Real-Time Detection of Malicious URLs Using Feature-Based Machine Learning Approaches

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Abstract
Malicious URLs serve as primary vectors for cyber threats such as phishing, defacement, and malware attacks. Traditional blacklist-based detection methods fail to identify newly emerging threats, necessitating the use of machine learning techniques for improved detection accuracy. In this study, we propose a Random Forest-based classification model for malicious URL detection, utilizing lexical and structural features extracted from URLs. The dataset was balanced to ensure fair training across all classes, including benign, defacement, phishing, and malware URLs. The trained model achieved an accuracy of 88.32%, with high precision and recall for defacement detection. While the model demonstrates promising results, further improvements in feature engineering and dataset diversity could enhance detection performance against evolving threats.

Keywords: Malicious URL, Cybersecurity Threat, Phishing, Malware Propagation, Blacklist, Heuristics, Machine Learning, Deep Learning, Data Scarcity

INTRODUCTION

The internet is a powerful tool that offers vast resources and opportunities for users worldwide. However, with its extensive reach comes the significant risk of cyber threats, particularly from malicious URLs that can lead to various forms of attacks, including phishing, malware distribution, and data breaches. As the volume of online threats continues to grow, there is an urgent need for effective and efficient methods to detect and mitigate these risks. Traditional security measures, such as signature-based detection, are often inadequate against the rapidly evolving tactics employed by cybercriminals. [1]

Machine learning has emerged as a promising solution for the detection of malicious URLs, leveraging algorithms that can learn from vast amounts of data and identify patterns indicative of malicious activity. By analyzing features from URL structures, domain names, and associated metadata, machine learning models can differentiate between benign and harmful URLs with a high degree of accuracy. This proactive approach not only enhances the detection capabilities of security systems but also enables real-time responses to emerging threats. [2]

In this context, the aim of this research is to develop a robust machine learning framework for malicious URL detection. We will explore various machine learning techniques, including supervised and unsupervised learning algorithms, to identify effective patterns and s associated with malicious URLs. By employing a comprehensive dataset that encompasses a wide range of URL features, our objective is to build a model that can accurately classify URLs as either safe or malicious. [3]

Furthermore, this study will emphasize the importance of feature engineering and selection, as the effectiveness of machine learning models heavily relies on the quality and relevance of the input data.

LITERATURE SURVEY

Malicious URLs are one of the major security threats to organizations and end-users on the Internet because they are associated with various types of attacks and misuses, such as spreading malwares and launching phishing attacks.: This paper talks about how malicious URLs are a big problem on the internet. These URLs are used by attackers to spread viruses (malware) or trick people into giving up personal information (phishing). The authors highlight how dangerous these links are for both regular users and organizations. [1]

In recent years, the digital world has advanced significantly, particularly on the Internet, which is critical given that many of our activities are now conducted online. As a result of attackers' inventive techniques, the risk of a cyberattack is rising rapidly.The authors of this paper discuss how the internet has become essential to our lives, but at the same time, cyberattacks are increasing because hackers are becoming smarter. This paper stresses the growing risk of cyber threats and the importance of better protection strategies.[2]

Malicious URLs are a very prominent, dangerous form of cyber threats in view of the fact that they can enable many evils like phishing attacks, malware distribution, and several other kinds of cyber fraud.This paper also focuses on the threat of malicious URLs. It explains how these dangerous links are responsible for serious online crimes like phishing and malware spreading. The authors emphasize the need for strong detection systems to protect users from such threats. [3]

In recent years, phishing events occur frequently, and the detection of phishing URL has become a common concern in the field of network security. In previous studies, researchers distinguish phishing URLs from normal URLs by the string characteristics.This study looks specifically at phishing URLs. It points out that phishing is becoming more common, and one way to detect phishing is by analyzing the structure and patterns of the URLs. Earlier methods looked at how the URL "looks" (its characters and format) to tell if it's suspicious.[4]

In 2024, researchers have focused on enhancing phishing URL detection using deep learning techniques. Recent studies have explored transformer-based models to analyze sequential patterns in URLs, significantly improving classification accuracy compared to traditional machine learning approaches. These methods leverage contextual embeddings to identify subtle phishing characteristics more effectively.This recent paper (2024) talks about using deep learning, especially transformers (a type of AI model), to detect phishing URLs. These models can understand patterns in how URLs are written, helping identify tricky or hidden signs of phishing better than older methods.[5]

In 2025, phishing URL detection research has integrated federated learning to ensure privacy-preserving detection across distributed systems. By leveraging decentralized training, models can learn from multiple sources without compromising sensitive data, leading to more robust and adaptive phishing detection mechanisms.This paper (2025) explores using federated learning for phishing detection. Instead of collecting all the data in one place (which could be risky), the system learns from data across different devices or locations without moving the data. This approach keeps user data private while still improving phishing detection.[6]

