

Detection of Malicious URLs through an Ensemble of Machine Learning Techniques

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Abstract—The following paper aims to classify URLs and web pages into legitimate and malicious sites to alert users and allow safer browsing through the internet. Through this process we have found various points of interest and attributes that bring to light the characteristics of these malicious sources, allowing us to be aware of and prevent any damage it might cause. These attributes relate to the domain registration of the URLs, the URL text, the structure of the web page and its contents. The application of models such as BERT, LSTM, Decision Trees and their amalgamation as an ensemble result in a pragmatic solution to the problem in the form of an ensemble giving an accuracy of 95.3%. It also includes concepts such as webpage reputation, Internal Links and External Links of a web page. Further research would allow us to augment the potential and performance to prevent such attacks thus enabling a secure environment for internet users.

Index Terms—Malicious URLs and Web Pages, Machine Learning Models, BERT, LSTM, Decision Trees

I. INTRODUCTION

There are approximately 4.66 billion users who utilize the internet and web search engines today. Being active all the time, threats to it can cause serious damage, which include social engineering attacks such as Trojans or key-loggers, malware through phishing, or even worms and viruses. Such attacks could be devastating to the user and can cause a computer to crash or personal data being stolen with just one click. One of the most common methods used to do this is through Uniform Resource Locators or URLs, since they are the most accessible forms of links apart from other sources such as emails. Earlier methods such as blacklists[1] are still prevalent today, which hold all such malicious URLs, but with the rising technology, it has become easier to cause disruptions while evading detection making it a huge security threat. Through the course of this paper, we aim to introduce a new method complementing the technology today to safely classify these URLs in a more efficient manner.

II. LITERATURE SURVEY

The classification of URLs requires a potent list of testing links, which in our case has been obtained from various sites[2][3] as well as extraction from different sources [4][5][6]. Through research we have uncovered six most common ways of classifying malicious URLs[7] which include Blacklists, Search Engine methods, domain based, visual similarity, heuristic machine learning methods, and finally proactive phishing. Blacklists have been the most prevalent method to prevent the access to malicious URLs but the need to improve over these static lists gave rise to new techniques. Search Engine methods are based on the reputation of a web page using metrics such as page ranks [8] and their variants [9] introduced a new perspective of looking into such issues[10], since it connected all the pages across the internet together based on its accessibility as well as their importance[11][12]. Variations into this led to domain based searches [13][14] which look into various features of each URLs domain names and their properties such as its validity, time to live and so on. The proactive phishing method looks into the text of the URL[15] and identifies the lexemes and the pattern with which it is framed. Visual similarity looks into the HTML and CSS pages[16][17] to distinguish legitimate website structures from malicious ones. Finally, a recent and growing advancement in this field includes the heuristic machine learning techniques[18][19] which make use of a range of Machine Learning models to classify URLs based on the previous techniques discussed. In one of the most recent surveys[29] conducted on the application of ML models to this problem, the techniques for doing so are categorized into Natural Language Processing, Machine Learning and Deep Learning methods. According to the survey, although these methods have been applied and detect malicious web pages to a certain extent, the problem still persists. It recommends the use of more advanced models of this field such as extremely

modern neural network models. Similar recent and complex models along with ensemble techniques to achieve better efficiency have been used here.

