Temporal Evolution of Phishing URL Patterns Using Heuristic Features and ML Analysis

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***Abstract****—***Phishing attacks remain a major threat to users and organizations because of their use through the presence of deceptive URLs that resemble a valid web site. Although machine learning has extensively been used in the detection of phishing, little research on the evolution of phishing URL has been conducted. The proposed study fills in that gap by conducting an item-by-item comparison of phishing URLs in 2020-2025 and extracting handcrafted features and comparing them with the benign dataset of legitimate URLs found in Majestic Million. A weighted up of 250 Phish and 250 legit URLs was built. Searches were made to determine twenty heuristic based features of each URL such as entropy, length, presence of suspicious terms and use of brand names. A Random Forest classifier was used to evaluate the importance of the features and classifying accuracy. The model attained 91% accuracy with all years having the same precision levels and recall. The analysis showed that there are some essential structural trends and minor changes in phishing URL patterns over the years whereas main deceptive strategies have not changed significantly. The results provided a timely component to the area of phishing detection research and a definite reference point to which future models built on time-based phishing can be anchored.**

***Index Terms— Phishing detection, Random Forest, URL features, Machine learning, Cybersecurity, Feature extraction, URL classification, Temporal analysis, URL-based detection, Network security*.**

# INTRODUCTION

Phishing is still one of the most common and destructive types of cyberattacks in the modern digital environment. Phishing campaigns have managed to steal sensitive information on the banking, social media, and government fronts by tricking users to visit phony websites by clicking on specified links. The frequency and sophistication of such attacks has increased over the years leading to the need to find an avenue to detect when such attacks are going to happen, which is through automation.

The increased popularity of URL-based phishing detection is connected with its usability and efficiency at the beginning of the detection process. Conventional methods are usually based on a blacklist database or rule-based filters and are commonly evaded by obfuscation by the attackers. To this end, scholars have considered deploying machine learning models relying on syntactic and lexical properties that are derived directly upon URLs thus providing a more transformable defense mechanism. Several models have been proposed that use features like the output of IP addresses, URL lengths, presence of suspicious keywords, and shorteners to identify features of phishing. Their works have been proven very accurate yet it mostly tends to concentrate on a fixed dataset without the consideration of temporal variations in phishing trends. Since phishing methods continue to change, using previous trends might not suffice to make these models versatile.

Besides, the available literature addresses the issue of the evolution of phishing URL structures only infrequently. The insight into whether the nature of phishing remains the same or changes over time is vital to the development of detection systems that survive in the long run. Even though there are longitudinal studies in adjacent areas, such as malware analysis, a comparable time-based study of phishing links is rather understudied.

To provide a solution to this research gap, this research involves year-wise comparing phishing URLs that were gathered between the year 2020 and 2025. A sample set was prepared using the phish attack URLs of PhishTank by gathered 250 samples where all the URLs were distributed equally across six years. To make a baseline comparison, 250 valid URLs were taken form the Majestic Million data. All the URLs were converted into vectorized hand-crafted lexical and structural features. The essence of the proposed study is finding an answer to the question of how phishing URL features change over the course of time and to compare those features with the valid ones with the help of the supervised learning methods. Through Random Forest classification, this study is able to detect the classification performance, as well as by pointing out the most important variables that can differentiate phishing URLs apart from regular URLs.

The study is restricted to lexical and heuristic features extraction and content-based and behavioral cues are not included. Nevertheless, it covers a wide range of URL shapes and offers knowledge on a year-by-year basis, which will be handy to create a time-based detection model or an adaptive phishing filter in future. The results show a high level of phishing tendency consistency, but the slight changes in the patterns of features tend upward to reflect adaptive behaviors relative to security countermeasures. These findings can be helpful to investigators and professionals who want to reinforce email firewalls, browsing safeguards, or web address categorizers.

