Phishing Website Detection using Machine Learning

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***Abstract*— Phishing attacks are a prevalent threat in cybersecurity, targeting users by tricking them into providing sensitive information through deceptive websites. This project aims to develop a robust method for detecting phishing websites by extracting and analyzing URL features using machine learning techniques. By leveraging various features such as URL length, special characters, subdomains, and suspicious keywords, we aim to build a predictive model that accurately identifies phishing URLs. This paper discusses the methodology, including data collection, preprocessing, feature selection, model training, and evaluation, ultimately highlighting the model's performance and potential applications in real-world scenarios.**

Keywords— Phishing Detection, Machine learning, Phish Tank

I. INTRODUCTION

A. Background and Motivation

Phishing attacks pose a significant risk to internet users, with cybercriminals continuously refining their tactics to deceive unsuspecting individuals. The traditional methods of combating phishing, such as user education and awareness programs, have proven insufficient against sophisticated attacks. As a result, there is a pressing need for automated and intelligent systems that can detect and prevent phishing attempts. This project addresses this need by focusing on developing a method to detect phishing websites through the analysis of URL features.

B. Scope and Objectives

The primary goal of this project is to create an effective detection system that utilizes machine learning algorithms to analyze URL features and identify phishing websites. Sub-goals include enhancing detection mechanisms, understanding phishing behaviors, and improving decision-making processes in cybersecurity. By achieving these objectives, we aim to contribute to the broader effort of securing online environments against phishing threats.

II. LITERATURE REVIEW

A. Traditional Methods

Initially, efforts to combat phishing relied heavily on user education and awareness programs. However, these approaches have proven inadequate due to the increasing sophistication of phishing techniques. Automated detection methods have become essential in addressing this evolving threat landscape.

B. Feature Extraction

Effective phishing detection relies on extracting relevant features from URLs. Key features include URL length, the presence of special characters, IP addresses, the number of subdomains, and suspicious keywords. Studies by Mohammad et al. (2012), Ma et al. (2009), Abdelhamid et al. (2014), Zhang et al. (2017), and Jain and Gupta (2018) have demonstrated the significance of these features in identifying phishing websites.

C. Machine Learning Techniques

Various machine learning algorithms, such as decision trees, random forests, support vector machines (SVM), and convolutional neural networks (CNN), have been employed to enhance phishing detection. Hybrid models that combine URL analysis with webpage content examination have shown promising results, offering a more comprehensive approach to identifying phishing attempts.

D. Real-Time Detection Systems

Balancing accuracy with performance is crucial for real-time detection systems. The aim is to minimize latency without compromising on the effectiveness of phishing detection. Garera et al. (2007) developed a system that exemplifies this balance, providing insights into designing real-time detection mechanisms.

III. Proposed Methodology

A. *Data Collection*

The dataset for this project was compiled from reputable sources such as PhishTank, Spamhaus, OpenPhish, and Alexa Top Sites. These sources provided a comprehensive collection of both phishing and legitimate URLs. Ensuring data privacy and compliance with regulations like GDPR and CCPA was a priority during the data collection process.

B. *Data Preprocessing*

Data preprocessing involved several steps, including cleaning, normalization, and feature extraction. Key features extracted from the URLs included URL length, the presence of special characters, the number of subdomains, and the use of HTTPS. Advanced techniques like tokenization and lexical analysis were employed to refine the feature set further. Collaboration with cybersecurity experts ensured that the selected features were relevant and effective.

C. *Feature Selection*

Selecting statistically relevant and domain-specific features was crucial to building an effective model. Addressing dataset imbalances was also a priority to prevent biases in the model. Techniques such as under-sampling, oversampling, and the use of synthetic data were considered to achieve a balanced dataset.

D. *Model Selection and Training*

Various machine learning algorithms, including Logistic Regression, Naive Bayes, SVM, Random Forest, and Gradient Boosting, were considered for model training. Evaluation metrics such as accuracy, precision, recall, F1-score, and cross-validation were used to assess model performance and ensure robustness.

E. *Evaluation and Comparison*

The performance of different algorithms was evaluated using established metrics to identify the most effective model for phishing detection. Comparative analysis helped in understanding the strengths and weaknesses of each approach, guiding the selection of the optimal model.

F. *Model Deployment and Interpretation*

The selected model was deployed for real-time phishing URL detection. Analysis of influential features and misclassifications provided insights into the model's decision-making process, helping to refine and improve its accuracy further.

IV. Results

A. *Model Performance*

The evaluation of the models revealed significant insights into their effectiveness. Metrics such as accuracy, precision, recall, and F1-score were used to assess performance. The comparison of different algorithms highlighted the superior performance of specific models in detecting phishing URLs..

B. *Feature Importance*

Analysis of feature importance revealed that certain URL characteristics, such as length, the presence of special characters, and the number of subdomains, played a crucial role in detecting phishing attempts. Understanding these patterns helped in refining the model and improving its detection capabilities.

V. Discussion

A. *Implications of Findings*

The findings of this study have significant implications for enhancing phishing detection and prevention mechanisms. By identifying key features and effective models, the project contributes to improving cybersecurity measures and protecting users from phishing attacks. The improved understanding of phishing behaviors also aids in developing more robust and adaptive security solutions.

B. *Limitations and Future Work*

Despite the promising results, the project faced challenges such as dataset imbalances and ensuring real-time detection accuracy. Future work will focus on addressing these limitations and exploring advanced techniques to further enhance the detection system. Additionally, expanding the dataset and incorporating more diverse features will be considered to improve the model's robustness.

VI. Models and Accuracy

TABLE I.

Models	***Train Accuracy***	***Test Accuracy***
XGBoost	0.868	0.857
Decision Tree	0.812	0.810
Random Forest	0.817	0.821
Multilayer Perceptrons	0.865	0.860
SVM	0.803	0.800

VII. Conclusion

This project successfully developed a method for detecting phishing websites using URL feature extraction and machine learning techniques. The findings highlight the effectiveness of specific algorithms and features in identifying phishing URLs. By enhancing detection and prevention mechanisms, this study contributes to the broader effort of securing online environments against phishing threats. Future research will continue to refine the model and explore new avenues for improving cybersecurity.

ACKNOWLEDGMENT

We extend our heartfelt gratitude to our Guide, Mrs. Gayathri N, for their invaluable guidance and continuous support throughout this project. We also thank the Department of Artificial Intelligence and Machine Learning faculty and staff at Sri Shakthi Institute of Engineering and Technology for providing essential resources and facilities—special thanks to our colleagues and peers for their constructive feedback and collaboration. We appreciate the data support from PhishTank, Spamhaus, OpenPhish, and Alexa Top Sites, which was crucial for our research. Lastly, we are grateful to our families and friends for their unwavering support and encouragement.

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