Phishing Detection Based On Convolutional Neural Networks

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Abstract- *Phishing websites can have demoralizing effects on governmental, monetary and social services, as well as on individual privacy. Currently, many phishing detection solutions are evaluated using small datasets and, thus, are prone to sampling issues, such as representing genuine websites by only high-ranking websites, which could make their assessment less appropriate in practice. Phishing detection solutions which based only on the URL are striking, as they can be used in restricted systems, such as with firewalls. In this expose we present a URL-only phishing revealing solution base on a convolutional neural network (CNN) model. The proposed CNN takes the URL as the input, rather than using prearranged features such as URL. For training and assessment we have self-possessed over two million URLs in a massive URL phishing detection (MUPD) dataset. We split MUPD into training, corroboration and testing datasets. The proposed CNN achieves roughly 96% precision on the testing dataset; this accuracy is achieved with URL schemes (such as HTTP and HTTPS) detached from the URL. Our proposed solution achieved enhanced exactness compared to a presented state-of -the-art URL-only model on an presented dataset. Finally, the results of our research recommend keeping the CNN up-to-date for better results in practice.*

Keywords- Phishing Detection, Machine Learning, Deep Learning, Convolutional Neural Network (CNN), Cyber Security

I. INTRODUCTION

Phishing websites attempt to imitate other websites or entities to induce users to enter their individual information. This makes phishing websites hazardous, especially for recreational users. Various approaches have been planned in the literature for defending against phishing, one of which is employing machine learning for the automatic recognition of phishing websites. However, numerous state-of-the-art phishing exposure models have been evaluated on small data sets. This can be seen in the correlated work section, where seven of the eleven models we reviewed were qualified and evaluated on data sets which had only up to 3000 instances. In addition, evaluations are less dependable when the dataset is small, specially for classifiers with a high number of features or with composite classification rules. In addition, non-simple phishing finding models which demand complex features are harder to approve depending on the usage circumstances. For instance in firewalls, this may have a inadequate storage, restricted connectivity, and need for high throughput. Similarly, it may not be preferable for web browsers to utilize models which establish avoidable network delay.

In this paper, we intend a URL phishing detection solution which utilizes a character-level convolutional neural network (CNN) model to organize the URL. The CNN learns from the URL string as a character succession, in order to avoid prearranged URL features (e.g., the number of dots or the extent of the URL). Many of the methods reviewed in the related works have been based on determined URL features. On the other hand, with the anticipated model, we discover a dissimilar direction, which achieves enhanced results while also being more convenient. We consider that other approaches, such as n-gram and bag-of-words models, are less appropriate for URL phishing detection, compared to character-level classification, for two reasons: The first rationale is that URLs are harder to tokenize, unlike sentences (which are divide naturally by spaces). The second reason is that the ordering of words for domain names is very significant for example; domains similar to login.some.com and some.login.com are totally different domains and may submit to different pages. The benefit of being URL-only resources that the representation does not depend on any third-party service or network connectivity.

For our proposed solution, we recommend a character-level CNN architecture. To train and evaluate the CNN, we have composed and preprocessed a large data set of more than two million distinctive URL instances. The data set contains over 1 million established phishing websites from PhishTank and over 1 million legitimate websites sampled as of the top 4 million domains. We would like to accentuate that our data set is much superior than the data sets used in the works we review in the related works section, in which the largest data set had 26,052 instances after elimination of

duplicated hosts. In addition, we removed the URL scheme to avoid building the CNN overly reliant on the scheme. Using a simple decision rule with URL schemes such HTTPS, roughly 74% precision can be achieved on the constructed data set. To estimate the CNN, we split the data set into training, validation, and testing data sets, and the planned CNN achieved roughly 96% accuracy on the testing data set. The large data set is a primary focal point of our paper, as it helps to address sampling issues and overfitting, which may inflate the reported precision. For example, a data set that contains only rightful websites from the top 1 thousand websites is much less delegate of legitimate websites, in general, than our data set, which contains legitimate URLs from the top 4 million domains. This is difficult when ranking in sequence is used as a feature for the model, as ranking information alone is enough to get very high precision on the less representative data set.