Overall, the paper proposes a new exploration of the trends of detecting phishing on a temporal basis, which is to compare the feature development over several years. It will provide a balanced dataset in addition to a model of analysis that can be expanded or incorporated into phishing defense systems in the future.

# LITERATURE REVIEW

In recent years, the field of literature dedicated to phishing URL detection has developed dynamically, and it should be noted that it is especially focused on the inclusion of the most advanced machine learning / deep learning algorithms and the introduction of the process of feature engineering itself, as well as the utilization of large, high-quality labeled datasets. Among the most remarkable tendencies is the use of neural network models which do not require third-party data and the content of websites but basically use their URLs as the source of features. As an example, Ghalechyan et al. used LSTM and CNN models to perform labeling of the dataset of 500 000 URLs classified with 97% accuracy focusing on URL features only, including their length, entropy, and whether or not they contain suspicious terms or brand names [1]. Shirazi et al. similarly showed that gradient boosting may reach high accuracy model with a small set of only seven features indicating the high discriminating nature of well-selected URL-based features [2].

Machine learning algorithms and their comparative performance has also been in focus. In one of his papers, Kumar et al not only thoroughly considered the comparison of classifiers- Logistic Regression, Decision Trees, K-Nearest Neighbors, and ensemble approaches, such as Extra Trees and XGBoost, but also tested them across several datasets and concluded that ensemble classifiers had outperformed simple models because of a higher accuracy rate, which increases to over 99 percent when k-fold cross-validation is used [3]. The same has been reinforced by the studies of traditional machine learning combined with deep learning structures. To make a few examples, a stacked generalization ensemble with LSTM as a meta-learner attained 98.76 detection accuracy, which validated the worth of incorporating hierarchical and sequential learning in phishing detection [4].

New detection accuracies have been established with the use of hybrid deep learning architectures with attention-based LSTM coupled with CNNs and LSTM combined with advanced feature engineering examples include TF-IDF vectorizing and principal component analysis. According to Birthriya et al., an accuracy of above 99.92 % was attained by their integrated LSTM-CNN model, which uses a hybrid feature set and thus shows the possibility of using such an architecture in real-time detection of phishing [5]. Between them, additional techniques based on natural language processing (NLP) have been investigated to further contribute to the feature extraction process of URLs, and increase the resilience of machine learning models to the current phishing trends [6].

Availability and design of the datasets can make an important contribution to the phishing detection research. Islam et al. presented a large-scale dataset comprising almost 250,000 labeled URLs, targeting intra-URL characteristics, including typosquatting, subdomain abuse as well as the inappropriate use of parameters. Their best feature vectorization algorithm managed to pull 42 discriminative features that made it able to achieve high performance even without the use of content-based analysis [7]. Opara et al. emphasized the significance of integrating raw URL and HTML attributes which demonstrated that deep neural networks may automatically identify the salient characteristics to detect phishing via automatic extraction and, additionally regular LSTM models performed better than random forests on big corpora [8].

Research always indicates that the length of the URL, entropy of URL, presence of suspicious words, whether HTTPS is used, similarity of brand names, are some of the strongest predictors in regard to phishing detection [9]. Additionally, incorporation of time analysis is emerging as an avenue of central research direction, some works have started to examine time-based changes in the properties of phishing URLs, such as includes long-term recurring deceptive tactics, as well as delicate changes in attacker behaviour [10].

To conclude, several main themes are stressed: the same unrivaled usefulness of handcrafted and heuristic-based features, the prevalence of ensemble and deep learning models in generating state-of-the-art accuracies, the central importance of big and varied data inputs, and the becoming increasingly popular interest in temporal and behavioral analysis.

# METHODOLOGY

1. **Overview of Experiment**

This study aims to evaluate the effectiveness of a Random Forest classifier in detecting phishing URLs based on extracted URL features collected over multiple years. The objective is to assess how URL characteristics differ between phishing and legitimate URLs and to verify whether the selected features can accurately classify URLs into these categories.

