DEPARTMENT OF SOFTWARE ENGINEERING

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Project Report
on

Detection of malicious URLs using Machine learning algorithms

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1. ABSTRACT

One of the most common problems on the internet is phishing attacks. Many internet users are targeted by hackers on a daily basis, resulting in daily losses of billions of dollars around the world. Users connected through internet who are unaware of cyber-attacks may lead to these kind of issues. As a result, free malicious detection algorithms are required to address these critical issues. In this research, we show how several ML algorithms can be used to detect malicious URLs. The results of several ML algorithms on the dataset has been calculated and is presented in the tables, indicating that ML algorithms can produce good results with respect to precision, accuracy, recall, f-score, and ROC AUC.

2. INTRODUCTION

ML algorithms is extensively used in various fields to solve various real-world problems [1]. From accelerating businesses to providing better healthcare, the use of machine learning algorithms is well explored [2]. The priorities of researchers in making the use of artificial intelligence (AI) for making lives easier has changed our lives in different ways. The never-ending exploration of the applications of AI in smart cities has led to numerous discoveries [3]. With the technologies evolving day by day, there have been some dark sides associated with it. The fraudulent activities are happening on a very large scale which needs to be stopped. It has been anticipated that the loss because of cyber-attacks is likely to achieve $6 trillion till end of 2021, that is quite huge amount of money [4]. One of the fraudulent activities that happen over the internet is phishing activities. There are a lot of ways in which attackers lure the victims into clicking the malicious links which may result in the victim losing their personal data and even money in some cases. Mostly, the attackers use emails, blog posts, chat sessions, etc. for posting the malicious URLs where it is highly likely that the victims click on them. [5] The links appear to be very tempting where attackers promise free money, high paying jobs, etc. Victims often fall into such fake promises and click the URLs. Phishing is even widespread with more users using the internet who don't even have basic knowledge about phishing and cyber-attacks. In this situation, there is a need for an automated system that helps in the identification of phishing URLs by using sophisticated learning techniques. Detecting malicious URLs is one of the most important steps towards preventing fraud over the internet. Thus, to make the internet a safer place, there is a great need for systems that help in identifying malicious URLs.

3. RELATED WORKS

A lot of work has been done in using machine learning techniques for the detection of suspicious URLs. James et al. [6] have researched the detection of malicious URLs using host-based features, lexical features, and page importance features. The URLs they used were collected from phistank.com, alexa.com, dmoz.com. The novelty in their approach lies in the feature extraction and the types of features they used. In their feature extraction technique firstly host-based analysis is performed and then relevant host-based features are extracted, and subsequently page/popularity-based feature analysis and lexical feature analysis are performed extracting the relevant features. Host-based features are those features that define the who hosts the websites

and where/ how it is hosted. Page/popularity based features define how popular the website is among the users of the internet. Lexical features comprise those properties that arise out of the text of the URL itself and not the contents of the website. After feature extraction, they use a machine learning classifier. The classifiers they train on are the Naive Bayes classifier, support vector machines, regression trees, and k-nearest neighbours. In their experiment, regression trees gave the highest accuracy. Similarly, Yan et al. [7] proposed an unsupervised learning algorithm that learns URL embeddings to get some features that can be used with machine learning algorithms. Kim et al. [8] also did a comprehensive research on exploring the similarity in the suspicious URLs which are due to the attacker's behavior. This enabled the authors to successfully classify the malicious and benign URLs with an accuracy of 70%. The past works give holistic information of what features can make URLs look more suspicious.

4. METHODOLOGY

The process goes through five major steps. The first and foremost step is to collect data for the research. The data collection step is followed by feature engineering where we take the features that are relevant and of our interest. After that, data preprocessing is done before feeding the data into machine learning algorithms. The performance of each classifier is evaluated as the final step. The overview of the methodology used in this research is as shown in Fig. 1.
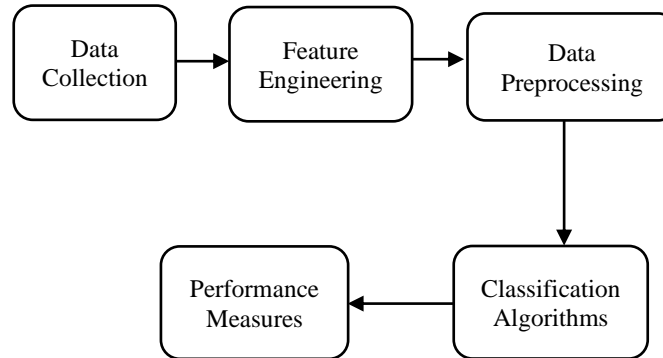

