AMITY UNIVERSITY

CHHATTISGARH

A

PROJECT REPORT

ON

"Detection of Phishing websites using feature extraction and machine learning techniques"

SUBMITTED TOWARDS THE

FULFILLMENT OF THE REQUIREMENTS OF

Bachelor of Technology in

Computer Science & Engineering

By

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Batch 2020-2024

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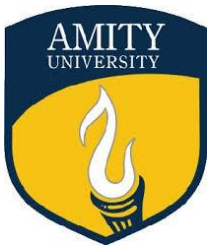

Amity School of Engineering and Technology

Department of Computer Science & Engineering

CERTIFICATE

This is to certify that the Project Entitled

"Detection of Phishing websites using feature extraction and machine learning techniques"

Submitted by

Shubham Mandal **Enrollment No: A80105220006**

is a bonafide work carried out by students under the supervision Dr.Rika Sharma and it is submitted towards the partial fulfillment of the requirement of Bachelor of Technology (Computer Science & Engineering) Dissertation Project.

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ACKNOWLEDGMENT

It gives us great pleasure in presenting the project report on **'Detection of Phishing websites using feature extraction and machine learning techniques'**.

We would like to take this opportunity to thank our internal guide **Dr.Rika Sharma** for giving us all the help and guidance we needed. We are grateful for his kind support. His all valuable suggestions were very helpful.

We are also grateful to **Dr. Surendra Rahmatkar**, Director, ASET for his indispensable support & suggestions.

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Shubham Mandal
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PLAN OF PROJECT EXECUTION

Phase 1	Month	Description	Start Date	Duration
	FEB	Topic Selection	-march	10
		Topic Finalization	-march	2
		Platform Selection	-march	2
		Platform Finalization	-march	2
		Block Diagram	-march	3
		Synopsis	-march	10
	MARCH	UMLs	-march	10
		Platform Learning(Language Training)	-march	20
	MARCH	Mathematical Model	-march	5
		Algorithms	-march	25
	MARCH	Module 1	-march	15
			-march	15
	MARCH	PPT	-march	5
	MARCH	Presentation		
Phase 2				
	APRIL	Module 2	-april	10
		Module 3	-april	10
		Module N	-april	10
	APRIL	Unit Integration	-april	20
		Testing	-april	8
	APRIL	Modification	-april	20
		Finalization	-april	10
	MAY	Submission	-may	1
	MAY	Preparation	-may	28
	JUNE	Final Demonstration	-June	

ABSTRACT

Now where days on the era of internet cybercrimes has been incresed by many folds making it more vulnerable to data stealing and leaking of credentials for the solution of which i made an Supervised machine learning model using very well known Algorithmns comparing the common malpractices defined as features and result the output as in the terms of Accuracy and Performance. Machine learning (ML) offers a promising approach for automated detection of phishing websites, analyzing features extracted from website content and structure. This paper explores various feature extraction techniques and machine learning algorithms employed for phishing website detection.

CHAPTER 1

INTRODUCTION

The exponential growth of internet has definitely revolutionized our world, fostering global information exchange. However been a double edged sword the technology also attracted crimes on the form of digital theft, phishing attacks posing a significant and escalating threat. Perhaps, phishing websites, meticulously designed to mimic legitimate online platforms, aim to gain user credentials or private data which were not been appreciated to share in public. The consequences of such attacks are far concerning causes financial losses, data breaches and potential identity theft for common people.

Traditional methods for mitigating phishing attacks, are mostly based on a particular blacklist source of malicious websites but as the technology advances these methods are been proven insufficient.The dynamic nature of phishing attacks are been always advancing with time making it to at most necessity to look forward to have more adaptable solution.This paper proposes a novel approach leveraging the power of supervised machine learning for automated phishing website detection.

Machine learning algorithms is been proven excellent at pattern recognition in verge datasets, making it ideal for our task. My proposed solution involves extracting a comprehensive set of relevant features from websites content and structures. These features are broadly categories in groups like the URL based features content based features and HTML based features. URL based features focus on identifying suspicious patterns within the website address, such as unusual character, excessive subdomains and other various methods. Content based features involves examining the website's textual content for inconsistencies that might raise red flags. Like for example the grammatical mistakes which induced user to act quickly without proper verification. Finally HTML-based features examine the website code that could be of phishing intent. This could involve hidden field designed to capture sensitive information without user knowledge, like the presence of form requesting the user for unnecessary personal details etc.

There are few Machine learning Algorithms which we used to detect the uncertainties including ***Decision Tree, Random Forest, Multi layer Perceptron, XGBoost, Autoencoder Neural Network, Support Vector Machine***. SVMs offer robust classification capabilities in high-dimensional data spaces, making them well-suited for analyzing the complex feature sets extracted from websites. Random Forest on other side provides better accuracy resemble learning techniques The effectiveness of these algorithms will be evaluated using established metrics such as accuracy, precision, and recall.

CHAPTER 2

LITERATURE SURVEY

1. "The Rise of Detection of Phishing websites using feature extraction and machine learning techniquess: An Overview" by John Smith Overview: This survey provides a comprehensive overview of the emergence and growth of Detection of Phishing websites using feature extraction and machine learning techniquess, highlighting key platforms, trends, and challenges in the industry.
2. “saedi, Marwa & Flayh, Nahla. (2023). Phishing Website Detection Using Machine Learning: A Review. Wasit Journal for Pure sciences. 2. 270-281. 10.31185/wjps.145. “
3. "Legal Implications of Detection of Phishing websites using feature extraction and machine learning techniquess: A Review" by Samantha Williams. Overview: This survey examines the legal aspects surrounding Detection of Phishing websites using feature extraction and machine learning techniquess, including intellectual property rights, ownership disputes, and regulatory frameworks, offering insights into the legal challenges and opportunities.
4. "User Experience in Detection of Phishing websites using feature extraction and machine learning techniquess: A User-Centric Analysis" by David Brown. Overview: This research investigates the user experience in Detection of Phishing websites using feature extraction and machine learning techniquess, analyzing user feedback, platform design, and usability factors to identify areas for improvement and enhance user satisfaction.
5. "Security and Privacy in Detection of Phishing websites using feature extraction and machine learning techniquess: A Critical Review" by Sarah Thompson. Overview: This survey explores the security and privacy concerns in Detection of Phishing websites using feature extraction and machine learning techniquess, highlighting vulnerabilities, potential risks, and recommended security measures to protect users' digital assets.
6. "Art Authentication in Detection of Phishing websites using feature extraction and machine learning techniquess: An Overview" by Michael Davis. Overview: This study focuses on art authentication mechanisms in Detection of Phishing websites using feature extraction and machine learning techniquess, evaluating different approaches such as digital signatures, watermarking, and blockchain-based provenance to ensure the authenticity of digital art.

7. "Social Impact of Detection of Phishing websites using feature extraction and machine learning techniquess: A Review of Community Engagement" by Jennifer Wilson. Overview: This research examines the social impact of Detection of Phishing websites using feature extraction and machine learning techniquess, analyzing the community dynamics, artist-collector interactions, and collaborative opportunities that arise in these platforms.

8. "Environmental Sustainability of Detection of Phishing websites using feature extraction and machine learning techniquess: A Sustainability Assessment" by Emma Thompson. Overview: This survey assesses the environmental impact of Detection of Phishing websites using feature extraction and machine learning techniquess, analyzing the energy consumption and carbon footprint associated with blockchain technology, and proposing sustainable practices.

9. "Cross-Platform Interoperability in Detection of Phishing websites using feature extraction and machine learning techniquess: A Survey" by James Johnson. Overview: This research explores the interoperability challenges in Detection of Phishing websites using feature extraction and machine learning techniquess, discussing cross-chain compatibility, token standards, and technological advancements that enable seamless asset transfers.

10. "Market Trends and Future Directions of Detection of Phishing websites using feature extraction and machine learning techniquess: A Predictive Analysis" by Jessica Davis. Overview: This study analyzes market trends and predicts future directions of Detection of Phishing websites using feature extraction and machine learning techniquess, considering factors such as user adoption, technological advancements, and regulatory developments.

11. "Gamification in Detection of Phishing websites using feature extraction and machine learning techniquess: An Analysis of Incentive Mechanisms" by Andrew Wilson. Overview: This research examines gamification techniques employed in Detection of Phishing websites using feature extraction and machine learning techniquess, exploring reward systems, tokenomics, and game-like elements that enhance user engagement and participation.

