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CONTENTS

ABSTRACT

This project proposes a phishing detection plugin for chrome 1 browser that can detect and warn the user about phishing web sites in real-time using random forest classifier. Based on the paper Intelligent phishing website detection[3] using random forest classifier, the 2 random forest classifier seems to outperform other techniques in detecting phishing websites. One common approach is to make the classification in a server and then let the plugin to request the server for result. Unlike the old approach, this project aims to run the classification in the browser itself. The advantage of classifying in the client side browser has advantages like, better privacy (the user's browsing data need not leave his machine), detection is independent of network latency. This project is mainly of implementing the above mentioned paper in Javascript for it to run as a browser plugin. Since javascript doesn't have much ML libraries support and considering the processing power of the client machines, the approach needs to be made lightweight. The random forest classifier needs to be trained on the phishing websites dataset using python scikit-learn and then the learned model parameters 3 need to be exported into a portable format for using in javascript.

LIST OF FIGURES

LIST OF ABBREVATIONS

URL	Uniform Resource Locator
API	Application Programming Interface
HTTP	Hyper Text Transfer Protocol
SSL	Secured Socket Layer
DNS	Domain Name System
GDPR	General Data Privacy Regulation
JSON	JavaScript Object Notation
DOM	Document Object Model
UI	User Interface
HTML	Hyper Text Markup Language
CSS	Cascading Style Sheet

CHAPTER 1

INTRODUCTION

Phishing is the fraudulent attempt to obtain sensitive information such as usernames, passwords, and credit card details (and money), often for malicious reason. It is typically carried out by email spoofing or instant messaging, and it often directs users to enter personal information at a fake website, the look and feel of which are identical to the legiti-mate site, the only difference being the URL of the website in concern. Communications purporting to be from social web sites, auction sites, banks, online payment processors are often used to lure victims. Phishing emails may contain links to websites that distribute malware.Detecting phishing websites often include lookup in a directory of malicious sites. Since most of the phishing websites are short lived, the directory cannot always keep track of all, including new phishing web-sites. So the problem of detecting phishing websites can be solved in a better way by machine learning techniques. Based on a comparison of different ML techniques, the random forest classifier seems to perform better.Only way for an end user to benefit from this is to implement detection in a browser plugin. So that the user can be warned in real time as he browses a phishing site. However, browser extensions have restric-tions such as they can be written only in javascript and they have limited access to page URLs and resources. Existing plugins send the URL to a server, so that the classification can be done in the server and the result is returned to the plugin. With this approach, user privacy is questioned and also the detection may be delayed due to network latency and the plugin may fail to warn the user in right time. As it is an important security problem and also considering the privacy aspects, we decided to implement this on a chrome browser plugin which can do the classification without an external server. We referred Papers [3]and [4]

CHAPTER 2

RELATED WORKS

This chapter gives a survey of the possible approaches to phishing website detection. This survey helps to identify various existing approaches and to find the drawbacks in them. The difficulty in most of the approaches is that they are not implemented in real time so that an end user will benefit from it.

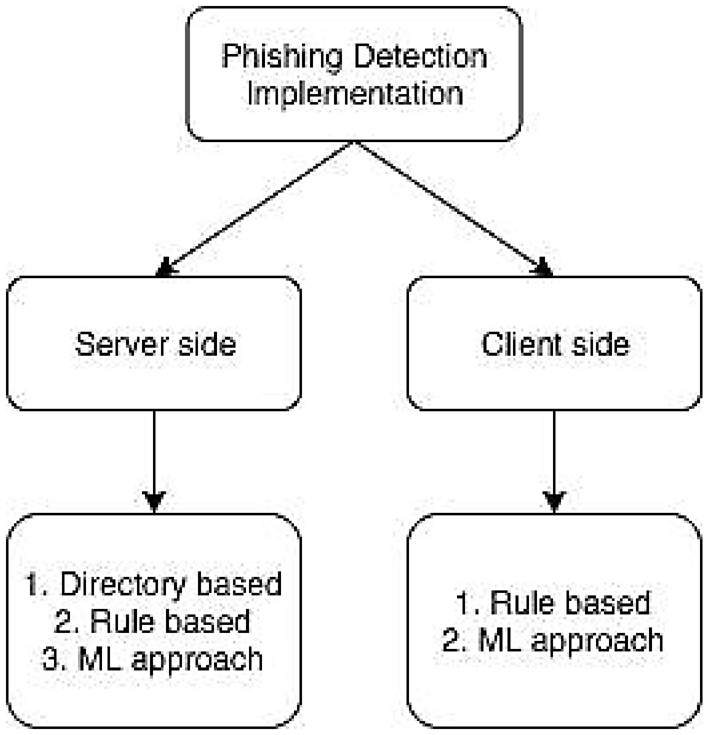


Figure 2.1 Approaches to phishing detection

2.1 DIRECTORY BASED APPROACHES

Most popular one of this kind is PhishTank. According to Phish-Tank4, it is a collaborative clearing house for data and information about phishing on the Internet. Also, PhishTank provides an open API for developers and researchers to integrate anti-phishing data into their applications at no charge. Thus PhishTank is a directory of all phishing websites that are found and reported by people across the web so that developers can use their API for detecting phishing websites.

Google has a API called Google Safe Browsing API which also follows directory based approach and also provides open API similar to PhishTank.

This kind of approach clearly can’t be effective as new phishing web sites are continuously developed and the directory can’t be kept up to date always. This also leaks users browsing behaviour as the URLs are sent to the PhishTank API.

2.2 RULE BASED APPROACHES

An existing chrome plugin named PhishDetector5 uses a rule based approach so that it can detect phishing without external web ser-vice. Although rule based approaches support easier implementation on client side, they can’t be accurate compared to Machine Learning based approaches. Similar work by Shreeram.V on detection of phishing at-tacks using genetic algorithm6 uses a rule that is generated by a genetic algorithm for detection.

PhishNet is one such Predictive blacklisting approach. It used rules that can match with TLD, directory structure, IP address, HTTP header response and some other.

SpoofGuard7 by Stanford is a chrome plugin which used similar rule based approach by considering DNS, URL, images and links.

Phishwish: A Stateless Phishing Filter Using Minimal Rules by Debra L. Cook, Vijay K. Gurbani, Michael Daniluk worked on a phish - ing filter that offers advantages over existing filters: It does not need any training and does not consult centralized white or black lists. They used only 11 rules to determine the veracity of an website.

2.3 ML BASED APPROACHES

Intelligent phishing website detection using random forest classifier (IEEE-2017) by [1]discusses the use the random forest classifier for phishing detection. Random Forest has performed the best among the classification methods by achieving the highest accuracy 97.36%.PhishBox: An Approach for Phishing Validation and Detection (IEEE-2017) by [3] discusses ensemble models for phishing detection. As a result, The false-positive rate of phishing detection is dropped by 43.7% in average.Real time detection of phishing websites (IEEE-2016) by [4]discusses an approach based on features from only the URL of the website. They were able to come up with a detection mechanism that is capable of detecting various types of phishing attacks maintaining a low rate of false alarms.Using Domain Top-page Similarity Feature in Machine Learning-Based Web Phishing Detection.

Arnon Rungsawang presents a study on using a concept feature to detect web phishing problem. They applied additional domain top-page similarity feature to a machine learning based phishing detection system. The evaluation result in terms of f-measure was up to 0.9250, with 7.50% of error rate.Netcraft[8]is one popular phishing detection plugin for chrome that uses server side prediction

2.4 DRAWBACKS

Based on the above mentioned related works, It can be seen that the plugins either use rule based approach or server side ML based ap-proach. Rule based approach doesn't seem to perform well compared to ML based approaches and on the other side ML based approaches need libraries support and so they are not implemented in client side plugin. All the existing plugins send the target URL to an external web server for classification. This project aims to implement the same in browser plugin removing the need of external web service and improving user privacy.