Fig. 1. Step wise Methodology

A. Data Collection
The websites URL were collected from various sources like PhishTank etc. There are a total of 450,176 URLs out of which consists of 345,738 benign websites and 104,438 malicious websites. Statistically, 77% of the websites are benign and 23% of them are malicious. The URLs in the original form are unprocessed and need some preprocessing to extract the useful and relevant features that may serve as attributes for classifiers trained for the delineation of malicious URLs from the benign ones. The dataset used is publicly available.

B. Feature Engineering
The URLs that are related to malicious have certain anomalous features that distinguish themselves from the benign ones. Jeeva et al. used different features like domain length, number of slashes in the URLs, the number of special characters, etc. It is unanimously accepted by the

researchers that certain length features and count of special tokens, digits, letters, directories, etc. play a vital role in the detection of anomalies in the URLs [9]. In our experiments, we use similar features like the length of the URLs, length of the hostname, length of the first directory, length of the path, and length of the top-level domain. Similarly, count features are also used like count of certain special characters (-, @, $, ?, /, %, . , =) and certain keywords like http, https, and www. Similarly, the count of digits, letters, and the number of directories were also taken as features that can influence the URLs trustability. On top of this, the binary features like the usage of IP (either "yes" or "no") and the use of shortening URL ("yes" or "no") have been used to make the features more robust. For the list shortening, if the shortening has been done using bit.ly, goo.gl, shorte.st, go2l.ink, x.co, ow.ly, t.co, tinyurl, tr.im, is.gd, cli.gs, yfrog.com, migre.me, ff.im, tiny.cc, doiop.com, short.ie, kl.am, wp.me, rubyurl.com, om.ly, to.ly, bit.do, t.co, lnkd.in, db.tt, qr.ae, adf.ly, bitly.com, cur.lv, tinyurl.com, url4.eu, twit.ac, su.pr, twurl.nl, snipurl.com, short.to, BudURL.com, ping.fm, post.ly, Just.as, bkite.com, snipr.com, fic.kr, loopt.us, ity.im, q.gs, is.gd, po.st, bc.vc, twitthis.com, u.to, j.mp, buzurl.com, cutt.us, u.bb, yourls.org, x.co, prettylinkpro.com, scrnch.me, filoops.info, vzturl.com, qr.net, 1url.com, tweez.me, v.gd, tr.im, and link.zip.net, the link has been labeled as shortened and the other links have been labeled as "not-shortened". In total, 21 features (5 lengths based + 14 counts based + 2 binary) were extracted and used in this research. In this experiment, the features are not just based on length but also based on counts of letters, numbers and binary values. Thus, the features are hybrid features and such features can help in building robust classifiers.

C. Data Preprocessing
The statistics of data used in this research show that more than 3/4th of the data belongs to one category and less than 1/4th of the data belongs to the other category. This situation cannot give correct performance measures in terms. The unbalanced data simply means that one class is very well represented in the dataset whereas the representation of the minority class is low. In order to tackle the unbalanced data, two major techniques are used in this research. First of all, the unbalanced data is undersampled so that both categories have nearly the same amount of data. After that, the performance measures are calculated for different classifiers. Similarly, the performance measures are also measured for original imbalanced data and oversampled data. For the undersampling of the data, the Near-miss technique is used whereas for oversampling of the data Synthetic Minority Oversampling Technique (SMOTE) is used.

Near-Miss: Near-miss [10] is an undersampling method that selects examples based on the distance of majority class examples to minority class examples. In this research, the technique that selects majority class examples with minimum distance to each minority class example is used. This particular near-miss method used in this research is often known as Near-miss-3. After undersampling with Near-Miss-3, the data distribution becomes a bit balanced with 104,438 malicious websites and 70,574 benign websites. Statistically, there is 60% data belonging to the malicious category and 40% belonging to the benign category.

SMOTE: Synthetic Minority Oversampling Technique, popularly known as SMOTE, is an oversampling technique that generates synthetic samples from minority-class [11]. It is a technique that is based on nearest neighbors judged by Euclidean distance between data points in feature space. It has been broadly used technique for handling imbalanced data and data augmentation especially when there is very little data in one category like fraud detection and

malicious website detection. After oversampling using SMOTE, the data distribution becomes perfectly balanced with 345,738 observations in both malicious and benign websites category.

