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Can Features for Phishing URL Detection Be Trusted Across Diverse Datasets? A Case Study with Explainable AI

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Can Features for Phishing URL Detection Be Trusted Across Diverse Datasets? A Case Study with Explainable AI

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Abstract

Phishing has been a prevalent cyber threat that manipulates users into revealing sensitive private information through deceptive tactics, designed to masquerade as trustworthy entities. Over the years, proactively detection of phishing URLs (or websites) has been established as an widely-accepted defense approach. In literature, we often find supervised Machine Learning (ML) models with highly competitive performance for detecting phishing websites based on the extracted features from both phishing and benign (i.e., legitimate) websites. However, it is still unclear if these features or indicators are dependent on a particular dataset or they are generalized for overall phishing detection. In this paper, we delve deeper into this issue by analyzing two publicly available phishing URL datasets, where each dataset has its own set of unique and overlapping features related to URL string and website contents. We want to investigate if overlapping features are similar in nature across datasets and how does the model perform when trained on one dataset and tested on the other. We conduct practical experiments and leverage explainable AI (XAI) methods such as SHAP plots to provide insights into different features' contributions in case of phishing detection to answer our primary question, "Can features for phishing URL detection be trusted across diverse dataset?". Our case study experiment results show that features for phishing URL detection can often be dataset-dependent and thus may not be trusted across different datasets even though they share same set of feature behaviors.

CCS Concepts

• **Security and privacy** → *Phishing Detection*; • **Computing Methodologies** → *Artificial Intelligence.*

Keywords

Phishing, Detection, Machine Learning, Explainable AI, SHAP, Phishing Features

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1 Introduction

Phishing attacks come in various forms, such as deceptive emails or mobile messages attached with fraudulent website URLs, all designed to trick users into revealing sensitive information or click on to malicious attachments [34]. Moreover, the potential abuse of generative AI and large language models may add more stress towards defenders to cope with these attacks [14, 28, 32]. According to recent statistics, the United States alone had a total of around 300K phishing victims, with financial losses exceeding $52 million due to these attacks [19]. Historically, phishing website detection relied on traditional blacklisting where various publicly available blacklists like *PhishTank* [12] and other private blacklists are leveraged. While these black-box detection models may achieve high accuracy, they lack transparency and explainability. Due to this shortcoming, black-box models hinder trust and adoption in practice. Moreover, the dynamic nature of phishing website data involves concept drift [21], which describes a situation where the relationship between the input data and the target variable varies over time in an online supervised learning environment. Although detecting the concept drift and retraining the model with newly extracted features [33] can partially resolve the issue, the overall feature importance in different deployment scenarios with different schemes of features can still be varied and not generalized.

To bridge this gap, SHAP (SHapley Additive exPlanations), a popular explainable AI (XAI) method, can be used to interpret the individual (i.e., local explanation) and overall model predictions, which can aid in the decision-making process [18]. In this paper, we propose to leverage XAI approaches to understand the generalization of phishing URL detection features across datasets. We incorporate XAI as a means to provide insight into the model's decision-making process, shedding light on features which are more impactful in the classification of an instance as *phishing* versus *benign.* Our primary objective is to answer the following question- *"Can features' importance for phishing URL detection be trusted across diverse datasets?".* By answering the question, we want to know if certain set of features are ubiquitous for phishing URLs detection, or if the features are closely tied to a specific dataset.

In addition, we also evaluate the performance of different ML models on multiple datasets to select the best ML model for generating SHAP explanations. Furthermore, we create various experiment scenarios where training and testing portion of one dataset is used with another dataset. This is particularly beneficial when common overlapping features are present in multiple datasets, and training and testing with different datasets can provide insights on their generalizability. We hereby hypothesize that the claimed accuracy of any particular ML model achieved by the researchers on a specific dataset, may get declined while the test environment changes or new data appears. If this is true, then we have got our answer for the primary question and need to be cautious about phishing detection results.

To guide our experiments in this paper, we are driven by the following **three research questions (RQs)**.

RQ1: What are the top impactful overlapping features and their impact distribution for a specific prediction outcome across multiple datasets for phishing detection?

RQ2: When multiple datasets share overlapping features, how do a ML-based phishing detection model perform, when trained on one dataset and tested on another dataset? Does it improve the detection performance if both datasets are merged for training?

RQ3: Are overall features' contribution ranks for the shared overlapping phishing URL features showing a similar contribution order in different datasets?

In summary, motivated by these above research questions we make the following major contributions in this paper:

- Analyze overlapping features from multiple phishing URL datasets consisting more than $108K$ unique URLs.
- Answer the RQs with experimental evidences if features for phishing URL detection can be generalized across datasets where training and testing of ML models are conducted on different datasets.
- Use popular XAI SHAP module to provide new insights and find deviations in features' contribution behaviors for phishing detection when multiple datasets are involved.

The rest of the paper is organized as follows: Section 2 discusses related works on AI based phishing detection. Section 3 presents the methodology and results with data-driven insights from the experiments. Section 4 discuss the current state and limitations in the present study while Section 5 concludes the paper.

