PhishAlert: An Efficient Phishing URL Detection via Hybrid Methodology

Bhawna Sharma, Parvinder Singh

Abstract: In spite of various research endeavors, phishing assaults stay common and exceedingly successful in attracting clueless clients to uncover delicate data, including account details and government managed savings numbers. Misfortunes due to phishing are developing consistently. A solitary methodology isn’t effective for distinguishing a wide range of phishing assaults. So we propose a hybrid approach to deal with the classification of URLs as phishing or real. The investigation aftereffects of our proposed methodology, in view of a dataset gathered from phishing and legitimate URLs, have demonstrated that PhishAlert framework can successfully counteract phishing assaults and can thus ensure system security.

Keywords: Phishing, Whitelist, Heuristics, Style Similarity, Hybrid Approach

I. INTRODUCTION

Phishing is a crime that takes sensitive information of users by misdirecting messages or phony sites [2], [5], [6]. "Phishing" word was taken from the word "fishing". The term phishing came into record in 1996 in America. Fishers (for example assailants) utilize a snare (for example counterfeit email enticing clients for entering touchy data) to get a fish (for example to befoul a client). Telephone Phreaking was the oldest type of hacking. So the character “f” of fishing was substituted by "ph" and the expression "phishing" came into picture. Online clients can be effectively beguiled into entering their own data in light of the fact that phishing sites are exceedingly like genuine ones.

Perniciously, by making phishing locales, "phishers" utilize various systems to trick their targeted people, including email messages, texts, discussion posts, telephone calls, and long range informal communication data. Phishing brings about serious monetary misfortune everywhere throughout the world, and phishing destinations are additionally developing quickly in amount and multifaceted nature [3]. The phishing assaults can be completed from various perspectives like email, SMS, voice, malware, website etc. In this work, PhishAlert algorithm is used to identify phishing URLs. As indicated by the Anti-Phishing Working Group (APWG), the number of phishing locales recognized in first quarter of the year 2019 was 1.81lac, Which was up outstandingly from the 1.38 lac seen in fourth quarter of the year 2018, and from the 1.51 lac seen in the third quarter of the year 2018. Phishing that focused mail services and Software-as-a-Service (SaaS) turned into the greatest classification of phishing. At 36 percent of all phishing assaults, it obscured phishing against the payment services category for the first time [39].

Some of the widely used anti-phishing techniques are listed below [7]:

- List-based techniques- Majority of the web-browsers (e.g. Google Chrome, Internet Explorer, Mozilla Firefox etc) utilize list based techniques. Blacklist and whitelist are two main types of list-based techniques. Whitelist is a list of all genuine URLs [1]. If the input URL is available in the whitelist, then the user can safely visit the URL. Because of this conduct, even the genuine sites which are not present in the whitelist are likewise choked bringing about high False Positive Rate. The blacklist contains phishing URLs which are hindered by the web browsers. Because of this conduct, the phishing URLs which are not available in the blacklist are allowed to visit by the user. This leads to high False Negative Rate. List based techniques are prone to zero-hour attacks since the most recent phishing site or the most recent legitimate site takes time for getting updated in blacklist or whitelist. Whitelists and blacklists are effective only if they are updated timely.

- Heuristic-based technique- This technique extracts features from the phishing site and uses these features to detect phishing attack [9], [12], [13], [14], [16], [23]. Heuristic method can detect zero-day phishing attacks [8]. Low false negatives and low false positives are achieved by using this technique. But this technique has less classification accuracy because all phishing sites do not have common features.

- Visual Similarity-based Technique- The user is tricked by the attacker by creating a website that has an analogous look as that of the genuine website [10], [11], [26]. This technique compares the image of the suspicious webpage with all the images present in the database containing legitimate webpages. The suspicious site is classified as phishing site when the parameter describing site-similarity comes out to be greater than threshold; otherwise the website is declared as legitimate. The comparison of images is a time consuming process. The consumption of storage becomes high due to the creation of a database containing images of legitimate webpages.

