## **IBM**

## **NALAIYA THIRAN**

## PROJECT REPORT

**ON** 

## WEB PHISHING DETECTION

# **TEAM ID: PNT2022TMID21985**

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#### **ABSTRACT**

A web service is one of the most important Internet communications software services. Using various fraudulent methods to get personal information is becoming increasingly widespread these days. However, it makes our lives easier, it leads to numerous security vulnerabilities to Internet's private structure. Web phishing is just one of the many security risks that web services face. Phishing assaults are usually detected by experienced users however, security is a primary concern for system users who are unaware of such situations. Phishing is the act of portraying malicious web runners as genuine web runners to obtain sensitive information from the end-user. Phishing is currently regarded as one of the most dangerous threats to web security. Vicious Web sites significantly encourage Internet criminal activity and inhibit the growth of Web services. As result, there has been a tremendous push to build a comprehensive solution to prevent users from accessing such websites. We suggest a literacy-based strategy to categorize Web sites into three categories: benign, spam, and malicious. Our technology merely examines the Uniform Resource Locator (URL) itself, not the content of Web pages. As a result, it removes run-time stillness and the risk of drug users being exposed to cyber surfer-based vulnerabilities. When compared to a blacklisting service, our approach performs better on generality and content since it uses learning technique

KEYWORDS:			
PHISHING			
URL			
FRADULENT			
MALICIOUS			
	4		
	4		

## **PRE-REQUISITES**

**TOOLS:** JUPITER NOTEBOOK

**OPERATING SYSTEM:** WINDOWS 11

**LANGUAGE:** PYTHON

#### **INSTALLING LIBRARIES**

In this first step, we have to import the most common libraries used in python for machine learning such as

- Pandas
- Numpy
- Pickle
- Flask
- Jsonify

#### **IMPORTING DATA**

In this project, we have used the URL pre processed data.

#### CHAPTER 1

#### INTRODUCTION

Phishing imitates the characteristics and alternatives of emails and makes it appear similar due to the fact the original one. It seems nearly like that of the legitimate supply. The consumer thinks that this e-mail has come back from a real employer or a corporation. This makes the consumer to forcefully visit the phishing internet site thru the hyperlinks given inside the phishing email. These phishing web sites region unit created to mock the seams of an ingenious website. The phishers force person to inventory up the non-public info via giving baleful messages or validate account messages etc. so that they inventory up the preferred data which might be utilized by them to misuseit. They devise things such as the user isn't always left with the other choice but to go to their spoofed web site. Phishing is the most hazardous criminal physical activities in the cyber region. Since the maximum of the customers logs on to get admission to the services supplied with the aid of government and financial establishments, there has been a significant boom in phishing attacks for the beyond few years. Phishers commenced to earn cash and that they try this as a thriving business.

#### 1.1 PROJECT OVERVIEW

- To develop a novel approach to detect malicious URL and alert users.
- To apply Machine learning techniques in the proposed approach in order to analyze the real time URLs and produce effective results.
- To implement the concept of RNN, which is a familiar ML technique that as the capability to handle huge amount of data.

#### 1.2 PURPOSE

The purpose of this project is to design an intelligent system for detecting phishing websites. Phishing is one of the social attack which aims in stealing sensitive information of the users such as login credentials, credit card numbers etc. Here we have collected phishing dataset from phish Tanks as well as from phishing sites and are compared with the algorithms which classifies the phishing dataset into phishing or legitimate. We propose a web application for detection. The algorithm used is random forest in order to get better performance and accuracy. This system uses a database in order to store phishing websites which are already tested and can be used as blacklist, which makes the classification even faster, as it reduces repetition.

#### CHAPTER 2

#### **LITERATURE SURVEY**

#### **PAPER 2.1** Phishing Detection

Authors: Mahmoud Khonji, Youssef Iraqi, Senior Member, IEEE, and Andrew Jones Abstract-This article surveys the literature on the detection of phishing attacks. Phishing attacks target vulnerabilities that exist in systems due to the human factor. Many cyber attacks are spread via mechanisms that exploit weaknesses found in end-users, which makes users the weakest element in the securitychain. The phishing problem is broad and no single silver-bulletsolution exists to mitigate all the vulnerabilities effectively, thus multiple techniques are often implemented to mitigate specificattacks. This paper aims at surveying many of the recentlyproposed phishing mitigation techniques. A high-level overview of various categories of phishing mitigation techniques is also presented, such as: detection, offensive defense, correction, and prevention, which we belief is

PAPER 2.2: Detection of URL based phishing attacks using machine learning

critical to present where the phishing detection techniques fit in the overall mitigation

Authors: Ms. Sophiya. Shikalgar, Dr. S. D. Sawarkar, Mrs. Swati Narwane

#### **Abstract:**

process

A fraud effort to get sensitive and personal information like password, username, and bank details like credit / debit card details by masking as a reliable organization in electronic communication. It most of the time redirects the users to similar looking website as legitimate website. The phishing website will appear same as the legitimate website and directs the user to a page to enter personal details of the user on the fake website. The system administration is very important these days as any failure can be detected and solved instantly. The system administration also need to define rules and set firewall settings to avoid phishing attacks through URL. Researchers have been studying various machine learning algorithm in lines to predict and avoid phishing attacks. Through machine learning algorithms one can improve the accuracy of the prediction. The machine learning, no one algorithm works best for every problem, and it's especially relevant for supervised learning. Using a single machine learning algorithm will give us good accuracy to predict the

phishing attacks but to get better accuracy we need something more. The propose

system predicts the URL based phishing attacks with maximum accuracy. We shall talk about various machine learning, the algorithm which can help in decision making and prediction. We shall use more than one algorithm to get better accuracy of prediction. The algorithms namely the Naive Bayes and Random forest are used in the proposed system to detect URL based phishing attacks. The hybrid algorithm approach by combining.

PAPER 2.3: An Ideal Approach for Detection and Prevention of Phishing Attacks

Authors: Narendra.M & Chaithali shah

#### **Abstract:**

In this paper, we propose a phishing detection and prevention approach combining URL-based and Webpage similarity based detection. URL-based phishing detection involves extraction of actual URL (to which the website is actually directed) and the visual URL (which is visible to the user). LinkGuard Algorithm is used to analyze the two URLs and finally depending on the result produced by the algorithm the procedure proceeds to the next phase. If phishing is not detected or Phishing possibility is predicted in URL-based detection, the algorithm proceeds to the visual similarity based detection. A novel technique to visually compare a suspicious page with the legitimate oneis presented.

