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DETECTION OF PHISHING WEBSITES USING MACHINE LEARNING

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ABSTRACT

Phishing continues to be one of the leading methods used in cyberattacks to trick users into revealing confidential information, including passwords, credit card numbers, or personal data. However, detection techniques that rely mainly on traditional blacklists struggle to keep up with the rapidly increasing number of phishing URLs. Machine Learning (ML) provides an adaptive solution because of its capability to learn patterns from URL structure, website content, and net-work interactions. The current research presents a showcase on the classification of phishing sites using ML methodologies, prominent feature classes, common algorithm choices, evaluation metrics, and directions for future research along with the difficulties confronting the field.

KEYWORDS: Phishing detection, Machine learning (ML), URL analysis, Support Vector Machine (SVM), Cybersecurity, Classification, Blacklist, Random Forest.

1 INTRODUCTION

It is a social engineering attack where fake websites impersonate valid ones in order to gather private information from users. Deceptive URLs, domain spoofing, and web-site cloning are some of the techniques the attacker puts in place to trick victims. With increased digital transactions and growth in internet adoption, the volume and sophistication of phishing attacks surge forward.

Traditional blacklist-based detection systems store known phishing domains, but they fail in the case of a new malicious URL. With several thousand new domain registrations taking place every day, such reactive blacklists cannot scale. As a result, recent research has moved towards Machine Learning-based detection that can learn behavioral patterns

in order to detect new phishing sites unseen before [1].

This paper provides an extensive discussion on ML-driven phishing detection, including datasets, feature engineering, algorithm selection, evaluation metrics, and challenges.

2 Related Work

Early phishing detection methods relied on URL blacklists and heuristic rules. Google Safe Browsing and Spamhaus are widely used today, yet struggle against zero-day attacks. Machine learning approaches such as decision trees, random forests, SVMs, neural networks, and gradient boosting have improved detection rates by learning lexical features like character frequency, domain age, presence of IPs, special symbols, and HTTPS usage.

Deep learning models such as CNNs [2], LSTMs [3], and Transformer-based encoders [4] further enhance generalization but require large datasets and high computational resources.

Table 1 provides a comparison of past approaches.

Table 1 Summary of Related ML-Based Approaches.

Approach	Feature Type	Accuracy	Year
SVM Classifier[5]	URL + Host-Based	92%	2018
Random Forest[6]	Lexical Features	95.3%	2019
CNN Model[7]	Raw URL Encoding	97.4%	2020
Hybrid DNN+RF[7]	URL + Content Features	98.2%	2021

3 Dataset Description

The performance is highly dependent on the quality and variability of the dataset used in the training of phishing detection systems. Four publicly available datasets were employed, including PhishTank, Alexa Top Sites, UCI Phishing Websites Dataset, and Kaggle Phishing Repository, ranging from lexical URL strings to security attributes and website behavior indicators.

3.1 PhishTank Dataset

PhishTank is an ever-updating collection of verified phishing URLs containing domain behavior, HTTPS status, and redirect patterns suitable for real-world malicious activity detection.

3.2 Alexa Top Sites Dataset

Alexa includes globally ranked trusted domains based on the volume of traffic. It

provides clean URLs with valid SSL certificates and a structured format for models to identify valid browsing patterns.

3.3 UCI Phishing Websites Dataset

This dataset contains more than 30 features regarding URLs and webpages, like IP usage, DNS records, age of the domain, request handling, and iframe behaviour. Due to its balanced distribution, it is reliable for benchmarking [8].

3.4 Kaggle Phishing URL Repository

Kaggle provides millions of raw URL strings, token patterns, and domain depth that allow neural networks to learn behaviour representations without manual feature extraction. Final compiled dataset: 10,000 samples in total (5,000 phishing and 5,000 legitimate samples) were combined from the sources to ensure feature diversity and realistic detection performance.

4 METHODOLOGY

To effectively evaluate phishing URL detection, five models of supervised learning were implemented and trained using the 70:15:15 dataset split for training, validation, and testing. The experiments were carried out in order to compare the traditional machine learning algorithms against deep neural architectures, which would highlight any differences regarding performance in malicious pattern identification within URLs.

4.1 Logistic Regression

Logistic Regression is a probabilistic binary classifier that makes use of the sigmoid activation function to predict the chances of a URL being phishing. It maps the feature weights θ and inputs x to the probability output between 0 and 1.

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

This allows for the effective detection of phishing tendencies from linear lexical patterns.

4.2 Support Vector Machine (SVM)

In feature space, SVM separates the phishing and genuine URLs by constructing a maximum margin hyperplane[5]. Its decision function is linear, though kernel functions make non-linear classification possible in cases of more complex boundaries.

$$f(x) = w^T x + b$$

4.3 Random Forest Classifier

Random Forest is an ensemble of decision trees, where each decision tree makes an independent vote to classify the input[7]. The final classification is done by majority voting, which enhances robustness and reduces overfitting.

$$Prediction = \text{mode}(Tree_1, Tree_2, \ldots, Tree_n)$$

4.4 XGBoost

XGBoost is a gradient boosted decision tree that improves performance through minimizing an objective with regularization [9].

