International Journal of Engineering and Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 14 Issue 4 April 2025 || PP 05-10

Smart Detection of Malicious URLs Using a Hybrid Machine Learning Approach

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Abstract: *As digital technologies are advancing at a very fast rate, network security threats have also become more common. Cyber attackers use several techniques, including phishing, social engineering, and pharming, to take advantage of weaknesses and mislead users. A key part of these attacks is the employment of misleading Uniform Resource Locators (URLs) to trick people into visiting malicious websites. To mitigate this emerging threat, scholars have thoroughly examined machine learning and deep learning-based techniques for malicious URL detection. In this work, we present a sophisticated malicious URL detection methodology that utilizes machine learning methods based on distinctive URL features and behavioral patterns. We also incorporate big data analytics to improve detection performance by detecting suspicious URL anomalies in real time. Our detection system includes state-of-the-art URL-based feature extraction, a stable classification model, and highly scalable big data processing. Experimental results verify that our design improves the accuracy and efficiency of malicious URL detection significantly. The observations reflect the capability of our system as an efficient and scalable approach to reducing cyber threats from malicious URLs*

Keywords **:***Malicious URL Detection,Machine Learning Algorithms, Naïve Bayes ,Decision Trees, k-Nearest Neighbors ,Neural Network ,Feature Extraction.*

Date of Submission: 27-03-2025 Date of Acceptance: 06-04-2025

I. INTRODUCTION

The swift growth of the internet has markedly heightened the risk of cyberattacks, with harmful URLs acting as a primary means for phishing, malware dissemination, and various other threats. Effectively identifying such URLs is essential for maintaining online security. Conventional methods, including blacklist-based and heuristic strategies, frequently find it challenging to keep pace with new threats due to their inherent static characteristics.

Machine learning (ML) has emerged as a robust alternative, providing dynamic and adaptable solutions for the detection of malicious URLs. By utilizing ML models, systems can examine URL patterns, domain attributes, and content features to categorize URLs as either safe or harmful. This research investigates a range of ML techniques, encompassing supervised learning algorithms, feature engineering approaches, and model evaluation methods, aimed at improving detection accuracy and reducing false positives.The proposed model integrates critical features such as lexical analysis, host-based data, and URL structural patterns to enhance predictive performance. A comparative analysis of various classifiers underscores the efficacy of ML in recognizing evolving threats in real-time situations.

1.1 Malicious URL’s and its Impact

Malicious URLs are dangerous web links designed to deceive users and facilitate phishing, malware distribution, or data theft. They use social engineering tactics and mimic legitimate websites to bypass security measures. The risks tied to these URLs are considerable, leading to financial losses, data breaches, and damage to an organization's reputation, while individuals may face identity theft and fraud. As the landscape of these threats continually evolves, traditional blacklist methods often prove inadequate. In response, machine learning models have emerged as a powerful solution, offering adaptive detection by analyzing URL patterns, domain features, and behavioral signals to enhance cybersecurity.

1.2 The Need for Malicious URL Detection

Malicious URLs are commonly utilized in various cyberattacks, such as phishing, malware dissemination, and identity theft. Traditional methods, including blacklists and signature-based detection, often find it challenging to identify newly generated or dynamic malicious URLs. As cyber threats continue to advance, these static approaches become less effective. Machine learning (ML) offers a more adaptable solution by analyzing URL structures, domain features, and behavioral patterns. ML models excel at detecting suspicious URLs, even those that closely mimic legitimate sites, thereby playing a crucial role in modern cybersecurity strategies.

1.3 Scientific Approach And Data Realibilty

The successful identification of harmful URLs is heavily reliant on the availability of precise and extensive data. Nevertheless, challenges such as insufficient datasets and the rapid advancement of attack strategies can hinder the effectiveness of models. To overcome these obstacles, researchers employ methods including web crawling, the incorporation of DNS information, and the monitoring of IP reputations. By combining open-source threat intelligence with proprietary data, they improve machine learning models, thereby increasing their ability to detect emerging threats. Ensuring high standards of data quality and diversity is essential for the creation of reliable detection systems

1.4 Contribution to this Study

This research significantly advances the domain of malicious URL detection by proposing a novel methodology that does not rely on specialized features or extensive datasets commonly utilized in conventional studies. Instead, it emphasizes the integration of easily computable characteristics with sophisticated big data processing technologies, achieving an optimal balance between processing efficiency and system precision. The results have practical implications for information security technologies, leading to the development of a complimentary tool for identifying malicious URLs within web browsers. Additionally, the study introduces innovative features derived from both the static and dynamic behaviors of URLs, thereby enhancing the detection capabilities of the system. By employing machine learning techniques such as Support Vector Machine (SVM) and Random Forest (RF), this research provides a comprehensive framework aimed at improving malicious URL detection, ultimately contributing to the enhancement of cybersecurity strategies.

