Phishing identification on websites

Pattern recognition

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Abstract:
A phishing website is a common social engineering method that mimics trustful uniform resource locators (URLs) and webpages. The objective of this project is to train machine learning models and deep neural networks on the dataset created to predict phishing websites. Both phishing and benign URLs of websites are gathered to form a dataset and from them required URL and website content-based features are extracted. The performance level of each model is measures and compared.

1. Introduction

1.1. What is phishing?

Phishing is the most commonly used social engineering and cyber attack.Through such attacks, the phisher targets naïve online users by tricking them into revealing confidential information, with the purpose of using it fraudulently.

1.2. Solution

1.In order to avoid getting phished, users should have awareness of phishing websites.
2.Have a blacklist of phishing websites which requires the knowledge of the website being detected as phishing.
3.Detect them in their early appearance, using machine learning and deep neural network algorithms.
4.Of the above three, the machine learning based method is proven to be the most effective than the other methods.
5.Even then, online users are still being trapped into revealing sensitive information in phishing websites.

2. Mutual Information

Mutual information(MI) between two random variables is a non-negative value,which measures the dependency between the variables .It is equal to zero if and only if two random variables are independent ,and higher values mean higher dependency.

3. Project Implementation

Below mentioned are the steps involved in the completion of this project:

• Collect dataset containing phishing and legitimate websites from the open source platforms.

• Write a code to extract the required features from the URL database.

• Analyze and preprocess the dataset by using EDA techniques.

• Divide the dataset into training and testing sets.

• Run selected machine learning and deep neural network algorithms like SVM, Random Forest, Autoencoder on the dataset.

• Write a code for displaying the evaluation result considering accuracy metrics.

• Compare the obtained results for trained models and specify which is better.

3.1. Data Collection

• Legitimate URLs are collected from the dataset provided by University of New Brunswick,
https://www.unb.ca/cic/datasets/url-2016.html

• From the collection, 5000 URLs are randomly picked.

• Phishing URLs are collected from opensource service called PhishTank . This service provide a set of phishing URLs in multiple formats like csv, json etc. that gets updated hourly.

• From the obtained collection, 5000 URLs are randomly picked.

3.2. Feature extraction

The following category of features are selected:

3.2.1 Address Bar based Features:-

1.Domain of the url

2.IP address in url

3.'@' symbol in url

4.Length of url

5.Depth of url

6.Redirection '//' in url

7.'http/https' in domain name

8.Using url shortening service

9.Prefix or suffix "-" in domain

3.2.2 Domain based Features:-

1.DNS Record

2.Website Traffic

3.Age of Domain

4.End Period of Domain

3.2.3 HTML and Java script based Feature:-

1.Iframe Redirection

2.Disabling Right click

3.Website forwarding

4.Status bar Customization

3.3. Machine learning models:

This is a supervised machine learning task. There are two major types of supervised machine learning problems, called classification and regression.
This data set comes under classification problem, as the input URL is classified as phishing (1) or legitimate (0). The machine learning models (classification) considered to train the dataset in this notebook are:

• Random Forest

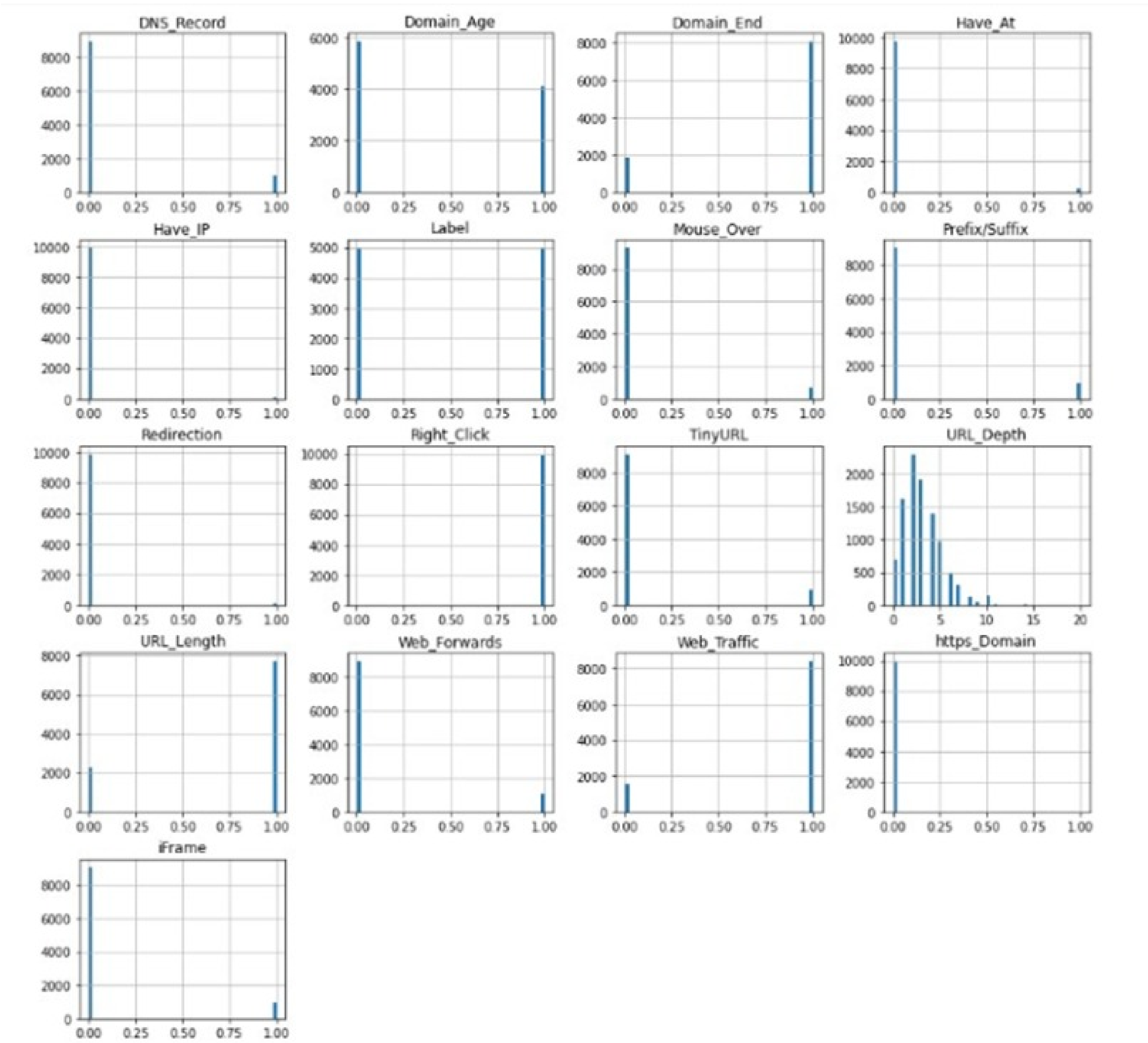
- XGBoost
- Support Vector Machines

3.4. Model Evaluation:

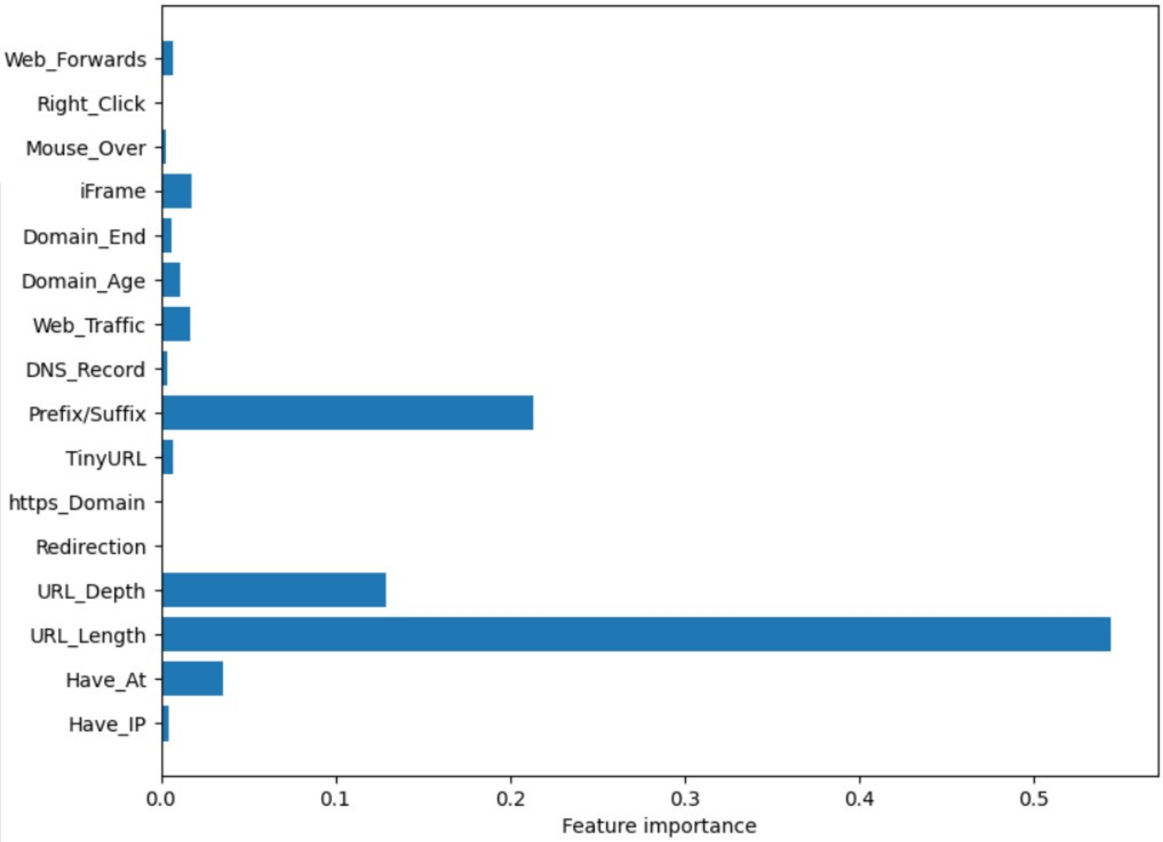
- The models are evaluated, and the considered metric is accuracy.
- The best model is selected for further use based on train and test accuracies.

