WEB PHISHING DETECTION USING MACHINE LEARNING

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WEB PHISHING DETECTION REPORT

1. INTRODUCTION

1.1 Project Overview

Internet consumers lose billions of dollars each year due to phishing. In order to fish for personal information in a pool of naive Internet users, identity thieves use luring strategies. To acquire usernames and passwords for financial accounts as well as personal information, phishers employ faked emails and phishing software. The topic of this study is how to use machine learning techniques to analyse different characteristics of legitimate and phishing URLs to identify phishing websites.

Nowadays Phishing has become a main area of concern for security researchers because it is very easy to create fake websites which look very similar to legitimate websites. Experts can identify fake websites but not all the users can identify the fake website and such users become victims of phishing attack. To overcome this drawback, we have proposed an intelligent, flexible, and effective system that is based on using classification data mining algorithm to analyse various URLs to accurately detect phishing websites.

The main aim of the attacker is usually to steal banks account credentials. If this continues, clients who become victims to phishing will face huge financial losses. So, to protect internet users from these kinds of phishing attacks and to create awareness, phishing website detection system has been implemented.

The Phishing website detection system is a web-based application which can run on any web browser. Every internet user will have the ability to detect phishing websites by entering URLs which they suspect of being phishing links. Those reported URLs are verified and rated.

1.2 Purpose

The purpose of the project is to determine whether a given URL is phishing website. This is done by building a Machine Learning model that is trained and tested on 11,056 rows of data with 32 different attributes. The machine learning algorithm used to carry this out is Logistic Regression classifier. The model will classify any given URL as safe or unsafe. Logistic regression is a Machine Learning classification algorithm that is used to predict the probability of certain classes based on some dependent variables.

2. LITERATURE SURVEY

2.1 Existing problem

Phishing scams are a form of cybercrime that involves defrauding users to obtain sensitive information. Cybercriminals act as legitimate companies or organizations to obtain the information. Phishing remains cybercriminals' method-of-choice to infect users' computers. Corporate employees are particularly vulnerable since they are heavily targeted as an easy entry into sensitive data. Cybercriminals use social engineering to trick their victims into launching malicious files on their computers, opening a link to an infected website or sending criminals their private data.

Phishing scams involve sending out emails or texts disguised as legitimate sources. They may look like they are from a trusted vendor or a law enforcement authority, but secretly, they contain malware. These messages are specifically designed to trick the victim into opening the email through the tactics of fear and intimidation. Once a person opens it, the malicious software downloads onto their computer, and the cybercriminal is in your system. Common social engineering methods include sending messages with embedded URLs. Once the person clicks on the link, they are re-directed to a phishing site. A phishing email can be sent with a malicious attachment that is rigged with exploits, often with the claim that the attachment is an unpaid invoice that needs attention.

According to recent research from Iron Scales, 81% of organizations around the world have experienced an increase in email phishing attacks since March 2020. Despite the very real threat that phishing poses to businesses today, almost 1 in 5 organizations only deliver phishing awareness training to their employees once per year. This lack of awareness is a large contributing factor to the fact that phishing remains the threat type most likely to cause a data breach.

2.2 References

[1]. Mehmet Korkmaz, Ozgur KoraySahingoz, BanuDiri, "Detection of Phishing Websites by Using Machine Learning-Based URL Analysis", 2020.

[2]. Lizhen Tang , Qusay H. Mahmoud, "A Deep Learning-Based Framework for Phishing Website Detection", 2021

[3]. BuketGeyik, Kubra Erensoy, EmreKocyigit, "Detection of Phishing Websites from URLs by using Classification Techniques on WEKA", 2021

[4]. Abdulghani Ali Ahmed, Nurul Amirah Abdullah, “Real Time Detection of Phishing Websites”, 2016

[5]. Manuel sánchez-paniagua , eduardo fidalgo fernández ,enrique alegre ,wesam alnabki, víctor gonzález-castro, “Phishing URL Detection: A Real-Case Scenario Through Login URLs”, 2022

[6]. Ishant Tyagi, Jatin Shad, Shubham Sharma, Siddharth Gaur, Gagandeep Kaur, “A Novel Machine Learning Approach to Detect Phishing Websites”, 2018

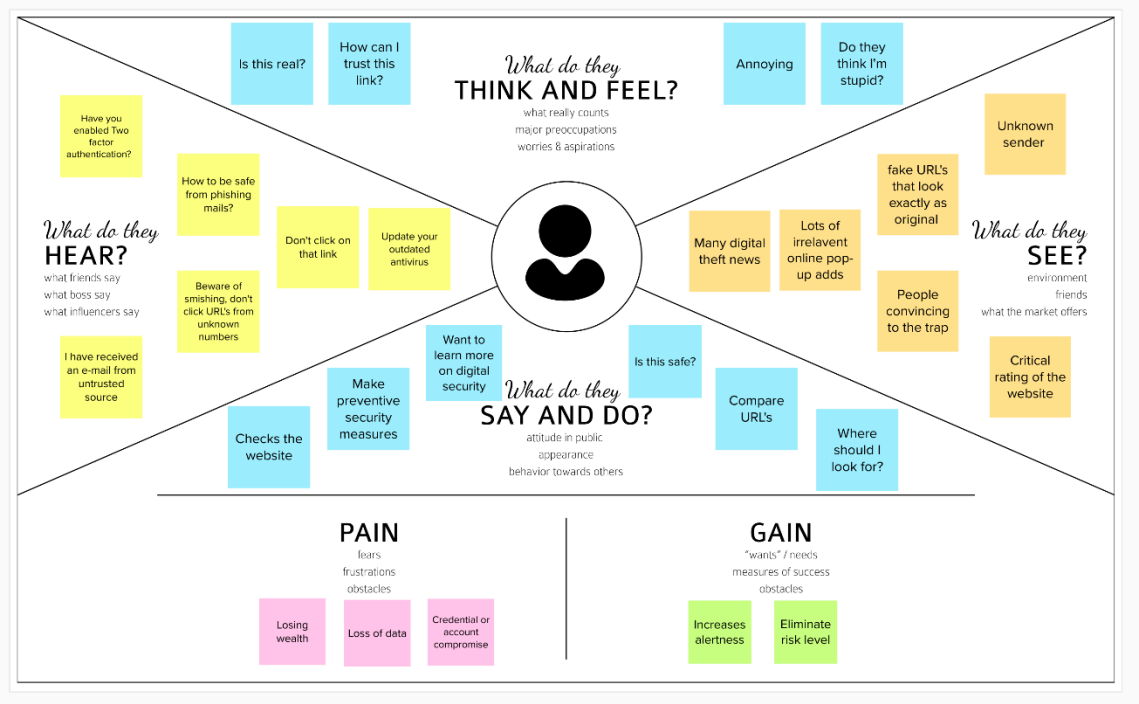
2.3 Problem Statement Definition

This project identifies whether a given URL is a phishing website. This is accomplished by developing a machine learning model that uses 11,056 rows of data with 32 different attributes which include: URL length, HTTPS token, web traffic, google index and age of domain among other attributes. The model is built using Logistic Regression. Logistic regression is a statistical method that is used for building machine learning models where the dependent variable is dichotomous: i.e., binary. Here, the dependant variable is the safety status of a given URL i.e., safe and unsafe.

