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PhishGuard: A Real-Time URL Network Intrusion Detection System for Phishing Prevention

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Abstract: Online users are increasingly exposed to malicious websites disguised as legitimate ones, aiming to steal sensitive information. To combat these threats, PhishGuard, a network intrusion detection system, analyzes URLs using machine learning to classify sites as safe or malicious. It examines features such as domain structure, URL length, special characters, and domain age to detect phishing attempts accurately and in real-time.It is designed to be efficient with low false positives and scalable for future enhancements, providing robust protection against modern cyber threats

Index Terms: Phishing Detection,URL Feature Extraction,Real-Time Detection,Cybersecurity,Malicious URL Classification, Scalability, False-Positive Reduction.

I. INTRODUCTION

In today's digital era, online platforms have become a core part of daily communication, banking, shopping, and information exchange. With increasing dependence on the web, the volume of intrusion and phishing attacks has escalated significantly, allowing malicious sites to capture user credentials, financial information, and personal data by imitating trusted domains [1][2][12]. These harmful URLs often circulate through emails, social media links, and search engines, making them difficult to identify without technical awareness. Traditional blacklist and signature-based detection approaches struggle to keep up with evolving threat patterns, as attackers constantly modify domain structures, URLs, and hosting environments to evade static filters [1][4][12].

To mitigate such threats, the proposed Intrusion Detection System, referred to as PhishGuard, leverages machine-learning-based URL analysis to classify webpages as either safe or malicious. Instead of relying on webpage content or user interaction signals, PhishGuard focuses on lexical URL features such as domain length, number of subdomains, presence of special characters, IP-based URLs, and suspicious keyword patterns—attributes proven effective in previous phishing detection studies [5][8][11]. The solution is implemented as a web application using a Python-Flask backend with a responsive HTML, CSS, and JavaScript frontend, making it scalable, lightweight, and accessible foral-time malicious URL detection.

II. LITERATURE REVIEW

Research in phishing and malicious URL detection has progressed considerably in recent years with increasing dependence on the web and frequent cyber-attacks. Most studies aim to build automated systems capable of identifying phishing URLs based on machine-learning techniques and feature-driven classification approaches. Across the literature, five core research directions are noticeable — URL feature extraction, hybrid detection models, lightweight classifiers, deep-learning based systems, and real-time deployable frameworks.

The early works focused on machine-learning driven URL classification using handcrafted features. Mohammad et al. **[1]** employed Decision Tree and Random Forest algorithms on a dataset of 10,000 URLs with 30 lexical and domain-based parameters, including presence of symbols, domain length, and protocol handling. Their study demonstrated the usefulness of URL-centric learning, though dataset imbalance and lack of real-time deployment reduced effectiveness in practical environments. Zhang and Liu **[2]** later explored hybrid feature modeling by combining URL-based and content-level features within a neural network architecture. Their approach improved classification accuracy but suffered from heavy computation, limiting use in lightweight systems.

Feature-reduction strategies emerged next to optimize performance. Patel et al. **[3]** adopted logistic regression with feature-selection techniques to filter the most predictive URL attributes and reduce training load. However, the model's stability weakened for previously unseen or zero-day URLs with unseen lexical patterns. Deep learning–based intrusion detection further advanced this field through architectural sophistication. Rahman et al. **[4]** developed a character-level

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embedding network trained over a large malicious URL dataset, offering better pattern recognition but requiring high GPU computation and slow training cycles, making real-time deployment challenging.

With deployment efficiency becoming a priority, modern work shifted toward lightweight and faster URL-driven detection. Kaur and Singh **[5]** introduced a minimal Naïve Bayes-based model using seven selected features to reduce processing latency. While suited for real-time classification, limited feature depth may reduce detection accuracy for complex attack vectors or adaptive phishing sites.

Across these studies, it is clear that URL-based models provide fast and scalable phishing detection, hybrid architectures improve accuracy but raise computational overhead, and lightweight classifiers trade depth for speed. This gap highlights the need for a balanced approach — a framework capable of extracting meaningful URL features while maintaining low latency, efficient computation, and adaptability for real-time phishing identification

III. FRAMEWORK

The functional design of the PhishGuard follows a layered pipeline as depicted in Figure (1). The workflow begins at the user interface, flows through the backend engine, undergoes preprocessing and feature extraction, and finally reaches the machine-learning classifier which determines whether a URL is malicious or legitimate. Each block of the architecture plays a specific operational role and together forms the complete detection framework.