We do not find straight comparisons with reported accuracies very functional, due to differences such as the methodologies and the data sets used. This is particularly true when the difference is very small. However, we provide straight comparisons beside a state-of-the-art URL-only model, which achieved high correctness. To offer these comparisons, we estimate our proposed model using the equal data set used to guesstimate the state-of-the-art model. In addition, to present competing benchmarks on our data set, we trained various machine learning models on determined URL features which have been frequently used in the literature. Furthermore, to evaluate how our proposed solution may price in the future, we evaluated our anticipated solution with a different data set split. The preparation data set contained phishing instances from September 2006 to September 2013. The substantiation data set was from September 2013 to August 2015. The test data set was from August 2015 to October 2018. This resulted in a drop of 7.5% in the accurateness of the CNN. This drop is important, considering phishing instances are approximately half of the data set. Thus, keeping the model up to date is suggested for better accuracy in practice. In addition, the results for the other models may recommend that URL phishing instances are not self-sufficient and identically distributed.

II. RELATED WORK

We classify the machine learning solutions surveyed here into URL limited—which only utilize the URL—and non-URL fashionable—which can develop any information. Our proposed solution mainly competes with the URL fashionable solutions, as it belongs to the same type and has the same usage scenarios.

The main critique we have for most of the works we surveyed is the little sizes of the datasets used, which may diminish confidence in the assessment of the models as a small data set is usually accompanied with difficulties in sampling. For example, a set of genuine websites collected from top 1000 popular websites possibly represent accepted websites more than legitimate websites. Furthermore, lesser data sets are more prone to overfitting. The main impenetrability on collecting phishing websites, which inadequate the size of the data sets in most works, is that phishing websites are usually short-lived. Even if the website is reachable and gives a reaction, it may not be the phishing website itself; it could, for example, be a answer from the domain supplier that the domain is no longer used. Many features need the phishing website to be online, such as the comfortable of the page. Websites like PhishTank record phishing URLs, but do not preserve their content.

III. PROPOSED METHOD

In this section, we disagree the used data sets, the preprocessing steps performed, our anticipated CNN, the contending models, the tentative setup, and the related arithmetical measures. Fig. 1 gives an overview of our proposed solution.

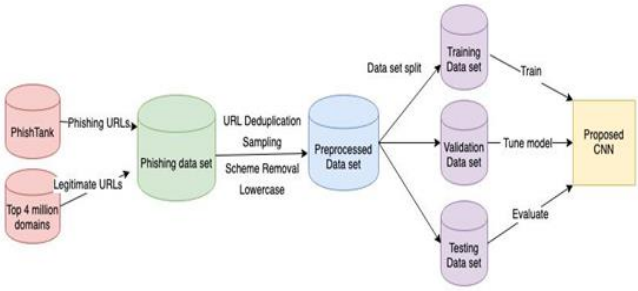

Fig. 1. Overview of the Proposed system

3.1 Data sets

In our experiments, we develop two data sets: the large data set we collected, comprised of 2,220,853 genuine URLs and 2,353,933 phishing URLs. As shorthand, in this paper we will suggest to this large URL phishing recognition data set as the MUPD data set. We will demonstrate the collection progression of the MUPD data set in this section.

