Detecting Phishing Sites - An Overview

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Abstract

Phishing is one of the most severe cyber-attacks where researchers are interested to find a solution. In phishing, attackers lure end-users and steal their personal information. To minimize the damage caused by phishing must be detected as early as possible. There are various phishing attacks like spear phishing, whaling, vishing, smishing, pharming and so on. There are various phishing detection techniques based on white-list, black-list, content-based, URL-based, visual-similarity and machine-learning. In this paper, we discuss various kinds of phishing attacks, attack vectors and detection techniques for detecting the phishing sites. Performance comparison of 18 different models along with nine different sources of datasets are given. Challenges in phishing detection techniques are also given.

Keywords- Phishing, Websites, Detection, Machine-learning

1 Introduction

In recent days cyber-attacks are increasing at an unprecedented rate. Phishing is one among those cyber-attacks \cite{55}. In phishing, attackers lure the end-users by making them click the hyper-links which make them lose their personally identifiable information, banking and credit card details, and passwords. In this attack the attackers disguise themselves as trusted entities such as service providers, employees of the organization or technical-support team from the organization so that end-users never doubt them. It is mainly done through emails asking to update the system, or saying that account has been suspended, or asking to claim the prize and so on \cite{59}. The main goal of phishing is to make end-users share their sensitive information. Now-a-days information regarding anything is available online and that information is stored in websites. Websites help the end-users by providing them information about their respective products, services or helping the end-users if they face any problem by chatbots, message forums and so on. Websites also store the personal information of the end-users. As websites help the end-users in gaining information they can be used as bait for trapping the end-users to obtain confidential information from them. Websites can be forged easily with the help of many online tools. The forged websites look exactly similar to the legitimate websites and end-users will not get any doubt while browsing these sites. The illegitimate websites must be detected as early as possible to make sure that there is no loss of information.

1.1 Types of Phishing Attacks

There are different types of Phishing attacks. The main goal of these attacks are to obtain sensitive information from the end-users. Figure 1 shows various types of phishing attacks.

1.1.1 Email Phishing

In this type of phishing an attacker sends an email regarding any problem, update or any sensitive matter that must be changed immediately once the user clicks the email and all the input the details entered by the end-users will be redirected to the attacker \cite{56}.
1.1.2 Spear Phishing

In this attackers aims for specific individuals or enterprises, as opposed to random application users. It’s a more in-depth version of phishing that requires special knowledge about an organization, including its power structure. In this attack emails are sent to specific persons unlike phishing [56].

1.1.3 Whaling

It is known as whaling phishing or a whaling phishing attack. It is a form of spear phishing where, in this phishing attackers target high-profile employees, such as the CEO or CFO, in order to steal sensitive information from a company. As these people hold higher positions within the company, they will have complete access to sensitive data. It will be easy to obtain more information [57].

1.1.4 Smishing

It is also known as SMS phishing. It is a type of social engineering attack carried out in order to steal user data including personal information, financial information, and credentials. Smishing also aims at laundering money from victims. In Smishing, scammers send phishing messages via an SMS text that includes a malicious link. The phishing messages trick recipients into clicking the malicious link, which redirects them to a phishing page where personal information is harvested [56][58].

Example: Lucky Draw campaign - In this attackers send SMS to end-users asking them to claim the account that they have won through lucky draw. Attackers ask them to click the link and provide their information so that amount will be transferred to their accounts.

1.1.5 Vishing

It is also known as Voice Phishing. It is a type of phone fraud that uses voice messages to obtain personal information or money from victims. Vishing uses automated voice recordings to lure victims. In Vishing, an automated voice call stating that the recipients’ bank account has been compromised is sent. The voice message then asks the recipient to call a specified toll-free number. Once users call to that toll-free number, the user’s bank account number and other personal details are harvested via the phone keypad [56][58].

1.1.6 Pharming

Pharming is sometimes known as “phishing without a lure”. When a user attempts to navigate to a site, their computer can determine the IP address by either consulting a local file of defined mappings—a hosts file—or by consulting a DNS server on the Internet. Pharming is usually conducted either by changing the hosts file on a victim’s computer (hosts file pharming) or by exploiting a vulnerability in DNS server software (DNS poisoning) [60].

1.1.7 Content-injection Phishing

In this, the content of the legitimate website is replaced with some random content with different input fields similar to legitimate site so that end –users trust easily and give their data easily [60].

