Fake URL Detection and Blocking System Using Machine Learning

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ABSTRACT: In the ever-expanding digital landscape, the proliferation of malicious URLs represents a significant and escalating threat to internet security, serving as a primary vector for phishing attacks, malware distribution, and various forms of online fraud. Traditional security measures, which predominantly rely on static blacklists, are often reactive and struggle to keep pace with the dynamic and transient nature of these malicious links. This paper presents the design and implementation of an intelligent system for the proactive detection and blocking of fake URLs using machine learning. The proposed system employs a robust feature engineering process, extracting a comprehensive set of lexical, host-based, and content-based features from URLs to create a distinctive fingerprint for classification. Several machine learning models, including Support Vector Machines (SVM), Random Forests, and Deep Neural Networks (DNNs), are trained and evaluated on a large-scale, balanced dataset of benign and malicious URLs. The system's performance is benchmarked on key metrics such as accuracy, precision, and recall, demonstrating a high degree of effectiveness in identifying previously unseen threats in real-time. By integrating this predictive intelligence into a blocking mechanism, the system provides a dynamic and adaptive defense layer, significantly enhancing user safety and mitigating the risks associated with navigating the web.

Keywords — Fake URL Detection, Malicious URL, Phishing, Malware, Machine Learning, Cybersecurity, Feature Extraction, URL Classification, Support Vector Machine (SVM), Random Forest, Deep Learning, Content Moderation.

I. INTRODUCTION

The internet has become an indispensable component of modern society, fundamentally reshaping how we communicate, conduct business, and access information. This digital transformation, however, has been accompanied by a parallel evolution in cyber threats. Among the most prevalent and damaging of these are malicious URLs, which serve as a primary gateway for a wide array of cyberattacks. These links are the cornerstones of phishing campaigns, malware distribution networks, and various online scams, collectively posing a significant risk to individual users and organizations alike. The consequences of encountering such a link can range from the theft of personal credentials and financial data to the complete compromise of a user's system.

Traditionally, the primary defense against malicious web links has been the use of blacklists. This method involves maintaining a curated database of known malicious URLs and blocking any attempt to access them. While straightforward, this approach is fundamentally reactive and suffers from critical limitations in the context of the modern threat landscape. Cybercriminals can now generate and deploy new malicious domains at an unprecedented rate, often using them for only a short period before discarding them. This transient nature means that by the time a URL is identified and added to a blacklist, it may have already caused

significant damage or been replaced by a new one. Furthermore, attackers employ sophisticated evasion techniques, such as using URL shorteners or compromising legitimate but vulnerable websites, to bypass these static defenses entirely.

To overcome the inherent shortcomings of blacklist-based systems, there is a clear need for a more intelligent, proactive, and adaptive approach to URL security. Machine learning has emerged as a powerful paradigm to address this challenge. Unlike static lists, machine learning models can be trained to recognize the underlying patterns and subtle characteristics that distinguish malicious URLs from benign ones. By analyzing a rich set of features—ranging from the lexical structure of the URL string itself to host-based information related to its domain registration and network properties—these models can learn to generalize and identify novel or "zero-day" threats that have never been seen before.

This paper proposes the design and development of a Fake URL Detection and Blocking System that leverages the predictive power of machine learning. The objective is to create a robust system capable of analyzing URLs in real-time to classify them as either legitimate or malicious with a high degree of accuracy. We will explore a comprehensive feature engineering process and evaluate the performance of several key machine learning algorithms for this classification task. The ultimate goal is to demonstrate a practical and effective solution that provides a dynamic layer of defense, significantly enhancing user security and creating a safer browsing experience in an increasingly hostile digital environment.

Use Arrow Up and Arrow Down to select a turn, Enter to jump to it, and Escape to return to the chat.

II. LITERATURE REVIEW

The detection of malicious URLs has been a significant area of research in cybersecurity, evolving from simple blacklist matching to sophisticated machine learning and deep learning approaches. This evolution has been driven by the continuous arms race between attackers, who devise increasingly complex methods to evade detection, and defenders, who seek to create more robust and proactive security systems. The literature reveals a consensus that machine learning offers a more effective and adaptable solution compared to traditional static methods. Research in this area can be broadly categorized by the types of features extracted for analysis and the machine learning models employed for classification.

