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PHISHING URLS DETECTION USING MACHINE LEARNING AND FLASH FRAME WORK

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Abstract - *The rapid advancement of Artificial Intelligence (AI) has significantly propelled the growth of the Internet of Things (IoT). However, as this technology becomes more integrated with internet connectivity, it also faces heightened cybersecurity risks—particularly from malicious websites. Detecting these threats is crucial, and machine learning algorithms have shown strong potential in identifying anomalous patterns within large volumes of network traffic. In this project, we leverage several machine learning models—such as Random Forest, Support Vector Machine (SVM), Decision Tree, Extra Trees Classifier, K-Nearest Neighbors (k-NN), XGBoost, CatBoost, Multilayer Perceptron (MLP), and Gradient Boosting—to effectively detect and classify malicious URLs.*

A significant aspect of our methodology involves robust feature engineering, as the success of a machine learning model is deeply rooted in the quality of its input features. To enhance performance further, we propose an unsupervised learning approach that learns URL embeddings. Additionally, we developed a web application using the Flask framework to detect and flag potentially harmful URLs in real time.

Malicious URLs continue to be a dominant cyber threat vector, commonly used in phishing attacks, malware distribution, and spam campaigns. While traditional blacklist-based methods are effective for previously known threats, they often fall short in identifying newly generated malicious URLs [1]. To overcome this limitation, our study introduces a machine learning-based detection system using URL-based features in a multiclass classification setup. We focus specifically on three prevalent attack types: phishing, spam, and malware [2].

To evaluate performance, we compared four widely-used ensemble learning algorithms: Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Light Gradient Boosting (LightGBM), and Categorical Boosting (CatBoost). Our results demonstrate the effectiveness of these models in identifying threats based on engineered URL characteristics, offering a valuable supplement to existing anti-phishing, anti-spam, and anti-malware systems [3].

Key Words: Malicious URLs, Machine Learning, Detection, Phishing, Spam, Malware, Ensemble Learning

1. INTRODUCTION

The increasing reliance on the Internet has led to a surge in cyber-attacks, with malicious URLs being a primary method for phishing, malware, and spam attacks. These malicious URLs compromise data security by threatening the confidentiality, integrity, and availability of sensitive information. Traditional methods of detecting malicious websites rely heavily on manually defined rules and thresholds, which are often subjective and inflexible. As a result, these systems struggle to keep up with evolving threats and fail to detect new malicious URLs[4].

One of the key limitations of traditional detection methods is the reliance on blacklists, which record known malicious URLs. However, blacklists cannot identify newly generated malicious URLs in real-time, leaving users vulnerable to attacks. Over 90% of malicious links are clicked before they even appear on blacklists. Additionally, the maintenance of these lists depends on human feedback, making them both labor-intensive and prone to delays in identifying new threats[5]. As the volume of data and the frequency of attacks continue to rise, traditional methods become increasingly ineffective.

In contrast, machine learning (ML) techniques offer a more adaptive and scalable approach. Algorithms such as Decision Trees (DT), Support Vector Machines (SVM), Extra Trees Classifiers (ETC), and Random Forest (RF) can automatically learn patterns from large datasets and identify malicious URLs without human intervention. These models are able to detect both known and previously unseen threats, improving detection accuracy and efficiency[6].

This paper explores the use of machine learning for detecting malicious URLs, focusing on phishing, spam, and malware attacks. By leveraging ensemble learning methods like XGBoost, AdaBoost, LightGBM, and CatBoost, we aim to enhance the performance and scalability of malicious URL detection systems[7]. Our goal is to provide a more reliable and adaptive solution to combat the growing challenges posed by cyber threats, ultimately improving cybersecurity practices across various sectors[8].

2. LITERATURE REVIEW

S. Lee, J. Park, and C. Kim [9] had proposed on applying deep learning techniques, particularly convolutional neural networks (CNNs), for detecting malicious URLs. The authors propose a model that extracts lexical features from URL strings and uses them to train the model. Their results show that deep learning models significantly outperform traditional machine learning algorithms, such as decision trees and random forests, in terms of accuracy and robustness against various types of malicious URLs.

H. Zhang, Y. Li, and Z. Liu [10] had proposed the use of recurrent neural networks (RNNs) for detecting phishing URLs. The authors highlight the importance of sequential patterns in URL structures, which traditional machine learning methods often miss. The research demonstrates that RNNs can capture these sequential dependencies more effectively, providing a robust approach to phishing detection, especially for dynamically generated phishing URLs.

