IBM

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PROJECT REPORT ON WEB PHISHING DETECTION

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ABSTRACT

Phishing is the most commonly used social engineering and cyber attack. Through such attacks, the phisher targets naive online users by tricking them into revealing confidential information, with the purpose of using it fraudulently. In order to avoid getting phished, Users should have awareness of phishing websites. Have a blacklist of phishing websites which requires the knowledge of website being detected as phishing. Detect them in their early appearance, using machine learning and deep neural network algorithms. Of the above three, the machine learning based method is proven to be most effective than the other methods. A phishing website is a commonsocial engineering method that mimics trustful uniform resource locators (URLs) and webpages. The objective of this project is to train machine learning models and deep neural nets on the dataset created to predict phishing websites. Both phishing and benign URLs of websites are gathered to form a dataset and from them required URL and website content-based features are extracted. The performance level of each model is measured and compared.

Keywords: Deep learning, Machine learning, Phishing website attack, Phishing website detection, Anti-phishing website, Legitimate website , Phishing website datasets, Phishing website features.

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

1. Pandas
2. Numpy
3. Seaborn Matplotlib

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 misuse it. 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.

Phishing may be law-breaking, the explanation behind the phishers doing this crime is that it is terribly trustworthy to try to do this, it doesn't value something and it effective. The phishing will truly get entry to the email identity of somebody it's terribly sincere to are looking for out the email identification currently every day and you will send an email to every person is freely offered throughout the globe. These attacker's vicinity terribly much less price and electricity to urge valuable know-how quick and truly. The phishing frauds effects malware infections, statistics loss, fraud, etc.

information at some stage. in which those cyber criminals have an interest is that the crucial data of a user similar to the password, OTP, credit/ debit card numbers CVV, sensitive know- how associated with business, medical understanding, confidential information, etc commonly these criminals conjointly acquire data which may provide them directly get admission to do the social media

account their emails.

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.

1.1 PROJECT OVERVIEW

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

1.2 PURPOSE

1. To develop an unsupervised deep learning method to generate insight from a URL.

2. The study can be extended in order to generate an outcome for a larger network and protect the privacy of an individual.

CHAPTER 2

LITERATURE SURVEY

PAPER 2.1: PHISH-SAFE: URL Features-Based Phishing Detection System UsingMachine Learning.

Authors: An kit Kumar Jain **&** B.B.Gupta

Abstract:

Today, phishing is one of the most serious cyber-security threat in which attackers steal sensitive information such as personal identification number(PIN), credit card details, login, password, etc., from Internet users. In this paper, we proposed a machine learning based anti-phishing system (i.e., named as PHISH- SAFE) based on Uniform Resource Locator (URL) features. To evaluate the performance of our proposed system, we have taken 14 features from URL to detect a website as a phishing or non-phishing. The proposed system is trained using more than 33,000 phishing and legitimate URLs with

SVM and Naïve Bayes classifiers.

Our experiment results show more than 90% accuracy in detecting phishing websites using SVM classifier.

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

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

Abstract:

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 proposed 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: Phishing website detection based on effective machine learning approach **Authors:** Lokesh.G & Gowtham.B **Abstract:** Phishing a form of cyber-attack, which has an adverse effect on people where the user is directed to fake websites and duped to reveal their sensitive and personal information which includes passwords of accounts, bank details, atm pin-card details etc. Hence protecting sensitive information from malwares or web phishing is difficult. Machine learning is a study of data analysis and scientific study of algorithms, which has shown results in recent times in opposing phishing pages when distinguished with visualization, legal solutions, including awareness workshops and classic anti-phishing approaches. This paper examines the applicability of ML techniques in identifying phishing attacks and report their positives and negatives. In specific, there are many ML algorithms that have been explored to declare theappropriate choice that serve as anti-phishing tools. We have designed a Phishing Classification system which extracts features that are meant to defeat common phishing detection approaches. We also make use of numeric representation along with the comparative study of classical machine learningtechniques like Random Forest, K nearest neighbours, Decision Tree, Linear SVC classifier, One class SVM classifier and wrapper-based features selection which contains the metadata of URLs and use the information to determine if a

website is legitimate or not.

