# IBM
# NALAIYA THIRAN

## 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 intheir early appearance, using machine learning and deep neural network algorithms. Of the above three, the machine learning based method is provento 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 anddeep 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

- Pandas
- Numpy
- 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 e-mail 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

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

## 1.2 PURPOSE

- To develop an unsupervised deep learning method to generate insight from a URL.
- 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:** Ankit 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, September-October-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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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

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[13] Rami M. Mohammad, Fadi Thabtah, Lee McCluskey: An Assessment of Features Related to Phishing Websites using an Automated Technique:In The 7th International Conference for Internet Technology and Secured Transactions,IEEE,2012

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

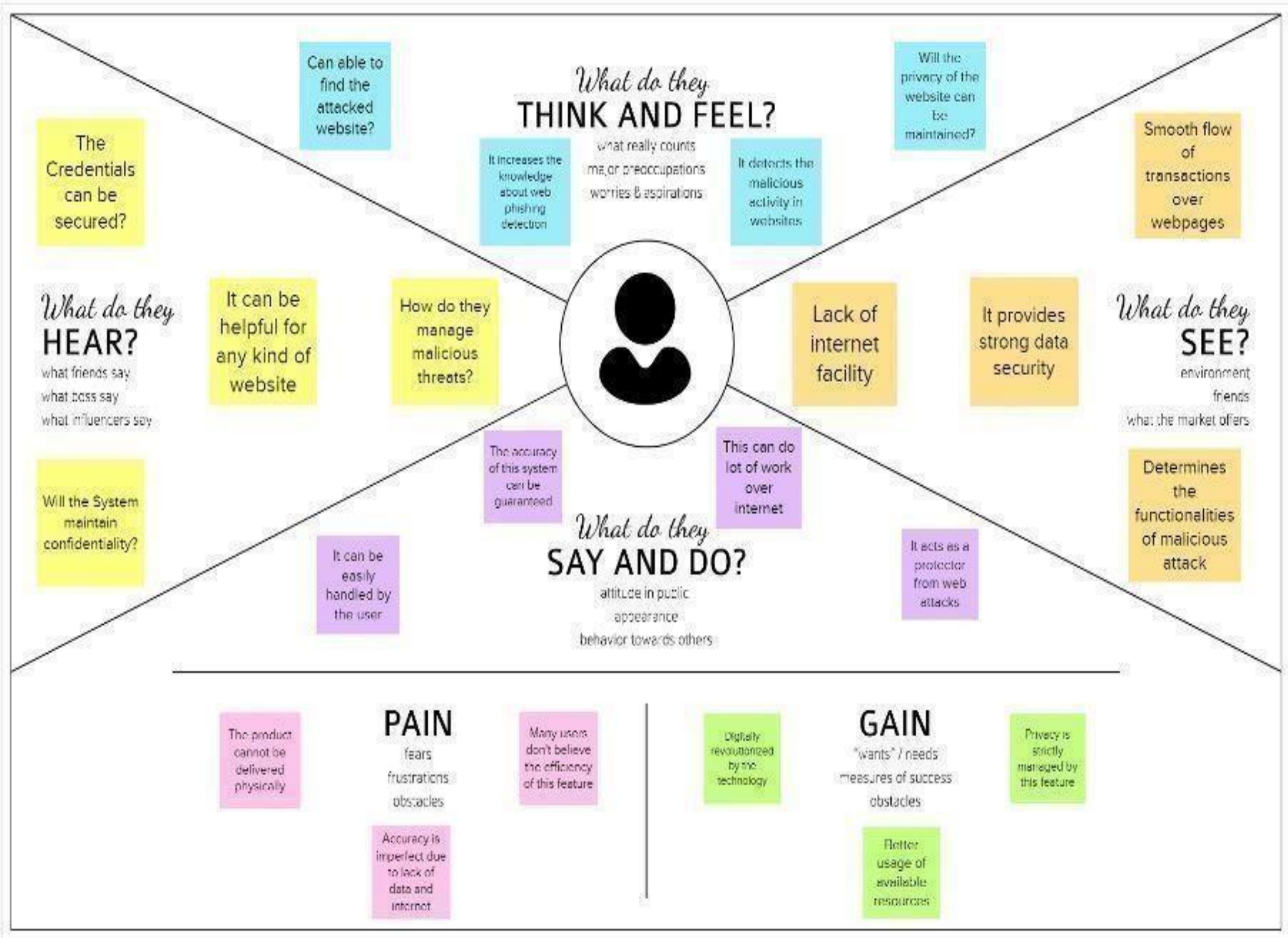
In order to detect and predict e-banking phishing websites, we proposed an intelligent, flexible and effective system that is based on using classification algorithms. We implemented classification algorithms and techniques to extract the phishing datasets criteria to classify their legitimacy. The e-banking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

