WEB PHISHING DETECTION

IBM PROJECT

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ABSTRACT

There are a number of users who purchase products online and make payments through e-banking. There are e-banking websites that ask users to provide sensitive data such as username, password & credit card details, etc., often for malicious reasons. This type of e-banking website is known as a phishing website. Web service is one of the key communications software services for the Internet. Web phishing is one of many security threats to web services on the Internet. In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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. Once a user makes a transaction online when he makes payment through an e-banking website our system will use a data mining algorithm to detect whether the e-banking website is a phishing website or not.

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CHAPTER 1

INTRODUCTION

1.1 PROJECT OVERVIEW

There are a number of users who purchase products online and make payments through e-banking. There are e-banking websites that ask users to provide sensitive data such as username, password & credit card details, etc., often for malicious reasons. This type of e-banking website is known as a phishing website. Web service is one of the key communications software services for the Internet. Web phishing is one of many security threats to web services on the Internet.

Common threats of web phishing:

 Web phishing aims to steal private information, such as usernames, passwords, and credit card details, by way of impersonating a legitimate entity.

- It will lead to information disclosure and property damage.
- Large organizations may get trapped in different kinds of scams
- In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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. Once a user makes a transaction online when he makes payment through an e-banking website our system will use a data mining algorithm to detect whether the e-banking website is a phishing website or not.

1.2 PURPOSE

In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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. Once a user makes a transaction online when he makes payment through an e-banking website our system will use a data mining algorithm to detect whether the e-banking website is a phishing website or not.

CHAPTER 2

LITERATURE SURVEY

Survey 1:

Title: Phish-Defence: Phishing Detection Using Deep Recurrent Neural

Networks

Abstract:

In the growing world of the internet, the number of ways to obtain crucial data such as passwords and login credentials, as well as sensitive personal information has expanded. Page impersonation, often known as phishing, is one method of obtaining such valuable information. Phishing is one of the most straightforward forms of cyber-attack for hackers, as well as one of the simplest for victims to fall for. It can also provide hackers with everything they need to access their targets' personal and corporate accounts. Such websites do not provide a service but instead gather personal information from users. In this paper, we achieved state-of-the-art accuracy in detecting malicious URLs using recurrent neural networks. Unlike previous studies, which looked at online content, URLs, and traffic numbers, we merely look at the text in the URL, which makes it quicker and catches zero-day assaults. The network has been optimized so that it may be utilized on tiny devices like Mobiles, Raspberry Pi without sacrificing the inference time.

Algorithm Used: Long Short-Term Memory, Gated Recurrent unit

Survey 2:

Title: Phishing website detection using machine learning and deep learning techniques

Abstract:

Phishing has become more damaging nowadays because of the rapid growth of internet users. The phishing attack is now a big threat to people's daily life and to the internet environment. In these attacks, the attacker impersonates a trusted entity intending to steal sensitive information or the digital identity of the user, e.g., account credentials, credit card numbers and other user details. A phishing website is a website which is similar in name and appearance to an

official website otherwise known as a spoofed website which is created to fool an individual and steal their personal credentials. So, to identify the websites which are fraud, this paper will discuss the machine learning and deep learning algorithms and apply all these algorithms on our dataset and the best algorithm having the best precision and accuracy is selected for the phishing website detection. This work can provide more effective defenses for phishing attacks of the future.

Algorithm Used: Logistic Regression, K Nearest Neighbour, Decision Tree, Random Forest, XG Boost, Ada Boost

Survey 3:

Title: Intelligent Phishing Detection Scheme Algorithms Using Deep Learning

Abstract:

Phishing attacks have evolved in recent years due to high-tech-enabled economic growth worldwide. The rise in all types of fraud loss in 2019 has been attributed to the increase in deception scams and impersonation, as well as to sophisticated online attacks such as phishing. The global impact of phishing attacks will continue to intensify and thus a more efficient phishing detection method is required to protect online user activities. To address this need, this study focused on the design and development of a deep learning-based phishing detection solution that leveraged the universal resource locator and website content such as images, text and frames.

Algorithm Used: Convolutional Neural Network, Long Short Term Memory, Intelligent Phishing Detection System

Survey 4:

Ttitle: Phishing Website Detection Based on Deep Convolutional Neural Network and Random Forest Ensemble Learning

Abstract:

Phishing has become one of the biggest and most effective cyber threats, causing hundreds of millions of dollars in losses and millions of data breaches every year. Currently, anti-phishing techniques require experts to extract phishing sites features and use third-party services to detect phishing sites. These techniques have some limitations, one of which is that extracting phishing features requires expertise and is time-consuming. Second, the use of third-party services delays the detection of phishing sites. Hence, this paper proposes an

integrated phishing website detection method based on convolutional neural networks (CNN) and random forest (RF). The method can predict the legitimacy of URLs without accessing the web content or using third-party services. The proposed technique uses character embedding techniques to convert URLs into fixed-size matrices, extract features at different levels using CNN models, classify multi-level features using multiple RF classifiers, and, finally, output prediction results using a winner-take-all approach. On our dataset, a 99.35% accuracy rate was achieved using the proposed model. An accuracy rate of 99.26% was achieved on the benchmark data, much higher than that of the existing extreme model

Algorithm Used: Random Forest, Convolutional Neural Network

2.1 EXISTING PROBLEM

The existing system uses the Classifiers, Fusion Algorithm, and Bayesian Model to detect the phishing sites. The classifiers can classify the text content and image content. Text classifier is to classify the text content and Image classifier is to classify the image content.

2.2 REFERENCES

- 1. Aman Rangapur, Tarun Kanakam and Dhanvanthini P, "Phish-Defence: Phishing Detection Using Deep Recurrent Neural Networks" -September 2022
- 2. M Selvakumari et al, "Phishing website detection using machine learning and deep learning techniques" 2021
- 3. M.A.Adebowale, K.T.Lwin, M.A.Hosaain, "Intelligent Phishing Detection Scheme

Algorithms Using Deep Learning"

4. Rundong Yang, Kangfeng Zheng, Bin Wu, Chunhua Wu and Xiujuan Wang, "Phishing Website Detection Based on Deep Convolutional Neural Network and Random Forest Ensemble Learning"

2.3 PROBLEM STATEMENT DEFINITION

The problem statement is In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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. Once a user makes a transaction online when he makes payment through an e-banking website our system will use a data mining algorithm to detect whether the e-banking website is a phishing website or not.

CHAPTER 3 IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS

A collaborative tool teams can use to gain a deeper insight into their customers. This Empathy map canvas discuss about what they hear about web phishing detection, What they think about web phishing detection, What they see and What they say and Do.