There must be a simple and easy to use user interface where the user should be able to quickly identify the phishing website. The input should be automatically taken from the webpage in the current tab and the output should be clearly identifiable. Further the user should be inter-rupted on the event of phishing.

The main disadvantage is that rule-based methods are usually not the best performers in terms of prediction quality. Other methods (forests, SVM, deep nets) tends to be better. Also, rule-based methods are better for data with categorical features. With numeric feature there is extra difficulty due to need to discretize the data or identify thresholds for the rules.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

The plugin warns the user when he/she visits a phishing website. The plugin should adhere to the following requirements: The plugin should be fast enough to prevent the user from submitting any sensitive information to the phishing website. The plugin should not use any external web service or API which can leak user's browsing pattern. The plugin should be able to detect newly created phishing websites. The plugin should have a mechanism of updating itself to emerging phishing techniques.

3.2 NON FUNCTIONAL REQUIREMENTS

3.2.1 User Interface

There must be a simple and easy to use user interface where the user should be able to quickly identify the phishing website. The input should be automatically taken from the webpage in the current tab and the output should be clearly identifiable. Further the user should be interrupted on the event of phishing.

3.2.2 Hardware

No special hardware interface is required for the successful implementation of the system.

Hardware Requirements

Processor	: Quad Core
Hard Disk	: 120 GB
RAM	: 2 GB
Monitor	: acer aspire
Mouse	: Genius Scroll Mouse
Keyboard	: 107 keys

3.2.3 Software

Python is used for training the model and the plugin is exported to Chrome Browser.

Operating system: Any

Software tools: Chrome

3.2.4 Performance

The plugin should be always available and should make fast detection with low false negatives. when a website is opened it will detect whether that website is phishing or not in quick time.

3.3 CONSTRAINTS AND ASSUMPTIONS

3.3.1 Constraints

Certain techniques use features such as SSL, page rank etc. Such information cannot be obtained from client side plugin without external API. Thus those features can’t be used for prediction.

Heavy techniques can’t used considering the processing power of client machines and the page load time of the website.

Only JavaScript can be used to develop chrome plugins. Machine learning libraries support for JavaScript is far less com-pared to python and R.

3.3.2 Assumption

The plugin is provided with the needed permissions in the chrome environment.

The user has a basic knowledge about phishing and extensions.

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

The block diagram of the entire system is shown in the figure 4.1. A Random Forest classifier is trained on phishing sites dataset using python scikit-learn. A JSON format to represent the random forest classifier has been devised and the learned classifier is exported to the same. A browser script has been implemented which uses the exported model JSON to classify the website being loaded in the active browser tab.

The system aims at warning the user in the event of phishing. Random Forest classifier on 17 features of a website is used to classify whether the site is phishing or legitimate. The dataset arff file is loaded using python arff library and 17 features are chosen from the existing 30 features. Features are selected on basis that they can be extracted com-pletely offline on the client side without being dependent on a web ser-vice or third party. The dataset with chosen features are then separated for training and testing. Then the Random Forest is trained on the training data and exported to the above mentioned JSON format. The JSON file is hosted on a URL.

The client side chrome plugin is made to execute a script on each page load and it starts to extract and encode the above selected features. Once the features are encoded, the plugin then checks for the exported model JSON in cache and downloads it again incase it is not there in cache.

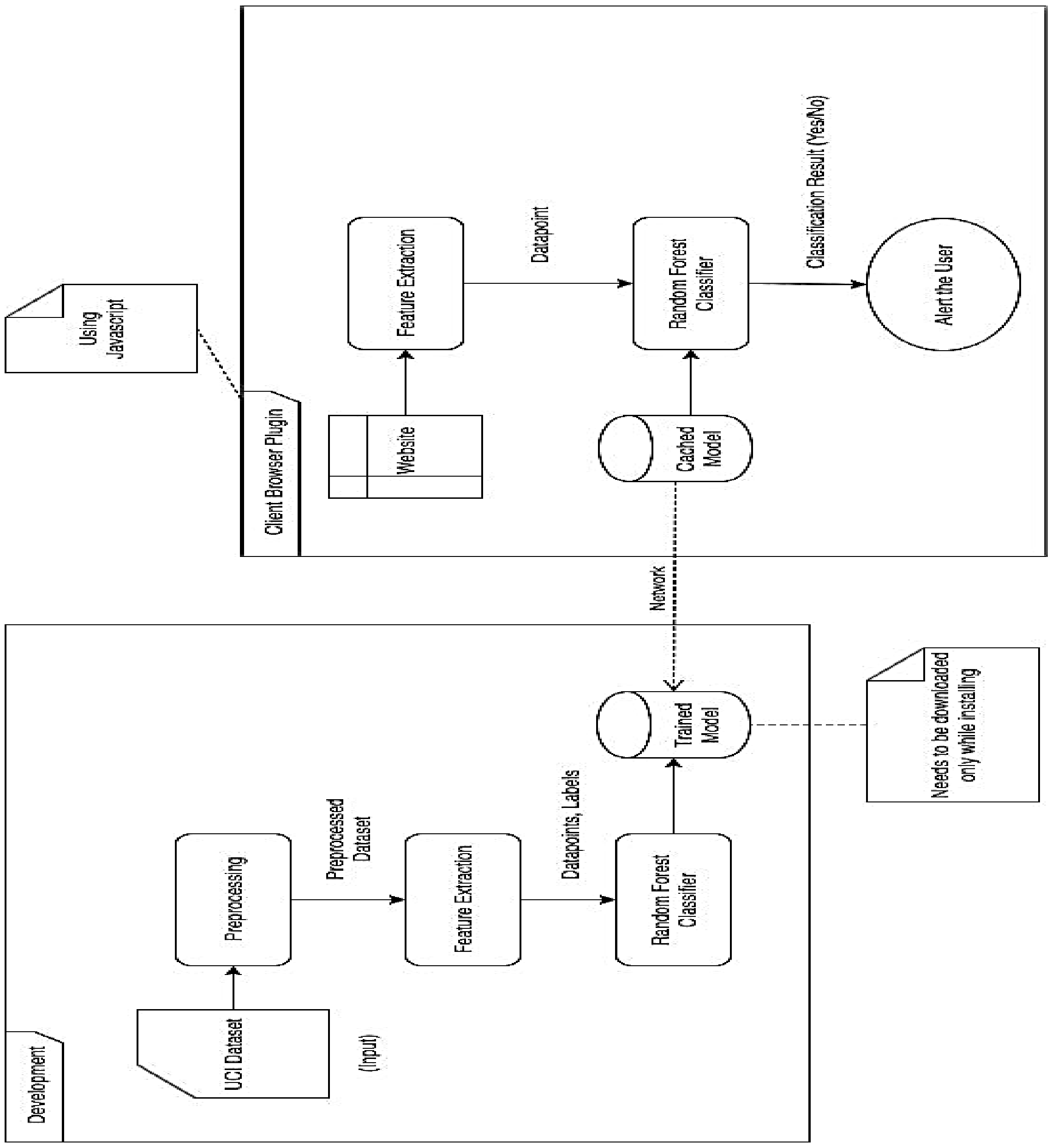


Figure 4.1 System Architecture

With the encoded feature vector and model JSON, the script can run the classification. Then a warning is displayed to the user, incase the website is classified as phishing. The entire system is designed lightweight so that the detection will be rapid.

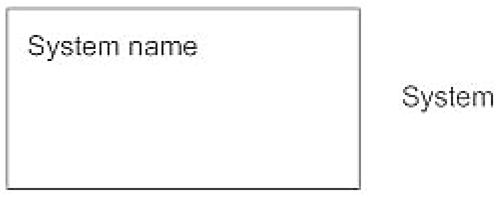
4.1.1 Use Case Diagram

The overall use case diagram of the entire system is shown in figure 4.1.1 The user can install the plugin and then can continue his normal browsing behaviour. He only needs to download the model once. This plugin will automatically check the browsing pages for phishing and warns the user of the same.

