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PhishCatcher: Client-Side Defence Against Web Spoofing Attacks Using Machine Learning

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Abstract –Phishing attacks have become one of the most significant cybersecurity threats, where attackers create fraudulent websites to device users and steal sensitive information such as login credentials and financial data. Traditional detection techniques, such as blacklist-based approaches ,are ineffective against newly generated phishing websites and lack real-time protection. This paper presents PhishCatcher, a client-side defense mechanism that utilizes machine learning techniques to detect web spoofing attacks efficiently. The proposed system extracts multiple features from websites, including URL characteristics, domain information and webpage content, and applies a Random Forest classifier to identify malicious websites. The system is implemented as a browser extension, enabling real-time detection and user alerts without relying on server-side processing. Experimental results demonstrate that the proposed model achieves high accuracy, low latency, and improved detection performance compared to conventional methods. The solution enhances user security and provides an effective approach to mitigate phishing attacks in modern web environments.

Key Words: Phishing, Web Spoofing, Machine Learning, Cyber Security, Random Forest, Client-side Security, Browser Extension, URL Analysis.

I .INTRODUCTION

With the rapid growth of internet usage and online services, cybersecurity threats have increased significantly, among which phishing attacks are one of the most common and dangerous. Traditional phishing detection techniques, such as blacklist and rule-based approaches, are widely used but have significant limitations. Blacklist-based systems can detect previously identified malicious websites and failed identify newly created phishing URL's. Similarly heuristic and signature-based methods are often unable to adapt to the evolving nature of phishing attacks, resulting in reduced detection accuracy. To overcome this limitations ,machine learning techniques have been introduced in recent years for phishing detection. This techniques analyze various features of websites including URL structure, domain characteristics ,and webpage content, to classify them as legitimate or malicious. Machine Learning models have shown promising results due to their ability to learn patterns and detect previously unseen attacks.

In this paper, We propose PhishCatcher a client-side phishing detection system that utilizes a machine learning approach to identify web spoofing attacks in real-time.

II. RELATED WORKS

Phishing and web spoofing attacks have been extensively studied in the field of cybersecurity, leading to the development of various detection and prevention techniques. These approaches can be broadly categorized into blacklist-based, heuristic-based, visual similarity-based, and machine learning-based methods.

Traditional **blacklist-based techniques** rely on maintaining a database of known phishing URLs.

Heuristic and rule-based approaches analyze URL structures, domain properties, and webpage content to identify suspicious patterns. Tools such as CANTINA use content-based analysis techniques like TF-IDF to detect phishing websites. **Visual similarity-based techniques** compare the appearance of a webpage with legitimate websites. For example, systems like SpoofCatch store login page images and compare them with newly visited pages to detect spoofing attempts.

In recent years, **machine learning-based approaches** have gained significant attention due to their ability to learn complex patterns from data. Algorithms such as Decision Trees, Support Vector Machines (SVM), Naïve Bayes, and Random Forest have been widely used for phishing detection. These models analyze features extracted from URLs, domain information, and webpage content to classify websites as legitimate or malicious.

Hybrid approaches combining multiple techniques.

III. LITERATURE SURVEY

Table 1: Literature Survey on Phishing Detection Techniques

Sl. No	Author(s) & Year	Title	Methodology Used	Key Findings	Limitations
1	A. Jain et al. (2019)	Phishing Website Detection using ML	Random Forest, Decision Tree	High accuracy in detecting phishing URLs	Requires large dataset
2	S. Kumar & R. Singh (2020)	Machine Learning Based Phishing Detection	SVM, Logistic Regression	Effective classification of phishing sites	Cannot detect zero-day attacks
3	M. Gupta et al. (2021)	URL-Based Phishing Detection	Feature extraction + ML classifiers		Limited to URL-based attacks
4	L. Zhao et al. (2022)	Deep Learning for Phishing Detection	CNN, Neural Networks	Improved accuracy over traditional ML	High computational cost
5	P. Sharma & K. Verma (2018)	Browser-Based Anti-Phishing System	Client-side detection using heuristics	Real-time protection	Lower accuracy compared to ML models
6	R. Patel et al. (2021)	Hybrid Phishing Detection Approach	Combination of ML + blacklist		Needs continuous updates
7	T. Nguyen et al. (2023)	Real-Time Phishing Detection System	Ensemble Learning	High precision and recall	Complex implementation
8	D. Roy & S. Das (2022)	Phishing Detection using NLP	Text analysis of webpage content		Ignores URL features
9	K. Lee et al. (2021)	Anti-Phishing using Deep Learning	Detects content-based phishing		Training time is high
10	Proposed Work	PhishCatcher (Your System)	Real-time detection, lightweight, improved accuracy		Yet to be evaluated on large-scale datasets

IV. PROPOSED SYSTEM

The proposed system, PhishCatcher ,is a client-side phishing detection mechanism designed to identify web spoofing attacks in real-time using machine learning techniques. Unlike traditional server-based solutions, the system operates directly within the user's browser, ensuring faster response time, improved privacy, and reduced dependency on external servers.

System Overview

PhishCatcher is implemented as a browser extension that continuously monitors the websites visited by the user. When a webpage is loaded, the system extracts relevant features from the URL, domain, and webpage content. These features then analyzed using a trained machine learning model to determine whether the website is legitimate or a phishing attempt.

Feature Extraction Module:

Extracts important attributes from the website, such as URL length, presence of special characters, domain age, and webpage content characteristics.

Machine Learning Model:

A Random Forest classifier is used to analyze the extracted features and classify the website as either phishing or legitimate.

Working Procedure:

The working of the system can be summarized by the following steps:

The user accesses a website through the browser.

