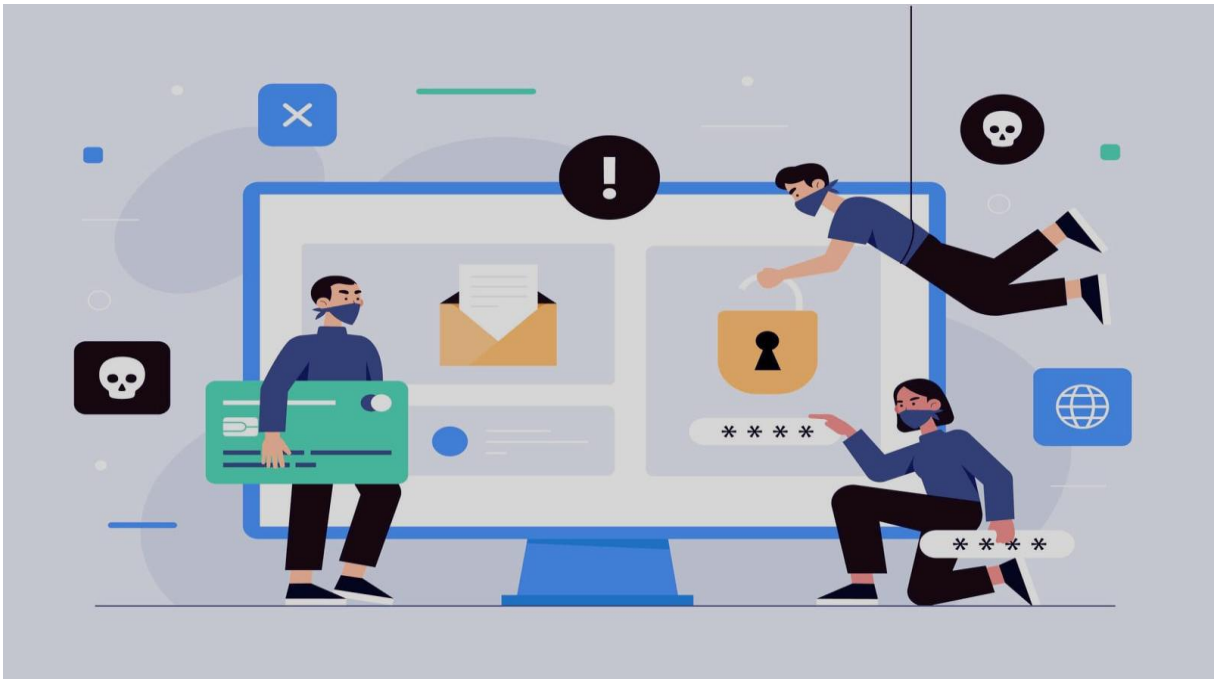
URL-Based Phishing Detection Using Machine Learning



Team Members

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Table of Contents

1. INTRODUCTION

1.1 Overview: -

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

Common threats of web phishing:

- Web phishing aims to steal private information, such as usernames, passwords, and credit card details, by way of impersonating a legitimate entity.
- It will lead to information disclosure and property damage.
- Large organizations may get trapped in different kinds of scams.

1.2 Purpose: -

This Guided Project mainly focuses on applying a machine-learning algorithm to detect Phishing websites.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.

2. LITERATURE SURVEY

2.1 Existing problem: -

Imbalanced Datasets: The dataset used for training ML models may be imbalanced, meaning there might be significantly more legitimate URLs than phishing URLs, affecting the model's ability to accurately detect phishing attempts.

Data Privacy Concerns: The analysis of URLs may inadvertently reveal sensitive information or violate user privacy, raising ethical and legal concerns.

Scalability: As the volume of URLs increases, the computational resources and time required for processing and analysis can become a challenge.

2.2 Proposed solution: -

Feature Engineering: Extract relevant features from URLs, such as domain reputation, URL length, presence of certain keywords, and domain age. These features can provide valuable information for ML models to distinguish between legitimate and phishing URLs.

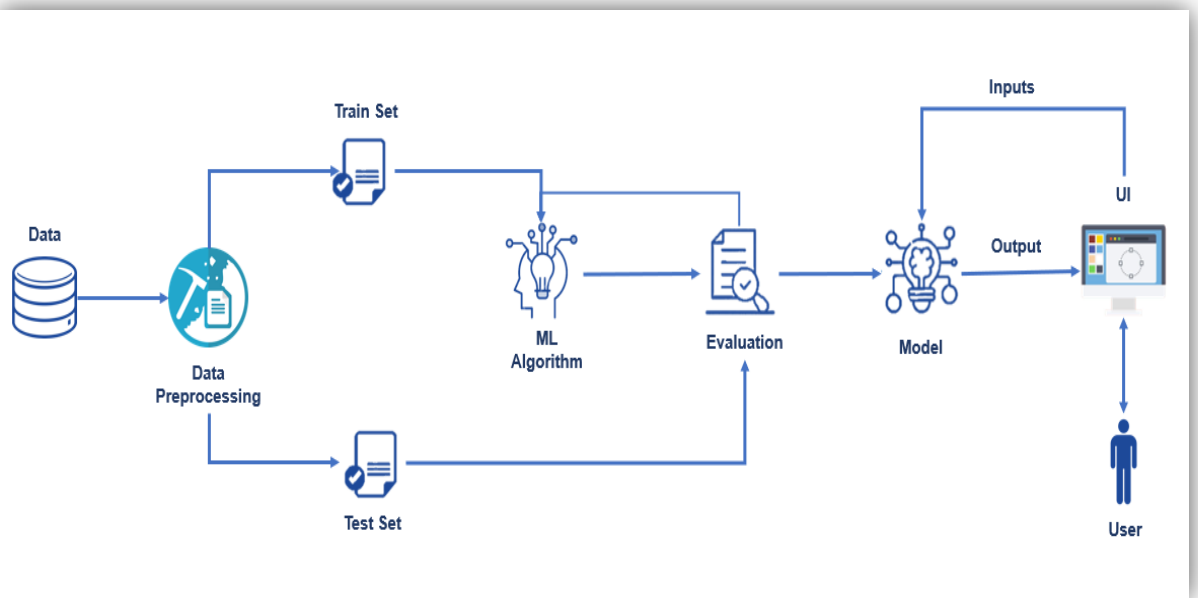
Ensemble Learning: Combine multiple ML models, such as Random Forests, Gradient Boosting, and Decision tree classification in an ensemble to leverage their strengths and mitigate individual weaknesses, improving overall detection performance.

Imbalanced Data Handling: Address imbalanced datasets by using techniques like oversampling, undersampling, or using synthetic data generation methods like SMOTE (Synthetic Minority Over-sampling Technique) to balance the proportion of legitimate and phishing URLs in the training data.

Transfer Learning: Utilize pre-trained models on large-scale datasets related to web data or URLs and fine-tune them with domain-specific phishing data to benefit from the knowledge and features learned from broader contexts.

3. THEORETICAL ANALYSIS

3.1 Block diagram



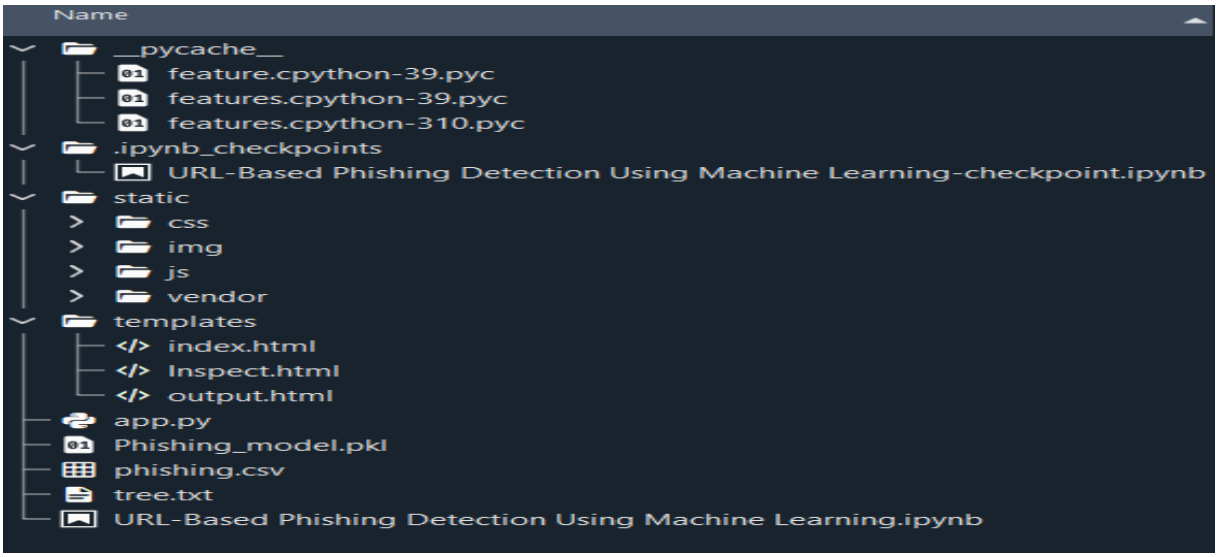
3.2 Software designing: -

To complete this project, you must required following software's, concepts and packages

- **Anaconda navigator:**
  - Refer the link below to download anaconda navigator.
  - Link : https://youtu.be/1ra4zH2G4o0
- **Python packages:**
  - Open anaconda prompt as administrator
  - Type "pip install numpy" and click enter.
  - Type "pip install pandas" and click enter.
  - Type "pip install scikit-learn" and click enter.
  - Type "pip install matplotlib" and click enter.
  - Type "pip install scipy" and click enter.
  - Type "pip install pickle-mixin" and click enter.
  - Type "pip install seaborn" and click enter.
  - Type "pip install Flask" and click enter.