D. Classification Algorithms

The classification is done with ten different algorithms so that the best can be used for real-time inference. In this research, five machine learning algorithms and five ensemble learning algorithms have been used. All algorithms have been used with all three kinds of data i.e. undersampled, oversampled, and unbalanced data. The first five methods discussed below are machine learning methods and the remaining five are ensemble learners.

I. K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a nonparametric clustering technique or algorithm that helps in classification problems [12]. It works on a very simple idea of storing all the available observations and predicting the class of new instances by measuring its similarity with the stored observations. It is very useful especially with datasets with lower feature dimensions. When the dimension of data increases, it has a bit of difficulty in classification. Nevertheless, it is one of the widely used algorithms in machine learning and pattern recognition.

II. Support Vector Machine (SVM)

SVM is popular ML classifiers developed by Vapnik et al. which are used in both classification and regression problems [13]. It has the ability to distinguish between the categories by drawing a hyperplane for categorization. When the algorithm is fed with the data, it creates an optimal hyperplane that categorizes given newer examples. In this experiment, SVM with Gaussian kernel is used. SVM is a bit slower with a large number of data because it requires the order of n2 computation while the model is trained, where n is the number of training data.

III. Decision Tree (DT)

A decision tree is a flowchart or tree-like representation which is based on the decisions and their possible consequences. It is a very basic algorithm and is capable of handling both categorical and numerical values [14]. This algorithm also works well with problems with multiple outputs. It is very simple and interpretable. Decision trees can moreover be visualized with the help of different libraries. In this research, the Gini index is utilized to compute the quality of the split. Unlike SVMs, the cost of using a decision tree is lower. It is logarithmic in the number of observations that are used for training the tree.

IV. Logistic Regression (LR)

It is a simplest kind of ML algorithm which is used in solving both regression & classification problems. It is based on a logistic function for the prediction of the target values. The outcome of a logistic function is a probability value between 0 and 1 which gives the likelihood of a category being the correct one. In this experiment, the logistic regression has been used with C and penalty parameters as 1.0 and 'l2' respectively [15].

V. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is a technique to locate the ideal boundary design for a machine learning calculation. It iteratively makes little changes in accordance with a network setup of a machine-learning algorithm to diminish the mistake of the system [16]. After each

training point, the configuration of the network is tuned to find the global minimum. Hingle loss and 'l2' penalty are used in this experiment.

VI. Random Forest (RF)

Random Forest is a kind of ensemble of learners that builds multiple decision trees at the time of training and the output is the modal class or the prediction of individual trees [15]. Though computationally expensive, it helps in better classification and also avoids overfitting to a larger extent. This amazing property of avoiding overfitting is due to the fact that the results of decision trees are averaged in a random forest algorithm.

VII. Gradient Boosting Classifier (GB)

It is used in solving both classification and regression problems. It is a very powerful boosting algorithm that uses decision trees. With its use increasingly in the Kaggle competitions for better performance, it has been widely used in classification tasks [17].

VIII. Adaptive Boosting (AdaBoost) (ADB)

Adaptive boosting, popularly known by its alias AdaBoost, is one of the most widely used classification algorithms that use decision trees [18]. It gives the flexibility of combining really weak classifiers into strong classifiers. The decision stumps which are the decision trees with a single split are used as weak learners which are combined into strong classifiers using adaptive boosting schemes.

IX. Extreme Gradient Boosting (XGBoost) (XGB)

It is one of the most popular ML algorithm. The algorithm is often implemented using XGBoost library which is an open-source software library. XGBoost is very fast for the implementation and hence is used in a wide range of applications [19].

X. Light Gradient Boosting Machine (LGBM)

Light Gradient Boosting Machine (LGBM) is yet another tree-based algorithm that is widely used in a variety of machine learning problems. Unlike other boosting algorithms that grow trees horizontally, LGBM is a quite different one that grows trees vertically [19].