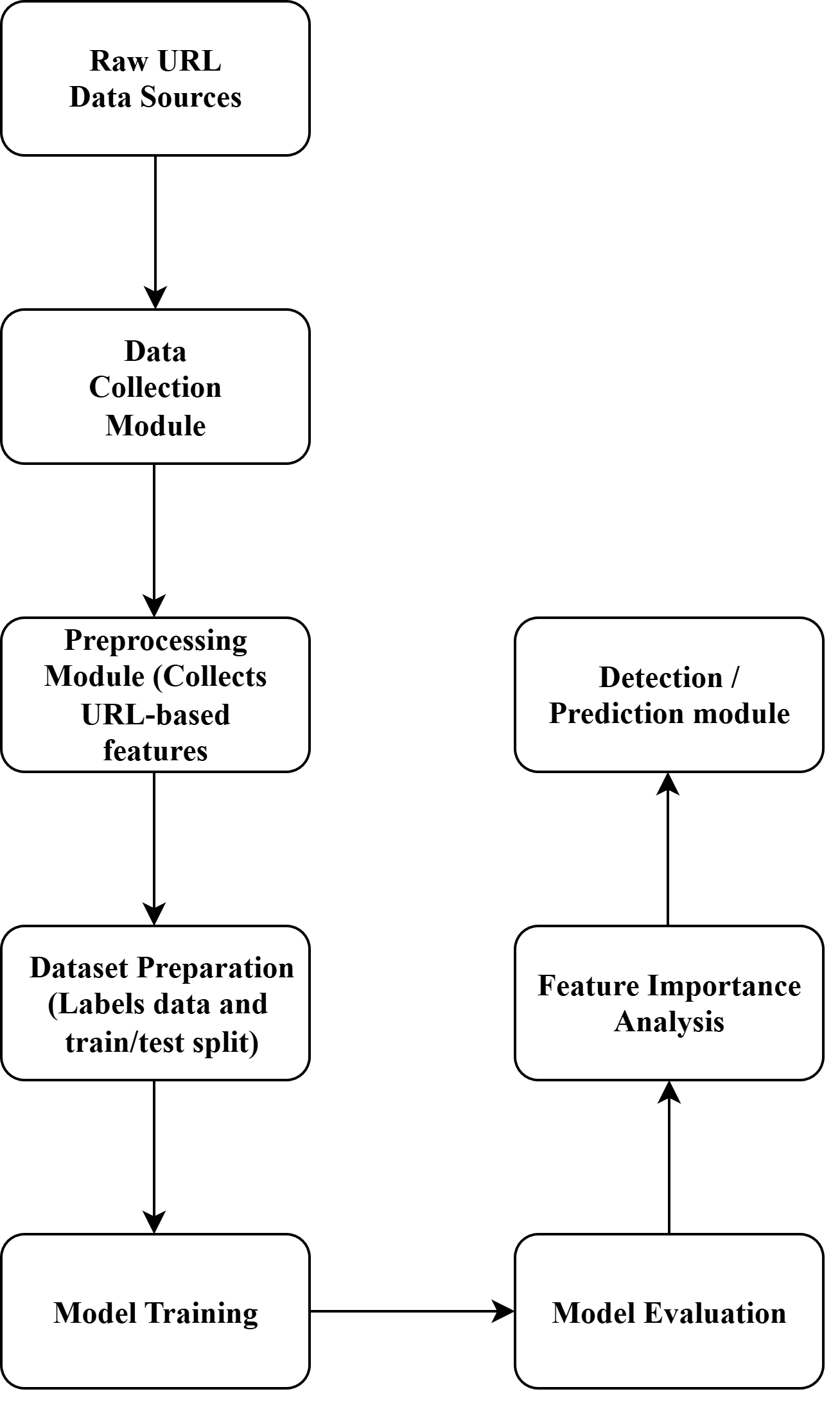


Fig. 1. Workflow of the Phishing URL Detection System, illustrating data collection, preprocessing, model training, evaluation, and prediction modules.