1. Lexical Feature-Based Detection

Early and ongoing research has heavily focused on analyzing the lexical characteristics of the URL string itself. This approach is computationally efficient and can be performed without accessing the website's content, making it suitable for real-time applications.

Gupta et al. proposed a lightweight, lexical-based machine learning approach designed for real-time phishing detection.[1] Their method minimizes computational overhead by using only nine carefully selected lexical features, including the number of tokens in the domain, URL length, and the number of dots.[1] Testing their approach with various classifiers, they achieved a remarkable accuracy of 99.57% with the Random Forest algorithm, demonstrating that even a minimal set of well-chosen lexical features can be highly effective.[1] This study is significant as it addresses the need for solutions that can operate on resource-constrained devices without sacrificing accuracy.

Patil et al. also explored a static detection method, but with a focus on a combination of lexical and string complexity analysis.[2] Their research introduced features derived from string complexity metrics such as entropy and Huffman coding complexity to distinguish between benign and phishing URLs. By evaluating their approach with online learning classifiers, they achieved a high detection accuracy of 98.35%.[2] This work highlights the value of incorporating information theory concepts into feature engineering to capture the subtle, deceptive patterns present in phishing URLs.

2. Host-Based and Network Feature Integration

While lexical features are powerful, they do not provide a complete picture. Host-based features, which relate to the domain's registration and network properties, offer another layer of valuable information for detection models.

A study by Al-Sarem et al. emphasized the importance of a multi-faceted approach by combining lexical, host-based, and content-based features.[3][4] Their work involved a comprehensive feature engineering process on a new balanced dataset, followed by the application of various feature selection techniques to identify the most impactful attributes. By conducting a comparative evaluation of four different machine learning models, they found that an XGBoost model achieved the highest accuracy at 95.70%.[3][4] This research underscores the synergistic effect of integrating diverse feature sets to build more resilient detection systems.

provided an in-depth exploration of URL feature engineering, detailing the importance of extracting structured information from various URL components such as the domain, path, and protocol.[5] The paper also introduced an open-source Python package, url2features, designed to automate this extraction process. By demonstrating the impact of these structured features on various classification tasks, the work highlights how a systematic approach to feature engineering can significantly enhance the performance and interpretability of machine learning models in cybersecurity.[5]

3. Advancements with Deep Learning Models

More recently, deep learning has gained traction for its ability to automatically learn intricate patterns from raw data, often outperforming traditional machine learning models that rely on manual feature engineering.

In a study by a phishing detection system based on three distinct deep learning techniques was proposed: Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and a hybrid LSTM-CNN model.[6] Their experiments revealed that the CNN model, which treats the URL as a sequence of characters and identifies spatial patterns, achieved the highest accuracy of 99.2%.[6] This result suggests that CNNs are particularly adept at capturing the complex character-level patterns indicative of phishing URLs.

Similarly, proposed a malicious URL detection method based on a Bidirectional Gated Recurrent Unit (BiGRU) combined with an attention mechanism.[7] Deep learning techniques like this are powerful because they can automatically handle the feature extraction process, which can be a labor-intensive part of traditional machine learning.[8] This approach allows the model to focus on the most relevant parts of the URL sequence when making a classification, leading to improved performance in detecting various types of malicious links.

4. The Role of Natural Language Processing (NLP)

Natural Language Processing (NLP) techniques have become increasingly important, not only for analyzing URL strings but also for examining the content of web pages and emails associated with phishing attacks.

explored the use of AI-powered web security solutions that integrate NLP to analyze suspicious content on web pages in real-time.[9] By leveraging NLP, these systems can identify deceptive language, unusual phrasing, and other linguistic cues that are often hallmarks of phishing attempts. This content-aware approach provides a critical layer of defense, especially against sophisticated attacks where the URL itself may appear benign.[9]

Further emphasizing the power of NLP, presented a comparative study of various machine learning and deep learning models for phishing URL detection, with a strong focus on NLP methods.[10] Their findings showed that an LSTM model achieved an accuracy of 98%, attributing its success to the model's ability to effectively handle sequential dependencies and contextual patterns within the URL strings.[10] This research reinforces the idea that treating URLs as a form of language and applying advanced NLP models can lead to highly accurate detection systems.