III. PROPOSED METHODOLOGY

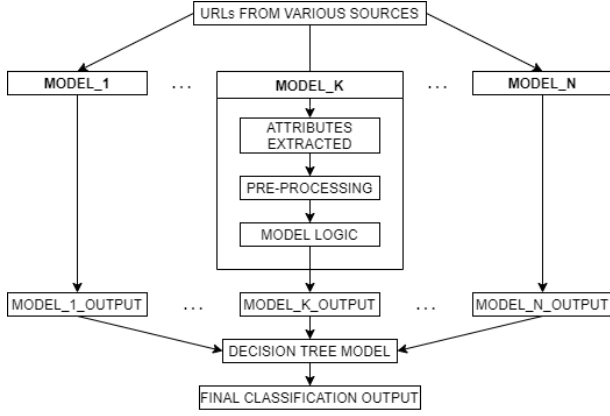


Fig. 1. Proposed Methodology Flow Diagram

As indicated by Fig. 1, the solution to the problem is divided into various models. Each model performs either a natural language processing, machine learning or artificial intelligence function. The attributes of a model belong to a specific aspect of URL classification such as one set of attributes for the characters present in the URL text, another set relating to the domain name of a URL and so on. To build this system, first the relevant URLs are taken from various sources. Then, features are extracted by pre-processing them in different ways depending on the functionality of each model. These extracted features are grouped into the models they belong to which uses them to determine whether the page is malicious or not. The results of these models are combined using a decision tree to come up with the final output displayed at the front-end section where the input from the user is a URL which is provided in a text box on the website interface. Besides selecting the attributes and grouping them for different models, the appropriate model for the attributes, the hyper-parameters of the model and the methodology to compare each model output is completely data-driven and hence has minimal human bias.

IV. DATA COLLECTION AND TRANSFORMATION

The datasets used are listed in references [2] to [6]. These include standard datasets along with data extracted with the help of continuous web scraping. This is done using the python library BeautifulSoup[27] along with the cron technique[28] which extracts the various URLs periodically. These URLs are then labeled with zeros for legitimate and ones for malicious to create a binary classification for the same. New datasets are derived based on the attributes extracted from the existing ones. Table 1 shows these derived datasets, the steps taken to obtain their features as well as their size. Each of these datasets are cleaned by removing duplicates and empty or null values.

TABLE I
LIST OF DATASETS

Dataset Name	Extraction & Transformation Steps	Number of Examples
Special Characters Dataset	Perform Lexical Analysis to extract special characters	295364
HTML Tags Dataset	From the markup obtained from cron extract the tags of the webpage and remove columns and rows that had only zeroes	5615
Domain Related Information Dataset	Extract the duration in days for which the domain name of the URL is valid, the number of internal and external links it points to via web scraping with BeautifulSoup	4000
Web Page Text Dataset	Extract the information enclosed in the HTML tags that represent the text via web scraping with BeautifulSoup	5615
DOM Tree Dataset	Get a depth-first-search traversal of the tags of the markup via web scraping with BeautifulSoup	232
BERT Dataset	URLs from [2] to [6]	295364
Alexa Dataset	Contains the most popular domain names which are highly unlikely to be malicious	1000000
Ensemble Dataset	Classifier outputs along with the results for determining how the models can be pieced together	3005

Fig. 2, shows the composition of the derived datasets with respect to those that have been collected.

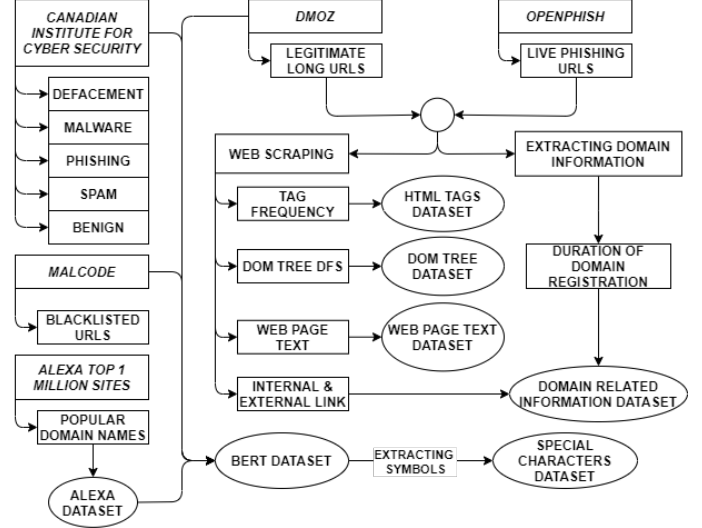


Fig. 2. Description of Datasets

V. MODELS AND INTERFACES

In this paper, a variety of models have been used and integrated together to form a single functioning unit. Each model pertains to a specific functionality performed to classify the URL and plays a crucial role in determining the legitimacy of a URL, which are displayed to the user by the frontend.