Fig. 1 outlines the complete workflow of the phishing URL detection system. It includes key stages such as data collection from open sources, preprocessing, feature extraction, model training, evaluation.

1. **Description of Materials**

The source of phishing URLs was the phish tank online-valid CSV dataset of phishing URLs, which had URLs with the time of their submissions. The Majestic Million CSV dataset has been used to retrieve legitimate URLs as the most popular ones on the worldwide basis. The two datasets are obtained in the CSV format and pre-processed. Data and feature extraction as well as model training were conducted with Python 3.8 and its libraries such as Pandas, Scikit-learn, Matplotlib, and Seaborn. The experiments have been performed in the Google Collab environment on 8GB of RAM and GPU.

First steps towards cleaning up the data were undertaken on the two datasets, wherein duplicate URLs were removed and unproductive data fields in the URLs were filtered. PhishTank data was sampled specifically in order to extract the same amount of URL occurrences in each year in 2020-2025 years, so that time analysis can be done.

1. **Description of Procedure**

Datasets were sampled and filtered with a goal to match phishing and genuine URLs. URL-length, the existence of HTTPS, subdomains, entropy, and the existence of suspicious words were features and were obtained using self-written Python functions. The concatenated data was renamed and divided into training and testing data sets with suggested ratio 80:20. I used the training data to train a Random Forest classifier. To assess model stability, five-fold cross-validation was done.