4. EXPERIMENTAL INVESTIGATIONS

Create the Project folder which contains files as shown below



We are building a flask application which needs HTML pages stored in the templates folder.

➢ Milestone 1: Data Collection & Data Pre-processing

Activity 1: Importing Required Libraries:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn import metrics
import warnings
warnings.filterwarnings('ignore')
```

Collection Of Dataset

To start with, we have to select or identify a dataset that contains a set of features through which a phishing website can be identified.

Activity 2: Download the dataset

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc.

In this project we have used phishing.csv data. This data is downloaded from kaggle.com. Please refer the link given below to download the dataset.

Dataset Link: https://www.kaggle.com/eswarchandt/phishing-website-detector

As we have understood how the data is collected lets pre-process the collected data.

Activity 3: Data Pre-processing

The download data set is not suitable for training the machine learning model as it might have so much of randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

- Handling missing values
- Handling categorical data
- Handling outliers
- Scaling Techniques
- Splitting dataset into training and test set

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

Activity 4: Checking for null values

Let's find the shape of our dataset first, To find the shape of our data, df.shape method is used. To find the data type, df.info() function is used.

```
df.shape
```

```
(11054, 32)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11054 entries, 0 to 11053
Data columns (total 32 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Index                 11054 non-null  int64
 1   UsingIP               11054 non-null  int64
 2   LongURL               11054 non-null  int64
 3   ShortURL              11054 non-null  int64
 4   Symbol@               11054 non-null  int64
 5   Redirecting//         11054 non-null  int64
 6   PrefixSuffix-         11054 non-null  int64
 7   SubDomains            11054 non-null  int64
 8   HTTPS                 11054 non-null  int64
 9   DomainRegLen          11054 non-null  int64
 10  Favicon               11054 non-null  int64
 11  NonStdPort            11054 non-null  int64
 12  HTTPSDomainURL        11054 non-null  int64
 13  RequestURL            11054 non-null  int64
 14  AnchorURL             11054 non-null  int64
 15  LinksInScriptTags     11054 non-null  int64
 16  ServerFormHandler     11054 non-null  int64
 17  InfoEmail             11054 non-null  int64
 18  AbnormalURL           11054 non-null  int64
 19  WebsiteForwarding     11054 non-null  int64
 20  StatusBarCust         11054 non-null  int64
 21  DisableRightClick     11054 non-null  int64
 22  UsingPopupWindow      11054 non-null  int64
 23  IframeRedirection     11054 non-null  int64
 24  AgeofDomain           11054 non-null  int64
 25  DNSRecording          11054 non-null  int64
 26  WebsiteTraffic        11054 non-null  int64
 27  PageRank              11054 non-null  int64
 28  GoogleIndex           11054 non-null  int64
 29  LinksPointingToPage   11054 non-null  int64
 30  StatsReport           11054 non-null  int64
 31  class                 11054 non-null  int64
dtypes: int64(32)
memory usage: 2.7 MB
```

For checking the null values, df.isnull() function is used. To sum those null values we use .sum() function to it. From the below image we found that there are some null values present in our dataset. So we have to handle the missing values.

```
df.isnull().sum()
```

```
Index                0
UsingIP              0
LongURL              0
ShortURL             0
Symbol@              0
Redirecting//        0
PrefixSuffix-        0
SubDomains           0
HTTPS                0
DomainRegLen         0
Favicon              0
NonStdPort           0
HTTPSDomainURL       0
RequestURL           0
AnchorURL            0
LinksInScriptTags    0
ServerFormHandler    0
InfoEmail            0
AbnormalURL          0
WebsiteForwarding    0
StatusBarCust        0
DisableRightClick    0
UsingPopupWindow     0
IframeRedirection    0
AgeofDomain          0
DNSRecording         0
WebsiteTraffic       0
PageRank             0
GoogleIndex          0
LinksPointingToPage  0
StatsReport          0
class                0
dtype: int64
```

There is no null values in our dataset

There is no categorical data in our dataset.

Activiy 5: Checking for duplicated data

```
df.duplicated().sum()
```

```
5205
```

we had duplicate data in our dataset so we have to remove it.

Handling duplicate data

```
df.drop_duplicates(inplace=True)
```

```
df.duplicated().sum()
```

```
0
```

```
df.shape
```

```
(5849, 22)
```

Activity 6: Outliers

We had outliers in our dataset in the columns 'PrefixSuffix-','NonStdPort', 'HTTPSDomainURL','AnchorURL','ServerFormHandler','InfoEmail','AbnormalURL','WebsiteForwarding','StatusBarCust','DisableRightClick','GoogleIndex','StatsReport'

Handling Outliers

```
# Z-score method
z_scores = np.abs((df - df.mean()) / df.std())
outliers = df[z_scores > 3]
```

```
# IQR method
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
outliers = df[(df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))]
```

```
#Handle outliers
# Remove outliers
df_cleaned = df.drop(outliers.index)
```

```
# Replace outliers with median
df_cleaned = df.copy()
df_cleaned=np.where(z_scores>3,df.median(),df)
```

```
# Apply log transformation
df_cleaned = np.log1p(df+0.0001)
```

```
# Validate the results
print(df_cleaned.describe())
```

Activity 7: Checking data is balanced or not?

```
clmns=['class','HTTPS','SubDomains']
for i in clmns:
    print(f"The Value counts of {i} :")
    print(df[i].value_counts().to_string(),'\n')
```

```
The Value counts of class :
-1    3019
 1    2830

The Value counts of HTTPS :
 1    3000
-1    2128
 0     721

The Value counts of SubDomains :
 1    2088
 0    2058
-1    1703
```

From the above we can understand that our data set is imbalanced

```
             UsingIP  PrefixSuffix-   SubDomains        HTTPS  NonStdPo
count  5849.000000    5849.000000  5849.000000  5849.000000  5849.000
mean     -3.600763      -8.023406    -2.434195    -2.995374    -0.903
std       4.908301       3.216801     4.353017     4.705445     3.642
min      -9.210340      -9.210340    -9.210340    -9.210340    -9.210
25%      -9.210340      -9.210340    -9.210340    -9.210340     0.693
50%       0.693197      -9.210340     0.000100     0.693197     0.693
75%       0.693197      -9.210340     0.693197     0.693197     0.693
max       0.693197       0.693197     0.693197     0.693197     0.693

       HTTPSDomainURL   RequestURL    AnchorURL  LinksInScriptTags  \
count     5849.000000  5849.000000  5849.000000        5849.000000
mean        -1.022016    -3.660025    -3.011206          -3.341746
std          3.747949     4.915881     4.479933           4.606370
min         -9.210340    -9.210340    -9.210340          -9.210340
25%          0.693197    -9.210340    -9.210340          -9.210340
50%          0.693197     0.693197     0.000100           0.000100
75%          0.693197     0.693197     0.000100           0.000100
max          0.693197     0.693197     0.693197           0.693197

       ServerFormHandler  ...  WebsiteForwarding  StatusBarCust  \
count        5849.000000  ...        5849.000000    5849.000000
mean           -6.775943  ...           0.091462      -0.678296
std             4.197679  ...           0.234489       3.421059
min            -9.210340  ...           0.000100      -9.210340
25%            -9.210340  ...           0.000100       0.693197
50%            -9.210340  ...           0.000100       0.693197
75%             0.000100  ...           0.000100       0.693197
max             0.693197  ...           0.693197       0.693197

       DisableRightClick  AgeofDomain  DNSRecording  WebsiteTraffic  \
count        5849.000000  5849.000000   5849.000000     5849.000000
mean            0.207248    -4.152746     -1.905868       -1.979872
std             2.139451     4.951061      4.357527        4.201293
min            -9.210340    -9.210340     -9.210340       -9.210340
25%             0.693197    -9.210340     -9.210340       -9.210340
50%             0.693197     0.693197      0.693197        0.000100
75%             0.693197     0.693197      0.693197        0.693197
max             0.693197     0.693197      0.693197        0.693197

          PageRank  GoogleIndex  StatsReport        class
count  5849.000000  5849.000000  5849.000000  5849.000000
mean     -6.357295    -0.981379    -0.806980    -4.418579
std       4.485400     3.712463     3.550871     4.949606
min      -9.210340    -9.210340    -9.210340    -9.210340
25%      -9.210340     0.693197     0.693197    -9.210340
50%      -9.210340     0.693197     0.693197    -9.210340
75%       0.693197     0.693197     0.693197     0.693197
max       0.693197     0.693197     0.693197     0.693197

[8 rows x 22 columns]
```

Activity 8: Scaling

Splitting the data

The data is split into train & test sets, 80-20 split.