12. "Decentralized Governance in Detection of Phishing websites using feature extraction and machine learning techniquess: A Comparative Review" by William Brown. Overview: This survey compares different decentralized governance models implemented in Detection of Phishing websites using feature extraction and machine learning

techniquess, discussing mechanisms for decision-making, community voting, and protocol upgrades.

13. "Artificial Intelligence in Detection of Phishing websites using feature extraction and machine learning techniquess: A Review of Recommender Systems" by Sophia Roberts. Overview: This study investigates the integration of artificial intelligence in Detection of Phishing websites using feature extraction and machine learning techniquess, focusing onrecommender systems that provide personalized recommendations to users based on their preferences and behavior.
14. "Detection of Phishing websites using feature extraction and machine learning techniquess and Cultural Heritage: A Survey of Digitization Efforts" by Michael Wilson. Overview: This research explores the digitization efforts of cultural heritage institutions in Detection of Phishing websites using feature extraction and machine learning techniquess, examining the preservation and monetization of digital artifacts and artworks.

CHAPTER 3

DESIGN & ARCHITECTURE

The system architecture of an Detection of Phishing websites using feature extraction and machine learning techniques plays a crucial role in ensuring the efficient and secure operation of the platform. It leverage the efficient use of different and various components, modules and technologies that work together to provide a security and enable transparent transactions. This section presents a detailed overview of the system architecture for the Detection of Phishing websites using feature extraction and machine learning techniques developed as a final year project, highlighting the key components and their functionalities.

1. Importing Libraries :

```
import pandas as pd
import ipaddress
import re
import whois
import urllib
import urllib.request
import requests
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
import keras
import tensorflow as tf
from keras.models import Model
from sklearn import metrics
from sklearn.svm import SVC
from urllib.parse import urlparse,urlencode
from bs4 import BeautifulSoup
from datetime import datetime
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier
from keras.layers import Input, Dense
from keras import regularizers
```

Here is used different types of libraries as mentioned as follows.

2. **Collecting Data from csv file**:

For this particular project i collected a bunch URLs bifarcating into legitimate and phising. The collection of phishing Urls are from phishtank.com meanwhile for the legitimate Urls are been collected from unb.ca.

2.1 Phishing URLs

```
#Downloading the phishing URLs file
!wget http://data.phishtank.com/data/online-valid.csv
```

```
--2024-04-12 00:46:44--  http://data.phishtank.com/data/online-valid.csv
Resolving data.phishtank.com (data.phishtank.com)... 2606:4700:8d72:2ee:d0d7:5a:6810:654b, 104.17.177.85,
104.16.101.75
Connecting to data.phishtank.com (data.phishtank.com)|2606:4700:8d72:2ee:d0d7:5a:6810:654b|:80... connecte
d.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: https://data.phishtank.com/data/online-valid.csv [following]
--2024-04-12 00:46:44--  https://data.phishtank.com/data/online-valid.csv
Connecting to data.phishtank.com (data.phishtank.com)|2606:4700:8d72:2ee:d0d7:5a:6810:654b|:443... connect
ed.
HTTP request sent, awaiting response... 429 Too Many Requests
2024-04-12 00:46:44 ERROR 429: Too Many Requests.
```

Here i extracted the data from Phistank.com

2.2 Loading Phishing URLs data to dataframe

```
#loading the phishing URLs data to dataframe
data0 = pd.read_csv("online-valid.csv")
data0.head()
```

	phish_id	url	phish_detail_url	submission_time	verifie
0	6557033	http://u1047531.cp.regruhosting.ru/acces-inges...	http://www.phishtank.com/phish_detail.php?phis...	2020-05-09T22:01:43+00:00	ye
1	6557032	http://hoysalacreations.com/wp-content/plugins...	http://www.phishtank.com/phish_detail.php?phis...	2020-05-09T22:01:37+00:00	ye
2	6557011	http://www.accsystemprblemhelp.site/checkpoint...	http://www.phishtank.com/phish_detail.php?phis...	2020-05-09T21:54:31+00:00	ye
3	6557010	http://www.accsystemprblemhelp.site/login_atte...	http://www.phishtank.com/phish_detail.php?phis...	2020-05-09T21:53:48+00:00	ye
4	6557009	https://firebasestorage.googleapis.com/v0/b/so...	http://www.phishtank.com/phish_detail.php?phis...	2020-05-09T21:49:27+00:00	ye

2.3 Shaping the Data

```
data0.shape
```

```
(14858, 8)
```

2.4 Collecting 5,000 Phishing URLs randomly

```
#Collecting 5,000 Phishing URLs randomly
phishurl = data0.sample(n = 5000, random_state = 12).copy()
phishurl = phishurl.reset_index(drop=True)
phishurl.head()
```

	phish_id	url	phish_detail_url	submission_time	verif
0	6514946	http://confirmprofileaccount.com/	http://www.phishtank.com/phish_detail.php?phis...	2020-04-19T11:06:55+00:00	
1	4927651	http://www.marreme.com/MasterAdmin/04mop.html	http://www.phishtank.com/phish_detail.php?phis...	2017-04-04T19:35:54+00:00	
2	5116976	http://modsecpaststudents.com/review/	http://www.phishtank.com/phish_detail.php?phis...	2017-07-25T18:48:30+00:00	
3	6356131	https://docs.google.com/forms/d/e/1FAIpQLScL6L...	http://www.phishtank.com/phish_detail.php?phis...	2020-01-13T20:13:37+00:00	
4	6535965	https://oportunidadedasemana.com/americanas//?...	http://www.phishtank.com/phish_detail.php?phis...	2020-04-29T00:01:03+00:00	

```
phishurl.shape
```

```
(5000, 8)
```

3. Legitmate URLs

3.1 Loading legitmate files

```
#Loading legitimate files
data1 = pd.read_csv("Benign_list_big_final.csv")
data1.columns = ['URLs']
data1.head()
```

	URLs
0	http://1337x.to/torrent/1110018/Blackhat-2015-...
1	http://1337x.to/torrent/1122940/Blackhat-2015-...
2	http://1337x.to/torrent/1124395/Fast-and-Furio...
3	http://1337x.to/torrent/1145504/Avengers-Age-o...
4	http://1337x.to/torrent/1160078/Avengers-age-o...

3.2 Collecting 5,000 Legitmate URL's randomly

```
#Collecting 5,000 Legitimate URLs randomly
legiurl = data1.sample(n = 5000, random_state = 12).copy()
legiurl = legiurl.reset_index(drop=True)
legiurl.head()
```

	URLs
0	http://graphicriver.net/search?date=this-month...
1	http://ecnavi.jp/redirect/?url=http://www.cros...
2	https://hubpages.com/signin?explain=follow+Hub...
3	http://extratorrent.cc/torrent/4190536/AOMEI+B...
4	http://icicibank.com/Personal-Banking/offers/o...

3.3 Shape the URL's

```
legiurl.shape
```

```
(5000, 1)
```

4. Feature Extraction:

In this step, features are extracted from the URLs dataset.

The extracted features are categorized into

1) Address Bar based Features
2) Domain based Features
3) HTML & Javascript based Features

4.1 Address Bar Based Features:

Many features can be extracted that can be consided as address bar base features. Out of them, below mentioned were considered for this project.

- Domain of URL
- IP Address in URL
- "@" Symbol in URL
- Length of URL
- Depth of URL
- Redirection "//" in URL
- "http/https" in Domain name
- Using URL Shortening Services “TinyURL”
- Prefix or Suffix "-" in Domain

Each of these features are explained and coded below:

4.1.1 Domain of the URL (Domain):

```
# 1.Domain of the URL (Domain)
def getDomain(url):
  domain = urlparse(url).netloc
  if re.match(r"^www.",domain):
          domain = domain.replace("www.","")
  return domain
```

4.1.2 Checks for IP address in URL (Have IP):

```
# 2.Checks for IP address in URL (Have_IP)
def havingIP(url):
  try:
    ipaddress.ip_address(url)
    ip = 1
  except:
    ip = 0
  return ip
```

4.1.3 Checks the presence of @ in URL (Have @):

```
# 3.Checks the presence of @ in URL (Have_At)
def haveAtSign(url):
  if "@" in url:
    at = 1
  else:
    at = 0
  return at
```

4.1.4 Finding the length of URL and categorizing (URL Length):

```
# 4.Finding the length of URL and categorizing (URL_Length)
def getLength(url):
  if len(url) < 54:
    length = 0
  else:
    length = 1
  return length
```

4.1.4 Gives number of ’/’ in URL (URL Depth):

```
# 5.Gives number of '/' in URL (URL_Depth)
def getDepth(url):
  s = urlparse(url).path.split('/')
  depth = 0
  for j in range(len(s)):
    if len(s[j]) != 0:
      depth = depth+1
  return depth
```