2 RELATED WORKS

ML and Deep Learning (DL) based phishing detection research has seen significant progress with the advancement of the Artificial Intelligence. In literature, there are number of studies proposed to incorporate ML for phishing URL, malicious domain or website detection and supporting law-enforcement take-down decisions based on URL features and webpage contents [1, 4, 7, 13, 16, 17, 20, 25, 26, 38–40]. However, a common limitation across these studies is the lack of interpretability of the underlying decision-making processes of the models used, often referred to as the "black box" problem. Furthermore, there is a scarcity of research that compares the performance and feature importance across diverse datasets. Sarasjati *et al.* [31] and Preeti *et al.* [24] presented comparison of various ML models across multiple phishing website datasets, and the usage of multiple datasets with varying class labels allows for a more robust analysis. These studies may provide insights about the best available ML models with a given set of features, but they can not provide any insights on the interpretation or explainability of the models. Next, Rugangazi *et al.* [29] proposed an automated phishing detection strategy that picks important features using the global feature importance method to achieve high accuracy but it is limited to a single dataset and does not discuss model interpretability to assess the features generalizability for phishing detection. In another study, Ali *et al.* [2] proposed to rely on URL character sequences using character-level convolutional neural network (CNN) while Tao *et al.* [11] proposed character-level recurrent neural network (RNN) for phishing detection. However, these models mostly lack transparency for detection of phishing versus benign URLs, which may be targeted by adversaries by tweaking domain names to avoid detection. Moreover, Youness *et al.* [22] showed CNN outperforming blacklisting, lexical, content-based, and visual & behavioral similarity methods. In literature, we also find articles where natural language processing (NLP) is used with ML to effectively detect phishing attempts [30].

In phishing research, there are a number of features explored in literature, but among them lexical features are the ones those are very easily available and used mostly [27, 35]. Other than lexical features, we observe URL statistics, HTML code, webpage javascript, webpage text, website external links, website structure, domain ranking, SSL certificates, TLD reputation, WHOIS data, DNS, and passive DNS based features [3, 8, 23]. We also find pre-trained transformer-based models such as BERT for feature extraction from websites [10], which suffers from dataset-dependency biases.

Furthermore, researchers have proposed benchmark datasets for phishing detection with combination of four categories of features based on URL, website's contents (HTML and Javascipts), external third-party (WHOIS, Google, OpenPageRank) or visual similarity using common sources (e.g., PhishTank, OpenPhish, Alexa, PhishMonger) [6, 9, 15, 41]. In our case studies, we have analyzed the features that are common within these benchmark datasets. In summary, all the existing approaches either lack transparency (i.e., interoperability) or generalizability (i.e., reproducing results with another dataset context). In this paper, we showcase how XAI can bring transparency of detection models as well as how they can be leveraged to test the generalizability of models across datasets.

3 Experimental Case Studies and Insights

To address the RQs, we propose the methodology highlighted in Fig. 1, which has the following five components– (i) Datasets collection and pre-processing; (ii) Feature analysis; (iii) Train and test XAI models; (iv) Evaluate model performances in various dataset-based experiment scenarios; (v) Generate insights from XAI outputs.

3.1 Data Collection and Data Pre-processing

3.1.1 Dataset-1 (D_1). This dataset is collected from Vrbančič *et al.* [36] and consists of 88,647 instances with 58,000 being benign and 30,647 being phishing URLs. Additionally, there are 111 features in this dataset taken from URL attributes and web contents. The dataset annotators considered different types of feature columns

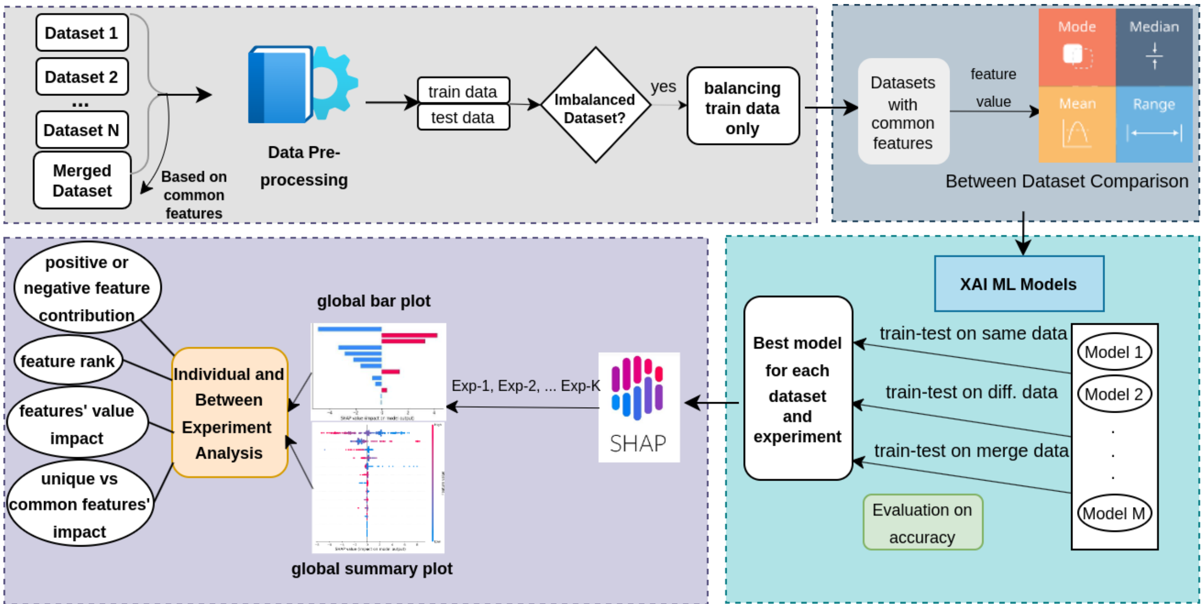


Figure 1: Overview methods for evaluating phishing features' generalizability

based on the whole URL, domain name, URL directory, URL file name, URL parameters, resolving URL, and third-party services.