PAPER 2.5: Machine Learning and Deep Learning Based Phishing Websites Detection: The Current 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 attackers 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 era, the Internet has made its way to become an inevitable part of our lives. It leads to many convenient experiences in our lives regarding communication, entertainment, education, shopping and so on. As we progress into online life, criminals view the Internet as an opportunity to transfer their physical crimes into a virtualenvironment. The Internet not only provides convenience in various aspects but also has its downsides, for example, the anonymity that the Internet provides to its users. Presently, many types of crimes have been conducted online. Hence, the main focus of our research is phishing. Phishing is a type of cybercrime where the targets are lured or tricked into giving up sensitive information, such as Social Security Number personal identifiable information and passwords. This obtainment of such information is done fraudulently. Given that phishing is a very broad topic, we have decided that this research should specifically focus on phishing websites.

Rao et al. [1] proposed a novel classification approach that use heuristic-based feature extraction approach. In this, they have classified extracted features into three categories

such as URL Obfuscation features, Third-Party-based features, Hyperlink-based features. Moreover, proposed technique gives 99.55% accuracy. Drawback of this is that as this model uses third party features, classification of website dependent on speed of third-party services. Also this model is purely depends on the quality and

quantity of the training set and Broken links feature extraction has a Volume 3.

Chunlin et al. [2] proposed approach that primarily focus on character frequency 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, SeptemberOctober-2018 | http:// ijsrcseit.com Purvi Pujara et al. Int J S Res CSE & IT. 2018 September-October-2018; 3(7) : 395-399 398 features such as lexical features, URL based feature, network based features and domain based feature.

Luong et al. [11] proposed new technique to detect phishing website. In proposed method, Author used six heuristics that are primary domain, sub domain, path domain, page rank, and alexa rank, alexa reputation whose weight and values are evaluated. This approach gives 97 % accuracy but still improvement can be done by enhancing more heuristics.

Ahmad et al.[12] proposed three new features to improve accuracy rate for phishing website detection. In this paper, Author used both type of features as commonly known and new features for classification of phishing and non-phishing site. At the end author has concluded this work can be enhanced by using this novel features with decision tree machine learning classifiers.

2.2 REFERENCES

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Mohammad et al. [13] proposed model that automatically extracts important features for phishing website detection without requiring any human intervention. Author has concluded in this paper that the process of extracting feature by their tool is much faster and reliable than any manual extraction

2.3 PROBLEM STATEMENT DEFENETION

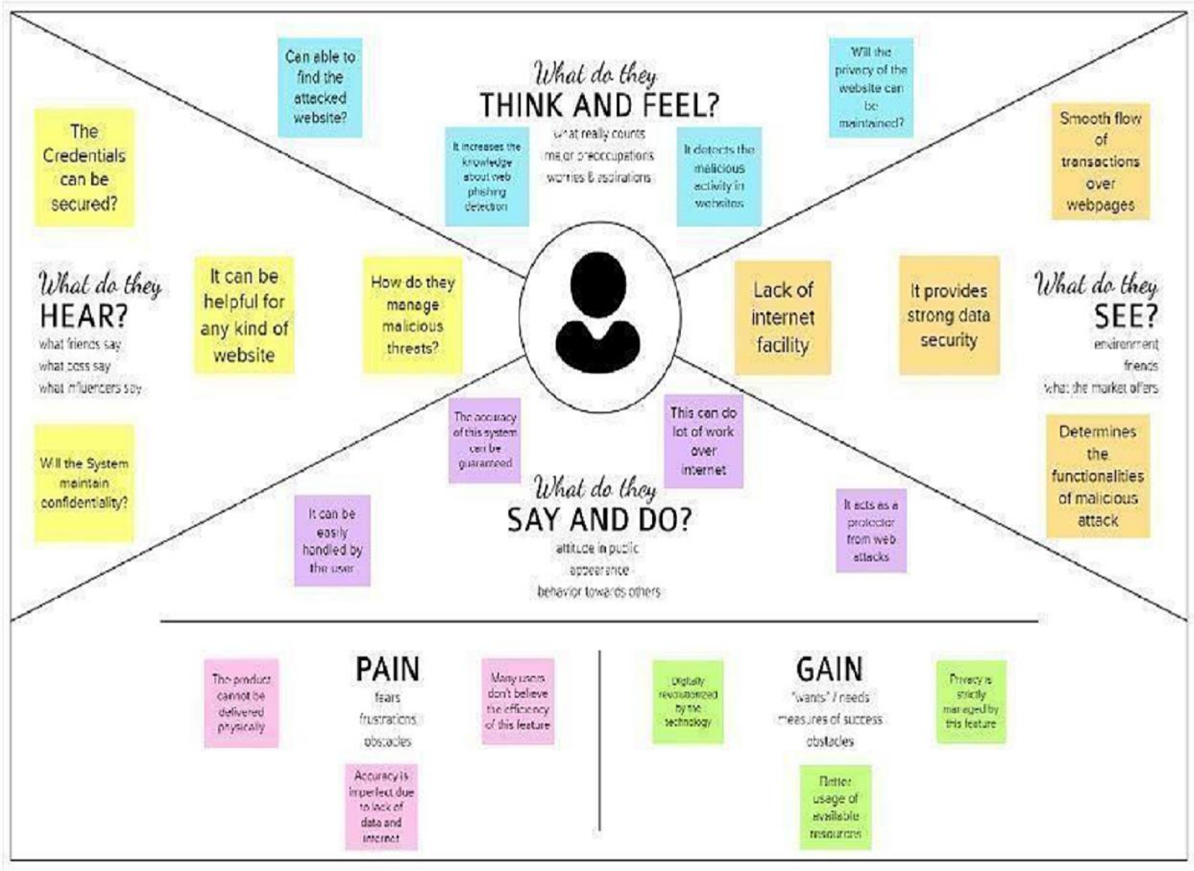
In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking 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.