**PAPER 2.4:** Machine Learning and Deep Learning Based Phishing Websites Detection: TheCurrent Gaps and Next Directions

Authors: Kibreab Adane & Berhanu Beyene

#### **Abstract:**

There are many phishing websites detection techniques in literature, namely white-listing, black-listing, visual-similarity, heuristic-based, and others.

However, detecting zero-hour or newly designed phishing website attacks is an inherent property of machine learning and deep

learning techniques. By considering a promising solution of machine learning and deep learningtechniques, researchers have made a great deal of effort to tackle the this problem, which persists due to attagkers constantly devising novel strategies to exploit vulnerability or gaps in existing anti-phishing measures. In this study, an extensive effort has been made to rigorously review recent studies focusing on

Machine Learning and Deep Learning Based Phishing Websites Detection to excavate the root cause of the aforementioned problems and offer suitable solutions. The study followed the significant criterion to search, download, and screen relevant studies, then to evaluate criterion-based selected studies. The findings show that significant research gaps are available in the rigorously reviewed studies. These gaps are mainlyrelated to imbalanced dataset usage, improper selection of dataset source(s), the unjustified reason for using specific train-test dataset split ratio, scientific disputes on website features inclusion and exclusion, lack of universal consensus on phishing website lifespans and on what is defining a small dataset size, and run-time analysis issues.

**PAPER 2.6:** Detection of phishing websites using an efficient feature-based machine learning framework.

**Authors:** Royhu Srinivas rao & sathvik

**Abstract:** In this paper, we propose a novel classification model, based on heuristic features that are extracted from URL, source code, and third-party services to overcome the disadvantages of existing anti-phishing techniques. Our model has been evaluated using eight different machine learning algorithms and out of which, the Random Forest (RF) algorithm performed thebest with an accuracy of 99.31%. The experiments were repeated with different (orthogonal and oblique) random forest classifiers to find the best classifier for the phishing website detection. Principal component analysis Random Forest (PCA-RF) performed the best out of all oblique Random Forests (oRFs) with anaccuracy of 99.55%. We have also tested our model with the third-party-based features and without third-party-based features to determine the effectiveness of third-party services in the classification of suspicious websites. We also compared our results with the baseline models (CANTINA and CANTINA+).

Our proposed technique outperformed these methods and also detected zero-day.

#### **CHAPTER 3**

#### 3.1 EXISTING PROBLEM

In this technological period, the Web has advanced toward turned into an unavoidable piece of our lives. It prompts numerous advantageous encounters in our lives with respect to correspondence, amusement, schooling, shopping, etc. As we progress into online life, crooks view the Web as a valuable chance to move their actual violations into a virtual environment. The Web gives comfort in different perspectives as well as has its disadvantages, for instance, the namelessness that the Web gives to its clients. As of now, many kinds of violations have been led on the web. Consequently, the primary focal point of our examination is phishing. Phishing is a sort of cybercrime where the objectives are lured or tricked into surrendering touchy data, for example, Government managed retirement Number individual recognizable data and passwords. This acquisition of such data is done falsely. Considering that phishing is an extremely expansive point, we have concluded that this examination ought to explicitly zero in on phishing sites.

Rao et al. (1) proposed a clever characterization approach that utilization heuristic-based highlight extraction approach. In this, they have ordered extricated highlights into three classifications, for example, URL Confusion highlights, Outsider based highlights, Hyperlink-based highlights. Besides, proposed method gives 99.55% precision. Disadvantage of this is that as this model purposes outsider elements, arrangement of site subject to speed of outsider administrations. Likewise this model is simply relies upon the quality and amount of the preparation set and Broken joins highlight extraction has a Volume 3.

features. In this they have combined statistical analysis of URL with machine learning technique to get result that is more accurate for classification of malicious URLs. Also they have compared six machine-learning algorithms to verify the effectiveness of proposed algorithm which gives 99.7% precision with false positive rate less than 0.4%. Sudhanshu et al. [3] used association data mining approach. They have proposed rule based classification technique for phishing website detection. They have concluded that association classification algorithm is better than any other algorithms because of their simple rule transformation. They achieved 92.67% accuracy by extracting 16 features but this is not up to mark so proposed algorithm can be enhanced for efficient detection rate.

M. Amaad et al.[4] presented a hybrid model for classification of phishing website. In this paper, proposed model carried out in two phase. In phase 1,they individually perform classification techniques, and select the best three models based on high accuracy and other performance criteria. While in phase 2, they further combined each individual model with best three model and makes hybrid model that gives better accuracy than individual model. They achieved 97.75% accuracy on testing dataset. There is limitation of this model that it requires more time to build hybrid model.

Hossein et al.[5] developed an open-source framework known as "Fresh-Phish". For phishing websites, machine-learning data can be created using this framework. In this, they have used reduced features set and using python for building query . They build a large labelled dataset and analyse several machine-learning classifiers against this dataset . Analysis of this gives very good accuracy using machine-learning classifiers. These analyses how long time it takes to train the model.

Gupta et al. [6] proposed a novel anti phishing approach that extracts features from client-side only. Proposed approach is fast and reliable as it is not dependent on third party but it extracts features only from URL and source code. In this paper, they have achieved 99.09% of overall detection accuracy for phishing website. This paper have concluded that this approach has limitation as it can detect webpage written in HTML .Non-HTML webpage cannot detect by this approach.

Bhagyashree et al.[7] proposed a feature based approach to classify URLs as phishing and nonphishing. Various features this approach uses are lexical features, WHOIS features, Page Rank and Alexa rank and Phish Tank-based features for disguising phishing and non-phishing website. In this paper, web-mining classification is used. Mustafa et al.[8] developed safer framework for detecting phishing website. They have extracted URL features of website and using subset based selection technique to obtain better accuracy. In this paper, author evaluated CFS subset based and content based subset selection methods And Machine learning algorithms are used for classification purpose.

Priyanka et al.[9] proposed novel approach by combining two or more algorithms. In this paper ,author has implemented two algorithm Adaline and Backpropion along with SVM for getting good detection rate and classification purpose.