3.1.2 Dataset-2 (D_2). This dataset is collected from Kaggle [37] that consists of 19, 431 row entries with 9, 716 being benign and 9, 715 being phishing samples. There are 85 total features in this dataset including features extracted from the URL, the HTML content, and the web domain.

3.1.3 Data Pre-processing. By analyzing the above two datasets, D_1 and D_2, we find 20 common features between them (while it is important to note that some common features have different names given by the annotators in these datasets, which is addressed by manually looking at the feature definitions of both datasets).
Addressing missing values If there is a null value in any rows for a particular feature (i.e., a column in the dataset), we fill it with the median value of that corresponding feature column.
Removal of features We have removed the columns that have no insights and only provided a single constant value in all rows. The preprocessing steps resulted in dataset D_1 being reduced to 98 features, D_2 being reduced to 79 usable features.

Table 1: Final train-test data distributions (SMOTE applied on D_1 training portion only for data balancing)

Dataset	Train		Test	
	Phish	Benign	Phish	Benign
D_1	40,614	40,614	9,209	17,386
D_2	6,770	6,831	2,945	2,885
D_{merge}	13,570	13,631	12,154	20,271

3.1.4 Correcting Data Imbalance and Optimizing Data Splitting. Dataset D_2 is already balanced for both classes, while we observe imbalance in D_1, with 88, 647 *benign* and 30, 647 *phishing* instances (ratio of 2.9 : 1). This imbalance can lead to biased models, as they tend to more accurate in predicting the majority class, leading to poor generalization performance when predicting minority class. To address this issue, we adopt the Synthetic Minority Oversampling Technique (SMOTE) [5], which is a popular oversampling method that generates synthetic instances of the minority class by interpolating between existing minority instances. We apply SMOTE only on the training portion of dataset D_1. This can produce more comparative model outcomes with the already balanced D_2. In this paper, we adopt a 70 : 30 split ratio for the train-test data splits. After correcting class imbalance, for some experiment scenarios, we have merged the two datasets D_1 and D_2 considering the 20 common features (defined in table 2) and created a third dataset, $D_{merge} = D_{merge(train)} + D_{merge(test)}$. To maintain the class balance and to generate fair explanation from SHAP, in $D_{merge(train)}$, we have taken 6,800 random instances for each groups (phishing and benign) in D_1's training portion and merged them with the D_2's training portion to get a total of 13, 570 phishing instances and 13, 631 benign instances. The test data for the merged dataset D_{merge} is the direct concatenation of the test data for D_1 and D_2. Table 1 depicts the distribution of all datasets D_1, D_2, and D_{merge}.

3.2 Feature Analysis

In both datasets D_1 and D_2, we have found that the majority of the features are extracted from the URL string (i.e., lexical features). Moreover, dataset D_1 does not have any HTML and JavaScript features while those are present in D_2 (i.e., existence of login form, iframe, favicon-based external links, and click event). So, between these two datasets, there are differences in the feature list if we consider all features. However, we want to know the impact of unique features (F_u) and the common features (F_c) as listed in Table

Table 2: Feature definitions for common features ($|F_c| = 20$)

ID	Feature Name	Feature Definition
f_1	qty_dot_url	Number of dot characters '.' in URL
f_2	qty_equal_url	Number of '=' character in URL
f_3	domain_length	Length of the domain name string
f_4	url_google_index	If the URL is indexed by Google
f_5	qty_dollar_url	Number of '$' character in URL
f_6	qty_slash_url	Number of '/' character in URL
f_7	qty_redirects	Number of redirects for landing page
f_8	url_shortened	If the URL is shortened
f_9	tld_present _params	If TLD present in the parameters of URL
f_{10}	qty_comma_url	Number of ',' character in URL
f_{11}	qty_hyphen_url	Number of '-' character in URL
f_{12}	qty_underline_url	Number of '_' character in URL
f_{13}	length_url	Length of entire URL
f_{14}	qty_percent_url	Number of '%' character in URL
f_{15}	qty_asterisk_url	Number of '*' character in URL
f_{16}	qty_questionmark _url	Number of '?' characters in URL
f_{17}	qty_tilde_url	Number of '~' character in URL
f_{18}	qty_at_url	Number of '@' character in URL
f_{19}	domain_in_ip	If the domain is an IP address
f_{20}	qty_and_url	Number of '&' character in URL

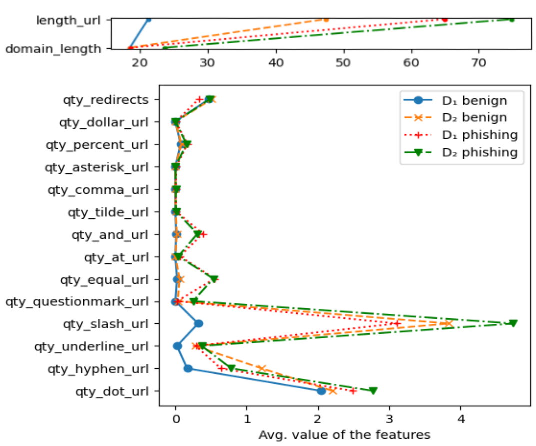


Figure 2: Mean values for the common *numerical* features

2 on the prediction models. That is why we consider the full feature list ($F_u \cup F_c$) along with only the common ones (F_c) to evaluate prediction model performance.