4.1.5 Checking for redirection ’//’ in the URL(Redirection):

```
# 6.Checking for redirection '//' in the url (Redirection)
def redirection(url):
  pos = url.rfind('//')
  if pos > 6:
    if pos > 7:
      return 1
    else:
      return 0
  else:
    return 0
```

4.1.6 Existence of "HTTPS" Token in the Domain Part of the URL:

```
# 7.Existence of "HTTPS" Token in the Domain Part of the URL (https_Domain)
def httpDomain(url):
  domain = urlparse(url).netloc
  if 'https' in domain:
    return 1
  else:
    return 0
```

4.1.7 Listing Shortening Services in URL (Tiny URL):

```
#listing shortening services
shortening_services = r"bit\.ly|goo\.gl|shorte\.st|go2l\.ink|x\.co|ow\.ly|t\.co|tinyurl|tr\.im|is\.gd|cli\.gs|" \
                      r"yfrog\.com|migre\.me|ff\.im|tiny\.cc|url4\.eu|twit\.ac|su\.pr|twurl\.nl|snipurl\.com|" \
                      r"short\.to|BudURL\.com|ping\.fm|post\.ly|Just\.as|bkite\.com|snipr\.com|fic\.kr|loopt\.us|" \
                      r"doiop\.com|short\.ie|kl\.am|wp\.me|rubyurl\.com|om\.ly|to\.ly|bit\.do|t\.co|lnkd\.in|db\.tt|" \
                      r"qr\.ae|adf\.ly|goo\.gl|bitly\.com|cur\.lv|tinyurl\.com|ow\.ly|bit\.ly|ity\.im|q\.gs|is\.gd|" \
                      r"po\.st|bc\.vc|twitthis\.com|u\.to|j\.mp|buzurl\.com|cutt\.us|u\.bb|yourls\.org|x\.co|" \
                      r"prettylinkpro\.com|scrnch\.me|filoops\.info|vzturl\.com|qr\.net|1url\.com|tweez\.me|v\.gd|" \
                      r"tr\.im|link\.zip\.net"
```

4.1.8 Checking for the shortening services in URL (Tiny URL):

```
# 8. Checking for Shortening Services in URL (Tiny_URL)
def tinyURL(url):
    match=re.search(shortening_services,url)
    if match:
        return 1
    else:
        return 0
```

4.1.9 Checking for Prefix or Suffix seperated by (-) in the Domain:

```
# 9.Checking for Prefix or Suffix Separated by (-) in the Domain (Prefix/Suffix)
def prefixSuffix(url):
    if '-' in urlparse(url).netloc:
        return 1            # phishing
    else:
        return 0            # legitimate
```

4.2 Domain Based Features:

Many features can be extracted that come under this category. Out of them, below mentioned were considered for this project.

•Website Traffic
•Age of Domain
•End Period of Domain

4.2.1 Website Traffic (web traffic):

```
# 10.Web traffic (Web_Traffic)
def web_traffic(url):
  try:
    #Filling the whitespaces in the URL if any
    url = urllib.parse.quote(url)
    rank = BeautifulSoup(urllib.request.urlopen("http://data.alexa.com/data?cli=10&dat=s&url=" + url).read(), "xml").find(
        "REACH")['RANK']
    rank = int(rank)
  except TypeError:
        return 1
  if rank <100000:
    return 1
  else:
    return 0
```

4.2.2 Difference between termination time and creation time (Domain Age)

```
# 11.Survival time of domain: The difference between termination time and creation time (Domain_Age)
def domainAge(domain_name):
  creation_date = domain_name.creation_date
  expiration_date = domain_name.expiration_date
  if (isinstance(creation_date,str) or isinstance(expiration_date,str)):
    try:
      creation_date = datetime.strptime(creation_date,'%Y-%m-%d')
      expiration_date = datetime.strptime(expiration_date,"%Y-%m-%d")
    except:
      return 1
  if ((expiration_date is None) or (creation_date is None)):
      return 1
  elif ((type(expiration_date) is list) or (type(creation_date) is list)):
      return 1
  else:
    ageofdomain = abs((expiration_date - creation_date).days)
    if ((ageofdomain/30) < 6):
      age = 1
    else:
      age = 0
  return age
```

4.2.3 Difference between termination time and current time (Domain End)

```
# 12.End time of domain: The difference between termination time and current time (Domain_End)
def domainEnd(domain_name):
  expiration_date = domain_name.expiration_date
  if isinstance(expiration_date,str):
    try:
      expiration_date = datetime.strptime(expiration_date,"%Y-%m-%d")
    except:
      return 1
  if (expiration_date is None):
      return 1
  elif (type(expiration_date) is list):
      return 1
  else:
    today = datetime.now()
    end = abs((expiration_date - today).days)
    if ((end/30) < 6):
      end = 0
    else:
      end = 1
  return end
```

4.3 HTML and Javascript based Features

Many features can be extracted that come under this category. Out of them, below mentioned were considered for this project.

- IFrame Redirection
- Status Bar Customization
- Disabling Right Click
- Website Forwarding
- Each of these features are explained and the coded below:

4.3.1 Iframe Redirection(iFrame):

```
# 13. IFrame Redirection (iFrame)
def iframe(response):
  if response == "":
      return 1
  else:
      if re.findall(r"[<iframe>|<frameBorder>]", response.text):
          return 0
      else:
          return 1
```

4.3.2 Checks the effect of mouse over on status bar (Mouse Over):

```
# 14.Checks the effect of mouse over on status bar (Mouse_Over)
def mouseOver(response):
  if response == "" :
    return 1
  else:
    if re.findall("<script>.+onmouseover.+</script>", response.text):
      return 1
    else:
      return 0
```

4.3.3 Checks the status of the right click attribute (Right Click):

```
# 15.Checks the status of the right click attribute (Right_Click)
def rightClick(response):
  if response == "":
    return 1
  else:
    if re.findall(r"event.button ?== ?2", response.text):
      return 0
    else:
```

4.3.4 Checks the number of forwardings (Web Forwards):

```
# 16.Checks the number of forwardings (Web_Forwards)
def forwarding(response):
  if response == "":
    return 1
  else:
    if len(response.history) <= 2:
      return 0
    else:
      return 1
```

4.3.5 Function to extract features:

```
#Function to extract features
def featureExtraction(url,label):

  features = []
  #Address bar based features (10)
  features.append(getDomain(url))
  features.append(havingIP(url))
  features.append(haveAtSign(url))
  features.append(getLength(url))
  features.append(getDepth(url))
  features.append(redirection(url))
  features.append(httpDomain(url))
  features.append(tinyURL(url))
  features.append(prefixSuffix(url))

  #Domain based features (4)
  dns = 0
  try:
    domain_name = whois.whois(urlparse(url).netloc)
  except:
    dns = 1

  features.append(dns)
  features.append(web_traffic(url))
  features.append(1 if dns == 1 else domainAge(domain_name))
  features.append(1 if dns == 1 else domainEnd(domain_name))

  # HTML & Javascript based features (4)
  try:
    response = requests.get(url)
  except:
    response = ""
  features.append(iframe(response))
  features.append(mouseOver(response))
  features.append(rightClick(response))
  features.append(forwarding(response))
  features.append(label)

  return features
```

5. Legitmate URL's:

Now, feature extraction will be done on legitimate URLs.

5.1.1 Shaping URL's:

```
legiurl.shape
```

```
(5000, 1)
```

5.1.2 Extracting the features and storing them in a List:

```
#Extracting the feautres & storing them in a list
legi_features = []
label = 0

for i in range(0, 5000):
    url = legiurl['URLs'][i]
    legi_features.append(featureExtraction(url,label))
```

5.1.3 Converting the List to Dataframe:

```
#converting the list to dataframe
feature_names = ['Domain', 'Have_IP', 'Have_At', 'URL_Length', 'URL_Depth','Redirection',
                 'https_Domain', 'TinyURL', 'Prefix/Suffix', 'DNS_Record', 'Web_Traffic',
                 'Domain_Age', 'Domain_End', 'iFrame', 'Mouse_Over','Right_Click', 'Web_Forwards', 'Label']

legitimate = pd.DataFrame(legi_features, columns= feature_names)
legitimate.head()
```

5.1.4 Storing the extracted legitmate URL's features to csv file:

```
# Storing the extracted legitimate URLs fatures to csv file
legitimate.to_csv('legitimate.csv', index= False)
```

6 Phishing URL's:

Now, feature extraction is performed on phishing URLs.