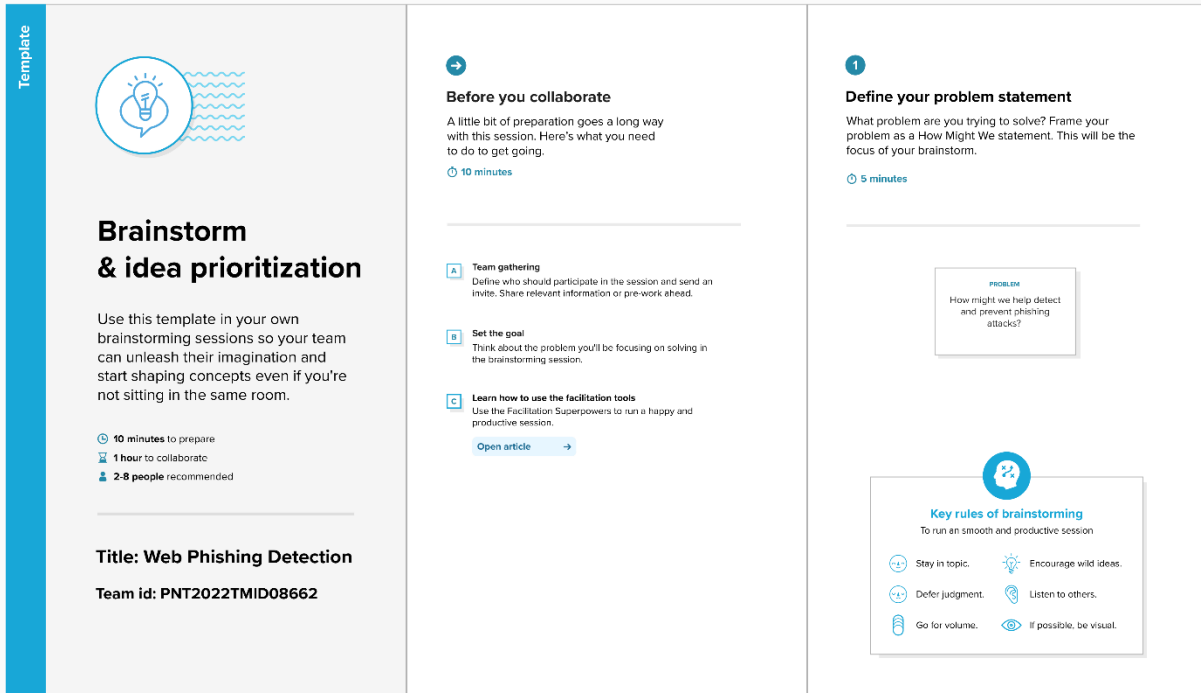
Problem Statement (PS)	I am (Customer)	I’m trying to	But	Because	Which makes me feel
PS-1	A buyer	Make payment for the product	The payment details are tampered	The website is not secured	Helplessness
PS-2	A Gamer	Purchase loots and upgrades for the character	It always directing to third-part website	The game application is infected with Malware	How can I trust this link?

3. IDEATION AND PROPOSED SOLUTION

3.1 Empathy Map



3.2 Ideation & Brainstorming



2

Brainstorm

Write down any ideas that come to mind that address your problem statement.

10 minutes

TIP

You can select a sticky note and hit the pencil [switch to sketch] icon to start drawing!

Dharun Aditya

Sharathsooryа

Perumal

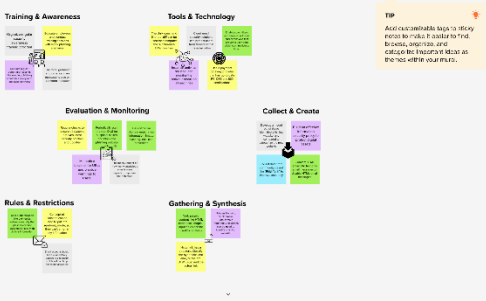
Tamilarasan

3

Group ideas

Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.

20 minutes



TIP

Add customizable tags to sticky notes to make it easier to find, browse, organize, and categorize important ideas as the rules within your mural.

4

Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

20 minutes

Importance

If each of these tasks could get done without any difficulty or cost, which would have the most positive impact?

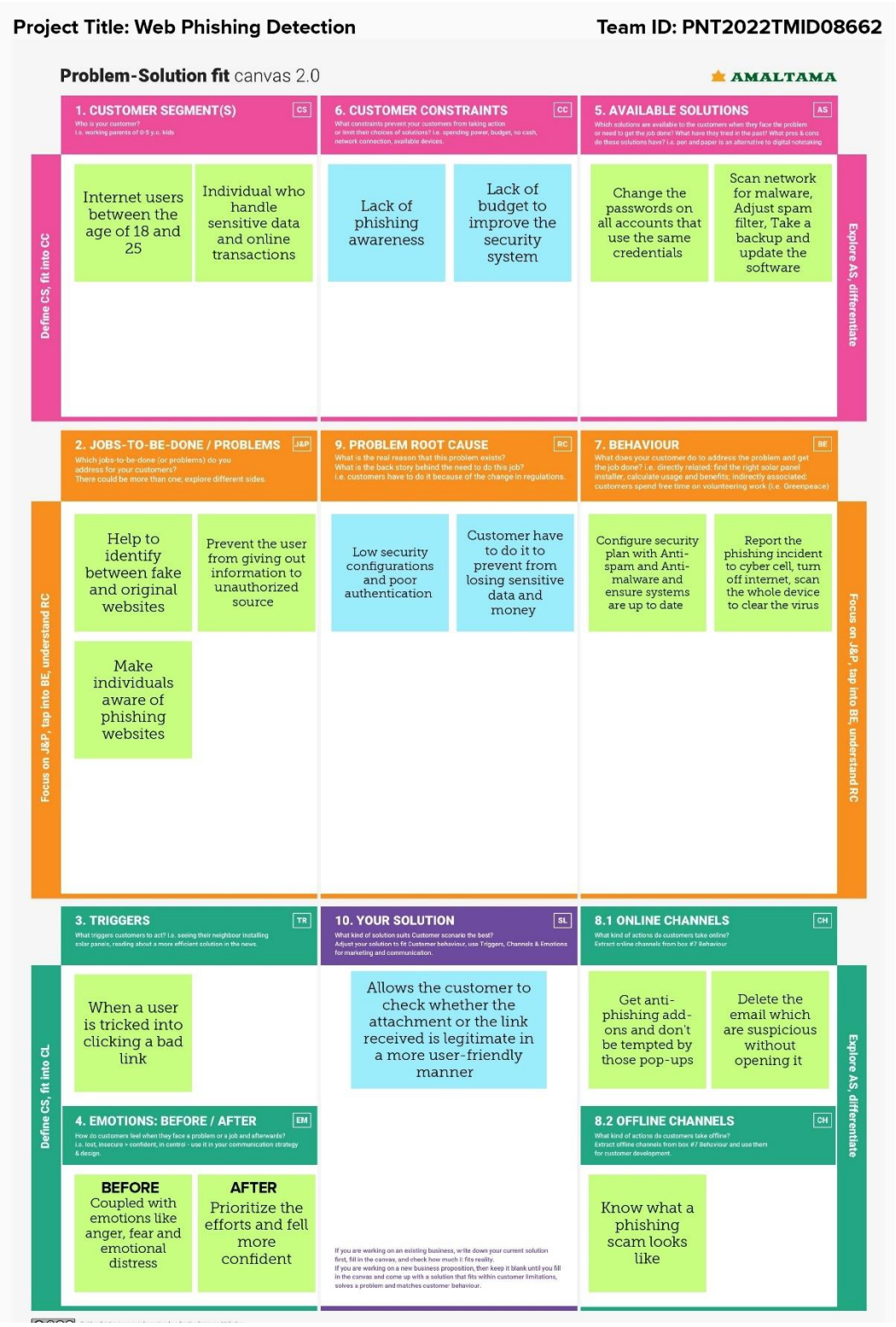
Feasibility

Regardless of their importance, which tasks are more feasible than others? (Cost, time, effort, complexity, etc.)