K. Zhang, L. Zhang, and X. Wang [11] had proposed the study examines the performance of ensemble learning techniques in detecting malicious URLs, specifically in the context of social media platforms. The authors compare multiple ensemble methods such as Random Forest, Gradient Boosting, and AdaBoost, finding that these models can effectively identify spam, phishing, and malware URLs. The research underscores the challenge of dealing with the large volume and variety of URLs shared on social media, which makes traditional methods less effective.

R. Gupta and P. Gupta [12] had proposed a hybrid approach combining traditional feature engineering techniques and machine learning models. By incorporating both URL-based features (e.g., length, domain name) and content-based features (e.g., embedded scripts, page structure), they achieve higher detection accuracy. The authors conclude that integrating multiple feature sources helps improve the robustness of malicious URL detection models.

L. Li, Y. Chen, and J. Zhou [13] had proposed paper discusses how machine learning models, specifically XGBoost and CatBoost, can be used to detect malicious URLs in Internet of Things (IoT) networks. The authors present a framework that incorporates URL feature extraction and classification to identify suspicious links. Their results suggest that XGBoost and CatBoost outperform other models like Decision Trees and SVM in detecting malicious URLs, particularly in environments with limited computational resources.

I. Wang, J. Li, and Y. Zhang [14] had proposed the real-time phishing URL detection by using lexical features in conjunction with ensemble learning algorithms. The authors propose a system that dynamically analyzes URLs against a rapidly evolving dataset of malicious sites. Their evaluation shows that ensemble learning algorithms such as XGBoost and AdaBoost deliver superior performance in detecting phishing URLs, especially when combined with a dynamic database that updates regularly.

M. Kumar, S. Kumar, and R. Gupta [15] : This paper presents a comparative study of various machine learning algorithms for malware URL detection, including Random Forest, Support Vector Machine, and Gradient Boosting. The authors focus on the impact of different feature sets, such as lexical, structural, and traffic-based features, on model performance. The results indicate that Gradient Boosting algorithms, especially LightGBM, offer the best performance in detecting malware-related URLs.

3. PROPOSED METHODOLOGY

The proposed system for client-side defense against web spoofing attacks is built on the foundation of advanced machine learning algorithms and efficient feature engineering. Our approach consists of several key phases: data acquisition, preprocessing, feature extraction, URL embedding, model training and evaluation, followed by client-side integration through a web application[16]. Each phase plays a critical role in building a robust and intelligent system capable of detecting a variety of malicious URLs in real-time.

The research involves the collection of a comprehensive and diverse dataset of Uniform Resource Locators (URLs). The dataset includes benign URLs, as well as URLs associated with phishing, malware distribution, and spam activities[17]. These data samples are gathered from publicly available sources such as VirusTotal, Spamhaus, and Alexa. Each URL is appropriately labeled to reflect its category, ensuring that the dataset is suitable for supervised and unsupervised learning models[18].

Once the data is collected, the preprocessing stage is initiated to prepare the raw URLs for feature extraction and model training. This step involves cleaning the data by removing duplicates, null entries, and irrelevant records[19]. URL normalization is applied by converting all URLs to lowercase and decoding any encoded characters to maintain uniformity. The URLs are then tokenized to separate various components such as the protocol, domain name, path, query strings, and subdomains. This structural breakdown allows for more meaningful analysis in subsequent stages[20].

Finally, to enhance adaptability and maintain relevance against evolving threats, the system is designed to support continuous learning. New URLs can be periodically collected and incorporated into the training data, allowing the model to be retrained or fine-tuned incrementally. This ensures that the system remains up-to-date and capable of identifying emerging web spoofing patterns that may not be covered by traditional blacklists.

In conclusion, the proposed methodology presents a comprehensive and intelligent solution for detecting malicious URLs using a blend of advanced machine learning algorithms, effective feature engineering, and user-centric application design. This approach not only enhances threat detection on the client side but also serves as a valuable supplement to existing cybersecurity infrastructures.