Pradeepthi et al.[10] In this paper ,Author studied different classification algorithm and concluded that tree-based classifier are best and gives better accuracy for phishing URL detection. Also Author uses various Volume 3, Issue 7, September-October-2018 | http://ijsrcseit.com Purvi Pujara et al. Int J S Res CSE & IT. 2018 September-October-2018; 3

#### 2.2 REFERENCES

- [1] Routhu Srinivasa Rao1, Alwyn Roshan Pais: Detection of phishing websites using an efficient feature-based machine learning framework: In Springer 2018. Volume 3, Issue 7, September-october-2018 | http://ijsrcseit.com Purvi Pujara et al. Int J S Res CSE & IT. 2018 September-October-2018; 3(7): 395-399 399
- [2] Chunlin Liu, Bo Lang: Finding effective classifier for malicious URL detection: InACM,2018
- [3] Sudhanshu Gautam, Kritika Rani and Bansidhar Joshi: Detecting Phishing Websites Using Rule-Based Classification Algorithm: A Comparison: In Springer, 2018.
- [4] M. Amaad Ul Haq Tahir, Sohail Asghar, Ayesha Zafar, Saira Gillani: A Hybrid Model to Detect Phishing-Sites using Supervised Learning Algorithms: In International Conference on Computational Science and Computational Intelligence IEEE ,2016.
- [5] Hossein Shirazi, Kyle Haefner, Indrakshi Ray: Fresh-Phish: A Framework for Auto-Detection of Phishing Websites: In (International Conference on Information Reuse and Integration (IRI)) IEEE,2017.
- [6] Ankit Kumar Jain, B. B. Gupta: Towards detection of phishing websites on client-side using machine learning based approach: In Springer Science+Business Media, LLC, part of Springer Nature 2017
- [7] Bhagyashree E. Sananse, Tanuja K. Sarode: Phishing URL Detection: A Machine Learning and Web Mining-based Approach: In International Journal of ComputerApplications, 2015
- [8] Mustafa AYDIN, Nazife BAYKAL : Feature Extraction and Classification Phishing Websites Based on URL : IEEE, 2015
- [9] Priyanka Singh, Yogendra P.S. Maravi, Sanjeev Sharma: Phishing Websites Detection through Supervised Learning Networks: In IEEE, 2015
- [10] Pradeepthi. K V and Kannan. A: Performance Study of Classification Techniques for Phishing URL Detection: In 2014 Sixth International Conference on Advanced Computing(ICoAC) IEEE,2014
- [11] Luong Anh Tuan Nguyen†, Ba Lam To†, Huu Khuong Nguyen† and Minh Hoang Nguyen: Detecting Phishing Web sites: A Heuristic URL-Based Approach: In The 2013 International Conference on Advanced Technologies for Communications (ATC'13)
- [12] Ahmad Abunadi, Anazida Zainal ,Oluwatobi Akanb: Feature Extraction Process: A Phishing Detection Approach: In IEEE, 2013.
- [13] Rami M. Mohammad, Fadi Thabtah, Lee McCluskey: An Assessment of Features

#### 2.3 PROBLEM STATEMENT DEFENITION

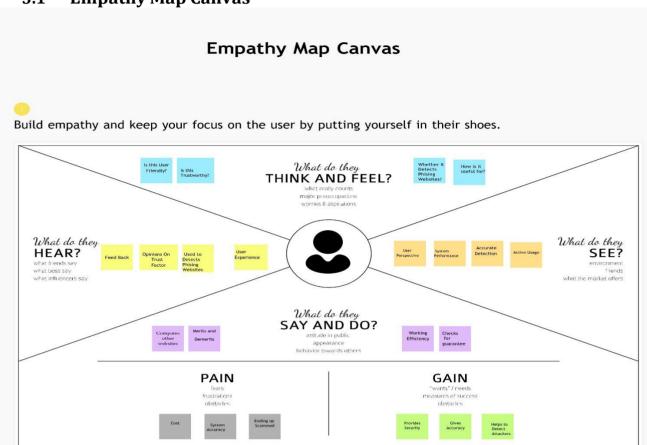
To distinguish and predict e-banking phishing sites, we proposed an astute, adaptable and compelling framework that depends on utilizing grouping calculations. We executed order calculations and strategies to remove the phishing datasets rules to characterize their authenticity. The e-banking phishing site can be recognized in view of a few significant qualities like URL and space character, and security and encryption standards in the last phishing recognition rate. When a client makes an exchange online when he makes installment through an e-banking site our framework will utilize an information mining calculation to recognize regardless of whether the e-banking site is a phishing site.

Web has overwhelmed the world by hauling half of the total populace dramatically into the digital world. With the blasting of web exchanges, cybercrimes quickly expanded and with secrecy introduced by the web, Programmers endeavor to trap the end-clients through different structures, for example, phishing, SQL infusion, malware, man-in-the-center, space name framework burrowing, ransomware, web trojan, etc. Among this large number of assaults, phishing reports to be the most misdirecting assault. Our fundamental point of this paper is order of a phishing site with the guide of different AI procedures to accomplish greatest precision and succinct model.