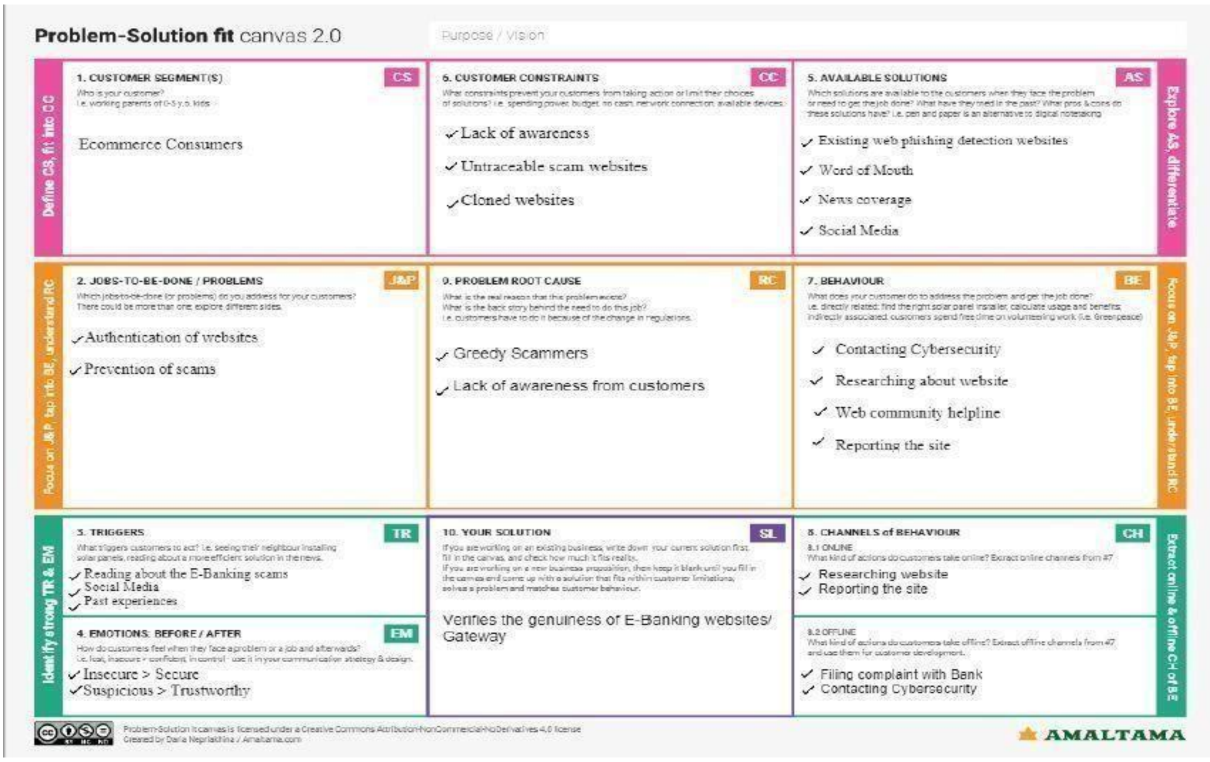

Brainstorm
& idea prioritization
Use this template in your own brainstorming sessions so your team can unleash their imagination and start shaping concepts even if you're not sitting in the same room.
Before you collaborate
Define your problem statement
Brainstorm
Group ideas
Prioritize
After you collaborate