Internet has dominated the world by dragging half of the world's population exponentially into the cyber world. With the booming of internet transactions, cybercrimes rapidly increased and with anonymity presented by the internet, Hackers attempt to trap the end-users through various forms such as phishing, SQL injection, malware, man-in-the-middle, domain system tunnelling, ransomware, web trojan, and so on. Among all these attacks, phishing reports to be the most deceiving attack. Our main aim of this paper is classification of a phishing website with the aid of various machine learning techniques to achieve maximum accuracy and concise model'

CHAPTER 3

IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas



3.2 Ideation & Brainstorming

3.3 Proposed Solution

S.No.	Parameter	Description

1.	Problem Statement (Problem to besolved)	1. Web phishing aims to steal private information, such as usernames, passwords, and credit card details, byway of impersonating a legitimate entity. 2. It will lead to information disclosureand property damage. 3. Large organizations may get trapped indifferent kinds of scams.
2.	Idea / Solution description	In order to detect and predict ebanking 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.
3.	Novelty / Uniqueness	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 auser 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 ebanking website is a phishing website or not.

4.	Social Impact / Customer Satisfaction	The feasibility of implementing this idea ismoderate neither easy nor tough becausethe system needs to satisfy the basic requirements of the customer as well as itshould act as a bridge towards achieving high accuracy on
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 systemcan also be integrated with the future technologies

3.4 Problem Solution

REQUIREMENT ANALYSIS

4.1 Functional Requirements

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	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.

4.2 Non-f unctional Requirements:

Following are the non-functional requirements of the proposed solution

FR No.	**Non-Functional Requirement**	**Description**
NFR-1	**Usability**	Analysis of consumers' product usability in the design process with user experience as the core maycertainly help designers better grasp users' prospective demands in web phishing detection, behaviour, and experience.