A. Long Short Term Memory

The Long Short Term Memory (LSTM) is a recurrent neural network which works on the principle of feedback data points allowing it to process multiple inputs simultaneously making it a viable option for URL classification[24]. As part of the pre-processing of this model, tokenization is done in order to feed the textual data in the appropriate numeric form to the neural network. In this work, it is performed as a supervised method for datasets containing attributes with a significant amount of sequential data.

1) *Text Classification of the Web Pages:* Here, it is used on the Web Page Text Dataset. This consists of what a user will read when looking at a web page. The text in a web page determines the topic that it addresses as well as the relevance of the topic under scrutiny. It is classified as malicious if the topics it describes falls under something that is commonly regarded as a source of threat. So, the tokenization here involves, converting the text of a web page into tokens of text in a numeric form with padding that can be processed at a time. Fig. 3, describes the complete process. The LSTM model here, has been trained on 5 epochs, with Adam optimizer and binary cross-entropy activation function. Early-stopping has been applied on compilation and a dropout mechanism has been applied on the neural network architecture. to reduce overfitting. Despite this, the model seems to be overfitting.

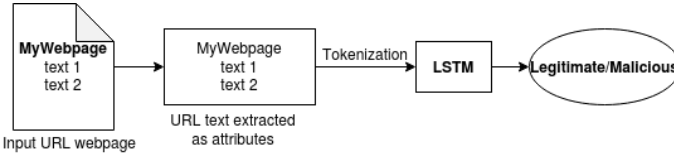


Fig. 3. LSTM model for text classification of web pages

2) *DOM Tree Classification of the Web Pages:* A Document Object Model(DOM) defines the structure of HTML pages. In this paper, the extraction of these trees allow us to compare similarly organized pages and classify them into their respective classes. The DOM tree compares these tree structures [24] in order to identify any deviation from normal behaviour. This can be done by mapping the HTML tags of both classes in order to create this structure and then creating a comparative study. Since, an awareness of the complete sequence of the tree traversal is required for the machine to learn the behavior of web pages in each of the classes an LSTM is used as it works very well with sequential data. Fig. 4, describes the complete process. The tokenization here would primarily group the tag names and their sequences, if commonly found, as they frequently appear in the corpus. Following a similar architecture to the Text Classification model, this LSTM is trained over a smaller dataset over 8 epochs to produce the final result.

B. The BERT model

The Bidirectional Encoding Representational Transformer [25] provides one of the most sophisticated yet accurate ways

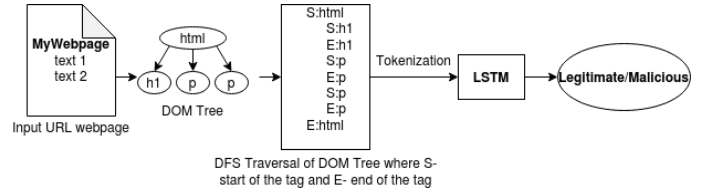


Fig. 4. LSTM model for DOM tree classification of web pages

of determining whether a URL formatting structure is feasible or not by the use of transfer learning. The advantage of a pre-trained model such as BERT is that it performs lexical analysis from left to right direction and vice versa. This allows it to capture dependencies that might not be possible to do in most machine learning models. First tokenization is performed, which encodes the URLs by converting them into numeric tokens with unique identities, where each token represents one or more characters from the URL. This allows the model to analyze the attention, or the components of the tokenized URL together. Fig. 5 shows the mechanism of applying the BERT model in this paper.

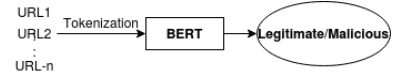


Fig. 5. BERT model for URL classification

C. Decision Trees

Decision trees are very popular and powerful tools that are used for machine learning as they have a very good ability to handle non-linear data. In this work, decision trees are used when the number of attributes are large and the attributes involved are discrete.