Build empathy and keep your focus on the user by putting yourself in their shoes. The The Worries proposed nethodology Too many functionality What do they about complex of the uncertain of the THINK AND FEEL? process outcome Working & Affordability Effectiveness major preoccupations Reliability of proposed of the worries & aspirations algorithm system What do they What do they Types of How well it HEAR? SEE? attacks it what friends say what boss say predicts attacks . friends what influencers say what the market offers Time taken The to model the accuracy What do they of the predict the detection. SAY AND DO? Use software to deny outcome Not to give safe& attitude in public secured platforms fo access from confidential appearance information sources. sources PAIN GAIN frustrations measures of success obstacles obstacles Efficient Fears of the failure of the errors in the model prediction efficient

Fig 3.1 Empathy map

3.2 IDEATION & BRAINSTORMING



Define your problem statement

What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

(5 minutes

1. The victim has received a popup message while searching a product

2. The victim
has clicked on
the spoofed link
that has been
sent through
mail

3. The victim receives a strongly worded voicemail that tends to send reply or immediately call to the phone number

4. A fraudulent message that says the recipient to change the account details immediately so that they can get the details

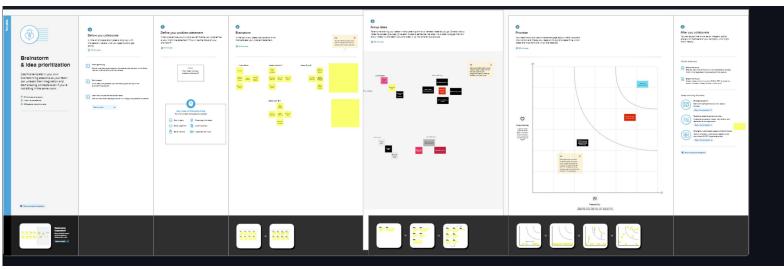


Fig 3.2 Problem statement



Brainstorm

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

① 10 minutes

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

Person 1

Use firewalls
 Verify Site's
 security
 Sixeep learning
 about the basics of phising techniques

Person 2

Avoid using public networks
 Think twice before clicking
 Rotate password regularly

Person 3

1. Report
suspicious
emails or calls
2.Be skeptical of
trading personal
information

Person 4

Use spam filters
 and block
 unwanted
 websites

 Avoid calls from
 unkown numbers

Fig 3.3 Brainstorm



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.

① 20 minutes

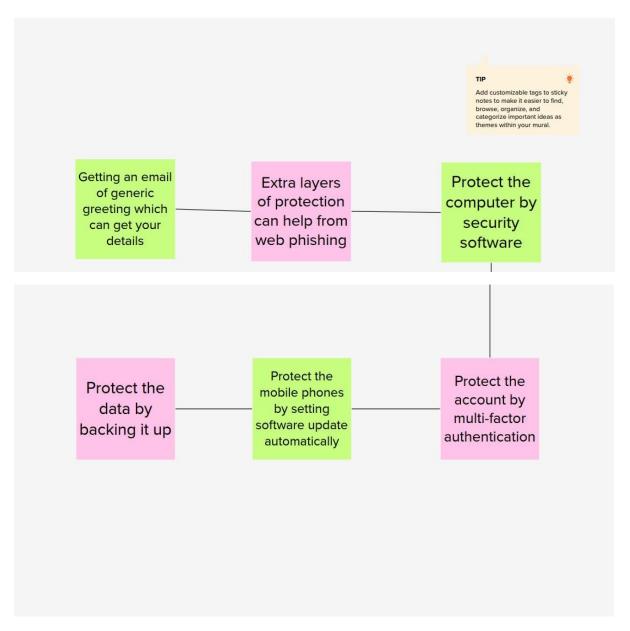


Fig 3.4 Group Ideas



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.

(5) 20 minutes

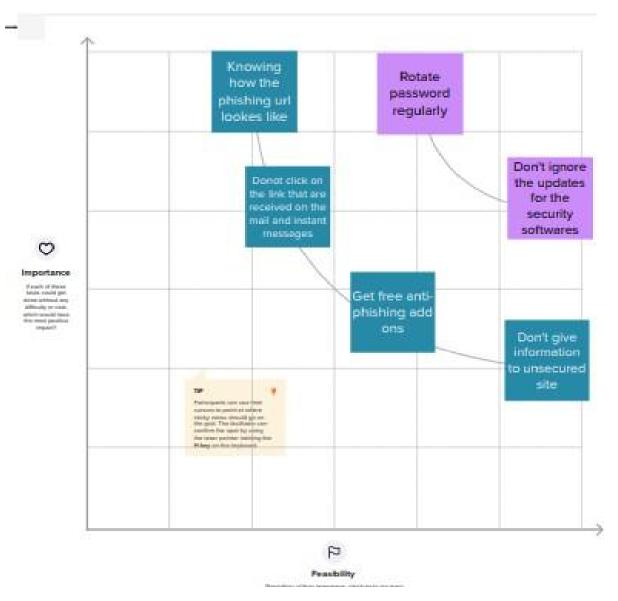


Fig 3.5 Prioritize

3.3 PROPOSED SOLUTION

The proposed solution is that, in order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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. Once a user makes a transaction online when he makes payment through an e-banking website our system will use a data mining algorithm to detect whether the e-banking website is a phishing website or not.

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	A user of the internet had to make an online purchase. He then used the internet to access the webpage. The process of displaying the goods takes time. He started to look at every item. He looks for the required products on an online page. Finally, he located the required products. He then entered all of his credit card information. password and username for making purchases via the internet. Then he got the notification "Your order" is entered successfully, and the transaction is finished. You will receive the merchandise they requested in two days. the following. He received a notification from the bank and his mobile device within 24 hours. The customer was astonished to find their account empty. Then only he realized that was a fake website and his bank

		account details was stolen by hacker .To avoid this scenario. We need to solve this problem by using the Web Phishing Detection
2.	Idea / Solution description	Every time we click on a website, an alert box stating whether it is secure or not must appear in order to combat the issue of phishing websites. The website can also be scanned to shield our computer or mobile device against phishing attacks. Although technology exists, it is still important for us as users to be aware of whether a website is secure or not. We should avoid visiting any unwelcome websites.
3.	Uniqueness	In the suggested method, the hyperlink-specific attributes were separated into 12 different categories and then used to train the machine learning algorithms. Using a dataset of phishing and non-phishing websites, we assessed how well our suggested phishing detection technique performed against several categorization algorithms.
4.	Customer Satisfaction	While utilising certain websites, an alert box will appear when we click on them, making the user aware of the website and increasing their pleasure with it. Additionally, we can scan the website to stop information from being hacked, which would increase consumer satisfaction even further.
5.	Scalability of the Solution	Thus, software-based phishing detection techniques are preferred for fighting against the phishing attack. Mostly available methods for detecting phishing attacks are blacklists/whitelists, natural language processing, visual similarity, rules, machine learning techniques

3.4 PROBLEM SOLUTION FIT



Fig 3.6 Proposed Solution Fit

CHAPTER 4 REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT

Functional requirements are the details and instructions that dictate how software performs and behaves. Functional requirements can vary in behaviours, features and protocols, depending on the user's industry. Functional requirements help software engineers determine the features that support a system to operate smoothly. User can ensure that software is easy for users to operate using functional requirements. Functional requirements can help you identify the features of a system to see where you may enhance functionality. Functional requirements increase the usability of the software. A software system may include a specific feature that made the system more convenient for the users to operate.