Use case shape in use case diagram is a horizontal oval that represents something an actor uses the system to achieve a goal. An include relationship defines that a use case contains the behavior defined in another use case.

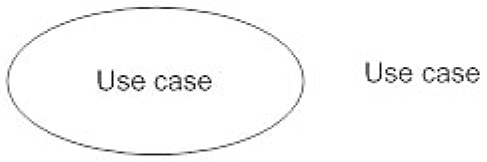
System

Draw your system's boundaries using a rectangle that contains use cases. Place actors outside the system's boundaries.



Use Case

Draw use cases using ovals. Label the ovals with verbs that represent the system's functions.

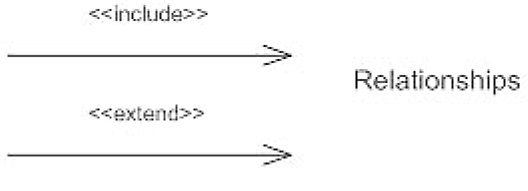


Actors

Actors are the users of a system. When one system is the actor of another system, label the actor system with the actor stereotype.

Relationships

Illustrate relationships between an actor and a use case with a simple line. For relationships among use cases, use arrows labeled either "uses" or "extends." A "uses" relationship indicates that one use case is needed by another in order to perform a task. An "extends" relationship indicates alternative options under a certain use case.



Pre condition: The user visits a website and have plugin installed.

Post condition: The user is warned incase it’s a phishing website.

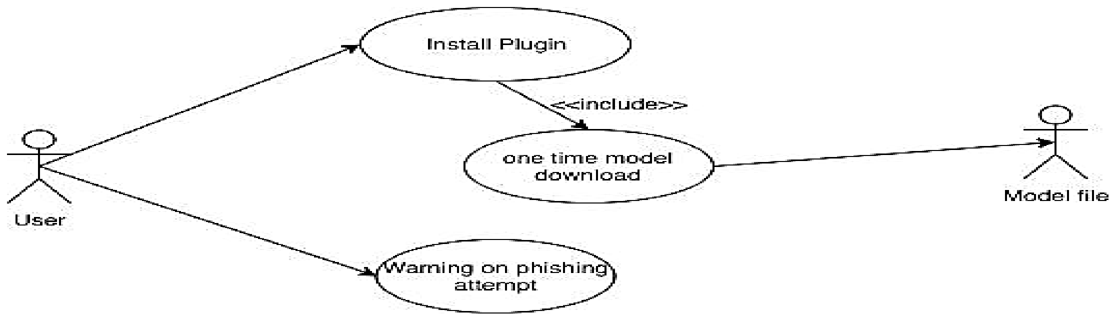


Figure 4.1.1 Use case diagram of the system

4.1.2 Sequence diagram

The sequence of interactions between the user and the plugin are shown in the figure 4.1.2 When the user enters a website.The plugin will start working in the background of chrome and by using the random forest classifier algorithm the plugin will detect whether the website is phishing or not by showing a pop window.

Class Roles or Participants

Class roles describe the way an object will behave in context. Use the UML object symbol to illustrate class roles, but don't list object attributes.

:Object
component

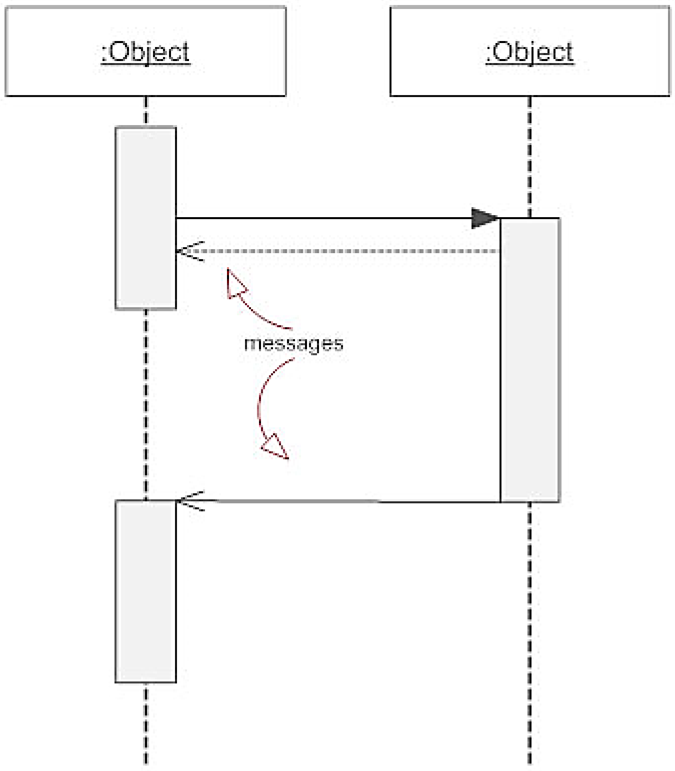
Activation or Execution Occurrence

Activation boxes represent the time an object needs to complete a task. When an object is busy executing a process or waiting for a reply message, use a thin gray rectangle placed vertically on its lifeline.

Activation or Execution Occurrence

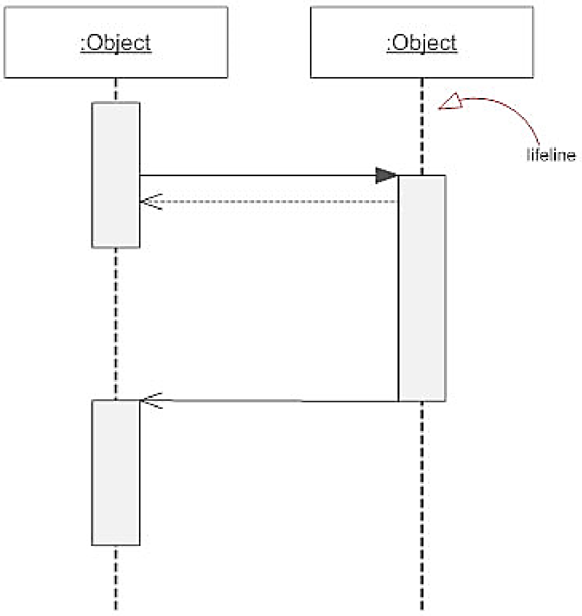
Messages

Messages are arrows that represent communication between objects. Use half-arrowed lines to represent asynchronous messages. Asynchronous messages are a response from the receiver fore continuing its tasks. For message types, seebelow.sent from an object that will not wait



Lifelines

Lifelines are vertical dashed lines that indicate the object's presence over time.



Destroying Objects

Objects can be terminated early using an arrow labeled "<< destroy >>" that points to an X. This object is removed from memory. When that object's lifeline ends, you can place an X at the end of its lifeline to denote a destruction occurrence.