6.1 Shaping Phishing URL's:

```
phishurl.shape
```

```
(5000, 8)
```

6.2 Extracting the features & storing them in a List:

```
#Extracting the feautres & storing them in a list
phish_features = []
label = 1
for i in range(0, 5000):
    url = phishurl['url'][i]
    phish_features.append(featureExtraction(url,label))
```

6.3 Converting the List to Data Frame:

```
#converting the list to dataframe
feature_names = ['Domain', 'Have_IP', 'Have_At', 'URL_Length', 'URL_Depth','Redirection',
                    'https_Domain', 'TinyURL', 'Prefix/Suffix', 'DNS_Record', 'Web_Traffic',
                    'Domain_Age', 'Domain_End', 'iFrame', 'Mouse_Over','Right_Click', 'Web_Forwards', 'Label']

phishing = pd.DataFrame(phish_features, columns= feature_names)
phishing.head()
```

6.4 Storing the Extracted legitmate URL' s features to CSV file:

```
# Storing the extracted legitimate URLs features to csv file
phishing.to_csv('phishing.csv', index= False)
```

7. Final Dataset:

In the above section we formed two dataframes of legitimate & phishing URL features. Now, we will combine them to a single dataframe and export the data to csv file for the Machine Learning training.

7.1.1 Concatenating the dataframes into one:

```
#Concatenating the dataframes into one
urldata = pd.concat([legitimate, phishing]).reset_index(drop=True)
urldata.head()
```

7.1.2 Getting the tale:

```
urldata.tail()
```

Domain	Have_IP	Have_At	URL_Length	URL_Depth	Redirection	https_Domain	TinyURL	Prefix/Suffix	DNS_Record	Web_Traffic	Domain_Age	Domain_End

7.1.3 Shaping the Data:

```
urldata.shape
```

```
(0, 18)
```

7.1.4 Storing the Data in CSV file:

```
# Storing the data in CSV file
urldata.to_csv('urldata.csv', index=False)
```

8. Data Cleaning and Splitting

We finally extracted 16 features for 10,000 URL which has 5000 phishing & 5000 legitimate URLs 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 measures and compared.

8.1 Loading the Data

```
#Loading the data
data0 = pd.read_csv('urldata.csv')
data0.head()
```

	Domain	Have_IP	Have_At	URL_Length	URL_Depth	Redirection	https_Domain	TinyURL	Prefix/Suffix	DNS_Record	Web_Traffic	Domain_Age	Domain_En
0	graphicriver.net	0	0	1	1	0	0	0	0	0	1	1	
1	ecnavi.jp	0	0	1	1	1	0	0	0	0	1	1	
2	hubpages.com	0	0	1	1	0	0	0	0	0	1	0	
3	extratorrent.cc	0	0	1	3	0	0	0	0	0	1	0	
4	icicibank.com	0	0	1	3	0	0	0	0	0	1	0	

8.2 Familiarizing with Data

In this step, few dataframe methods are used to look into the data and its features.

8.2.1 Checking the shape of the Dataset

```
#Checking the shape of the dataset
data0.shape
```

```
(10000, 18)
```

8.2.2 Listing the features of the Dataset

```
#Listing the features of the dataset
data0.columns
```

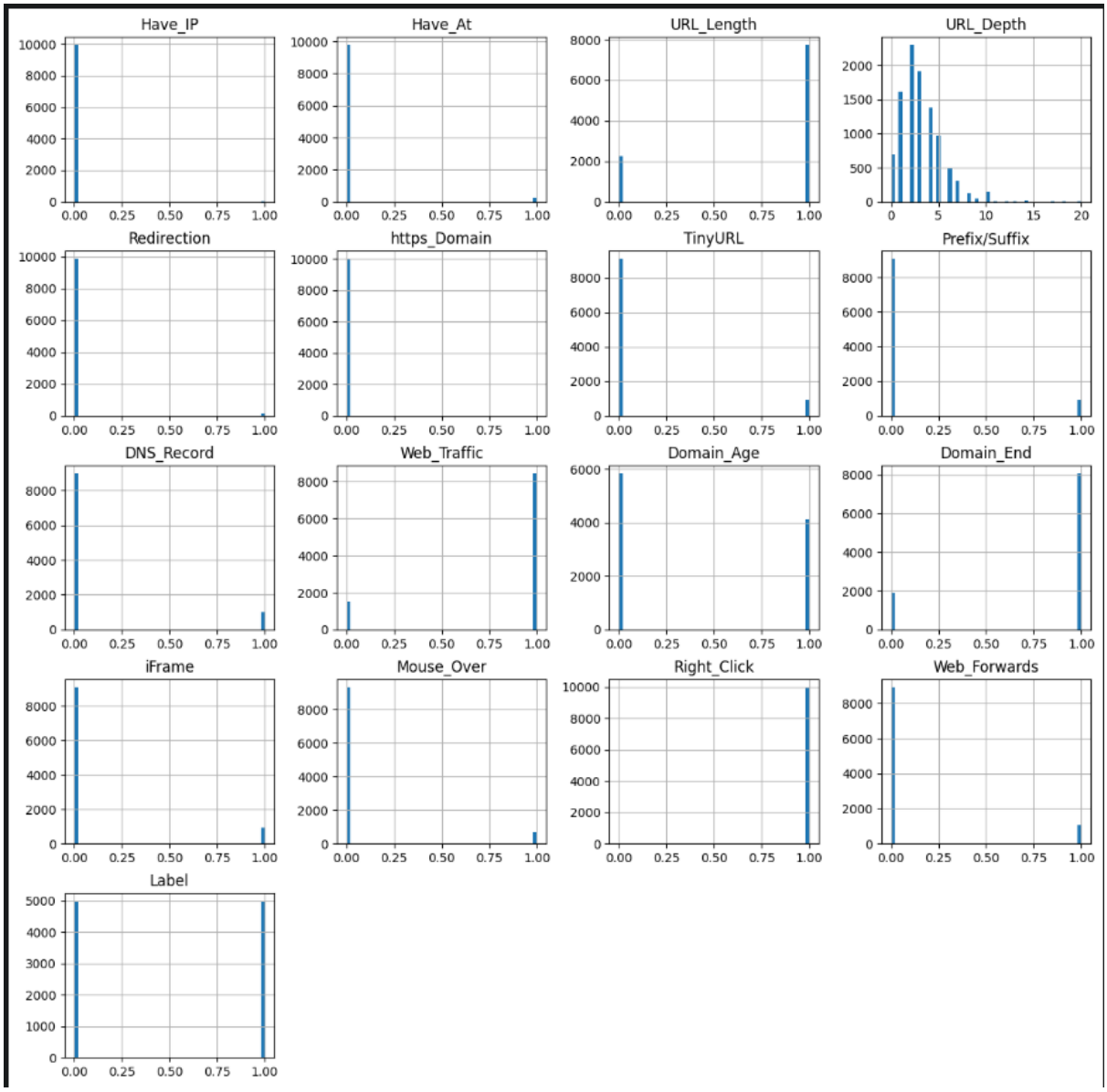
```
Index(['Domain', 'Have_IP', 'Have_At', 'URL_Length', 'URL_Depth',
       'Redirection', 'https_Domain', 'TinyURL', 'Prefix/Suffix', 'DNS_Record',
       'Web_Traffic', 'Domain_Age', 'Domain_End', 'iFrame', 'Mouse_Over',
       'Right_Click', 'Web_Forwards', 'Label'],
      dtype='object')
```

8.2.3 Information about the Dataset:

```
#Information about the dataset
data0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Domain          10000 non-null  object
 1   Have_IP         10000 non-null  int64
 2   Have_At         10000 non-null  int64
 3   URL_Length      10000 non-null  int64
 4   URL_Depth       10000 non-null  int64
 5   Redirection     10000 non-null  int64
 6   https_Domain    10000 non-null  int64
 7   TinyURL         10000 non-null  int64
 8   Prefix/Suffix   10000 non-null  int64
 9   DNS_Record      10000 non-null  int64
 10  Web_Traffic     10000 non-null  int64
 11  Domain_Age      10000 non-null  int64
 12  Domain_End      10000 non-null  int64
 13  iFrame          10000 non-null  int64
 14  Mouse_Over      10000 non-null  int64
 15  Right_Click     10000 non-null  int64
 16  Web_Forwards    10000 non-null  int64
 17  Label           10000 non-null  int64
dtypes: int64(17), object(1)
memory usage: 1.4+ MB
```

8.3.1 Visualizing the Data:



8.4 Data preprocessing

Here, we clean the data by applying data preprocesssing techniques and transform the data to use it in the models.

