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# Machine Learning-based Phishing URL Detection using Lexical and Structural Features

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## ABSTRACT

Phishing attacks, which use fraudulent sites to gather sensitive information from users, continue to be one of the major threats in cybersecurity. Thus, this work proposes a machine learning-oriented method for detecting phishing URL by leveraging the lexical and structural characteristics of URLs to overcome such difficulty. Over 100,000 URLs from the dataset were encoded as sixteen hand-crafted features which contained domain, path and character level information. For detection performance, Random Forest classifier with balanced class weights was used to decrease class imbalance. The aforementioned outcomes from the experiments validate that the proposed model plays a highly effective role in classifying if a given URL is phishing or legal with high accuracy attaining equal precision and recall. The proposed method has lower computing complexity and performs competitively to deep learning techniques, thus its suitability for real time phishing prevention systems.

## General Terms

Machine Learning, Classification

## Keywords

Phishing Detection, URL Classification, Machine Learning, Random Forest, Lexical Features, Cybersecurity.

## 1. INTRODUCTION

Phishing is among the most prevalent and rapidly evolving cybersecurity threats in this day and age. This type of social engineering attack consists of attackers impersonating legitimate businesses or services to trick users into revealing sensitive information, such as their financial records, personal details, and passwords. Is there also room for its creators to take advantage of and compromise the evolving technology? python note = """Recent cybersecurity statistics reveal that phishing accounts for a significant percentage of global cyber incidents, resulting in financial losses, identity theft, and breaches of organizational security [1], [2].

Both are used preemptively to exploit people's trust and bypass technical security vulnerabilities, something that may also help their attackers in crafting better attacks. Current day phishing uses homograph attacks, shortened URLs, domain spoofing, and dynamically generated web pages to slip under detection systems. Such attacks can be more influential and successful because they are widely spread through messaging applications, social networking sites, and emails [3]. Because many phishing websites exist for such a short period of time, most traditional security systems fail to detect fraudulent URLs in real-time.

Then, rule-based Filtering system One of the necessary features of traditional phishing detection methods is rule-based filtering systems. Feature-based approaches classify networks according to different features, and build a system from a set of rules aligned in a rule basis (RB). Blacklists are effective against known URLs, but completely ineffective against zero-day [3] phishing campaigns and domains that were practically registered within minutes or seconds during the attack. Nevertheless, blacklists keep track of previously discovered malicious URLs (maintaining contents of same realist) [4].Heuristic approaches apply handcrafted strategies to detect phishing behaviors, but such approaches are hard to adapt to evolving attack vectors and require frequent updates [6], [8]. Traditional techniques have limited accuracy and scalability in detecting phishing as the complexity of phishing increases.

This paper focuses on doing a comparative analysis based detection of phishing links using machine learning (ML), ML has promise and edge over traditional methods as it can learn the patterns from the historical data and generalize on unseen instances. By intrinsically learning descriptive features that differentiate malicious URLs from normal ones, ML-based detection systems can outperform static filtering systems when it comes to detection performance [5], [7]. A number of studies have shown that learning

based models applied on URL features and behavioral patterns can successfully identify phishing websites [9], [13].

Among various approaches, URL-based phishing detection has been explored extensively, as it allows early detection without downloading webpage content, which consequently reduces both computation cost and the latency for phishing identification. Lexical features are properties of the URL text that include length, number of characters, presence of suspicious keywords and non-standard naming. Structural characteristics encode syntactic information including subdomain hierarchy, directory depth, query parameters and use of IP addresses. It has been previously shown [8], [10], [15] that mix lexical with structural features significantly improves both robustness and accuracy of the classification.

Deep learning architectures have also been explored and used in the field of phishing detection in recent years. The sequential nature of the raw URL calls is successfully exploited by using neural network–based methods such as those employing recurrent neural networks or attention mechanisms. For instance, Asiri et al. proposed a PhishingRTDS framework for real-time detection of phishing sites with a BiLSTM model using attention mechanisms, achieving high accuracy [14]. The text above also illustrates in current literatures how neural models as implemented in the popular deep learning frameworks can automatically extract representational features from input texts [12]. However, the deployment of these models in light real-time environments may be hampered by the fact that they often require substantial training data sets and processing resources.