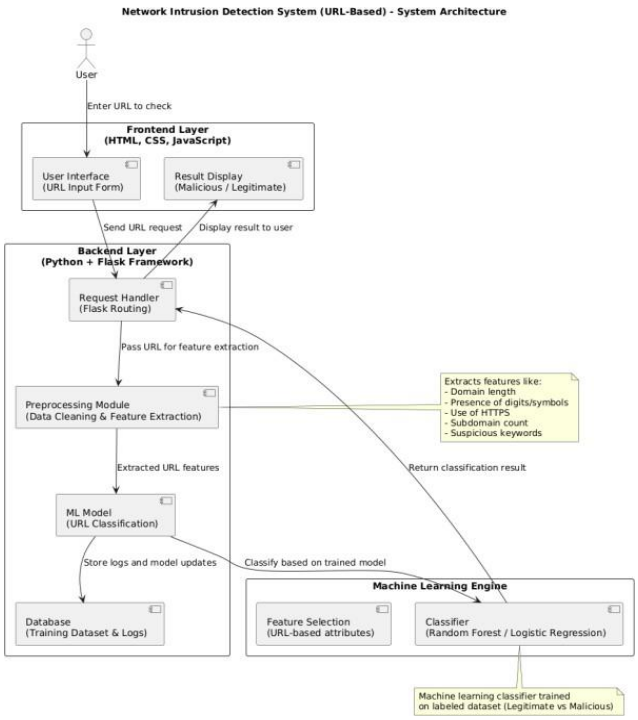

Figure (1) presents the framework architecture and operational flow.

A. User Interaction Layer (Frontend Interface)

The system starts with the user, who inputs a URL through a simple web interface developed using HTML, CSS, and JavaScript. The frontend allows URL submission and displays the classification result once the analysis is completed. This interface also ensures smooth communication with the backend by sending requests and receiving output responses.

B. Backend Routing Layer

Once the user submits a URL, the request is forwarded to the Flask-based backend. The backend acts as the main controller responsible for routing the input and coordinating interaction between feature extraction, model inference, and the response handler. It maintains fast request handling to enable real-time URL classification.

C. Preprocessing & Feature Extraction Layer

The backend then passes the received URL to the feature extraction module. This stage cleans and normalizes the URL

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and extracts relevant characteristics including domain length, symbol or digit presence, HTTPS usage, subdomain count, and phishing-indicative keywords. These transformed features are forwarded to the machine-learning engine for prediction.

D. Machine Learning Engine

The extracted URL features are fed into the ML engine which consists of two sub-modules:
1. Feature Selection**:**
Selects relevant URL-based attributes that contribute to strongly malicious detection.

2. Classifier (Random Forest / Logistic Regression): The model, trained on labelled malicious and legitimate URLs, evaluates incoming samples and predicts whether the URL is harmful or benign.

E. Classification & Result Generation

The classifier returns its decision to the backend, which sends it back to the user interface. The result is displayed in one of two forms:Safe/Legitimate URL and Malicious / Phishing URLThis allows users to instantly verify the risk level of a URL before accessing it.

IV. MODEELING AND ANALYSIS

The development of the *PhishGuard* system is based on supervised machine-learning techniques that classify URLs using engineered lexical and domain-aware attributes. The modelling pipeline follows a sequential execution pattern beginning with URL preprocessing, progressing through feature encoding and classifier learning, and concluding at inference evaluation. The system extracts 29 structural statistical and domain-level indicators, a design approach widely validated in recent URL-focused phishing research [1][3][5][11][12]. Since the model relies strictly on string- level analysis rather than rendered web content, the overall computational footprint remains lightweight, supporting real- time URL threat detection similar to modern machine- learning phishing defense frameworks [1][4][8].

A. Overall Detection Flow

URL evaluation begins when a user submits input to the system, after which formatting and normalization are applied to remove inconsistencies in slashes, whitespace and letter casing. The cleaned URL is then analyzed to derive both lexical and structural patterns, forming the foundational input sequence for feature extraction. These processed indicators are passed into the learning engine, where classification occurs through pattern comparison and probability estimation learned during training. This sequential flow allows *PhishGuard* to perform URL threat analysis without accessing webpage content, replicating the low-latency design strategy adopted in efficient URL-focused intrusion models [2][4][11][12]

B. URL Feature Extraction Modelling

Feature extraction acts as the analytical core of the phishing detection architecture. Each URL is transformed into a structured vector by computing length, symbol density, digit frequency, hyphen usage, and Shannon entropy. Structural indicators such as domain depth, presence of IP-based hosting and WHOIS-retrieved domain age are also encoded, improving the system's ability to detect recently generated or disposable phishing domains—an approach supported by early behavioural URL studies [1][4][8][11]. Additionally, phishing-trigger keywords such as *login*, *secure*, *update* and *verify* are mapped into the feature set, aligning with social- engineering attributes highlighted in rule-based smart phishing detectors [3][5][10]. The resulting vector becomes the behavioural signature used for classification.