We also provide the basic statistics (i.e., mean values) comparison plot for both datasets in terms of phishing and benign URLs as shown in Fig. 2 and Fig. 3. This analysis is important, because if there exists innate differences in the dataset feature values, then it indicates an obvious difference in the explanations as well. Now, Fig. 2 shows that the mean values for the numerical features are very similar in both the datasets. However, in Fig. 3, the percentages of binary features' values for doimain_in_ip and url_google_index features are highly deviating between the datasets while the other binary features have very similar distribution. Additionally, we have also checked other statistical values such as min, max, median, and standard deviation for the features and observe a very similar values across the datasets.

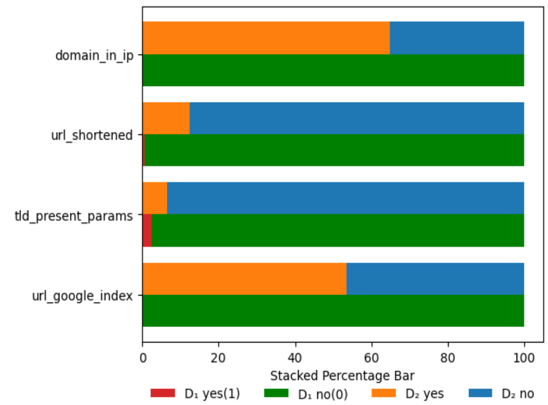


Figure 3: Percentages for the common *binary* features

3.3 Train and Test with Supervised Models

Next, we experiment with various machine learning models that can be further incorporated with SHAP XAI module. We train and test with different dataset portions in various experiment scenarios leveraging models such as *Logistic Regression* (LR), *Decision Tree* (DT), *Random Forest* (RF), *Naive Bayes* (NB), *Gradient Boosting Machine* (GBM), *XGBoost* (XGB), *Explainable Boosting Machine* (EBM) and *Support Vector Machine* (SVM). The performances of these ML models are evaluated using the standard evaluation metrics- *Accuracy*, *Precision*, *Recall*, and *F1 Score*. Among both the D_1 and D_2 datasets, *XGBoost* (XGB) performs the best for the detection of phishing URLs as shown in Table 3 with an accuracy of 97.1% in dataset D_1 and 99% in dataset D_2 when considered all features. The XGB model is followed by *Random Forest* with an accuracy of 97% for D_1 and 98.6% for D_2. Then, in order from highest accuracy to least accuracy we observe *Explainable Boosting Machine* (EBM), *Decision Tree*, *Gradient Boosting Machine*, *Logistic Regression*, *Naive Bayes*, and *Support Vector Machine* models. Thus, we use the *XGBoost* model to generate SHAP explanation plots for the various experiment scenarios in finding the feature's contributions.

3.4 Model Evaluation in Different Experiments

To strengthen our hypothesis on declining model accuracy in multiple dataset scenarios, we conduct several experiments with different training and testing data portions. The experiment scenarios include finding features' contributions when training and testing the model on the same dataset with all features, training and testing the model on the same dataset with only common features, and training the model on one dataset but testing on a different dataset, and finally training and testing on a merged dataset. We use the *XGB* model in this experiment scenarios to understand the features' behavior. Table 4 shows that using all features in a train-test scenario on the same dataset (i.e., Exp-1 and Exp-2) provides us with the best accuracy. Also, only using the 20 common features and conducting the train-test on the same dataset (i.e., Exp-3, Exp-4) gives us reasonably good accuracy results. However, when we apply train-test scenarios from different datasets, the accuracy drops drastically to 51% when model trained on D_1 and tested on dataset D_2, and 59%

Table 3: Comparison of different ML models on both datasets (in percentage)

Dataset	Metrics	LR	DT	RF	NB	GBM	XGB	EBM	SVM
D_1	Acc.	90.4	95.5	97.0	86.0	94.9	97.1	96.8	71.6
	Prec.	86.0	93.1	94.5	88.1	90.5	94.9	94.8	55.8
	Recall	86.3	94.0	96.9	68.9	95.4	96.7	96.2	86.3
	F-1	86.2	93.6	95.7	77.3	92.9	95.8	95.5	67.7
D_2	Acc.	80.0	97.2	98.6	74.1	96.2	99.0	98.2	60.2
	Prec.	81.4	97.0	98.5	71.2	96.4	99.1	98.3	56.8
	Recall	78.3	97.5	98.7	81.8	96.2	98.8	98.1	88.1
	F-1	79.8	97.2	98.6	76.2	96.3	99.0	98.2	69.1

when trained on D_2 and tested on D_1. In contrast, with the merged dataset D_{merge} in Exp-7, the accuracy is drastically increased to 91%, which can be implemented to get more generalized results.

Table 4: Performances of the *XGB* model using different train-test dataset experiment scenarios

Features	ID	Experiment	Acc.	Prec.	Rec.	F1
All (98)	Exp-1	train on D_1, test on D_1	97.1	94.9	96.7	95.8
All (79)	Exp-2	train on D_2, test on D_2	99.0	99.1	98.8	99.0
Common (20)	Exp-3	train on D_1, test on D_1	92.0	92.0	92.0	92.0
	Exp-4	train on D_2, test on D_2	93.0	93.0	93.0	93.0
	Exp-5	train on D_1, test on D_2	51.0	59.0	51.0	36.0
	Exp-6	train on D_2, test on D_1	59.0	70.0	58.0	50.0
	Exp-7.1	train on D_{merged}, test on D_{merged}	91.0	92.0	91.0	91.0
	Exp-7.2	train on D_{merged}, test on D_1	91.0	91.0	91.0	91.0
	Exp-7.3	train on D_{merged}, test on D_2	92.0	92.0	92.0	92.0