```
X = df.drop(["class"],axis =1)
y = df["class"]
```

Scaling

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
clmn_names=X.columns
scaled=scaler.fit_transform(X)
features=pd.DataFrame(scaled,columns=clmn_names)
features
```

	UsingIP	PrefixSuffix-	SubDomains	HTTPS	NonStdPort	HTTPSDomainURL	RequestURL	AnchorURL	LinksInScriptTags	ServerFormHandler	...	Abn
0	0.874911	-0.369011	-0.082035	0.920511	0.438422	-2.184935	0.885618	0.190783	-1.108454	-0.550407	...	
1	0.874911	-0.369011	-1.328329	-1.243069	0.438422	-2.184935	0.885618	0.190783	-1.108454	-0.550407	...	
2	0.874911	-0.369011	-1.328329	-1.243069	0.438422	-2.184935	-1.129155	0.190783	0.190814	-0.550407	...	
3	0.874911	-0.369011	1.164259	0.920511	0.438422	0.457680	0.885618	0.190783	0.190814	-0.550407	...	
4	-1.142973	-0.369011	1.164259	0.920511	0.438422	-2.184935	0.885618	0.190783	0.190814	-0.550407	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
5844	0.874911	-0.369011	-1.328329	-1.243069	0.438422	-2.184935	0.885618	-1.186860	1.490083	-0.550407	...	
5845	0.874911	-0.369011	1.164259	-1.243069	0.438422	0.457680	0.885618	0.190783	1.490083	-0.550407	...	
5846	0.874911	-0.369011	-1.328329	0.920511	0.438422	0.457680	-1.129155	0.190783	0.190814	-0.550407	...	
5847	-1.142973	-0.369011	1.164259	-1.243069	0.438422	-2.184935	-1.129155	0.190783	-1.108454	-0.550407	...	
5848	-1.142973	-0.369011	-1.328329	-1.243069	0.438422	0.457680	-1.129155	-1.186860	0.190814	-0.550407	...	

5849 rows × 21 columns

Activity 9: Train Test and Split

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, y, test_size = 0.2, random_state = 42)
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

```
((4679, 21), (4679,), (1170, 21), (1170,))
```

Activity 10: Handling Balance Data

```
from imblearn.over_sampling import SMOTE
smote=SMOTE(sampling_strategy=1)
X_train,y_train=smote.fit_resample(X_train,y_train)
pd.DataFrame(y_train).value_counts()
```

```
class
-1       2388
 1       2388
dtype: int64
```

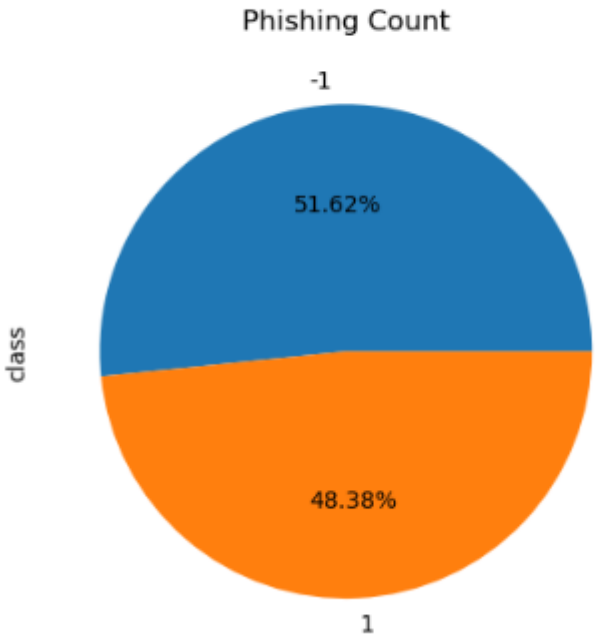
From the above we understand that our data is balanced.

➢ Milestone 2: Visualizing and analysing the data

Activity 1: Univariate analysis

In simple words, univariate analysis is understanding the data with single feature. Here we have displayed two different graphs such as distplot and countplot.

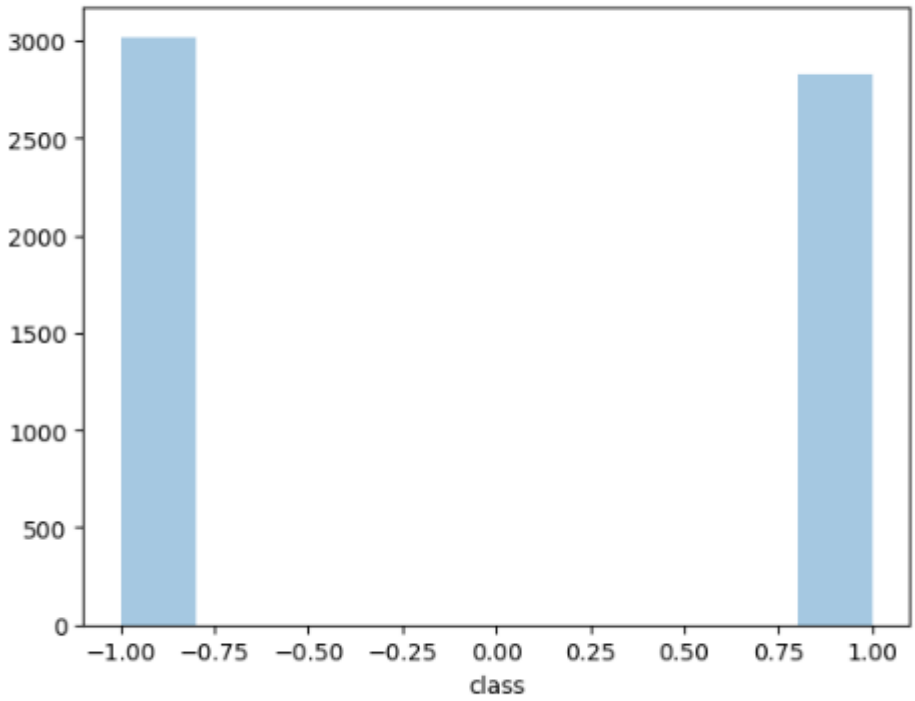
```
df['class'].value_counts().plot(kind='pie',autopct='%1.2f%%')
plt.title("Phishing Count")
plt.show()
```



- From the above plot we came to know, the highest distribution of phishing is unsafe with 51.62%

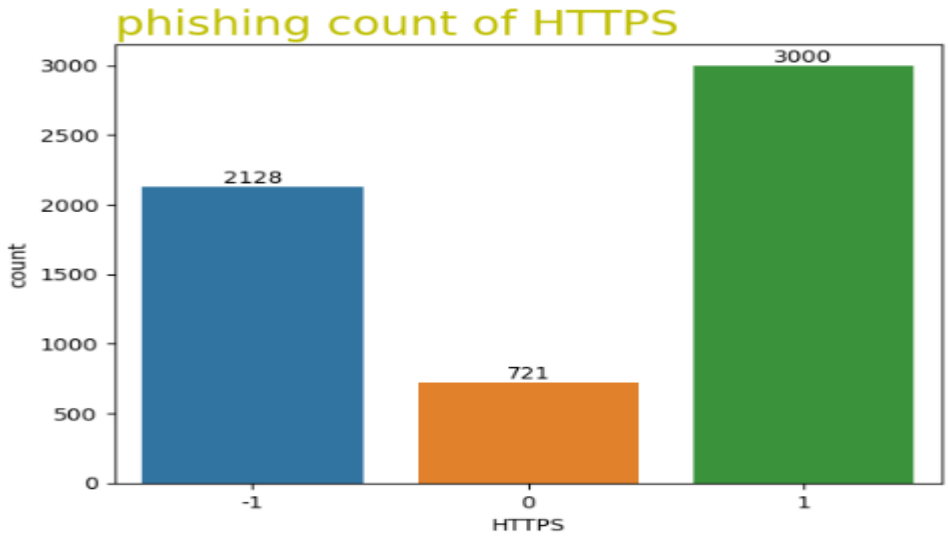
```
sns.distplot( a=df["class"], hist=True, kde=False, rug=False )
```

```
<Axes: xlabel='class'>
```