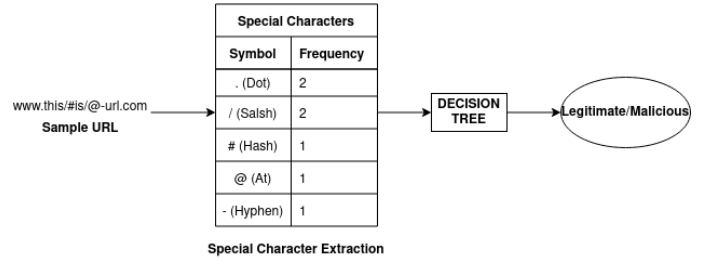


Fig. 6. Decision Tree for Special Symbols

1) *Special Symbols:* This decision tree uses the Special Characters Dataset that consists of the frequency of various special characters present in the URL[22]. There are 30 different special characters taken into consideration. It is seen that the URLs that are malicious tend to have an unnaturally large frequency of special characters. To test this hypothesis, this dataset is created and is used for classification. The decision tree thus formed involves branching out depending on the frequency of a certain special character processed at a time. The final classification will hence be characterized by a

frequency range of a specific combination of special characters that are present in the URL. Fig. 6, shows process of how it has been created.

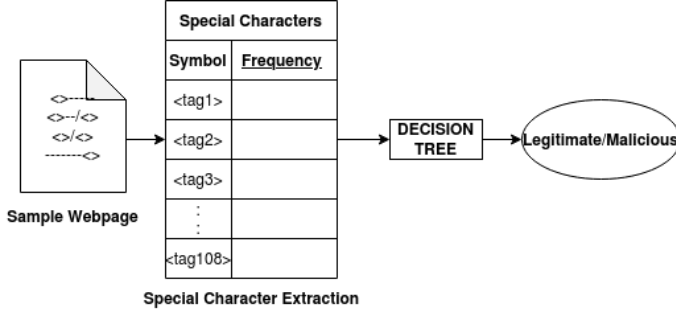


Fig. 7. Decision Tree for HTML Tags

2) *HTML Tags*: This decision tree uses the HTML Tags Dataset which will give the frequency of each HTML tag in the markup of the URL as shown in Fig. 7. It is possible that the usage of some tags more frequently such as an anchor tag increases the probability of the URL being a malicious one and vice-versa. Thus the classification in this case, similar to that of the previous decision tree would involve a combination of some HTML tags that concludes the legitimacy of the URL.

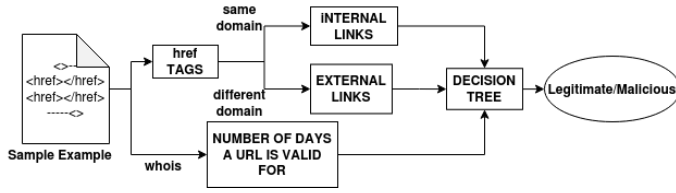


Fig. 8. Decision Tree for Domain Name specific features

3) *Domain Name specific features*: This decision tree uses the Domain Related Information Dataset which consists of the number of internal and external links of the URL along with the duration in days for which the domain name of the URL is valid[23]. A reasonable URL is pinpointed by the decision tree based on the ratio between these two types of links. Reputed domains tend to have a registration for a longer period of time than malicious ones which try to remain latent from Blacklists. Hence, the number of days for which a domain name is valid is also included in this model. Fig. 8, shows the process of implementing this model.

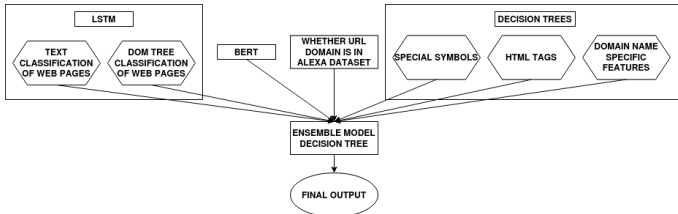


Fig. 9. Decision Tree for ensemble model

TABLE II
MODEL ACCURACIES

Model Name	Dataset Used	Accuracy	Importance %
LSTM for Text Classification of the Web Pages	Web Page Text Dataset	99.98	4.6594%
LSTM for DOM Tree Classification of the Web Pages	DOM Tree Dataset	78.26	0.2673%
BERT Model	BERT Dataset	98.6	0.0000%
Decision Tree for Special Symbols	Special Characters Dataset	73.87	10.3107%
Decision Tree for HTML Tags	HTML Tags Dataset	87.6	10.0575%
Decision Tree for Domain Name Specific Features	Domain Related Information Dataset	89.2	74.3075%
Decision Tree for Ensemble Model	Ensemble Dataset	95.3%	-