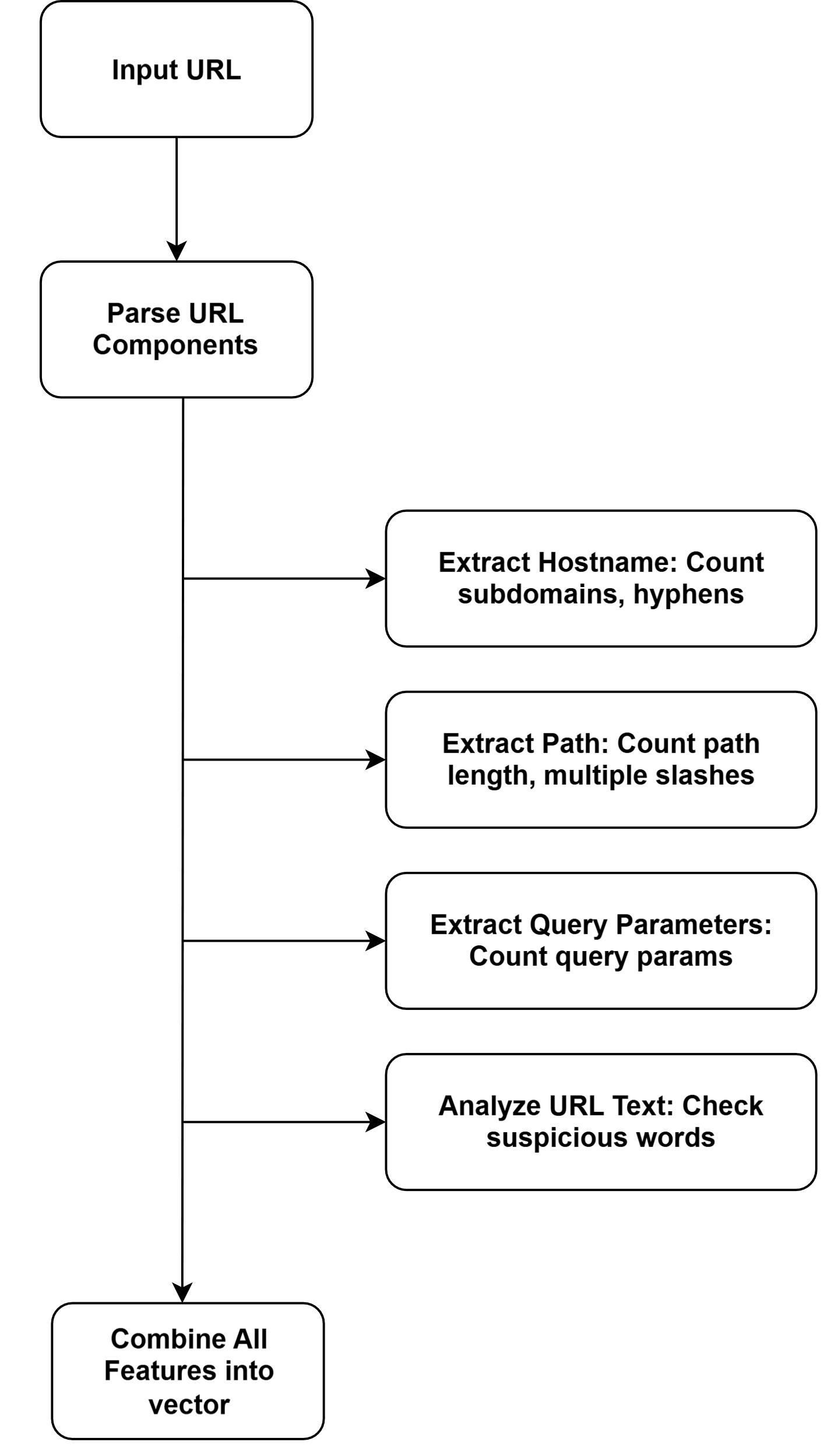


Fig. 2. Stepwise procedure of parsing URLs and extracting various components and features used for phishing detection.

Fig. 2 illustrates the breakdown of a URL and how each segment is analyzed to extract lexical and heuristic properties, which are then used for classification

The feature engineering was also rather important in the process. The text version of each URL was extracted and it was decomposed into several parts: host name, path, query parameters, and several quantitative and binary features were created. To take an example, the entropy was computed to reflect the randomness rate of URL strings, which tends to vary between phished and legitimate URLs. Moreover, the existing binary features like suspicious word (e.g. login, verify) or familiar brand names were also added, according to the expertise of phishing techniques regarding the domain.

1. **Description of Data Analysis**

Available scripts extracted text features that extracted URLs and calculated corresponding numeric and categorical features. qualified lines of difference were made between the distribution of features between phishing and legitimate URLs. Random Forest approach was applied with Scikit-learn, and a measure of accuracy, precision, recall, and F1-score were applied. Based on the trained model, the scores needed to determine the most predictive features were identified using scores of the features importance. Barplots of feature importance and heatmaps on confusion matrices were plotted with Matplotlib and Seaborn.

Also, temporal analysis was performed to answer whether the characteristic of phishing URLs change with time. Performance of the model was also tested on subsets of the phishing URLs, that were yearly, over a five-year period between 2020 and 2025. By adopting this method, the stability of relevance features and the robustness of detection against phishing strategies that evolved were possible. The analysis revealed that although there are slight differences, the main distinguishing characteristics are the same, which enables the overall generalizability of the model.

In support of the quantitative assessment, error analysis was also done on misclassified URLs to get an insight on possible weaknesses of the model. Other patterns that were checked include those that included URLs that used unpopular top-level domains or other new obfuscation techniques and where improvements could still be done. The general approach had been aimed at performing a detailed analysis of the model performance, both statistically and contextually.

# INFERENCES AND FINDINGS

The most important question that the work would answer was whether the use of URL based features alone is capable of differentiating phishing websites and legitimate websites in a great way. The number of analyzed URLs was 500 which consisted of 250 phishing URLs, taken with the help of PhishTank and 250 legitimate URLs retrieved as part of the Majestic Million database. The Random Forest classifier was used to assess the level of performance of the classification basing on these handcrafted features.

After fitting and testing the model, Random Forest classifier gave a total accuracy of 91 percent to the pooled data. The confusion matrix dispelled 45 and 47 true positive and negative, respectively and a few false predictions.