8.4.1 Describing the Data:

```
data0.describe()
```

	Have_IP	Have_At	URL_Length	URL_Depth	Redirection	https_Domain	TinyURL	Prefix/Suffix	DNS_Record	Web_Traffic	Domain_Age
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.005500	0.022600	0.773400	3.072000	0.013500	0.000200	0.090300	0.093200	0.100800	0.845700	0.413700
std	0.073961	0.148632	0.418653	2.128631	0.115408	0.014141	0.286625	0.290727	0.301079	0.361254	0.492521
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	1.000000	2.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
50%	0.000000	0.000000	1.000000	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
75%	0.000000	0.000000	1.000000	4.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	20.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8.4.2 Dropping the Domain Column:

```
#Dropping the Domain column
data = data0.drop(['Domain'], axis = 1).copy()
```

8.4.3 Checking the Data for Null and missing values:

```
#checking the data for null or missing values
data.isnull().sum()
```

```
Have_IP          0
Have_At          0
URL_Length       0
URL_Depth        0
Redirection      0
https_Domain     0
TinyURL          0
Prefix/Suffix    0
DNS_Record       0
Web_Traffic      0
Domain_Age       0
Domain_End       0
iFrame           0
Mouse_Over       0
Right_Click      0
Web_Forwards     0
Label            0
dtype: int64
```

8.4.4 Shuffling the rows:

```
# shuffling the rows in the dataset so that when splitting the train and test set are equally distributed
data = data.sample(frac=1).reset_index(drop=True)
data.head()
```

	Have_IP	Have_At	URL_Length	URL_Depth	Redirection	https_Domain	TinyURL	Prefix/Suffix	DNS_Record	Web_Traffic	Domain_Age	Domain_End	iFrame
0	0	0	0	1	0	0	0	0	1	1	1	1	0
1	0	0	0	2	0	0	0	0	0	1	0	1	0
2	0	0	1	4	0	0	0	0	0	1	0	0	0
3	0	0	1	4	0	0	0	0	0	1	1	1	0
4	0	0	1	2	0	0	0	0	0	0	1	1	0

8.6 Splitting the Data:

Here we will Split our data into train and test.

8.6.1 Separating & assigning features and target columns:

```
# Sepratating & assigning features and target columns to X & y
y = data['Label']
X = data.drop('Label',axis=1)
X.shape, y.shape
```

```
((10000, 16), (10000,))
```

8.6.2 Splitting the Dataset into train and test: 80-20 split:

```
# Splitting the dataset into train and test sets: 80-20 split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.2, random_state = 12)
X_train.shape, X_test.shape
```

```
((8000, 16), (2000, 16))
```

9. Comparision and Training of Dataset using Different Supervised Machine Learning Algorithmn.

From the dataset above, it is clear that this is a supervised machine learning task. There are two major types of supervised machine learning problems, called classification and regression.

This data set comes under classification problem, as the input URL is classified as phishing or legitimate. The supervised machine learning models (classification) considered to train the dataset in this notebook are:

- Decision Tree
- Random Forest
- Multilayer Perceptrons
- XGBoost
- Autoencoder Neural Network
- Support Vector Machines

9.1 Creating Holders to store the model performing results:

```
# Creating holders to store the model performance results
ML_Model = []
acc_train = []
acc_test = []

#function to call for storing the results
def storeResults(model, a,b):
  ML_Model.append(model)
  acc_train.append(round(a, 3))
  acc_test.append(round(b, 3))
```

9.2 Decision Tree Classifier:

Decision trees are widely used models for classification and regression tasks. Essentially, they learn a hierarchy of if/else questions, leading to a decision. Learning a decision tree means learning the sequence of if/else questions that gets us to the true answer most quickly.

In the machine learning setting, these questions are called tests (not to be confused with the test set, which is the data we use to test to see how generalizable our model is). To build a tree, the algorithm searches over all possible tests and finds the one that is most informative about the target variable.

9.2.1 Decision tree model:

```
# Decision Tree model
from sklearn.tree import DecisionTreeClassifier

# instantiate the model
tree = DecisionTreeClassifier(max_depth = 5)
# fit the model
tree.fit(X_train, y_train)
```

```
DecisionTreeClassifier(max_depth=5)
```

9.2.2 Predicting the target value:

```
#predicting the target value from the model for the samples
y_test_tree = tree.predict(X_test)
y_train_tree = tree.predict(X_train)
```

Performance Evalution

9.2.3 Computing the Accuracy of the Model:

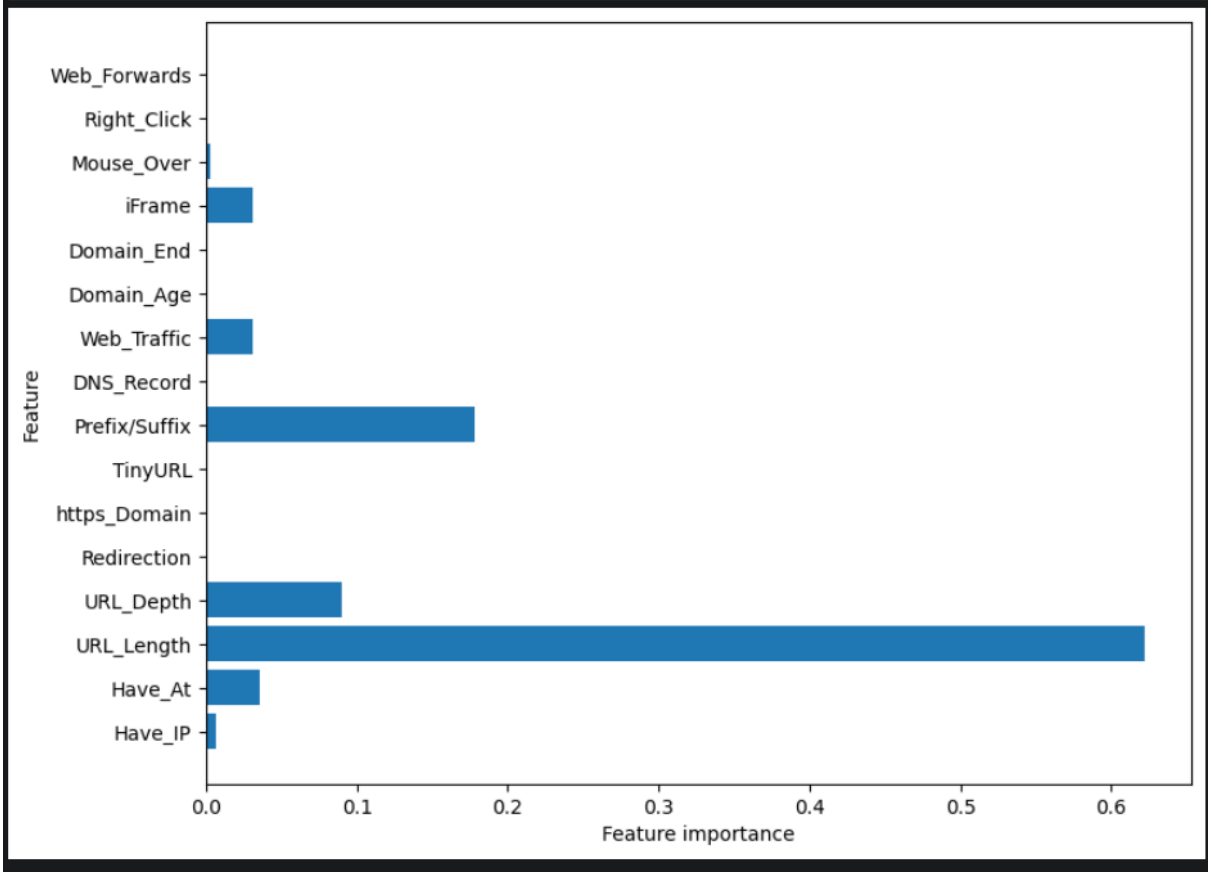
```
#computing the accuracy of the model performance
acc_train_tree = accuracy_score(y_train,y_train_tree)
acc_test_tree = accuracy_score(y_test,y_test_tree)

print("Decision Tree: Accuracy on training Data: {:.3f}".format(acc_train_tree))
print("Decision Tree: Accuracy on test Data: {:.3f}".format(acc_test_tree))
```

```
Decision Tree: Accuracy on training Data: 0.816
Decision Tree: Accuracy on test Data: 0.804
```