1.1.8 Search Engine Phishing

It occurs when phishers create websites with attractive sounding offers and have them indexed legitimately with search engines. Users find these sites in the normal course of searching for products or services and are fooled into giving up their information [60].
1.2 Phishing techniques

There are different techniques used by attackers to execute different types of phishing attacks. By using these techniques the attackers can bypass the security and are able to obtain confidential information from the end-users [61].
1. Link Manipulation
2. Website Forgery
3. Pop-ups

1.2.1 Link Manipulation

Link manipulation [61] is a widely used technique for phishing scams. It is done by directing a user through fraud to click a link to a fake website. Hackers are now using manipulative ways to get the users to click such as:
1. Use of sub-domains
2. Hidden URLs
3. Misspelled URLs
4. IDN (internationalized domain name) Homograph attacks

1.2.2 Website Forgery

Website forgery [61] is another phishing technique that works by making a malicious website impersonate an authentic one, so as to make the visitors give up their sensitive information like account details, passwords, credit card numbers, etc. Web forgery is mainly carried out in two ways:
1. Cross-site scripting
2. Website spoofing

1.2.3 Pop-ups

Pop-up messages are one of the easiest techniques to conduct successful phishing scams. They allow hackers to steal login details by sending users pop-up messages and eventually leading them to forged websites through these pop-ups. A variant of phishing attacks, also known as “in-session phishing,” works by displaying a pop-up window during an online banking session and appears to be a message from the bank [61].

1.3 Phishing Websites

Phishing websites are replicas of legitimate websites. For phishing websites, entire website is not created, only the home page or page where user can give inputs is created so that any information entered is sent to the attacker. There are many ways to create a phishing website such as downloading source code of any particular website, clone the website or use any specific tools. In kali-linux there is a tool called SET (social-engineering toolkit) which is mainly used for cloning of web-pages [70]. The difference between the phishing websites and legitimate websites can be seen in their URLs, content of the websites, logos seen on the websites, hyperlinks, hosting domains, domain age, source-code, SSL certificates [43] etc. Now-a-days as URLs being too large, they are being shortened. These are done by URL shorteners [50]. These URLs look different from normal URLs, they don’t contain any domain, sub-domain, Top-level domain (TLD), they just contain protocol and path. These URLs just redirects to the original URL. In this method as there is no information regarding about website, attackers make use of this method and send this type of URLs to the end-users. End-users doesn’t pay much attention to URL, they just click the URL and enter the credentials, in that way they lose their confidential information. These websites must be identified as early as possible to prevent loss of data.

The rest of the paper is organized into different sections: Section 2 lists various website detection methods over time, Section 3 describes about different sources of datasets, comparison between different models along with their accuracy and different challenges to be worked on, Section 4 presents challenges and discussions, and Section 5 presents the conclusion followed by references.

2 Phishing Website Detection Techniques

There are different types of detection techniques for detecting the phishing sites. Figure 2 shows various types of phishing detection techniques.
2.1 List based

In this method there are two types:
1) Blacklisting
2) White-listing.
These are also known as traditional approaches or database-oriented approaches. Their response time and detection accuracy is very high [36][42].

2.1.1 Black-Listing

In this technique, the URL’s which are considered as phishing sites are stored in database so when a new URL is entered it compares with the URLs in the database and if it matches it is blocked by the browser and is stored in the database for future purpose. The limitation of this technique is that detection of zero-hour phishing attacks is not possible [42].

2.1.2 White-Listing

In this technique, the legitimate URLs are stored in the database and are used for checking new URLs. In this technique when a new URL is entered, first they check for that URL in the database, if there is no record of that URL then the entire information of that URL is checked such as domain names, age, SSL certificates, hyper-links connected to the website and then they are stored in the database. The drawback in case of white-listing technique is, are the websites registered as legitimate are really legitimate or they present themselves as legitimate. The limitation of listing techniques is they require large amount of space [42].

2.2 Heuristic Oriented Detection

It is extension of listing technique. In this technique, features of the websites are extracted such as URL’s, content and they are used for comparison among different sites. If they match then those new websites are considered as phishing sites. These are better than listing techniques and their results gives more accuracy but their response time is low [5][42][43][12]. A different approach for detection of zero-hour phishing attack is discussed in [37].

2.2.1 URL-based

For increasing the speed of the detection, URL based detection mechanisms are more popular. If URL-based features combined with machine learning gives better accuracy-rate [7][14][35].

2.2.2 Content-based

In this, the content of the websites are compared with the legitimate websites to determine whether the sites are legitimate or not [12]. But there are many websites which doesn’t have much content then this detection strategy fails. Now-a-days website contents are replaced by images [36].