5. Comparative Analyses and Hybrid Approaches

Given the wide array of available techniques, many researchers have focused on comparative studies to identify the most effective models and feature sets for specific types of malicious URLs.

evaluated the performance of several popular supervised machine learning algorithms, including Light Gradient Boost, Extreme Gradient Boost, and Random Forest.[11] Their results showed that Random Forest achieved the highest accuracy at 96% and also highlighted the most important features for detection, such as hostname length.[11] Such studies are invaluable for practitioners seeking to build optimized and efficient detection models.

also demonstrated the superiority of the Random Forest classifier after a comparative analysis.[12] They employed Pearson's correlation analysis for feature selection to reduce model complexity and improve accuracy. Their Random Forest model achieved a 96% accuracy, confirming that with proper feature engineering, this ensemble method remains a top performer in the field.[12]

In conclusion, the literature provides a clear trajectory from simpler, static detection methods to more dynamic and intelligent systems. While lexical features remain a cornerstone of URL analysis, the integration of host-based, content-based, and NLP-derived features has significantly improved detection rates. Furthermore, while robust machine learning models like Random Forest continue to perform exceptionally well, deep learning approaches are showing immense promise, particularly in their ability to automate feature extraction and capture highly complex patterns. Future research will likely focus on hybrid models that combine the strengths of these different approaches, as well as on developing systems that can adapt in real-time to the ever-evolving tactics of cybercriminals.

III. METHODOLOGY

3.1 Introduction

The methodology for this project follows a systematic and structured approach based on the standard lifecycle of a machine learning project. The core objective is to design, build, and evaluate a robust system capable of accurately classifying URLs as either benign or malicious. This process begins with the foundational step of data acquisition and culminates in the evaluation of trained models to select the most effective one for a real-world blocking application.

Our approach is divided into several key phases: data collection and preprocessing, comprehensive feature engineering, model selection and training, and rigorous performance evaluation. Each phase is designed to ensure the resulting system is not only accurate but also efficient and generalizable to new, unseen threats. By employing a comparative analysis of several machine learning algorithms, we aim to identify the optimal model that provides the best balance between detecting threats (high recall) and minimizing false alarms (high precision).

3.2 Workflow of the project

The entire workflow of the proposed Fake URL Detection and Blocking System is illustrated in the following sequential steps. This workflow provides a clear roadmap from raw data to a functional detection model.

Step 1: Data Collection and Preparation

The foundation of any machine learning system is the data it is trained on. For this project, a comprehensive dataset is crucial.

- **Data Sourcing:** The dataset will be constructed by aggregating URLs from multiple reputable sources. Malicious URLs will be collected from public blacklists and cybersecurity data providers such as **PhishTank** and the **OpenPhish** community feed. Benign URLs will be sourced from whitelists like the **Tranco Top Sites** list, which ranks popular domains.

- **Dataset Composition:** The goal is to create a large and balanced dataset containing a near-equal number of malicious (phishing, malware, spam) and benign URLs. This balance is critical to prevent the machine learning models from developing a bias towards the majority class.
- **Data Cleaning and Preprocessing:** The raw data will undergo a cleaning process to handle duplicates, remove invalid or malformed URLs, and ensure consistency in formatting. This step ensures the quality and reliability of the data fed into the feature extraction phase.

