Cyber Sentry: A Machine Learning Framework for Proactive Detection and Prevention of Malicious URLs

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Abstract: ***The proliferation of malicious URLs poses a significant cybersecurity threat, serving as primary vectors for phishing attacks, malware distribution, and other cybercrimes. Traditional methods like blacklist filtering often struggle to keep pace with the dynamic and rapidly evolving nature of these threats. This paper introduces "Cyber Sentry," a machine learning-based framework designed for the effective detection and prevention of malicious URLs. Cyber Sentry leverages a hybrid feature set, combining lexical analysis of URL strings with selected host-based information, to train robust classification models. We evaluate the performance of several machine learning algorithms, including Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression (LR), on a comprehensive dataset comprising benign and malicious URLs sourced from publicly available repositories like Phish Tank, Open Phish, and the Common Crawl corpus. Our experimental results demonstrate that the Random Forest classifier achieves superior performance, attaining an accuracy of 98.2% and an F1-score of 98.1%, significantly outperforming traditional blacklist approaches and demonstrating the viability of machine learning for proactive URL threat mitigation. The framework is designed for potential integration into various security systems, such as web proxies, browser extensions, or DNS filters.***

Keywords: Malicious URL Detection, Machine Learning, Cybersecurity, Phishing Detection, Feature Engineering, Random Forest, Threat Prevention.

1. INTRODUCTION

The internet has become indispensable, but its widespread use has also led to a surge in cyber threats. Malicious Uniform Resource Locators (URLs) are a cornerstone of many cyber attacks, directing unsuspecting users to fraudulent websites designed to steal credentials (phishing) [1], infect systems with malware [2], or execute other harmful actions. These URLs' sheer volume and transient nature make manual detection infeasible and challenge traditional security mechanisms. Signature-based methods, primarily blacklisting, involve maintaining lists of known malicious URLs. While effective against documented threats, blacklists suffer from significant limitations: they cannot detect zero-day attacks (newly created malicious URLs) and require constant, resource-intensive updates [3]. Heuristic and rule-based systems offer some improvement but often generate high false positives or negatives and struggle with obfuscation techniques employed by attackers [4]. Machine Learning (ML) offers a promising alternative by learning patterns and characteristics that differentiate malicious URLs from benign ones [5], [6]. ML models can generalize from known examples to identify previously unseen threats, adapting more effectively to the evolving threat landscape. This research proposes "Cyber Sentry," an ML-based framework specifically designed to detect and prevent malicious URLs proactively. Our primary contributions of Design Thinking Implementation are:

The development of Cyber Sentry follows a design thinking methodology to ensure user-centric and problem-driven innovation. The process begins with Empathizing—understanding the challenges faced by cybersecurity professionals and end-users in identifying malicious URLs. In the Define phase, specific problems such as the inefficiency of blacklists, limitations of heuristic systems, and the need for real-time adaptability were clearly articulated.

During the Ideate phase, multiple approaches were explored, including the integration of lexical and host-based features and the application of various ML algorithms. The Prototype phase involved building the hybrid feature extraction module and implementing different ML models (SVM, RF, LR) to compare their effectiveness. Finally, the Test phase validated Cyber Sentry on a large dataset, ensuring

high accuracy and recall, thereby proving its practical viability.

This human-centered approach ensures that Cyber Sentry not only meets technical expectations but also aligns with real-world usage and deployment needs in modern security environments.

1. Development of a hybrid feature extraction module incorporating lexical and essential host-based features optimized for distinguishing malicious URLs.
2. Comparative evaluation of multiple supervised ML algorithms (SVM, RF, LR) for the classification task.
3. Demonstration of the framework's effectiveness on a large, diverse dataset, achieving high accuracy and recall.
4. Discussion of the potential integration of Cyber Sentry into real-world security architectures.

