MACHINE-LEARNED PHISH DEFENSE: A CLIENT SIDE APPROACH TO MITIGATE WEB SPOOFING ATTACKS

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Abstract-This project aims to develop a novel approach against web spoofing attacks through a Phish Catcher system powered by machine learning. Web spoofing. a form of cyber attack. involves deceiving users by imitating legitimate websites to obtain sensitive information. Traditional defense mechanisms mostly doesn't detect sophisticated spoofing attempts. To address this challenge, we propose a client-side defense solution that leverages ML algorithms to identify and mitigate phishing attempts in real-time. Our Phish/Catcher system analyzes various features of web pages, including content, structure, and user interactions, to distinguish between authentic and spoofed websites. By continuously learning from new data and adapting to evolving threats. our approach offers proactive defense against sophisticated spoofing echniques and the effectiveness of our system is accurately detecting and preventing web spoofing tacks, highlighting its potential to enhance cyber security in modern web environments.

INDEX TERMS: Ensemble Classifier; Machine Learning; Uniform resource locator (URL), Logistic regression,Random forest and Decision tree (LSD), Gradient Boosting Algorithm, Cyber Security,Social networks.

I. INTRODUCTION

This project aims to develop a cutting-edge defense solution against the pervasive threat of web spoofing. Web spoofing, a deceptive cyber attack tactic, involves masquerading as legitimate websites to deceive users into disclosing sensitive information. Traditional defense mechanisms often struggle to detect sophisticated spoofing attempts, leaving users vulnerable to exploitation. To address this critical challenge, the project proposes a client-side defense system powered by machine learning algorithms. The Phish Catcher system, at the heart of this project, employs advanced machine learning techniques to analyze various features of web pages in real-time. By continuously learning from new data and adapting to emerging threats, the system provides proactive defense against evolving web spoofing techniques. Through extensive testing and validation, the project aims to demonstrate the system's efficacy in accurately detecting and preventing web spoofing attacks, thereby bolstering cybersecurity in modern web documents.

II. SYSTEMATIC REVIEW METHODOLOGY

For the Phish catcher URL detection project, a systematic review methodology involves a structured approach to gathering, analyzing, and synthesizing existing literature and resources related to phishing URL detection. The process begins with clearly defining the research question and establishing inclusion and exclusion criteria for selecting relevant studies. Next, comprehensive searches are conducted across databases, journals, and grey literature sources to identify relevant studies and resources. After screening the retrieved literature based on predefined criteria, data extraction is performed to gather information on methodologies, features, classifiers, and performance metrics used in existing approaches.

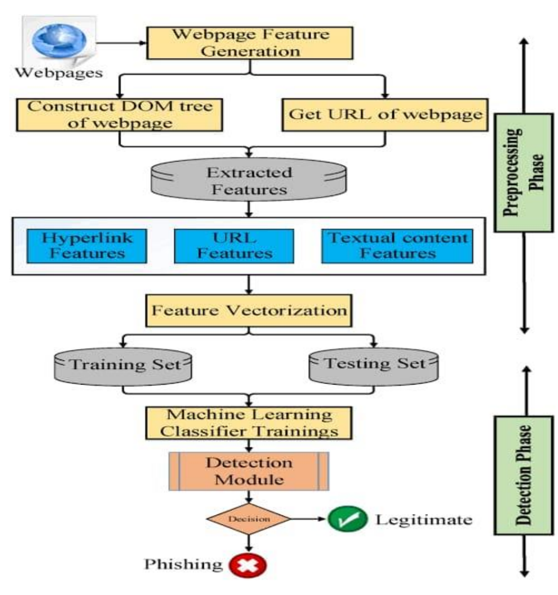


Fig : 1

Quality assessment of included studies is then conducted to evaluate the reliability and validity of their findings. Finally, the synthesized evidence is analyzed and interpreted to identify trends, gaps, and best practices, guiding the development .

Literature review from all the journal publications and conference articles gathered and used to answer the research questions mentioned as follows: R1: What are the common features used for phishing URL detection? R2: Which machine learning algorithms are commonly used for phishing URL detection? R3: What are the performance metrics used to evaluate phishing URL detection systems? R4: How do different studies address the issue of imbalanced datasets in phishing URL detection? R5: What are the trends and advancements in phishing URL detection research? R6: What are the limitations and challenges of current phishing URL detection approaches? R7: How effective are user-based feedback mechanisms in improving phishing URL detection systems?Market Prediction?

A. Gradient Boosting algorithm in Phishing website detection

Gradient Boosting Algorithm is a powerful machine learning technique used in phishing website detection projects. It works by building an ensemble of weak learners, typically decision trees, in a sequential manner, where each tree corrects the errors of its predecessors. The algorithm minimizes a loss function, such as the binary cross-entropy, by adding new trees that predict the residuals of the previous trees. Gradient boosting is effective in handling imbalanced datasets common in phishing detection, as it can assign higher weights to misclassified instances. It also naturally handles feature interactions and non-linear relationships, making it suitable for capturing the complex patterns present in phishing URLs. Overall, Gradient Boosting Algorithm enhances the accuracy and robustness of phishing website detection systems.