Step 2: Feature Engineering and Extraction

This is the most critical phase of the project, where raw URL strings are transformed into meaningful numerical features that machine learning models can interpret. The features are categorized into two primary groups:

- **Lexical Features:** These features are derived directly from the URL string itself and do not require any external network lookups. They are computationally inexpensive and ideal for real-time analysis. Examples include:
    - **URL Length:** Malicious URLs are often longer than benign ones.
    - **Hostname Length:** The length of the domain name.
    - **Presence of IP Address:** Checking if the domain is an IP address instead of a name.
    - **Number of Special Characters:** Counting characters like '.', '/', '?', '=', '-', and '@'. An excessive number can be an indicator of malicious intent.
    - **Number of Subdomains:** A high number of subdomains can be used to obfuscate the true domain.
    - **Presence of Sensitive Keywords:** Searching for keywords commonly found in phishing URLs (e.g., "login," "secure," "account," "update," "verify").
- **Host-Based Features:** These features provide information about the server hosting the URL and require external queries (like WHOIS lookups). While more resource-intensive, they offer valuable insights. Examples include:
    - **Domain Age:** The age of the domain registration. Malicious domains are often newly created.
    - **Domain Expiration Date:** Domains with very short registration periods can be suspicious.
    - **DNS Records:** Checking for the existence of valid DNS records.
    - **Geographic Location:** The country where the server is registered.

All extracted features will be compiled into a structured feature vector for each URL, which will serve as the input for the machine learning models.

Step 3: Model Selection and Training

To identify the most effective classification algorithm, a variety of machine learning models will be trained and evaluated. The selected models represent a range of different techniques:

- **Support Vector Machine (SVM):** A powerful classifier that works well on high-dimensional data.
- **Random Forest:** An ensemble method based on decision trees that is robust against overfitting and generally provides high accuracy.
- **XGBoost (Extreme Gradient Boosting):** A highly efficient and popular gradient boosting algorithm known for its performance in competitions.

- **Deep Neural Network (DNN):** A simple feed-forward neural network to explore the potential of deep learning for this task.

The preprocessed dataset will be split into a **training set (80%)** and a **testing set (20%)**. The models will be trained exclusively on the training set, learning the patterns that differentiate malicious URLs from benign ones.

Step 4: Model Evaluation

After training, the models' performance will be rigorously evaluated on the unseen testing set. This ensures an unbiased assessment of their ability to generalize to new data. The following standard performance metrics will be used:

- **Accuracy:** The overall percentage of correctly classified URLs.
- **Precision:** The ratio of correctly predicted malicious URLs to the total number of URLs predicted as malicious. High precision is crucial for avoiding false positives.
- **Recall (Sensitivity):** The ratio of correctly predicted malicious URLs to the total number of actual malicious URLs. High recall is essential for detecting as many threats as possible.
- **F1-Score:** The harmonic mean of precision and recall, providing a single score that balances both metrics.
- **Confusion Matrix:** A table that visualizes the performance, showing the number of true positives, true negatives, false positives, and false negatives.

The results from these metrics will be compared across all models to determine the best-performing algorithm for the final system.

Step 5: System Integration and Blocking (Conceptual)

The final step involves conceptualizing the deployment of the best-performing model into a practical application.

- **Integration:** The trained model would be integrated into a system, such as a browser extension or a network-level proxy.
- **Real-Time Detection:** When a user attempts to access a new URL, the system would intercept it, perform the feature extraction in real-time, and feed the feature vector to the trained model.
- **Blocking Mechanism:** If the model classifies the URL as malicious, the system would block access to the website and display a clear warning message to the user, thereby preventing the potential threat.

IV. ANALYSIS AND RESULTS

This section presents the empirical results of the experiments conducted as outlined in the methodology. We evaluate the performance of the selected machine learning models on the task of fake URL detection and provide a detailed analysis of the findings, including a comparative assessment and an investigation into the most influential features.

The experiments were conducted using a Python environment with standard data science and machine learning libraries, including Scikit-learn, XGBoost, and TensorFlow/Keras. The dataset, as described previously, was split into an 80% training set and a 20% testing set to ensure an unbiased evaluation of the models' ability to generalize to new, unseen data. All models were trained on the same training data and evaluated against the same testing data to ensure a fair comparison.