Loops

A repetition or loop within a sequence diagram is depicted as a rectangle. Place the condition for exiting the loop at the bottom left corner in square brackets [ ]

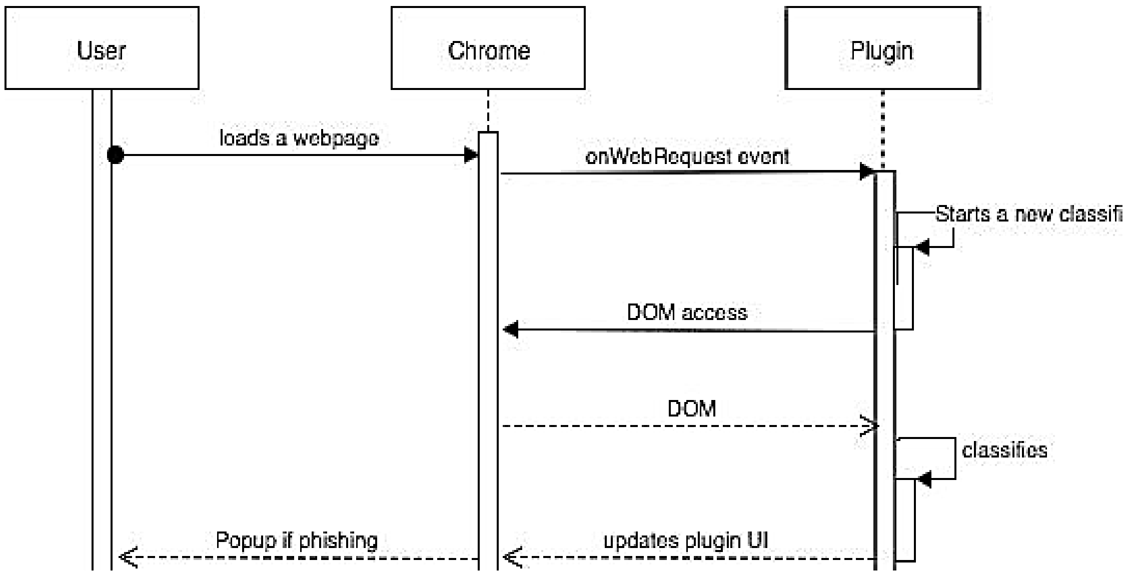


Figure 4.1.2 System Sequence diagram

4.2 UI DESIGN

A simple and easy to use User Interface has been designed for the plugin using HTML and CSS. The UI contains a large circle indicating the percentage of the legitimacy of the website in active tab. The circle also changes its colour with respect to the classification output (Green for legitimate website and Light Red for phishing). Below the circle, the analysis results containing the extracted features are displayed in the following colour code

Green	-	Legitimate
Yellow	-	Suspicious
Light Red	-	Phishing

The plugin also displays a alert warning incase of phishing to pre-vent the user from entering any sensitive information on the website. The test results such as precision, recall and accuracy are displayed in a separate screen. The UI is shown in figure 4.2

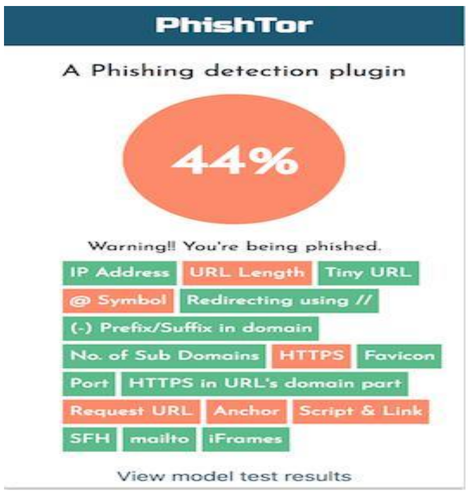


Figure 4.2 UI Design

4.3 CLASS DIAGRAM

The class diagram of the entire Machine Translation system is shown in figure 4.3. This diagram depicts the functions of various mod-ules in the system clearly. It also shows the interaction between the modules of the system thereby providing a clear idea for implementation.

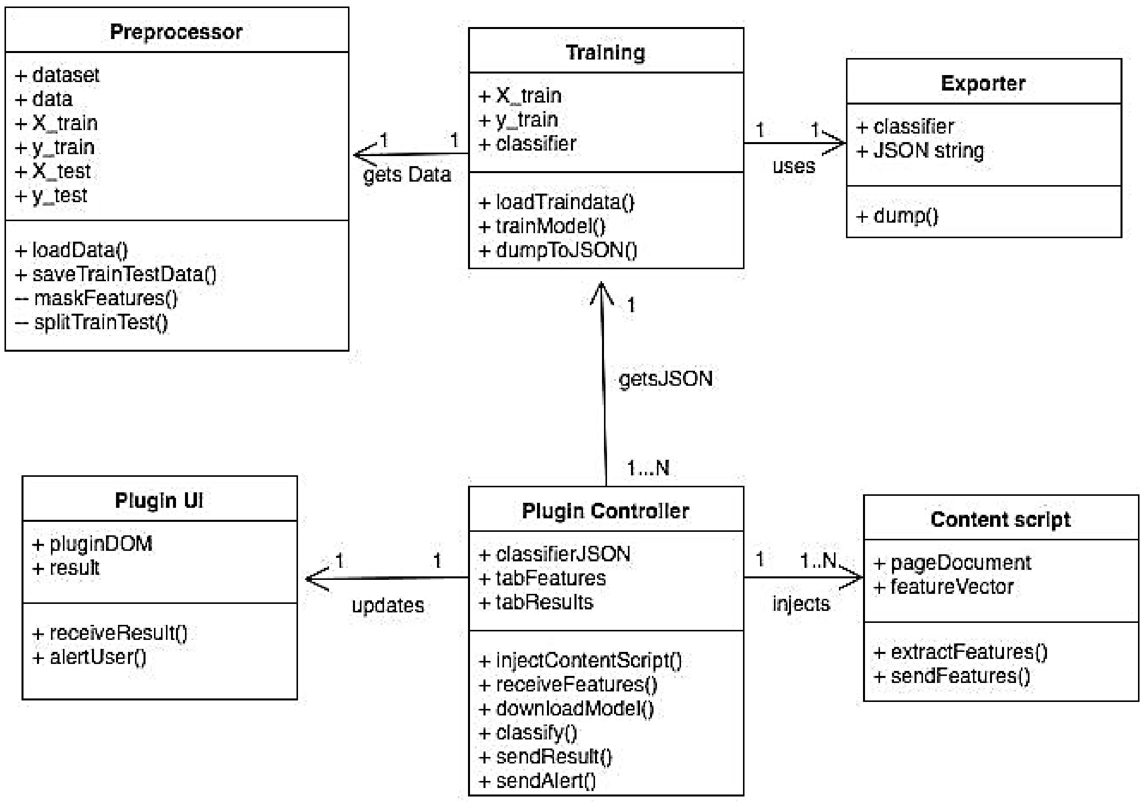


Figure 4.3 Class Diagram

4.4 MODULE DESIGN

4.4.1 Preprocessing

The dataset is downloaded from UCI repository and loaded into a numpy array. The dataset consists of 30 features, which needs to be reduced so that they can be extracted on the browser. Each feature is experimented on the browser so that it will be feasible to extract it without using any external web service or third party. Based on the experiments, 17 features have been chosen out of 30 without much loss in the accuracy on the test data.

IP address	Degree of subdomain	Anchor tag href domains
URL length	HTTPS	Script & link tag domains
URL shortener	Favicon domain	Empty server form handler
@' in URL	TCP Port	Use of mailto
Redirection with '//'	HTTPS in domain name	Use of iFrame
-' in domain	Cross domain requests	

Table 4.1 Webpage Features

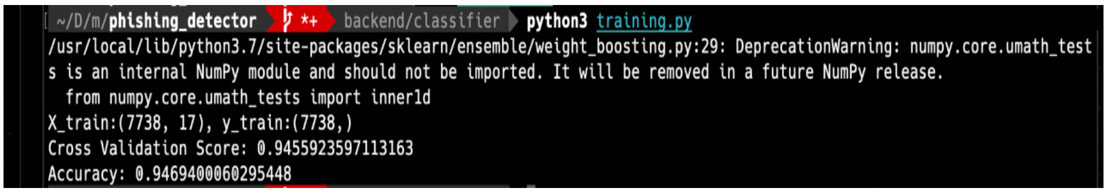
Then the dataset is split into training and testing set with 30% for testing. Both the training and testing data are saved to disk.

4.4.2 Training

The training data from the preprocessing module is loaded from the disk. A random forest classifier is trained on the data using scikit-learn library. Random Forest is an ensemble learning technique and thus
an ensemble of 10 decision tree estimators is used. Each decision tree follows CART algorithm and tries to reduce the gini impurity.

$$Gini(E) = 1 - \sum_{j=1} p_j^2$$

The cross validation score is also calculated on the training data. The F1 score is calculated on the testing data. Then the trained model is exported to JSON using the next module.