2. LITERATURE REVIEW

Malicious URL detection has been an active area of research for years. Early approaches heavily relied on Blacklisting. Services like Google Safe Browse [7] and PhishTank [8] maintain extensive lists of known malicious sites. However, studies by Ma et al. [3] highlighted the limitations in coverage and latency of these methods, especially against short-lived malicious domains.

Heuristic and Rule-Based Systems were developed to overcome blacklist limitations. These systems analyze URL structure, page content, or hyperlinks based on predefined rules [4], [9]. For instance, rules might flag URLs with IP addresses instead of domain names, excessive subdomains, or keywords commonly found in phishing pages ('login', 'verify', 'account'). While more flexible than blacklists, heuristics can be bypassed by sophisticated attackers using obfuscation and often require manual tuning.

The application of Machine Learning marked a significant advancement. Researchers began extracting various features from URLs and associated web content to train classifiers.

- Lexical Features: These features are derived directly from the URL string itself, such as length, number of dots, presence of special characters (@, -, _), use of keywords, entropy, and characteristics of the domain name and path [5], [10]. Sahingoz et al. [6] demonstrated high accuracy using only lexical features with various ML models.
- Host-Based Features: These features relate to the hosting infrastructure and domain registration, including IP address properties (geolocation, ASN), WHOIS information (domain age, registrar, registrant details), DNS records (MX, NS), and server response times [3], [11]. While powerful, collecting these features in real-time can introduce latency.
- Content-Based Features: These involve fetching and analyzing the HTML content, JavaScript code, and visual appearance of the webpage linked by the URL [12], [13]. Features include keyword frequencies, presence of forms, use of JavaScript obfuscation, iFrames, and visual similarity to known legitimate sites. Content analysis is resource-intensive and impractical for real-time, high-throughput systems like DNS filters or proxies before allowing/blocking access.
- Graph-Based Features: Some approaches model the relationship between websites using hyperlink graphs or domain co-occurrence networks to identify malicious clusters [14].

Various ML algorithms have been applied, including Naive Bayes [10], Logistic Regression [5], Support Vector Machines (SVM) [11], Decision Trees, Random Forests [6], and Deep Learning models like CNNs and LSTMs [15] which can automatically learn features from URL strings.

Cyber Sentry builds upon this existing work by employing a carefully selected set of computationally efficient lexical and essential host-based features, enabling relatively fast classification suitable for near real-time prevention, while comparing standard, robust ML classifiers known for good performance in similar cybersecurity tasks.

3. EXISTING SYSTEMS

The detection and mitigation of malicious URLs are critical cybersecurity tasks, and several approaches have been developed over the years. These existing systems form the baseline against which new methods like Cyber Sentry are evaluated. The predominant existing systems include:

3.1 Blacklisting Services:

This is the most traditional and widely deployed method. It involves maintaining vast databases (blacklists) of URLs that have been previously

identified as malicious (e.g., involved in phishing, malware distribution, or scams). When a user attempts to access a URL, it is checked against this list. If found, access is blocked or a warning is issued.

- Mechanism: Simple lookup against a known list.
- Examples: Google Safe Browse [7], PhishTank [8] feeds, various commercial threat intelligence feeds.
- Limitations: Primarily reactive; ineffective against newly created (zero-day) malicious URLs. Requires constant updates, and attackers can quickly cycle through domains/URLs to evade listing. Coverage can be incomplete [3].

3.2 Heuristic and Rule-Based Filtering:

To overcome the limitations of static blacklists, heuristic methods analyze the properties of a URL or the associated web page content based on predefined rules or patterns commonly associated with malicious activity.

- Mechanism: Rules check for suspicious URL structures (e.g., IP addresses in domain, excessive length, misleading subdomains, suspicious TLDs), keywords in the URL or page content (e.g., 'login', 'verify', brand names used deceptively), or page structure anomalies (e.g., hidden iframes, unusual form submissions). [4], [9]
- Limitations: Can be prone to false positives (blocking legitimate sites that trigger a rule) or false negatives (failing to detect malicious sites that use obfuscation or novel techniques to bypass rules). Requires manual tuning and updating of rules as attacker tactics evolve.