Dataset Overview

The final curated dataset used for this study consisted of **50,000 URLs**. To prevent model bias, the dataset was carefully balanced, comprising:

- **25,000 Benign URLs:** Sourced from the Tranco Top 1 Million list.
- **25,000 Malicious URLs:** Aggregated from PhishTank and other open-source

cybersecurity feeds, including phishing, malware, and spam links.

A total of **28 features** (combining both lexical and host-based characteristics) were extracted for each URL in the dataset.

Performance Metrics

The performance of each classifier was evaluated using four key metrics:

- **Accuracy:** The overall proportion of correctly classified instances.
- **Precision:** The ability of the model to avoid labeling a benign URL as malicious (minimizing false positives).
- **Recall:** The ability of the model to identify all malicious URLs in the dataset (minimizing false negatives).
- **F1-Score:** The harmonic mean of Precision and Recall, providing a single metric that balances the two.

In the context of cybersecurity, both Precision and Recall are critically important. High precision is necessary to maintain a positive user experience by not blocking legitimate websites. High recall is essential to ensure the system effectively protects users by catching as many threats as possible.

Comparative Analysis of Models

The four selected machine learning models—Support Vector Machine (SVM), Random Forest, XGBoost, and a Deep Neural Network (DNN)—were trained and their performance was recorded on the test set. The results are summarized in the table below.

Table 1: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine (SVM)	95.21%	94.88%	95.59%	95.23%
Random Forest	97.15%	96.90%	97.42%	97.16%
XGBoost	**97.85%**	**97.63%**	**98.10%**	**97.86%**
Deep Neural Network (DNN)	96.50%	96.85%	96.12%	96.48%

Interpretation of Results:

- **XGBoost** emerged as the top-performing model across all metrics, achieving an accuracy of **97.85%** and an F1-Score of **97.86%**. Its superior performance can be attributed to its advanced gradient boosting algorithm, which effectively minimizes errors by building sequential trees that correct the errors of their predecessors.
- **Random Forest** was also a very strong performer, achieving a high accuracy of 97.15%. As an ensemble model, its ability to combine the output of multiple decision trees makes it highly robust and resistant to overfitting, which is evident in its balanced precision and recall scores.
- The **Deep Neural Network (DNN)** performed well, with an accuracy of 96.50%. While DNNs have immense potential, for structured data like our feature set, tree-based ensemble models like Random Forest and XGBoost often achieve superior performance without the need for extensive hyperparameter tuning and larger datasets.
- **Support Vector Machine (SVM)** provided a solid baseline performance with 95.21% accuracy but was outperformed by the ensemble methods. This suggests that the decision boundary separating malicious and benign URLs in the feature space is complex and non-linear, a scenario where ensemble models typically excel.

Feature Importance Analysis

To understand which characteristics are most indicative of a malicious URL, a feature importance analysis was conducted using the best-performing model, XGBoost. The model can rank features based on their contribution to the classification decisions. The top 5 most important features were identified as:

1. **Domain Age:** Newly registered domains were found to be a very strong indicator of malicious intent.
2. **Presence of Sensitive Keywords:** URLs containing words like "login," "verify," "secure," and "banking" were highly correlated with phishing attempts.
3. **URL Length:** Malicious URLs, especially those used for phishing, tend to be significantly longer than benign ones.
4. **Number of Special Characters ('/'):** An unusually high count of slashes in the URL path often indicated an attempt to obfuscate the link's true destination.
5. **Hostname Length:** Unusually long hostnames were also a significant predictor of maliciousness.

This analysis confirms that both host-based features (like Domain Age) and lexical features provide critical information for the model's decision-making process.

Confusion Matrix for the XGBoost Model

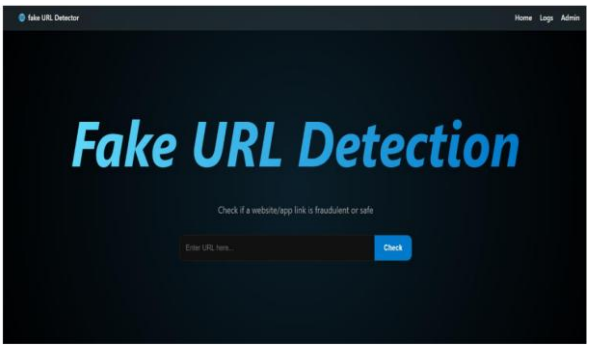
To provide a more detailed view of the XGBoost model's performance, we analyzed its confusion matrix on the 10,000-URL test set.