### 3.3 Proposed Solution

| S.No. | Parameter | Description |
|---|---|---|
| 1. | Problem Statement (Problem to besolved) | • Web phishing aims to steal private information, such as usernames, passwords, and credit card details, byway of impersonating a legitimate entity.<br>• It will lead to information disclosureand property damage.<br>• Large organizations may get trapped indifferent kinds of scams. |
| 2. | Idea / Solution description | 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. |
| 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 e-banking 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 |
| | | 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 systemcan also be integrated<br><br>with the future technologies |

**3.4 Problem Solution fit:**


Problem-Solution fit canvas 2.0
Purpose / Vision
Define CS, fit into CC
1. CUSTOMER SEGMENT(S)
CS
Who is your customer?
i.e. working parents of 0-5 y.o. kids
Ecommerce Consumers
6. CUSTOMER CONSTRAINTS
CC
What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices.
✓ Lack of awareness
✓ Untraceable scam websites
✓ Cloned websites
5. AVAILABLE SOLUTIONS
AS
Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros & cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking
✓ Existing web phishing detection websites
✓ Word of Mouth
✓ News coverage
✓ Social Media
Explore AS, differentiate
Focus on J&P, tap into BE, understand RC
2. JOBS-TO-BE-DONE / PROBLEMS
J&P
Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one; explore different sides.
✓ Authentication of websites
✓ Prevention of scams
9. PROBLEM ROOT CAUSE
RC
What is the real reason that this problem exists?
What is the back story behind the need to do this job?
i.e. customers have to do it because of the change in regulations.
✓ Greedy Scammers
✓ Lack of awareness from customers
7. BEHAVIOUR
BE
What does your customer do to address the problem and get the job done?
i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace)
✓ Contacting Cybersecurity
✓ Researching about website
✓ Web community helpline
✓ Reporting the site
Focus on J&P, tap into BE, understand RC
Identify strong TR & EM
3. TRIGGERS
TR
What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.
✓ Reading about the E-Banking scams
✓ Social Media
✓ Past experiences
4. EMOTIONS: BEFORE / AFTER
EM
How do customers feel when they face a problem or a job and afterwards?
i.e. lost, insecure > confident, in control - use it in your communication strategy & design.
✓ Insecure > Secure
✓ Suspicious > Trustworthy
10. YOUR SOLUTION
SL
If you are working on an existing business, write down your current solution first, fill in the canvas, and check how much it fits reality.
If you are working on a new business proposition, then keep it blank until you fill in the canvas and come up with a solution that fits within customer limitations, solves a problem and matches customer behaviour.
Verifies the genuiness of E-Banking websites/ Gateway
8. CHANNELS of BEHAVIOUR
CH
8.1 ONLINE
What kind of actions do customers take online? Extract online channels from #7
✓ Researching website
✓ Reporting the site
8.2 OFFLINE
What kind of actions do customers take offline? Extract offline channels from #7 and use them for customer development.
✓ Filing complaint with Bank
✓ Contacting Cybersecurity
Extract online & offline CH of BE
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Created by Daria Nepriakhina / Amaltama.com
AMALTAMA

## 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.<br>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-functional 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. |