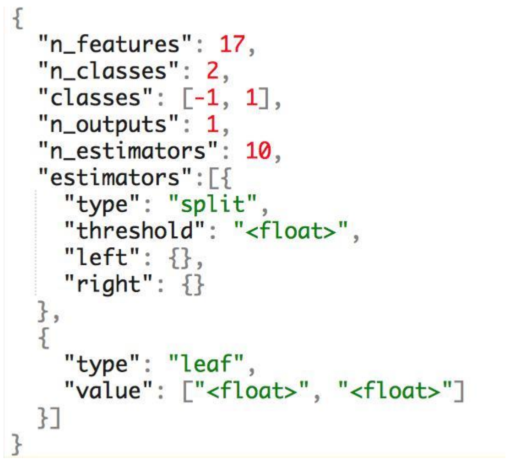


```
~/D/m/phishing_detector  ᚠ *+  backend/classifier  python3 training.py
/usr/local/lib/python3.7/site-packages/sklearn/ensemble/weight_boosting.py:29: DeprecationWarning: numpy.core.umath_test
s is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
X_train:(7738, 17), y_train:(7738,)
Cross Validation Score: 0.9455923597113163
Accuracy: 0.9469400060295448
```

4.4.3 Exporting Model

Every machine learning algorithm learns its parameter values dur-ing the training phase. In Random Forest, each decision tree is an inde-pendent learner and each decision tree learns node threshold values and the leaf nodes learn class probabilities. Thus a format needs to be de-vised to represent the Random Forest in JSON.

The overall JSON structure consists of keys such as number of es-timators, number of classes and etc. Further it contains an array in which each value is an estimator represented in JSON. Each decision tree is encoded as a JSON tree with nested objects containing threshold for that node and left and right node objects recursively.



```
{
  "n_features": 17,
  "n_classes": 2,
  "classes": [-1, 1],
  "n_outputs": 1,
  "n_estimators": 10,
  "estimators":[{
    "type": "split",
    "threshold": "<float>",
    "left": {},
    "right": {}
  },
  {
    "type": "leaf",
    "value": ["<float>", "<float>"]
  }]
}
```

Figure 4.4 Random Forest JSON structure

4.4.4 Plugin Feature Extraction

The above mentioned 17 features needs to be extracted and encod-ed for each webpage in realtime while the page is being loaded. A con-tent script is used so that it can access the DOM of the webpage. The content script is automatically injected into each page while it loads. The content script is responsible to collect the features and then send them to the plugin. The main objective of this work is not to use any external web service and the features needs to be independent of network latency and the extraction should be rapid. All these are made sure while developing techniques for extraction of features.

Once a feature is extracted it is encoded into values {-1, 0, 1} based on the following notation.

-1	-	Legitimate
0	-	Suspicious
1	-	Phishing

The feature vector containing 17 encoded values is passed on to the plugin from the content script.

4.4.5 Classification

The feature vector obtained from the content script is ran through the Random Forest for classification. The Random Forest parameters JSON is downloaded and cached in disk. The script tries to load the JSON from disk and incase of cache miss, the JSON is downloaded again.

A javascript library has been developed to mimic the Random Forest behaviour using the JSON by comparing feature vector against the threshold of the nodes. The output of the binary classification is based on the leaf node values and the user is warned if the webpage is classified as phishing.

4.5 COMPLEXITY ANALYSIS

4.5.1 Time Complexity

The time complexity of each module of the system is shown in Table 4.2

S.No	Module	Complexity
1	Preprocessing	O(n)
2	Training	O(E * v * nLog(n))
3	Exporting model	O(E * nLog(n))
4	Plugin feature extraction	O(v)
5	Classification	O(E * nLog(n))

Table 4.2 Time Complexity of various modules

- ‘n’ denotes number of data points.
- ‘E’ denotes number of ensembles (decision trees).
- ‘v’ denotes number of features.

4.5.2 Complexity of the project

The complexity of the project lies in balancing the tradeoff between accuracy and rapid detection. Choosing a subset of features that will make the detection fast and at the same time without much drop in accuracy.

Porting of scikit-learn python object to javascript compatible for-mat. For example, JSON.

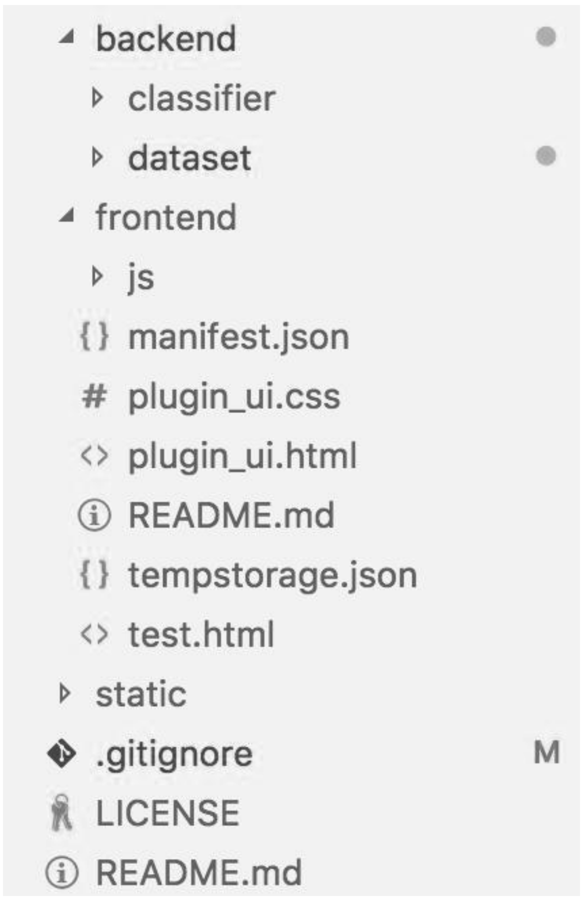
Reproducing the Random Forest behaviour in javascript reduced the accuracy by a small margin.

Many features are not feasible to extract without using a external web service. Use of an external web service will again affect the detection time.

CHAPTER 5

SYSTEM DEVELOPMENT

The system is overall split into backend and plugin. The backend consists of dataset preprocessing and training modules. The frontend which is the plugin consists of javascript files for content script and background script including the Random Forest script. The plugin also consists of HTML and CSS files for the user interface. The overall code overview showing the organization of these various modules can be seen in figure 5.1



```
backend                ●
  classifier
  dataset              ●
frontend
  js
  manifest.json
  plugin_ui.css
  plugin_ui.html
  README.md
  tempstorage.json
  test.html
static
.gitignore             M
LICENSE
README.md
```

Figure 5.1 Code Overview

5.1 PROTOTYPE ACROSS THE MODULES

The input and output to each module of the system is described in this section.

Preprocessing: This module takes the downloaded dataset in arffformat and the creates four new files listed as training features, training class labels, testing features, testing class labels.

Training: This module takes the four output files from pre-processor and gives a trained Random Forest object along with the cross validation score on the training set.

Exporting model: This module takes the learned Random Forest classifier object and the recursively generates its JSON representation which is written to file in disk.

Plugin Feature Extraction: This module takes a webpage as in-put and generates a feature vector with 17 encoded features.

Classification: This module takes the feature vector from feature extraction module and the JSON format from the Exporting mod-el module and then gives a boolean output which denotes whether the webpage is legitimate or phishing.

5.2 EXPORTING ALGORITHM

The algorithm used to export Random Forest model as JSON is as follows.