- Machine learning-based techniques: These days, majority of the analysts are utilizing Machine Learning (ML) algorithms [15], [19], [20], [38] for classifying sites as phishing or legitimate.
These systems are a blend of Machine Learning algorithms and heuristic strategies. Some ML methods are: AdaBoostM1, Sequential Minimum Optimization (SMO), Support Vector Machine (SVM), J48 Tree etc. These algorithms can detect zero-hour phishing attacks. These algorithms are capable of handling large datasets efficiently. The performance of ML based techniques relies on the type of classifiers, training-data’s size, features used and feature-set’s size.

Phishing is complicated cyber theft, and it is using a variety of phishing attacks [27], [28]. A single approach can’t identify all phishing sites efficiently [22], [30]. PhishAlert identifies phishing sites using a hybrid approach that combines whitelist, heuristics, content similarity and style similarity.

The primary objectives of this paper are:

- To put forward a vigorous solution to recognize phishing URLs rendering to a hybrid approach named PhishAlert which makes use of whitelist, heuristics, content similarity and style similarity.
- To prototype PhishAlert and to perform its evaluation on an enormous dataset.
- To compare PhishAlert with existing methods which are used for classifying sites as: phishing or legitimate.

The remaining paper is structured in this manner: Section II organizes the related work. Section III describes the proposed work. Section IV illustrates experimentation and results. The conclusion is deliberated in Section V.

## II. RELATED WORK

Some investigations have tended to the issue of phishing lately. The key elements of every method are investigated in this section.

Blacklists are every now and again refreshed arrangements of recently distinguished phishing sites, locations of Internet Protocol (IP) or catchphrases [2, 7]. Google Safe Browsing API enables customer to receive warnings for phishing sites. It uses two blacklists namely goog-phishshavar (for phishing) and goog-malware-shavar (for malware).

Whitelists are arrangements of checked authentic URLs. Ankit et al. [1] proposed an automated whitelist that keeps up a whitelist of the features depicting trusted Login User-Interfaces (LUIs). The automated whitelisted contains all trusted LUIs.

Wenyin Liu et al. [10] anticipated a method that utilized visual-layout based attributes to distinguish potential phishing websites and measure their similarity with legitimate sites. It developed a framework containing two procedures. The first procedure kept running on nearby mail servers and screened messages for watchwords and suspicious URLs. The second procedure looked at the phishing pages and determined visual-layout based likenesses between both of them as far as key areas, page designs, and generally styles. Kuan-Ta Chen et al. [11] introduced an anti-phishing method based on discriminative keypoints. This method used Contrast Context Histogram (CCH) to calculate the visual-similarity between phishing site and legitimate site.

S.Carolin Jeeva [14] proposed an approach based upon Intelligent Phishing in URL detection which extricated the important highlight that impact on authentic and phishing URLs. Further the identified highlights are exposed to apriori based algorithm and predictive apriori based algorithm in associative rule mining. The predominant highlights are considered. The proposed algorithm identified important feature i.e. security in Transport layer, absence of URL’s Top Level Domain and availability of reserve-word in the URL.

Zhang et al. [12] proposed CANTINA algorithm, based upon HTML content technique to recognize phishing sites and also examines the website page code and utilizes TF-IDF to identify the keywords which frequently occurred. The domain name and the frequent keywords are combined to form a search engine query. If no links are returned by the search query then the website is declared as phishing. Xiang et al. proposed the CANTINA+ algorithm [13]. This algorithm was reformatted from CANTINA algorithm. CANTINA+ added new features to the feature set of CANTINA. CANTINA+ used a rich feature set and applied machine learning techniques to identify phishing sites.

Jail-Phish [18] method utilized URL as info and showed the result as genuine or phishing. This method works for all languages and is independent of web history. This method was tried on old phishing set and new phishing set. It considered a large size dataset and achieved True Positive Rate of 97.92%.

Routhu Srinivasa Rao et al. [19] proposed CatchPhish to identify phishing websites depending on the highlights extricated from the URL of a given site. CatchPhish utilized two types of feature sets. One was based upon URL while other was based upon TF-IDF. TF-IDF algorithm was based upon Term Frequency- Inverse Document Frequency. Random Forest algorithm was utilized to identify phishing websites. On an enormous dataset, Catch-Phish accomplished 94.26% accuracy.

Rao and Pais [20] anticipated a method to identify phishing sites utilizing heuristic-based approach. The highlights utilized in this model to identify phishing sites don’t rely upon image database or web history. This technique detected the phishing websites using URL features (highlights). This model accomplished high accuracy of 99.55% utilizing Random Forest algorithm.