2.3 Visual Similarity

In this technique screenshots of web pages are taken and are stored in the databases. Then if there are look alike websites then the screenshots of both the web-pages are compared to detect if it is phishing website.
or not. The limitations of this technique are it consumes a longer execution time leading to be unrealistic. It requires large storage space for storing the screenshots of websites. When multiple websites with same URL appear the first one to appear is considered as legitimate. But there can be any chance that the first to appear can be a phishing site [27][36][42][54].

2.4 Machine learning

Based on different datasets obtained from the different features of the websites, machine learning trains model from those datasets and tests them with different machine learning classifiers such as Random forest classifier, Support vector machine, Decision Tree, Naive Bayes, Logistic regression and so on [32]. These classifiers help in predicting the websites even before they are created, thus machine learning solves the problem of zero-hour phishing attacks. The classifier’s accuracy varies depending on the size of the dataset and type of features used [2][26][45][48]. Frameworks are also developed to detect phishing attacks [51][53].

2.4.1 Naive-Bayes

Naive Bayes classifier is a generative probabilistic model in machine learning and is based on the Bayes theorem. It is mostly used in classification areas, such as text classification, spam detection, because of its simplicity. Its features are independent among each other. Detection of websites using lexical analysis of URL in which Naive Bayes achieved the highest accuracy [6][16][52].

2.4.2 Random Forest

Random Forest is an ensemble classifier used for classification and regression. It constructs decision trees based on randomly selected sets in training samples and then aggregate decisions from these trees by averaging or majority voting. It improves accuracy and also reduces over-fitting [4][9][16].

2.4.3 Decision Tree

Decision tree classifiers are one of the most popular classifiers used in classification and regression. It divides the training data-set until it reaches to a leaf node, which is a label in classification. Decision tree classifier uses the entire training data-set while constructing a tree unlike Random Forest [9][16][52].

2.4.4 Support Vector Machine

Support vector machine can solve linear or non-linear problems. In linear problems, it simply finds a hyperplane in N-dimensional feature space [52]. Different versions of support vector machine can also be used for detection purposes [5][16][53].

2.4.5 K-Nearest Neighbour

KNN is a non-parametric algorithm used in both classification and regression. Its classification works on unknown data closest to k in the training feature space. Closest points are selected using distance functions such as Hamming, Euclidean and Minkowski. KNN works slow if the data size is large [16].

2.4.6 Logistic Regression

Logistic regression is a discriminative probabilistic model mainly used in which the output is binary. Logistic regression performs better than Naive Bayes model when training size is close to infinity [16][52].

2.4.7 AdaBoost

AdaBoost (Adaptive Boosting) works as a conjunction algorithm because it is used to classify by training different weak learning algorithms to form a strong one i.e. to improve performance. The output of weak classifiers are combined by setting correct weights for final decision. Since AdaBoost is sensitive to outliers and focuses on hard-to-classify samples, it is less resistant to overfitting [21][46][52].

2.4.8 Artificial Neural Networks

Artificial neural networks(ANN) consist of information processing elements known to mimic neurons of the brain. ANN is classified into two types depending on the number of layers, they are shallow and deep neural networks. If the number of layers is two i.e. only input and output layer then it is shallow neural networks. If the neural networks consists of three layers in which there is at least one hidden layer then it is deep neural network [11][16][49][69].
2.4.8.1 Deep Neural Network

Deep neural network represents the type of machine learning when the system uses many layers of nodes to derive high-level functions from input information. It means transforming the data into a more creative and abstract component [25][77]. To detect the problem of over-fitting, a new method has been proposed namely, OFS-NN, an effective phishing websites detection model based on the optimal feature selection method and neural network. The proposed algorithm is able to alleviate the over-fitting problem of the underlying neural network to a large extent [40].

2.4.8.1.1 Feed-Forward Neural Network

A feed-forward neural network is an artificial neural network wherein connections between the nodes do not form a cycles. In this network, information travels from the input nodes, through the hidden nodes (if any) and to the output nodes in just one direction, forward. The network does not have any cycles or loops [13][71].

2.4.8.1.1.1 Convolutional Neural Networks

Convolutional Neural Networks(CNN) belongs to the family of Artificial Neural Networks. A CNN is a deep learning technique that works well for identifying simple patterns in the data which will then be used to form more complex patterns in subsequent layers. It gives high accuracy when compared to other machine learning classifiers [8][10]. PhishingNet, a deep learning-based approach for timely detection of phishing Uniform Resource Locators (URLs) which uses CNN as well as RNN to extract the features [3][17][19][24][27][33][41][52].