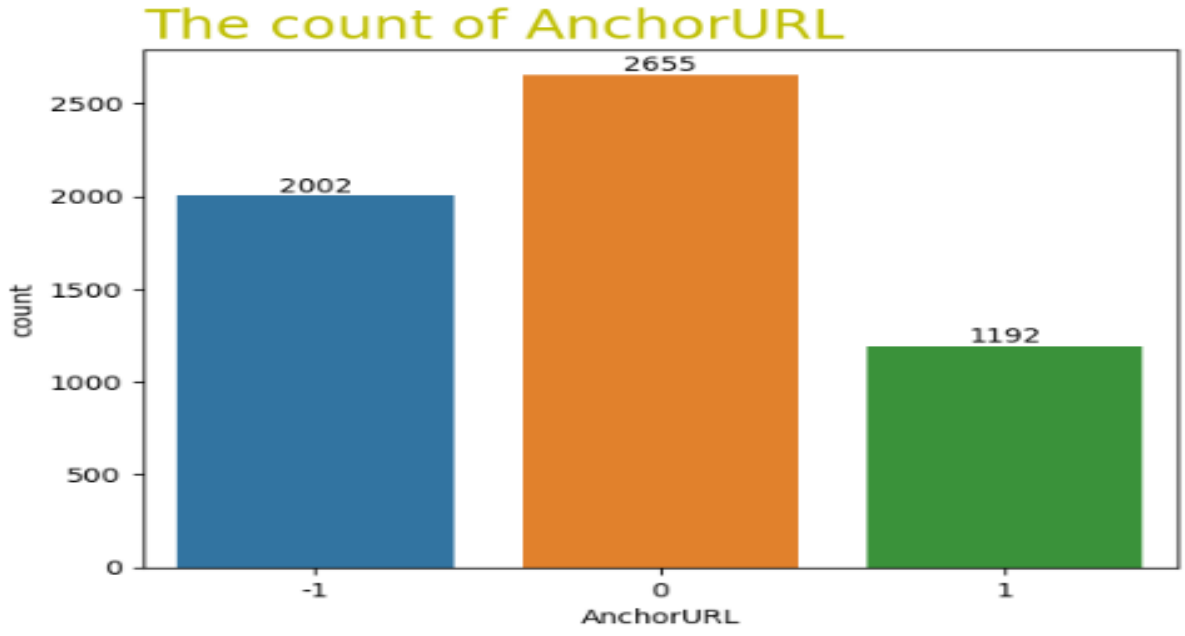
Phishing count is more here also as the class which has 1 is greater than the class which has -1

```
count=sns.countplot(x=df.HTTPS,data=df)
for i in count.containers:
    count.bar_label(i)
plt.title("phishing count of HTTPS",color='y',size=20,loc='left')
plt.show()
```



- phishing URLS are 2128.
- legitimate HTTPS URLS or non_phishing URLS are 3000.
- Suspicious URLS are 721 (0 indicates a potential risk of features that indicate a potential risk of phishing, but they are not confirmed phishing URLS).

```
count=sns.countplot(x=df.AnchorURL,data=df)
for i in count.containers:
    count.bar_label(i)
plt.title("The count of AnchorURL ",color='y',size=20,loc='left')
plt.show()
```

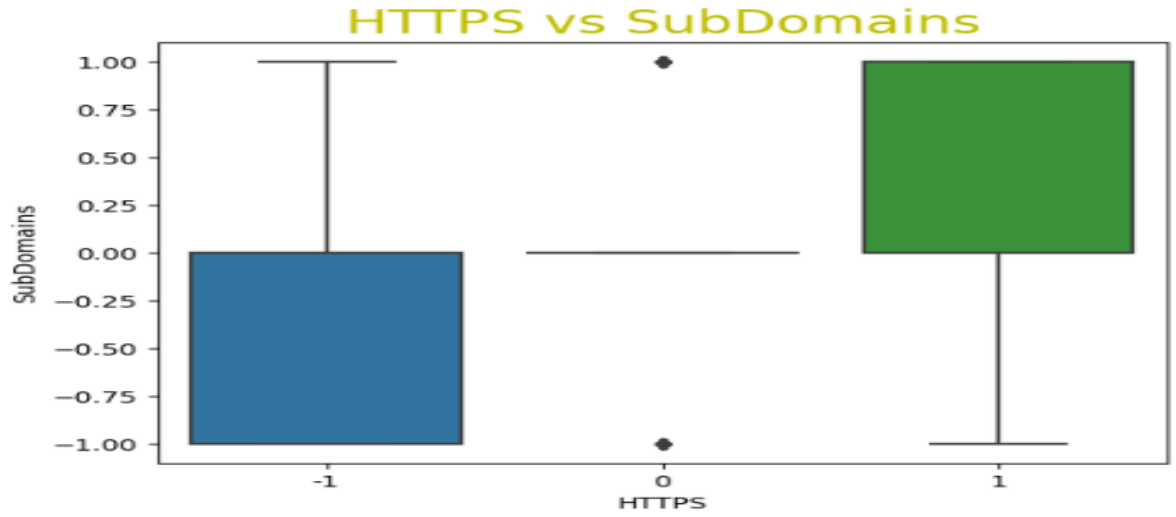


In the AnchorURL suspicious URLS are more than the Non-phishing and phishing URLS

Activity 2: Bivariate analysis

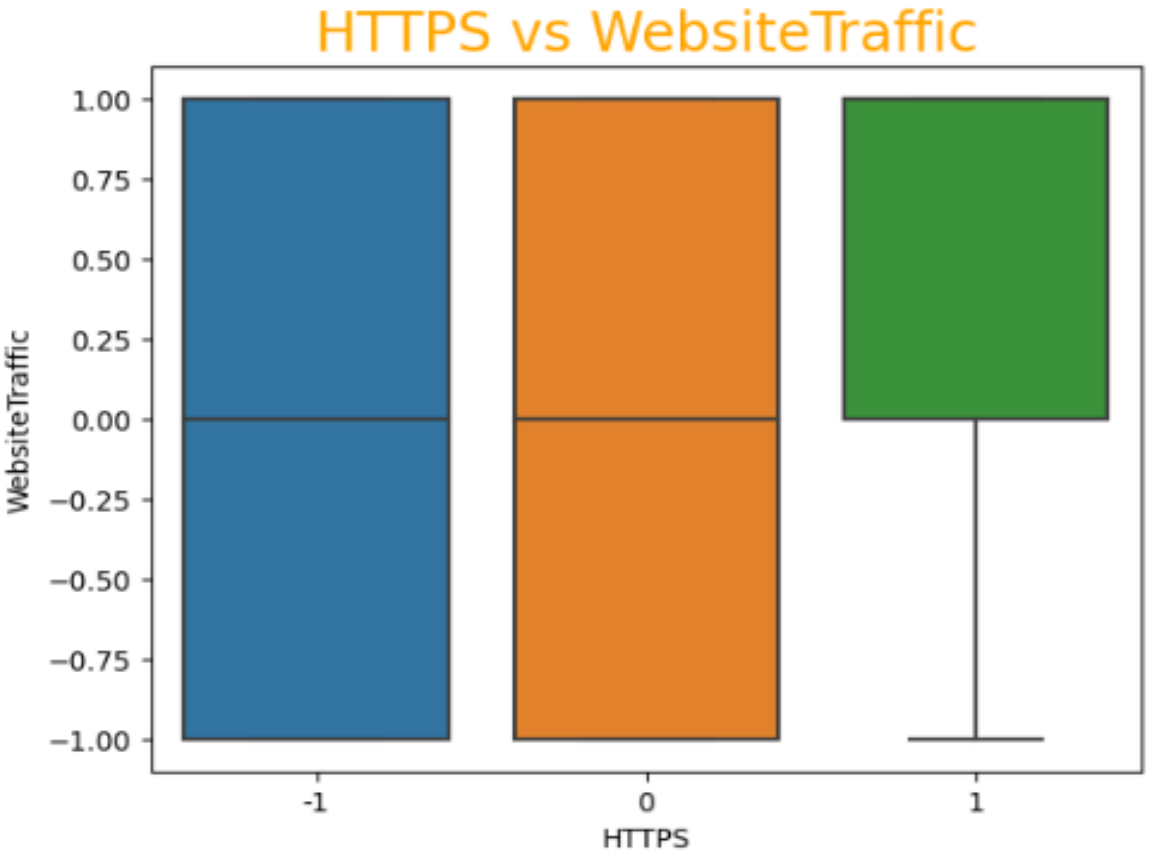
To find the relation between two features we use bivariate analysis.

```
sns.boxplot(x=df.HTTPS,y=df.SubDomains)
plt.title("HTTPS vs SubDomains",color='y',size=20)
plt.show()
```