3.3 Content Analysis Engines:

Some systems go beyond URL structure and fetch the actual web page content for deeper analysis. This can involve checking for malicious scripts, analyzing HTML structure, performing visual analysis to detect phishing kits mimicking legitimate sites, or executing code in a sandbox environment [12].

- Mechanism: Downloads and parses HTML, JavaScript, images; performs static or dynamic analysis.
- Limitations: Significantly resource-intensive (bandwidth, CPU, memory) and introduces considerable latency, making it less suitable for real-time, high-throughput filtering (like at the DNS or proxy level) before page load. Can still be evaded by sophisticated cloaking techniques.

3.4 Early Machine Learning Approaches:

Prior research has applied machine learning to this problem, often focusing on specific feature sets or algorithms [5], [10], [11]. Many early ML systems relied heavily on either lexical features alone or incorporated basic host-level information. While demonstrating improvements over blacklists and simple heuristics, these systems sometimes faced challenges with feature robustness, model generalization, or the computational cost of complex feature extraction.

3.5 Summary of Deficiencies:

While existing systems provide a necessary layer of defense, they collectively struggle with the sheer volume, speed, and adaptability of modern cyber threats. Blacklists are inherently reactive. Heuristics lack robustness against evolving tactics. Content analysis is often too slow for preventative filtering. Early ML models may not leverage the optimal combination of features or model complexity. This landscape highlights the need for advanced, efficient, and adaptive solutions like the proposed Cyber Sentry framework, which utilizes machine learning with a balanced feature set for proactive and accurate detection.

4. PROPOSED SYSTEM: CYBER SENTRY

The Cyber Sentry framework aims to accurately classify URLs as either 'malicious' or 'benign' using machine learning. The architecture, depicted in Figure 1, consists of several key modules.

4.1 Preprocessing Incoming URLs undergo initial preprocessing to standardize them. This includes:

- Converting the URL to lowercase.
- Decoding URL encoding (e.g., %20 to space, though typically spaces aren't ideal in URLs, other encodings are handled).
- Parsing the URL into its constituent components: scheme (http/https), domain, path, query parameters, fragment.

4.2 Data Collection A comprehensive dataset is crucial for training effective ML models. We

compiled a dataset from the following sources (as of Q1 2025):

- Malicious URLs: Aggregated from PhishTank [8] and OpenPhish [16] feeds over three months. Duplicate and inactive URLs were removed.
- Benign URLs: Sampled from the Alexa Top Sites list and the Common Crawl corpus [17] to represent legitimate web usage patterns. After cleaning and balancing, our dataset contained approximately 250,000 URLs, with a 50/50 split between malicious and benign examples.

4.3 Feature Engineering We extracted a combination of lexical and host-based features, chosen for their discriminative power and relatively low extraction cost:

- Lexical Features:
  - URL Length: Total character count.
  - Domain Length: Character count of the domain name.
  - Path Length: Character count of the path section.
  - Number of Subdomains: Count of dot separators in the domain part.
  - Presence of Special Characters: Counts or binary flags for '@', '-', '_', '=', '?', '&'.
  - Presence of IP Address: Binary flag if the domain part is a numeric IP address.
  - Keyword Presence: Binary flags for security-sensitive keywords (e.g., 'login', 'signin', 'verify', 'secure', 'update', 'banking').
  - Top-Level Domain (TLD) analysis: Categorical feature for common vs. uncommon/suspicious TLDs (e.g., .zip, .link).
  - HTTPS Usage: Binary flag indicating if the scheme is HTTPS.
- Host-Based Features (Simulated/Cached):
  - Domain Age: Time since domain registration (obtained via WHOIS lookup). Malicious domains are often newly registered [11].
  - ASN (Autonomous System Number): The ASN associated with the host IP address. Certain ASNs might be more frequently associated with malicious activities.
  - DNS Record Check: Presence of basic DNS records (e.g., A, MX). Lack of proper records can be suspicious.