E. Performance Measures

The classifiers are used and the validation is done using a 10 fold cross-validation technique. The accuracy, precision, recall, f-score, and AUC measures are calculated after a 10 fold cross-validation scheme. The formulas for the performance measures are given as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

5. RESULTS AND DISCUSSION

First of all, the classifiers are used with the original dataset which is an unbalanced one. Then, the dataset is balanced once using the undersampling technique and again using the oversampling technique. The performance of the machine learning algorithms, as well as ensemble learners with original data, can be found in Table I. For the original dataset, AdaBoost shows the best performance with an accuracy of 99.07%. The precision and recall for the same are 0.98 and 0.99 respectively. Similarly, the f-score and ROC AUC for the AdaBoost algorithm are 0.99 and 0.9908 respectively. Also, further analysis was done with an undersampling technique called near-miss. The results given by the dataset which was undersampled using near-miss is shown in Table II. With an undersampled dataset as well, the best performing algorithm was AdaBoost with an accuracy of 98.43%. The precision, recall & f-score all are equal to 0.98. ROC AUC for the AdaBoost in undersampled data is 0.929. However, the gradient boosting classifier has a better performance in terms of ROC AUC with a value of 0.9837. Further experiments with oversampled data using SMOTE is shown in Table III. **Support Vector Machines (SVM) algorithm is the one which shows an accuracy of 99.50% and that means it is the best performing algorithm**. Similarly, the precision, recall & f-score all were equal to 0.999. Also, ROC AUC was very high when SVM was used with oversampled dataset. The accuracy of 99.07% with original dataset is good but the phishing detection is a kind of problem where we need very high accuracy. Even a slightest decline in performance can cause a huge monetary loss. Thus, using oversampled dataset is a great choice for this problem. Despite a high time for computation due to high amount of data in oversampled dataset, the better accuracy makes it very useful to use.

TABLE I.   PERFORMANCE OF ALGORITHMS FOR ORIGINAL DATA

Classifier	Accuracy	Precision	Recall	F-score	ROC AUC
K-Nearest Neighbors (KNN)	0.9125	0.88	0.87	0.87	0.8669
Support Vector Machine (SVM)	0.9836	0.99	0.97	0.98	0.9667
Decision Tree (DT)	0.9873	0.98	0.99	0.98	0.9879
Logistic Regression (LR)	0.9937	0.99	0.99	0.99	0.9899
Stochastic Gradient Descent (SGD)	0.9941	0.98	0.99	0.98	0.9881
Random Forest (RF)	0.9906	0.98	0.99	0.99	0.9906
Gradient Boosting Classifier (GB)	0.9906	0.98	0.99	0.99	0.9404
Adaptive Boosting (AdaBoost) (ADB)	0.9907	0.98	0.99	0.99	0.9908
Extreme Gradient Boosting (XGBoost) (XGB)	0.9906	0.98	0.99	0.99	0.9906
Light Gradient Boosting Machine (LGBM)	0.9906	0.98	0.99	0.99	0.9905

TABLE II. PERFORMANCE OF ALGORITHMS FOR UNDERSAMPLED DATA

Classifier	Accuracy	Precision	Recall	F-score	ROC AUC
K-Nearest Neighbors (KNN)	0.7819	0.79	0.78	0.78	0.7789
Support Vector Machine (SVM)	0.9452	0.94	0.95	0.95	0.9471
Decision Tree (DT)	0.9733	0.98	0.97	0.97	0.9693
Logistic Regression (LR)	0.9828	0.98	0.98	0.98	0.9816
Stochastic Gradient Descent (SGD)	0.9782	0.97	0.97	0.97	0.9712
Random Forest (RF)	0.9786	0.98	0.98	0.98	0.9756
Gradient Boosting Classifier (GB)	0.985	0.99	0.98	0.98	0.9837
Adaptive Boosting (AdaBoost) (ADB)	0.9843	0.98	0.98	0.98	0.9824
Extreme Gradient Boosting (XGBoost) (XGB)	0.9816	0.98	0.98	0.98	0.9794
Light Gradient Boosting Machine (LGBM)	0.9813	0.98	0.98	0.98	0.9789