II LITERATURE SURVEY

The identification of harmful URLs is a crucial aspect of cybersecurity. Numerous studies have explored innovative methodologies utilizing machine learning techniques to enhance detection accuracy and reduce false positives. This literature review emphasizes significant contributions from prominent research efforts.Recent studies have thoroughly investigated the identification of harmful URLs through the application of machine learning techniques. A variety of methods have been introduced to improve both the precision and efficiency of detection processes.

One prominent approach utilizes the Extra Tree classifier for proactive identification via lexical analysis, which has proven effective in recognizing malicious URLs, as highlighted by Aryan Nandu, J. A. Gordillo Sosa, Yagna Raj Pant, and their colleagues [1]. Furthermore, extensive reviews have examined essential algorithms such as Random Forest, Decision Trees, and Support Vector Machines, emphasizing the importance of feature extraction and dataset balancing to enhance model performance, as discussed by Rihan Bani Hani, Motasem Amoura, Mohammad Ammourah, and others [2]. Another investigation addressed the shortcomings of conventional blacklist methods by incorporating statistical analyses of both harmful and legitimate websites, thereby enhancing URL detection efficiency through advanced feature extraction techniques, as proposed by Long Zhang and Lei Hun [3]. Additionally, feature selection methods have played a crucial role in refining prediction accuracy. Mutual information techniques have been employed to identify key factors influencing detection performance, as explored by Sajjad Hussain Shah, Amit Garu, and Duong Nguyen [4]. Likewise, factor analysis has been utilized to assess the impact of variables such as URL structure, domain age, and content characteristics on the detection of malicious URLs, as presented by Tasfia Tabassum, Md. Mahbubul Alam, and Md. Sabbir Ejaz [5].

Convolutional Neural Network (CNN) frameworks have been employed to examine URL patterns by converting textual information into feature matrices, thereby improving learning efficiency, as demonstrated by Maruti Patil [6]. Additionally, researchers have explored real-time URL analysis using computer vision methods to identify suspicious patterns, which enhances detection accuracy, as investigated by Dinesh Kumar K, K. Manikandan, and S. Edwin Raja [7]. Moreover, reinforcement learning approaches have been studied to develop adaptive URL detection systems capable of dynamically updating their models in response to emerging threats, as highlighted by M Karthick Kumar and N. Sivakumar [8]. Furthermore, interpretable models such as SHAP and LIME have been utilized to increase transparency and trust in models for detecting malicious URLs, as shown by

Benfaress et al. [9]. Techniques involving multi-modal data fusion, which integrate various data sources like domain registration information, web traffic patterns, and historical attack data, have proven to enhance predictive accuracy, as discussed by Jiang et al. [10].

Ensemble learning techniques that integrate several weak classifiers have significantly improved detection models, as highlighted by Moosavi et al. [11]. Furthermore, federated learning approaches have been studied to safeguard data privacy while maintaining high detection accuracy across diverse networks and regions, as indicated by Huang et al. [12]. Recent advancements have also explored natural language processing techniques, leveraging text patterns and URL content to improve classification, as examined by Rout et al. [13]. Investigations into graph-based learning methods have demonstrated their efficacy in detecting malicious URL networks by scrutinizing domain relationships and link structures, as discussed by Ramnath et al. [14]. Additionally, cloud-based AI systems have enhanced real-time detection capabilities by employing distributed computing resources for faster analysis, as emphasized by San et al. [15].

Hybrid models that integrate various learning methodologies have been explored to bolster resilience against evasion attacks, thereby improving adaptability to new threats, as indicated by P. Anusri, S. Sneha, and Prabhu Natarajan [16]. The implementation of anomaly detection techniques has demonstrated effectiveness in recognizing previously unknown malicious URLs by identifying deviations from standard behavior, as proposed by Michael Doorumun Ishima and Samuel Apigi Ikirigo [17]. Furthermore, researchers have examined lightweight detection models specifically designed for use on devices with constrained resources, ensuring rapid and efficient identification of malicious URLs in low-power environments, as emphasized by B K Nirupama [18]. Another innovative strategy employs graph neural networks (GNNs) to investigate intricate relationships among URLs, thereby enhancing detection by analyzing the overall framework of interconnected malicious links, as studied by Liu Yuanming and Rodziah Latih [19]. Despite these advancements, challenges such as data imbalance, complexities in real-time implementation, and vulnerabilities to adversarial attacks remain, highlighting the need for robust and explainable AI methodologies in future investigations, as articulated by Zinedine et al. [20].