Random Forest classifiers are a viable substitute for this approach since they are a reliable and comprehensible model that can capture the nonlinear relationships found in structured datasets [11]. Because Random Forest hybridizes numerous decision trees while maintaining generalization efficacy and avoiding overfitting, it is appropriate for phishing detection tasks using fabricated features.

We propose a machine learning-based system for phishing URL detection that makes use of a wide range of manually created lexical and structural characteristics. To identify the optimal classifier for phishing detection while addressing issues with class imbalance, we investigate various machine learning approaches. We see our suggested approach as a scalable, computationally effective solution that can be implemented into systems like network defense infrastructures, email filtering platforms, and browser add-ons.

The main contributions of this work are summarized below:

Feature Engineering: Construction of an exhaustive feature set that encodes lexical and structural aspects from URLs.

**Model Development**: Several machine learning algorithms were considered including Decision Tree, Random Forest, Support Vector Machine (SVM) and Gradient Boosting.

**Performance Evaluation**: Evalauting performance using accuracy, precision, recall, and F1-score metrics.

**Practical Applicability:** Design a lightweight detection framework to be deployed in real-time cybersecurity applications.

## 2. METHODOLOGY

The proposed phishing URL detection system is based on a machine learning–based approach to detect a malicious URL applying lexical and structural features as shown in Fig. 1. The end-to-end pipeline involves dataset preparation, preprocessing step, feature extraction, model training and performance evaluation. This research develops lightweight and accurate detection methods, which are applicable in real-time cybersecurity settings.

First, it was assigned the collection of a large-scale dataset with over 100k URLs for both legitimate and phishing samples. The labels shown for each URL instance were utilized to mark whether it is benevolent or phishing. Dataset preprocessing, such as eliminating inconsistencies, addressing missing values and ensuring consistent feature representation occurred before model training. Phishing datasets are frequently imbalanced, and copious preprocessing strategies were employed here to retain decision-making authority throughout training.

The core of the proposed system is feature engineering. Rather than extracting information from returned webpage contents or querying outside services, the model employs a set of handcrafted lexical and structural URL features. Lexical features refer to content-based attributes that describe the composition of URL such as length of a URL, number of special characters, presence of suspicious symbols and frequency of digits. Structural features reflect the structure of URL, e.g., number of subdomain, directory level; how many tokens are abnormal in the URL. A feature vector comprising sixteen features were extracted for each URL, which encapsulates its behavioral characteristics.

After feature extraction, the dataset was split into training and testing subsets to assess model generalization. Because of its robustness, ability to capture non-linear relationships between features, and resistance to overfitting, we choose a Random Forest classifier learning technique. In one case, the class imbalance between phishing and real data was addressed by using balanced class weights during model training. To provide predictions that are more precise and dependable, an ensemble learning method known as Random Forest builds multiple decision trees and integrates them (Bajpai et al., 2019).

The classifier is trained to identify distinctive patterns in the URL feature vectors that can distinguish between benign and malicious URLs. After training, the model was evaluated using test data that had not yet been seen. Standard criteria like accuracy, precision, recall, and F1-score, which provide a comprehensive picture of detection capabilities and false positive behavior, were used to assess the performance.

After that, the trained model generates predictions that identify incoming URLs as either real or phishing. The suggested approach can be implemented in real-world settings like browser plug-ins, email filtering systems, or network security gateways to offer proactive defense against evolving phishing attacks because it makes use of lightweight feature calculation followed by an extremely effective ensemble learning approach.