2.4.8.1.1.2 Radial basis Function

Radial Basis Function(RBF) is a type of feed forward neural network that has been used broadly for classification and regression problems because of its simplest architecture and effective results for numerical data [20].

2.4.8.1.2 Multi-layer perceptron

Multilayer Perceptron (MLP) is a successful model in the field of deep learning. It is a class of feed-forward supervised learning techniques. It has multiple layers of perceptron with a non-linear activation function rather than a single-layer perceptron; that’s why it is called multiple layer perceptron. It uses a back propagation algorithm for supervised learning [13][22].

2.4.8.1.3 Recurrent Neural Networks

A class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence is recurrent neural network (RNN). This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs [15][18][41][72].

2.4.8.1.3.1 Long term Short memory

The artificial recurrent neural network (RNN) architecture[1] used in the field of deep learning is long short-term memory (LSTM). LSTM has feedback links, unlike normal feedforward neural networks. It can process not only single data points (such as images), but also entire data sequences, such as speech or video [15][18][33][52][74].

2.4.8.1.4 Capsule Neural Network

The machine learning system that is a type of artificial neural network (ANN) that can be used to better model hierarchical relationships is Capsule Neural Network (CapsNet). Add structures to a convolution neural network (CNN) called "capsules" and to reuse output from some of those capsules to form more stable representations for higher capsules is their idea. The output is a vector consisting of the likelihood of an observation and a pose for that observation[31][73].

2.4.8.1.5 Deep Belief Network

Deep Belief Network(DBN) is a generative graphical model composed of multiple hidden layers with connection between layers and, there is no connection between units within each layer. DBN involves two steps that is, training in unsupervised way and training in supervised way. In unsupervised way, DBN learns to probabilistically reconstruct to input, this layer is called feature detectors on input. In supervised way, DBN works as classifier and does classification. DBN
extracts the deep hierarchical representation (knowledge) and learns from this knowledge to make best model [29].

### 2.4.8.1.6 Auto-encoder

Auto-Encoder (AE) is an unsupervised deep learning method. The basic framework of AE comprises an input layer, an output layer, and a hidden layer. Therein, the input layer and the output layer have the same structure, and when the input is equal to the output, the hidden layer represents potential structure and characteristics of the input. The aim of AE is to transform inputs into outputs with the least possible amount of deviation [30].

### 2.4.9 Fuzzy logic

Machine learning detects the sites through feature extraction but what types of features are considered, does the features considered are enough to detect the phishing sites and are those features present in all the sites. These can be known by using Fuzzy rough set, which is used as a tool to select the most effective features for detecting phishing websites by using most commonly used features such as domain based, address-bar, abnormal-based and HTML/JavaScript based [23][38][44][47].

### 3 Datasets & Performance comparison

In this section performance comparison of different models along with different datasets are discussed. Datasets play an important role in predicting illegitimate websites. In techniques like Machine learning, deep learning and neural networks: first data will be collected from the different sources, then the collected data will be used for training the model and then the model will be used for testing to check whether it can predict the websites correctly or not. Some of the common sources of datasets are shown below in Table 1. Alexa and Common crawl contains names of the legitimate sites which are likely to be used for phishing [62][63]. Phish-tank, Open-Fish are the sites where end-users report the suspicious URL’s to know whether they are phishing sites or not [64][65]. In UCI-Machine learning repository the data-set is collected from different sources and stored. This dataset is mainly used for research purposes [66]. In Majestic, the data-set contains domains with the referring subnets [67]. Ebbu2017 dataset is used in [39] to train the model. The data-set contains 73,575 URLs, out of which 36,400 are legitimate and 37,175 are phishing. Kaggle is an online repository which contains different datasets collected from different sources [75]. These datasets are helpful in training the models.

Performance results from different papers are collected. These results differ based on the datasets used, features extracted from the websites, algorithms used and the different classifiers used for comparison. These all factors play a vital role in determining the accuracy. The results are shown in the Table 2. It has the details of the sources of the datasets taken for experimenting, number of instances of website URLs taken to train model which can predict the phishing sites, along with the model which gave highest accuracy when compared with the other models. This data is taken from the papers collected.