The browser extension activates automatically.

The system extracts feature from the URL and webpage.

The extracted data is passed to the trained Random forest model.

The result is displayed to the user as a warning or safe message.

Key Feature of the System

Real-time phishing detection, Client-side implementation, High accuracy using machine learning, Lightweight and easy integration as a browser extension

Reduced dependency on server-side processing

The proposed system effectively combines feature-based analysis with machine learning to provide an efficient and reliable solution for detecting phishing attacks in modern web environment.

V. RESEARCH METHODOLOGY

A. System Architecture

The proposed system, PhishCatcher, is a client-side web security solution designed to detect and prevent web spoofing (phishing) attacks using machine learning techniques. The architecture

consists of four main modules: data acquisition, feature extraction, model training, and real-time detection. The system is deployed as a browser-based or local client application, enabling real-time analysis of visited URLs.

B. Data collection

A comprehensive dataset comprising both phishing and legitimate URLs is collected from publicly available sources such as PhishTank and Kaggle repositories. The dataset is labeled into two classes: phishing (malicious) and legitimate (benign). Care is taken to ensure diversity and balance in the dataset to improve model generalization.

C. Feature Extraction

To effectively distinguish phishing websites from legitimate ones, multiple features are extracted from URLs and webpage content. These features are categorized as follows:

1. URL-based features:

Include URL length, presence of special characters, use of IP addresses, and abnormal URL structure

2. Domain-based Features:

Includes domain age, DNS record availability, and SSL certificate validity.

3. Content-based Features:

Includes detection of login forms, suspicious JavaScript code, redirection behavior, and mismatch between displayed and actual URL's.

D. Data Preprocessing

The collected dataset undergoes preprocessing steps to improve data quality and model performance. These steps include:

1. Removal of duplicate and irrelevant entries.
2. Handling of missing values.
3. Encoding categorical variables into numerical format.
4. Feature scaling and normalization.

E. Model Development

Several machine learning algorithms are implemented and evaluated, including Decision Tree, Random Forest, Support Vector Machine (SVM), and Logistic Regression. The dataset is divided into training and testing subsets using standard split ratios (e.g., 80:20).

The models are trained on labeled data, and hyperparameter tuning is performed using cross-validation techniques to enhance performance.

F. Model Evaluation

The performance of each model is evaluated using standard metrics:

- Accuracy
- Precision
- Recall
- F1-score

The model with the highest overall performance and lowest false positive rate is selected for deployment.

G. Client-Side Deployment

The selected mo0del is integrated into a client-side application, such as a browser extension. When a user accesses a webpage:

1. The URL is captured in real time.
2. Relevant features are extracted dynamically.
3. The trained model classifies the website as phishing or legitimate.

H. Defense Mechanism

The proposed system effectively defends against web spoofing attacks by:

- Identifying phishing websites prior to user interaction
- Generating real-time alerts for suspicious URLs
- Preventing users from submitting sensitive information on malicious pages

- Enhing user awareness through visual warning indicators

I .Testing and Validation

The system is tested using real-world phishing URLs and legitimate websites to evaluate its robustness. Performance is analyzed in terms of detection accuracy, response time, and false alarm rate.

VI. LIMITATIONS AND FUTURE SCOPE

A .LIMITATION

Despite the promising performance of the proposed PhishCatcher system, certain limitations remain:

1. Limited Dataset Coverage

The model is trained on a finite dataset, which may not fully represent the wide variety of evolving phishing techniques.

2. Feature Dependency

The detection accuracy depends on the selected set of features. Advanced phishing websites that closely mimic legitimate features may reduce the effectiveness of the system.

3. Zero-Day Attack Handling

The system may face challenges in detecting completely new phishing attacks that were not present in the training data.

4. Client-Side Constraints

As the system operates on the client side, its performance is dependent on the computational capability of the user's device.

5. Platform Limitation

The current implementation as a browser extension restricts its applicability to supported web browsers only.

6. Possibility of Misclassification

There remains a small probability of false positives and false negatives, which can affect user trust and system reliability.

7. Static Model Updates

The model does not automatically update itself and requires periodic retraining with new data to maintain effectiveness.

B. FUTURE SCOPE

The proposed system can be further enhanced in the following ways:

1. Incorporation of Advanced Models

The use of deep learning techniques can improve detection accuracy and adaptability to complex phishing patterns.

2. Dynamic Dataset Updating

Integrating real-time phishing data sources can help in continuously improving the model performance.

3. Cross-Platform Deployment

Extending the system to mobile devices and desktop applications can provide broader protection.

4. Hybrid Detection Approach

Combining machine learning with traditional methods such as blacklisting and heuristic analysis can improve robustness.

5. Cloud-Based Integration

Utilizing cloud resources can reduce the computational load on client devices and improve scalability.

6. User Behavior Analysis

Incorporating user interaction patterns can enhance detection of sophisticated phishing attacks.

7. Automated Model Updating

Implementing continuous learning mechanisms can enable the system to adapt automatically to new threats.

VII. CONCLUSION

Cybersecurity is essential for protecting sensitive user information from threats like phishing attacks, where fake websites are used to steal login details. To address this problem, the proposed system PhishCatcher uses a client-side machine learning approach with a Random Forest algorithm to detect spoofed websites. Implemented as a Google Chrome extension, it analyzes web features and classifies URLs as safe or malicious un real time. The system achieved high performance with 98.5% accuracy and precision, along with a fast response time of 62.5 milliseconds. Overall, PhishCatcher provides an efficient, reliable, and user-friendly solution to enhance online security and protect users from phishing attacks.

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