TREE_TO_JSON(NODE):

```
1.   tree_json ← {}
2.   if (node has threshold) then
3.       tree_json[“type”] ← “split”
4.       tree_json[“threshold”] ← node.threshold
5.       tree_json[“left”] ← TREE_TO_JSON(node.left)
6.       tree_json[“right”] ← TREE_TO_JSON(node.right)
7.   else
8.       tree_json[“type”] ← “leaf”
9.       tree_json[“values”] ← node.values
10.  return tree_json
```

RANDOM_FOREST_TO_JSON(RF):

```
1.    forest_json ← {}
2.    forest_json['n_features'] ← rf.n_features_
3.    forest_json['n_classes'] ← rf.n_classes_
4.    forest_json['classes'] ← rf.classes_
5.    forest_json['n_outputs'] ← rf.n_outputs_
6.    forest_json['n_estimators'] ← rf.n_estimators
7.    forest_json['estimators'] ← []
8.    e ← rf.estimators
9.    for (i←0 to rf.n_estimators)
10.       forest_json['estimators'][i] ← TREE_TO_JSON(e[i])
11.   return forest_json
```

Each generated training set is composed of random subsamples from the original data set. Each of these training sets is of the same size as the original data set, but some records repeat multiple times and some records do not appear at all. Then, the entire original data set is used as the test set. Thus, if the size of the original data set is N, then the size of each generated training set is also N, with the number of unique records being about (2N/3); the size of the test set is also N. each node is split on the best feature that minimizes error, in Random Forests, we choose a random selection of features for constructing the best split. The reason for randomness is: even with bagging, when decision trees choose the best feature to split on, they end up with similar structure and correlated predictions. But bagging after splitting on a random subset of features means less correlation among predictions from subtrees. The number of features to be searched at each split point is specified as a parameter to the Random Forest algorithm. The model is then exported as a JSON file.

5.3 DEPLOYMENT DETAILS

The backend requires Python 3 and the Classifier JSON and Test set are served over HTTP using Github. The plugin is distributed as sin-gle file and requires Chrome browser to run. The plugin (frontend) is packed into a crx file for distribution.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 DATASET FOR TESTING

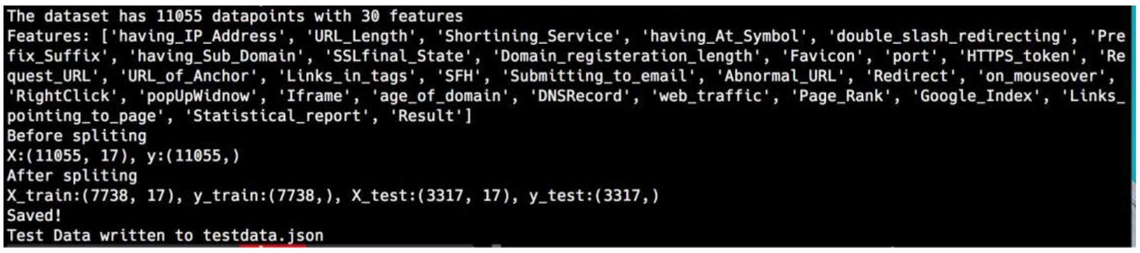
The test set consists of data points separated from the dataset by ratio 70:30. Also the plugin is tested with websites that are listed in phishTank. New phishing sites are also added to PhishTank as soon as they are found. It should be noted that the plugin is able detect new phishing sites too. The results of this module testing as well as the test-ing of the entire system are summarised below.

6.2 OUTPUT OBTAINED IN VARIOUS STAGES

This section shows the results obtained during module testing.

6.2.1 Preprocessing

The output the preprocessing module is shown in figure 6.1.

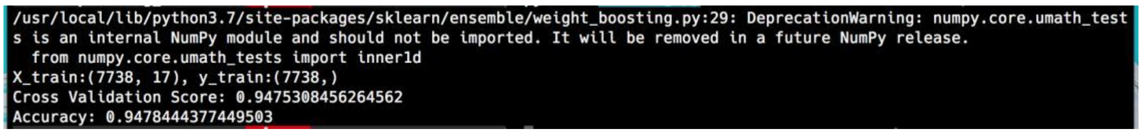


```
The dataset has 11055 datapoints with 30 features
Features: ['having_IP_Address', 'URL_Length', 'Shortining_Service', 'having_At_Symbol', 'double_slash_redirecting', 'Pre
fix_Suffix', 'having_Sub_Domain', 'SSLfinal_State', 'Domain_registeration_length', 'Favicon', 'port', 'HTTPS_token', 'Re
quest_URL', 'URL_of_Anchor', 'Links_in_tags', 'SFH', 'Submitting_to_email', 'Abnormal_URL', 'Redirect', 'on_mouseover',
'RightClick', 'popUpWidnow', 'Iframe', 'age_of_domain', 'DNSRecord', 'web_traffic', 'Page_Rank', 'Google_Index', 'Links_
pointing_to_page', 'Statistical_report', 'Result']
Before spliting
X:(11055, 17), y:(11055,)
After spliting
X_train:(7738, 17), y_train:(7738,), X_test:(3317, 17), y_test:(3317,)
Saved!
Test Data written to testdata.json
```

Figure 6.1 Preprocessing output

6.2.2 Trainings

The output the training module is shown in figure 6.2.

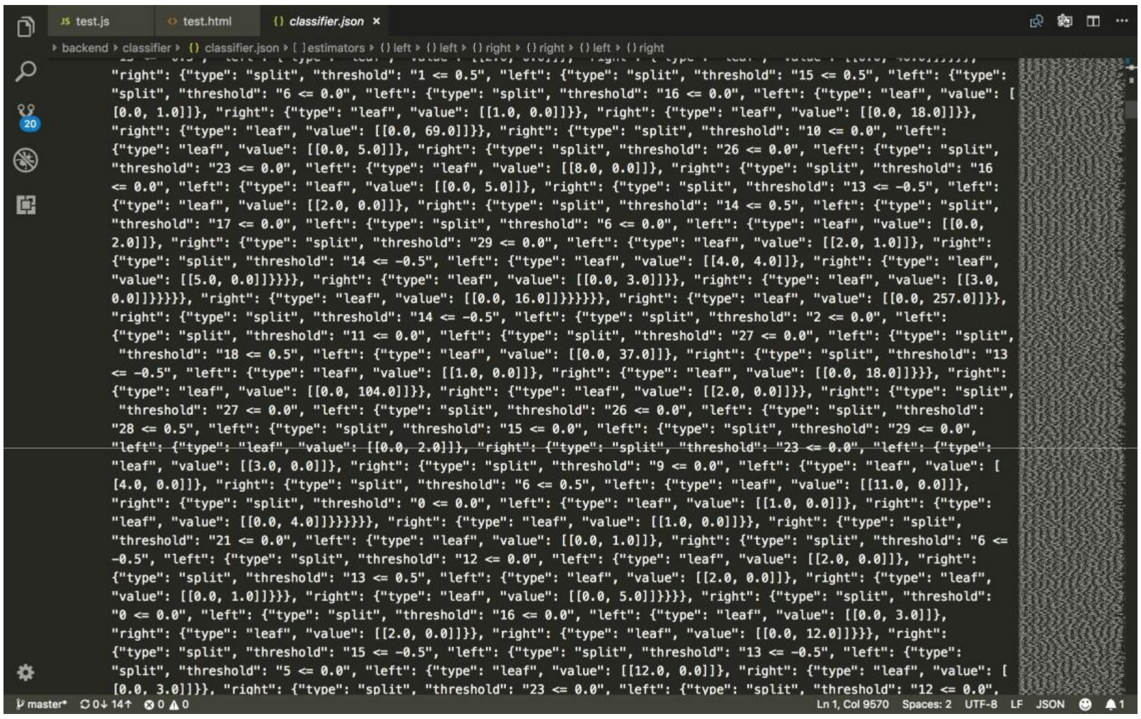


```
/usr/local/lib/python3.7/site-packages/sklearn/ensemble/weight_boosting.py:29: DeprecationWarning: numpy.core.umath_test
s is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
X_train:(7738, 17), y_train:(7738,)
Cross Validation Score: 0.9475308456264562
Accuracy: 0.9478444377449503
```

Figure 6.2 Training output

6.2.3 Exporting model

The output the export module is shown in figure 6.3. It outputs a JSON file representing the Random Forest parameters.