## 3. EXPERIMENTAL SETUP

### 3.1 Dataset

We performed the experiments on a large dataset of 100000 real-world phishing URL samples. The data contains legitimate and phishing URL dataset from public sources like Cybersecurity Archives, Phishing Intelligence. Each URL is assigned a binary class where 0 represent legitimate URLs and 1 represent phishing URLs. Each URL can be rebuilt by its sixteen associated semantic and structural elements which are established from the URL string. Some of them are URL length, digit frequency, special character presence, subdomain count, directory depth and structurally malformed patterns, duplicate entries were eliminated and unique values were examined. The dataset was divided from 80:20 split into the training and testing subsets with to evaluate model generalization capability.

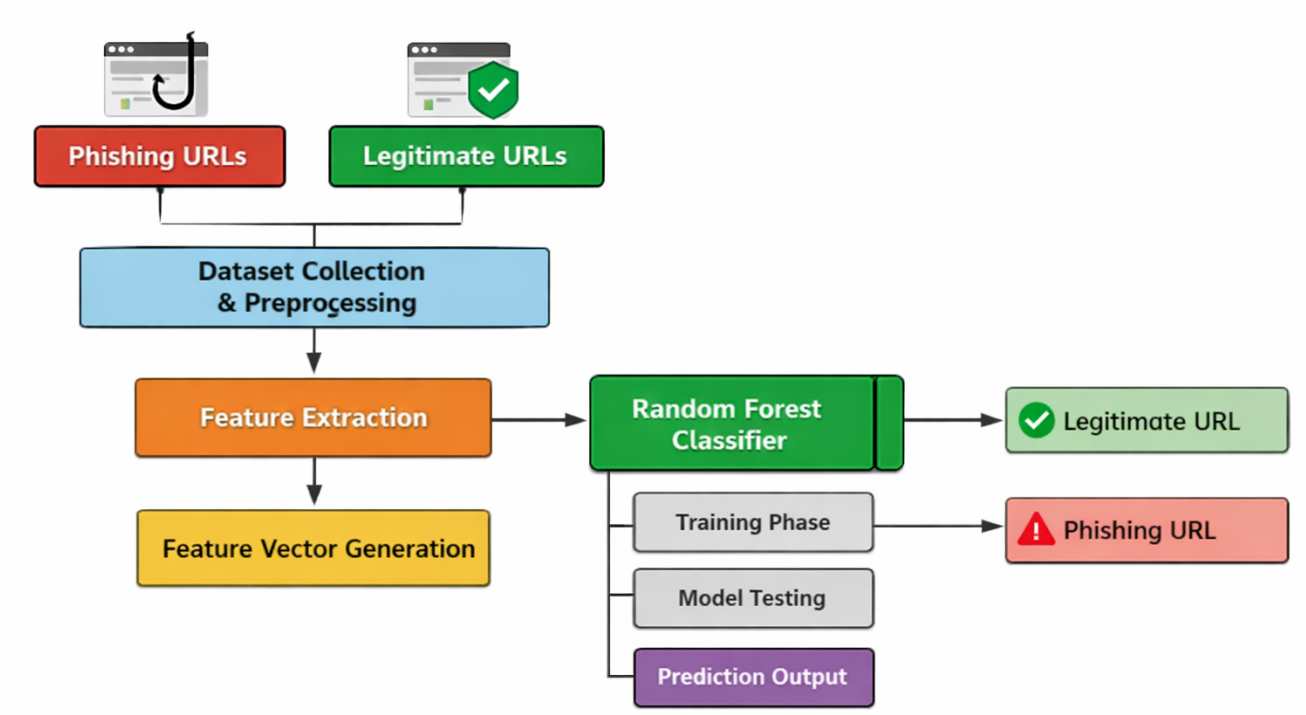


Fig. 1. Block diagram of the proposed machine learning–based phishing URL detection system illustrating the workflow from dataset collection, preprocessing, feature extraction, model training using Random Forest classifier, and final classification of URLs into phishing and legitimate categories

Table 1. Training Parameters

| Parameter | Value |
|---|---|
| Classifier | Random Forest |
| Number of Trees | 200 |
| Train-Test Split | 80:20 |
| Class Weight | Balanced |
| Evaluation Metrics | Accuracy, Precision, Recall, F1-score |

### 3.2 System Implementation

Python was used to incorporate the phishing detection system described in the study into the Google Colab environment. In contrast to machine learning, the second step involved feature engineering and data preprocessing using the Pandas and NumPy libraries.
Note: All the experiments were conducted using Scikit-learn framework. Note that this implementation is centered on computational efficiency, enabling rapid model and streaming prediction without requiring specialized hardware.We used the cloud-based computational resources offered by Google Colab during experimentation.