4) *Ensemble Model*: It is the final model that collectively integrates and computes an aggregate of the predictions made by all the previous models to determine the final outcome of the URL as shown in Fig. 9. It also provides a comparative study of the performance of each of the models used. The ensemble construct allows us to obtain a non-biased multi-source contribution to classify each URL as legitimate or malicious. The Decision tree takes the outputs of the above models and creates multiple binary decisions that leads to the final conclusion about the URL to be displayed on the web page to the user.

D. Front End Display

The result of the ensemble model is delivered to the user via a web page, where the user can enter the desired URL to obtain this result. The model is hosted via Flask[41] which not only displays to the user whether the given URL is legitimate or not, but also the outcomes of each individual model.

VI. OBSERVATIONS

Table II shows the accuracies obtained for each model for classification along with the contribution of each model into the ensemble indicated by the importance in the table. It is seen that the LSTM for text classification has the highest accuracy, however this is not considered significant as an independent model as a predictor because it will be very difficult to extract the contents of a URL. Moreover, the time taken for a prediction increases greatly with an increase in the size of a web page. The BERT model exhibits a small scale of overfitting, and similar to LSTM cannot act as an independent model for the reason that the structure of a URL alone does not provide enough proof for a website being safe or not. Similar reasons apply to every model that make the ensemble when used individually. However, because each model looks into a different facet of a web page in an exhaustive manner the ensemble is the best solution.

Further, based on the architecture of the various decision trees the relative importance of the attributes involved can be

TABLE III
SOME IMPORTANT SPECIAL CHARACTERS AND THEIR IMPORTANCE IN THE MODEL

Symbol	Importance %
+	3.0302
-	8.9676
.	14.7311
-	18.6924
=	42.2431

TABLE IV
SOME IMPORTANT SPECIAL CHARACTERS AND THEIR IMPORTANCE IN THE MODEL

HTML tags	Importance %
table	5.4450
script	5.7386
h1	6.0793
a	19.8721
input	20.8373

observed. From these observations certain interpretations can be made. Table III shows the important special characters that influence the safeness of a URL the most according to the Decision Tree for Special Symbols. This may be because these symbols do not appear very often in a legitimate URL.

Table IV shows the most important HTML tags that influence the classification according to the Decision Tree for HTML Tags. The "input" tag has the greatest influence and this may be because many phishing sites try to take details from users such as their banking details and for doing so they would need "input" tags. "a" tags also influence the classification because many malicious URLs redirect to some other pages through "href"s present in the a tags. Following this "h1" and "table" tags also influence the classification if not as significantly as the "a" and "input" tags. This can be because the "h1" tag text catches the eye of the user and "table" tags make the forms that take in inputs in HTML look better structured. Further, malicious URLs that don't have very complex functionality tend to have "script" tags within their markups.

Table V shows that the most important domain related feature that is influencing the Decision Tree for Domain Name Specific Features is the duration in days for which the domain is registered. This may be because the malicious URLs want to escape the attention of the browser and hence try to remain hidden and short-lived.

VII. DISCUSSION

The methods employed by people creating the malicious URLs is continuously evolving. Hence, this topic will have

TABLE V
IMPORTANCE OF DOMAIN RELATED FEATURES IN THE MODEL

Feature	Importance %
duration	82.1588
internal links	10.3852
external links	7.4559

constant research for a long time to come. This work, has tried to create a system that will continue to catch malicious URLs even as they evolve since the ensemble looks into almost all components in web page creation. The ensemble enables better modularity, error handling and it also reduces the overfitting. Besides, each of these models are the best for the given data as they have performed better in comparison to other models such as SVM, KMeans and so on.

VIII. CONCLUSION

This work gives an ensemble of models with different attributes to classify whether a URL is malicious or legitimate with an accuracy of 95.3%. A method which takes into account so many different types of attributes in one framework is rare and will also make sure that a hacker cannot easily infiltrate this system and become successful.

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