4. Experimental Results

4.1. Feature Distribution



4.2. Feature importance



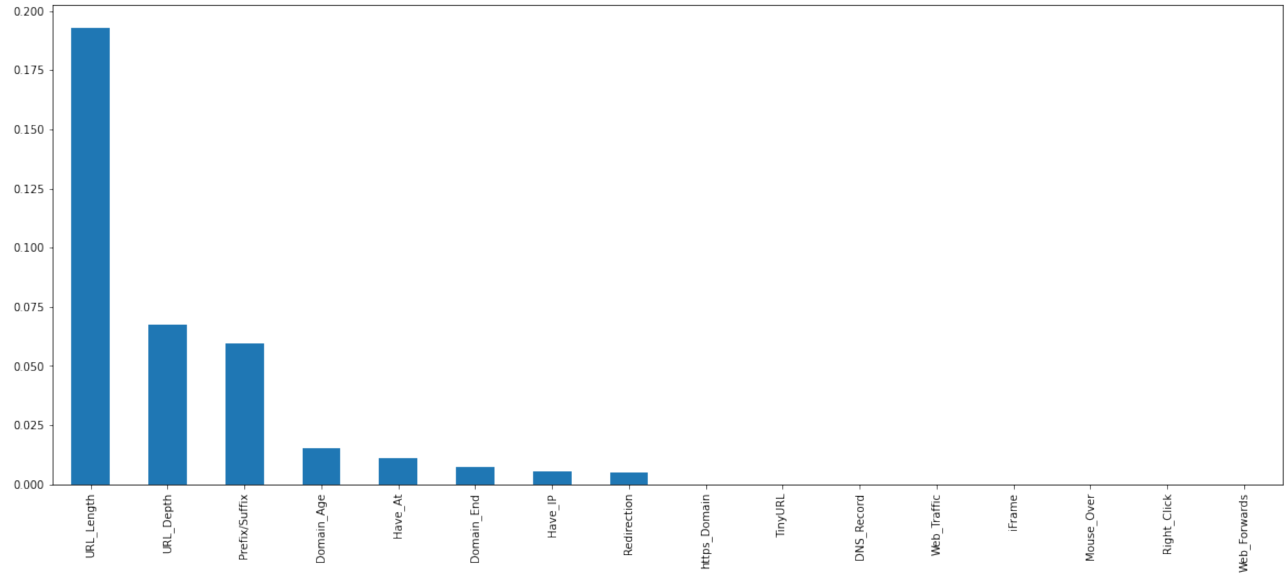
4.3. Correlation Matrix

	Have_IP	Have_At	URL_Length	URL_Depth	Redirection	https_Domain	TinyURL	Prefix/Suffix	DNS_Record	Web_Traffic	Domain_Age	Domain_End	iFrame	Mouse_Over	Right_Click	Web_Forwards	Label
Have_IP	1.000000	-0.011308	-0.076021	-0.030466	-0.008700	-0.001052	-0.023430	-0.023841	-0.011425	0.024279	0.047349	0.018799	-0.004701	0.007251	0.001968	-0.003487	0.074367
Have_At	-0.011308	1.000000	0.067844	0.029944	-0.000297	-0.002151	0.067122	0.018369	0.025073	-0.017002	-0.017072	0.001651	-0.008294	-0.021728	0.004025	-0.030246	0.118419
URL_Length	-0.076021	0.067844	1.000000	0.439378	0.038482	0.007656	-0.005318	-0.146102	-0.019508	0.063717	0.071029	0.028755	-0.039903	-0.068104	0.030833	-0.023651	-0.541287
URL_Depth	-0.030466	0.029944	0.439378	1.000000	-0.040189	-0.000478	0.010980	-0.114919	-0.086073	0.075315	-0.070101	-0.061798	-0.039297	-0.105889	-0.002657	-0.051248	-0.119707
Redirection	-0.008700	-0.000297	0.038482	-0.040189	1.000000	-0.001655	0.026634	-0.025581	-0.027654	0.018784	0.012581	0.025758	-0.012876	-0.017346	0.003096	-0.023193	0.002600
https_Domain	-0.001052	-0.002151	0.007656	-0.000478	-0.001655	1.000000	-0.004456	-0.004534	0.042243	-0.033112	0.016837	0.006852	-0.004472	-0.003778	0.000374	-0.004852	0.014144
TinyURL	-0.023430	0.067122	-0.005318	0.010980	0.026634	-0.004456	1.000000	0.087421	0.059078	0.040888	0.095944	0.006812	-0.062000	-0.054771	0.008339	-0.003508	0.072921
Prefix/Suffix	-0.023841	0.018369	-0.146102	-0.114919	-0.025581	-0.004534	0.087421	1.000000	-0.006793	-0.046843	-0.019954	0.031711	0.050594	0.070263	-0.017527	0.030102	0.302705
DNS_Record	-0.011425	0.025073	-0.019508	-0.086073	-0.027654	0.042243	0.059078	-0.006793	1.000000	0.065776	0.398583	0.162210	0.103266	0.094410	0.008861	0.042050	0.015943
Web_Traffic	0.024279	-0.017002	0.063717	0.075315	0.018784	-0.033112	0.040888	-0.046843	0.065776	1.000000	0.013681	0.015998	0.006990	0.057473	0.051495	0.073485	-0.108793
Domain_Age	0.047349	-0.017072	0.071029	-0.070101	0.012581	0.016837	0.095944	-0.019954	0.398583	0.013681	1.000000	0.329345	-0.034648	-0.018343	0.022232	-0.028860	-0.085077
Domain_End	0.018799	0.001651	0.028755	-0.061798	0.025758	0.006852	0.006812	0.031711	0.162210	0.015998	0.329345	1.000000	-0.042731	-0.007557	0.006449	-0.022273	-0.068556
iFrame	-0.004701	-0.008294	-0.039903	-0.039297	-0.012876	-0.004472	-0.062000	0.050594	0.103266	0.006990	-0.034648	-0.042731	1.000000	0.807077	0.008369	0.617989	0.098446
Mouse_Over	0.007251	-0.021728	-0.068104	-0.105889	-0.017346	-0.003778	-0.054771	0.070263	0.094410	0.057473	-0.018343	-0.007557	0.807077	1.000000	0.007070	0.749877	0.051338
Right_Click	0.001968	0.004025	0.030833	-0.002657	0.003096	0.000374	0.008339	-0.017527	0.008861	0.051495	0.022232	0.006449	0.008369	0.007070	1.000000	0.009080	-0.026467
Web_Forwards	-0.003487	-0.030246	-0.023651	-0.051248	-0.023193	-0.004852	-0.003508	0.030102	0.042050	0.073485	-0.028860	-0.022273	0.617989	0.749877	0.009080	1.000000	-0.041376
Label	0.074367	0.118419	-0.541287	-0.119707	0.002600	0.014144	0.072921	0.302705	0.015943	-0.108793	-0.085077	-0.068556	0.098446	0.051338	-0.026467	-0.041376	1.000000