4.2 NON – FUNCTIONAL REQUIREMENT

Non-functional requirements or NFRs are a set of specifications that describe thesystem's operation capabilities and constraints and attempt to improve its functionality. These are basically the requirements that outline how well it will operate including things like speed, security, reliability, data integrity Nonfunctional requirements specify the quality attributes of the system, hence their second name — quality attributes.

Usability:

A system can have adequate functionality, but inadequate usability because it is too difficult to use. A usability requirement specifies how easy the system must be to use. Usability is a non-functional requirement, because in its essence it doesn't specify parts of the system functionality, only how that functionality is to be perceived by the user, for instance how easy it must be to learn and how

efficient it must be for carrying out user tasks. The usability requirements must be tangible so that we are able to verify them and trace them during the development. They must also be complete so that if we fulfil them, we are sure that we get the usability we intend. Usability can predict digitswith accuracy. The model can be used in bank check processing, data entry etc

Security:

Security is a non-functional requirement assuring all data inside the system or its part will be protected against malware attacks or unauthorized access. So, the nonfunctional requirements part will set up specific types of threats that functional requirements will address in more detail. If your security relies on specific standards and encryption methods, these standards don't directly describe the behaviour of a system, but rather help engineers with implementation guides. How well are the system and its data protected against attacks. It ensures security as the uploaded image is not stored in any database.

Availability:

Availability describes how likely the system is accessible to a user at a given point in time. While it can be expressed as an expected percentage of successful requests, you may also define it as a percentage of time the system is accessible for operation during some time period. As you can see, these three metrics are closely connected. And more importantly, you should approach them together if you decide to document them as non-functional requirements for your system.

Reliability

Reliability specifies how likely the system or its element would run without a failure for a given period of time under predefined conditions. Reliability is defined as the probability that a product, system, or service will perform its intended function adequately for a specified period of time, or will operate in a defined environment without failure.

Example - The system must perform without failure in 95 percent of use cases during a month. Can process confidential information without data leakage as the data is never stored in any database. Performance improvement in fast prediction. We use Logistic regression for accurate prediction

Maintainability

Maintainability defines the time required for a solution or its component to be fixed, changed to increase performance or other qualities, or adapted to a changing environment. Like reliability, it can be expressed as a probability of repair during some time. For example, if you have 75 percent maintainability for 24 hours, this means that there's a 75 percent chance the component can be fixed in 24 hours. Maintainability is often measured with a metric like MTTRS — the mean time to restore the system.

Compatibility:

Compatibility, as an additional aspect of portability, defines how a system can coexist with another system in the same environment. For instance, software installed on an operating system must be compatible with its firewall or antivirus protection. Portability and compatibility are established in terms of operating systems, hardware devices, browsers, software systems, and their versions. For now, a cross-platform, cross-browsing, and mobile-responsive solution is a common standard for web applications.

CHAPTER 5 PROJECT DESIGN

5.1 DATA FLOW DIAGRAMS

A data flow diagram is a graphical or visual representation using a standardized set of symbols and notations to describe a business's operations through data movement. They are often elements of a formal methodology such as Structured Systems Analysis and Design Method. Superficially, DFDs can resemble flow charts or Unified Modelling Language, but they are not meant to represent details of software logic.

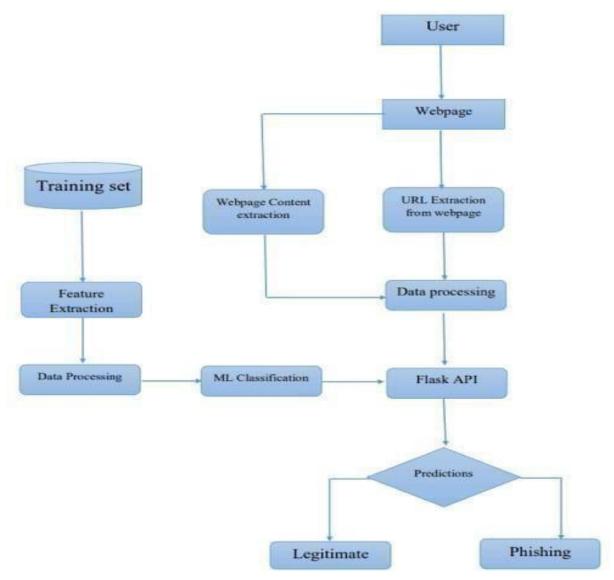


Fig 5.1 Data Flow Diagram

The data flow diagram represented in the figure 5.1 gets a URL as an input. It Scrapes feature data from the URL. Then the URL is sent to the prediction model and the website is tested whether the website is safe or not.

5.2 SOLUTION ARCHITECTURE

Solution architecture is the process of developing solutions based on predefined processes, guidelines and best practices with the objective that the developed solution fits within the enterprise architecture in terms of information architecture, system portfolios, integration requirements and many more.

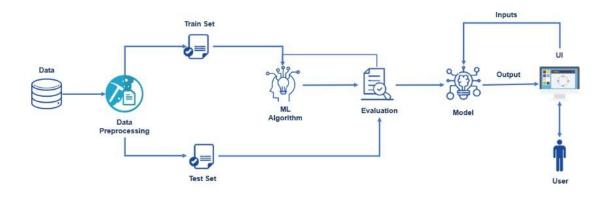


Fig 5. 2 Solution Architecture

The architecture explained above is the data is pre processed and it is divided into training set and testing set. Then the model is processed through a machine learning algorithm and it is send for the process of evaluation. The model is built using the flask and html and an user interface is produced for the user to use. The user gives the input to the model and the output is produced to the user.

5.3 USER STORIES

A user story is an informal, general explanation of a software feature written from the perspective of the end user. Its purpose is to articulate how a software feature will provide value to the customer.

User Type	Functional	User	User Story / Task	Acceptance	Priority	Release
	Requirement	Story		criteria		
	(Epic)	Number				
Customer	Registration	USN-1	As a user, I can	I can access	High	Sprint-
(Mobile user)			register for the	my account /		1
			application by	dashboard		
			entering my			
			email, password,			
			and			
			confirmingmy			
		TIGNI 0	password.	Ŧ .	TT' 1	<u> </u>
		USN-2	As a user, I will	I can receive	High	Sprint-
			receive confirmation	confirmation		1
			email once I	email & click confirm		
			have registered	Commi		
			for the			
			application			
		USN-3	As a user, I can	I can register	Low	Sprint-
			register for the	& access the		2
			application	dashboard		
			through	with		
			Facebook	Facebook Login		
		USN-4	As a user, I can		Medium	Sprint-
		,	register for the			1
			application			
			through Gmail			
	Login	USN-5	As a user, I can		High	Sprint-
			log into the			1
			application by			
			entering email &			
			password			