3.3 Proposed Solution

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	The Phish report states that around 74% people were sent fraudulent messages every month. While this cannot be stopped completely, some preventable actions can be taken. To prevent and predict phishing websites, we proposed an intelligent, flexible, and effective system that is based on using classification Data mining algorithm.
2.	Idea / Solution description	In a replicated website there must have some flaws, The phishing website can be detected based on some important characteristics like URL and Domain Identity, and security and encryption criteria in the final phishing detection rate.
3.	Novelty / Uniqueness	In this techy world, there are many technologies offer solution to protect ourselves from phishing attacks, But the data mining algorithm used in this system provides better performance as compared to other traditional classification algorithms.
4.	Social Impact / Customer Satisfaction	The proposes help the user to safely make online transaction without any fear of losing money or sensitive data to the attacker and help them gain some awareness of cyber-threat.
5.	Business Model (Revenue Model)	The number of visitors to the website becomes the number of opportunities the business has at giving an impression, generating qualified leads, sharing the brand, and building relationship.
6.	Scalability of the Solution	The features can progressively increase to scan the attachment, file hash, IP address, etc.,

3.4 Problem Solution Fit



4. REQUIREMENT ANALYSIS

4.1 Functional Requirements

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Gmail
FR-2	User Confirmation	Confirmation via Email
FR-3	User Authentication	Authentication via Password
FR-4	User Input	The suspicious URL is entered to check its status
FR-5	Reporting	The latest phishing URL can be reported for further verification if the accuracy is not satisfied
FR-6	Result/output	Model after comparison and analysis displays the safe/unsafe message with percentage

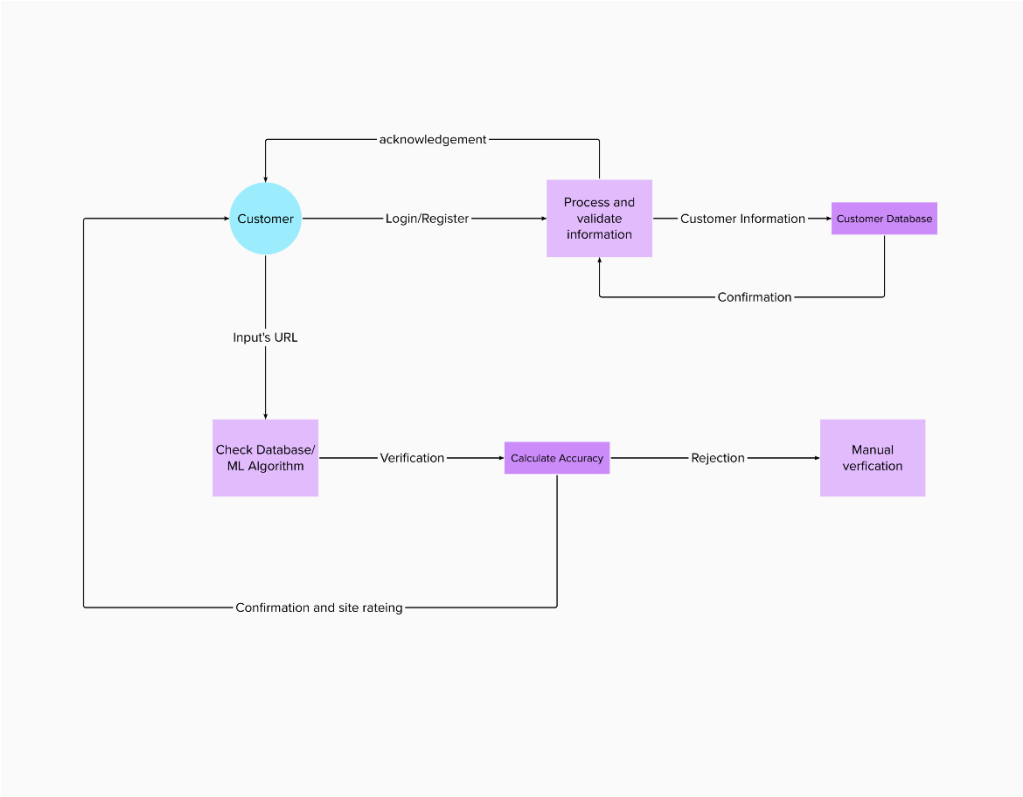
6.1 Non-Functional Requirements

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	The user interface is clean, so that the user gets the expected result without any difficulties.
NFR-2	**Security**	The database is prevented from any tampering to provide a genuine result.
NFR-3	**Reliability**	If due to some injection attack or failure the backup updates are rolled back.
NFR-4	**Performance**	The result for the search will not take more than a minute to give out the result.
NFR-5	**Availability**	The server can handle required amount of response and are available even in the database updating process.
NFR-6	**Scalability**	The traffic limit and the accuracy will be increased to offer a better service.

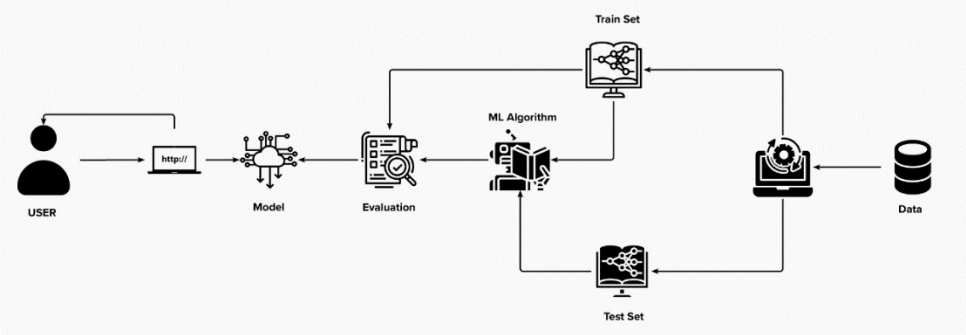
5. PROJECT DESIGN

5.1 Data Flow Diagram

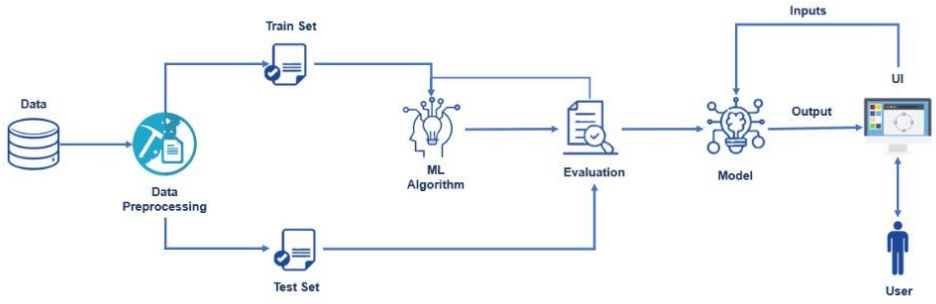


5.2 Solution & Technical Architecture

5.2.1 Solution Architecture



5.2.2 Technical Architecture



5.3 User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Web user)	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through Gmail	I can register & access the dashboard with Gmail Login	Medium	Sprint-2
	Login	USN-4	As a user, I can log into the application by entering email & password	I can access the website features	High	Sprint-2
	User Input	USN-5	As a user, I can input the URL in the required field and wait for validation	I can access the detailed result of the URL	High	Sprint-3
Administrator	Data Collection	USN-6	The data to identify the phishing link is to be collected	The model is ready to train	High	Sprint-3
	Data Pre-Processing	USN-7	The data is to be cleaned to provide better accuracy	The model is ready with high accuracy	High	Sprint-4

