Phishing detection by classification of URLs using Machine learning Algorithms

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Abstract- **Since phishing does not initially appear to be malicious, it is difficult to track down or defend against. Additionally, the cost and difficulty of carrying out such attacks are significantly declining. As it is challenging to know if an URLis safe or not, we created a model which serves in classifying URLs into safe or legitimate class. URLs contain components of its page and hence are used to identify the purpose of the web page without checkingits actual content. We are proposing a method based on a deep learning algorithm (Bi-Directional Long short-term memory), which predicts the status of URL without the use of domain expertise or manual feature extraction with more significant accuracy points than already existing systems.**

Keywords: **Phishing, deep learning; URL classification; cybercrime; recurrent neural networks; bidirectional long short-term memory**

1. INTRODUCTION

Phishing is an act of deceiving an online user to gather personal data by acting as a trustworthy institution or entity.Phishing is a significant threat to all users on the internet. Attackers attempt phishing to obtain sensitive information such as usernames, passwords, and credit card details through electronic communication. It is done through calls, emails, websites and electronic mediums. For example, onecan receive a mail which looks like a regular request, but it may download malicious software and can gather saved passwords. These attacks are fabricated in a way that leads consumers to expose their financial data such as usernames and passwords in fraudulent websites pretending as legitimate ones.

The "phishing" name appeared in the mid-1990s among hackers trying to dupe AOL users into revealing their login information. The "ph" is an element of a tradition of whimsical hacker spelling and was influenced by the term "phreaking," short for "phone phreaking," an original form of hacking that involved using sound tones to make free phone calls through telephone handsets.

Nowadays, phishing attacks can be originated from anywhere in the world at small costs by people with little tono technical skills. Institutions trying to protect their users from these attacks are having a difficult time dealing with alarge number of rising sites, which must be classified and labelled as malicious or safe before users can access them. Also, the number of attacks and phishing webpages are on rising. According to recent data, phishing has risen by 1300% in 4th quarter of 2019.

The method of analysing URLs instead of the entire contentgives a decisive advantage in identifying malicious websites.By this method, we reduce computational cost and effort significantly, which is required by sophisticated methods like the content analysis. For this work, we are focusing on a all classification modeltechnique, specifically naive bayes, for analysing the URLs. Catboost and XGboost models perform exceptionally at detecting long patterns in sequences. They have solved different text analysis problems recently. It learns directly from URL'ssequence of characters to find a pattern. When each model trains on a portion of data and evaluates a different subset of data, this is known as ordered boosting. Ordered boosting has advantages, such as improving robustness to unknown data.

2. RELATED WORK

Earlier, there were systems which used to analyse the contentof webpages to predict their status. In 2007, Yue Zhang, Jason Hong, and Lorrie Cranor introduced a method that identifies phishing websites based on the retrieval of information about webpage content, providing about 95% accuracy. In 2011, Mona Ghotaish Alkhozae and Omar Abdullah Batarfi presented a phishing classification methodthat validates the reliability of a web page by looking into the source code. In 2013, Jian Mao, Pei Li, Kun Li, Tao Wei,and Zhenkai Liang presented a new approach to identify phishing efforts that use an algorithm to assess the web a page's legitimacy is determined by how similar it seems to other pages. These systems demanded a lot of operational costs and computational time. It is far more efficient to analyse an URL and its nature than to analyse the entire content.

Recently, machine-learning algorithms and other statistical methods predicted the nature of URLs. In 2010, Maher Aburrous, Md Alamgir Hossain, Keshav Hahal, and Fadi That developed an intelligent fuzzy data mining algorithm toclassify phishing sites that disguised as online banking sites.They were able to conclude from their research that the URLand the domain identity are essential criteria for evaluating

phishing sites. Over time, with research, it was inferred thatthe random forest algorithm is best suited for such problems.

In another paper, Bahnsen showed that LSTM could give atleast five higher accuracy points than the random forest. AsLSTM learns the sequential pattern, we do not need toextract features manually. Additionally, there is little to no need for domain-specific knowledge when using this algorithm. However, even then, it holds room for improvisation through some modification in the algorithm.

3. PROPOSED METHODOLOGY

We propose a system which uses various machine learning algorithm for predicting the malicious status of URLs.