There are outliers are in my dataset

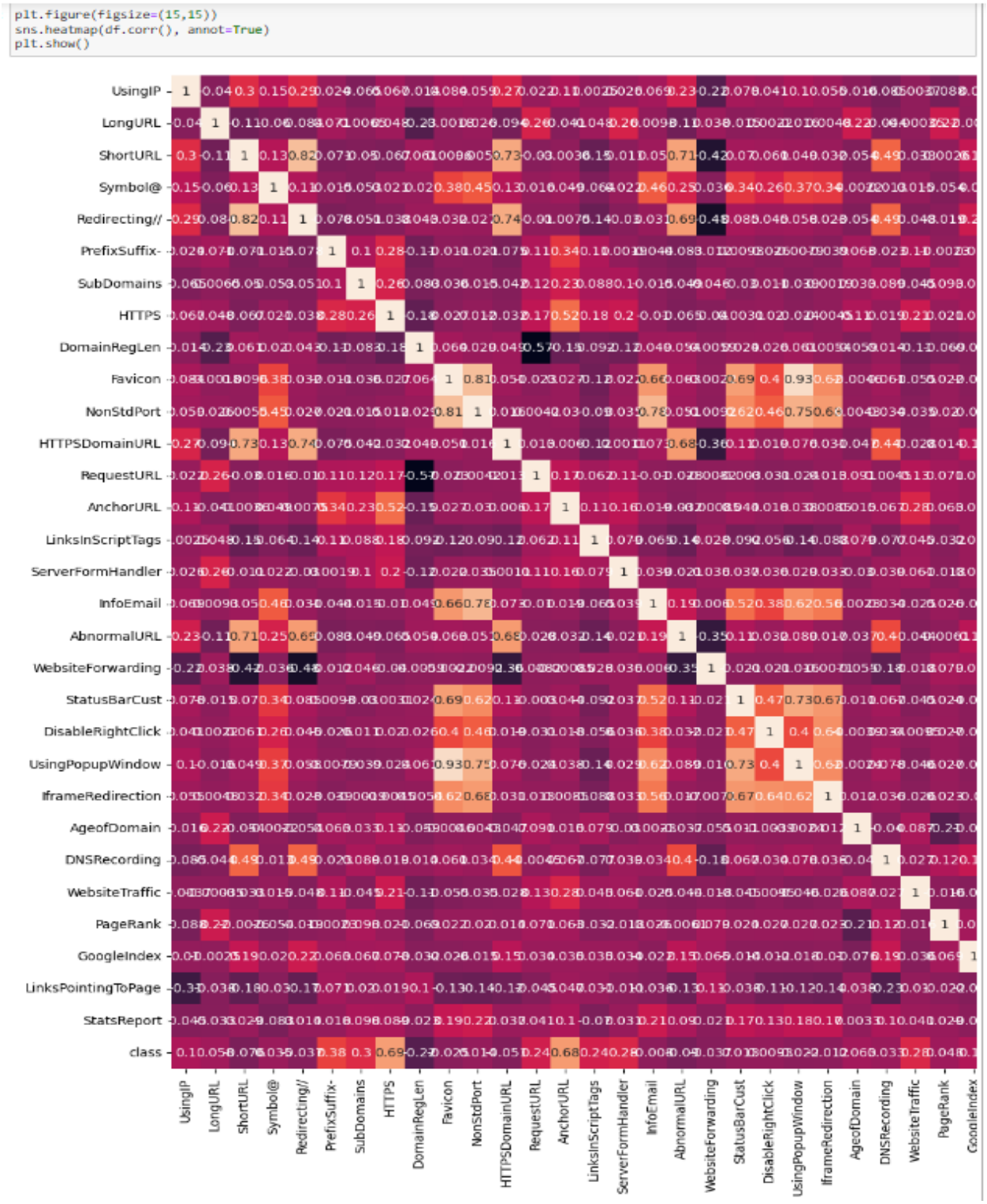
```
sns.boxplot(x=df.HTTPS,y=df.WebsiteTraffic)
plt.title("HTTPS vs WebsiteTraffic",color='orange',size=20)
plt.show()
```



Activity 3: Multivariate analysis

In simple words, multivariate analysis is to find the relation between multiple features. Here we have used heatmap from seaborn package.

- From the below image, we came to a conclusion that how data is distributed and how they are and how much they are correlated each other.
- All the features weather following the normal distribution or not ?



here in this dataset some features have no good reationship so we can delete those we can delete the columns based on dependent variable class So, here I'm going to delete

LongURL,ShortURL,Symbol@, Redirecting //,DomainRegLen, Favicon, UsingPopupWindow, IframeRedirection, LinksPointingToPage

```
drop(columns=['LongURL','Symbol@','ShortURL','Redirecting//','DomainRegLen', 'Favicon', 'UsingPopupWindow', 'IframeRedirection',
```

```
df.head()
```

	UsingIP	PrefixSuffix-	SubDomains	HTTPS	NonStdPort	HTTPSDomainURL	RequestURL	AnchorURL	LinksInScriptTags	ServerFormHandler	...	WebsiteFor
0	1	-1	0	1	1	-1	1	0	-1	-1	...	
1	1	-1	-1	-1	1	-1	1	0	-1	-1	...	
2	1	-1	-1	-1	1	-1	-1	0	0	-1	...	
3	1	-1	1	1	1	1	1	0	0	-1	...	
4	-1	-1	1	1	1	-1	1	0	0	-1	...	

5 rows × 22 columns

```
df.shape
```

```
(5849, 22)
```

After completion of training and splitting the data we had 21 column.

➢ Milestone 3

Model Building and Comparision of Models

Supervised machine learning is one of the most commonly used and successful types of machine learning. Supervised learning is used whenever we want to predict a certain outcome/label from a given set of features, and we have examples of features-label pairs. We build a machine learning model from these features-label pairs, which comprise our training set. Our goal is to make accurate predictions for new, never-before-seen data.

There are two major types of supervised machine learning problems, called classification and regression. Our data set comes under classification problem, as the phishing detection is a discrete number. The machine learning models considered to train the dataset in this notebook are:

The metrics considered to evaluate the model performance are Accuracy & F1 score.

To compare the models performance, a dataframe is created. The columns of this dataframe are the lists created to store the results of the model.

```python
# Instantiate the models
logistic_regression = LogisticRegression()
knn = KNeighborsClassifier()
naive_bayes = GaussianNB()
decision_tree = DecisionTreeClassifier(max_depth=30)
random_forest = RandomForestClassifier(n_estimators=10)
gradient_boosting = GradientBoostingClassifier(max_depth=4, learning_rate=0.7)
mlp = MLPClassifier()
svc = SVC()

# Train and predict for each model
models = [
    ("Logistic Regression", logistic_regression),
    ("K-Nearest Neighbors", knn),
    ("Naive Bayes", naive_bayes),
    ("Decision Tree", decision_tree),
    ("Random Forest", random_forest),
    ("Gradient Boosting", gradient_boosting),
    ("Multi-Layer Perceptron", mlp),
    ("Support Vector", svc)
]

for model_name, model in models:
    print(f"Model: {model_name}")

    # Fit the model
    model.fit(X_train, y_train)

    # Predict
    y_pred = model.predict(X_test)

    # Evaluation metrics
    accuracy = accuracy_score(y_test, y_pred)
    confusion = confusion_matrix(y_test, y_pred)
    classification = classification_report(y_test, y_pred)

    print(f"Accuracy: {accuracy}")
    print(f"Confusion Matrix:\n{confusion}")
    print(f"Classification Report:\n{classification}")
    print("-" * 50)
```

Model: Logistic Regression
Accuracy: 0.9222222222222223
Confusion Matrix:
[[573 58]
[33 506]]
Classification Report:

	precision	recall	f1-score	support
-1	0.95	0.91	0.93	631
1	0.90	0.94	0.92	539
accuracy			0.92	1170
macro avg	0.92	0.92	0.92	1170
weighted avg	0.92	0.92	0.92	1170

Model: K-Nearest Neighbors
Accuracy: 0.9222222222222223
Confusion Matrix:
[[588 43]
[48 491]]
Classification Report:

	precision	recall	f1-score	support
-1	0.92	0.93	0.93	631
1	0.92	0.91	0.92	539
accuracy			0.92	1170
macro avg	0.92	0.92	0.92	1170
weighted avg	0.92	0.92	0.92	1170

Model: Naive Bayes
Accuracy: 0.6623931623931624
Confusion Matrix:
[[631 0]
[395 144]]
Classification Report:

	precision	recall	f1-score	support
-1	0.62	1.00	0.76	631
1	1.00	0.27	0.42	539
accuracy			0.66	1170
macro avg	0.81	0.63	0.59	1170
weighted avg	0.79	0.66	0.61	1170

Model: Decision Tree
Accuracy: 0.9145299145299145
Confusion Matrix:
[[591 40]
[60 479]]
Classification Report:

	precision	recall	f1-score	support
-1	0.91	0.94	0.92	631
1	0.92	0.89	0.91	539
accuracy			0.91	1170
macro avg	0.92	0.91	0.91	1170
weighted avg	0.91	0.91	0.91	1170