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
	Model Deployment	USN-8	The trained and tested model is deployed using the Machine learning algorithm	I have the model which is successfully deloyed	High	Sprint-5
	Application Building	USN-9	As a admin, The user page must be designed to access the feature in more ease manner	I have the live website	High	Sprint-5

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Collection of Dataset	USN-1	As a developer, I need to collect related data stored in a digital format to make machine learning models to understand.	3	High	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-1	Data Pre-Processing	USN-2	As a developer, I need to prepare (cleaning and organizing) the raw data to make it suitable for building and training the model	5	High	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-2	Exploratory Data Analysis (EDA)	USN-3	As a developer, EDA approach Is used to analyse the data to shortlist the	8	Medium	Dharun Aditya Sharathsoorya Perumal Tamilarasan

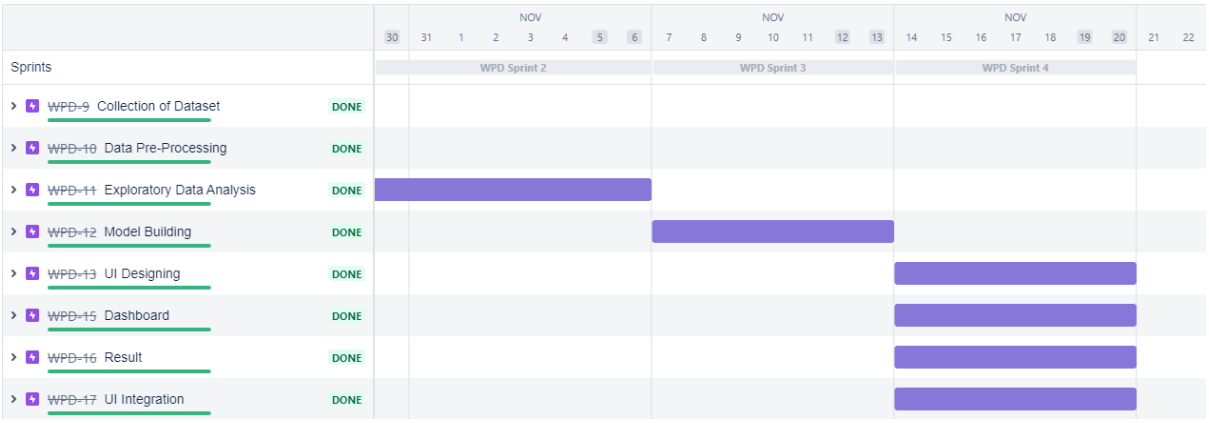
Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
			relevant columns required to train the model.			
Sprint-3	Model Building	USN-4	As a developer, I need to explore the data and type of algorithm, train and test it to provide better accuracy.	13	High	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-4	UI Designing	USN-5	As a developer, I need to design an awesome UI to provide a better solution with less effort.	3	Medium	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-4	UI Integration	USN-6	As a developer, I need to integrate UI page and the model to get user input and display the result in more user-friendly manner.	8	High	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-4	Dashboard	USN-7	As a user, I can enter the suspicious URL to check the status of the link.	3	Medium	Dharun Aditya Sharathsoorya Perumal Tamilarasan
Sprint-4	Result	USN-8	As a user, I can receive whether the URL is safe or not.	5	High	Dharun Aditya Sharathsoorya Perumal Tamilarasan

6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	8	6 Days	24 Oct 2022	29 Oct 2022	8	29 Oct 2022
Sprint-2	8	6 Days	31 Oct 2022	05 Nov 2022	8	05 Nov 2022
Sprint-3	13	6 Days	07 Nov 2022	12 Nov 2022	13	13 Nov 2022
Sprint-4	19	6 Days	14 Nov 2022	19 Nov 2022	19	19 Nov 2022

6.3 Reports from JIRA

Roadmap:

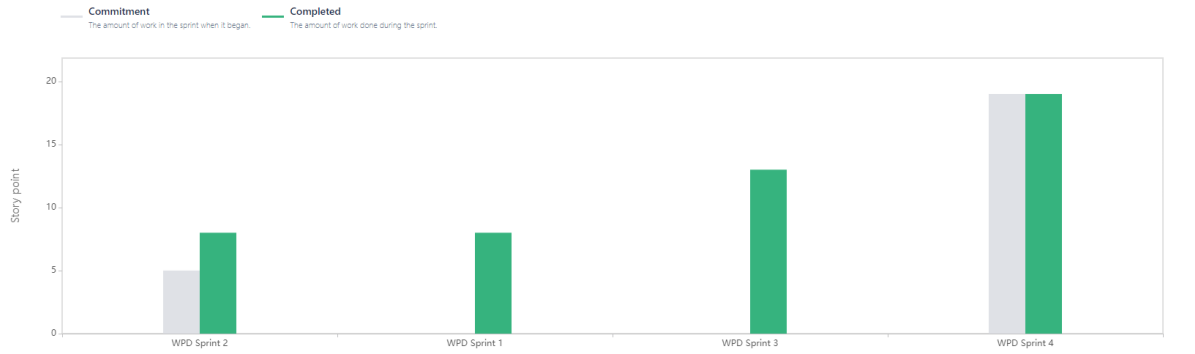


Burndown Chart:

Velocity Chart:

Velocity report

› How to read this report



Sprint	Commitment	Completed
WPD Sprint 2	5	8
WPD Sprint 1	0	8
WPD Sprint 3	0	13
WPD Sprint 4	19	19

7. CODING & SOLUTIONING

7.1 Feature 1

The Machine Learning model has been trained to detect the Phishing Website using Classification Algorithms with an accuracy of 95%.

In [43]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as  plt
import seaborn as sns
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

In [3]:
```
data = pd.read_csv("dataset_website.csv")
```

In [4]:
```
data.head()
```

Out[4]:

	index	having_IPhaving_IP_Address	URLURL_Length	Shortining_Service	having_At_Symbol	double_slash_redirecting	Prefix_Suffix	having_Sub_Domain	SSl
0	1	-1	1	1	1	-1	-1	-1	
1	2	1	1	1	1	1	-1	0	
2	3	1	0	1	1	1	-1	-1	
3	4	1	0	1	1	1	-1	-1	
4	5	1	0	-1	1	1	-1	1	