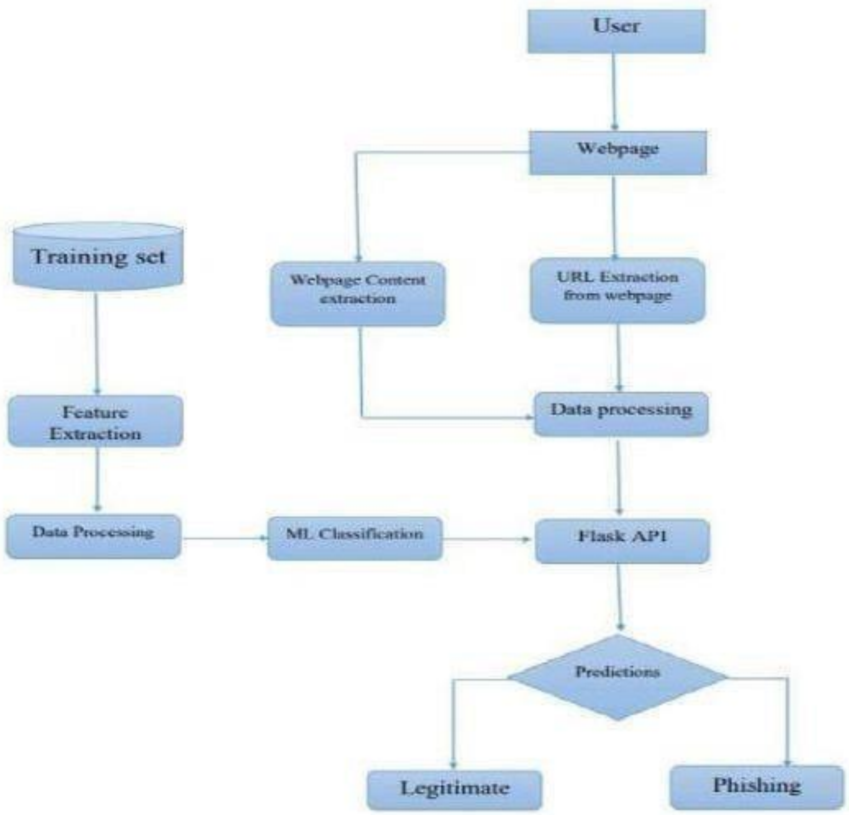
| | | |
|---|---|---|
| NFR-3 | **Reliability** | It specifies the likelihood that the system or itscomponent will operate without failure for a specified amount of time under prescribed conditions. |
| NFR-4 | **Performance** | It is concerned with a measurement of the system'sreaction time under various load circumstances. |

| | | |
|---|---|---|
| NFR-5 | **Availability** | It represents the likelihood that a user will be ableto access the system at a certain moment in time. Whilst 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

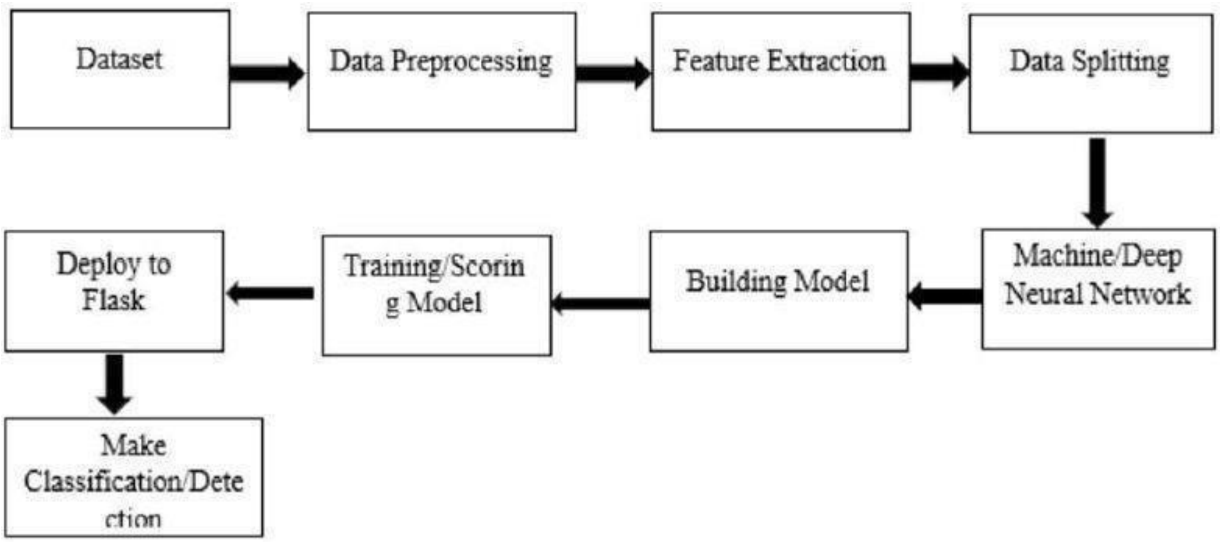
### 5.1 Data Flow Diagrams:

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.



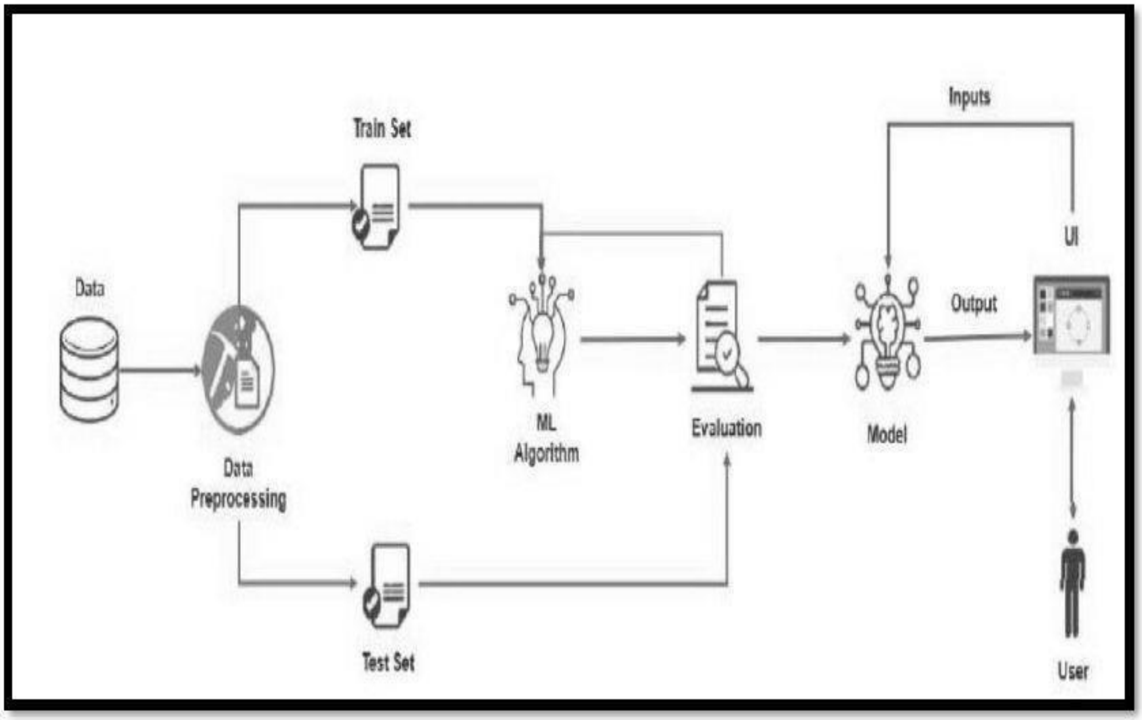
### 5.2 Solution and Technical Architecture