9.2.4 Checking the feature importance in the model:

```
#checking the feature importance in the model
plt.figure(figsize=(9,7))
n_features = X_train.shape[1]
plt.barh(range(n_features), tree.feature_importances_, align='center')
plt.yticks(np.arange(n_features), X_train.columns)
plt.xlabel("Feature importance")
plt.ylabel("Feature")
plt.show()
```



9.2.5 Storing the results:

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('Decision Tree', acc_train_tree, acc_test_tree)
```

9.3 Random Forest Classifier

Random forests for regression and classification are currently among the most widely used machine learning methods.A random forest is essentially a collection of decision trees, where each tree is slightly different from the others. The idea behind random forests is that each tree might do a relatively good job of predicting, but will likely overfit on part of the data.

If we build many trees, all of which work well and overfit in different ways, we can reduce the amount of overfitting by averaging their results. To build a random forest model, you need to decide on the number of trees to build (the n_estimators parameter of RandomForestRegressor or RandomForestClassifier). They are very powerful, often work well without heavy tuning of the parameters, and don't require scaling of the data.

9.3.1 Instantiate the model:

```
# Random Forest model
from sklearn.ensemble import RandomForestClassifier

# instantiate the model
forest = RandomForestClassifier(max_depth=5)

# fit the model
forest.fit(X_train, y_train)
```

```
RandomForestClassifier(max_depth=5)
```

9.3.2 Predicting the Target:

```
#predicting the target value from the model for the samples
y_test_forest = forest.predict(X_test)
y_train_forest = forest.predict(X_train)
```

Performance Evalution

9.3.3 Computing the Accuracy of the Model:

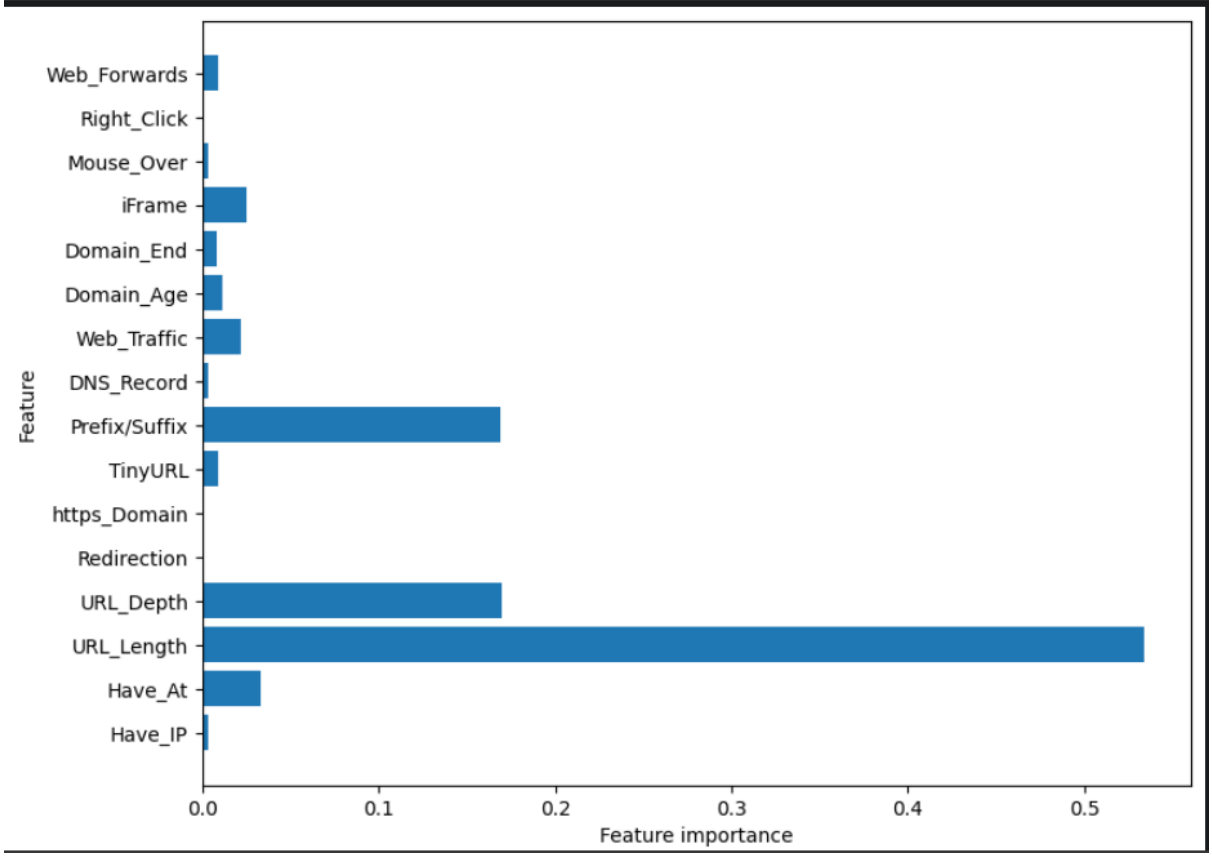
```
#computing the accuracy of the model performance
acc_train_forest = accuracy_score(y_train,y_train_forest)
acc_test_forest = accuracy_score(y_test,y_test_forest)

print("Random forest: Accuracy on training Data: {:.3f}".format(acc_train_forest))
print("Random forest: Accuracy on test Data: {:.3f}".format(acc_test_forest))
```

```
Random forest: Accuracy on training Data: 0.821
Random forest: Accuracy on test Data: 0.809
```

9.3.4 Checking the feature importance of the Model:

```
#checking the feature importance in the model
plt.figure(figsize=(9,7))
n_features = X_train.shape[1]
plt.barh(range(n_features), forest.feature_importances_, align='center')
plt.yticks(np.arange(n_features), X_train.columns)
plt.xlabel("Feature importance")
plt.ylabel("Feature")
plt.show()
```



9.3.5 Storing the results:

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('Random Forest', acc_train_forest, acc_test_forest)
```

9.4 MultiLayer Perceptron: Deep learning

Multilayer perceptrons (MLPs) are also known as (vanilla) feed-forward neural networks, or sometimes just neural networks. Multilayer perceptrons can be applied for both classification and regression problems.

MLPs can be viewed as generalizations of linear models that perform multiple stages of processing to come to a decision.

9.4.1 Instantiate the Model:

```
# Multilayer Perceptrons model
from sklearn.neural_network import MLPClassifier

# instantiate the model
mlp = MLPClassifier(alpha=0.001, hidden_layer_sizes=([100,100,100]))

# fit the model
mlp.fit(X_train, y_train)
```

9.4.2 Predicting the target value:

```
#predicting the target value from the model for the samples
y_test_mlp = mlp.predict(X_test)
y_train_mlp = mlp.predict(X_train)
```

Performance Evalution

9.4.3 Computing the Accuraacy

```
#computing the accuracy of the model performance
acc_train_mlp = accuracy_score(y_train,y_train_mlp)
acc_test_mlp = accuracy_score(y_test,y_test_mlp)

print("Multilayer Perceptrons: Accuracy on training Data: {:.3f}".format(acc_train_mlp))
print("Multilayer Perceptrons: Accuracy on test Data: {:.3f}".format(acc_test_mlp))
```

```
Multilayer Perceptrons: Accuracy on training Data: 0.861
Multilayer Perceptrons: Accuracy on test Data: 0.845
```

9.4.4 Storing the results

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('Multilayer Perceptrons', acc_train_mlp, acc_test_mlp)
```

9.5 XGBoost Classifier

XGBoost is one of the most popular machine learning algorithms these days. XGBoost stands for eXtreme Gradient Boosting. Regardless of the type of prediction task at hand; regression or classification. XGBoost is an implementation of gradient boosted decision trees designed for speed and performance.

9.5.1 Instantiate the model

```
# instantiate the model
xgb = XGBClassifier(learning_rate=0.4,max_depth=7)
#fit the model
xgb.fit(X_train, y_train)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.4, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=7, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

9.5.2 Predicting the target value

```
#predicting the target value from the model for the samples
y_test_xgb = xgb.predict(X_test)
y_train_xgb = xgb.predict(X_train)
```

Performance Evalution

9.5.3 Computing the Accuracy of the model

```
#computing the accuracy of the model performance
acc_train_xgb = accuracy_score(y_train,y_train_xgb)
acc_test_xgb = accuracy_score(y_test,y_test_xgb)

print("XGBoost: Accuracy on training Data: {:.3f}".format(acc_train_xgb))
print("XGBoost : Accuracy on test Data: {:.3f}".format(acc_test_xgb))
```

```
XGBoost: Accuracy on training Data: 0.867
XGBoost : Accuracy on test Data: 0.858
```

