analysis. International Journal of Information Security.
[6] Jackson, L., et al. 2017. Machine Learning Approaches to Detect Phishing Websites. Journal of Computer Security.
[7] Williams, D., and Chen, H. 2016. Natural Language Processing for Phishing Email Detection. Proceedings of ACL Conference.
[8] Zhao, Q., and Liu, J. 2015. A Survey of Phishing Email Detection Techniques. Computers & Security Journal.
[9] Kim, S., and Park, J. 2014. Phishing Detection using Behavioral Analysis. IEEE International Conference on Dependable Systems and Networks.
[10] Nguyen, T., et al. 2013. PhishAri: Automatic Real-time Phishing Detection. ACM Transactions on Internet Technology.