### 3.3 Training and Testing Configuration

The use of a Random Forest classifier as the main learning model was chosen owing to its resilience and ensemble learning capabilities. To address class imbalance,balanced class weights during training were used. The key training hyperparameters used in the experiments are summarized in Table 1.
In training, numerous decision trees were constructed using the bootstrap sampling method and random subsets of features for each split. The final prediction was a majority vote aggregating all trees.
Additionally, we performed confusion matrix to analyze misclassification patterns between phishing and legitimate URLs as shown in Table 2.

## 4. RESULTS AND DISCUSSION

In this section, we present the performance assessment of proposed machine learning based phishing URL detection system. Random Lexical and structural URL features were trained a forest classifer features based from ¿ 100,000 URLs. We will explore classification accuracy, training dynamics and performance metrics such as confusion matrix and classification report. To correct this class imbalance between phishing and benign URLs, we trained a Random Forest classifier with balanced class weights. It was found to work well for classification tasks, in particular with malicious URL classification as shown in Table 3.
Table **??** presents the evaluation metrics obtained on the test dataset. The results indicate that the proposed model maintains balanced precision and recall values, which is essential for phishing detection systems where false negatives can lead to severe security risks.

### 4.1 Training Performance

The training and validation accuracy obtained during model training as shown in Fig. 2.
are illustrated in Fig. 2. The model demonstrates rapid convergence within the initial epochs and stabilizes afterward, indicating effective learning of discriminative URL patterns.

Table 2. URL Dataset Features and Description

| S.No | Feature Name | Description |
|---|---|---|
| 1 | URL | Original URL string used for feature extraction |
| 2 | url_length | Total number of characters present in the URL |
| 3 | has_ip_address | Indicates whether an IP address is used instead of a domain name (0/1) |
| 4 | dot_count | Number of dots appearing in the URL |
| 5 | https_flag | Indicates presence of HTTPS protocol (secure connection) |
| 6 | url_entropy | Entropy value measuring randomness of characters in the URL |
| 7 | token_count | Number of tokens obtained after splitting the URL |
| 8 | subdomain_count | Number of subdomains contained in the URL |
| 9 | query_param_count | Number of query parameters present |
| 10 | tld_length | Length of the top-level domain (TLD) |
| 11 | path_length | Length of the path section in the URL |
| 12 | has_hyphen_in_domain | Presence of hyphen symbol in domain name (0/1) |
| 13 | number_of_digits | Total numeric characters appearing in the URL |
| 14 | tld_popularity | Popularity score of the top-level domain |
| 15 | suspicious_file_extension | Indicates suspicious file extensions (.exe, .zip, etc.) |
| 16 | domain_name_length | Length of the domain name |
| 17 | percentage_numeric_chars | Percentage of numeric characters in URL |
| 18 | ClassLabel | Target class (0 = Legitimate, 1 = Phishing) |

Table 3. Performance Evaluation of the Proposed Model

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Legitimate (0) | 0.99 | 0.99 | 0.99 | 12749 |
| Phishing (1) | 0.99 | 0.99 | 0.99 | 7495 |
| **Accuracy** | **99.9%** | | | |