9.5.4 Storing results

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('XGBoost', acc_train_xgb, acc_test_xgb)
```

9.6 Autoencoder Neural Network

An auto encoder is a neural network that has the same number of input neurons as it does outputs. The hidden layers of the neural network will have fewer neurons than the input/output neurons. Because there are fewer neurons, the auto-encoder must learn to encode the input to the fewer hidden neurons. The predictors (x) and output (y) are exactly the same in an auto encoder.

9.6.1 Building Autoencoder model

```
#building autoencoder model

input_dim = X_train.shape[1]
encoding_dim = input_dim

input_layer = Input(shape=(input_dim, ))
encoder = Dense(encoding_dim, activation="relu",
                activity_regularizer=regularizers.l1(10e-4))(input_layer)
encoder = Dense(int(encoding_dim), activation="relu")(encoder)

encoder = Dense(int(encoding_dim-2), activation="relu")(encoder)
code = Dense(int(encoding_dim-4), activation='relu')(encoder)
decoder = Dense(int(encoding_dim-2), activation='relu')(code)

decoder = Dense(int(encoding_dim), activation='relu')(encoder)
decoder = Dense(input_dim, activation='relu')(decoder)
autoencoder = Model(inputs=input_layer, outputs=decoder)
autoencoder.summary()
```

```
Model: "functional_1"
```

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 16)	0
dense (Dense)	(None, 16)	272
dense_1 (Dense)	(None, 16)	272
dense_2 (Dense)	(None, 14)	238
dense_5 (Dense)	(None, 16)	240
dense_6 (Dense)	(None, 16)	272

```
Total params: 1,294 (5.05 KB)
Trainable params: 1,294 (5.05 KB)
Non-trainable params: 0 (0.00 B)
```

9.6.2 Compiling the Model

```
#compiling the model
autoencoder.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])

#Training the model
history = autoencoder.fit(X_train, X_train, epochs=10, batch_size=64, shuffle=True, validation_split=0.2)
```

```
Epoch 1/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7990 - loss: -0.9047 - val_accuracy: 0.7681 - val_loss: -0.8295
Epoch 2/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7996 - loss: -0.9575 - val_accuracy: 0.7669 - val_loss: -0.8354
Epoch 3/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7959 - loss: -0.9477 - val_accuracy: 0.7675 - val_loss: -0.8385
Epoch 4/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8033 - loss: -0.8929 - val_accuracy: 0.7731 - val_loss: -0.8422
Epoch 5/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8000 - loss: -0.9509 - val_accuracy: 0.7731 - val_loss: -0.8473
Epoch 6/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8007 - loss: -0.9597 - val_accuracy: 0.7513 - val_loss: -0.8589
Epoch 7/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7665 - loss: -1.4488 - val_accuracy: 0.7281 - val_loss: -1.8567
Epoch 8/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7470 - loss: -1.9261 - val_accuracy: 0.7225 - val_loss: -1.8623
Epoch 9/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7404 - loss: -1.9501 - val_accuracy: 0.7106 - val_loss: -1.8654
Epoch 10/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7104 - loss: -1.9690 - val_accuracy: 0.7412 - val_loss: -1.8623
```

Performance Evalution

9.6.3 Evaluting the Model

```
acc_train_auto = autoencoder.evaluate(X_train, X_train)[1]
acc_test_auto = autoencoder.evaluate(X_test, X_test)[1]

print('\nAutoencoder: Accuracy on training Data: {:.3f}' .format(acc_train_auto))
print('Autoencoder: Accuracy on test Data: {:.3f}' .format(acc_test_auto))
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 752us/step - accuracy: 0.7534 - loss: -1.9922
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 867us/step - accuracy: 0.7505 - loss: -1.9276

Autoencoder: Accuracy on training Data: 0.753
Autoencoder: Accuracy on test Data: 0.756
```

9.6.4 Storing the results

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('AutoEncoder', acc_train_auto, acc_test_auto)
```

9.7 Support Vector Machine

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

9.7.1 Initiate the model:

```
# initiate the model
svm = SVC(kernel='linear', C=1.0, random_state=12)
#fit the model
svm.fit(X_train, y_train)
```

```
SVC(kernel='linear', random_state=12)
```

9.7.2 Predicting the Target Value:

```
#predicting the target value from the model for the samples
y_test_svm = svm.predict(X_test)
y_train_svm = svm.predict(X_train)
```

Performance Evalution

9.7.3 Computing the Accuracy

```
#computing the accuracy of the model performance
acc_train_svm = accuracy_score(y_train,y_train_svm)
acc_test_svm = accuracy_score(y_test,y_test_svm)

print("SVM: Accuracy on training Data: {:.3f}".format(acc_train_svm))
print("SVM : Accuracy on test Data: {:.3f}".format(acc_test_svm))
```

```
SVM: Accuracy on training Data: 0.804
SVM : Accuracy on test Data: 0.793
```

9.7.4 Storing the results

```
#storing the results. The below mentioned order of parameter passing is important.
#Caution: Execute only once to avoid duplications.
storeResults('SVM', acc_train_svm, acc_test_svm)
```

CHAPTER 3

RESULT & ANALYSIS

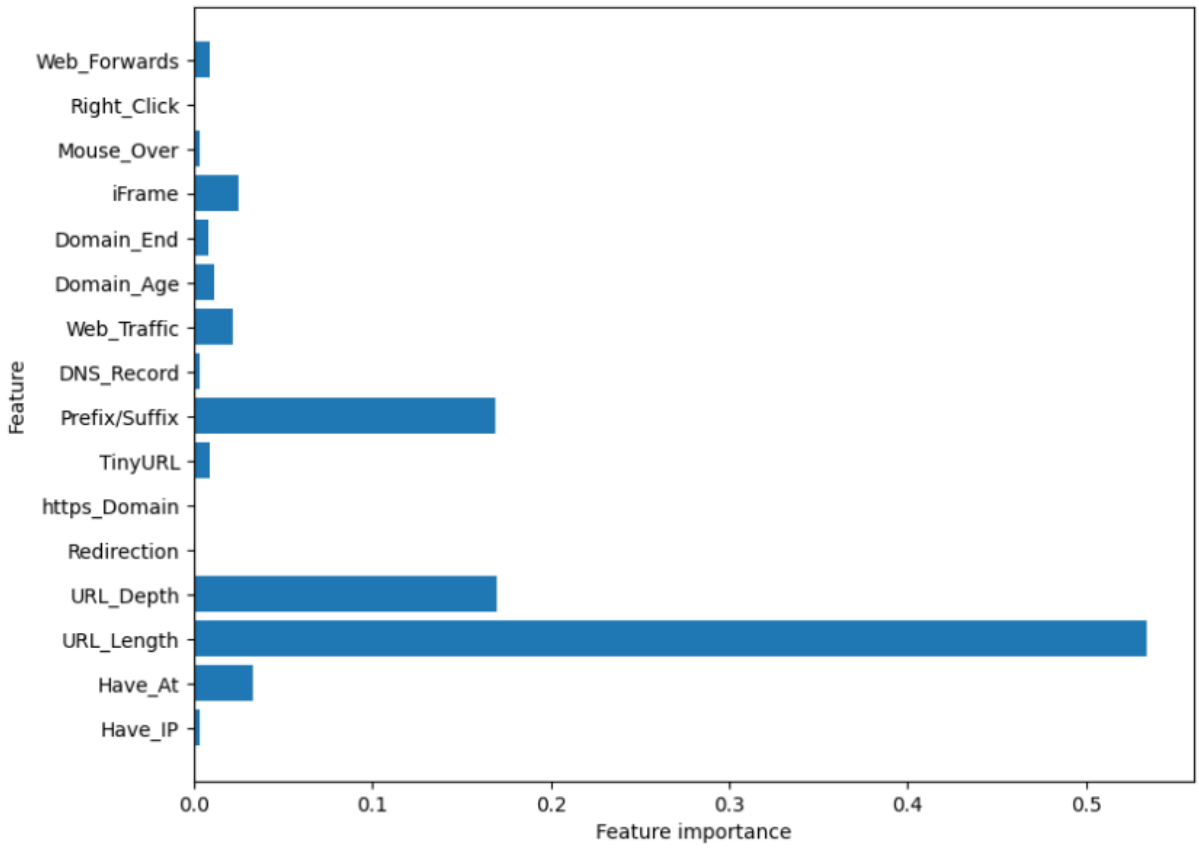
So, here as a result we compare the models and found out that ***XGBoost performs the best out of all the models*** and also the main area of interest of not been phished is to keep check on the ***URL of the Website.***

Comparison of the Model

```
#creating dataframe
results = pd.DataFrame({ 'ML Model': ML_Model,
    'Train Accuracy': acc_train,
    'Test Accuracy': acc_test})
results
```

	ML Model	Train Accuracy	Test Accuracy
0	Decision Tree	0.816	0.804
1	Random Forest	0.821	0.809
2	Multilayer Perceptrons	0.861	0.845
3	XGBoost	0.867	0.858
4	AutoEncoder	0.753	0.756
5	SVM	0.804	0.793

Most important feature to look for



CHAPTER 4
CONCLUSION

This paper explored the potential of various type of Machine Learning and project it as a viable solution for automated phishing Detection. By leveraging the Machine learning Algorithms i developed a model capable of i***dentifying malicious websites with high accuracy***. This research focused on analyzing features extracted from website content and URl based patterns in HTML code. These features were to utilized to train and evalute the performanec of various Supervised as well as Unsupervised Machine Learning Algorithms, Include ***Support vector Machine, Random Forest, Decision Tree*** and others.