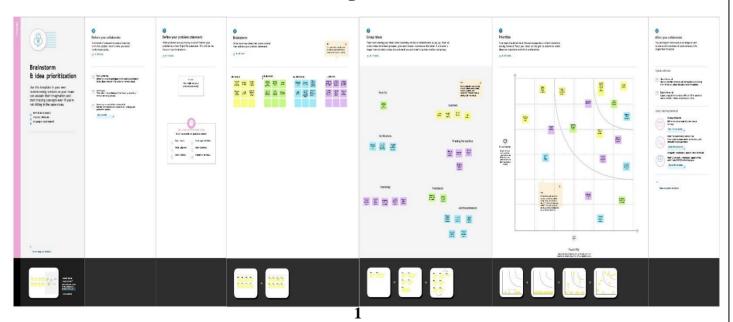
#### **CHAPTER 3**

#### **IDEATION & PROPOSED SOLUTION**

#### 3.1 Empathy Map Canvas



## 3.2 Ideation & Brainstorming



## 3.3 Proposed Solution

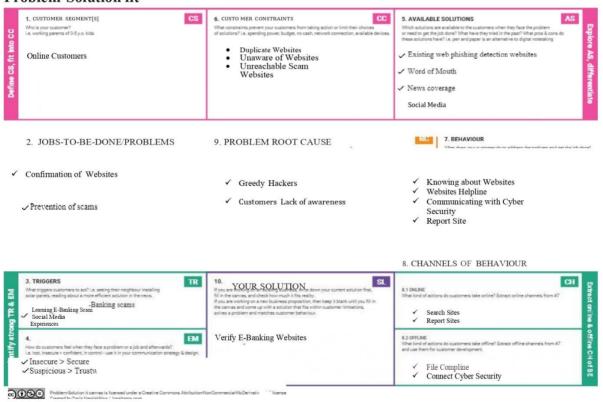
S.No	Parameter	Description				
2.	Problem Statement (Problem to besolved)  Idea / Solution description	Web phishing plans to take private data, for example, usernames, passwords, and charge card subtleties, via mimicking a genuine element. It will prompt data exposure and property harm. Huge associations might get caught in various types of scams.  To recognize and detect e-banking phishing sites, we proposed an intelligent, adaptable and successful framework that depends on utilizing grouping calculations(algorithms). We executed characterization calculations				
3.	Novelty / Uniqueness	and methods to extract the phishing datasets models to order their authenticity.  The e-banking phishing site can be recognized in view of a few significant qualities like URL and space personality, and security and encryption measures in the last phishing location rate. When a client				
		makes an exchange online when he makes installment through an e-banking site our framework will utilize an information mining calculation to identify whether the e-banking site is a phishing website or not.				

4.	Social Impact / Customer Satisfaction	The possibility of executing this thought is moderate neither simple nor intense in light of the fact that the framework needs to fulfill the fundamental prerequisites of the client as well as it should be an extenion(bridge) towards accomplishing high precision on,

		predicting and analysing the detected websitesor files to protect our customer to the fullest.
5.	Business Model (Revenue Model)	People buy subscription annually,to protect their files both locally and at remote location with the help of our cloud integrated flask app for web phishing detection.
6.	Scalability of the Solution	By implementing this system, the people canefficiently and effectively to gain knowledge about the web phishing techniques and waysto eradicate them by detection. This system can also be integrated with the future technologies

#### 3.4 Problem Solution fit:

#### **Problem-Solution fit**



## REQUIREMENT ANALYSIS

## **4.1 Functional Requirements**

Following are the functional requirements of the proposed solution.

#### **4.2 Non-functional Requirements:**

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

FR No.	Non-Functional Requirement	Description					
NFR-1	Usability	Analysis of customers' product					
		convenience in the plan cycle with					
		client experience as the center					
		maycertainly assist designers with					
		better getting a handle on clients					
		forthcoming requests in web phishing					
		discovery, conduct, and experience.					
NFR-2	Security	It ensures that any information included inside the framework or its parts will be protected from malwarethreats or unapproved access. On the off chance that you wish to forestall unapproved admittance to the administrator board, depict the login stream and different client jobs as framework conduct or client activities.					
NFR-3	Reliability	It specifies the likelihood that the system or its component will operate without failure for specified amount of time under prescribed conditions.					

NFR-4	Performance	It is concerned with a measurement of the	
		system's reaction time under various load	
		circumstances.	

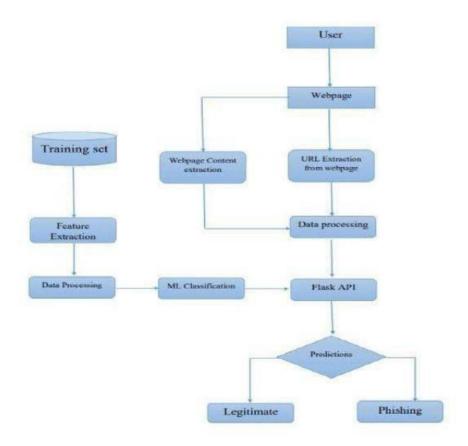
FR No.	_	Sub Requirement (Story / Sub-Task)
	(Epic)	
FR-1	Verifying input	User inputs an URL (Uniform Resource Locator)
		innecessary field to check its validation.
FR-2	Website Evaluation	Model evaluates the website using Blacklist and Whitelist approach
FR-3	Extraction and Prediction	It retrieves features based on heuristics and
		visual similarities. The URL is predicted by
		the model using Machine Learning methods
		such as Logistic Regressionand KNN.
FR-4	Real Time monitoring	The use of Extension plugin should provide a
		warningpop-up when they visit a website that
		is phished.
		Extension plugin will have the capability to also
		detectlatest and new phishing websites
FR-5	Authentication	Authentication assures secure site, secure
		processes
		and enterprise information security.

NFR-5	Availability	It represents the likelihood that a user will be ableto access the system at a certain moment in time. While it can be represented as an expected proportion of successful requests, it can also be defined as a percentage of time the system is operational within a certain time period.
NFR-6	Scalability	It has access to the highest workloads that will allow the system to satisfy the performance criteria. There are two techniques to enable the system to grow as workloads increase: Vertical and horizontal scaling.

#### **PROJECT DESIGN**

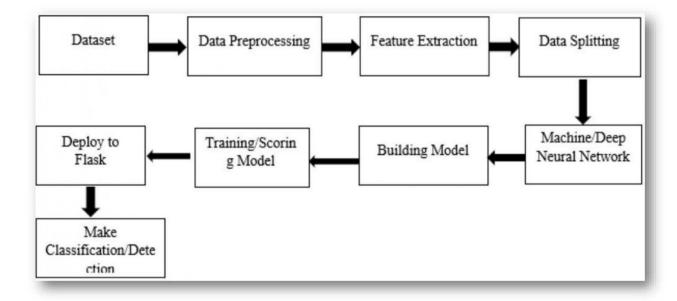
#### **5.1 Data Flow Diagrams:**

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.

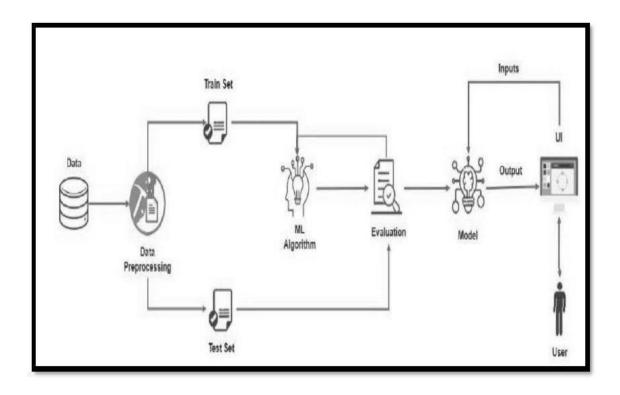


#### **5.2 Solution and Technical Architecture**

#### **Solution Architecture**



# **Technical Architecture: MODEL FOR WEB PHISHING DETECTION**



#### **5.3 USER STORIES**

Use the below template to list all the user stories for the product.