5 rows × 32 columns

In [5]:
```
data.shape
```

Out[5]:
```
(11055, 32)
```

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11055 entries, 0 to 11054
Data columns (total 32 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   index                        11055 non-null  int64
 1   having_IPhaving_IP_Address   11055 non-null  int64
 2   URLURL_Length                11055 non-null  int64
 3   Shortining_Service           11055 non-null  int64
 4   having_At_Symbol             11055 non-null  int64
 5   double_slash_redirecting     11055 non-null  int64
 6   Prefix_Suffix                11055 non-null  int64
 7   having_Sub_Domain            11055 non-null  int64
 8   SSLfinal_State               11055 non-null  int64
 9   Domain_registeration_length  11055 non-null  int64
 10  Favicon                      11055 non-null  int64
 11  port                         11055 non-null  int64
 12  HTTPS_token                  11055 non-null  int64
 13  Request_URL                  11055 non-null  int64
 14  URL_of_Anchor                11055 non-null  int64
 15  Links_in_tags                11055 non-null  int64
 16  SFH                          11055 non-null  int64
 17  Submitting_to_email          11055 non-null  int64
 18  Abnormal_URL                 11055 non-null  int64
 19  Redirect                     11055 non-null  int64
 20  on_mouseover                 11055 non-null  int64
 21  RightClick                   11055 non-null  int64
 22  popUpWidnow                  11055 non-null  int64
 23  Iframe                       11055 non-null  int64
 24  age_of_domain                11055 non-null  int64
 25  DNSRecord                    11055 non-null  int64
 26  web_traffic                  11055 non-null  int64
 27  Page_Rank                    11055 non-null  int64
 28  Google_Index                 11055 non-null  int64
 29  Links_pointing_to_page       11055 non-null  int64
 30  Statistical_report           11055 non-null  int64
 31  Result                       11055 non-null  int64
dtypes: int64(32)
memory usage: 2.7 MB
```

UNIVARIATE ANALYSIS

In [8]:
```
data['Result'].value_counts()
```

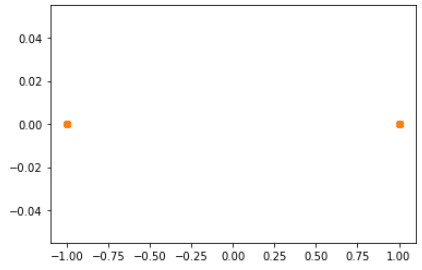
Out[8]:
```
 1    6157
-1    4898
Name: Result, dtype: int64
```

In [9]:
```
data_phish = data.loc[data['Result'] == -1]
data_no_phish = data.loc[data['Result'] == 1]
```

In [10]:
```
data['DNSRecord'].value_counts()
```

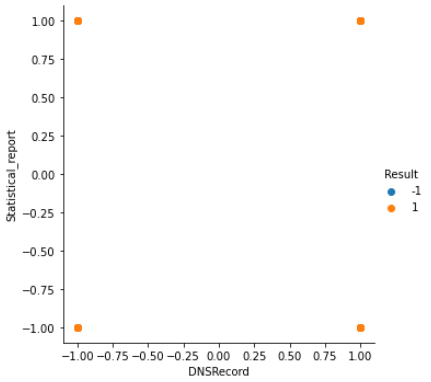
Out[10]:
```
 1    7612
-1    3443
Name: DNSRecord, dtype: int64
```

In [11]:
```
plt.plot(data_phish['DNSRecord'], np.zeros_like(data_phish['DNSRecord']),'o')
plt.plot(data_no_phish['DNSRecord'], np.zeros_like(data_no_phish['DNSRecord']),'o')
plt.show()
```



BIVARIATE ANALYSIS

In [12]:
```
sns.FacetGrid(data, hue = 'Result', height=5).map(plt.scatter,'DNSRecord','Statistical_report').add_legend()
plt.show()
```

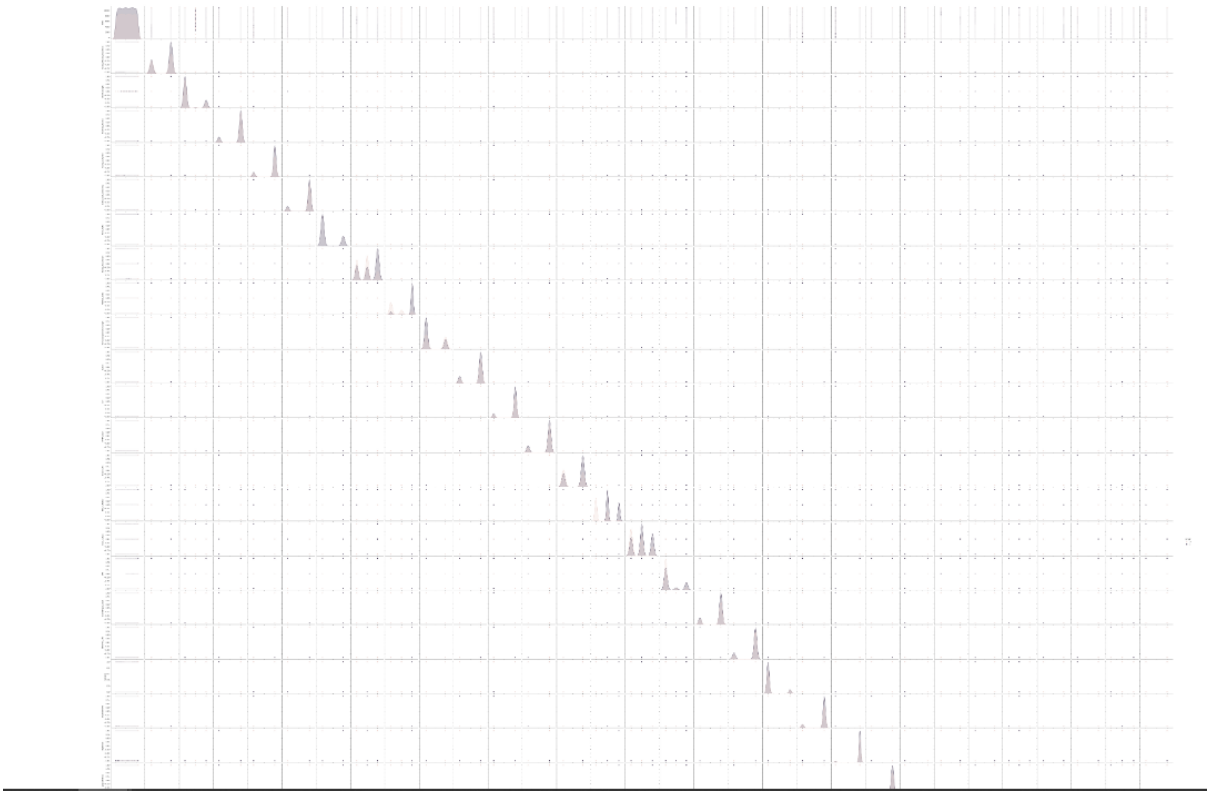


MULTIVARIATE ANALYSIS

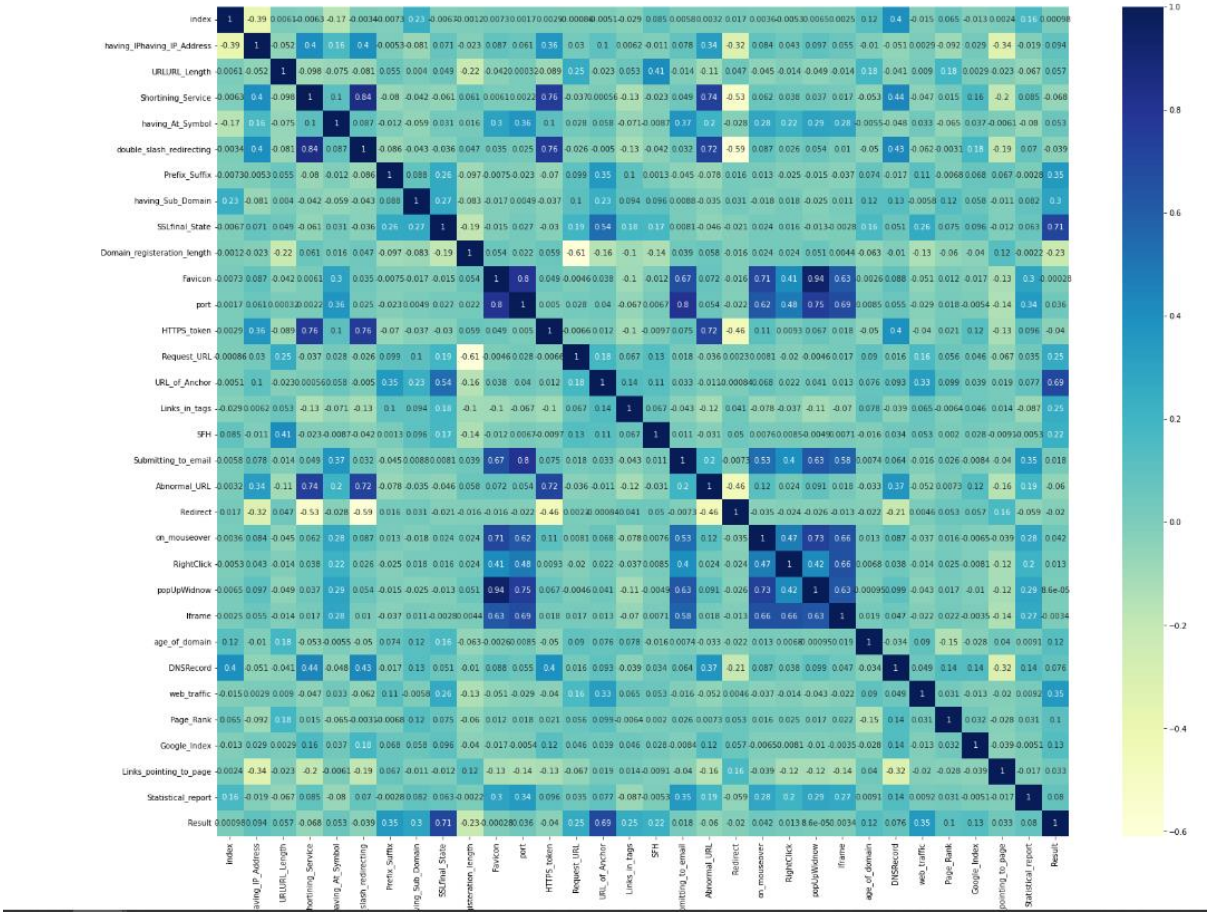
In [ ]:
```
sns.pairplot(data, hue='Result',size=3)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:2076: UserWarning: The `size` parameter has been renamed to `height
`; please update your code.
  warnings.warn(msg, UserWarning)
```

Out[12]:
```
<seaborn.axisgrid.PairGrid at 0x7fe9847f1550>
```



In [13]:
```
fig, ax = plt.subplots(figsize=(25, 20))
dataplot = sns.heatmap(data.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