4.4. Rank Features Based on Mutual Information

```
[0.00035321 0.00499223 0.19297504 0.06877098 0.         0.
 0.00078275 0.05477873 0.         0.         0.00600592 0.00866887
 0.00734582 0.         0.01514874 0.00299198]
URL_Length       0.192975
URL_Depth        0.068771
Prefix/Suffix    0.054779
Right_Click      0.015149
Domain_End       0.008669
iFrame           0.007346
Domain_Age       0.006006
Have_At          0.004992
Web_Forwards     0.002992
TinyURL          0.000783
Have_IP          0.000353
Mouse_Over       0.000000
Web_Traffic      0.000000
DNS_Record       0.000000
https_Domain     0.000000
Redirection      0.000000
dtype: float64
```

```
#         Feature        Rank
#         URL_Length      1
#         URL_Depth       2
#        Prefix/Suffix    3
#        Right_Click      4
#        Domain_End       5
#        iFrame           6
#        Domain_Age       7
#        Have_At          8
#        Web_Forwards     9
#        TinyURL          10
#        Have_IP          11
#        Mouse_Over       12
#        Web_Traffic      13
#        DNS_Record       14
#        https_Domain     15
#        Redirection      16
```



4.5. Accuracies

	ML Model	Train Accuracy	Test Accuracy
0	SVM	0.817	0.821
1	Random Forest	0.819	0.820
2	XGBoost	0.865	0.866

Figure 1: Model accuracies

5. Conclusion

Thus we have built a models to predict the phishing websites based on url features.The accuracy depends on the problem we are solving and the dataset available.With doing proper exploration of data we got highest accuracy of 86.6 percentage with XGBoost model.This could be improved further if we have more data.For the above it is clear that the XGBoost model gives better performance. The model is saved for further usage.Now we can use this model in real world scenario to find phising websites.

6. Link for Project Repository

Repository link