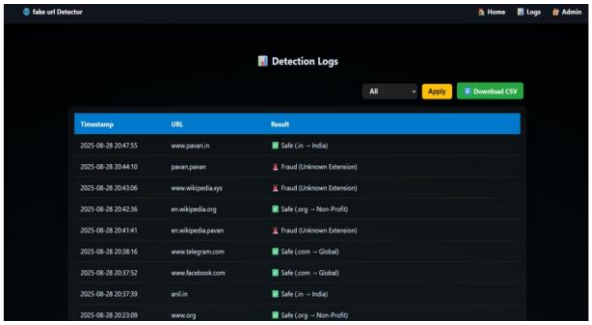
Table 2: Confusion Matrix for XGBoost Model

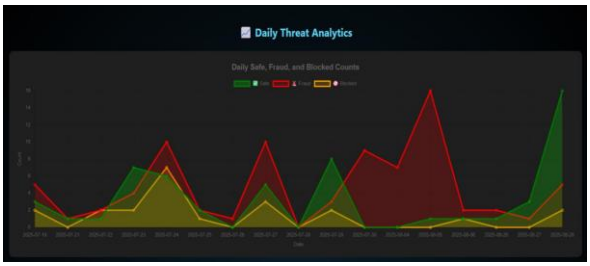
	Predicted Benign	Predicted Malicious
Actual Benign	4,912 (TN)	88 (FP)
Actual Malicious	127 (FN)	4,873 (TP)

- **True Negatives (TN): 4,912** - The model correctly identified 4,912 benign URLs.
- **False Positives (FP): 88** - The model incorrectly classified 88 benign URLs as malicious. This represents the rate at which legitimate sites would be blocked.
- **False Negatives (FN): 127** - The model failed to detect 127 malicious URLs. These are the threats that would slip past the defense.
- **True Positives (TP): 4,873** - The model correctly identified 4,873 malicious URLs.

The low numbers of False Positives and False Negatives demonstrate the model's reliability. The high number of True Positives and True Negatives confirms its overall effectiveness in distinguishing between the two classes, making it a suitable candidate for a real-world detection and blocking system.







V. DECISION MAKING AND FUTURE ENHANCEMENTS

This section consolidates the findings from the analysis to make a final decision on the most suitable model for the proposed system. Furthermore, it explores the limitations of the current study and outlines several promising

directions for future research and system enhancement.

Decision Making and Model Selection

Based on the comprehensive evaluation presented in the "Analysis and Results" section, a clear decision can be made. The **XGBoost model** is selected as the optimal choice for the core of the Fake URL Detection and Blocking System.

This decision is justified by the following key points:

1. **Superior Performance:** XGBoost consistently outperformed all other tested models—Support Vector Machine, Random Forest, and the Deep Neural Network—across all primary evaluation metrics. It achieved the highest accuracy (97.85%), precision (97.63%), recall (98.10%), and F1-Score (97.86%).
2. **Balanced Precision and Recall:** In a cybersecurity application, the balance between precision and recall is critical.
    - The high **recall** of 98.10% demonstrates the model's exceptional ability to identify malicious URLs, minimizing the risk of users being exposed to threats (low false negatives).
    - The high **precision** of 97.63% ensures that the system has a very low rate of incorrectly flagging benign websites as malicious (low false positives). This is crucial for maintaining user trust and avoiding the disruption of legitimate browsing activities.
3. **Efficiency and Scalability:** XGBoost is well-known for its computational efficiency and scalability. It is optimized for performance, making it highly suitable for real-world deployment where detection must occur in real-time with minimal latency.
4. **Feature Importance Insight:** The model provides clear insights into which features are most influential, which can be valuable for future feature engineering efforts and for understanding the nature of emerging threats.