OBJECTIVES

1. Develop an automated system for accurate URL classification, minimizing manual inspection.

2. Evaluate supervised and unsupervised learning techniques to identify the best model for malicious URL detection.

3. Extract and select key URL features indicative of malicious intent.

4. Build a diverse dataset to improve model generalization and performance.

PROBLEM DEFINITION

The proliferation of the internet has significantly transformed how individuals and organizations access information and conduct business. However, this transformation has also given rise to a myriad of cyber threats, particularly through malicious URLs that can lead to serious security breaches, data theft, and financial losses. Malicious URLs are often used in phishing attacks, where unsuspecting users are tricked into clicking links that direct them to harmful websites designed to steal sensitive information or install malware on their devices.

METHODOLOGY

1. Data Collection

The dataset for training and evaluation was compiled from multiple reputable threat intelligence sources to ensure comprehensive coverage of malicious and legitimate URLs. These sources include:

1. Public cybersecurity databases: PhishTank, VirusTotal, Google Safe Browsing, and OpenPhish.

2. Open-source datasets: Labeled repositories containing known malicious and benign URLs.

3. Industry reports and threat feeds: Data extracted from real-world threat reports published by cybersecurity firms.

4. Web scraping: URLs collected from forums, blogs, and dark web sources to enhance diversity.

To ensure dataset representativeness, URLs were classified into various threat types, including:

1. Phishing websites – Sites mimicking legitimate services to steal user credentials.

2. Malware distribution sites – Websites hosting malicious software such as Trojans and ransomware.

3. Spam URLs – Links used for spreading advertisements, scams, and fraud.

A balanced dataset was curated by incorporating an equal distribution of benign and malicious URLs to prevent model bias.

2. Feature Engineering and Selection

The effectiveness of the model heavily relies on feature selection. Features were extracted across three primary categories:

1. URL-based features: Length, entropy, presence of special characters, presence of HTTP vs HTTPS, number of subdomains.

2. Domain-based features: Domain age, WHOIS information, DNS record validity, presence in blacklists.

3. Content-based features: HTML structure, presence of JavaScript-based redirects, number of hyperlinks, and external resource loading patterns.

To enhance model performance, the following feature selection techniques were applied:

1. Chi-Square Test: Used to determine feature relevance for categorical variables.

2. Mutual Information: Measured the dependency between features and the target variable.

3. Recursive Feature Elimination (RFE): Iteratively removed the least important features to improve computational efficiency and accuracy.

3. Data Preprocessing

Preprocessing ensures data quality and consistency before feeding it into the model. The following steps were performed:

1. Normalization & Standardization: Numerical features were scaled using Min-Max Scaling or Z-score Standardization to normalize feature distribution.

2. Encoding Categorical Data: Features such as domain registrars and hosting ASNs were encoded using One-Hot EncodingorLabel Encoding.

3. Handling Missing Values: Missing values were imputed using statistical methods such as mean/median imputation or predictive modeling.

4. Data Augmentation: Synthetic URL samples were generated using adversarial techniques to improve robustness.

The dataset was split into an 80-20 train-test ratio, ensuring a representative sample for training and evaluation.

4. Model Selection and Training

Multiple machine learning models were evaluated to identify the most effective approach for threat detection. The following algorithms were considered:

1. Logistic Regression: For baseline performance.

2. Decision Trees & Random Forests: For rule-based URL classification.

3. Gradient Boosting (XGBoost, LightGBM): For improved accuracy and handling complex relationships.

4. Deep Learning Models (LSTMs, CNNs): To capture sequential and structural patterns in URLs.

5. Model Evaluation and Performance Metrics

The trained models were evaluated on unseen test data using multiple performance metrics:

1. Accuracy**:** Measures overall classification performance.

2. Precision: Ensures a high proportion of correctly identified malicious URLs.

3. Recall: Detects all true malicious URLs while minimizing false negatives.

4. F1-score: Provides a balance between precision and recall.

5. ROC-AUC Score: Measures the trade-off between true positives and false positives.

Confusion matrices were analyzed to identify misclassification trends.