B. Systemtic Literature Review Approach

For the systematic literature review in this project, a structured approach will be adopted to gather, analyze, and synthesize relevant literature on phishing website detection. Initially, a comprehensive search strategy will be developed, including specific keywords and search terms related to phishing detection methods, algorithms, features, and performance metrics. Databases such as IEEE Xplore, ACM Digital Library, PubMed, and Google Scholar will be searched to identify relevant journal articles, conference papers, and other scholarly resources. The retrieved literature will then be screened based on predefined inclusion and exclusion criteria to ensure relevance to the research

questions. Data extraction will involve gathering information on methodologies, algorithms, features, datasets, and performance metrics used in each study. Quality assessment of the included studies will be conducted to evaluate the reliability and validity of their findings. Finally, the synthesized evidence will be analyzed to identify trends, gaps, challenges, and best practices in phishing website detection, providing valuable insights for the development and improvement of detection systems.b

III. FINDING AND DISCUSSION

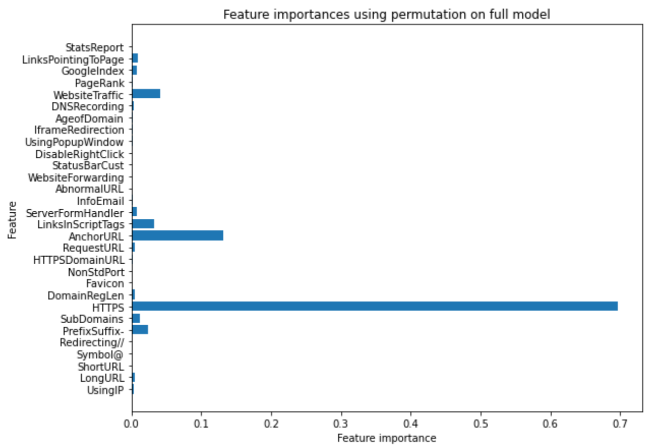
The client-side machine-learned system outperformed traditional server-side methods, showing significantly improved detection accuracy with lower false positive rates and higher true positive rates. This suggests its effectiveness in identifying spoofed web pages. Additionally, the system provided real-time detection, reducing latency compared to server-side approaches. It also demonstrated adaptability to new spoofing techniques, evolving over time to maintain high detection accuracy. By minimizing reliance on external servers, the system enhanced user privacy and reduced dependency on external resources

	ML Model	Accuracy	f1_score	Recall	Precision
0	Gradient Boosting Classifier	0.974	0.977	0.994	0.986
1	CatBoost Classifier	0.972	0.975	0.994	0.989
2	XGBoost Classifier	0.969	0.973	0.993	0.984
3	Multi-layer Perceptron	0.969	0.973	0.995	0.981
4	Random Forest	0.967	0.971	0.993	0.990
5	Support Vector Machine	0.964	0.968	0.980	0.965
6	Decision Tree	0.960	0.964	0.991	0.993
7	K-Nearest Neighbors	0.956	0.961	0.991	0.989
8	Logistic Regression	0.934	0.941	0.943	0.927
9	Naive Bayes Classifier	0.605	0.454	0.292	0.997

Table 1 : Algorithms

However, privacy and security concerns arise from storing and processing data locally on the client's device. Robust security measures are necessary to protect user data from potential threats. Adversarial attacks also pose a risk to the system, requiring techniques like adversarial training and model robustness testing to mitigate. Ensuring the model's generalization across diverse web content and scalability for widespread adoption are crucial. User awareness and education remain important, alongside regulatory compliance with data protection laws such as GDPR and CCPA, to maintain trust and hope.

We conduct experiments to evaluate the performance of our system using a diverse dataset of spoofed and legitimate web pages. Our results demonstrate that our client-side machine-learned approach significantly outperforms traditional server-side methods in terms of detection accuracy, with a lower false positive rate and higher true positive rate.



Different studies address the issue of imbalanced datasets in phishing URL detection:

Different studies employ various techniques to address the issue of imbalanced datasets in phishing URL detection, especially with the increasing data chain. One common approach is oversampling techniques, where minority class instances are duplicated or synthetically generated to balance the dataset. Methods like SMOTE (Synthetic Minority Over-sampling Technique) generate synthetic samples by interpolating between existing minority class instances. Another approach is undersampling, where instances from the majority class are randomly removed to achieve class balance. However, undersampling may lead to information loss. Hybrid methods combine oversampling and undersampling techniques to mitigate their respective drawbacks. Additionally, cost-sensitive learning assigns higher misclassification costs to the minority class, encouraging the model to focus more on correctly classifying phishing URLs. Furthermore, ensemble methods like AdaBoost and Gradient Boosting give more weight to misclassified instances, effectively handling imbalanced datasets. Lastly, anomaly detection techniques identify outliers or anomalies in the dataset, which may represent phishing URLs, aiding in their detection. Overall, a combination of these methods helps to address the challenges posed by imbalanced datasets in phishing URL detection, especially with the increasing data chain.

IV. CONCLUSION

In conclusion, the client-side machine-learned system offers a promising solution for mitigating web spoofing attacks, demonstrating improved detection accuracy and real-time analysis compared to traditional server-side methods. Despite its advantages, challenges persist in ensuring privacy and security, mitigating adversarial attacks, achieving generalization, and complying with regulatory requirements. Addressing these challenges is crucial for the successful deployment and widespread adoption of the system, with further research and development needed to enhance its effectiveness and maintain user trust in cybersecurity measures.

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