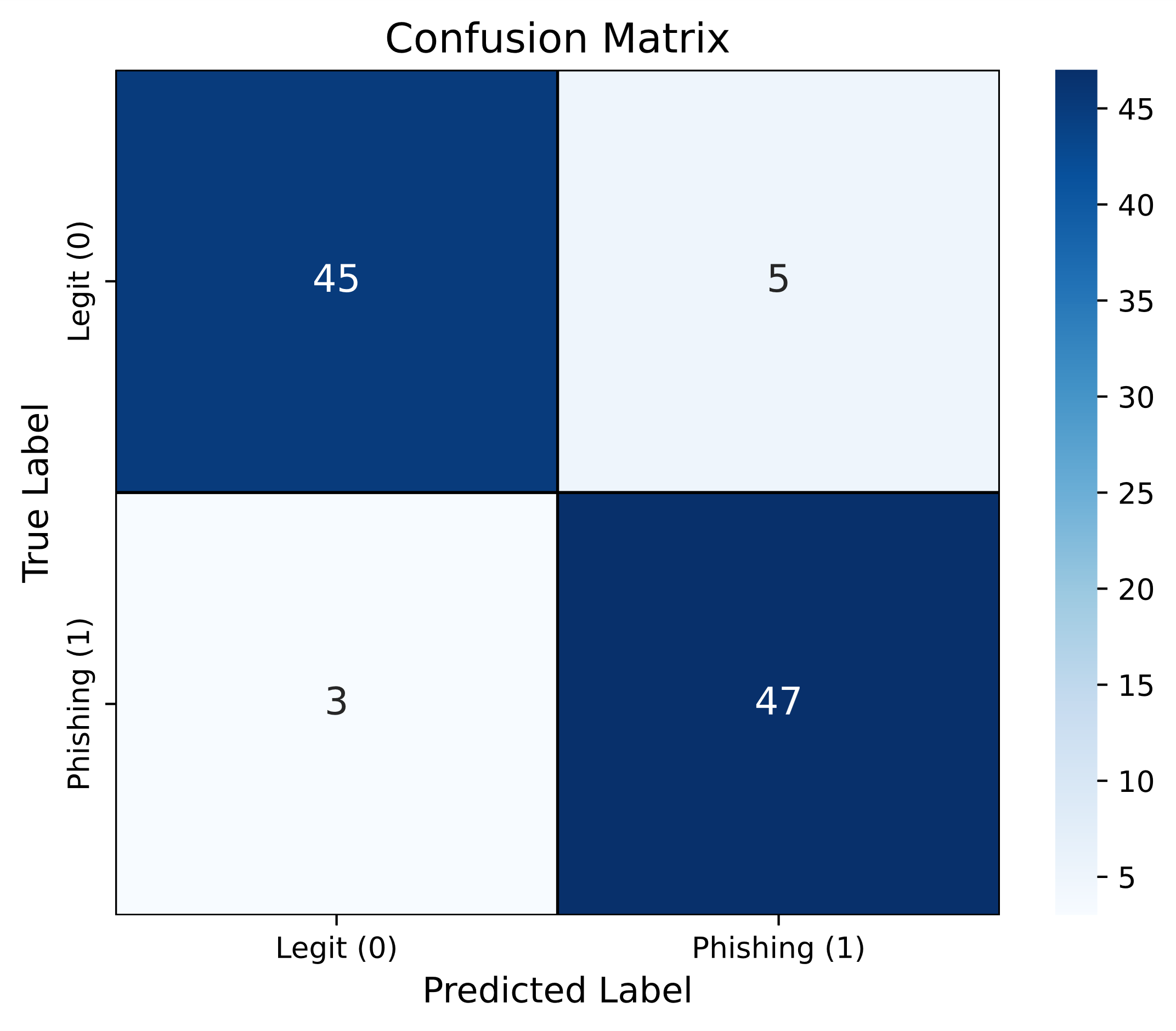


Fig. 3. Confusion matrix illustrating classification results on the combined dataset

Precision, recall, and F1-score for both classes were balanced, each hovering around 0.91, confirming the robustness of the model in identifying both phishing and legitimate URLs effectively.