| S.No | Name of the datasets | Size of data-set | Description |
|------|----------------------|------------------|-------------|
| 1    | Alexa database[62]   | 1 million URLs   | Top 1 million sites |
| 2    | Common-Crawl [63]    | 940 million URLs | 2.8 billion web-pages |
| 3    | Phish-tank [64]      | 68,40,198 URL’s  | updated-daily |
| 4    | Open-Fish [65]       | 4,253 URL’s      | updated-daily |
| 5    | UCI Machine learning repository [66] | 11,055 URL feature values collected from 2456 different websites |
| 6    | Majestic [67]        | 1 million URLs  | Top 1 million website in the world |
| 7    | Ebbu2017 [68]        | 73,575 URL’s     | both legitimate & phishing URLs |
| 8    | Kaggle [75]          | 11,000 URL’S     | contains different datasets |
| 9    | 5000 Best Websites[76] | 5000 URLs     | Information about website is provided |
Table 2: Performance comparison of different techniques

| S.No | Detection technique | Source of the datasets | Accuracy |
|------|---------------------|------------------------|----------|
| 1    | Naive-Bayes[6]      | Phish-tank, OpenFish, Majestic | 97.18    |
| 2    | CNN [3]             | Common-Crawl, Phish-tank | 96       |
| 3    | Random-forest [9]   | Kaggle                 | 97       |
| 4    | CNN [10]            | UCI Machine Learning Repository | 97.3    |
| 5    | CNN+RNN[41]         | Phish-tank, OpenPhish, Alexa | 97.9 |
| 6    | Deep Reinforcement Learning[39] | Ebbu2017Phishing Dataset | 90.1 |
| 7    | Character-level CNN[8] | Alexa, Openphish, spamhaus.org, techhelplist.com, isc.sans.edu&phishtank | 95.02 |
| 8    | OFS-NN[40]          | UCI Machine Learning Repository, Phishtank, Alexa | 99.3 |
| 9    | XCS [45]            | Alexa, Phishtank       | 98.3     |
| 10   | TWSVM[5]            | Alexa, Phishtank       | 98.05    |
| 11   | Random Forest [4]   | Common-Crawl, Alexa, Phishtank | 94.26  |
| 12   | Multilayer Perceptron [13] | Kaggle | 98.4 |
| 13   | CNN+LSTM [33]       | Phishtank, Common-Crawl | 93.28 |
| 14   | Random Forest with NLP based features[34] | Phishtank | 97.99 |
| 15   | Adaboost + SVM [21] | UCI Machine Learning Repository | 97.61 |
| 16   | CNN-MHSA [24]       | Phishtank, 5000 Best Websites | 99.84 |
| 17   | Multilayer Perceptron[22] | UCI Machine Learning Repository, Kaggle | 96.65 |
| 18   | HNB+J48[28]         | UCI Machine Learning Repository | 96.25 |

4 Challenges & Discussion

Some of the challenges are collected from the existing methods to improve their accuracy rate.

1. Reduce False positives
   In classification problem machine-learning gives a confusion matrix. In some classifiers, false positive rates are high i.e, even though the websites are legitimate the model classifies them as illegitimate sites, in this way end-users can’t access the real website. If they can be reduced then the end-users can be able to access the legitimate sites without any problem.

2. Eliminate False negatives
   While predicting the accuracy, the classifiers give false negatives i.e, even though the websites are illegitimate the model classifies them as legitimate and this will result in damage, which includes loss of fame, corruption of systems and so on. These must be eliminated in order to prevent any harm to end-users and organisations.

3. Datasets and their modelling time
   Datasets play an important role in training models. By using old datasets the trained model may not be able to predict correctly as the model is unaware of new phishing attack vectors. Using current datasets is the solution. When the datasets are small, modelling time of the classifiers is not known as they will be trained in less time. When datasets differ in size their modelling time will alter so when we use larger datasets the modelling time will be known properly.

4. Selection and usage of features
   There are many features of a website such as URL, page, content features, domain features, source-code and so on which are used for detecting the sites. To decide what features can be used to train a model which can give more accuracy in detection is difficult. When only a single feature is used for detection then the prediction results may not be accurate. Using of multiple features of a website give more information about the site which can help in the detection process.

5. Sensitive words
   Use of sensitive words such as mail, bank, SMS and so on will have impact while predicting the sites. This may reflect in the results.

6. Embedded objects
When a detection technique uses source code of a website for predicting the sites it extracts all the html tags but when there are any embedded objects such as i-frames, flash etc, it may be not able to detect properly.

7. Overfitting
Overfitting happens when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data. The problem is that these concepts do not apply to new data and negatively impact the models ability to generalize [78].

5 Conclusion

We discussed phishing website detection techniques. The techniques include list-based, heuristic-based, visual-similarity and machine-learning. We compared the performance of different methods with respect to datasets. Future work includes, finding solutions for the challenges, so that any type of phishing sites can be detected as early as possible.

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