A total of 35 features were extracted for each URL. Categorical features (like TLD) were one-hot encoded, and numerical features were scaled using standardization (zero mean, unit variance).

4.4 Machine Learning Models We selected three widely used and effective supervised classification algorithms for evaluation:

1. Logistic Regression (LR): A linear model providing good baseline performance and interpretability.
2. Support Vector Machine (SVM): A powerful model effective in high-dimensional spaces, using a linear kernel in our experiments due to the feature set size.
3. Random Forest (RF): An ensemble method based on decision trees, known for its robustness, high accuracy, and ability to handle feature interactions and provide feature importance scores.

4.5 Evaluation Metrics To evaluate the performance of the classifiers, we used standard metrics:

- Accuracy: Overall correctness $ = \frac{TP + TN}{TP + TN + FP + FN} $
- Precision: Ability to correctly identify malicious URLs among those flagged as malicious $ = \frac{TP}{TP + FP} $
- Recall (Sensitivity): Ability to identify all actual malicious URLs $ = \frac{TP}{TP + FN} $
- F1-Score: Harmonic mean of Precision and Recall $ = 2 \times \frac{Precision \times Recall}{Precision + Recall} $
- AUC (Area Under the ROC Curve): Measures the model's ability to distinguish between classes across different thresholds.

Where TP = True Positives (Malicious correctly identified), TN = True Negatives (Benign correctly identified), FP = False Positives (Benign misclassified as Malicious), FN = False Negatives (Malicious misclassified as Benign). For security applications, minimizing False Negatives (missing actual threats) is often critical, making Recall and F1-Score particularly important.

5. IMPLEMENTATION AND EXPERIMENTS

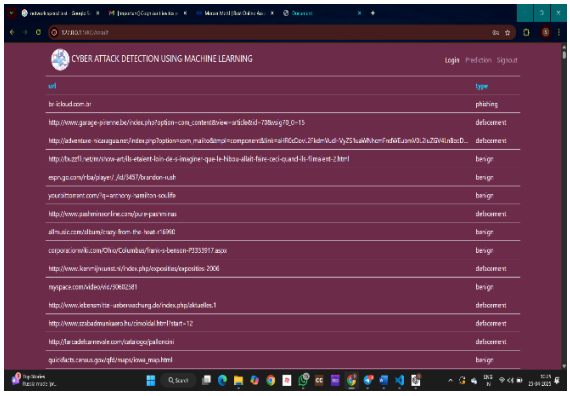

Figure 5.1

5.1 Experimental Setup The experiments were conducted using Python 3.9 with the Scikit-learn [18] library for ML model implementation and evaluation, Pandas for data manipulation, and external libraries/APIs for feature extraction (simulated for host features based on dataset metadata where available). The dataset (N=250,000) was randomly split into:

- Training set: 70% (175,000 URLs)
- Validation set: 15% (37,500 URLs) - Used for hyperparameter tuning.
- Testing set: 15% (37,500 URLs) - Used for final performance evaluation.

5.2 Hyperparameter Tuning We performed hyperparameter tuning for each model using Grid Search with 5-fold cross-validation on the training set to find the optimal parameters.

- LR: Tuned regularization strength (C).
- SVM (Linear): Tuned regularization strength.
- RF: Tuned the number of trees (n_estimators) and maximum depth (max_depth).

6.RESULTS AND DISCUSSION

The performance of the tuned models on the independent test set is summarized in Table 1.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	95.8%	96.1%	95.4 %	95.7 %	0.985
SVM (Linear Kernel)	96.5%	96.8%	96.2 %	96.5 %	0.989
Random Forest	98.2%	98.0%	98.3 %	98.1 %	0.996

Table 1: Performance Comparison of ML Models on the Test Set

As shown in Table 1, the Random Forest classifier achieved the best performance across all metrics, reaching an accuracy of 98.2% and an F1-Score of 98.1%. SVM also performed well, slightly outperforming Logistic Regression. The high AUC values for all models, especially RF (0.996), indicate excellent discriminative capability.