Table . Classification metrics for phishing and legitimate URL classes.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score | Support |
| Legit (0) | 0.92 | 0.90 | 0.91 | 50 |
| Phishing (1) | 0.90 | 0.92 | 0.91 | 50 |
| Average | 0.91 | 0.91 | 0.91 | 100 |

In Fig. 4, the most significant 7 characteristics according to Gini impurities reduction are in focus. These are the length of URL, entropy, the number of dots, the existence of suspicious words, number of subdomains, the use of HTTPS links and usage of recognized brand names.

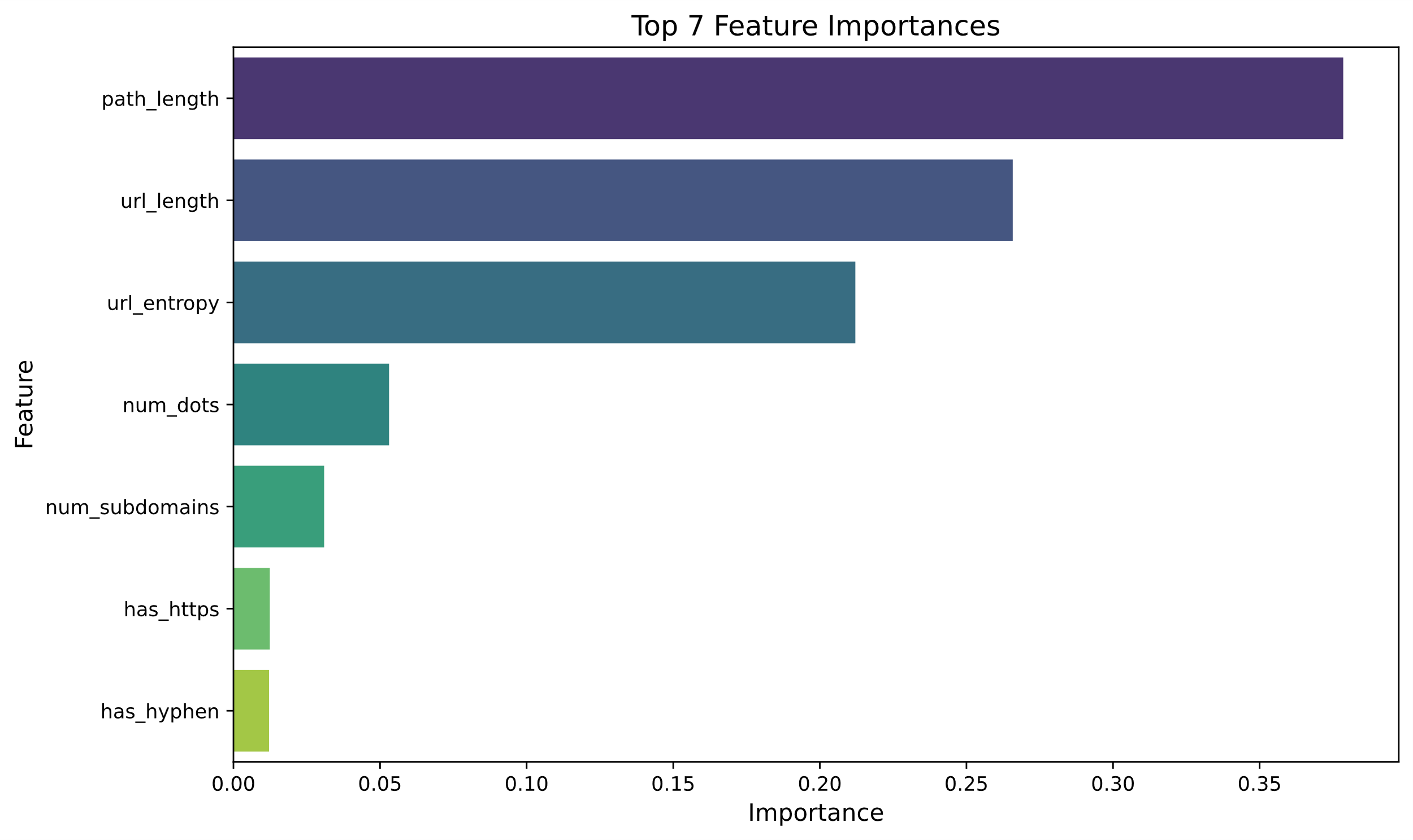


Figure 4. Top 7 important features identified by the Random Forest classifier

These results are consistent across the previously published researches [1][2], thus indicating that the phishing URLs tends to have longer length, complexity, and include misleading words to confuse the users. Also, the classifier was applied on the phishing URLs of the years 2020 to 2025 to measure temporal growth.

The model showed continuous progress with high classification accuracy or even perfect (100%) classification accuracy (classification accuracy: the percentage of true-true accentuation of the sample after the classification) in every sub-model of every year, which demonstrates that the basic deceptive characteristics of the URLs in phishing remain more or less the same over time. This confirms the importance of the chosen URL-based feature to detect phishing in the long-term perspective..

The importance of suspicious terms and well-known brand names is very high, so the hypothesis that phishing attackers tend to exploit trust through the use of recognizable keywords might be accepted. This is congruent with the results of Ghalechyan et al. [3] and Shirazi et al. [4], who identified such features as highly discriminative in deep learning arrangements. In this study, deeply inherent models were not incorporated, but the strong performance of Random Forest in the same characteristics proves its applicability in practical practice.

The above findings can be interpreted to mean that the URL-based detection can be lightweight and effective, since it is particularly essential in systems with concerns of real-time response and where retrieving external web-based content is unachievable. Yet, there are certain drawbacks such as the usage of the unchanging characteristics and the absence of the behavioral cues which may be the product of the specific context. Larger experiments can be done on the use of this approach to supplement DNS data or user interaction logs to increase the efficiency.