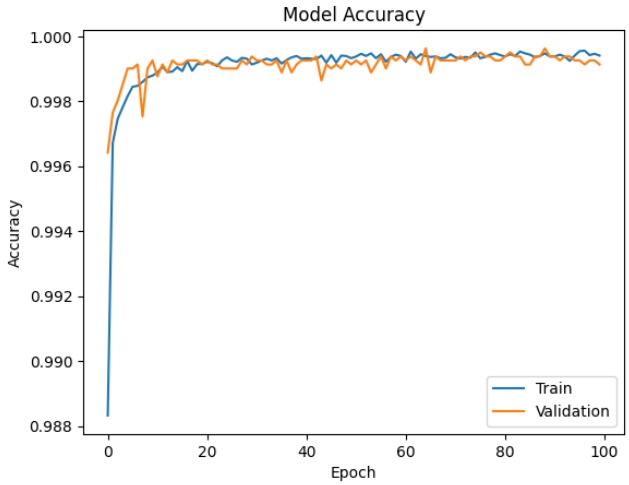


Fig. 2. Training and testing curve of the model

The training accuracy starts to increase sharply in the early epochs and gradually settles down at a value, close to 99.9%. The validation accuracy follows the training curve closely without much divergence, indicating that model is not suffering from overfitting. The small difference between the training and validation accuracy validates a good generalization ability.

## 4.2 Confusion Matrix Analysis

The confusion matrix shown in Table 4 provides a detailed representation of classification outcomes. This means that the model accurately classifies a large percentage of legitimate/benign and

Table 4. Confusion Matrix of the Proposed Model

| Actual / Predicted | Legitimate (0) | Phishing (1) |
|---|---|---|
| Legitimate (0) | 12680 | 69 |
| Phishing (1) | 58 | 7437 |

Table 5. Classification Report

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Legitimate (0) | 0.99 | 0.99 | 0.99 | 12749 |
| Phishing (1) | 0.99 | 0.99 | 0.99 | 7495 |
| **Accuracy** | 0.999 | | | |
| **Macro Avg** | 0.99 | 0.99 | 0.99 | 20244 |
| **Weighted Avg** | 0.999 | 0.999 | 0.999 | 20244 |

phishing URLs. A very low number of false positives and false negatives was observed, illustrating the efficiency of the selected feature set and classification strategy. In real-time cybersecurity applications, it is important to accurately identify phishing or fraudulent URLs as the entity can potentially lead to vast financial losses, and hence the results presented validate that the proposed methodology is robust.

## 4.3 Classification Performance Metrics

To further evaluate model performance, precision, recall, and F1-score were calculated for each class, as presented in Table 5.
We see that the precision and recall are balanced for legitimate and phishing classes in the classification report. High recall means that most phishing URLs are detected, and high precision means that there are not too many false alarms. This is further confirmed by the f1-score which indicates that performance across classes is consistent despite dataset imbalance.

## 4.4 Discussion

Evaluate with the experimental results which shows that our proposed Random Forest model is able to well capture discriminative URL features using hand-craft lexical and structural features. The method achieves competitive accuracy with a considerably lower demand of computational resource than deep learning methods. This makes the

model that can be used in network security programs, email filtering systems, and online browsers for real-time phishing detection. In conclusion, the findings support the idea that feature-based machine learning models, which offer good accuracy, reliable performance, and scalability, are still a successful and efficient method for identifying such phishing URLs.

## 5. CONCLUSION

The authors of this study suggested a machine learning-based phishing detection system that makes use of URL lexical and structural characteristics. The analysis showed that manually created features present in the URL can accurately express behaviors that differentiate a phishing webpage from a legitimate one. A Random Forest classifier with balanced class weights was utilized to address the dataset imbalance and ensure the detection was trustworthy. We show that the suggested model maintains good precision and recall while achieving high detection accuracy through experimental evaluation on a dataset of more than 100,000 URLs.
The method effectively lowers false positive and false negative error rates, both of which are critical in actual cybersecurity domains, according to the confusion matrix and classification metrics. There was also a stable convergence trend and high generalization capacity without obvious overfitting based on the training and validation results. This is backed up with deep learning methods, finding computationally expensive JPEG-like techniques to have a lower-thought out cost for performance and speed than those from the ideas I put forth. This allows the framework to be utilized in real-time deployment applications such as browser security plugins, email filtering nets, and network intrusion detection systems.

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