Identifying URL-Based Attacks using IP Data

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***Abstract*—This paper presents a practical implementation of a system for identifying URL-based attacks using IP intelligence data. Unlike traditional approaches that rely solely on URL structure or webpage content, the proposed system integrates backend logic to extract IP addresses using DNS lookup and analyze them using threat intelligence techniques. The system is implemented as a web-based application where users can input URLs and receive real-time threat analysis. Key features include IP extraction, DNS resolution, and basic reputation analysis. The backend is developed using modern web technologies and demonstrates how machine learning and rule-based analysis can be combined for detecting malicious URLs. The system aims to provide a lightweight, efficient, and user-friendly solution for real-time cybersecurity applications.URL-based attacks such as phishing and malware distribution are increasing rapidly and pose serious threats to users and organizations. Traditional detection methods rely mainly on URL structure or blacklisting, which can be bypassed by attackers. This project presents a hybrid system for identifying malicious URLs using a combination of heuristic analysis and IP intelligence.**

The system is implemented as a web-based application using Fast API. It analyses URLs in real-time by performing multiple checks such as URL structure analysis, domain similarity detection, domain age verification using WHOIS, DNS-based IP extraction, and integration with external threat intelligence APIs like Virus Total and Abuse IPDB. A scoring-based approach is used to classify URLs as Safe, Suspicious, or Malicious. The results show that combining multiple techniques improves detection accuracy and reduces false positives. The system is efficient, scalable, and suitable for real-time cybersecurity applications.

I. INTRODUCTION

In this project, we move beyond theoretical models and implement a working prototype system. The application allows users to input a URL through a web interface, after which the backend processes the request by performing DNS lookup and extracting IP-related information. This real-time processing makes the system more practical compared to traditional offline detection methods. With the rapid growth of the internet, cyber threats such as phishing attacks and malicious websites have increased significantly. Attackers use deceptive URLs to trick users into revealing sensitive information or downloading harmful software.

Traditional approaches like blacklist-based detection are not effective against new or unknown attacks. Similarly, simple URL analysis techniques can be easily bypassed by attackers using URL obfuscation or shortening services.

To overcome these challenges, this project proposes a hybrid approach that combines heuristic-based detection with IP intelligence. The system is designed as a practical implementation where users can input a URL and receive real-time analysis result

The key contributions made by this paper can be stated as follows. Firstly, there is provided an explanation of the system architecture of the newly designed GUARDIAN framework, which focuses on the detection of URL-based threats using a multi-layered approach. The second contribution is represented by the development of a feature engineering method aimed at transforming raw IP data into the feature vector used in machine learning models for improved performance.

Besides, there is performed a thorough analysis of the performance of the GUARDIAN framework showing higher accuracy scores as well as fewer false positive results compared to the benchmark models. Finally, there is conducted an in-depth analysis of key IP-based features, which helped understand the nature of such campaigns in more details.

The remainder of this paper is structured as follows: Section II reviews related work in URL-based attack detection. Section III details the methodology and system architecture of GUARDIAN. Section IV

discusses the system's effectiveness and challenges. Section V presents the experimental results. Finally, Section VI concludes the paper and outlines directions for future research.

II. LITERATURE REVIEW

Several techniques have been proposed in the past to detect URL-based attacks such as phishing and malware distribution. These methods mainly focus on blacklist-based detection, heuristic analysis, and machine learning approaches.

Traditional blacklist-based methods, such as those used by Google Safe Browsing, rely on maintaining a database of known malicious URLs. While these methods are fast and efficient, they fail to detect newly generated or zero-day attacks.

Heuristic-based approaches analyze the structure of URLs, including length, presence of special characters, and suspicious keywords. These techniques are simple and fast but can generate false positives and are often bypassed by attackers using obfuscation techniques.

Machine learning-based methods have gained popularity in recent years. These methods use features extracted from URLs, webpage content, and domain information to train classification models. Techniques such as Decision Trees, Random Forest, and Support Vector Machines have shown good performance in detecting phishing URLs. However, these approaches require large datasets and high computational resources.

Some research has also focused on IP-based detection, where the characteristics of the hosting server, such as IP reputation, geolocation, and Autonomous System Number (ASN), are analysed. These methods provide more stable indicators but are not always sufficient when used alone.