Phishing-Aware [21] used neuro-fuzzy approach. It structured an anti-phishing model, named Fi-NFN, to ensure security for nearby devices effectively and rapidly. Without expending numerous assets from nearby devices, Fi-NFN model straightforwardly secured clients progressively, yet in addition improved the nature of services at the edge of the system.

PhiDMA [22] planned by Sonowal and Kuppusamy, represented a Phishing Detection Model with Multi-layered Approach. Auto-updated whitelist, URL features-extractor, lexical-signature generator, string matching algorithm and accessibility-score comparator were used to identify phishing sites. From the trial results model could identify phishing websites effectively with an accuracy of 92.72%.

Phishing-Alarm [25] introduced a model to measure the suspiciousness of websites using the similitude of visual appearance between the websites. This methodology utilized Cascading Style Sheets (CSSs) as the premise to precisely evaluate the visual similitude of each page component.

Erzhou Zhu [29] et al. proposed OFS-NN, a viable phishing sites recognition model dependent on the optimal feature assortment and neural-network based method.
Over-fitting problem was resolved using OFS-NN.

Peng et al. [35] introduced a methodology which utilized natural language processing to detect phishing attacks.

Patil et al. [37] proposed three methodologies for identifying phishing sites. First methodology was to examine different highlights of URL. Second methodology was to check the authenticity of site by finding the place where the site is being facilitated and the people who are overseeing it. Third methodology utilized visual layout based examination to check validity of site.

### III. PROPOSED APPROACH

PhishAlert is an algorithm that classifies URLs as phishing (fake) or legitimate (genuine). It is proposed on the idea that a single approach cannot deal with all types of phishing attacks. So a hybrid approach is a better solution for the phishing problem. PhishAlert makes use of whitelist, heuristics, content similarity and style similarity. PhishAlert takes URL as input. The URL is checked in a whitelist. Whitelist is a list containing legitimate URLs. We initialize the list to GoogleIndex. If the input URL is available in GoogleIndex, then it is classified as legitimate; else it is passed to the next step. Features of URL are extracted in the next step. Phishing features are listed in Table-I. If the URL comprises of phishing features, then exit; else forward it to the next step. In the next step, find the top 5 frequent terms in the given webpage. Feed the URL along-with top 5 frequent terms on Google. If Google does not find any result, at that point the URL is declared to be a phishing URL and exit. If Google is able to return one or more results, then pass the input URL to the next step. The input URL is compared with search engine results URL on the basis of styling rules. CSS (Cascading Style Sheets) are used for styling webpages. Cosine similarity can be used as a similarity measure which can be computed using equation 1.

\[
\text{cosine - similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\| \cdot \|B\|}
\]

Here A and B are two vectors and they will be similar to each other if they have high value for cosine similarity; \( \theta \) is the angle between A and B. If the resulting percentage of the style-similarity of all URLs with the input URL comes out to be less than threshold, then affirm the site as phishing and exit. Otherwise forward the URL to the next step. If the URL is Legitimate then update the white list with this URL.

### IV. EXPERIMENTATION AND RESULTS

#### A. Performance Measures

Here \( PP \) is number of Phishing instances that are classified as Phishing instances. \( LP \) is number of Legitimate instances classified as Phishing. \( PL \) is number of Phishing instances that are classified as Legitimate. \( LL \) is number of Legitimate instances that are classified as Legitimate. Table-II presents the confusion matrix [7].

| S.No. | PHISHING FEATURES                      |
|-------|----------------------------------------|
| 1     | HOST URL LENGTH>20                     |
| 2     | COUNT OF SLASHES IN URL>6              |
| 3     | COUNT OF DOTS IN URL-HOST>4            |
| 4     | COUNT OF TERMS IN URL-HOST >4          |
| 5     | COUNT OF DOTS IN URL-PATH >2           |
| 6     | COUNT OF HYPHENS IN URL-HOST >1        |
| 7     | URL-LENGTH>75                          |
| 8     | USE OF IP ADDRESS AS A SUBSTITUTE OF DOMAIN NAME |
| 9     | PRESENCE OF HTTP PROTOCOL               |
| 10    | NON-EXISTENCE OF TOP LEVEL DOMAIN      |
Table-II: Confusion Matrix

| Predicted as | Declared as | Declared as |
|--------------|-------------|-------------|
| TRUE         | Phishing?   | Legitimate? |
| Actually Phishing? | PP         | PL          |
| Actually Legitimate? | LP        | LL          |