	Dashboard					
Customer	User input	USN-1	As a user i can	I can go	High	Sprint-
(Web user)			input the particular	access the		1
			URL in the required	website		
			field and waiting	without any		
			for validation.	problem		
Customer	Feature	USN-1	After i	As a User i	High	Sprint-
Care	extraction		compare in	can have		1
Executive			case if none	comparison		
			found on	between		
			comparison	websites for		
			then we can	security.		
			extract			
			feature using			
			heuristic and			
			visual			
			similarity			
			approach.			
Administrator	Prediction	USN-1	Here the Model	In this i	High	Sprint-
			will predict the	can have		1
			URL websites	correct		
			using	prediction		
			Machine Learning	on the		
			algorithms such as	particular		
			Logistic	algorithms		
			Regression, KNN			
	Classifier	USN-2	Here i will send all	I this i will	Medium	Sprint-
			the model output to	find the		2
			classifier in order to			
			produce final result.	classifier		
				for		
				producing		
				the result		

Table 5.1 User Stories

CHAPTER 6 PROJECT PLANNING AND SCHEDULING

6.1 SPRINT & ESTIMATION PLANNING

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	2	High	Vishal Guna
Sprint-1		USN-2	As a user, I will receive confirmation email once I have registered for the application	1	High	Hema priya R
Sprint-2		USN-3	As a user, I can register for the application through Facebook	2	Low	Vembu Karthick K
Sprint-1		USN-4	As a user, I can register for the application through Gmail	2	Medium	Sabarissha n Gk
Sprint-1	Login	USN-5	As a user, I can log into the application by entering email & password	1	High	Vishal Guna

Table 6.1 Sprint estimation Table

6.2 SPRINT DELVERY 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	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

Table 6.2 Sprint delivery schedule

CHAPTER 7 CODING AND SOLUTIONING

7.1 LOGISTIC REGRESSION

This type of statistical model (also known as *logit model*) is often used for classification and predictive analytics. Logistic regression estimates the probability of an event occurring, such as voted or didn't vote, based on a given dataset of independent variables. Since the outcome is a probability, the dependent variable is bounded between 0 and 1. In logistic regression, a logit transformation is applied on the odds—that is, the probability of success divided by the probability of failure. This is also commonly known as the log odds, or the natural logarithm of odds, and this logistic function is represented by the following formulas:

$$Logit(pi) = 1/(1 + exp(-pi))$$

$$ln(pi/(1-pi)) = Beta_0 + Beta_1 * X_1 + ... + B_k * K_k$$

In this logistic regression equation, logit(pi) is the dependent or response variable and x is the independent variable. The beta parameter, or coefficient, in this model is commonly estimated via maximum likelihood estimation (MLE). This method tests different values of beta through multiple iterations to optimize for the best fit of log odds. All of these iterations produce the log likelihood function, and logistic regression seeks to maximize this function to find the best parameter estimate. Once the optimal coefficient (or coefficients if there is more than one independent variable) is found, the conditional probabilities for each observation can be calculated, logged, and summed together to yield a predicted probability. For binary classification, a probability less than .5 will predict 0 while a probability greater than 0 will predict 1. After the model has been computed, it's best practice to evaluate the how well the model predicts the dependent variable, which is called goodness of fit. The Hosmer–Lemeshow test is a popular method to assess model fit.

7.2 THE USER INTERFACE

The UI is built using HTML, CSS and JavaScript. The backend of the application is handled by Flask, a python framework for backend application development. The application consists of two pages,

- 1. Index.html
- 2. Style.css
- 3. Mainpage.Html



Info of Website

A URL based phishing attack is carried out by sending malicious links, that seems legitimate to the users, and tricking them into clicking on it. In phishing detection, an incoming URL is identified as phishing or not by analysing the different features of the URL and is classified accordingly. Different machine learning algorithms are trained on various datasets of URL features to classify a given URL as phishing or legitimate.

Machine Learning Algorithms

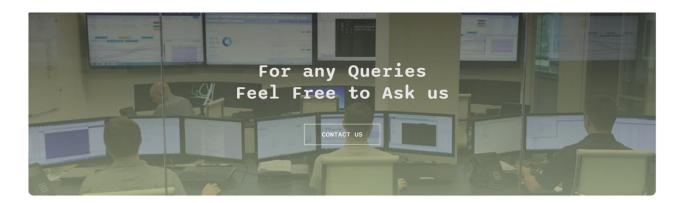
There are several machine learning algorithms such as Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression and K-Nearest-Neighbor for detecting phishing websites. This is a very popular approach that ha proved to be very efficient and accurate compared to other methods.

Used Algorithms

Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression and K-Nearest-Neighbor for detecting phishing websites. This is a very popular approach that ha proved to be very efficient and accurate compared to other methods.

Approaches

In List Based approach, there are two lists, called whitelist and blacklist to classify legitimate and phishing URLs respectively. In [5], access to websites takes place only if the URL is in the whitelist. In [6] blacklist is used. In Heuristic Based approach, the structure of a phishing URL is analysed. A pattern of URLs that were previously classified as phishing is created. URLs are classified according to their compliance with this pattern. The methods used to process the features of the URL plays a significant role in classifying websites accurately .



About Us

Phishing works by sending messages that look like they are from a legitimate company or website. The message will usually contain a link that takes the user to a fake website that looks like the real thing. The user is then asked to enter personal information, such as their credit card number. We are now currently working on the identifying process .In future , you hope that we come up with the best solution.







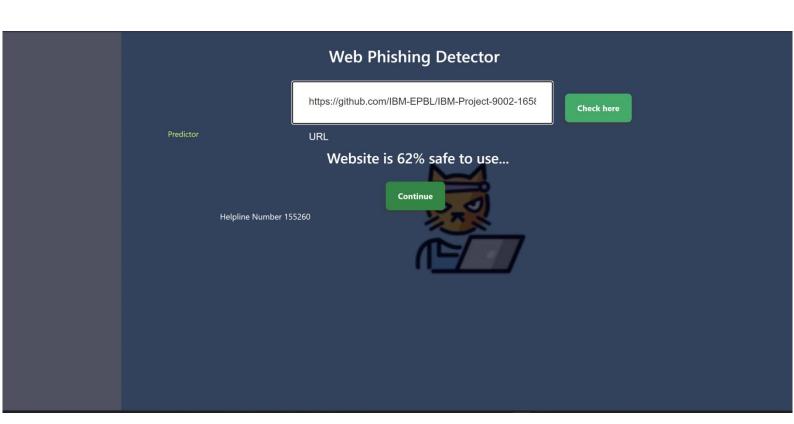


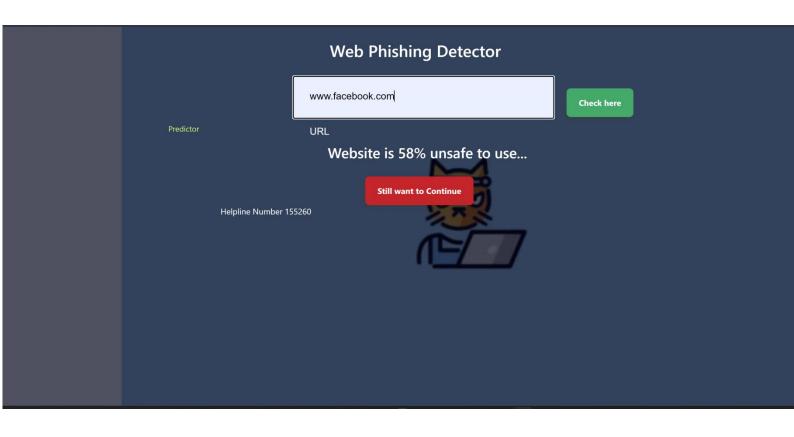
Made With Pleasure♥Bv Team IBM-PNT2022MID01661