test.js
test.html
classifier.json
backend › classifier › classifier.json › [ ]estimators › { } left › { } left › { } right › { } right › { } left › { } right
master* 0↓ 14↑ 0 0
Ln 1, Col 9570 Spaces: 2 UTF-8 LF JSON 1

```
"right": {"type": "split", "threshold": "1 <= 0.5", "left": {"type": "split", "threshold": "15 <= 0.5", "left": {"type":
"split", "threshold": "6 <= 0.0", "left": {"type": "split", "threshold": "16 <= 0.0", "left": {"type": "leaf", "value": [
[0.0, 1.0]]}, "right": {"type": "leaf", "value": [[1.0, 0.0]]}}, "right": {"type": "leaf", "value": [[0.0, 18.0]]}},
"right": {"type": "leaf", "value": [[0.0, 69.0]]}}, "right": {"type": "split", "threshold": "10 <= 0.0", "left":
{"type": "leaf", "value": [[0.0, 5.0]]}, "right": {"type": "split", "threshold": "26 <= 0.0", "left": {"type": "split",
"threshold": "23 <= 0.0", "left": {"type": "leaf", "value": [[8.0, 0.0]]}, "right": {"type": "split", "threshold": "16
<= 0.0", "left": {"type": "leaf", "value": [[0.0, 5.0]]}, "right": {"type": "split", "threshold": "13 <= -0.5", "left":
{"type": "leaf", "value": [[2.0, 0.0]]}, "right": {"type": "split", "threshold": "14 <= 0.5", "left": {"type": "split",
"threshold": "17 <= 0.0", "left": {"type": "split", "threshold": "6 <= 0.0", "left": {"type": "leaf", "value": [[0.0,
2.0]]}, "right": {"type": "split", "threshold": "29 <= 0.0", "left": {"type": "leaf", "value": [[2.0, 1.0]]}, "right":
{"type": "split", "threshold": "14 <= -0.5", "left": {"type": "leaf", "value": [[4.0, 4.0]]}, "right": {"type": "leaf",
"value": [[5.0, 0.0]]}}}}}, "right": {"type": "leaf", "value": [[0.0, 3.0]]}}, "right": {"type": "leaf", "value": [[3.0,
0.0]]}}}}}}, "right": {"type": "leaf", "value": [[0.0, 16.0]]}}}}}}, "right": {"type": "leaf", "value": [[0.0, 257.0]]}},
"right": {"type": "split", "threshold": "14 <= -0.5", "left": {"type": "split", "threshold": "2 <= 0.0", "left":
{"type": "split", "threshold": "11 <= 0.0", "left": {"type": "split", "threshold": "27 <= 0.0", "left": {"type": "split",
 "threshold": "18 <= 0.5", "left": {"type": "leaf", "value": [[0.0, 37.0]]}, "right": {"type": "split", "threshold": "13
<= -0.5", "left": {"type": "leaf", "value": [[1.0, 0.0]]}, "right": {"type": "leaf", "value": [[0.0, 18.0]]}}}, "right":
{"type": "leaf", "value": [[0.0, 104.0]]}}, "right": {"type": "leaf", "value": [[2.0, 0.0]]}}, "right": {"type": "split",
 "threshold": "27 <= 0.0", "left": {"type": "split", "threshold": "26 <= 0.0", "left": {"type": "split", "threshold":
"28 <= 0.5", "left": {"type": "split", "threshold": "15 <= 0.0", "left": {"type": "split", "threshold": "29 <= 0.0",
"left": {"type": "leaf", "value": [[0.0, 2.0]]}, "right": {"type": "split", "threshold": "23 <= 0.0", "left": {"type":
"leaf", "value": [[3.0, 0.0]]}, "right": {"type": "split", "threshold": "9 <= 0.0", "left": {"type": "leaf", "value": [
[4.0, 0.0]]}, "right": {"type": "split", "threshold": "6 <= 0.5", "left": {"type": "leaf", "value": [[11.0, 0.0]]},
"right": {"type": "split", "threshold": "0 <= 0.0", "left": {"type": "leaf", "value": [[1.0, 0.0]]}, "right": {"type":
"leaf", "value": [[0.0, 4.0]]}}}}}}, "right": {"type": "leaf", "value": [[1.0, 0.0]]}}, "right": {"type": "split",
"threshold": "21 <= 0.0", "left": {"type": "leaf", "value": [[0.0, 1.0]]}, "right": {"type": "split", "threshold": "6 <=
-0.5", "left": {"type": "split", "threshold": "12 <= 0.0", "left": {"type": "leaf", "value": [[2.0, 0.0]]}, "right":
{"type": "split", "threshold": "13 <= 0.5", "left": {"type": "leaf", "value": [[2.0, 0.0]]}, "right": {"type": "leaf",
"value": [[0.0, 1.0]]}}}, "right": {"type": "leaf", "value": [[0.0, 5.0]]}}}}, "right": {"type": "split", "threshold":
"0 <= 0.0", "left": {"type": "split", "threshold": "16 <= 0.0", "left": {"type": "leaf", "value": [[0.0, 3.0]]},
"right": {"type": "leaf", "value": [[2.0, 0.0]]}}, "right": {"type": "leaf", "value": [[0.0, 12.0]]}}}, "right":
{"type": "split", "threshold": "15 <= -0.5", "left": {"type": "split", "threshold": "13 <= -0.5", "left": {"type":
"split", "threshold": "5 <= 0.0", "left": {"type": "leaf", "value": [[12.0, 0.0]]}, "right": {"type": "leaf", "value": [
[0.0, 3.0]]}}, "right": {"type": "split", "threshold": "23 <= 0.0", "left": {"type": "split", "threshold": "12 <= 0.0",
```

Figure 6.3 Model JSON

6.2.4 Plugin Feature Extraction

The 17 features extracted for the webpage at thetechcache.science are logged in to the console which is shown in figure 6.4. The features are stored as key value pairs and the values are encoded from -1 to 1 as dis-cussed above.

6.2.5 Classification

The output of the classification is shown right in the Plugin UI.
Green circle indicates legitimate site and Light red indicates phishing.

	ANN	k-NN	SVM	C4.5	Random Forest	Rotation Forest
ROC Area	0.995	0.989	0.97	0.984	0.996	0.994
F – measure	0.969	0.972	0.972	0.959	0.974	0.968
Accuracy	96.91%	97.18%	97.17%	95.88%	**97.36%**	96.79%

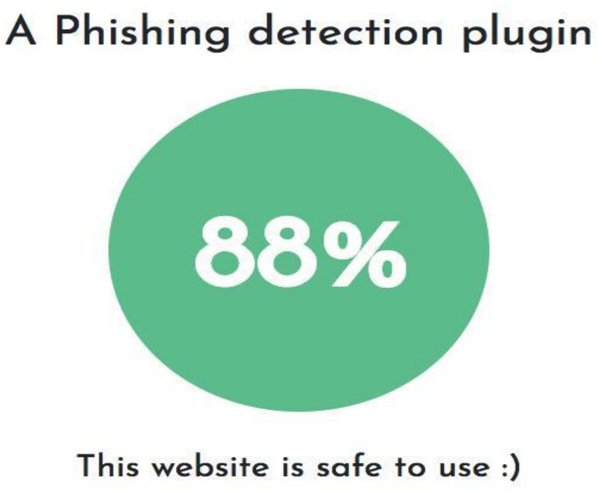


Figure 6.5 Classification Output

6.3 SAMPLE SCREENSHOTS DURING TESTING

The output of the plugin while visiting a phishing site taken from PhishTank. This site has a low trust value and also the light red circle in-dicates phishing.