Model: Random Forest
Accuracy: 0.9282051282051282
Confusion Matrix:
[[586 45]
[39 500]]
Classification Report:

	precision	recall	f1-score	support
-1	0.94	0.93	0.93	631
1	0.92	0.93	0.92	539
accuracy			0.93	1170
macro avg	0.93	0.93	0.93	1170
weighted avg	0.93	0.93	0.93	1170

Model: Gradient Boosting
Accuracy: 0.9452991452991453
Confusion Matrix:
[[596 35]
[29 510]]
Classification Report:

	precision	recall	f1-score	support
-1	0.95	0.94	0.95	631
1	0.94	0.95	0.94	539
accuracy			0.95	1170
macro avg	0.94	0.95	0.95	1170
weighted avg	0.95	0.95	0.95	1170

Model: Multi-Layer Perceptron
Accuracy: 0.9401709401709402
Confusion Matrix:
[[587 44]
[26 513]]
Classification Report:

	precision	recall	f1-score	support
-1	0.96	0.93	0.94	631
1	0.92	0.95	0.94	539

```
   accuracy                         0.94      1170
  macro avg       0.94      0.94      0.94      1170
weighted avg       0.94      0.94      0.94      1170
--------------------------------------------------
Model: Support Vector
Accuracy: 0.9384615384615385
Confusion Matrix:
[[584  47]
 [ 25 514]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.96      0.93      0.94       631
           1       0.92      0.95      0.93       539

   accuracy                           0.94      1170
  macro avg       0.94      0.94      0.94      1170
weighted avg       0.94      0.94      0.94      1170
--------------------------------------------------
```

Printing in sorted order

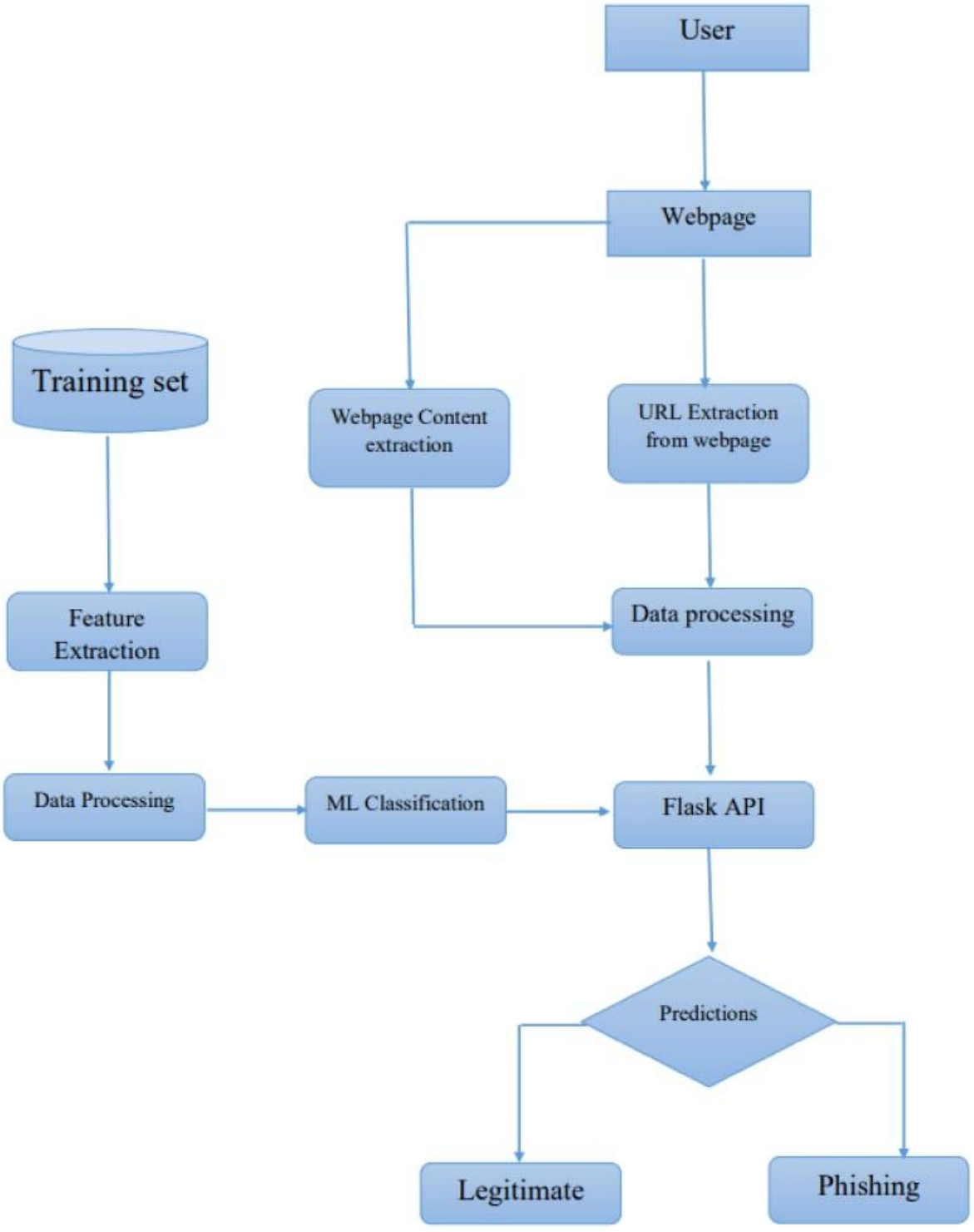
```python
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.svm import SVC

logistic_regression = LogisticRegression()
knn = KNeighborsClassifier()
naive_bayes = GaussianNB()
decision_tree = DecisionTreeClassifier(max_depth=30)
random_forest = RandomForestClassifier(n_estimators=10)
gradient_boosting = GradientBoostingClassifier(max_depth=4, learning_rate=0.7)
mlp = MLPClassifier()
svc = SVC()

# Train and predict for each model
models = [
    ("Logistic Regression", logistic_regression),
    ("K-Nearest Neighbors", knn),
    ("Naive Bayes", naive_bayes),
    ("Decision Tree", decision_tree),
    ("Random Forest", random_forest),
    ("Gradient Boosting", gradient_boosting),
    ("Multi-Layer Perceptron", mlp),
    ("Support Vector", svc)
]

results = []

for model_name, model in models:
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results.append((model_name, model, accuracy))

# Sort results based on accuracy
results.sort(key=lambda x: x[2], reverse=True)

for model_name, model, accuracy in results:
    print(f"Model: {model_name}")
    print(f"Accuracy: {accuracy}")
    y_pred = model.predict(X_test)
    confusion = confusion_matrix(y_test, y_pred)
    classification = classification_report(y_test, y_pred)
    print(f"Confusion Matrix:\n{confusion}")
    print(f"Classification Report:\n{classification}")
    print("-" * 50)
```

```
Model: Gradient Boosting
Accuracy: 0.9452991452991453
Confusion Matrix:
```

```
[[596  35]
 [ 29 510]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.95      0.94      0.95       631
           1       0.94      0.95      0.94       539

    accuracy                           0.95      1170
   macro avg       0.94      0.95      0.95      1170
weighted avg       0.95      0.95      0.95      1170

----------------------------------------------------
Model: Random Forest
Accuracy: 0.941025641025641
Confusion Matrix:
[[596  35]
 [ 34 505]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.95      0.94      0.95       631
           1       0.94      0.94      0.94       539

    accuracy                           0.94      1170
   macro avg       0.94      0.94      0.94      1170
weighted avg       0.94      0.94      0.94      1170

----------------------------------------------------
Model: Multi-Layer Perceptron
Accuracy: 0.9393162393162393
Confusion Matrix:
[[594  37]
 [ 34 505]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.95      0.94      0.94       631
           1       0.93      0.94      0.93       539

    accuracy                           0.94      1170
   macro avg       0.94      0.94      0.94      1170
weighted avg       0.94      0.94      0.94      1170

----------------------------------------------------
Model: Support Vector
Accuracy: 0.9384615384615385
Confusion Matrix:
[[584  47]
 [ 25 514]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.96      0.93      0.94       631
           1       0.92      0.95      0.93       539

    accuracy                           0.94      1170
   macro avg       0.94      0.94      0.94      1170
weighted avg       0.94      0.94      0.94      1170

----------------------------------------------------
Model: Logistic Regression
Accuracy: 0.9222222222222223
Confusion Matrix:
[[573  58]
 [ 33 506]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.95      0.91      0.93       631
           1       0.90      0.94      0.92       539

    accuracy                           0.92      1170
```

```
   macro avg       0.92      0.92      0.92      1170
weighted avg       0.92      0.92      0.92      1170

--------------------------------------------------
Model: K-Nearest Neighbors
Accuracy: 0.9222222222222223
Confusion Matrix:
[[588  43]
 [ 48 491]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.92      0.93      0.93       631
           1       0.92      0.91      0.92       539

    accuracy                           0.92      1170
   macro avg       0.92      0.92      0.92      1170
weighted avg       0.92      0.92      0.92      1170

--------------------------------------------------
Model: Decision Tree
Accuracy: 0.9128205128205128
Confusion Matrix:
[[589  42]
 [ 60 479]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.91      0.93      0.92       631
           1       0.92      0.89      0.90       539

    accuracy                           0.91      1170
   macro avg       0.91      0.91      0.91      1170
weighted avg       0.91      0.91      0.91      1170

--------------------------------------------------
Model: Naive Bayes
Accuracy: 0.6623931623931624
Confusion Matrix:
[[631   0]
 [395 144]]
Classification Report:
              precision    recall  f1-score   support

          -1       0.62      1.00      0.76       631
           1       1.00      0.27      0.42       539

    accuracy                           0.66      1170
   macro avg       0.81      0.63      0.59      1170
weighted avg       0.79      0.66      0.61      1170

--------------------------------------------------
```