III. METHODOLOGY

3.1 SYSTEM ARCHITECTURE AND WORKING

The architecture of the malicious URL detection system is designed to proficiently identify harmful URLs through a systematic approach that encompasses two primary stages: Training and Detection. This dual-stage framework enables the system to learn from historical data and evaluate new URLs in real-time with precision. In the training stage, a curated dataset comprising both malicious and legitimate URLs is scrutinized. This involves feature extraction, where various attributes of the URLs—such as domain details, length, occurrence of special characters, and content-related patterns—are analyzed. A range of machine learning models, including Random Forest, Extra Trees, and Support Vector Machines, are trained on these features to develop a robust predictive model. In the detection stage, incoming URLs are evaluated using the trained model to ascertain their authenticity. The system utilizes the same feature extraction methods and contrasts the URL against the established patterns to generate a prediction. By combining effective training techniques with real-time assessment capabilities, this architecture significantly mitigates the risks posed by the continuously evolving tactics of malicious URLs.

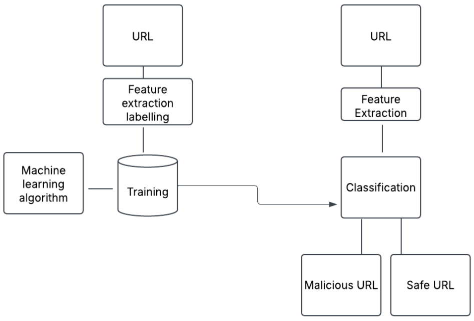

Fig 1 Architecture of the Proposed System

The training phase is essential for developing a robust model capable of distinguishing between malicious and benign URLs by recognizing specific patterns. This phase encompasses several critical steps:

3.1.1 Data Collection: A comprehensive dataset is assembled, comprising both safe and harmful URLs. This dataset is carefully curated to represent a wide range of malicious activities, facilitating thorough learning. Common sources such as Alexa Top 1M, Dmoz, Phishtank, and OpenPhish are utilized to create a balanced dataset of benign and malicious URLs.

3.1.2 Data Annotation: Each URL within the dataset is classified as either 'malicious' or 'benign,' establishing the groundwork for supervised learning models.
3.1.3 Feature Engineering: This process involves extracting various characteristics from each URL to improve detection efficacy:

- Lexical Features: These are derived from the URL text itself, including factors such as URL length, the presence of special characters, and domain structure.
- Host-based Features: These attributes pertain to the identity of the hosting server, considering elements like server reputation and geographic location.
- Content-based Features: These analyze the content of the web page associated with the URL, including its HTML structure, embedded JavaScript, and other on-page components.The objective of feature extraction is to highlight distinctive behaviors that may signal potential maliciousness.

3.1.4 Dataset Splitting: The labeled dataset is partitioned into two segments: a training set (generally 70% of the data) and a test set (30% of the data). The training set is utilized for model training, while the test set evaluates the model's performance.
3.1.5 Model Development: Machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) are trained using the extracted features. Through this training process, these models acquire the capability to identify unique patterns that differentiate malicious URLs from legitimate ones.

Following the training phase, the model transitions to the detection phase, where it assesses the safety of incoming URLs. This phase is structured as follows:
3.1.6 Input Processing: Upon submission of a URL for evaluation, the detection system initiates its processing. This involves extracting significant features using the same techniques employed during the training phase.
3.1.7 Feature Identification: The system discerns essential attributes from the URL, including lexical, host-based, and content-based characteristics. These attributes are organized into a feature vector, ensuring that the model possesses all requisite data for evaluation.
3.1.8 Classification Analysis: The prepared feature vector is subsequently analyzed by the trained machine learning models, such as Support Vector Machines (SVM) or Random Forest (RF). The model scrutinizes the input data, compares it with established patterns, and categorizes the URL as either 'malicious' or 'benign.'
3.1.9 Report Generation: Upon completing the evaluation, the system produces a comprehensive report that indicates the classification of the URL. In certain cases, the system may also highlight the key features that influenced the classification decision, thereby enhancing transparency and aiding users in understanding the results.Fig 1 will give you the glance of the working of the proposed system.

3.2 RESULTS AND DISCUSSION

The assessment of the proposed malicious URL detection system demonstrated its efficacy, particularly when employing the Random Forest algorithm. The results indicated that the system was proficient in distinguishing between malicious and benign URLs. The introduction of newly developed features, which highlighted both structural and behavioral dimensions of URLs, played a crucial role in enhancing detection accuracy. These features, encompassing aspects such as lexical analysis, host characteristics, and content assessment, provided significant insights that improved the models' ability to identify harmful URLs.