TABLE III. PERFORMANCE OF ALGORITHMS FOR OVERSAMPLED DATA

Classifier	Accuracy	Precision	Recall	F-score	ROC AUC
K-Nearest Neighbors (KNN)	0.9478	0.95	0.95	0.95	0.9478
Support Vector Machine (SVM)	0.9947	0.99	0.99	0.99	0.9947
Decision Tree (DT)	0.9919	0.99	0.99	0.99	0.9919
Logistic Regression (LR)	0.995	0.999	0.999	0.999	0.995
Stochastic Gradient Descent (SGD)	0.9945	0.99	0.99	0.99	0.9939
Random Forest (RF)	0.9938	0.99	0.99	0.99	0.9938
Gradient Boosting Classifier (GB)	0.9939	0.99	0.99	0.99	0.9939
Adaptive Boosting (AdaBoost) (ADB)	0.9935	0.99	0.99	0.99	0.9935
Extreme Gradient Boosting (XGBoost) (XGB)	0.9936	0.99	0.99	0.99	0.9936
Light Gradient Boosting Machine (LGBM)	0.9936	0.99	0.99	0.99	0.9936

TABLE IV. PERFORMANCE COMPARISON OF ALGORITHMS WITH BALANCED AND UNBALANCED DATA

Classifier	Original Data		Undersampled Data		Oversampled Data	
	F-score	ROC AUC	F-score	ROC AUC	F-score	ROC AUC
KNN	0.87	0.8669	0.78	0.7789	0.95	0.9478
SVM	0.98	0.9667	0.95	0.9471	0.99	0.9947
DT	0.98	0.9879	0.97	0.9693	0.99	0.9919
LR	0.99	0.9899	0.98	0.9816	0.999	0.995
SGD	0.98	0.9881	0.97	0.9712	0.99	0.9939
RF	0.99	0.9906	0.98	0.9756	0.99	0.9938
GB	0.99	0.9404	0.98	0.9837	0.99	0.9939
ADB	0.99	0.9908	0.98	0.9824	0.99	0.9935
XGB	0.99	0.9906	0.98	0.9794	0.99	0.9936
LGBM	0.99	0.9905	0.98	0.9789	0.99	0.9936

Table IV draws a comparison among the machine learning model's performances with balanced and unbalanced data. In most of the cases, the performance of the models with oversampled data is seen very well. Fig. 2 graphically represents and compares the performance of algorithms with balanced and unbalanced datasets.
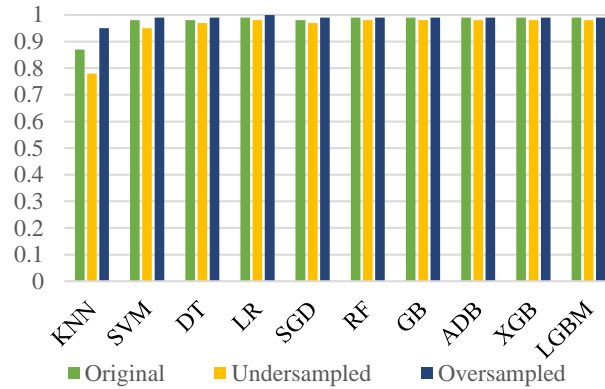
Fig. 2. F-score of the models with various data

It can thus be deciphered that with the given features and dataset, balanced data can be useful as compared to unbalanced data.

6. CONCLUSION & FUTURE WORK

In this research, we have discussed a framework for the detection of malicious URLs on the web using various features. The features are network-based and length based. The results are promising and can help us to detect the malicious URLs with great accuracy. Future works can involve the use of various other features which can be relevant to the detection of malicious URLs. More network-based features can be used in conjunction with length-based features to obtain higher accuracy. The algorithms used in the research are used with default hyperparameters. In the future, the algorithms can be made more robust with hyperparameter optimization. This work uses machine learning algorithms only whereas deep learning algorithms can be further explored. Also, phishing has become more sophisticated with attackers using more advanced techniques for attacking. So, recent datasets that account for more sophisticated attacks should be used for carrying out the experiments.

7. CONTRIBUTION

Aman Bhatia (2K18/SE/019) and Ashish Kumar (2K18/SE/041)

❖ **Literature Review** – We both read around 15-20 research papers on the selected topic to know about the ML techniques that helps in detecting malicious URLs. It was after this that we selected various ML algorithms that we found were most widely used in these kind of research.

❖ **Brainstorming on the strengths and weaknesses of each algorithm** – We divided the algorithms equally among ourselves and worked on our part to gather informations about each algorithm.

❖ **Concluding the best algorithm –** We both were of the opinion that each algorithm performed well in all the scenarios, so we both created a comparison table that includes accuracy, precision, recall, f-score to get know more about which algorithm performs well.

❖ **Report Writing –** We made the report using Google Docs so that we could work simultaneously on the report. Each member did the analysis of half of the ML techniques covered in this research and presented the report for that.

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