The MUPD data set had a disparate source for justifiable and phishing URLs. The resource for phishing website URLs was PhishTank, which was equally used by most of the works we reviewed in the related works section. We only considered phishing websites which were confirmed as phishing on PhishTank. PhishTank lets users distribute and validate phishing websites. PhishTank defines phishing as "a

fraudulent effort to get you to provide individual information, including, but not restricted to, account information". For practical purposes, we distinct the phishing websites in the MUPD data set as those websites that were established on PhishTank. This realistic definition may sometimes argument with what is usually regarded as a phishing website, because the users who suggest and authenticate websites as phishing may make mistakes or have different ideas of what is considered phishing. In short, we proclaim that all considerations about how precise phishing URLs in the MUPD are outside the scope of this paper. Finally, we reminder that PhishTank included the reported date of each phishing URL, which we make use of in one of our experiment. The phishing URLs we retrieved were dated commencing September 29th, 2006 to October 30th, 2018. The main critique we have for most of the works we surveyed is the diminutive sizes of the datasets used, which may decrease confidence in the valuation of the models as a small data set is usually accompanied with difficulties in sampling. For example, a set of justifiable websites together from top 1000 popular websites probably represent popular websites more than legitimate websites. Furthermore, minor data sets are additional level to overfitting. The main obscurity on collecting phishing websites, which limited the size of the data sets in most works, is that phishing websites are frequently short-lived. Even if the website is reachable and gives a response, it may not be the phishing website itself; it could, for example, be a response from the domain contributor that the domain is no longer used. Many features require the phishing website to be online, such as the comfortable of the page. Websites like PhishTank record phishing URLs, but do not defend their content.

This ranking is based on data that had been composed over the 7 years before July 2017. We assumed that the running websites on the top 4 million domains from this list were justifiable.Comparable assumptions have been used in several of the related works discussed beyond.

We consider that this supposition is reasonably accurate for two reasons: The first is that we experimental that most phishing websites are short-lived, whereas this data was over two years old. The second motive is that in advance and maintaining page rank is not easy, more so for phishing websites which would be black-listed and reported, for example, by web browsers. In the same way to phishing websites any considerations of how accurate the genuine URLs in the MUPD data set are outside the extent of this paper. To gather the justifiable URLs, we wrote a program to retrieve the index page (if it existed) for each of the top 4 million domains and, from the index page, retrieved a random inside URL. This was done to avoid using only index URLs, which would make categorization simple and useless as a simple rule to categorize index pages as legitimate websites would achieve very high accuracy.

3.2 Preprocessing

We performed the following preprocessing steps to create the data sets we published: sampling to ensure a balanced data set, data deduplication, and split the data set into training, validation, and testing data sets. We perform two additional preprocessing steps in memory: URL scheme deletion and alteration of URLs to ASCII lower case.

Due to the personality of the collection procedure, the collected data sets regularly contained many repeated URLs or different URLs from the equal host. For example, many pages from the same phishing website were normally reported as phishing pages. equally, our compilation process using the top domains may have resulted in repeated hosts due to diverse reasons, such as http redirects. This was not restricted to our assortment process, as the Sahingoz data set also contained repetitions. When we performed data reduplication, we detached repeated URLs and URLs with repeated hosts. The objective of the deduplication was to make the evaluation fairer and to check models from memorizing the host.

Having a balanced data set is frequently preferable in binary classification problems, mainly when the accuracy metric is used. Although the MUPD data set was disinterested before deduplication, when the deduplication was performed, the phishing URLs (which were more commonly repeated in the data set) characterize roughly only one third of the new data set. To solve this problem, we used a random sample of 1,200,000 genuine URLs. With this sample, we were able to obtain a impartial data set of1,167,201 phishing URLs and 1,140,599 valid URLs after deduplication. For the Sahingoz data set, we finished up with 11,696 phishing URLs and 14,356 justifiable URLs after deduplication, as compared to the original data set which had 36,400 genuine URLs and 37,175 phishing URLs. Table summarize the sizes of data sets used in our experiments.

Table 1. Sizes of data sets used in our experiments.