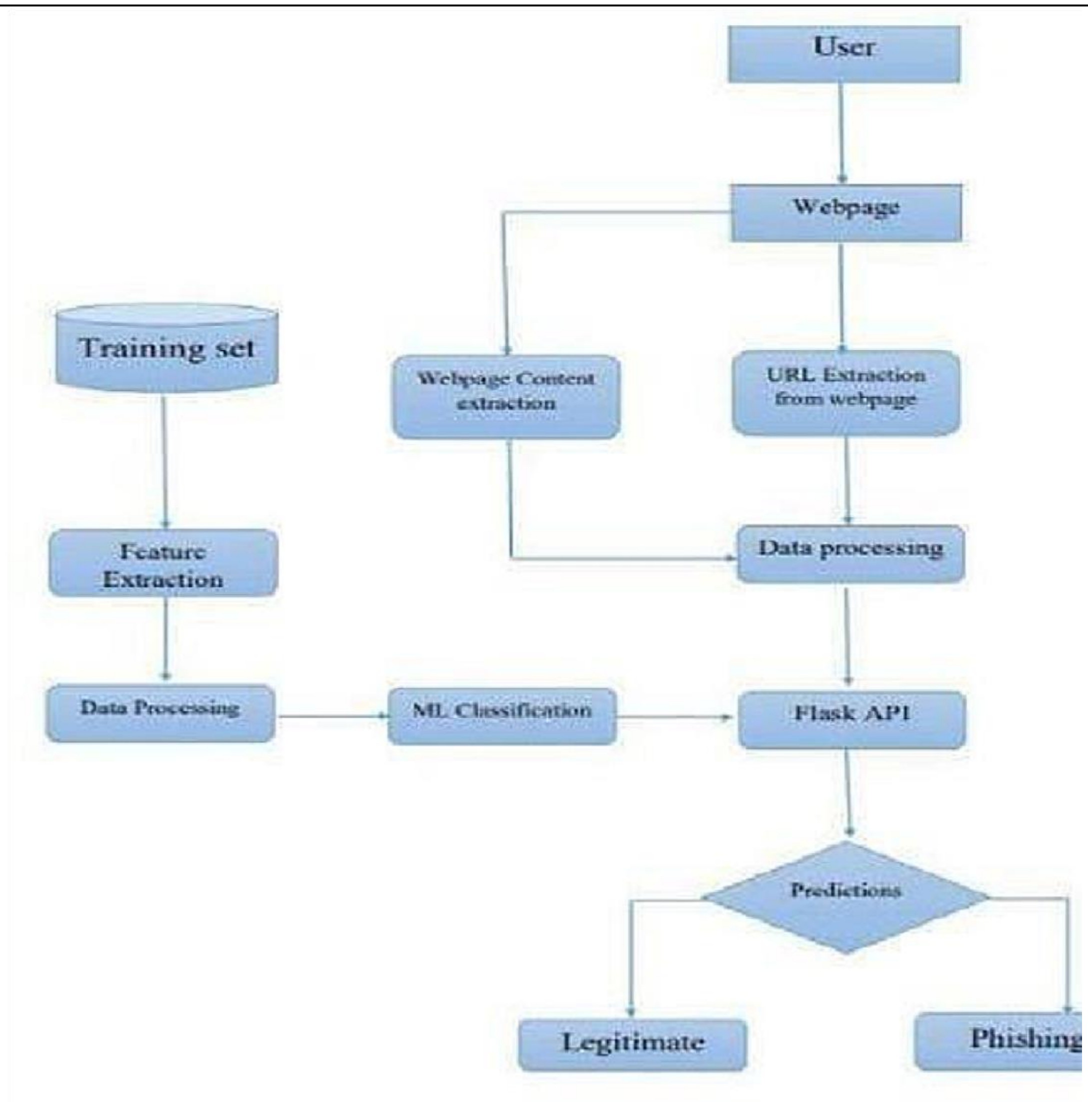
NFR-2	**Security**	It guarantees that any data included within the system or its components will be safe from malwarethreats or unauthorised access. If you wish to prevent unauthorised access to the admin panel, describe the login flow and different user roles as system behaviour or user actions.
NFR-3	**Reliability**	It specifies the likelihood that the system or itscomponent will operate
		without failure for a specified amount of time under prescribed conditions.
NFR-4	**Performance**	It is concerned with a measurement of the system'sreaction time under various load circumstances.

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

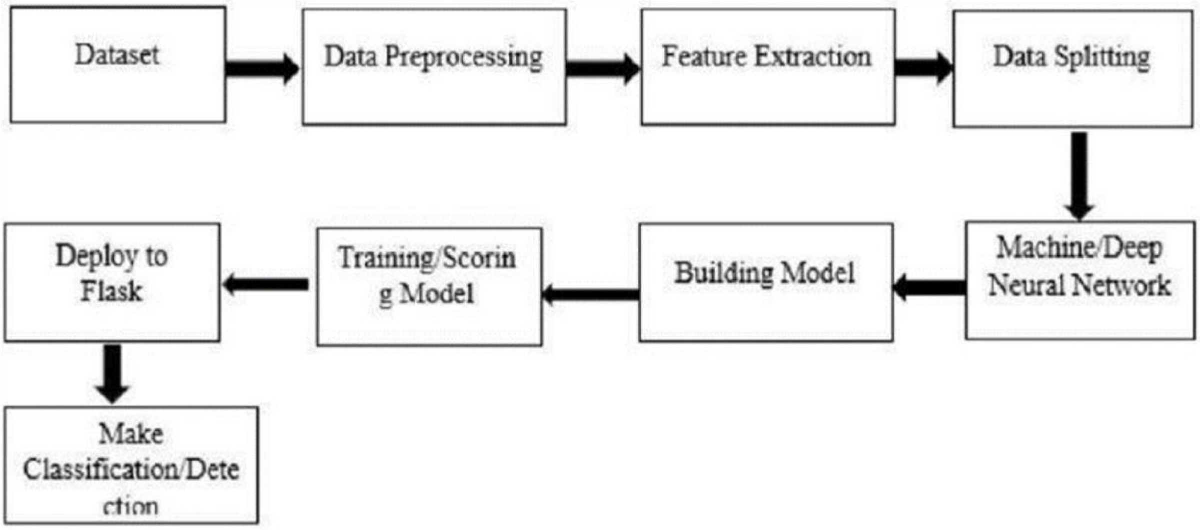
5.1 Data Flow Diagrams:

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.


User
Webpage
Training set
Webpage Content extraction
URL Extraction from webpage
Feature Extraction
Data processing
Data Processing
ML Classification
Flask API
Predictions
Legitimate
Phishing

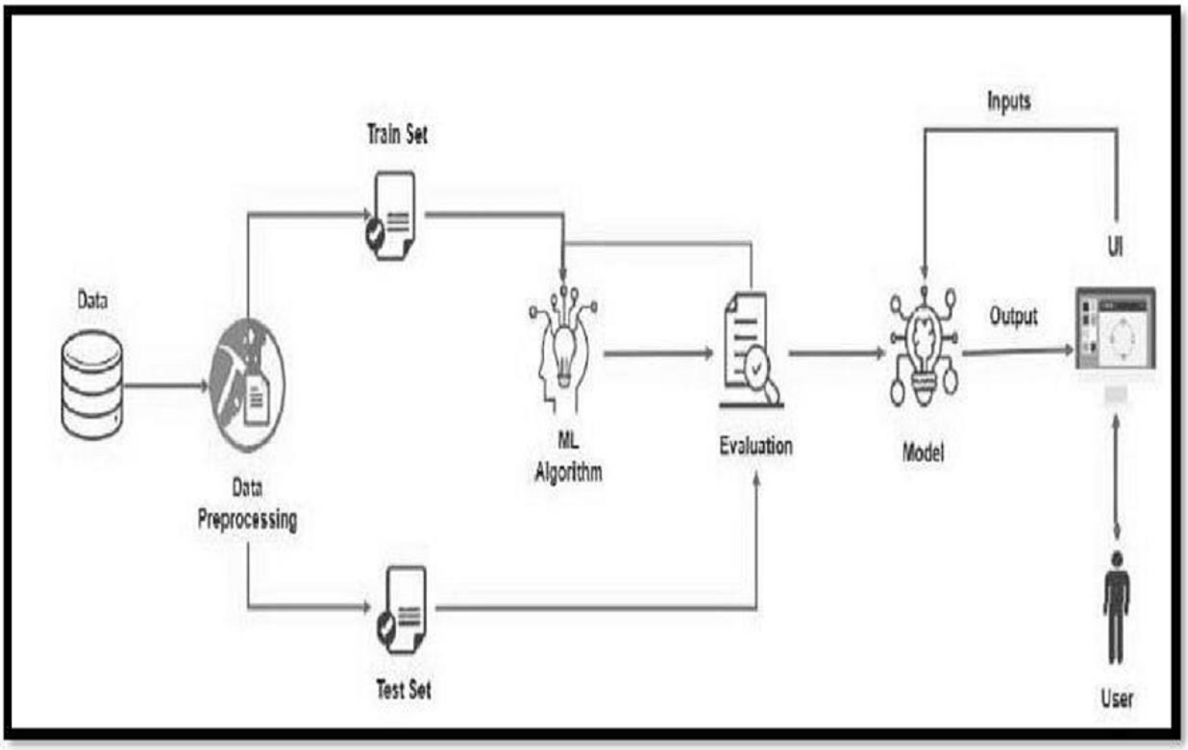
5.2 Solution and Technical Architecture

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
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through 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					
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