OUTPUT

Predictor page:







CHAPTER 8 RESULT

8.1 PERFORMANCE METRICS

Evaluating the performance of a Machine learning model is one of the important steps while building an effective ML model. To evaluate the performance or quality of the model, different metrics are used, and these metrics are known as performance metrics or evaluation metrics. These performance metrics help us understand how well our model has performed for the given data. In this way, we can improve the model's performance by tuning the hyperparameters. Each ML model aims to generalize well on unseen/new data, and performance metrics help determine how well the model generalizes on the new dataset.

The performance metrics of the model -01 is 62% safe to use site

The performance metrics of the model -02 is 58% unsafe to use the site

CHAPTER 9 ADVANTAGES AND DISADVANTAGES

9.1 ADVANTAGES AND DISADVANTAGES

ADVANTAGES

A mailbox-level anti-phishing solution offers an additional layer of protection by analyzing account information and understanding users' communication habits. This delivers an enhanced level of phishing protection to detect attacks faster, alert users and remediate threats as quickly as possible. Machine learning scores sender reputation enabling a baseline for what "normal communications" with a user should look like. It can then compare correspondence and incoming messages with multiple data points to identify and learn from anomalies.

DISADVANTAGES

Although our proposed approach has attained outstanding accuracy, it has some limitations. First limitation is that the textual features of our phishing detection approach depend on the English language. This may cause an error in generating efficient classification results when the suspicious webpage includes language other than English. About half (60.5%) of the websites use English as a text language. However, our approach employs URL, noisy part of HTML, and hyperlink based features, which are language-independent features. The second limitation is that despite the proposed approach uses URL based features, our approach may fail to identify the phishing websites in case when the phishers use the embedded objects (i.e., Javascript, images, Flash, etc.) to obscure the textual content and HTML coding from the anti-phishing solutions. Many attackers use single server-side scripting to hide the HTML source code. Based on our experiments, we noticed that legitimate pages usually contain rich textual content features, and high amount of hyperlinks (At least one hyperlink in the HTML source code). At present, some phishing webpages include malware, for example, a Trojan horse that installs on user's system when the user opens the website.

Hence, the next limitation of this approach is that it is not sufficiently capable of detecting attached malware because our approach does not read and process content from the web page's external files, whether they are cross-domain or not. Finally, our approach's training time is relatively long due to the high dimensional vector generated by textual content features. However, the trained approach is much better than the existing baseline methods in terms of accuracy.

CHAPTER 10
CONCLUSION

10.1 CONCLUSION

A systematic review of current trends in web phishing detection is carried out and a taxonomy of web phishing detection is proposed based on the input parameters chosen. The performance of the state-of-the-art web phishing detection approaches is evaluated and presented in detail. This paper also discussed the limitations of the existing web phishing detection techniques for future research direction. The analysis given in this paper will help the academia and industries to acknowledge the current status of web phishing detection and lead them to come up with new ideas to develop the best web anti-phishing technique.

CHAPTER 11

FUTURE SCOPE

11.1 FUTURE WORK

In future work, we plane to include some new features to detect the phishing websites that contain malware. As we said in "Limitations" section, our approach could not detect the attached malware with phishing webpage. Nowadays, blockchain technology is more popular and seems to be a perfect target for phishing attacks like phishing scams on the blockchain. Blockchain is an open and distributed ledger that can effectively register transactions between receiving and sending parties, demonstrably and constantly, making it common among investors. Thus, detecting phishing scams in the blockchain environment is a defiance for more research and evolution. Moreover, detecting phishing attacks in mobile devices is another important topic in this area due to the popularity of smart phones, which has made them a common target of phishing offenses.

CHAPTER 12

APPENDICES

SOURCE CODE

y_pred = response_text['predictions'][0]['values'][0][0]

```
app.py
import numpy as np
import requests as requests
from flask import Flask, request, jsonify, render_template
import pickle
# importing the feature file used to analyze the URL
import _json
import requests
import feature
from feature import FeatureExtraction
# NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud account.
API_KEY = "<j8gnwjgK1Pk7vrnA7wND_ivng17Bh4dlbFy3-ig_s-mt>"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey":
API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
mltoken = token_response.json()["access_token"]
header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
url = request.form['url']
      obj = feature.FeatureExtraction(url)
      x = np.array(obj.getFeaturesList()).reshape(1,30)
      print(x.tolist())
# NOTE: manually define and pass the array(s) of values to be scored in the next line
payload_scoring = {"input_data": [{"field": [["index", "having_IPhaving_IP_Address", "URLURL_Length",
"Shortining_Service","having_At_Symbol", "double_slash_redirecting", "Prefix_Suffix",
"Request_URL", "URL_of_Anchor",   "Links_in_tags",   "SFH", "Submitting_to_email", "Abnormal_URL",    "Redirect",
"Google_Index", "Links_pointing_to_page", "Statistical_report"
      17, "values": x.tolist()}7}
response_scoring = requests.post('https://us-south.ml.cloud.ibm.com/ml/v4/deployments/wpd/predictions?version=2022-
11-22', json=payload_scoring
headers={'Authorization': 'Bearer ' + mltoken})
print("Scoring response")
print(response_scoring.json())
response_text = response_scoring.json()
```

```
y_pro_non_phishing = response_text['predictions'][0]['values'][0][1][1]
# load model
class Flask:
app = Flask(__name__)
model = pickle.load(open('Phishing_website.pkl', 'rb'))
# fetches the URL given by the URL and passes to feature
@app.route('/_predict', methods=['POST'])
def y_predict():
   url = request.form['URL']
   checkprediction = feature.main(url)
   prediction = model.predict(checkprediction)
   print(prediction)
   output = prediction[0]
   if (output == 1):
      pred = "Your are safe!! This is a Legitimate Website."
      pred = "Your are on the wrong site. Be cautious!"
   return render_template('final.html', prediction_text='{}'.formate(pred), url=url)
@app.route('/predict_api', methods=['POST'])
def predict_api():
   data = request.get_json(force=True)
   prediction = model.y_predict([np.array(list(data.values()))])
   output = prediction[0]
   return jsonify(output)
```

y_pro_phishing = response_text['predictions'][0]['values'][0][1][0]

```
'__name__ == '__main__':
app.run(host='0.0.0.0', debug=True)
```