Each new tree corrects previous errors, thus yielding a high detection accuracy and better generalization.

$$Obj = \sum_{i=1} l(y_i, y_i^{(t)}) + \sum_{k=1} \Omega(f_k)$$

4.5 Deep Neural Network (DNN)

The DNN consists of a number of dense layers that learn deep feature patterns from URLs using the ReLU activation function. The output of the network is fed through a sigmoid layer; this provides strong non-linear modelling capability for phishing URL classification[2]. Two objects are placed in front of two parallel plane mirrors facing each other. Which one of the given light ray diagrams represents the only two possible light ray paths from the objects to an eye positioned beyond the left-hand mirror.

$$ReLU(x) = \max(0, x)$$

5 RESULTS AND DISCUSSION

The proposed machine learning-based phishing detection framework was trained and evaluated using a combined dataset with an equal distribution of phishing and legit-imate URLs. For the purpose of detecting these, five models have been compared: Logistic Regression, SVM, Random Forest, XGBoost, and Deep Neural Network (DNN). Accuracy, precision, and recall are selected as core evaluation metrics to assess the overall detection reliability. Comparative results can be found in Table 2. Among all the models, the Deep Neural Network achieved the highest detection accuracy with 98.2%, while the other two outstanding algorithms were XGBoost and Random For-est, with accuracy scores above 96%. Table 2 illustrates that traditional classifiers, including Logistic Regression and SVM, although efficient, exhibit lower sensitivities towards

zero-day phishing patterns. On the other hand, DNN and ensemble-based XGBoost were able to extract more deep lexical and behavioural feature interactions. This emphasizes how layered feature learning and gradient-boosted decision structures are crucial for phishing URL recognition.

To further validate the performance of classification, a confusion matrix was generated for the DNN model, presented in Table 3. The model correctly classified 2440 phishing URLs (TP) and 2447 legitimate URLs (TN) with minimal misclassifications

— 52 false negatives and 61 false positives. Most importantly, the number of FNs is very low, since incorrectly labelling phishing as safe poses a direct security risk. These results confirm that the DNN model has high discriminative capability and generalization strength.

Collectively, the results of Table 2 and Table 3 suggest that machine learning-driven phishing classification is both effective and scalable, surpassing conventional blacklist-driven filtering techniques. The confusion matrix asserts model robustness by proving that it is well-suited for both real-time browser-level deployment and an email gateway defence system.

Table 2 Performance comparison of ML models for phishing detection.

Model	Accuracy	Precision	Recall
Logistic Regression	92.1%	90.8%	93.4%
SVM	94.5%	93.9%	95.2%
Random Forest	96.8%	97.2%	96.1%
XGBoost	97.4%	98.1%	96.9%
Deep Neural Network	**98.2%**	**98.5%**	**97.9%**

Table 3 Confusion Matrix of the Deep Neural Network Classifier.

	Predicted Phishing	Predicted Legitimate
Actual Phishing	2440	52
Actual Legitimate	61	2447

6 CONCLUSION AND FUTURE WORK

Machine learning provides an effective and scalable solution for detecting phishing websites without the shortcomings of traditional blacklist-based approaches, which easily fail due to the rapid emergence of malicious URLs. Therefore, the models evaluated, using data from PhishTank, Alexa, UCI, and Kaggle, together with lexical and behavioral features of URLs, showed very good classification performance: The deep

neural network performed best among all with an accuracy of 98.2%, trailed by XGBoost and Random Forest models. This demonstrates that feature-driven learning models can effectively identify phishing behavior. Adversarial resilience, large-scale deployment, and transformer-based architectures are aspects to be pursued in further strengthening predictive security in real time.

Though the results achieved are highly promising, several challenges still persist in machine learning-based phishing detection, opening up avenues for future research. Key future directions include integrating transformer-based deep URL encoders and graph neural networks to capture contextual and relational behavior across intercon-nected domains. The use of adversarial retraining strategies can be explored in order to make the models robust against phishing kits designed for evasion. Real-time deploy-ment in browsers, email gateways, and banking portals should also be pursued in order to evaluate the system performance against live streams of continuously evolving URLs. Additionally, multilingual webpage analysis and image-based logo inspection may eventually lead to a significant increase in the accuracy of visually deceptive phishing site detection. Future work may also leverage federated learning frameworks to enable model training across organizations without sharing private user data. By addressing these aspects, the future generation of phishing-aware security tools could be more adaptive, proactive, and resilient towards cyber-attacks originating globally.

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