	Legitmate	Phishing
MUPD data set	1,140,599	1,167,201
Sahingoz data set	11,696	14,356
Sahingoz data set (No Preprocesing)	36,400	37,175

Finally, we split each data set into training, validation, and testing data sets in the following proportions: 0.6, 0.2, and 0.2, respectively. We performed the data set split

randomly. In addition, for the MUPD data set, we also performed a split based on date, where older phishing URLs were kept in the training data set and newer phishing URLs were kept in the testing data set, with the validation data set being in between. Legitimate instances were always split randomly, because we could not associate time with them (unlike the phishing instances, which had a report date). In the date split for the MUPD data set, the training data set contained phishing instances from September 2006 to September 2013, the validation data set was from September 2013 to August 2015, and the testing dataset was from August 2015 to October 2018. Interested authors can get in touch with us for the statistics sets. We encourage the usage of all these data sets to benchmark against our proposed solution.

Depending on the URL scheme, the model may be less robust; so, for our preprocessing, we in addition removed the scheme for all URLs. To illustrate how the proposal may lead to a less vigorous model, Table 3 shows the number of occurrences of HTTP and HTTPS for the phishing and genuine URLs in the MUPD data set. Based on the data in this table, simply predicting authority if the URL scheme was HTTPS and phishing otherwise, an accuracy of 73.98% can subsist achieved. Such a model is not very robust, because the scheme allocation will probably not stay the same; especially as the use of HTTP becomes connected with phishing or unconfident websites. In calculation the use of HTTPS has become easier. Finally, to decrease the size of alphabet needed for our proposed CNN, we renewed every URL to ASCII lower case.

Table 2. HTTP and HTTPS occurrences in the MUPD data set.

	HTTP	HTTPS
Legitimate	563,247	577,352
Phishing	1,129,904	37,297

3.3 Proposed CNN

In this section, we detail our projected phishing URL CNN, which we will refer as PUCNN during the respite of the paper. We planned the PUCNN structural design based on a few preliminary experiments on the validation data set. Many of the architectures we experimented with also achieved comparable accuracies on the legalization data set, and some of the more complex architectures achieved a slightly better accuracy. We opted for our chosen architecture due its effortlessness and high accuracy. Fig. 2 shows the PUCNN architecture. As can be seen from the embedding layer, we limited the input length to 256 letters, where additional letters (if any) are not input to the CNN. We believe that 256 letters would be enough, as most URLs are small and the start of the URL is usually enough, as it contains the domain. We chose an alphabet of 69 letters, together with the English lower-case alphabet, numbers, and diverse other characters.

In the embedding layer, every character from the alphabet is renewed into a vector of the embedding size. We chose the embedding size as 128. The embedding layer was the contribution of the one-dimensional convolutional layer with a tanh establishment function and kernel width of 10. The output of the pooling layer was used as the input to two fully associated neural network layers with 128 nodes every with a SELU (Scaled Exponential Linear Unit) activation role. The weights of the entirely connected layers are initialized using a Lecun Normal circulation. Finally, the output layers used a Softmax activation role with two yield nodes. Similarly, a Sigmoid commencement function with one output node may be used, because the predicament was binary organization. We used categorical cross-entropy as the loss role and used the Adam optimizer. We set the quantity of epochs to 25 or 100 depending on the data set extent. After every epoch, the model was evaluated on the substantiation data set