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile 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
	25	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 I can register & access through Facebook dashboard with Facebook		I can register & access the dashboard with Facebook Login	Low	Sprint-2	
	USN-4 As a user, I can register for the application through Gmail		Medium	Sprint-1		
	Login	USN-5	As a user, I can log into the application by entering email & password		High	Sprint-1
	Dashboard	3	84 %			
Customer (Web user)	User input	USN-1	As a user i can input the particular URL in the required field and waiting for validation.	I can go access the website without any problem	High	Sprint-1
Customer Care Executive	Feature extraction	USN-1	After i compare in case if none found on comparison then we can extract feature using heuristic and visual similarity approach.	As a User i can have comparison between websites for security.	High	Sprint-1
Administrator	Prediction	USN-1	Here the Model will predict the URL websites using Machine Learning algorithms such as Logistic Regression, KNN	In this i can have correct prediction on the particular algorithms	High	Sprint-1
	Classifier	USN-2	Here i will send all the model output to classifier in order to produce final result.	I this i will find the correct classifier for producing the result	Medium	Sprint-2

#### **PROJECT PLANNING & SCHEDULING**

#### **6.1 Sprint Planning & Estimation**

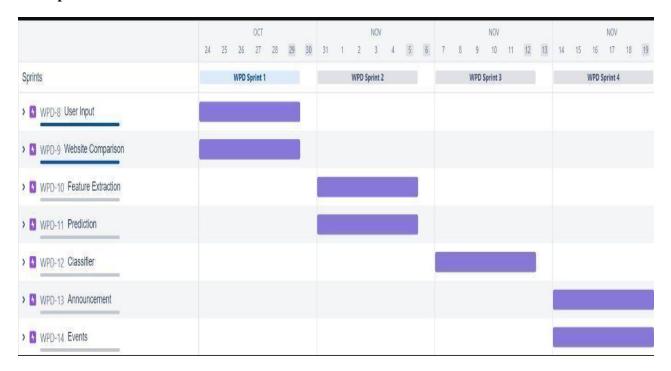
#### **Prepare Milestone & Activity List**

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	User input	USN-1	User inputs an URL in the required field to check its validation.	1	Medium	Najneen Banu
Sprint-1	Website Comparison	USN-2	Model compares the websites using Blacklist and Whitelist approach.	1	High	Najneen Banu
Sprint-2	Feature Extraction	USN-3	After comparison, if none found on comparison then it extract feature using heuristic and visual similarity.	2	High	Jahnavi . D
Sprint-2	Prediction	USN-4	Model predicts the URL using Machine learning algorithms such as logistic Regression, KNN.	1	Medium	Jahnavi . D
Sprint-3	Classifier	USN-5	Model sends all the output to the classifier and produces the final result.	1	Medium	M . Archana
Sprint-4	Announcement	USN-6	Model then displays whether the website is legal site or a phishing site.	1	High	A . AadhiLakshmi
Sprint-4	Events	USN-7	This model needs the capability of retrieving and displaying accurate result for a website.	1	High	A . AadhiLakshmi

## **6.2 Sprint Delivery Schedule**

SPRINT	TOTAL POINTS	DURATION	ATION SPRINT START SPR DATE DA		POINTS	SPRINT RELEASE DATE
SPRINT-1	20	6 DAYS	26October 2022	31October 2022	20	31October 2022
SPRINT-2	20	6 DAYS	1November 2022	6November 2022	20	6November 2022
SPRINT-3	20	6 DAYS	7November 2022	12November 2022	20	12November 2022
SPRINT-4	20	6 DAYS	13November 2022	18November 2022	20	18November 2022