FEATURE EXTRACTION

In [14]:
```
new_df = data.drop(['index'], axis=1)
```

In [15]:
```
new_df.head()
```

Out[15]:

	having_IPhaving_IP_Address	URLURL_Length	Shortining_Service	having_At_Symbol	double_slash_redirecting	Prefix_Suffix	having_Sub_Domain	SSLfinal_S
0	-1	1	1	1	-1	-1	-1	
1	1	1	1	1	1	-1	0	
2	1	0	1	1	1	-1	-1	
3	1	0	1	1	1	-1	-1	
4	1	0	-1	1	1	-1	1	

5 rows × 31 columns

In [16]:
```
xx = new_df.drop(['Result'], axis = 1)
y = new_df['Result']
```

In [17]:
```
xx.head()
```

Out[17]:

	having_IPhaving_IP_Address	URLURL_Length	Shortining_Service	having_At_Symbol	double_slash_redirecting	Prefix_Suffix	having_Sub_Domain	SSLfinal_S
0	-1	1	1	1	-1	-1	-1	
1	1	1	1	1	1	-1	0	
2	1	0	1	1	1	-1	-1	
3	1	0	1	1	1	-1	-1	
4	1	0	-1	1	1	-1	1	

5 rows × 30 columns

In [18]:
```
y.head()
```

Out[18]:
```
0   -1
1   -1
2   -1
3   -1
4    1
Name: Result, dtype: int64
```

TRAINING, TESTING DATA WITH MODEL BUILDING

In [19]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(xx, y, test_size = 0.3, random_state = 42)
```

In [20]:
```
from sklearn.linear_model import LogisticRegression
```

In [21]:
```
LR = LogisticRegression()
```

In [22]:
```
clf = LR.fit(x_train, y_train)
```

In [23]:
```
y_pred = clf.predict(x_test)
```

In [24]:
```
acc_sc = accuracy_score(y_test, y_pred)
```

In [25]:
```
acc_sc
```

Out[25]:
```
0.9222188724751281
```

In [26]:
```
from sklearn.tree import DecisionTreeClassifier
dc = DecisionTreeClassifier()
mode = dc.fit(x_train, y_train)
```

In [27]:
```
y_pred_dc = dc.predict(x_test)
```

In [28]:
```
acc_sc_dc = accuracy_score(y_test, y_pred_dc)
```

In [29]:
```
acc_sc_dc
```

Out[29]:
```
0.9568887548990052
```

In [30]:
```
from sklearn.neighbors import KNeighborsClassifier
import math


neigh = KNeighborsClassifier(n_neighbors=3)
mode_neigh = neigh.fit(x_train, y_train)
```

In [31]:
```
y_pred_neigh = neigh.predict(x_test)
```

In [32]:
```
acc_sc_neigh = accuracy_score(y_test, y_pred_neigh)
```

In [33]:
```
acc_sc_neigh
```

Out[33]:
```
0.9436237564063913
```

In [34]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
mode_rf = rf.fit(x_train, y_train)
```

In [35]:
```
y_pred_rf = mode_rf.predict(x_test)
```

In [36]:
```
acc_sc_rf = accuracy_score(y_test, y_pred_rf)
```

In [37]:
```
acc_sc_rf
```

Out[37]:
```
0.967741935483871
```

In [44]:
```
confusion_matrix(y_test, y_pred_rf)
```

Out[44]:
```
array([[1355,   73],
       [  34, 1855]], dtype=int64)
```

In [45]:
```
classification_report(y_test, y_pred_rf)
```

Out[45]:
```
'              precision    recall  f1-score   support\n\n          -1       0.98      0.95      0.96      1428\n           1
0.96      0.98      0.97      1889\n\n    accuracy                           0.97      3317\n   macro avg       0.97      0.97
0.97      3317\nweighted avg       0.97      0.97      0.97      3317\n'
```

In [38]:
```
from sklearn.svm import SVC
svc = SVC()
mode_svc = svc.fit(x_train, y_train)
```

In [39]:
```
y_pred_svc = svc.predict(x_test)
acc_sc_svc = accuracy_score(y_test, y_pred_svc)
acc_sc_svc
```

Out[39]:
```
0.9424178474525173
```

In [41]:
```
from sklearn.model_selection import ShuffleSplit,GridSearchCV,StratifiedKFold


def find_best_model(x,y):
    models={'Logistic_regression':{'model':LogisticRegression(solver='liblinear',penalty='l2',multi_class='auto'),'parameter':{'C
           'decision_tree':{'model':DecisionTreeClassifier(splitter='best'),'parameter':{'criterion':['gini','entropy'],'max_dept
           'svm':{'model':SVC(gamma='auto'),'parameter':{'kernel':['sigmoid','linear'],'C':[1,5,10,15]}},
           'random_forest':{'model':RandomForestClassifier(criterion='gini'),'parameter':{'max_depth':[5,10,15],'n_estimators':[1
    scores=[]
    cv_shuffle=StratifiedKFold(n_splits=10)

    for model_name,model_params in models.items():
        gs=GridSearchCV(model_params['model'],model_params['parameter'],cv=cv_shuffle,return_train_score=False)
        gs.fit(x,y)
        scores.append({'model':model_name,'best_parameters':gs.best_params_,'score':gs.best_score_})
    return pd.DataFrame(scores,columns=['model','best_parameters','score'])
find_best_model(x_train,y_train)
```

Out[41]:

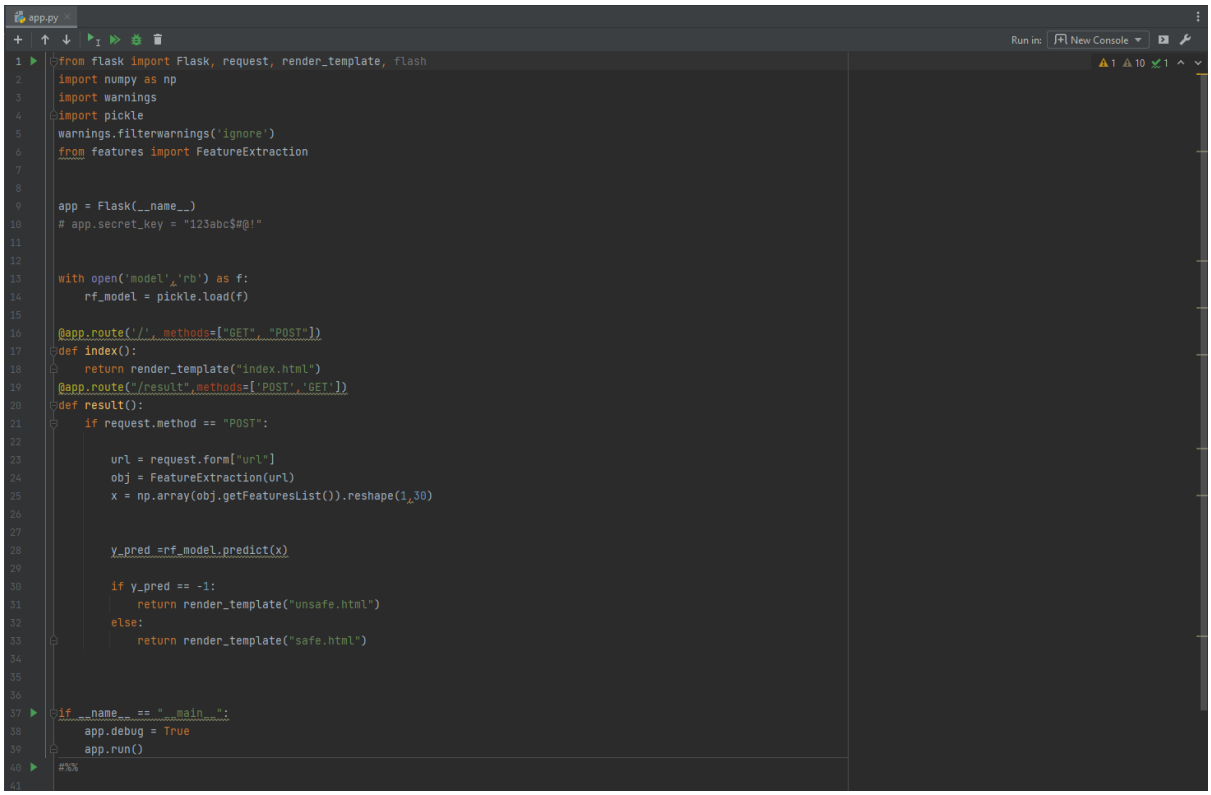
	model	best_parameters	score
0	Logistic_regression	{'C': 8}	0.930345
1	decision_tree	{'criterion': 'gini', 'max_depth': 15}	0.955932
2	svm	{'C': 5, 'kernel': 'linear'}	0.929569
3	random_forest	{'max_depth': 15, 'n_estimators': 5}	0.962134

In [14]:
```
import pickle
```

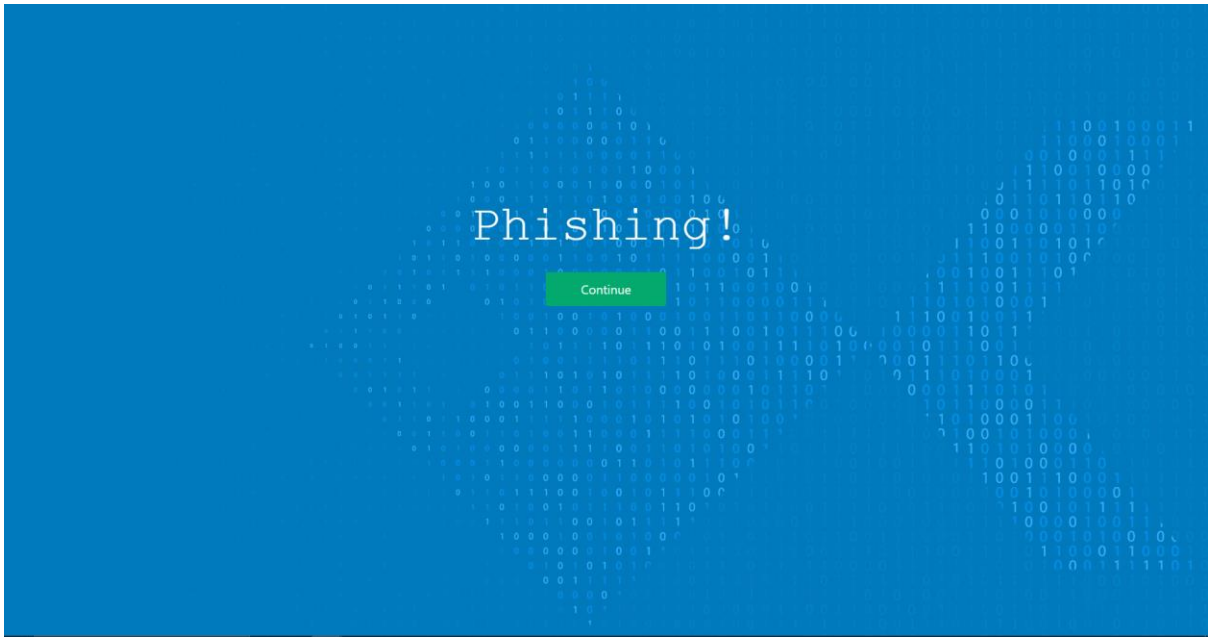
In [40]:
```
with open('model','wb') as f:
  pickle.dump(mode_rf,f)
```

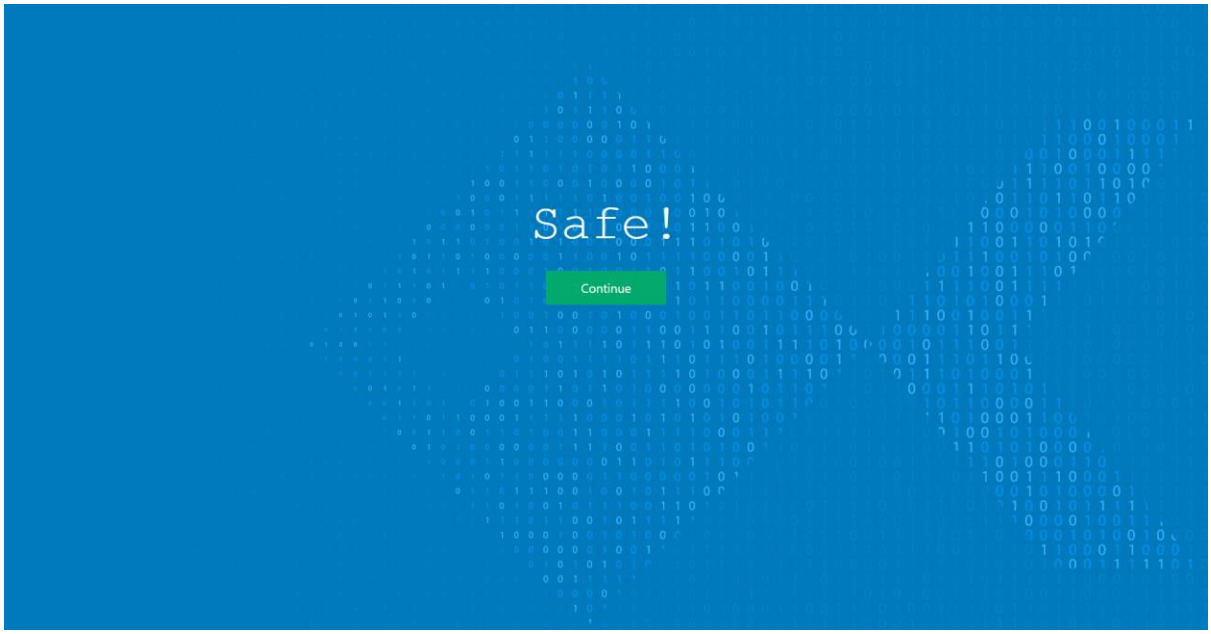
7.2 Feature 2

The Web Application contains an Input box where the suspicious link can be inputted to check the legitimacy.