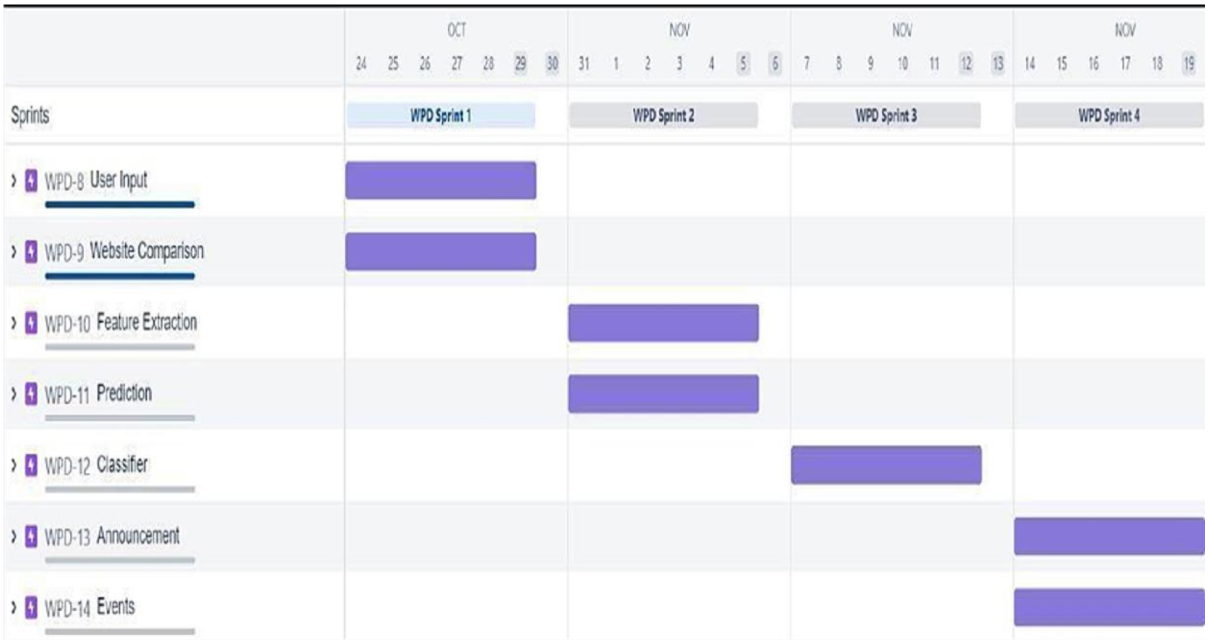
6.1 Sprint Planning & Estimation

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	High	VIJAY N
Sprint-1	Website Comparison	USN-2	Model compares the websites using Blacklist and Whitelist approach.	1	High	BAVYABAI S
Sprint-2	Feature Extraction	USN-3	After comparison, if none found on comparison then it extract feature using heuristic and visual similarity.	2	High	ARUN R
Sprint-2	Prediction	USN-4	Model predicts the URL using Machine learning algorithms such as logistic Regression, KNN.	1	Medium	AJITH D
Sprint-3	Classifier	USN-5	Model sends all the output to the classifier and produces the final result.	1	Medium	VIJAY N
Sprint-4	Announcement	USN-6	Model then displays whether the website is legal site or a phishing site.	1	High	BAVYABAI S
Sprint-4	Events	USN-7	This model needs the capability of retrieving and displaying accurate result for a website.	1	High	AJITH D

6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	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

6.3 Reports from JIRA



CHAPTER-7

CODING & SOLUTION

7.1 Feature 1

```
#app.py

# importing required libraries



from feature import FeatureExtraction from
flask import Flask, request, render_template
import numpy as np import pandas as pd
```

```
from sklearn import metrics import warnings
import pickle
warnings.filterwarnings('ignore')



file = open("model.pkl",
"rb") gbc = pickle.load(file)
file.close()



app = Flask(name__)



@app.route("/", methods=["GET", "POST"])  def

index():

   if request.method == "POST":


       url = request.form["url"]  obj
       = FeatureExtraction(url)

         x = np.array(obj.getFeaturesList()).reshape(1, 30)
```

```
y_pred = gbc.predict(x)[0]

#1 is safe #-1 is unsafe y_pro_phishing = gbc.predict_proba(x)[0,
0] y_pro_non_phishing =

gbc.predict_proba(x)[0, 1]

# if(y_pred ==1 ): pred = "It is {0:.2f} % safe to go
".format(y_pro_phishing*100) return render_template('index.html',
xx=round(y_pro_non_phishing, 2), url=url) return
render_template("index.html", xx=-1)


if __name_____==
"main":

app.run(debug=True, port=2002)
```