#### 6.3 Reports from JIRA



#### **CHAPTER-7 CODING &**

#### **SOLUTION**

## 7.1 Feature 1 app.py

```
import numpy as np
from flask import Flask, request, jsonify, render_template
import pickle
from feature import FeatureExtraction
from sklearn import *
app = Flask(_name_,template_folder='template')
model = pickle.load(open('Phishing.pkl', 'rb'))
@app.route('/')
def predict1():
  return render_template('index.html')
@app.route('/predict')
def predict():
  return render_template('web.html')
@app.route('/y_predict',methods=['GET','POST'])
def y_predict():
  For rendering results on HTML GUI
  if request.method == 'POST':
    url = request.form['URL']
    checkprediction = FeatureExtraction(url)
    prediction = model.predict(np.array(checkprediction.features).reshape(-1,30))
    print(prediction)
    output=prediction[0]
    if(output==1):
      prediction="Your are safe!! This is a Legitimate Website."
    else:
      prediction="You are on the wrong site. Be cautious!"
    return render_template('web.html', prediction_text='{}'.format(prediction),url=url)
@app.route('/predict_api',methods=['POST'])
def predict api():
  For direct API calls trought request
  data = request.get_json(force=True)
  prediction = model.y_predict([np.array(list(data.value2()))])
  output = prediction[0]
  return jsonify(output)
```

```
if name=="main ":
  app.run()
 7.2 Feature 2
 import ipaddress
 import re
 import urllib.request
 from bs4 import BeautifulSoup
 import socket
 import requests
 from googlesearch import search
 import whois
 from datetime import date, datetime
 import time
 from dateutil.parser import parse as date parse
 from urllib.parse import urlparse
 class FeatureExtraction:
   features = []
   def _init_(self,url):
     self.features = []
     self.url = url
     self.domain = ""
     self.whois response = ""
     self.urlparse = ""
     self.response = ""
     self.soup = ""
     try:
       self.response = requests.get(url)
       self.soup = BeautifulSoup(response.text, 'html.parser')
     except:
       pass
     try:
       self.urlparse = urlparse(url)
       self.domain = self.urlparse.netloc
     except:
       pass
     try:
       self.whois_response = whois.whois(self.domain)
     except:
       pass
```

```
self.features.append(self.Usinglp())
  self.features.append(self.longUrl())
  self.features.append(self.shortUrl())
  self.features.append(self.symbol())
  self.features.append(self.redirecting())
  self.features.append(self.prefixSuffix())
  self.features.append(self.SubDomains())
  self.features.append(self.Hppts())
  self.features.append(self.DomainRegLen())
  self.features.append(self.Favicon())
  self.features.append(self.NonStdPort())
  self.features.append(self.HTTPSDomainURL())
  self.features.append(self.RequestURL())
  self.features.append(self.AnchorURL())
  self.features.append(self.LinksInScriptTags())
  self.features.append(self.ServerFormHandler())
  self.features.append(self.InfoEmail())
  self.features.append(self.AbnormalURL())
  self.features.append(self.WebsiteForwarding())
  self.features.append(self.StatusBarCust())
  self.features.append(self.DisableRightClick())
  self.features.append(self.UsingPopupWindow())
  self.features.append(self.lframeRedirection())
  self.features.append(self.AgeofDomain())
  self.features.append(self.DNSRecording())
  self.features.append(self.WebsiteTraffic())
  self.features.append(self.PageRank())
  self.features.append(self.GoogleIndex())
  self.features.append(self.LinksPointingToPage())
  self.features.append(self.StatsReport())
#1.Usinglp
def UsingIp(self):
  try:
    ipaddress.ip_address(self.url)
    return -1
  except:
    return 1
# 2.longUrl
def longUrl(self):
  if len(self.url) < 54:
                                                2
    return 1
  if len(self.url) >= 54 and len(self.url) <= 75:
    return 0
```

```
return -1
# 3.shortUrl
def shortUrl(self):
  match =
 re.search(bit\.ly|goo\.gl|shorte\.st|go2l\.ink|x\.co|ow\.ly|t\.co|tinyurl|tr\.im|is\.gd|cli\.gs|'
 \'\ 'yfrog\.com|migre\.me|ff\.im|tiny\.cc|url4\.eu|twit\.ac|su\.pr|twurl\.nl|snipurl\.com|'
 'short\.to|BudURL\.com|ping\.fm|post\.ly|Just\.as|bkite\.com|snipr\.com|fic\.kr|loopt\.us|'
 'doiop\.com|short\.ie|kl\.am|wp\.me|rubyurl\.com|om\.ly|to\.ly|bit\.do|t\.co|lnkd\.in|'
            'db\.tt|qr\.ae|adf\.ly|goo\.gl|bitly\.com|cur\.lv|tinyurl\.com|ow\.ly|bit\.ly|ity\.im|'
 'q\.gs|is\.gd|po\.st|bc\.vc|twitthis\.com|u\.to|j\.mp|buzurl\.com|cutt\.us|u\.bb|yourls\.org|'
 x\co| prettylinkpro\.com|scrnch\.me|filoops\.info|vzturl\.com|gr\.net|1url\.com|tweez\.me|v\
 .gd|tr\.im|link\.zip\.net', self.url)
  if match:
    return -1
  return 1
#4.Symbol@
def symbol(self):
  if re.findall("@",self.url):
    return -1
  return 1
# 5.Redirecting//
def redirecting(self):
  if self.url.rfind('//')>6:
    return -1
  return 1
# 6.prefixSuffix
def prefixSuffix(self):
    match = re.findall('\-', self.domain)
    if match:
       return -1
    return 1
  except:
    return -1
#7.SubDomains
def SubDomains(self):
                                                3
  dot count = len(re.findall("\.", self.url))
  if dot count == 1:
    return 1
```

```
elif dot count == 2:
    return 0
  return -1
# 8.HTTPS
def Hppts(self):
  try:
    https = self.urlparse.scheme
    if 'https' in https:
       return 1
    return -1
  except:
    return 1
#9.DomainRegLen
def DomainRegLen(self):
  try:
    expiration date = self.whois response.expiration date
    creation_date = self.whois_response.creation_date
    try:
      if(len(expiration date)):
         expiration date = expiration date[0]
    except:
      pass
    try:
      if(len(creation_date)):
         creation date = creation date[0]
    except:
      pass
    age = (expiration date.year-creation date.year)*12+ (expiration date.month-
 creation date.month)
    if age >=12:
      return 1
    return -1
  except:
    return -1
# 10. Favicon
def Favicon(self):
  try:
    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
                                                 3
    return -1
  except:
    return -1
```

```
#11. NonStdPort
def NonStdPort(self):
    port = self.domain.split(":")
    if len(port)>1:
       return -1
    return 1
  except:
    return -1
# 12. HTTPSDomainURL
def HTTPSDomainURL(self):
  try:
    if 'https' in self.domain:
       return -1
    return 1
  except:
    return -1
#13. RequestURL
def RequestURL(self):
  try:
    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
       i = i+1
                                                   3
    try:
       percentage = success/float(i) * 100
```

```
if percentage < 22.0:
         return 1
       elif((percentage >= 22.0) and (percentage < 61.0)):
         return 0
       else:
         return -1
    except:
       return 0
  except:
    return -1
# 14. AnchorURL
def AnchorURL(self):
  try:
    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 (url in
 a['href'] or self.domain in a['href']):
         unsafe = unsafe + 1
       i = i + 1
    try:
       percentage = unsafe / float(i) * 100
       if percentage < 31.0:
         return 1
       elif ((percentage >= 31.0) and (percentage < 67.0)):
         return 0
       else:
         return -1
    except:
       return -1
  except:
    return -1
# 15. LinksInScriptTags
def LinksInScriptTags(self):
  try:
    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
      i = i+1
    try:
       percentage = success / float(i) * 100
      if percentage < 17.0:
         return 1
      elif((percentage >= 17.0) and (percentage < 81.0)):
         return 0
      else:
         return -1
    except:
       return 0
  except:
    return -1
# 16. ServerFormHandler
def ServerFormHandler(self):
    if len(self.soup.find all('form', action=True))==0:
      return 1
    else:
      for form in self.soup.find_all('form', action=True):
         if form['action'] == "" or form['action'] == "about:blank":
           return -1
         elif self.url not in form['action'] and self.domain not in form['action']:
           return 0
         else:
           return 1
  except:
    return -1
#17. InfoEmail
def InfoEmail(self):
  try:
    if re.findall(r"[mail\(\)|mailto:?]", self.soap):
      return -1
    else:
      return 1
  except:
    return -1
#18. AbnormalURL
def AbnormalURL(self):
  try:
    if self.response.text == self.whois response:
       return 1
    else:
       return -1
```

```
except:
    return -1
# 19. WebsiteForwarding
def WebsiteForwarding(self):
  try:
    if len(self.response.history) <= 1:</pre>
      return 1
    elif len(self.response.history) <= 4:
       return 0
    else:
      return -1
  except:
    return -1
# 20. StatusBarCust
def StatusBarCust(self):
    if re.findall("<script>.+onmouseover.+</script>", self.response.text):
       return 1
    else:
      return -1
  except:
    return -1
# 21. DisableRightClick
def DisableRightClick(self):
  try:
    if re.findall(r"event.button ?== ?2", self.response.text):
       return 1
    else:
       return -1
  except:
    return -1
# 22. UsingPopupWindow
def UsingPopupWindow(self):
  try:
    if re.findall(r"alert\(", self.response.text):
       return 1
    else:
      return -1
  except:
    return -1
#23. IframeRedirection
                                                 3
def IframeRedirection(self):
    if re.findall(r"[<iframe>|<frameBorder>]", self.response.text):
```

```
return 1
    else:
      return -1
  except:
    return -1
# 24. AgeofDomain
def AgeofDomain(self):
  try:
    creation_date = self.whois_response.creation_date
    try:
      if(len(creation date)):
        creation date = creation date[0]
    except:
      pass
    today = date.today()
    age = (today.year-creation date.year)*12+(today.month-creation date.month)
    if age >=6:
      return 1
    return -1
  except:
    return -1
# 25. DNSRecording
def DNSRecording(self):
    creation date = self.whois response.creation date
    try:
      if(len(creation_date)):
        creation date = creation date[0]
    except:
      pass
    today = date.today()
    age = (today.year-creation date.year)*12+(today.month-creation date.month)
    if age >=6:
      return 1
    return -1
  except:
    return -1
# 26. WebsiteTraffic
def WebsiteTraffic(self):
    rank = BeautifulSoup(urllib.request.urlopen("http://data.alexa.com/data?cli=10&dat=s&url=" +
 url).read(), "xml").find("REACH")['RANK']
    if (int(rank) < 100000):
      return 1
```

```
return 0
       except:
              return -1
#27. PageRank
def PageRank(self):
      try:
              prank_checker_response = requests.post("https://www.checkpagerank.net/index.php",
     {"name": self.domain})
              global_rank = int(re.findall(r"Global Rank: ([0-9]+)", rank_checker_response.text)[0])
              if global rank > 0 and global rank < 100000:
                     return 1
              return -1
      except:
              return -1
# 28. GoogleIndex
def GoogleIndex(self):
      try:
              site = search(self.url, 5)
              if site:
                     return 1
              else:
                     return -1
      except:
              return 1
# 29. LinksPointingToPage
def LinksPointingToPage(self):
      try:
              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 0
              else:
                     return -1
      except:
              return -1
# 30. StatsReport
def StatsReport(self):
      try:
              url match = re.search(
                                                                                                                                                          3
     \label{lem:com} \label{lem:c
     .lt|ow\.ly', url)
```

```
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\.14
 5\.981'
 '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|14
 1\.8\.224\.221|10\.10\.10\.10|43\.229\.108\.32|103\.232\.215\.140|69\.172\.201\.153|'
 '216\.218\.185\.162|54\.225\.104\.146|103\.243\.24\.98|199\.59\.243\.120|31\.170\.160\.61|2
 13\.19\.128\.77|62\.113\.226\.131|208\.100\.26\.234|195\.16\.127\.102|195\.16\.127\.157|'
 '34\.196\.13\.28|103\.224\.212\.222|172\.217\.4\.225|54\.72\.9\.51|192\.64\.147\.141|198\.20
 0\.56\.183|23\.253\.164\.103|52\.48\.191\.26|52\.214\.197\.72|87\.98\.255\.18|209\.99\.17\.2
 7|'
 '216\.38\.62\.18|104\.130\.124\.96|47\.89\.58\.141|78\.46\.211\.158|54\.86\.225\.156|54\.82\
 .156\.19|37\.157\.192\.102|204\.11\.56\.48|110\.34\.231\.42', ip address)
    if url match:
      return -1
    elif ip_match:
      return -1
    return 1
  except:
    return 1
def getFeaturesList(self):
     return self.features
```