phIshIng?
Enter URL: www.example.com
CHECK


Phishing!
Continue



8. TESTING

8.1 Test Cases

Test case ID	Feature Type	Component	Test Scenario	Pre-Requisite	Steps To Execute	Test Data	Expected Result	Actual Result	Status	Commnets	TC for Automation(Y/N)
InputPage_TC_OO 1	Functional	Home Page	Verify user is able to see the input page when user navigated to the website	Internet connection with any web browser	1.Enter URL and click go		Home page should display	Working as expected	Pass		
InputPage_TC_OO 2	Functional	Home Page	Verify user is able to enter the URL	Internet connection with any web browser	1.Enter URL and click go 2.Enter the doubtful url in the text box		URL should display in the text box	Working as expected	Pass		
InputPage_TC_OO 3	Functional	Home page	Verify user is able to get the expected out (Phishing)	Internet connection with any web browser	1.Enter URL and click go 2.Enter the doubtful url in the text box (Phishing URL)	URL: http://ww16.lojasmagalu.com/?sub1=20221114-2340-0043-849f-ebc30d941384	Result page should display "Phishing!"	Working as expected	Pass		
InputPage_TC_OO 4	Functional	Home Page	Verify user is able to get the expected out (Safe)	Internet connection with any web browser	1.Enter URL and click go 2.Enter the doubtful url in the text box (Safe URL)	URL: https://careereducation.smartinternz.com/college/dr-mahalingam-college-of-engineering-and-technology-29	Result page should display "Safe!"	Working as expected	Pass		

	Test Scenarios
1	Verify user is able to see input page
2	Verify user is able to input the URL into application or not?
3	Verify user is able to see the respected output for the query? (Phishing URL)
4	Verify user is able to see the respected output for the query? (Safe URL)

8.2 User Acceptance Testing

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	10	2	4	20	36
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	23	9	12	25	60

3. Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	Fail	Pass
Print Engine	10	0	0	10
Client Application	50	0	0	50
Security	5	0	0	5
Outsource Shipping	3	0	0	3
Exception Reporting	10	0	0	10
Final Report Output	10	0	0	10
Version Control	4	0	0	4

9. RESULTS

9.1 Performance Metrics

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1.	Metrics	**Classification Model:** Confusion Matrix - , Accuray Score- & Classification Report -	○ acc_sc_rf ○ confusion_matrix(y_test, y_pred_rf) ○ classification_report(y_test, y_pred_rf) 
2.	Tune the Model	Hyperparameter Tuning - Validation Method -	

10. ADVANTAGES & DISADVANTAGES

10.1 Advantages

Phishing detection has a lot of advantages such as preventing identity theft, saving naïve internet users for being scammed of their money and bank details, increasing awareness about deceptive lucrative scamming websites on the internet among the public.

10.2 Disadvantages

There aren't many disadvantages to being warned of a potential phishing website. One minor disadvantage could be wrongful categorization of an otherwise safe website as a phishing website due to some error on the part of the model.

11. CONCLUSION

In conclusion, a phishing detection website is the need of the hour right now and is a boon to the public to stay cybersafe on the internet. Phishing attacks are the most common cyber threat to many businesses. This form of cyber-attack can be remarkably unsophisticated. Yet, the disruption caused can be huge. Phishing emails prey on human behaviour. They will often claim to come from an authority figure. The suspicious email might foster a sense of urgency or offer reward to the recipient. In such an environment, websites such as these are an active effort to prevent such illicit activities.

12. FUTURE SCOPE

Although the use of URL lexical features alone has been shown to result in high accuracy (97%), phishers have learned how to make predicting a URL destination difficult by carefully manipulating the URL to evade detection. Therefore, combining these features with others, such as host, is the most effective approach.

For future enhancements, we intend to build the phishing detection system as a scalable extension and an anti-phish search engine which will incorporate online learning so that new phishing attack patterns can easily be learned and improve the accuracy of our models with better feature extraction

13. APPENDIX

App.py

```
from flask import Flask, request, render_template, flash
import numpy as np
import warnings
import pickle
warnings.filterwarnings('ignore')
from features import FeatureExtraction


app = Flask(__name__)
# app.secret_key = "123abc$#@!"


with open('model','rb') as f:
    rf_model = pickle.load(f)
```

```
@app.route('/', methods=["GET", "POST"])
def index():
    return render_template("index.html")
@app.route("/result",methods=['POST','GET'])
def result():
    if request.method == "POST":

        url = request.form["url"]
        obj = FeatureExtraction(url)
        x = np.array(obj.getFeaturesList()).reshape(1,30)


        y_pred =rf_model.predict(x)

        if y_pred == -1:
            return render_template("unsafe.html")
        else:
            return render_template("safe.html")



if __name__ == "__main__":
    app.debug = True
    app.run()
```

Index.html

```
<!DOCTYPE html>
<html>
    <head>
        <script src="js/test.js"></script>
        <link rel="stylesheet"
href="https://cdn.jsdelivr.net/npm/bootstrap@4.6.1/dist/css/bootstrap.min.css">
        <style>
            h1{
                text-align: center;
                margin-top: 16%;
                color: white;
                font-size: 500%;
                        font-family:courier;

            }
            #url{
                text-align: center;
                margin-top: 1%;
            }
           button
                        {
                                background-color: transparent;
```

```
            border: 2px solid darkslategrey;
                                color:black;
                                font-size: 20px;
            cursor: pointer;
                        }
        button:hover{
            background-color: darkslategrey;
            color: white;
        }
        body{
            background-image:
url("https://www.phishingbox.com/themes/phishingbox/assets/img/branding/pbox_binary_ba
ckground_1920-1080.jpg");
            background-size: 100%;
        }
        input[type=text]{
            width: 50%;
            padding: 12px;
            border: none;
            border-radius: 4px;
            box-sizing: border-box;
            margin-top: 6px;
            margin-bottom: 16px;
            resize: vertical;
            font-size: 20px;
        }
        input[type=submit] {
            background-color: #04AA6D;
            color: white;
            width: 10%;
            padding: 12px;
            border: none;
            border-radius: 4px;
            box-sizing: border-box;
            margin-top: 6px;
            margin-bottom: 16px;
            resize: vertical;
            font-size: 20px;
            font-style:inherit;
            font-family:
        }
        input[type=submit]:hover {
            background-color: #45a049;
        }
        #log{


        }

    </style>
```

```
    </head>
    <body>
        <h1><strong>phIshIng?</strong></h1>
        <div id="url">
        <form action="{{url_for('result')}}" method="POST">
            <input type="text" id="url" name="url" placeholder="Enter URL:
www.example.com"/>
            <input type="submit" value="CHECK"/>
        </form>
        </div>
    </body>
</html>
```

GitHub Link:

https://github.com/IBM-EPBL/IBM-Project-5296-1658756183

Project Demo Link:

https://drive.google.com/file/d/1rkBsKjbLJOLLMrXBRuK_Zq5CBgT503Hf/view?usp=sharing