7.2 Feature 2

```
#feature.py 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.UsingIp())
      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.IframeRedirection())
    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.UsingIp



 def UsingIp(self):  try:


      ipaddress.ip_address(self.u
    rl) return -1 except:


      return 1



 # 2.longUrl def
 longUrl(self):  if
 len(self.url) < 54:
```

```
        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\.u
 s|'

 '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|qr\.net|1url\.com|tweez\.
 me|v\.g
 d|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):

try:

      match = re.findall('\-',
      self.domain) if match:

         return 1
   return 1 except:

      return -1
```

```
# 7.SubDomains
def
SubDomains(self):

  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 return -1 except:

      return -1



# 11. NonStdPort
def

NonStdPort(self):

   try:

      port =
      self.domain.split(":") if
      len(port) > 1:

         return 1
   return 1
   except:
   return -1


# 12.
HTTPSDomainURL def HTTPSDomainURL(sel
```

```
f): 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


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):
```

```
try:  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: return 1 elif

      len(self.response.history) <= 4:


         return 0
      else:
```

```
        return -1
    except:

        return -1



# 20. StatusBarCust def

StatusBarCust(self): try: 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
def

IframeRedirection(self):

   try: 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):

      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



    # 26. WebsiteTraffic
    def

    WebsiteTraffic(self):  try:

        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(


'at\.ua|usa\.cc|baltazarpresentes\.com\.br|pe\.hu|esy\.es|hol\.es|sweddy\.com|myjino\.
ru|96\.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|7
8\.46\.

21

1\.158|181\.174\.165\.13|46\.242\.145\.103|121\.50\.168\.40|83\.125\.22\.219|46\.242\
.145\. 98
```

|'

'107\.151\.148\.44|107\.151\.148\.107|64\.70\.19\.203|199\.184\.144\.27|107\.151\.148\.108| 10

7\.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\.27|'

'216\.38\.62\.18|104\.130\.124\.96|47\.89\.58\.141|78\.46\.211\.158|54\.86\.225\.156|54\.82\.1

56\.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	PNT2022TMID40752
Project Name	Project - Web Phishing Detection
Maximum Marks	4 marks

Test case ID	Feature Type	Componen t	Test Scenario	Pre-Requisite	Steps To Execute	Test Data https://phishingshield.herokuapp.com/	Expected Result	Actual Result	Status	Comments	TC for Automation(Y/N)	BU G ID	Executed By
LoginPage_TC_OO 1	Functional	Home Page	Verify user is able to see the Landing Page when user can type the URL in the box		1.Enter URL and click go 2.Type the URL 3.Verify whether it is processing or not.		Should Display the Webpage	Working as expected	Pass		N		N Vijay
LoginPage_TC_OO 2	UI	Home Page	Verify the UI elements is Responsive		1.Enter URL and click go 2. Type or copy paste the URL 3. Check whether the button is responsive or not 4. Reload and Test Simultaneously	https://phishing shield.herokuapp.com/	Should Wait for Response and then gets Acknowledge	Working as expected	Pass		N		S Bavya bai
LoginPage_TC_OO 3	Functional	Home page	Verify whether the link is legitimate or not		1.Enter URL and click go 2. Type or copy paste the URL 3. Check the website is legitimate or not 4. Observe the results	https phishingshield://.herokuapp.com/	User should observe whether the website is legitimate or not.	Working as expected	Pass		N		R Arun
LoginPage_TC_OO 4	Functional	Home Page	Verify user is able to access the legitimate website or not		1.Enter URL and click go 2. Type or copy paste the URL 3. Check the website is legitimate or not 4. Continue if the website is legitimate or be cautious if it is not legitimate.	https://phishingshield.herokuapp.com/	Application should show that Safe Webpage or Unsafe.	Working as expected	Pass		N		D Ajith
LoginPage_TC_OO 5	Functional	Home Page	Testing the website with multiple URLs		1.Enter URL (https://phishingshield.herokuapp.com/) and click go 2. Type or copy paste the URL to test 3. Check the website is legitimate or not 4. Continue if the website is secure or be cautious if it is not secure	1.https://avbalajee.github.io/welcometotalpad.com 2.https://www.kince.edu 3.salescript.info 4.https://www.google.com/delgets.com	User can able to identify the websites whether it is secure or not	Working as expected	Pass		N		N Vijay

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 how they were resolved

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

3.Test Case Analysis

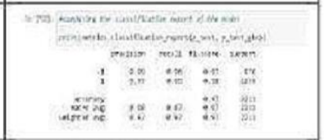
This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	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