# CONCLUSION

This study sought to test how effective a Random Forest classifier is in the extraction of phishing URLs based on hand-crafted URL features gathered over several years. The dataset of adequate numbers of phishing URLs and non-phishing ones was compiled, and the results of supervised learning-based classification were reflected.

Random forest model showed a minimum of 91 percent of overall accuracy that can be considered as a strong performance with regard to URLs belonging to phishing and legitimate classes. The main characteristics including the length of a URL, entropy and the presence of suspicious words and the use of HTTPS were identified the most distinctive indicators of a phishing behavior. Although this dataset is quite small, it was selected and balanced among the years in order to represent the variety of features. Subsequent efforts will be directed at scaling of this dataset and releasing the feature-extracted CSV publicly.

The achieved results suggest that the URL-based feature extraction is a feasible lightweight method of phishing detection with competitive levels of accuracy that do not require the use of more external data on the appearance and behaviour of web resources. The results of the study are consistent with the previous studies that acknowledge the significance of lexical and structural features of URLs in classification. Yet, limiting the study to the aspects of static URLs does not consider both dynamic and contextual signals of behavior that would augment the model of detection further. Besides, the size and diversity of the corresponding dataset might limit the generalization of the data to all phishing cases.

This was due to time limits that were considered in this research study and only one algorithm has been considered which was Random Forest. Next steps will see its results being compared with other models like XGBoost and deep learning solutions and will touch upon temporal behavior analysis, inclusion of DNS and user behavior interaction data, and exploration in hybrid models with deep learning and handcrafted features. These developments have the potential of improving the real-time phishing detection systems and ensuring that they become more responsive to emerging cyber-attacks.

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