feature.py

```
import ipaddress
import re
from urllib import response
import urllib.request
from bs4 import BeautifulSoup
import socket
import requests
from googlesearch import search
from sympy import Domain
import urllib3
import whois
from datetime import date, datetime
from urllib.parse import urlparse
class FeatureExtraction:
  features = []
     self.features = [7
     self.url = url
     self.domain = ""
     self.whois_response = ""
     self.urlparse = ""
     self.response = ""
     self.soup = ""
        self.response = requests.get(url)
        self.soup = BeautifulSoup(response.text, 'html.parser')
        self.urlparse = urlparse(url)
        self.domain = self.urlparse.netloc
```

```
self.whois_response = whois.whois(self.domain)
   self.features.append(self.having_IPhaving_IP_Address())
   self.features.append(self.URLURL_Length())
   self.features.append(self.Shortining_Service())
   self.features.append(self.having_At_Symbol())
   self.features.append(self.double_slash_redirecting())
   self.features.append(self.Prefix_Suffix())
   self.features.append(self.having_Sub_Domain())
   self.features.append(self.SSLfinal_State())
   self.features.append(self.Domain_registeration_length())
   self.features.append(self.Favicon())
   self.features.append(self.port())
   self.features.append(self.HTTPS_token())
   self.features.append(self.Request_URL())
   self.features.append(self.URL_of_Anchor())
   self.features.append(self.Links_in_tags())
   self.features.append(self.SFH())
   self.features.append(self.Submitting_to_email())
   self.features.append(self.Abnormal_URL())
   self.features.append(self.Redirect())
   self.features.append(self.on_mouseover())
   self.features.append(self.RightClick())
   self.features.append(self.popUpWidnow())
   self.features.append(self.Iframe())
   self.features.append(self.age_of_domain())
   self.features.append(self.DNSRecord())
   self.features.append(self.web_traffic())
   self.features.append(self.Page_Rank())
   self.features.append(self.Google_Index())
   self.features.append(self.Links_pointing_to_page())
   self.features.append(self.Statistical_report())
# 1.having_IPhaving_IP_Address
def having_IPhaving_IP_Address(self):
      ipaddress.ip_address(self.url)
      return -1
   except:
```

```
return 1
   def URLURL_Length(self):
      if len(self.url) < 54:
      if len(self.url) >= 54 and len(self.url) <= 75:
          return O
   # 3. Shortining_Service
   def Shortining_Service(self):
      match = re.search('bit\.ly|goo\.g||shorte\.st|go2|\.ink|x\.co|ow\.ly|t\.co|tinyurl|tr\.im|is\.gd|cli\.gs|'
self.url)
      if match:
   def having_At_Symbol(self):
      if re.findall("@", self.url):
   def double_slash_redirecting(self):
      if self.url.rfind('//') > 6:
          return -1
      return 1
   # 6.Prefix Suffix
   def Prefix_Suffix(self):
          match = re.findall('\-', self.domain)
          if match:
          return 1
      except:
```

```
# 7.having_Sub_Domain
def having_Sub_Domain(self):
   dot_count = len(re.findall("\.", self.url))
   if dot count == 1:
      return 1
   elif dot count == 2:
      return O
# 8.SSLfinal_State
def SSLfinal_State(self):
      https = self.urlparse.scheme
      if 'https' in https:
def Domain_registeration_length(self):
      expiration_date = self.whois_response.expiration_date
      creation_date = self.whois_response.creation_date
         if(len(expiration_date)):
             expiration_date = expiration_date[0]
         if(len(creation_date)):
            creation_date = creation_date[0]
      age = (expiration_date.year-creation_date.year)*12 + \
         (expiration_date.month-creation_date.month)
      if age >= 12:
      return -1
```

return -1

```
# 10. Favicon
def Favicon(self):
       for head in self.soup.find_all('head'):
          for head.link in self.soup.find_all('link', href=True):
             dots = [x.start(0)]
                    for x in re.finditer('\.', head.link['href'])]
             if self.url in head.link['href'] or len(dots) == 1 or Domain in head.link['href']:
                 return 1
      return -1
       return -1
def port(self):
      port = self.domain.split(":")
      if len(port) > 1:
   except:
def HTTPS_token(self):
      if 'https' in self.domain:
       return -1
def Request_URL(self):
       for img in self.soup.find_all('img', src=True):
          dots = [x.start(0) for x in re.finditer(\\.', img['src'])]
          if self.url in img['src'] or self.domain in img['src'] or len(dots) == 1:
             success = success + 1
          i = i+1
      for audio in self.soup.find_all('audio', src=True):
          dots = [x.start(0) for x in re.finditer('\.', audio['src'])]
          if self.url in audio['src'] or self.domain in audio['src'] or len(dots) == 1:
             success = success + 1
```

```
i = i+1
          for embed in self.soup.find_all('embed', src=True):
             dots = [x.start(0) for x in re.finditer(\\', embed['src'])]
             if self.url in embed['src'] or self.domain in embed['src'] or len(dots) == 1:
                success = success + 1
             i = i+1
         for iframe in self.soup.find_all('iframe', src=True):
             dots = [x.start(0) for x in re.finditer(\\', iframe['src'])]
             if self.url in iframe['src'] or self.domain in iframe['src'] or len(dots) == 1:
                success = success + 1
             percentage = success/float(i) * 100
             if percentage < 22.0:
             elif((percentage >= 22.0) and (percentage < 61.0)):
   def URL_of_Anchor(self):
         i, unsafe = 0, 0
         for a in self.soup.find_all('a', href=True):
             if "#" in a['href] or "javascript" in a['href].lower() or "mailto" in a['href].lower() or not (urllib3 in a['href] or
self.domain in a['href']):
                unsafe = unsafe + 1
             percentage = unsafe / float(i) * 100
             if percentage < 31.0:
             elif ((percentage >= 31.0) and (percentage < 67.0)):
                return O
```

```
except:
def Links_in_tags(self):
      i, success = 0, 0
      for link in self.soup.find_all('link', href=True):
          dots = [x.start(0) for x in re.finditer('\.', link['href'])]
          if self.url in link['href'] or self.domain in link['href'] or len(dots) == 1:
             success = success + 1
          i = i+1
      for script in self.soup.find_all('script', src=True):
          dots = [x.start(0) for x in re.finditer('\.', script['src'])]
          if self.url in script['src'] or self.domain in script['src'] or len(dots) == 1:
             success = success + 1
          percentage = success / float(i) * 100
          if percentage < 17.0:
          elif((percentage >= 17.0) and (percentage < 81.0)):
             return O
       except:
   except:
       return -1
# 16. SFH
def SFH(self):
       if len(self.soup.find_all('form', action=True)) == 0:
          for form in self.soup.find_all('form', action=True):
             if form['action'] == "" or form['action'] == "about:blank":
```

```
elif self.url not in form['action'] and self.domain not in form['action']:
                 return O
       return -1
# 17. Submitting_to_email
def Submitting_to_email(self):
      if re.findall(r"[mail\(\)|mailto:?]", self.soap):
          return 1
       return -1
# 18. Abnormal_URL
def Abnormal_URL(self):
       if self.response.text == self.whois_response:
# 19. Redirect
def Redirect(self):
       if len(self.response.history) <= 1:</pre>
       elif len(self.response.history) <= 4:</pre>
          return O
def on_mouseover(self):
       if re.findall("<script>.+onmouseover.+</script>", self.response.text):
```

```
def RightClick(self):
      if re.findall(r"event.button ?== ?2", self.response.text):
def popUpWidnow(self):
      if re.findall(r"alert\(", self.response.text):
          return 1
       return -1
def Iframe(self):
      if re.findall(r"[<iframe>|<frameBorder>]", self.response.text):
   except:
def age_of_domain(self):
       creation_date = self.whois_response.creation_date
          if(len(creation_date)):
             creation_date = creation_date[0]
       today = date.today()
```

```
age = (today.year-creation_date.year) * \
        12+(today.month-creation_date.month)
     if age >= 6:
     return -1
     return -1
# 25. DNSRecord
def DNSRecord(self):
     creation_date = self.whois_response.creation_date
        if(len(creation_date)):
           creation_date = creation_date[0]
     today = date.today()
     age = (today.year-creation_date.year) * \
        12+(today.month-creation_date.month)
     if age >= 6:
def web_traffic(self):
     rank = BeautifulSoup(urllib.request.urlopen(
        "http://data.alexa.com/data?cli=10&dat=s&url=" + urlsafe_b64decode).read(), "xml").find("REACH")['RANK']
     if (int(rank) < 100000):
def Page_Rank(self):
     prank_checker_response = requests.post(
        global_rank = int(re.findall(
```

```
r"Global Rank: ([0-9]+)", prank_checker_response.text)[0])
         if global_rank > 0 and global_rank < 100000:
            return 1
         return -1
      except:
   def Google_Index(self):
         site = search(self.url, 5)
        if site:
            return 1
      except:
         return 1
   def Links_pointing_to_page(self):
         number_of_links = len(re.findall(r"<a href=", self.response.text))
         if number_of_links == 0:
            return 1
         elif number_of_links <= 2:
            return O
         return -1
  def Statistical_report(self):
         url_match = re.search(
urlsafe_b64encode)
         ip_address = socket.gethostbyname(self.domain)
         ip_match =
re.search('146\.112\.61\.108|213\.174\.157\.151|121\.50\.168\.88|192\.185\.217\.116|78\.46\.211\.158|181\.
174\.165\.13|46\.242\.145\.103|121\.50\.168\.40|83\.125\.22\.219|46\.242\.145\.98|<sup>(</sup>
'107\.151\.148\.44|107\.151\.148\.107|64\.70\.19\.203|199\.184\.144\.27|107\.151\.148\.108|107\.151\.148
```