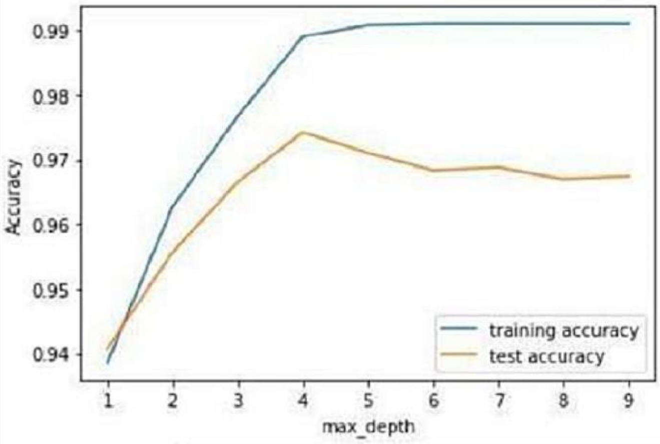
S.No.	Parameter	Values	Screenshot
1.	Metrics	**Classification Model:** **Gradient Boosting Classification** Accuray Score- 97.4%	
2.	Tune the Model	Hyperparameter Tuning - 97% Validation Method – KFOLD & Cross Validation Method	

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

          -1       0.99      0.96      0.97       976
           1       0.97      0.99      0.98      1235

    accuracy                           0.97      2211
   macro avg       0.98      0.97      0.97      2211
weighted avg       0.97      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

2. TUNE THE MODEL – HYPERPARAMETER TUNING

In [58]:
```
#HYPERPARAMETER TUNING
grid.fit(X_train, y_train)
```

Out[58]:
```
GridSearchCV

GridSearchCV(cv=5,
             estimator=GradientBoostingClassifier(learning_rate=0.7,
                                                  max_depth=4),
             param_grid={'max_features': array([1, 2, 3, 4, 5]),
                         'n_estimators': array([ 10,  20,  30,  40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140, 150, 160, 170, 180, 190, 200])})

estimator: GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=0.7, max_depth=4)

GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=0.7, max_depth=4)
```

In [59]:
```
print("The best parameters are %s with a score of %0.2f"
      % (grid.best_params_, grid.best_score_))
```

```
The best parameters are {'max_features': 5, 'n_estimators': 200} with a score of 0.97
```

VALIDATION METHODS: KFOLD & Cross Folding

Wilcoxon signed-rank test

```
In [78]: #KFOLD and Cross Validation Model

         from scipy.stats import wilcoxon
         from sklearn.datasets import load_iris
         from sklearn.ensemble import GradientBoostingClassifier
         from xgboost import XGBClassifier
         from sklearn.model_selection import cross_val_score, KFold

         # Load the dataset
         X = load_iris().data
         y = load_iris().target

         # Prepare models and select your CV method
         model1 = GradientBoostingClassifier(n_estimators=100)
         model2 = XGBClassifier(n_estimators=100)
         kf = KFold(n_splits=20, random_state=None)
         # Extract results for each model on the same folds
         results_model1 = cross_val_score(model1, X, y, cv=kf)
         results_model2 = cross_val_score(model2, X, y, cv=kf)
         stat, p = wilcoxon(results_model1, results_model2, zero_method='zsplit');
         stat

Out[78]: 95.0
```

5x2CV combined F test

```
In [89]: from mlxtend.evaluate import combined_ftest_5x2cv
         from sklearn.tree import DecisionTreeClassifier, ExtraTreeClassifier
         from sklearn.ensemble import GradientBoostingClassifier
         from mlxtend.data import iris_data

         # Prepare data and clfs
         X, y = iris_data()
         clf1 = GradientBoostingClassifier()
         clf2 = DecisionTreeClassifier()

         # Calculate p-value
         f, p = combined_ftest_5x2cv(estimator1=clf1,
                                     estimator2=clf2,
                                     X=X, y=y,
                                     random_seed=1)

         print('f-value:', f)
         print('p-value:', p)

         f-value: 1.727272727272733
         p-value: 0.2840135734291782
```

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 tackle a wide assortment of classification issues, the procedure of finding the ideal structure is very difficult, 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 a scope for future development of this project. We will implement this using advanced deep learning method to improve the accuracy and precision. Enhancements can be done in an efficient manner. Thus, the project is flexible and can be enhanced at any time with more 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-45239-1660728968

Project Demo Link: https://github.com/IBM-EPBL/IBM-Project-45409-1660729898#demo-video