In this project, a hybrid approach is proposed that combines heuristic analysis with IP intelligence and real-time API integration. This approach overcomes the limitations of individual methods and provides more accurate and reliable detection of malicious URLs.

III. METHODOLOGY

The proposed system follows a hybrid approach combining heuristic analysis, IP intelligence, and external threat intelligence services to detect malicious URLs in real time. The system is implemented as a web-based application using a fast API backend and follows a modular architecture. [1] System Overview the system processes a given URL through multiple stages, including domain extraction, DNS resolution, feature analysis, and scoring. Each stage contributes to identifying suspicious patterns and determining the final classification. [2] System Workflow The overall workflow of the system is as follows:

The request first goes to the backend API, where the pipeline for analyzing the data begins. After taking the input, the system pulls out the domain name from the URL so that further steps can be taken. Once the domain name is obtained, the next step involves carrying out a DNS lookup on the domain name so that an IP address can be identified and the details related to it be validated. The third step involves using various detection tools on the input URL as well as the obtained domain name on the basis of certain criteria and features. These detections produce results in terms of numerical scores, which are then combined together to provide an overall evaluation of the risk associated with the URL. The classification of the URL into Safe, Suspicious, and Malicious is determined on the basis of the aggregate result obtained from all these detection modules.

A. URL Structure Analysis

Structure Analysis of URL is developed to detect the linguistic structure of a particular URL so that any possible suspicious activity in terms of deception can be identified using heuristics. The process is based on heuristic analysis that consists of systematic analysis of those features associated with fraudsters.

There are several methods employed in this module to detect any suspicious activity in terms of URL. First of all, the program detects the presence of such keywords as “login,” “verify,” and “secure” since these words tend to be used by attackers to deceive users and obtain their confidential information. Secondly, the system analyzes the URL length and if it is too long, it indicates some fraudulent activity. Moreover, there is a special analysis conducted to check for special

characters such as '@', since these characters help fraudsters redirect users to other web pages.
Moreover, the type of protocol utilized in the URL is checked since the usage of HTTP and not HTTPS may lead to risks because of the unsecured transmission of information. In addition, the inclusion of numeric characters in the domain name is assessed because cyber criminals usually replace letters with numbers for creating fraudulent URLs.
These features serve as factors contributing to an aggregate risk score that reflects the chances of being dangerous. Therefore, the higher the score is, the more likely it will turn out to be a phishing site or another threat to cybersecurity. Such a risk scoring allows automating the process effectively.

B. Domain Similarity Detection
To detect impersonation attacks, the system compares the input domain with a list of trusted domains using string similarity techniques.
Levenshtein distance is used to measure similarity
small variations in domain names are flagged
This helps identify fake domains that mimic legitimate websites.

C. Domain Age Analysis
The system gets the necessary data from the domain's registration through WHOIS services for the evaluation of the credibility of the domain under consideration. This gives us such important details like the age of the domain. On the basis of this data, the system performs an analysis of the age of the domain as an important aspect of the reliability of the domain. Domains that were recently registered by someone else are considered risky since attackers tend to create new domains in order to conduct phishing attacks and other cybercrimes. Therefore, domain age becomes one of the key aspects in detecting phishing and can be used in our scheme.

D. DNS Resolution and IP Extraction
The algorithm resolves the provided domain name to an IP address using the DNS server, allowing for the verification of its existence and availability on the network. If the domain name successfully resolves to a valid IP address, then it can be inferred that the domain is legitimate, and vice versa. If the domain name fails to resolve to a valid IP address, then there is some doubt about its authenticity. Once a valid IP address has been obtained, the information can be used for further analysis in other modules.

E. IP Intelligence Analysis
The evaluation of the reputation of the IP address resolution is achieved by utilizing the capabilities of the threat intelligence services to estimate the likelihood that the IP address is engaged in any malicious activity. This includes looking at IP abuse records to find out whether the IP address was involved in any previous cases of IP abuse or blacklisted due to suspicious behavior. The reputations of the IP addresses are estimated based on the information about their malicious history from security databases, which helps in determining how much can be trusted the IP address.

F. External Threat Intelligence Integration
The system utilizes third-party threat intelligence API, for example, VirusTotal for conducting domain reputation analysis and AbuseIPDB for assessing the score for IP abuse. Both of these APIs offer comprehensive datasets that can be leveraged by the system for analyzing threats based on real-life threat intelligence, which includes details about known malicious domains, reported IPs, and attacks performed in the past.