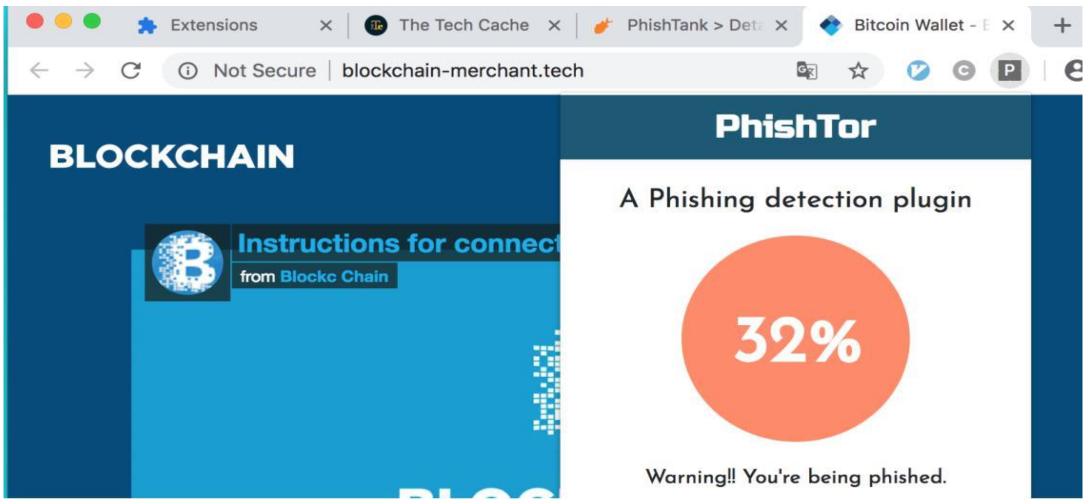


Figure 6.6 Test Output

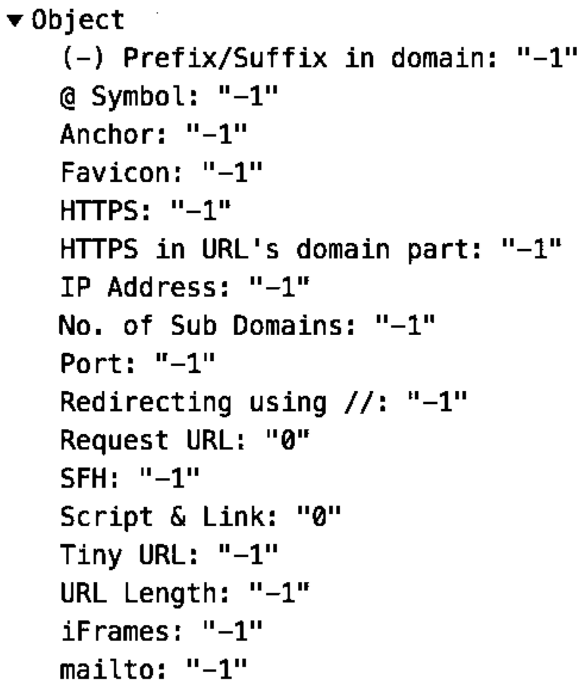
6.4 PERFORMANCE EVALUATION

The performance of the entire system is evaluated using the standard parameters described below.

6.4.1 Cross Validation score

Learning the parameters of a prediction function and testing it on the same data is a methodological mistake: a model that would just re-peat the labels of the samples that it has just seen would have a perfect score but would fail to predict anything useful on yet-unseen data. This situation is called **over fitting**.

To solve this problem, yet another part of the dataset can be held out as a so-called “**validation set**”: training proceeds on the training set,



```
▼Object
   (-) Prefix/Suffix in domain: "-1"
   @ Symbol: "-1"
   Anchor: "-1"
   Favicon: "-1"
   HTTPS: "-1"
   HTTPS in URL's domain part: "-1"
   IP Address: "-1"
   No. of Sub Domains: "-1"
   Port: "-1"
   Redirecting using //: "-1"
   Request URL: "0"
   SFH: "-1"
   Script & Link: "0"
   Tiny URL: "-1"
   URL Length: "-1"
   iFrames: "-1"
   mailto: "-1"
```

Figure 6.4 Webpage features

After which evaluation is done on the validation set, and when the experiment seems to be successful, final evaluation can be done on the test set. However, by partitioning the available data into three sets, we drastically reduce the number of samples which can be used for learning the model, and the results can depend on a particular random choice for the pair of (train, validation) sets.

A solution to this problem is a procedure called cross-validation (CV for short). A test set should still be held out for final evaluation, but the validation set is no longer needed when doing CV. In the basic ap-proach, called k-fold CV, the training set is split into k smaller sets (other approaches are described below, but generally follow the same princi-ples). The following procedure is followed for each of the k “folds”:

A model is trained using k of the folds as training data; the resulting model is validated on the remaining part of the data (i.e., it is used as a test set to compute a performance measure such as accuracy).

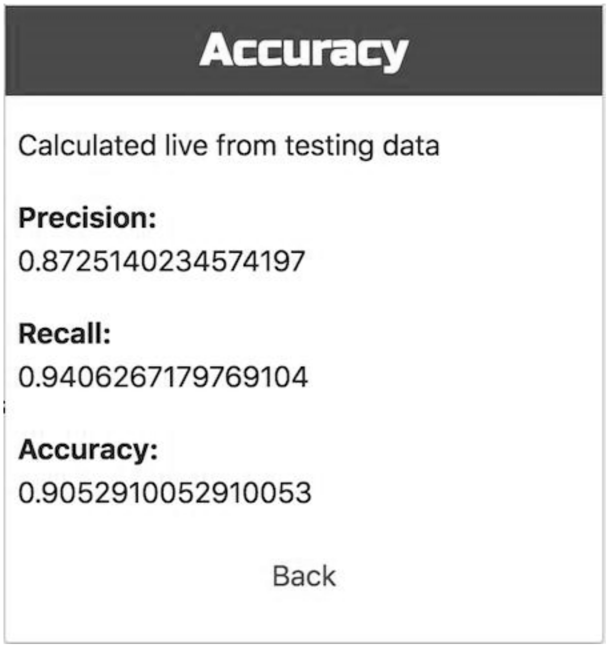
6.4.2 F1 score

F1 score is a measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score: precision is the number of correct positive results divided by the number of all positive results returned by the classifier, and recall is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive). The F1 score is the harmon-
ic average of the precision and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

The F1 score can be interpreted as a weighted average of the pre-cision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

F1 = 2 * (precision * recall) / (precision + recall)

The precision, recall and F1 score of the phishing classifier is cal-culated manually using javascript on the test data set. The results are shown in the figure 6.8



Accuracy

Calculated live from testing data

Precision:
0.8725140234574197

Recall:
0.9406267179769104

Accuracy:
0.9052910052910053

Figure 6.8 Performance measure

CHAPTER 7

CONCLUSIONS

This is a phishing website detection system that focuses on client side implementation with rapid detection so that the users will be warned before getting phished. The main implementation is porting of Random Forest classifier to javascript. Similar works often use webpage features that are not feasible to extract on the client side and this results in the de-tection being dependent on the network. On the other side, this system uses only features that are possible to extract on the client side and thus it is able to provide rapid detection and better privacy. Although using lesser features results in mild drop in accuracy, it increases the usability of the system. This work has identified a subset of webpage feature that can be implemented on the client side without much effect in accuracy.

The port from python to javascript and own implementation of Random Forest in javascript further helped in rapid detection as the JSON representation of the model and the classification script is de-signed with time complexity in mind. The plugin is able to detect the phishing even before the page loads completely. The F1 score calculated on the test set on the client side is **0.886**.

CHAPTER 8

FUTURE WORK

The classifier is currently trained on 17 features which can be in-creased provided that, they don’t make the detection slower or result in loss of privacy. The extension can made to cache results of frequently visited sites and hence reducing computation. But this may result in phishing attack being undetected. A solution needs to be devised for caching of results without losing the ability to detect phishing. The classification in javascript can be done using Worker Threads which may result in better classification time. Thus a lot of improvements and enhancements are possible this system offers a more usable solution in the field of phishing detection.

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