Different performance measures are [7], [18]:

1. **False Positive Rate (FPR)** - It computes the ratio of all legitimate instances that are classified as phishing to the total number of legitimate instances.\[ FPR = LP / (LP + LL) \] (2)

2. **True Positive Rate (TPR)** - It computes the ratio of all phishing instances that are classified as phishing to the total number of phishing instances.\[ TPR = PP / (PP + PL) \] (3)

3. **False Negative Rate (FNR)** - It computes the ratio of all phishing instances that are classified as legitimate to the total number of phishing instances.\[ FNR = PL / (PP + PL) \] (4)

4. **True Negative Rate (TNR)** - It computes the ratio of all legitimate instances that are classified as legitimate to the total number of legitimate instances.\[ TNR = LL / (LL + LP) \] (5)

5. **Accuracy (ACC)** - It quantifies the general rate of accurately recognized phishing and authentic occasions in connection to all examples.\[ ACC = (LL + PP) / (LL + LP + PL + PP) \] (6)

6. **Precision (P)** - It computes the ratio of all phishing instances that are classified as phishing to the total number of phishing instances that are identified as phishing.\[ P = PP / (LP + PP) \] (7)

7. **Recall (R)** - It is same as True Positive Rate\[ R = TP \] (8)

8. **f1-Score** - The Harmonic Mean of Precision and Recall is termed as f1-score.\[ f1 - Score = (2 * P * R) / (P + R) \] (9)

B. Results and Discussion

PhishAlert algorithm is used to classify every URL in the dataset as phishing or legitimate. PhishAlert algorithm has been implemented in Python.

An experiment was performed using a dataset containing 1000 URLs. Out of these, 500 URLs were legitimate and 500 were phishing. The legitimate URLs were collected from stuffgate database whereas the phishing URLs were collected from phishTank database as shown in Table-III.

Table-III: Database used

| S.No. | Database   | Links                                      | Instances |
|-------|------------|--------------------------------------------|------------|
| 1.    | Stuffgate  | [http://stuffgate.com/stuff/website/top-sites](http://stuffgate.com/stuff/website/top-sites) | 500        |
| 2.    | phishTank  | [https://www.phishTank.com](https://www.phishTank.com) | 500        |

Table-IV shows the confusion matrix used in the experiment. From the confusion matrix it is clear that PhishAlert correctly classifies all the legitimate instances but incorrectly classifies 25 phishing instances. So TPR=0.95, FPR=0.05, TNR=1, FNR=0 and Accuracy=0.975. Table-V shows the values computed in the experiment for measuring precision, recall and f1-score. The average precision of phishing and legitimate instances comes out to be 0.975. The average recall value results into 0.975. The average f1-score becomes 0.975. The comparison of PhishAlert with existing approaches is presented in Table-VI. It can be concluded from Fig. 1 that the average value for all three performance measures (precision, recall and f1-measure) is greater than 0.9 which is quite satisfactory. PhishAlert gives highest value for all the three performance measures (precision, recall and f1-score) as compared to CANTINA [12] and CANTINA + [13]. Fig. 2 shows that PhishAlert is more efficient algorithm as compared to CANTINA [12] and CANTINA+ [13].
Phishing is said to be a noteworthy cyber theft which has been making money related misfortune for the individual clients and associations. It is very complicated issue, and a solitary identification prototype is not able to differentiate all classes of phishing attacks. PhishAlert model was designed in this paper to recognize phishing i.e. fake URLs by utilizing hybrid approach which is a combination of various methodologies to be like whitelist, heuristics, content similarity and style similarity. PhishAlert performed more efficiently as compared to existing algorithms, namely, CANTINA and CANTINA +, on the experimental dataset that contained 500 phishing instances and 500 legitimate instances. PhishAlert was found to be 98% precise. This outcome demonstrates that the model could effectively distinguish all phishing URLs. PhishAlert model’s performance decreases with increment in size of dataset. More features ought to be incorporated into the future work to the PhishAlert algorithm so as to achieve better classification rate.

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