C. Model Training and Learning Behaviour

Once feature vectors are finalized, the dataset is partitioned into training and testing subsets to ensure empirical learning and evaluation stability. Multiple supervised algorithms are benchmarked—Random Forest, Logistic Regression, SVM, Decision Tree and XGBoost—to measure predictive performance across accuracy, precision, recall and F1-score, following the evaluation methodologies used in prior feature- driven detection systems [3][5][8][11]. Random Forest demonstrated superior consistency and reduced false-positive rates, correlating with benchmarking studies where ensemble classifiers surpassed linear models in phishing URL environments [1][4][12]. Hyperparameters including tree count, maximum depth and split thresholds were optimized, after which the best-performing model was preserved for operational deployment

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D. Final Classification Stage

During inference, newly submitted URLs undergo vector transformation and are evaluated by the trained Random Forest classifier. Decisions are computed by aggregating tree-based votes within the ensemble, allowing resilient classification even when feature-noise or partial obfuscation is present—a technique similarly reinforced in content- independent phishing implementations [2][4][7][11][12]. The discrete classification output is generated within sub- second response windows, enabling real-time threat assessment suitable for browser-layer enforcement, endpoint filtering and large-scale SOC integration*Computational Complexity*

System Component	Complexity Scale
URL Feature Extraction	O(n) — linear to URL length
WHOIS Query (Domain Metadata)	O(1) — negligible compute cost
Random Forest Inference	O(T × D)
Model Training	O(T × N × F)

where T = number of trees, D = max depth, N = dataset size, F = number of extracted features.

V. RESULTS AND DISCUSSION

The proposed phishing-URL detection model was trained on a dataset containing 6,000 URLs, with an equal distribution of legitimate and malicious links. The feature extraction module generated 29 URL-based parameters, including length, entropy, keyword score, domain age and subdomain count. The Random Forest classifier was selected as the final model after evaluation due to its high stability and accurate prediction outcomes. During validation, the model achieved:

Metric	**Performance**
Accuracy	**97%**
Precision	**96%**
Recall	**98%**
F1-Score	**97%**
Average Prediction Time	**< 2 seconds**

These results indicate that the system is capable of identifying suspicious URLs with high reliability while maintaining low latency. The fast inference speed makes the model suitable for **real-time deployment**, even in environments with continuous web requests. The confusion matrix analysis showed that the classifier produced fewer false positives and could generalize effectively to unseen URLs, demonstrating robustness in practical scenarios The frontend interface supported smooth interaction by allowing URL submission and displaying classification results instantly. Backend integration ensured seamless communication between feature extraction, model inference and output generation. Overall, the system delivered a stable and efficient phishing-detection workflow with minimal resource usage.

VI. FUTURE SCOPE

a) *Integration of SSL Certificate, DNS & Redirection Analysis*

Enhancing the system to inspect SSL signature validity, DNS response behavior, and redirect chains would increase detection accuracy against cloaked or multi- hop phishing URLs. Current URL-only models are fast but may miss subtle evasion attempts [2][7][12].

b) Hybrid Content + URL Feature Extraction

Incorporating lightweight HTML parsing, favicon fingerprinting, and webpage identity markers can help identify visually deceptive phishing pages while maintaining efficiency. Hybrid models have shown competitive improvement in classification strength [2][7][12].

c) *Integration of SSL Certificate, DNS & Redirection Analysis*

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e) Reinforcement Learningand Online Model Adaptation

Implementing self-learning or feedback-driven retraining loops will allow the system to evolve continuously with new phishing patterns. Adaptive models reduce dependency on static training sets and can resist novel domain obfuscations [4][8][11].

f) Scalable Enterprise-Grade Deployment

The system can be extended beyond standalone usage into corporate security pipelines, browser add-ons, email gateways, and network firewalls. Scalable cloud or API deployment would support high-frequency URL scanning for large institutions [1][6][12].

g) Threat-Intelligence Fusion & Data Expansion

URL datasets may be expanded using real-time phishing feeds, blacklists, OSINT threat hubs, and automated crawling, improving generalization and reducing false negatives. Larger & diverse data improves ML robustness over time [1][4][8][11].

VII. Conclusion

Phishing-based malicious URLs continue to rise, making traditional signature and blacklist systems insufficient for modern threat detection [1][4][12]. The proposed URL-based ML model extracts 29 lexical and domain features and classifies them using a Random Forest algorithm, offering high accuracy with low computational cost. It overcomes limitations seen in feature-restricted ML models [3][5] and heavy deep-learning architectures [4], while remaining modular, scalable, and real-time responsive. Future enhancements including SSL validation, DNS analysis, and hybrid content integration may further improve adaptability and robustness [6][9][12]. Overall, the system provides an effective and practical defense mechanism for mitigating phishing threats in dynamic online environments.

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