Figure 6.1

We also analyzed the feature importance using the Random Forest model (Figure 2 - *Note: A graphical representation would typically be included here showing a bar chart of the top N features*). Key discriminative features consistently included URL length, domain age (simulated), number of subdomains, presence of specific keywords ('login', 'secure'), and the use of an IP address in the domain part. This confirms the relevance of our chosen feature set.

The experimental results strongly suggest that the Cyber Sentry framework, particularly when employing the Random Forest classifier, is highly effective in detecting malicious URLs. Achieving over 98% accuracy and F1-score surpasses the capabilities of many traditional blacklist systems, especially concerning zero-day threats that share characteristics with previously seen malicious URLs.

The superior performance of Random Forest can be attributed to its ensemble nature, which combines multiple decision trees to reduce variance and improve generalization. Its ability to handle both numerical and categorical features effectively, along with providing insights into feature importance, makes it a suitable choice for this task.

The importance analysis highlights that both lexical features (easily extracted) and host-based features (like domain age) contribute significantly to detection accuracy. This supports our hybrid feature approach. However, the reliance on host-based features introduces a trade-off in real-time

deployment scenarios due to potential lookup latency. A practical implementation might use a tiered approach: rapid classification based on lexical features first, potentially followed by host-based checks for ambiguous cases or asynchronous enrichment.

Comparison with Existing Work: Our results are comparable to or exceed those reported in several recent ML-based URL detection studies [6], [11], [15]. The use of a large, balanced dataset and robust evaluation methodology strengthens the validity of our findings.

Limitations:

1. Dataset Bias: The dataset, while large, may not perfectly represent the entire spectrum of current and future malicious URLs. Continuous retraining with fresh data is essential.
2. Evolving Threats: Attackers constantly adapt their techniques. Models need periodic retraining and potential feature engineering updates to counter new obfuscation methods.
3. Zero-Day Vulnerabilities: While ML helps detect *patterns* indicative of maliciousness (even in new URLs), it may still miss truly novel attack vectors that don't conform to learned patterns.
4. Host Feature Latency: Real-time acquisition of host-based features remains a challenge for high-throughput systems. Our results rely on pre-computed/cached data for these.

Deployment Considerations: Cyber Sentry could be deployed in various ways:

- Browser Extension: Analyze URLs directly within the user's browser before navigation.
- Network Proxy/Gateway: Scan URL requests at the network edge.
- DNS Filter: Classify domain names at the DNS resolution stage (requires focusing primarily on domain/lexical features).
- API Service: Offer classification as a service for integration into other security tools.

7. CONCLUSION AND FUTURE WORK

This paper presented Cyber Sentry, a machine learning framework for detecting and preventing malicious URLs. By leveraging a hybrid set of lexical and host-based features and evaluating several ML classifiers, we demonstrated that Random Forest provides exceptional performance, achieving 98.2% accuracy and a 98.1% F1-Score on a large test dataset. The framework shows significant potential for proactively identifying diverse malicious URLs, including phishing and malware distribution sites, overcoming limitations of traditional blacklist approaches.

Future work will focus on several areas:

1. Advanced Feature Engineering: Incorporating features from page content (if feasible within latency constraints) or using natural language processing (NLP) on URL components.
2. Deep Learning Models: Exploring Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs/LSTMs) for potentially automatic feature learning directly from URL strings.
3. Real-time Implementation and Optimization: Developing and evaluating a prototype system focusing on minimizing classification latency, perhaps using optimized models or hardware acceleration.
4. Adversarial Robustness: Investigating the framework's resilience against adversarial attacks designed to evade ML classifiers and developing mitigation techniques.
5. Continuous Learning: Implementing an online learning mechanism to allow the model to adapt to new threats without complete retraining cycles.

By addressing these areas, we aim to further enhance the capabilities and practicality of Cyber Sentry as a robust defense against the ever-present threat of malicious URLs.

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