3.5 Insights with XAI Using SHAP Plots

In Explainable AI, feature importance can be classified into two categories: local and global. Local relevance refers to each feature's contribution to the prediction of a single instance, whereas global importance assesses each feature's overall impact on all instances. Phishing attempts are ubiquitous and diversified, therefore global importance is necessary to discover features that regularly influence the model's predictions, providing a more comprehensive view of feature significance. Here we apply the SHAP *TreeExplainer* object on the XGB model in all 7 experimental scenarios. Then, we have taken an equal number of phishing and legitimate instances from the test data and fed that to the explanation module to generate the corresponding SHAP values and plots. Each bar in the bar plot corresponds to a feature used in the phishing website detection model, where the length of the bar represents the mean absolute SHAP value for that feature - a measure of the impact of the feature on the model's output. A longer bar indicates a higher average impact, meaning that the feature strongly influences the model's predictions. This bar plot is also color-coded where the red bar represents the overall positive contribution and the blue bar represents a negative contribution of a specific feature. The summary plot provides us the overall picture of how each feature's actual value range (high, medium, or low) impacts the prediction for categorical target variable (i.e., *phishing* and *benign* in our case). Below, we discuss our findings of the features' importance for each of the 7 experiment scenarios.

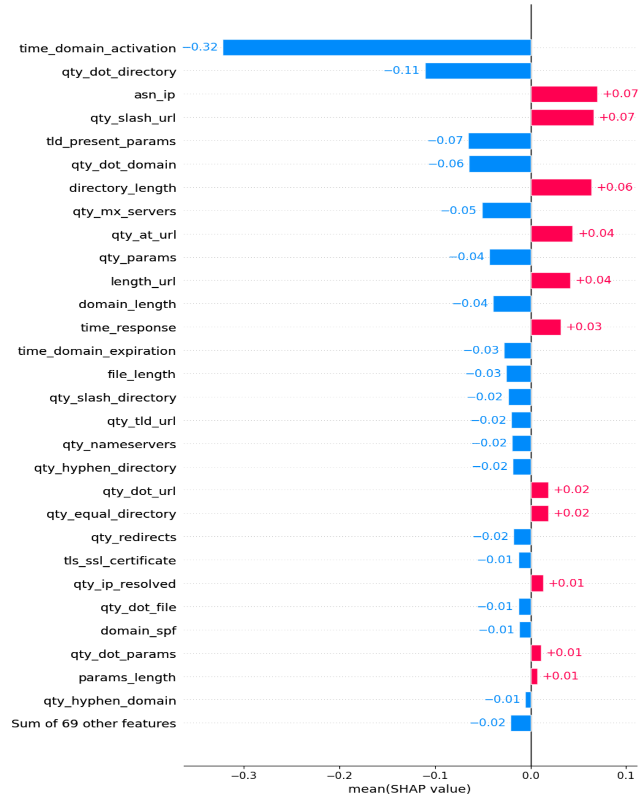


Figure 4: SHAP bar plot of Exp-1

3.5.1 *Exp-1 Feature Explanation.* Fig. 4 shows the top 30 influential features where we observe that 19 features are contributing negatively (blue bars), meaning on average, these features have contributed towards the *benign* class. Some of the highlighted negative contributing features are `time_domain_activation` (−0.32), `qty_dot_directory` (−0.11), `tld_present _params` (−0.07), `qty _dot_domain` (−0.06), `qty_mx_servers` (−0.05), etc. From these 19 features, 3 are from the common feature list F_c (f_3, f_7 and f_9). Figure 4 also shows that from the remaining 11 positively contributing features, top 4 are `qty_slash_url` (f_6) (+0.07),`qty_at_url` (f_{18}) (+0.04), `length_url` (f_{13}) (+0.04), and `qty_dot_url` (f_1) (+0.02).

3.5.2 *Exp-2 Feature Explanation.* Fig. 5 shows that 24 out of the top 30 most influential features are positively contributing (red bars). Some of the notable features are `page_rank` (+0.28), `total_of_www` (+0.19), `domain_age` (+0.17), `url_google_index` (+0.14) etc. From these 24 positively contributing features, 7 are in the F_c. Interestingly, we can clearly identify that a particularly common feature `domain_length` (f_3) is contributing positively in this case, which has shown a negative contribution in Exp-1 scenario. From the remaining 6 negatively contributing features, some notable ones are `shortest_word_path` (−0.08), `qty_slash_url` (−0.07), `phish_hints` (−0.05), `length_words_raw` etc. Here, the contribution direction of feature `qty_slash_url` (f_6), which is from the common features, is also completely opposite of the observation in Exp-1 scenario. Another interesting insight is that the relative order