\.109|119\.28\.52\.61|54\.83\.43\.69|52\.69\.166\.231|216\.58\.192\.225|

```
118\184\25\.86 | 67\208\.74\.71 | 23\253\126\.58 | 104\239\157\210 | 175\126\123\.219 | 141\.8\224\.221 | 10\.10\.10\.10\.10\.10 | 43\.229\.108\.32 | 103\.232\.215\.140 | 69\.172\.201\.153 | 126\.218\.185\.162| 54\.225\.104\.146 | 103\.243\.24\.98 | 199\.59\.243\.120 | 31\.170\.160\.61 | 213\.19\.128\.77 | 62\.113\.226\.131 | 208\.100\.26\.234 | 195\.16\.127\.102 | 195\.16\.127\.157 | 192\.64\.147\.141 | 198\.200\.56\.183 | 23\.253\.164\.103\.224\.212\.222 | 172\.217\.4\.225 | 54\.72\.9\.51 | 192\.64\.147\.141 | 198\.200\.56\.183 | 23\.253\.164\.103 | 52\.48\.191\.26 | 52\.214\.197\.72 | 87\.98\.255\.18 | 209\.99\.17\.27 | 192\.64\.147\.141 | 198\.200\.56\.183 | 23\.253\.164\.103 | 52\.48\.191\.26 | 52\.214\.197\.72 | 87\.98\.255\.18 | 209\.99\.17\.27 | 192\.64\.147\.141 | 198\.200\.56\.183 | 23\.253\.164\.103 | 52\.48\.191\.26 | 52\.214\.197\.72 | 87\.98\.255\.18 | 209\.99\.17\.27 | 192\.64\.13\.156\.19 | 37\.1 | 192\.204\.11\.56\.48 | 110\.34\.231\.42', ip_address\.18 | 110\.34\.231\.4
```