# CHAPTER 8 TESTING

#### 8.1 Test Cases

				Date	15-Nov-22								
				Team ID	PNT2022TMID21985	1							
				Project Name	Project-WebPhishing Detection								
				Maximum Marks	4marks								
Test case ID	Feature Type	Componen t	TestScenario	Pre-Requisite	Steps To Execute	TestData	Expected Result	Actual Result	Status	Comments	TC for Automation(Y/N)	BUG ID	Executed By
LoginPage_TC_OO 1	Functional	Home Page	Verify user is able to see the Landing Page when user can type the URLin the box		Enter URL and dick go     Type the URL     Werify whether it is processing or not.	https://phishing- shield.herokuapp.com/	Should Display the Webpage	Workingas expected	Pass		N		ARCHANA M
LoginPage_TC_OO 2	UI	Home Page	Verifythe UIeleme rits is Responsive		Enter URL and click go     Type orcopypaste the URL     Check whether the button is responsive or not     Reload and TestSimultaneously	https://phishing- shield.herokuapp.com/	Should Wait for Response and then getsAcknowledge	Workingas expected	Pass		N		aadhilakshmia
LoginPage_TC_OO 3	Functional	Home page	Verify whether the link is legitimate omot		Enter URL and click go     Type orcopypaste the URL     Check the website is legitimate or not     Observe the results	https://phishing- shield.herokuapp.com/	User should observe whether the websiteislegitimate ornot.	Workingas expected	Pass		N		JAHNAVI D
LoginPage_TC_OO	Functional	Home Page	Verify user is able to access the legitimate website ornot		Enter URL and click go Type orcopypaste the URL Check the website is legitimate or not Continue if the website is legitimate or be cautious if itis notlegitimate.	https://phishing- shield.herokuapp.com/	Application shouldshow that Safe We bpage or Unsafe.	Workingas expected	Pass		N		NAJNEEN BANU
LoginPage_TC_OO 5	Functional	Home Page	Testingthe website with multiple URLs		I. Enter URL ( https://phishing- shield.herokuapp.com /) and click 80 2. Type or copy paste the URL to test a. Check the website is legitimate or not 4. Continue if the website is secure orbe cautiousif itis not secure	1. https://avbalajee.github.io /welcome /welcome https://www.kince.edu salescript.info 5. https://www.spogle.com/ 6.delgets.com/	User can able to identify the websites whether it is secure or not	Workingas expected	Pass		N		ARCHANA M

#### 8.2 User Acceptance Testing

#### **UAT Execution & Report Submission**

#### 1. Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [Web Phishing Detection] project at the time of the release to User Acceptance Testing (UAT).