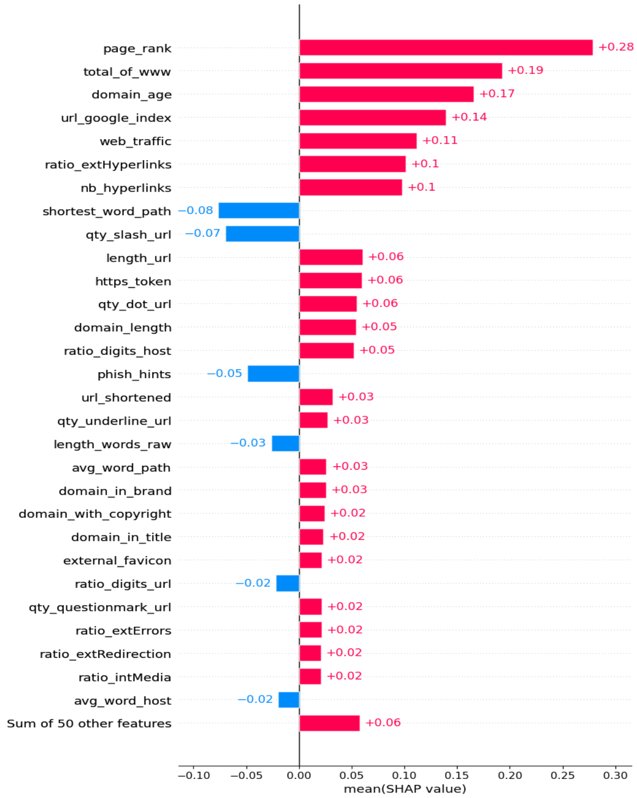


Figure 5: SHAP bar plot of Exp-2

of the common features based on the most influential contribution is also altered in Exp-2 compared to Exp-1. For example, in Exp-1 feature `url_google_index` (f_4) is not even in the top 30. However, in Exp-2 it is ranked as the 4-th most contributing feature. From Exp-1 and Exp-2 observations, we have the following insights.

Insight 1: From the top 30 most impactful features, the majority are unique features, meaning they are only present in one dataset, which shows the dataset-dependent features in phishing detection.

Insight 2: Even if common features are present in multiple phishing datasets, these features can contribute for predicting phishing class in one dataset while contribute for predicting benign class in the other dataset context.

Insight 3: A particular feature may contribute positively for phishing detection in one dataset while the same feature may impact negatively in another dataset scenario.

3.5.3 Exp-3 Feature Explanation . In this experiment scenario, we are using the 20 common features where training and testing are both conducted on dataset D_1. For this and the next experiment, we choose to depict the summary plot as it will show us the deviation in the value ranges for both dtasets. From the summary plot Fig. 6(a), we can see that higher value of features *qty_percent_url*, *tld_present_params*, *qty_slash_url*, *qty_at_url*, *domain_in_ip*, *url_shortened* and in addition, lower value of features *domain_length*, *qty_dot_url*, *qty_redirects*, *qty_hyphen_url*, *url_google_index*, *qty_questionmark_url* are contributing more on phishing prediction.

3.5.4 Exp-4 Feature Explanation . In this scenario, we are using the same common 20 features as Exp-3 but on a different dataset D_2. We expect that the apparent ranking order of features' contribution will be similar as both datasets share these same features. However, we observe the opposite of it. The summary plot in Fig. 6(b) shows that higher values of features `url_google_index`, `qty_percent_url`, `domain_length`, `qty_slash_url`, `qty_questionmark_url`, `qty_at_url` and lower values of features `qty_dot_url`, `qty_redirects`, `qty_hyphen_url`, `qty_underline_url` are contributing more on phishing prediction. This **answers RQ1** and unlike in Exp-3, we see that the lower value of features `domain_length`, `qty_questionmark_url` contribute more to phishing prediction. From these two features, f_3 or `domain_length` is the most influential cause it's the highest ranked feature in Exp-4 and 4-th ranked feature in Exp-3. Thus, the deviations between both Exp-3 and Exp-4 scenarios even when the same features are used for training and testing, raised a valid trust concern for features across different datasets. We can draw the following insights from both Exp-3 and Exp-4.

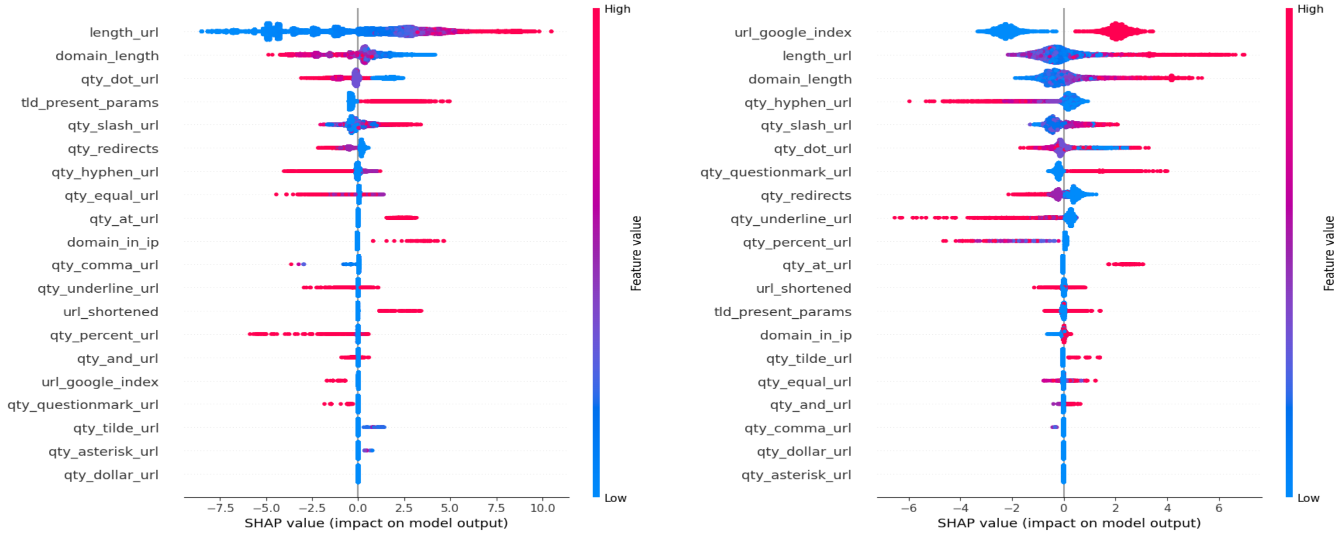
Insight 4: The relative orders of the features' contributions in various dataset-agnostic experiments can vary vastly.