The Random Forest algorithm proved especially effective due to its ensemble methodology, which integrates decisions from multiple trees to mitigate overfitting, making it particularly suitable for intricate classification challenges. Conversely, while the Support Vector Machine (SVM) algorithm also yielded commendable results, it exhibited slightly lower accuracy in comparison to Random Forest. This discrepancy can be attributed to SVM's challenges in managing the complexity and volume of the feature set, as classification in high-dimensional spaces may not yield as favorable results as ensemble techniques.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Training Time (s)	Testing Time (s)
SVM (100 iterations)	93.50	94.75	92.60	2.40	0.02
SVM (10 iterations)	93.20	94.50	92.50	3.00	0.01
RF (10 trees)	99.15	98.50	97.60	2.80	0.01
RF (100 trees)	99.80	98.85	97.90	3.40	0.01

Table 1 Results Overview

The promising outcomes indicate a substantial potential for the practical application of this detection system, suggesting that it could serve as a valuable tool in enhancing cybersecurity by assisting users in avoiding malicious websites. The integration of this technology into web browsers or security solutions could offer an additional layer of protection against phishing and other online threats. Furthermore, despite the encouraging findings, there remains an opportunity for further refinement. Future investigations could focus on optimizing feature selection and exploring various machine learning algorithms or hybrid approaches to further improve detection efficacy. In summary, the experimental findings validate the effectiveness of machine learning-based strategies in addressing the challenges associated with malicious URL detection, significantly contributing to enhanced online safety.Table 1 gives a brief glance of the results .

IV. ADVANTAGES

1. Enhanced Detection Accuracy:Machine learning models, particularly ensemble methods like Random Forest and XGBoost, can achieve impressive detection accuracy by thoroughly analyzing URL patterns, lexical characteristics, and host-based information.
2.Automated Identification of Key Features:Deep learning models, including CNNs and RNNs, can automatically identify essential features from URL data, minimizing the need for manual input and enhancing detection efficiency.
3. Continuous Adaptation to New Threats:Machine learning algorithms can adjust to new threats by continuously learning from fresh data, ensuring they stay effective against advanced phishing strategies and malicious URL obfuscation.
4. Swift and Efficient Threat Detection:By utilizing fast machine learning algorithms and lightweight models, malicious URLs can be detected in real-time, which helps to reduce response times and lower security risks.

V. CONCLUSION

Extensive studies on the detection of malicious URLs using machine learning reveal that no single model can act as a comprehensive solution. The most successful outcomes arise from the integration of multiple approaches. Classifiers such as Random Forest, Decision Trees, and Extra Trees have demonstrated consistently high accuracy, while hybrid models improve detection efficacy by merging various feature extraction techniques. Furthermore, deep learning methodologies, including Convolutional Neural Networks (CNNs) and natural language processing (NLP) strategies, enhance performance by recognizing intricate patterns within URL structures. Adaptive learning models and transfer learning approaches address the challenges posed by the evolving nature of phishing tactics, thereby increasing the flexibility and robustness of the models.

Future investigations should focus on creating interpretable models that can elucidate their predictions clearly. This will build trust in automated systems and aid cybersecurity professionals in combating online threats. Additionally, the integration of real-time analysis, adversarial defense strategies, and scalable cloud-based solutions will be crucial for improving detection efficiency and fortifying internet security.

VI. FUTURE SCOPE

The future of identifying malicious URLs presents numerous opportunities for advancement and innovation. By employing sophisticated deep learning frameworks such as Transformer models, Graph Neural Networks (GNN), and Capsule Networks, we can enhance detection capabilities by effectively capturing intricate URL patterns and their interrelations. Furthermore, the application of federated learning techniques facilitates secure model training across decentralized networks, thereby preserving user privacy while enhancing detection precision.

Real-time detection systems that leverage edge computing can further reduce latency, ensuring prompt identification and response to threats. Developing adaptive learning frameworks that can continuously update models to address emerging phishing tactics and URL obfuscation techniques will significantly improve long-term efficacy.

Integrating Explainable AI (XAI) methodologies, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), will bolster model interpretability, fostering greater trust and transparency in detection outcomes. Additionally, merging diverse data sources such as DNS information, web traffic patterns, and user behavior analytics will enrich the context, thereby enhancing detection accuracy.

Future investigations may also explore blockchain-based URL verification systems to ensure data integrity and mitigate risks associated with manipulated web content. By adopting these innovative approaches, future models for detecting malicious URLs can achieve enhanced accuracy, scalability, and adaptability, thereby fortifying global cybersecurity initiatives.

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