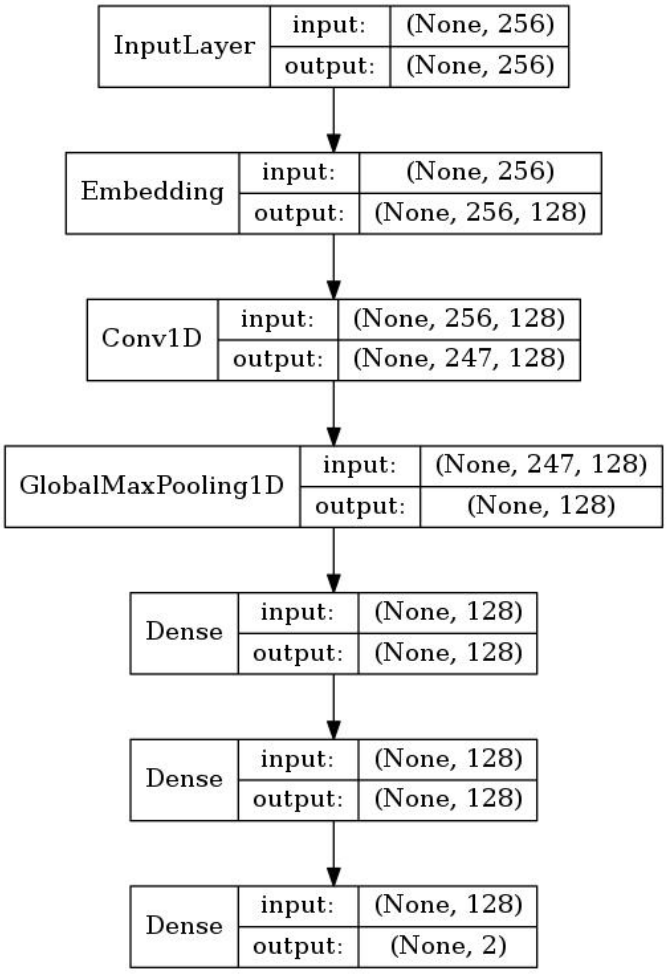

Fig. 2. The Proposed PUCNN Architecture.

Table 3. PUCNN Parameters

Parameter	Value
Input length limit	256
Alphabet	English lower-case alphabet, numbers, and various other characters
Alphabet Size	69
Character embedding size	128
Convolutional layer activation function	tanh
Convolutional layer kernel width	10
Optimization Algorithm	Adam optimizer
Loss function	Categorical cross-entropy
Dense layers weights initialization	Lecun Normal Distribution
Dense Layers activation function	SELU
Output layer activation function	Softmax with two output nodes
Number of epochs	25/100
Model selection criteria	Validation accuracy

3.4 Competing Models

We use the resolution by Sahingoz et al —RandomForest-NLP—as our major contender, due to its a mixture of similarities to our planned solution. First, it utilizes URLs only, making its usage scenarios comparable. In addition, it was also qualified and tested on the relatively huge Sahingoz data set, which increases the assurance of its routine. The Sahingoz data set has been available, so we could train and appraise our model on it. Furthermore, RandomForest - NLP provides a good contrast for our solution, as it was based on complex predetermined features. To conclude the clarification is recent and has achieved elevated accuracy.

Although RandomForest-NLP was our major contender, we also wanted to see how models based on simple and general URL features would tariff. We choose the subsequent features: whether the host is an IP, amount of dots, numeral of hyphens, numeral of numbers, length, and whether the URL contains an @ symbol. We chose these features since they were general throughout the related works and were simple to reproduce.

We performed the experiments with these features on the subsequent models: SVM through linear kernel, SVM through Gaussian kernel, SVM through third-degree polynomial kernel, RandomForest, J48, KNN with K=1, and KNN with K=5. For instruction the SVM and KNN models on the MUPD dataset, we had to use accidental sampling to eliminate half of the data set, as the guidance time was too long with the full amount. With only these easy features, it may be expected for the models to have fared poorer than the CNN; yet, the result of these models is tranquil useful, as it is investigative of the routine of models that use such easy URL features. In fact, many studies in the literature have used models which depend on such easy URL features, in accumulation to other non-URL features (e.g., ranking).

IV. EXPERIMENTAL RESULTS

We perform four experiments: The initial two experiments were on our MUPD data set and the second two were on the Sahingoz data set (i.e., the data set used to train and evaluate RandomForest-NLP in). We expected PUCNN to instruct enhanced and be evaluated more exactly on our MUPD dataset which was much superior however, with the Sahingoz data set, we were able to achieve direct comparisons with the precision of RandomForest-NLP. The fourth experiment was the only testing without data preprocessing, as we needed to be able to achieve comparisons with the exactness of RandomForest-NLP, which was evaluated without our data preprocessing. The difference among the third and fourth experiments was, thus, functional in estimating the effects of the preprocessing in our valuation. In each experiment—excluding for experiment 2—the data set was crack randomly. In experiment 2, we performed the data set crack by date to find roughly how PUCNN would fare, had it been skilled once and then used for three years without updating. Table 5 summarizes the arrangement of our experiments.