Insight 5: The value range of a particular feature may impact the prediction completely differently in multiple datasets.

3.5.5 Exp-5 Feature Explanation. In this experiment scenario, we use the model that is trained on dataset D_1, but test it on the test portion of dataset D_2 as they both contain these 20 common features. This experiment help us **answering RQ2** in particular as we would learn how well or badly the model performs when the same dataset is not used in both the training and testing portions. We observe from Fig. 7 that the impactful features with positive feature contributions are `tld_present_params` (+2.46), `length_url` (+2.08), `domain_in_ip` (+1.62), `qty_slash_url` (+0.4), `domain_length` (+0.37) and `url_shortened` (+0.31). Among the negatively contributing features, `url_google_index` (−0.96), `qty_dot_url` (−0.22), `qty_hyphen_url` (−0.13), `qty_redirects` (−0.12) and `qty_questionmark_url` (−0.06) are the highlighting ones. Interestingly, the direction of contributions for the features `url_google_index` and `qty_dot_url` are changed compared to Exp-4.

3.5.6 Exp-6 Feature Explanation . In this experiment setup, we do the reverse scenario of Exp-5 where the model that is trained on dataset D_2, but we test it on the test portion of dataset D_1. From Fig. 8, we observe that `url_google_index` (−2.57) is the most influential feature with negative contributions though the same feature has positive contributions for single dataset train-test scenarios in both Exp-3 and Exp-4. In this experiment the other negatively contributing features are `qty_slash_url` (−0.36), `qty_questionmark_url` (−0.21), `domain_length` (−0.06) and `domain_in_ip` (−0.06). On the contrary, some top positively contributing features are `length_url` (+0.52), `qty_dot_url` (+0.16), `qty_underline_url` (+0.16), `qty_redirects` (+0.13) and `qty_hyphen_url` (+0.12).

Insight 6: When we train on one dataset and test on the other dataset, the model performance degrades significantly and feature



(a) (b)

Figure 6: SHAP summary plot for Exp-3 [6(a) on the left] and Exp-4 [6(b) on the right]

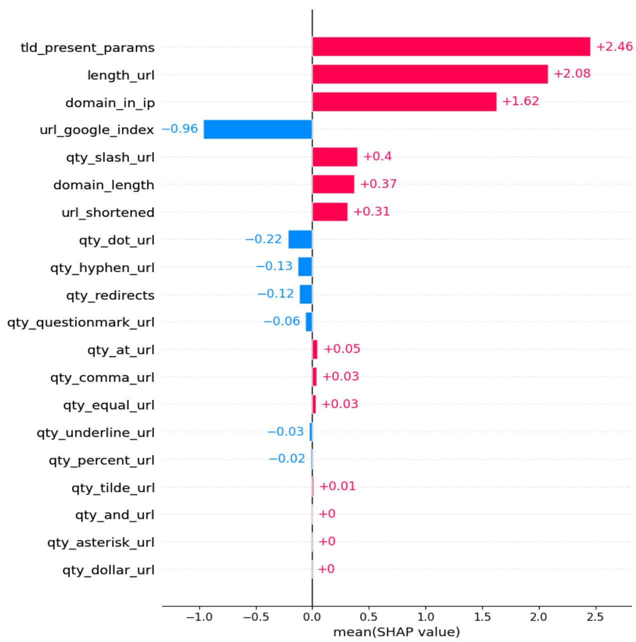


Figure 7: SHAP bar plot of Exp-5

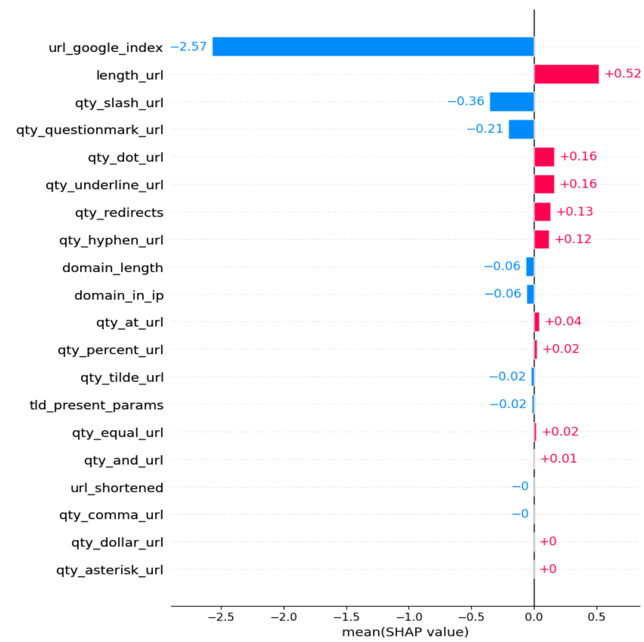


Figure 8: SHAP bar plot of Exp-6

contributions on the test set deviate remarkably from the scenario where training and testing has been conducted on the same dataset.