index.html

<!DOCTYPE html> <html lang="en">

```
<head>
<title>Phishing Detector</title>
<meta name="viewport" content="width=device-width, initial-scale=1">
<meta name="viewport" content="width=device-width, initial-scale=1">
<link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
<link rel="stylesheet" href="https://unicons.iconscout.com/release/v4.0.0/css/line.css">
<link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
<meta charset="UTF-8">
<meta charset="UTF-8">
<style>
@import url('https://fonts.googleapis.com/css2?family=Poppins:wght@300;400;500;600;700&display=swap');</mi>
*{
    margin: 0;
    padding: 0;
    box-sizing: border-box;
    font-family: 'Poppins', sans-serif;
```

```
body{
  scroll-behavior: smooth;
header{
   width:100%;
  display:flex;
  justify-content: space-between;
  padding:10px 10px;
   flex-direction: column;
   align-items: center;
  position:fixed;
  z-index:999;
html{
   scroll-behavior: smooth;
body{
   font-size: 100%;
  font-family: sans-serif;
div, section, span, ul, li, a, header,h1{
  box-sizing: border-box;
.joint{
   width:100%;
  display:flex;
   flex-direction:row;
.result{
   width:500px;
   border:2px solid black;
   margin-left:20px;
   text-align:center;
  justify-content: center;
   align-items: center;
   margin-top:10%;
   padding:5%;
```

```
text-decoration: underline;
   color:rgb(76, 76, 202);
.sec-container{
  width:450px;
  height:400px;
   background-color: #678efa;
   border-radius: 2%;
  display:flex;
  align-items: center;
  flex-direction: column;
   border: 1px solid;
  box-shadow: 5px 10px #adacac;
.sec-1-container{
  width:550px;
  height:250px;
   background-color: #678efa;
   border-radius: 2%;
  display:flex;
   align-items: center;
   flex-direction: column;
   border: 1px solid;
   margin-top:10%;
   margin-left:10%;
  padding:2%;
   box-shadow: 5px 10px #adacac;
.sec-container h2,p{
  align-items: center;
  position:relative;
   text-align: center;
  padding:5%;
.frst-container h2,p{
  align-items: center;
  position:relative;
   text-align: center;
  padding:5%;
.frst-container{
  width:450px;
  height:400px;
```

```
margin-right:10%;
   border: 1px solid;
 box-shadow: 5px 10px #888888;
   background-color: #fff;
   border-radius: 2%;
   display:flex;
   align-items: center;
   flex-direction: column;
   padding-right:4%;
#menu li{
   list-style: none;
  display: inline-block;
   margin: 20px;
#menu li a{
   color: black;
   text-decoration: none;
   font-size: 20px;
section{
   width: 100%;
   float: left;
   height: 100vh;
   position: relative;
.head{
   color:black;
   display:flex;
   margin-left:5%;
   text-decoration: none;
   font-size:20px
#home{
   background-color: #678efa;
.img-share{
   width:75%;
  height:500px;
   position:relative;
   float:right;
```

```
margin-top:5%;
   /* margin-left:8%; */
  /* border: 2px solid black; */
   /* margin-right:60%; */
   background-image: url('../static/bg2.png');
.frst-container img{
   width:100px;
   height:100px;
.wordings{
   width:280px;
   display: flex;
   margin-top: 20%;
   margin-left:2%;
   flex-direction: column;
.highlight{
   font-size: 30px;
   color:#ffb703
.wordings p{
  color:#fff;
.join{
   display: flex;
   flex-direction:row;
#about{
   display: flex;
   flex-direction: column;
   align-items: center;
  justify-content: center;
   background-color: rgb(110, 136, 89);
   /* background-color: #4070f4; */
#product{
    background-color: #B52B65;
#help{
    background-color: #678efa;
```

```
#contact{
   background-color: rgb(63, 109, 236);
h1{
   position: absolute;
   top: 50%;
   left: 50%;
   transform: translate(-50%, -50%);
   color: #fff;
.container{
  position: relative;
   max-width: 430px;
   width: 100%;
   background: #fff;
   border-radius: 10px;
   box-shadow: 0 5px 10px rgba(0, 0, 0, 0.1);
   overflow: hidden;
   margin: 0 20px;
button{
   margin-top:60px;
   display:flex;
   flex-direction:column;
   align-items:center;
   /* margin-left:100px; */
   width:150px;
   height:50px;
  justify-content: center;
   border-radius: 6%;
   background-color:#fff;
   border:none;
   color: black;
   font-size: 16px;
   font-weight: 500;
.second-container{
  display: flex;
   width:100%;
   height:100%;
```

```
.navbar{
   border:2px solid rgb(89, 96, 88);
  width:1200px;
   background-color: rgb(241, 246, 235);
   border-radius: 30px;
  margin-top:2%;
  overflow: hidden;
   margin-left:2%;
  z-index: 999;
.navbar ul{
  overflow: auto;
.navbar li{
  float:center;
  list-style: none;
   margin: 10px 10px;
.navbar li a{
  padding: 5px 30px;
  text-decoration: none;
  color: black;
.navbar li a:hover{
  color: red
.search{
  float: right;
  color: white;
  padding: 12px 75px;
.navbar input{
  border: 2px solid black;
   border-radius: 14px;
  padding: 3px 17px;
  width: 150px;
.sec-1-container input{
  width:400px;
  height:60px;
  padding:5%;
```

```
#contact div{
  width:500px;
  height: 480px;
  margin-top:5%;
  margin-left: 32%;
  padding:5%;
width: 100%; /* Full width */
  height:27px;
  /* padding: 5px; Some padding */
  border: 1px solid #ccc; /* Gray border */
  border-radius: 4px; /* Rounded borders */
  box-sizing: border-box; /* Make sure that padding and width stays in place */
  /* margin-top: 2px; Add a top margin */
  /* Bottom margin */
  resize: vertical /* Allow the user to vertically resize the textarea (not horizontally) */
 .point{
  text-decoration: none;
  color:#fff;
   margin-left:30%;
 /* Style the submit button with a specific background color etc */
 input[type=submit] {
  background-color: #ccc;
  color: white;
  padding: 8px 10px;
  border: none;
  border-radius: 4px;
  cursor: pointer;
 /* When moving the mouse over the submit button, add a darker green color */
 input[type=submit]:hover {
  background-color: #d7edc7;
 /* Add a background color and some padding around the form */
 .container {
  border-radius: 5px;
  background-color: #f2f2f2;
  padding: 8px;
```

```
</style>
</head>
<body>
  <nav class="navbar">
        ul id="menu">
            <a href="C:\Users\mathe\OneDrive\Desktop\Web Phishing Detection\MainPage.html">Home</a>
            <a href="C:\Users\mathe\OneDrive\Desktop\Web Phishing Detection\MainPage.html">About</a>
        </nav>
   <div class="joint">
<div class="sec-1-container">
   <form action = "/predictdata" method="post">
      <a href="mailto:label"></abel></a>
     <input type="text" name="url">
     <button class="button21" role="button" type="submit">Confirm</button>
   </form>
  </div>
<div class="result">
<h2 style="color:black">
  {{predicted}}</h2>
   <h4>{{url}}</h4>
</div>
</div>
<script src="https://code.jquery.com/jquery-3.5.1.slim.min.js"</pre>
integrity="sha384-DfXdz2htPHOlsSSs5nCTpuj/zy4C+OGpamoFVy38MVBnE+IbbVYUew+OrCXaRkfj"
crossorigin="anonymous"></script>
<script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
integrity="sha384-Q6E9RHvblyZFJoft+2mJbHaEWldlv1910Yy5n3zV9zzTtm13UksdQRVvoxMfooAo"
crossorigin="anonymous"></script>
<script src="https://stackpath.bootstrapcdn.com/bootstrap/4.5.0/js/bootstrap.min.js"
integrity="sha384-OgVRvuATP1z7JjHLkuOU7Xw7O4+h835Lr+6QL9UvYjZE3Ipu6Tp75j7Bh/kROJKI"
crossorigin="anonymous"></script>
<script>
   let x = '{\{xx\}}';
```

```
//console.log(rt);
   // debugger
   let num = x*100;
   if (0<=x && x<0.50){
      num = 100 - num;
   let txtx = num.toString();
   if (!(x=="" || x==" " || x==undefined || x==NaN)){}
         if(x<=1 && x>=0.50){
            var label = "Website is "+txtx +"% safe to use...";
            document.getElementById("prediction").innerHTML = label;
            document.getElementById("button1").style.display="block";
            flag=true;
         }else if (0<=x && x<0.50){
            var label = "Website is "+txtx +"% unsafe to use..."
            document.getElementById("prediction").innerHTML = label;
            //document.getElementById("button1").style.display="none";
            document.getElementById("button2").style.display="block";
            flag=true
          document.getElementsByClassName("button")[0].style.display="none";
          document.getElementsByClassName("button21")[0].style.display="block";
</script>
>Helpline Number <i class="fa fa-phone" ></i> 155260
</body>
</html>
```

GitHub Link: https://github.com/IBM-EPBL/IBM-Project-9002-1658942080

Demo-Video

Link: https://drive.google.com/drive/folders/1ys0a7RbJSPlzjEMwQijFVDuyarSMFOjR?usp

<u>=share_link</u>