6. Deployment and Real-World Testing

To ensure practical usability, the best-performing model was deployed in a real-world testing environment:

1. Integration with threat detection systems: The model was embedded into security tools for URL screening.

2. Live URL monitoring: Tested against real-time web traffic to assess effectiveness.

3. Periodic retraining: Regular updates with new threat intelligence data to maintain accuracy.

ARCHITECTURE DIAGRAM

The proposed system is a novel malicious URL detection framework that utilizes static feature classification to improve accuracy and precision. The system will incorporate machine learning models, specifically Support Vector Machine (SVM), Random Forest (RF), and Bayesian Network (BN), trained on a dataset of 5,00URLs collected from sources like URLhaus and PhishTank. The framework will be designed to address the limitations of traditional methods by focusing on features that are less susceptible to obfuscation and rapidly evolving threats. It will be evaluated for its accuracy and precision, and benchmarked against existing detection methods to demonstrate its superior performance.

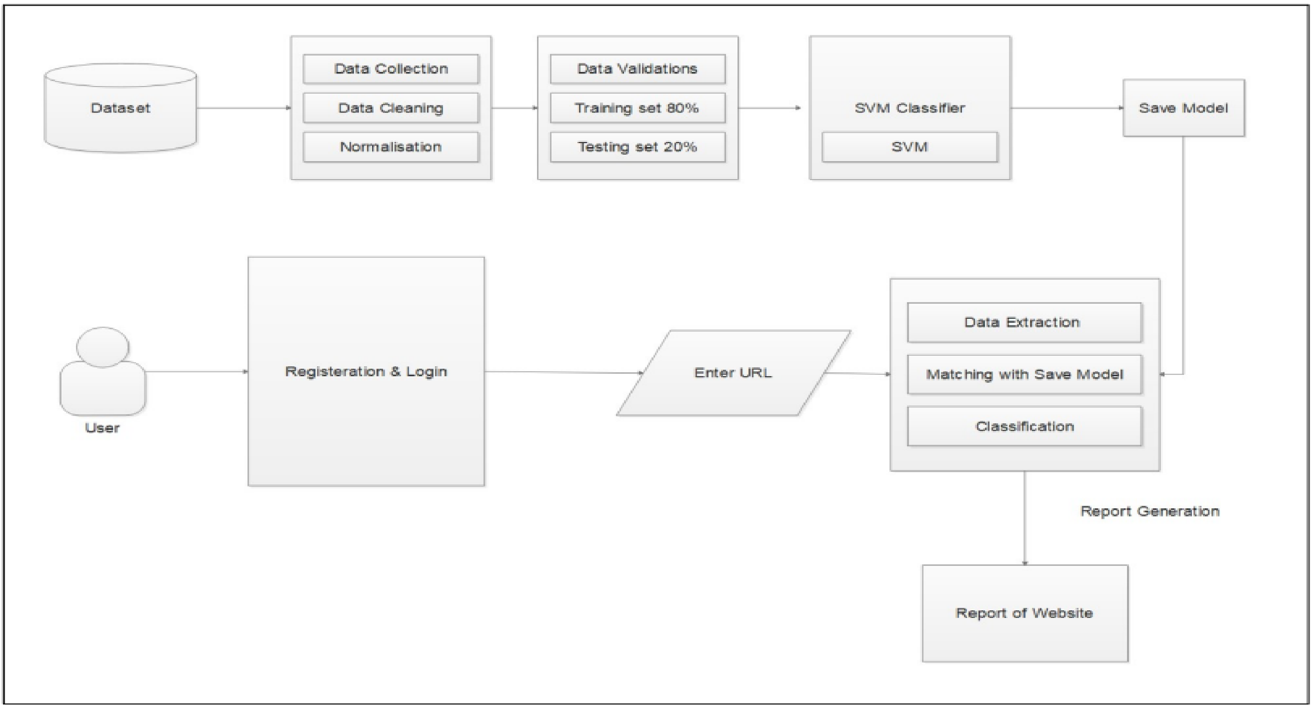

Fig. 1: Architecture Diagram

FUCTIONAL REQUIREMENTS

1. User Authentication Module: The system shall allow users to register and log in. The system shall support role-based access control (admin, user).

2. URL Submission Module: Users shall be able to submit URLs for analysis. The system shall allow batch submission of multiple URLs.

3. Data Preprocessing Module: The system shall extract relevant features from submitted URLs (e.g., length, presence of special characters, domain age). The system shall pre-process the data to prepare it for analysis.

4. Machine Learning Model Module: The system shall implement various machine learning algorithms (e.g., logistic regression, decision trees, and support vector machines) for URL classification. The system shall allow model training on a labeled dataset of URLs.

5. Real-Time Detection Module: The system shall provide real-time analysis and classification of submitted URLs. The system shall output a classification result (benign or malicious) along with a confidence score

NON FUCTIONAL REQUIREMENTS

1. Usability: The user interface shall be intuitive and easy to navigate for both admins and users. The system shall provide user documentation and support resources.