G. Brand Misuse Detection
The system conducts a brand name analysis through determining whether there are any mentions of known brand names within the analyzed domain. The rationale for this is based on the need to detect any cases of impersonation that have been identified as common among phishing sites. Any mention of known brands in domains considered untrusted or malicious will lead to the flagging of such domains as possible threats. This is due to the fact that such behavior has been linked to cases where attackers try to pose as legitimate institutions in order to fool their victims.

H. Trusted Domain Verification
There is a list of trusted domains that serves to increase the reliability of the process and decrease errors. When a URL matches one of the trusted domains, the algorithm will classify it as safe because it comes from a trustworthy source. In this way, it becomes possible to avoid false positives, which would otherwise lead to the misclassification of trusted URLs as harmful.

[5] Scoring and Classification each module contributes to a cumulative risk score based on its findings. **T**he final classification is determined using predefined thresholds: Score < 40 → SAFE, **Score** between 40 and 89 → SUSPICIOUS, Score ≥ 90 → MALICIOUS. This scoring mechanism allows flexible and interpretable decision-making. [6[Implementation Details **t**he system implementation is based on an amalgamation of contemporary technological solutions ensuring efficient operations and accurate threat assessment. The backend API was created using the FastAPI framework facilitating efficient request processing and smooth interaction between API and analytical engines. All the core processing and analysis functions were performed by Python due to a wide variety of libraries available in this programming language.

As for network functions, Socket was used for DNS resolving and connection with external services. All the domain details required for further analysis are provided by WHOIS services. They are needed since the system evaluates domain legitimacy based on the provided data. Moreover, REST APIs were used to connect with external security systems providing necessary threat intelligence information.

Such a combination of technologies ensures system efficiency and accurate URL and domain analysis.

[6] Advantages of Proposed Method: Real-time URL analysis, combines multiple detection techniques, reduces false positives, Scalable and efficient, Easy to integrate into web applications

IV. DISCUSSION

The proposed hybrid system demonstrates the effectiveness of combining heuristic analysis with IP intelligence for detecting URL-based attacks. Unlike traditional methods that rely on a single detection technique, this system integrates multiple layers of analysis, making it more robust against modern cyber threats.

One of the key strengths of the system is its ability to detect suspicious patterns in URLs using heuristic rules. Features such as unusual URL length, presence of phishing-related keywords, excessive subdomains, and insecure protocols provide early indicators of malicious intent. However, relying solely on heuristic analysis may lead to false positives, especially for legitimate websites with uncommon structures.

To overcome this limitation, the system incorporates IP intelligence and external threat data. Integration with services like VirusTotal and AbuseIPDB enhances detection accuracy by providing real-world reputation scores and historical abuse data. This significantly improves the system's ability to identify malicious domains that may appear legitimate at first glance.

Another important component is domain age analysis using WHOIS data. It is observed that many phishing websites are hosted on newly registered domains. By assigning higher risk scores to such domains, the system effectively captures this behaviour. Additionally, domain similarity detection using string comparison techniques helps identify impersonation attacks where attackers create domains similar to trusted websites.

The scoring-based classification approach used in the system offers flexibility and interpretability. Instead of making binary decisions, the system evaluates multiple factors and assigns a cumulative risk score. This allows better differentiation between safe, suspicious, and malicious URLs. However, the accuracy of the system depends on the proper tuning of scoring thresholds.

Despite its advantages, the system has certain limitations. It relies on external APIs for threat intelligence, which may introduce delays or dependency issues. Additionally, attackers using highly sophisticated techniques, such as compromised legitimate domains, may bypass detection.

Overall, the hybrid approach proves to be effective and practical for real-time URL analysis. By combining multiple detection strategies, the system achieves better performance compared to traditional methods and provides a strong foundation for further enhancements.

V. RESULTS

The proposed hybrid URL attack detection system was evaluated in a real-time environment using a FastAPI-based backend. The system was tested by providing various URLs as input through the frontend interface. It integrates multiple components such as DNS resolution for IP extraction, WHOIS lookup for domain age analysis, and external threat intelligence services like VirusTotal and AbuseIPDB. These

components work together to generate a cumulative risk score and classify URLs effectively.