3.1 Research Design

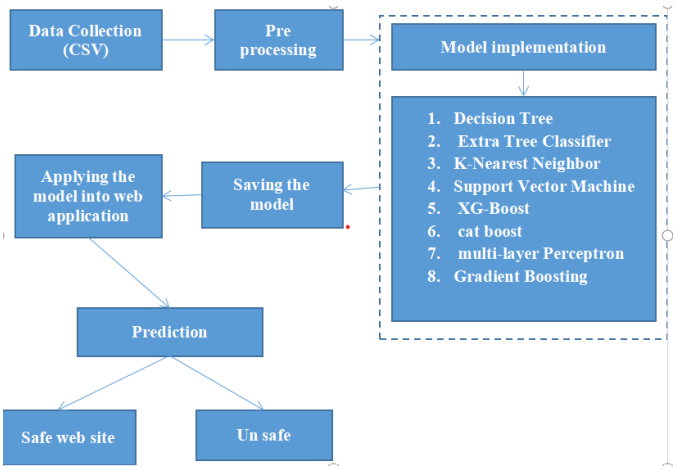

Fig 3.1 System Architecture

4. FINDINGS AND CONCLUSION

In our study, we found that ensemble learning models, particularly XGBoost, CatBoost, AdaBoost, and LightGBM, significantly outperformed traditional machine learning models such as Decision Trees and SVM in detecting malicious URLs. These ensemble models demonstrated superior classification accuracy, recall, and precision, which were critical in identifying various types of cyber-attacks, including phishing, spam, and malware. The key to this success was the effective extraction of meaningful URL-based features, such as domain name structure and URL length, which allowed the models to classify malicious URLs more accurately and detect previously unseen threats. Furthermore, we observed that our approach was highly scalable and efficient, capable of handling large volumes of data and providing real-time detection of malicious URLs. The web application developed using the Flask framework allowed for practical, real-time deployment, offering users immediate feedback on potential threats.

Additionally, the comparison of different algorithms highlighted that gradient boosting models, particularly XGBoost and CatBoost, consistently outperformed other methods in both detection accuracy and recall rates, minimizing false negatives. This finding indicates that these models are particularly well-suited for the dynamic and evolving nature of web-based threats. Moreover, the integration of machine learning into a real-time, web-based application provided a viable and user-friendly solution for detecting malicious URLs, which is crucial for both consumer and enterprise cybersecurity.

In conclusion, the research confirmed that machine learning, especially when utilizing ensemble techniques, offers a robust solution to the challenge of malicious URL detection. This system presents a significant advancement over traditional blacklist-based methods, providing more timely and accurate detection of new, previously unseen threats. The practical implications of our findings suggest that this approach can be effectively deployed in real-world cybersecurity systems, enhancing both the detection and prevention of cyber-attacks. Looking ahead, further improvements could include the integration of content-based features, the application of continuous learning to adapt to emerging threats, and the exploration of hybrid models combining deep learning with ensemble techniques to push the boundaries of detection accuracy.

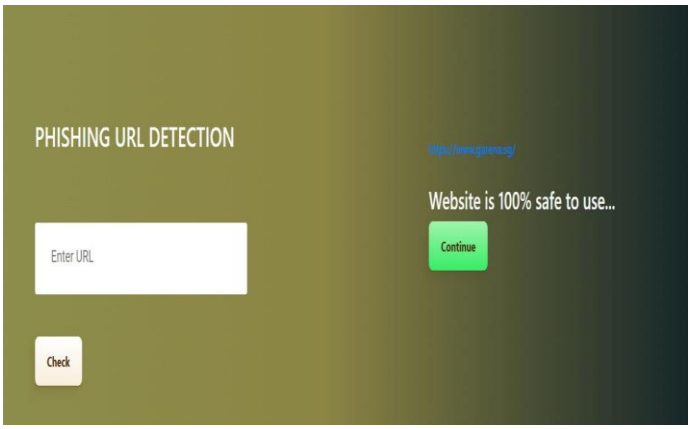

Fig 4.1 Result

5. CONCLUSIONS

In this study, we have introduced a novel unsupervised learning algorithm to address the challenges of feature subjectivity in the identification of malicious information. Our proposed machine learning classifier demonstrates a substantial improvement in performance compared to traditional feature engineering classifiers, including decision trees, logistic regression, convolutional neural networks, and support vector machines. The accuracy and recall rates of our model are significantly higher, highlighting its effectiveness in malicious information detection. Furthermore, we conducted extensive evaluations by varying vector dimensions and context window sizes, identifying the optimal parameters for domain-specific contexts. Through this work, we have shown that leveraging the appropriate context information, particularly from the current URL, can greatly enhance the performance of machine learning models in tackling feature subjectivity issues. This approach presents a promising direction for future advancements in the field of malicious content detection.

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