#### 2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and howthey 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 3	1	0	1

Skipped	0	0	0	0	0
Won't Fix	0	0	2	1	3
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	<b>Total Cases</b>	Not Tested	Fail	Pass
Print Engine	10	0	0	10
Client Application	50	0	0	50
Security	5	0	0	4
Outsource Shipping	3	0	0	3
Exception Reporting	10	0	0	9
Final Report Output	10	0	0	10
Version Control	4	0	0	4

#### **CHAPTER 9**

#### **RESULTS**

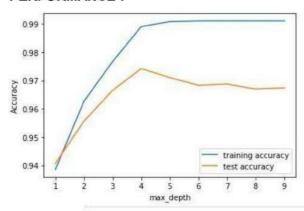
#### 9.1 Performance Metrics

S.No.	Parameter	Values	Screenshot			
1.	Metrics	Classification Model: Gradient Boosting Classification Accuray Score- 97.4%	to [10] economics the constitution found of the major promjection than those in prompts and promjection for the major promjection of the following promjection of			
2.	Tune the Model	Hyperparameter Tuning - 97% Validation Method – KFOLD & Cross Validation Method	Wilcome Speed such tool  [27] Shim and stress including the same and such as the same and suc			

#### 1. METRICS: CLASSIFICATION REPORT:

In [52]: #computing the classification report of the model print(metrics.classification\_report(y\_test, y\_test\_gbc)) precision recall f1-score support 0.99 0.96 0.97 -1 976 1 0.97 0.99 0.98 1235 0.97 2211 accuracy macro avg 0.98 0.97 weighted avg 0.97 0.97 2211 0.97 0.97 2211

#### PERFORMANCE:



Out[83]:		ML Model	Accuracy	f1_score	Recall	Precision
	0	Gradient Boosting Classifier	0.974	0.977	0.994	0.986
	1	CatBoost Classifier	0.972	0.975	0.994	0.989
	2	Random Forest	0.969	0.972	0.992	0.991
	3	Support Vector Machine	0.964	0.968	0.980	0.965
	4	Decision Tree	0.958	0.962	0.991	0.993
	5	K-Nearest Neighbors	0.956	0.961	0.991	0.989
	6	Logistic Regression	0.934	0.941	0.943	0.927
	7	Naive Bayes Classifier	0.605	0.454	0.292	0.997
	8	XGBoost Classifier	0.548	0.548	0.993	0.984
	9	Multi-layer Perceptron	0.543	0.543	0.989	0.983

## **Model Training**

# Reading the dataset

]: DS	S=pd.	read_c	sv("/content/dataset_we	bsite.csv")						
]: DS	S.hea	d								
]:										
]: DS	5									
]:	i	ndex	having_IPhaving_IP_Address	URLURL_Length	Shortining_Service	having_At_Symbol	double_slash_redirecting	Prefix_Suffix	having_Sub_Domain	SSLfinal_Stat
	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	
			10			***	***		***	
			IV.	-1	1	-1	1	1	1	
110	050	1051	1	-1		1/3				

#### **CHAPTER-10**

### Advantages of web phishing detection

- 1. Improve on Inefficiencies of SEG and Phishing Awareness Training
- 2. It Takes a Load off the Security Team
- 3. It Offers a Solution, Not a Tool
- 4. Separate You from Your Competitors
- 5. This system can be used by many e-commerce websites in order to have good customer relationships.
- 6. If internet connection fails this system will work

# Disadvantages of web phishing detection

- 1. All website related data will be stored in one place.
- 2. It is a very time-consuming process.

#### **CHAPTER 11**

#### **CONCLUSION**

It is outstanding that a decent enemy of phishing apparatus ought to anticipate the phishing assaults in a decent timescale. We accept that the accessibility of a decent enemy of phishing device at a decent time scale is additionally imperative to build the extent of anticipating phishing sites. This apparatus ought to be improved continually through consistent retraining. As a matter of fact, the accessibility of crisp and cutting-edge preparing dataset which may gained utilizing our very own device [30, 32] will help us to retrain our model consistently and handle any adjustments in the highlights, which are influential in deciding the site class. Albeit neural system demonstrates its capacity to tacklea wide assortment of classification issues, the procedure of finding the ideal structure is verydifficult, and much of the time, this structure is controlled by experimentation. Our model takes care of this issue via computerizing the way toward organizing a neural system conspire; hence, on the off chance that we construct an enemy of phishing model and for any reasons we have to refresh it, at that point our model will encourage this procedure, that is, since our model will mechanize the organizing procedure and will request scarcely any client defined parameters.

#### **CHAPTER-12**

#### **Future Scope**

There is an scope for future improvement of this implement. We will carry out this utilizing progressed profound learning technique to work on the exactness and accuracy. Upgrades can be done in a proficient way. Consequently, the venture is adaptable and can be upgraded whenever with further advanced features.

#### **CHAPTER-13**

#### **Appendix:**

- 1. Application Building
- 2. Collection of Dataset
- 3. Data Pre-processing
- 4. Integration of Flask App with IBM Cloud
- 5. Model Building
- 6. Performance Testing
- 7. Training the model on IBM
- 8. User Acceptance Testing
- 9. Ideation Phase
- 10. Preparation Phase
- 11. Project Planning
- 12. Performance Testing
- 13. User Acceptance Testing

Project Link: https://github.com/IBM-EPBL/IBM-Project-17682-1659675186

Project Demo Link:

https://drive.google.com/file/d/1CSBqRGSAKW9vQAHetZ4gC1\_grA\_v6I3M/view?usp=drivesdk