We used XGBoost and Catboost that can enhance model performance on sequence classification problem statements such as this. It is useful inproblems where all time steps of the input sequence are available. both on an inverted replica of the input sequence and the first on the input sequence as-is. This method can provide added context to the network and result in faster and even fuller learning on the problem.
Regression and Classification algorithms were also used to get the best possible output with highest precision and accuracy.

3.1 Dataset

In total, numerous URLs were scrapped to for dataset—half of them legitimate and half of the phishing. The legitimate URLs came from just Common Crawl, an organisation which collects web crawl data. The phishing URLs came from Phishtank, an anti-phishing site which has a dataset ofmillions of phishing URLs. One can easily see the similaritybetween legitimate URLs and phishing URLs. The URL's are classified by dividing it into various categories such as LongURL , ShortURL and so on into numerous categories.

Two-third of the dataset will be used for training purpose, while the remaining one-third will be used for validation of model.

RESULTS

We implemented various ML models in colab with theanoas backend. As already mentioned, we have divided our dataset into three folds. Two folds will be used for training.
the model, while the remaining fold will be used for validation of the model. Furthermore, in each fold, 90% of dataset was used for training and the remaining 10% for internal validation. In the figure, the learning curve for the model is shown, and it's clearly visible that after 15th epochaccuracy was over 99%.

In table 1, results for the model are shown. The Naïve Bayes Classifier model has an average accuracy of 99.26%, with a standard deviation of just 0.03%, suggesting stable performance across the different folds. Moreover, as shown in Fig. 7, theAUC of the model is very high, having an average of 99.91%.

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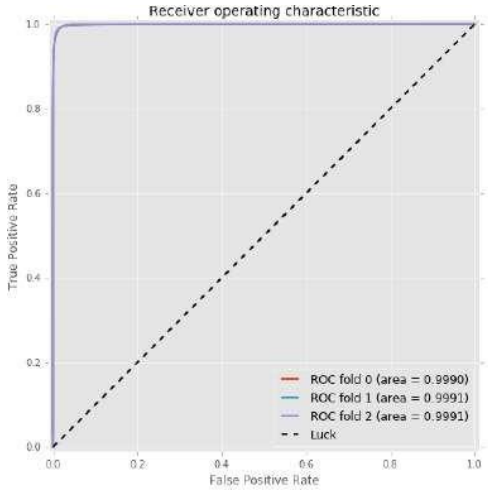

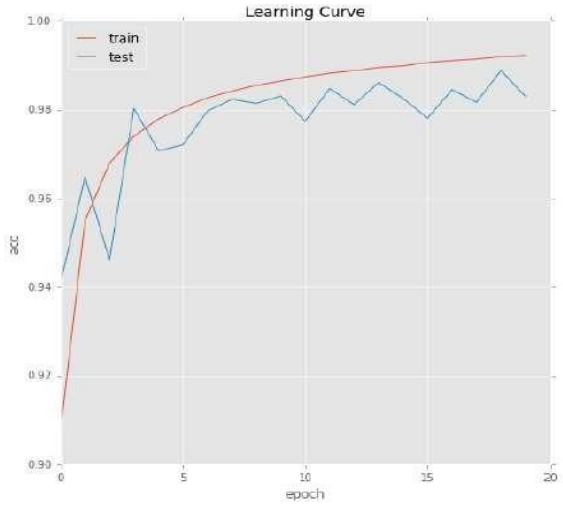

Fold	AUC	Accuracy	Recall	Precision	F1-Score
0	0.999	0.992	0.991	0.9832	0.9871
1	0.999	0.992	0.989	0.9863	0.9879
2	0.999	0.992	0.987	0.9885	0.9878
Average	0.999	0.992	0.989	0.9860	0.9876
Std. Dev.	4e-05	0.00037	0.0016	0.0021	0.0003

The training time for system is almost 256 minutes.
During the process, 0.623 MB of memory wasconsumed.

CONCLUSION/FUTURE WORK

The model provides proof that Naïve Bayes Classifier provides higher accuracy points as compared to other ML models.We get this result as our model propagates in both directions,hence finding better-fitted patterns with almost the same computational power. With these results, we can easilyconclude that a pattern of URLs can act as a deciding factorin classifying a web page into phishing or legitimate site. The accuracy can be increased further by changing the orderof neural network layers. For that, further research is necessary with different orders of layers. Use of Ind RNN will also be compared with the existing system to check thebest-suited model for this problem statement.

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