## 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 |
| | | 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

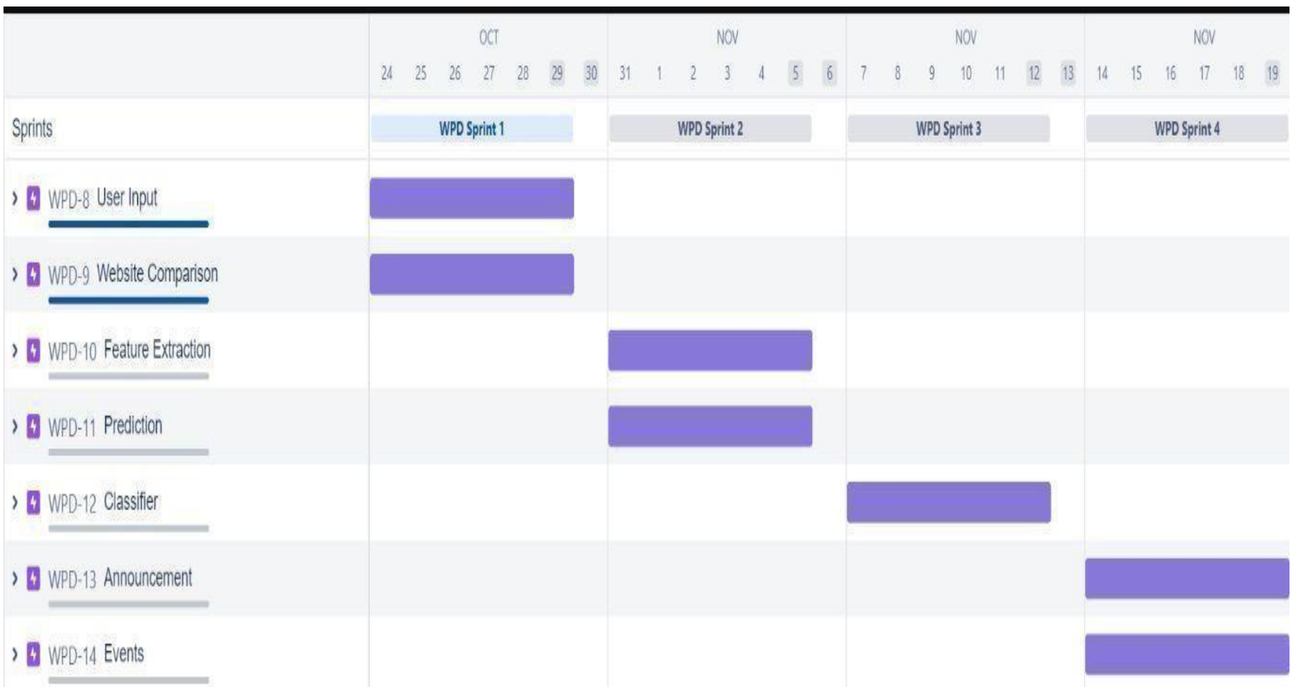
## 6.1 Sprint Planning & Estimation

| 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 | Thillai Raj S |
| Sprint-1 | Website Comparison | USN-2 | Model compares the Website using Blacklist and Whitelist approach. | 1 | Medium | Maheswaran p |
| Sprint-2 | Feature Extraction | USN-3 | After comparison .if none found on comparison then it extract feature using heuristic and visual similarity | 2 | High | Mohamed Najith J |
| Sprint-2 | Prediction | USN-4 | Model predict URL using machine learning algorithms such as logistic Regression,KNN. | 1 | Medium | Abishek B |
| Sprint-3 | Classifier | USN-5 | Model sends all the Output to the classifier and produces the final result | 1 | Medium | Thillai Raj S |
| Sprint-4 | Announcement | USN-6 | Model then displays whether the Website is legal site or a phishing site. | 1 | High | Abishek B |
| Sprint-4 | Events | USN-7 | This model needs the capability of retrieving and displaying accurate result for a website. | 1 | High | Maheswaran P |

## 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.url)
    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\.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|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(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