3.5.7 Exp-7 Feature Explanation. These sub-experiments help us **answering RQ3**. Here, we use the mixed training and testing dataset D_{merge}. Here, we observe from Fig. 9 that for Exp-7.1, feature `length_url` (−0.38) is contributing negatively, meaning contributing more towards *benign* class, while in all previous experiment scenarios, this specific feature has contributed positively to detect phishing URLs. Some negatively contributing features are `url_google_index` (−0.23), `qty_slash_url`,(−0.41), `domain_in_ip` (−0.15) and `domain_length` (−0.06). On the other hand, significant positively contributing features are `tld_present_params` (+0.84), `qty_dot_url` (+0.13), `qty _equal _url` (+0.11) and `qty_redirects` (+0.1). We can also see that the plot is quite similar to the Exp-6 plot

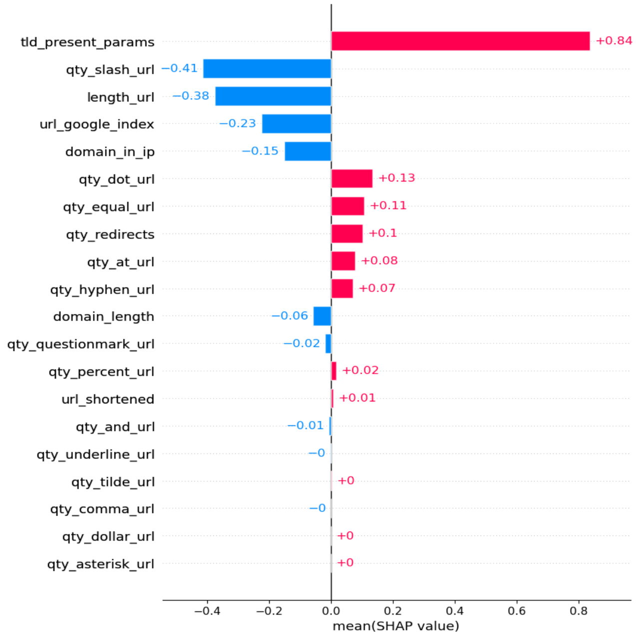


Figure 9: SHAP bar plot of Exp-7.1

in terms of features' contribution direction (positive or negative) except a very few features like `length_url` and `tld_present_params`. The SHAP plot results from Exp-7.2 and Exp-7.3 are also coherent with Exp-7.1 but not presented for space constraints.

Insight 7: Merging datasets for training can improve the model performance significantly even for diverse testing dataset scenarios and shows more consistent behaviors from the features' contribution and rank orders.

4 DISCUSSION AND LIMITATION

Amongst the 20 common features across dataset D_1 and D_2, these following six features- `qty_dot_directory`, `qty _slash _url`, `url_google_index`, `length_url`, `tld_present_params`, and `domain_length` play a major role in the model's predictions in all of the experiment scenarios. However, the contribution orders of these features changes depending on the dataset that has been used for the training and testing. Additionally, we observe the deviations where in a particular experiment a specific feature's higher range value is impacting more on phishing detection while the lower range value of that same feature contributes more in another experiment setup. This deviation can cause significant detection errors in practice when a new type of data is introduced for prediction in a pre-trained phishing detection model. Thus, we recommend developing a more complete publicly available bench-mark dataset from the research community for comparing model's performances as well as a comprehensive feature list. We also recommend keeping the dataset live and updated as data trends may change from time to time as attackers adjust their techniques and tactics through adversarial attacks.

Our experiments find that the model that works well when trained and tested on the same dataset, may not be effective when trained on one dataset and tested on another. This results into a very low accuracy for Exp-5 and Exp-6 scenarios, which infers that the model is not generalized well for phishing detection in practice and may only be effective in that particular dataset scenario. Initially, we have assumed that merging dataset D_1 and D_2 (in Exp-7) would result in better performance than Exp-5 or Exp-6 scenarios. Interestingly, that is turned out to be true as the trained model on the merged dataset capable of performing well on the test portion of not only the merged dataset but also the test portion of individual datasets D_1 and D_2. Thus, we recommend training on diverse datasets in practice for designing effective phishing URL or website detection models rather than using any singular dataset.

4.1 Limitations

Even though we shed light on the phishing detection features' deviation of effectiveness across datasets, there remain some limitations in the present study. **First**, the study does not take into consideration each feature's instance-specific contributions (local explanation) for identifying which features are deviating in the case of an individual test instance when trained on one dataset and tested on another. **Second**, we rely on the features' SHAP values when interpreting the model. While SHAP gives a single measure of feature relevance, it makes the assumption that features are independent, which may not be true always. **Third**, We also have not considered any datasets with shared visual similarity features because of scarcity of such features. **Fourth**, the common phishing versus benign URL classification features that we have analyzed are limited to mostly lexical features as they are more commonly found across multiple datasets. **Fifth**, we have not considered the deep learning methods which can be considered in future studies.

5 CONCLUSION

The usage of Explainable AI has allowed us to establish variables which are most important in detecting phishing websites, as well as how these features differ between datasets. The analysis discovered critical variables that contribute significantly to the model's predictions in several experiment scenarios. While the model performs well when trained and evaluated on the same dataset, its effectiveness is reduced when the training and test dataset are different even though they share the same features. This experimental evidences stress the need of training on different and representative datasets to improve model generalizability in practice before claiming a phishing detection model as effective with certain features. Thus, we can evidently state that phishing URL detection model that trained on singular dataset specifically using the lexical features can not be trusted across diverse datasets even if the features have very close data distributions. We recommend using multiple diverse merged dataset as a better method to use as training for the phishing detection model and always use explainable methods for AI/ML model's verification and trustworthiness for further decision-making on the outcome. The detail implementation code and dataset are shared in the following Github repository (https://anonymous.4open.science/r/Deviation-in-Feature-Contribution-7760/) for reproducing the experiments.

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