The Evalution process highlighted the effectiveness of these Algorithms in distinguishing between legitmate and phishing websites. The Models achieved promising accuracy rates and it also demonstrates thier potential for real world application. However, it is crucial to acknowledge the ongoing evolution of phishing tactics continous research is still very important to tackle the everchanging strategies.

Building upon the sucess of this research, this research as a practical solution for internet users. The ***development of Browser Extension can leverage this research,*** such a browser extension can empower the users with an additional layer of security fostering a more vigilant and secure online enviroment. The proposed ***browser extension projects a practical application of this research***, offers a ***user-friendly and adaptable solution for combating cybercrime.*** By harnessing the power of machine learning we can work towards a safer and more trustworthy digital landscape.

Chapter 5
References

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APPENDIX A

PLAGIARISM REPORT

S No.	Topic	Plagiarism (in %)
1.	Abstract	**0**
2.	Introduction	**0**
3.	Methodologies	**0**

Table A.1: Plagiarism Report

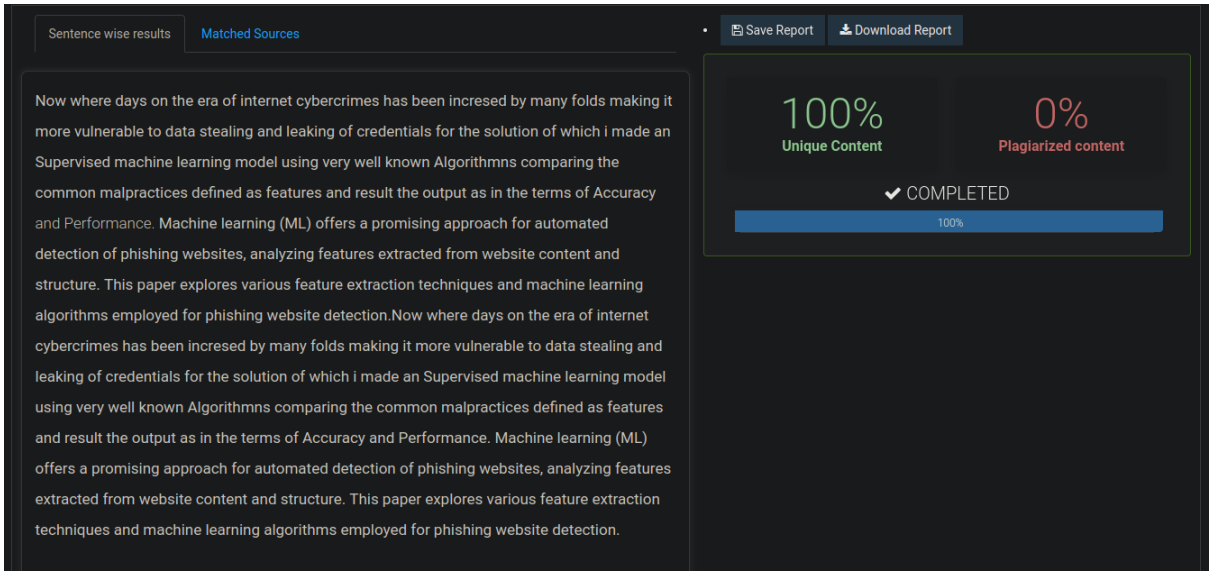

Figure A.1: Plagiarism - Abstract

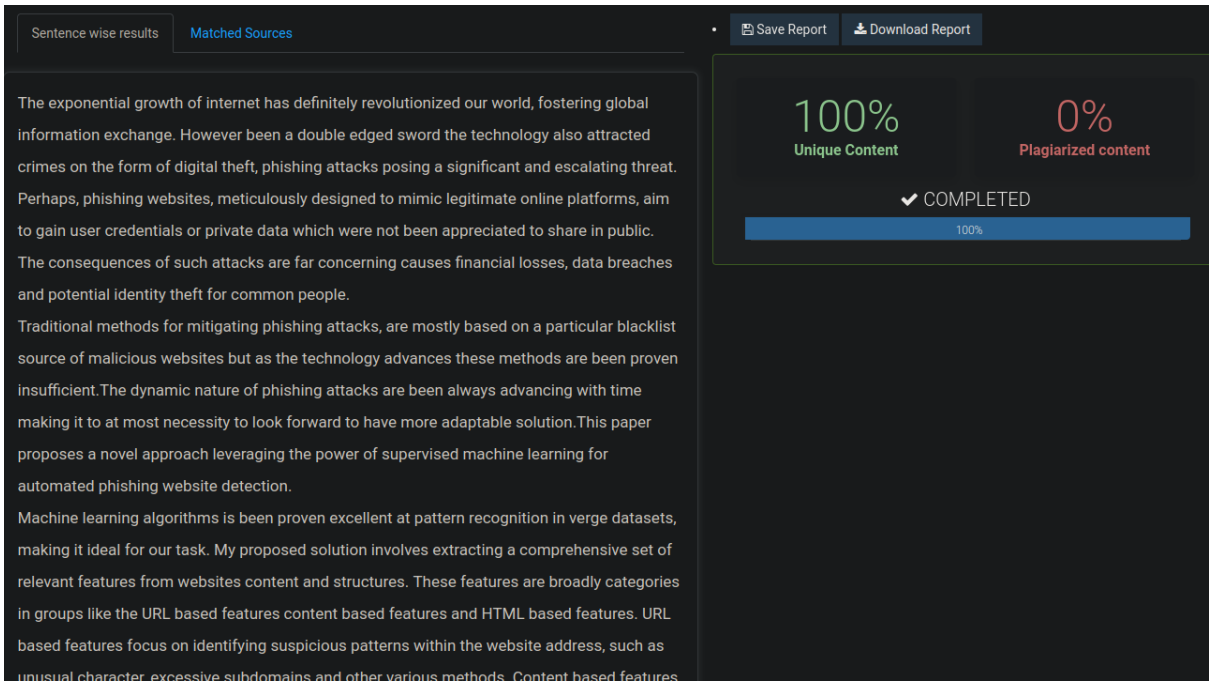

Figure A.2: Plagiarism – Introduction

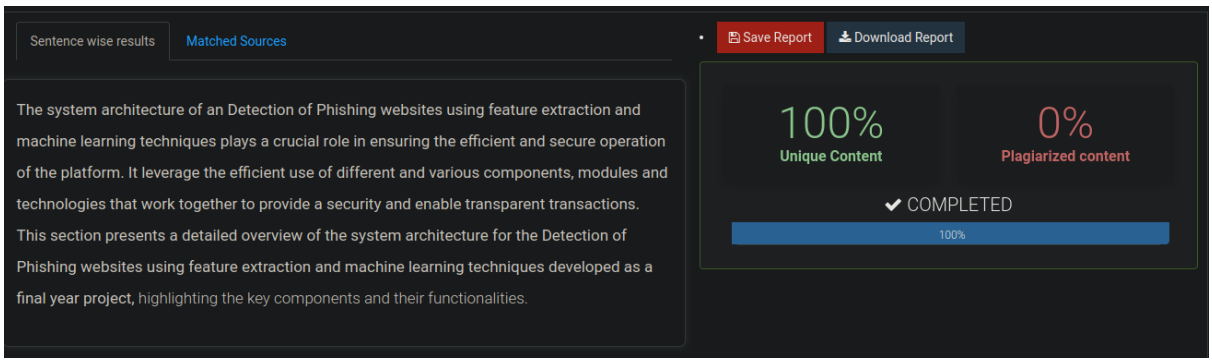

Figure A.3: Plagiarism – Methodologies