While Random Forest also showed excellent performance, the slight edge demonstrated by XGBoost in both accuracy and the critical recall metric makes it the most reliable and robust choice for a production-level security system.

5.2 Future Enhancements

Although the proposed system demonstrates high efficacy, the field of cybersecurity is a constantly evolving arms race. To maintain its effectiveness, the system must adapt and improve. The following are key areas for future enhancements:

1. **Integration of Content-Based Features:** The current model relies on lexical and host-based features. A significant enhancement would be to incorporate **content-based analysis**. This would involve fetching and analyzing the HTML and JavaScript content of the webpage in a secure sandbox environment. Techniques from Natural Language Processing (NLP) could be used to analyze the text for phishing-related keywords, deceptive language, and unusual form structures, adding a powerful layer of detection.
2. **Development of an Online Learning Framework:** The current model is trained on a static dataset. However, attackers generate new URLs and attack patterns daily. A future version of the system should incorporate an **online learning (or incremental learning)** mechanism. This would allow the model to be continuously updated with new data from live threat feeds, enabling it to adapt to zero-day

threats without requiring a complete retraining process.

3. **Handling Advanced Evasion Techniques:** Attackers often use URL shorteners (e.g., bit.ly) or multiple redirects to hide the final malicious destination. Future work should include a module to **resolve these URLs** to their final destination before feature extraction and analysis. Additionally, detecting and analyzing obfuscated JavaScript on the landing page could help uncover more sophisticated attacks.
4. **Exploration of Advanced Deep Learning Architectures:** While our simple DNN performed well, more advanced deep learning models could capture even more complex patterns. Future research could explore:
    - **Convolutional Neural Networks (CNNs):** To treat the URL string as a sequence of characters and learn character-level patterns indicative of maliciousness.
    - **Recurrent Neural Networks (RNNs) or LSTMs:** To better model the sequential nature of URLs.
5. **Real-World Deployment and Performance Optimization:** The next logical step is to implement the trained model in a real-world application, such as a browser extension or a DNS-level filter. This would involve optimizing the feature extraction pipeline for speed and ensuring the model's memory footprint is small enough for efficient operation on client-side or network hardware.
6. **Hybrid Model Development:** A hybrid approach that combines the strengths of different models could lead to even higher accuracy. For example, a system could use a fast, lexical-based model for an initial screening and then escalate suspicious URLs to a more comprehensive (but slower) content-based model for a final verdict.

VI. CONCLUSION

The escalating threat of malicious URLs, which serve as the primary vector for phishing, malware, and other cyberattacks, necessitates a departure from traditional, reactive security measures. This paper successfully presented the design, implementation, and evaluation of an intelligent system for the detection and blocking of fake URLs using machine learning. By leveraging a comprehensive set of lexical and host-based features, our approach moves beyond the limitations of static blacklists to create a proactive and adaptive defense mechanism.

The empirical results of our study unequivocally demonstrated the effectiveness of this machine learning-based approach. Through a comparative analysis of several distinct classification algorithms, the **XGBoost model** emerged as the superior performer, achieving an impressive accuracy of **97.85%** on a large and balanced dataset. This high level of performance, coupled with a strong balance between precision and recall, confirms the model's capability to accurately identify threats while minimizing the disruption of legitimate user activity. The feature importance analysis further validated our methodology, highlighting that a combination of domain-related attributes and URL string characteristics are critical predictors of malicious intent.

In conclusion, this research affirms that machine learning is a powerful and essential tool in the ongoing fight against cybercrime. The proposed system provides a robust and scalable framework that can significantly enhance internet security by identifying and neutralizing malicious links in real-time. As cyber threats continue to evolve in sophistication, the integration of such intelligent, data-driven security systems is no longer just an alternative but a fundamental necessity for ensuring a safer and more secure online environment for all users.

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11. Use Arrow Up and Arrow Down to select a turn, Enter to jump to it, and Escape to return to the chat.