5.2 Analysis of Legitimate URLs

The system was tested using well-known and trusted websites such as google.com and amazon.com. In these cases, the system consistently generated low risk scores and correctly classified them as safe. This is mainly because such domains have strong reputation scores, valid DNS resolution, and older domain age. Additionally, the trusted domain verification mechanism ensures that these websites are not falsely flagged as malicious. This demonstrates that the system effectively minimizes false positives.

5.3 Analysis of Suspicious URLs

Suspicious URLs with unusual patterns were also tested to evaluate the system's intermediate classification capability. These URLs often contained characteristics such as long URL length, excessive subdomains, or minor use of suspicious keywords. The system assigned moderate risk scores to such URLs and classified them as suspicious. This indicates that the scoring mechanism is capable of identifying potential threats without immediately categorizing them as malicious, thereby providing a balanced decision-making approach.

5.4 Analysis of Malicious URLs

The system showed strong performance when tested with phishing and malicious URLs. These included domains that mimic popular websites, newly registered domains, and URLs flagged by threat intelligence services. The system detected various indicators such as domain similarity, high IP abuse scores, malicious reports from APIs, and suspicious domain age. As a result, these URLs were assigned high risk scores and classified as malicious. This confirms the effectiveness of combining heuristic analysis with IP intelligence.

5.5 Performance Evaluation

The overall performance of the system demonstrates that the hybrid approach significantly improves detection accuracy. Heuristic analysis provides quick identification of suspicious patterns, while IP intelligence and API-based validation enhance reliability. The scoring system ensures that the classification is not based on a single factor but on a combination of multiple indicators. This reduces the chances of incorrect classification and improves system robustness.

5.6 Limitations

Despite its effectiveness, the system has certain limitations. It depends on external APIs for threat intelligence, which may introduce latency or availability issues. Additionally, highly sophisticated attacks using compromised legitimate domains may not always be detected. The accuracy of the system also depends on proper tuning of scoring thresholds.

5.7 Overall Outcome

In conclusion, the system successfully performs real-time URL analysis and provides accurate classification of URLs into safe, suspicious, and malicious categories. The integration of multiple detection techniques ensures improved performance compared to traditional methods. The results validate that the proposed system is practical, efficient, and suitable for real-world cybersecurity applications.

VI. CONCLUSION

In this project, a hybrid system for detecting URL-based attacks was successfully designed and implemented. The system combines heuristic analysis, IP intelligence, and external threat intelligence services to identify malicious URLs in real time. Unlike traditional methods that rely on a single detection technique, this approach integrates multiple modules such as URL structure analysis, domain similarity detection, domain age verification, DNS-based IP extraction, and API-based reputation analysis.[1] Key Achievements the system demonstrates several important achievements in the field of cybersecurity. It is capable of analyzing URLs in real time and classifying them into safe, suspicious, and malicious categories using a scoring-based approach. The integration of services like VirusTotal and AbuseIPDB enhances detection accuracy by incorporating real-world threat intelligence. Additionally, the use of domain similarity detection and WHOIS-based domain age analysis helps in identifying phishing attacks effectively.[2] Effectiveness of the Proposed System the results of the system indicate that the hybrid approach improves detection performance compared to traditional

methods. Heuristic analysis enables quick identification of suspicious patterns, while IP intelligence provides deeper insights into domain behaviour. The scoring mechanism ensures balanced classification and reduces false positives. Overall, the system proves to be efficient, scalable, and suitable for practical applications.[3] Limitations Despite its advantages, the system has certain limitations. It relies on external APIs for threat intelligence, which may affect performance due to latency or availability issues. Additionally, advanced attacks using compromised legitimate domains may not always be detected. The accuracy of the system also depends on proper tuning of scoring thresholds.[4] Future Scope the system can be further enhanced by integrating machine learning models to improve detection accuracy. Additional features such as real-time browser extensions, database logging, and analytical dashboards can also be implemented. Expanding support for IPv6 and improving detection of advanced attack techniques will further strengthen the system.[5] Final Remark In conclusion, the proposed hybrid URL attack detection system provides an effective and practical solution for identifying malicious URLs. By combining multiple detection techniques, it overcomes the limitations of traditional approaches and offers a reliable method for enhancing online security.

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