5. FLOWCHART


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

6. RESULT

For this project create three HTML files namely

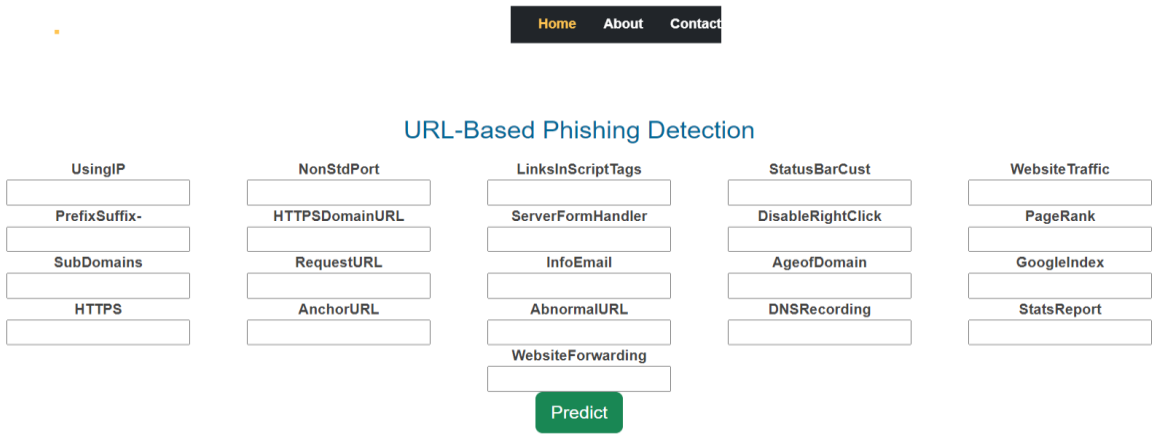
- index.html
- inspect.html
- output.html

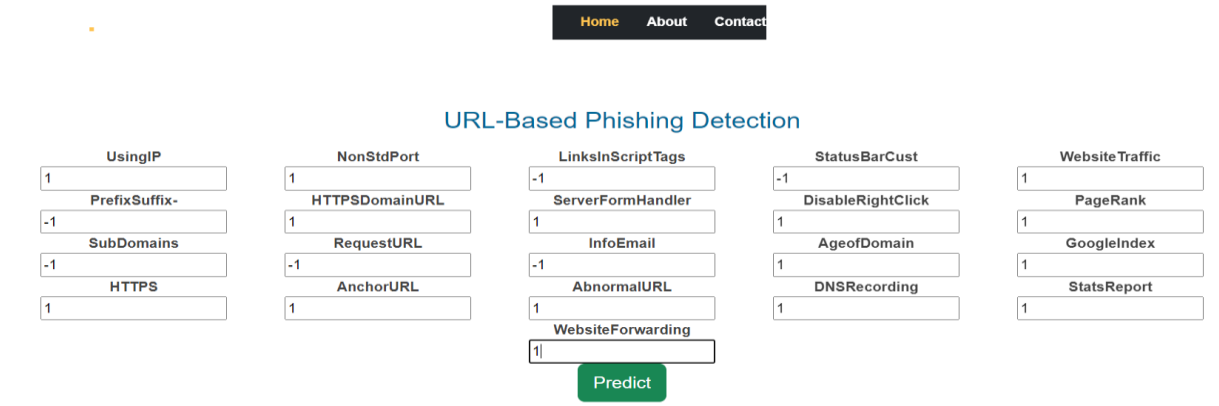
and save them in templates folder.

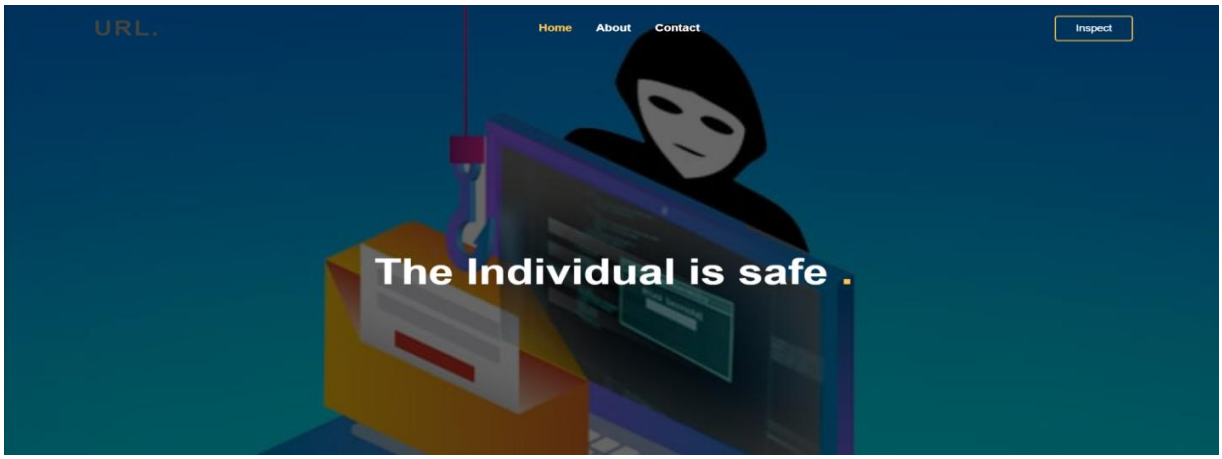
This is how our index.html page looks like:

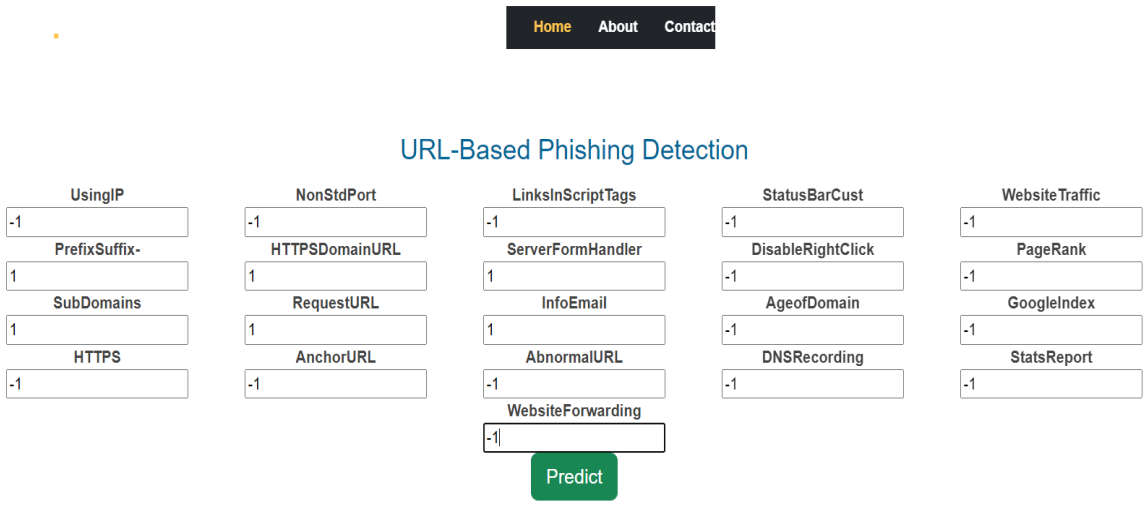
Now when you click on inspect button from top right corner you will get redirected to Inspect.html

Lets look how our Inspect.html file looks like:

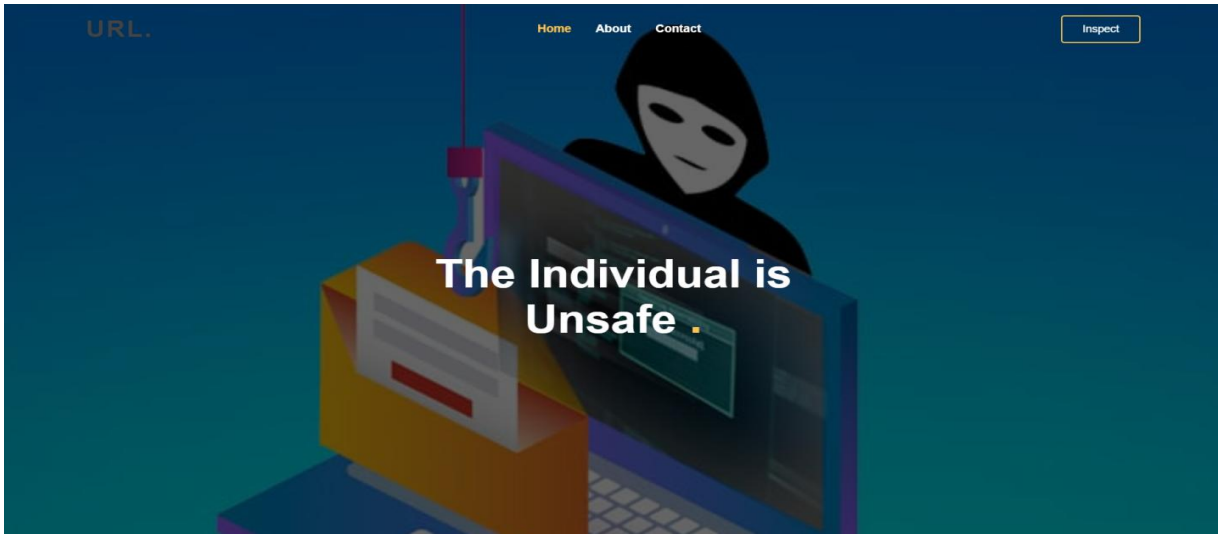








Will try with different numbers and then click on predict button.



7. ADVANTAGES & DISADVANTAGES

Advantages: -

- *Real-time Detection*: Machine learning models can analyze URLs quickly and in real-time, enabling rapid identification of phishing links, reducing the risk of falling victim to scams.
- *Scalability*: ML-based systems can handle a large number of URLs simultaneously, making them scalable to protect a vast user base or an entire organization from phishing threats.
- *Continuous Learning*: Machine learning models can adapt and improve over time by continuously learning from new phishing patterns, staying up-to-date with emerging threats.
- *Accuracy:* Advanced ML algorithms can achieve high accuracy in detecting phishing URLs, minimizing false positives and false negatives, leading to more reliable protection.
- And some other advantages are automation, customizability, early warning, multi-platform support, enhanced security, data driven insights.

Disadvantages:

- *False Positives and False Negatives*: Machine learning models may occasionally misclassify legitimate URLs as phishing or fail to detect sophisticated phishing attempts, leading to false positives and false negatives, respectively.
- *Data Privacy and Security*: ML-based phishing detection often involves analyzing URLs, which could raise privacy concerns if sensitive or personal data is unintentionally processed during the analysis.
- *Rapidly Evolving Phishing Techniques*: As phishing techniques evolve, ML models might struggle to keep up with the latest strategies used by attackers.
- *Dependency on Data Sources*: ML models for phishing detection depend on timely access to relevant data sources, and any disruption in data availability could impact their performance.

8. APPLICATIONS

URL-based phishing detection using machine learning has various practical applications, including:

1. Email Security: Integrating ML-based phishing detection in email systems helps identify and block phishing links, protecting users from clicking on malicious URLs sent via emails.
2. Web Browsers: Browser extensions or built-in features that utilize ML can alert users about potential phishing websites when they attempt to visit suspicious URLs.
3. Network Security: Employing ML models in network security systems can help detect and block phishing URLs in real-time, safeguarding users and organizations from cyber threats.
4. Mobile Security: Mobile apps can leverage ML-based phishing detection to warn users about fraudulent links, ensuring safer browsing on smartphones and tablets.

Some other applications are cloud services, anti-phishing solutions, social media platforms, anti-virus and security software.

By utilizing machine learning in URL-based phishing detection, these applications can effectively mitigate phishing risks and enhance overall cybersecurity.

9. CONCLUSION

1.The final take away form this project is to explore various machine learning models, perfor m Exploratory Data Analysis on phishing dataset and understanding their features.

2. Creating this notebook helped me to learn a lot about the features affecting the models to de tect whether URL is safe or not, also I came to know how to tuned model and how they affe ct the model performance.

3. The final conclusion on the Phishing dataset is that the some feature like "HTTTPS", "Anch orURL", "WebsiteTraffic" have more importance to classify URL is phishing URL or not.

4. Gradient Boosting Classifier correctly classify URL upto 94.52% respective classes and he n ce reduces the chance of malicious attachments.

10. FUTURE SCOPE

In future if we get structured dataset of phishing we can perform phishing detection much more faster than any other technique.In future we can use a combination of any other two or more classifier to get maximum accuracy.

11. BIBLIOGRAPHY

- **ML Concepts**
    - Supervised learning: https://www.javatpoint.com/supervised-machine-learning
    - Unsupervised learning: https://www.javatpoint.com/unsupervised-machine-learning
    - Decision tree: https://www.javatpoint.com/machine-learning-decision-tree-classification-algorithm
    - Random forest: https://www.javatpoint.com/machine-learning-random-forest-algorithm
    - KNN: https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning
    - Support vector machine algorithm: https://www.javatpoint.com/machine-learning-support-vector-machine-algorithm
    - Logistic Regression: https://www.javatpoint.com/logistic-regression-in-machine-learning
    - Naïve Bayes Classifier : https://www.javatpoint.com/machine-learning-naive-bayes-classifier
    - Gradient boosting: https://www.javatpoint.com/gbm-in-machine-learning

- Multi-layer Perceptron: https://www.javatpoint.com/multi-layer-perceptron-in-tensorflow
- Evaluation metrics: https://www.analyticsvidhya.com/blog/2019/08/11-important-model-evaluation-error-metrics/

- **Flask Basics** : https://www.youtube.com/watch?v=lj4I_CvBnt0

APPENDIX

11.1. Source Code

Import the libraries

```
from flask import Flask, request, render_template, url_for
import pickle
import numpy as np
import json
import requests
```

Load the saved model. Importing flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.

```
app = Flask(__name__)
with open('Phishing_model.pkl', 'rb') as file:
    model = pickle.load(file)
```

Render HTML page:

```
@app.route("/")
def f():
    return render_template("index.html")

@app.route("/inspect")
def inspect():
    return render_template("inspect.html")
```

Here we will be using declared constructor to route to the HTML page which we have created earlier.

In the above example, '/' URL is bound with index.html function. Hence, when the index page of the web server is opened in browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

Retrieves the value from UI:

```
@app.route("/output", methods=["GET", "POST"])
def output():
    if request.method == 'POST':
        var1 = request.form["UsingIP"]
        var2 = request.form["PrefixSuffix-"]
        var3 = request.form["SubDomains"]
        var4 = request.form["HTTPS"]
        var5 = request.form["NonStdPort"]
        var6 = request.form["HTTPSDomainURL"]
        var7 = request.form["RequestURL"]
        var8 = request.form["AnchorURL"]
        var9 = request.form["LinksInScriptTags"]
        var10 = request.form["ServerFormHandler"]
        var11 = request.form["InfoEmail"]
        var12 = request.form["AbnormalURL"]
        var13 = request.form["WebsiteForwarding"]
        var14 = request.form["StatusBarCust"]
        var15 = request.form["DisableRightClick"]
        var16 = request.form["AgeofDomain"]
        var17 = request.form["DNSRecording"]
        var18 = request.form["WebsiteTraffic"]
        var19 = request.form["PageRank"]
        var20 = request.form["GoogleIndex"]
        var21 = request.form["StatsReport"]
        # Convert the input data into a numpy array
        predict_data = np.array([var1, var2, var3, var4, var5, var6, var7, var8, var9, var10,
                                 var11, var12,var13,var14,var15,var16,var17,var18,var19,var20,
                                 var21]).reshape(1, -1)
        # Use the loaded model to make predictions
        predict = model.predict(predict_data)
        # 1 is safe
        #-1 is unsafe
        if (predict == 1):
            return render_template('output.html', predict="safe")
        else:
            return render_template('output.html', predict="Unsafe")
    return render_template("output.html")
if __name__ == "__main__":
    app.run(debug=False)
```

Here we are routing our app to output() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction. And this prediction value will rendered to the text that we have mentioned in the output.html page earlier.

Main function:

```
if __name__ == "__main__":
    app.run(debug=False)
```

To run the application:

- Open anaconda prompt from the start menu
- Navigate to the folder where your python script is.
- Now type “python app.py” command
- Navigate to the localhost where you can view your web page.
- Click on the inspect button from the top right corner, enter the inputs, click on the predict button, and see the result/prediction on the web.