2. Performance: The system shall process URL submissions and return results within 5 seconds for real-time analysis. The machine learning model shall achieve an accuracy of at least 90% on the validation dataset.

3. Security: The system shall implement secure user authentication mechanisms (e.g., password hashing). The system shall ensure the confidentiality and integrity of user data.

4. Scalability: The system shall be designed to handle multiple simultaneous users without performance degradation. The system shall support future integration with external threat intelligence sources.

RESULTS

The performance of three machine learning algorithms was evaluated based on their classification accuracy:

- **Random Forest** achieved the highest accuracy of **88.32%**, indicating its strong capability to handle complex patterns and feature interactions in the dataset. Its ensemble approach using multiple decision trees contributed to robust and consistent performance.
- **Naive Bayes** recorded an accuracy of **85.80%**. While slightly lower than the others, it still performed well, particularly considering its simplicity and efficiency. This result reflects its effectiveness when the assumption of feature independence is reasonably valid.
- **AdaBoost** obtained an accuracy of **87.93%**, closely competing with Random Forest. By combining multiple weak learners to form a strong classifier, AdaBoost effectively reduced bias and variance, demonstrating reliable performance.

Overall, Random Forest emerged as the most accurate model in this comparison, with AdaBoost following closely, and Naive Bayes offering a competitive yet more lightweight alternative.

Precision	Recall	F1-score	Support
0.95	0.94	0.95	1482
0.17	0.05	0.08	1777
0.17	0.05	0.08	1887
0.9	0.98	0.94	30418

Table 1

Random Forest Accuracy: 88.32%

Precision	Recall	F1-score	Support
0.56	0.59	0.57	1482
0.28	0.22	0.24	1777
0.32	0.00	0.01	1887
0.90	0.96	0.93	30418

Table 2

Naive Bayes Accuracy: 85.80%

Precision	Recall	F1-score	Support
0.57	0.51	0.55	1542

0.19	0.27	0.24	1777
0.17	0.00	0.03	1887
0.95	0.89	0.97	30418

Table 3

AdaBoost Accuracy: 87.93%

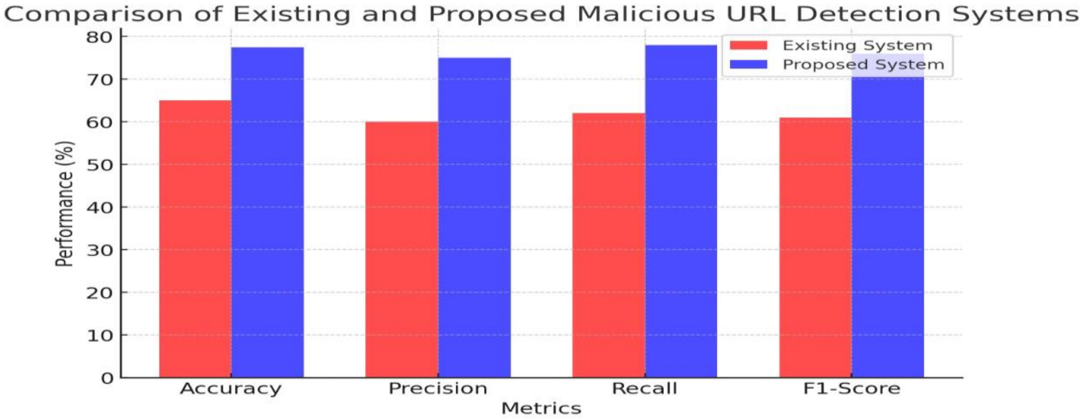

Fig. 2: Comparison of Existing and Proposed Malicious URL Detection Systems

CONCLUSION

The implementation of the Malicious URL Detection system using machine learning represents a significant advancement in the fight against cyber threats. As cybercriminals continuously evolve their tactics, traditional security measures often fall short, highlighting the urgent need for innovative solutions. By leveraging machine learning algorithms, this system not only enhances the accuracy and efficiency of malicious URL detection but also provides a scalable approach that adapts to emerging threats. The modular architecture of the system, which includes user authentication, URL submission, data preprocessing, machine learning model training, real-time detection, reporting, and an admin dashboard, ensures that all aspects of the detection process are seamlessly integrated. This design allows for a user-friendly interface that caters to both administrators and end-users, enabling efficient interaction and management of the system. Furthermore, the focus on feature extraction and data preprocessing enhances the model's ability to identify malicious URLs with a high degree of accuracy. The ability to generate real-time classification results empowers users to make informed decisions swiftly, significantly reducing the risk of falling victim to phishing attacks or malware infections. In conclusion, this project aims not only to provide an effective tool for detecting malicious URLs but also to contribute to the broader field of cyber security.

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