  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|78\.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|141\
.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|213
\.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\.200\
.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

| 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 |

| | |
|---|---|
| Date | 15-Nov-22 |
| Team ID | PNT2022TMID03926 |
| Project Name | Project - Web Phishing Detection |
| Maximum Marks | 4marks |

| Test case ID | Feature Type | Component | TestScenario | Pre-Requisite | Steps To Execute | TestData | Expected Result | Actual Result | Status | Comments | TC for Automation(Y/N) | BUG ID | Executed By |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LoginPage_TC_OO1 | 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<br>2.Type the URL<br>3.Verify whether it is pr ocessing or not. | https://phishing-shield.herokuapp.com/ | Should Display the Webpage | Workingas expected | Pass | | N | | S Balaji |
| LoginPage_TC_OO2 | UI | Home Page | Verify the UI eleme nts is Responsive | | 1.Enter URL and clic k go<br>2.Type orcopy paste the URL 3. Check whether the button is responsive or not<br>4. Reload and Test Simultaneously | https://phishing-shield.herokuapp.com/ | Should Wait for Response and then getsAcknowledge | Workingas expected | Pass | | N | | RAbisheik |
| LoginPage_TC_OO3 | Functional | Home page | Verify whether the link is legitimate ornot | | 1. Enter URL and clic k go<br>2. Type orcopy paste the URL<br>3. Check the website is legitimate or not<br>4. Observe the results | https://phishing-shield.herokuapp.com/ | User should observe whether the websiteis legitimate ornot. | Workingas expected | Pass | | N | | TS Aswin |
| LoginPage_TC_OO4 | Functional | Home Page | Verify user is able to access the legitimate website ornot | | 1. Enter URL and clic k go<br>2. Type orcopy paste the URL<br>3. Check the website is legitimate or not<br>4. Continue if the website is legitimate or be cautious if it is notlegitimate. | https://phishing-shield.herokuapp.com/ | Application should show that Safe Webpage orUnsafe. | Workingas expected | Pass | | N | | Balajee A V |
| LoginPage_TC_OO5 | Functional | Home Page | Testing the website with multiple URLs | | 1. Enter URL ( https://phishing-shield.herokuapp.com /) and click go<br>2. Type or copy paste the URL to test<br>3. Check the website is legitimate or not<br>4. Continue if the website is secure orbe cautious if it is not secure | 1. https://avbalajee.github.io/welcome<br>2. totalpad.com<br>3. https://www.klnce.edu<br>4. salescript.info 5. https://www.google.com/<br>6. delgets.com | User can able to identify the websites whether it is secure or not | Workingas expected | Pass | | N | | Balajee A V |

## 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

| | | | | | |
|---|---|---|---|---|---|
| Skipped | 0 | 0 | 0 | 0 | 0 |
| Won't Fix | 0 | 0 | 2 | 1 | 3 |
| Totals | 23 | 9 | 12 | 25 | 60 |

## 3. Test Case Analysis

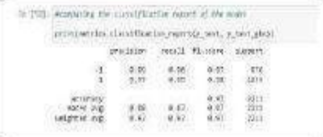
This report shows the number of test cases that have passed, failed, and untested

| 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

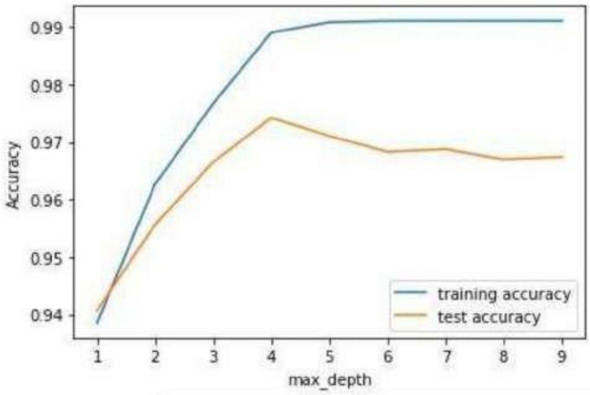
## 9.1 Performance Metrics

| S.No. | Parameter | Values | Screenshot |
|---|---|---|---|
| 1. | Metrics | **Classification Model:**<br>**Gradient Boosting Classification**<br>Accuray Score- 97.4% |  |
| 2. | Tune the Model | Hyperparameter Tuning - 97%<br>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 canbe 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-10377-1659175426

Project Demo Link: https://github.com/IBM-EPBL/IBM-Project-10377-1659175426