Table 4. Setup of our Experiments

Ex #	Data set	Epochs	Preprocessing	Split
1	MUPD Data set	25	Yes	Random
2	MUPD Data set	25	Yes	Date
3	Sahingoz Data set	100	Yes	Random
4	Sahingoz Data set	100	No	Random

For the reproducibility of the experiments, we worn seeded RNGs. However, we had to use GPUs to instruct PUCNN in a practical time. GPUs, due to their similar nature, make the results not completely reproducible and small differences may be professed. We also note that we could not use 10-fold cross-confirmation for evaluation, as in the valuation of RandomForest-NLP, because it was computationally exclusive and is not convenient for

preparation deep learning models.

Statistical Measures

Four statistical measures widely used to establish the accuracy of categorization models are precision, sensitivity, F-measure, and precision.

We note that an elevated accuracy is preferable in situations where false positives are not preferred while an elevated recollect is preferable when false negatives are not preferred. In the case of website phishing detection, high accuracy means minor number of genuine websites classified as phishing websites while elevated recall means lower number of phishing websites which were confidential as legitimate. Both of accuracy and recall are significant depending on the usage circumstances. For illustration, it may be preferable to have high accuracy on individual devices, while in the other hand for some firewalls it may be preferable to have high recall. F-measure is the harmonic signify of accuracy and recall.

In this work, we primarily used the precision measure for comparisons, because it is the general denominator in the related works reviewed; as it was not provided in only which provided F-measure, accuracy, and recall but did not provide precision. However, we also provide the other statistical measures for PUCNN.

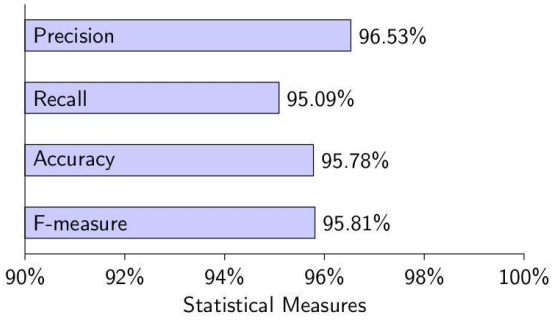

Fig. 3. Results of PUCNN.

V. CONCLUSION

In this work, we planned a vigorous phishing exposure solution which utilizes a character-level CNN on URL data. In distinction to having a set of prearranged URL features, such as the numeral of dots and the length of the URL, the URL itself was used as the contribution to a character-level CNN which handles it as a progression of characters. To instruct and test our proposed clarification, we collected over 2 million URLs, which we divide into training, confirmation, and testing data sets. We proposed a CNN structural design which achieved roughly 96% precision on the testing data set. Our proposed CNN achieved this precision with the URL scheme unconcerned, implication that our model did not depend on URL schemes such as HTTPS. Furthermore, the planned CNN outperformed a state-of-the-art URL-only model. In accumulation, the proposed explanation also outperformed different machine learning models based on normally used simple URL features on the collected data set.
To further estimate our proposed solution, we furthermore performed a data set divide of the phishing instances based on the date; that is, the instruction data set took phishing instances from 2006–2013, the confirmation data set took phishing instances from 2013–2015, and the test data set contained phishing instances from 2015–2018. This resulted in a 7.5% decline of precision. Although the precision was still good, the decline was still important; considering that the data divide affected only the phishing URLs, which were roughly semi of the data set. The results of our proposed CNN and the results of the other models recommended that the phishing data we have composed may not be autonomous and identically distributed and that models may need to be retrained or improved constantly with new data for better results in perform

VI. APPENDIX

Future work can be sustained in the method of Using Different Algorithm for Phishing detection solutions method more and more exact ad also more dependable.

VII. ACKNOWLEDGMENT

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