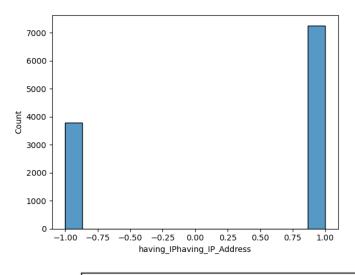
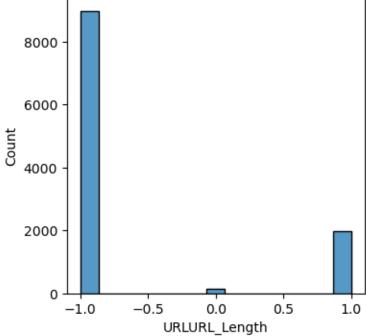
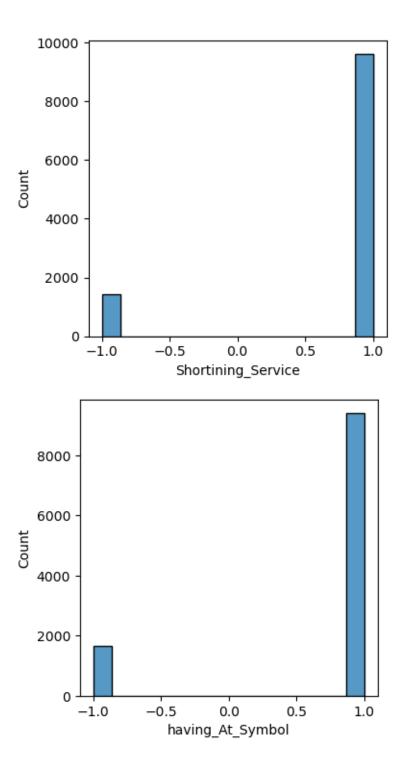
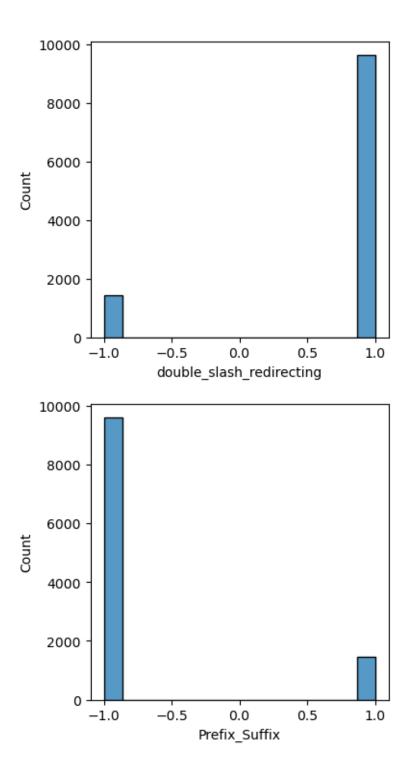
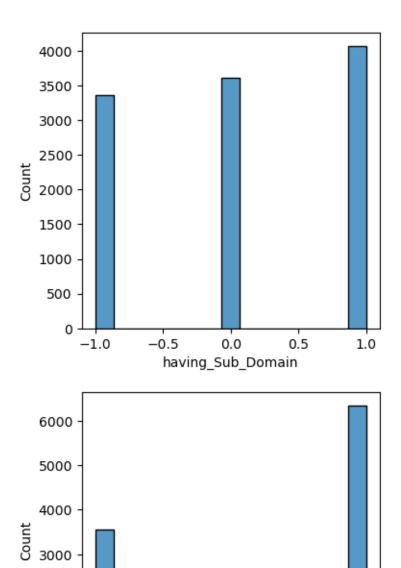
1. Each sample has 32 features ranging from -1,0,1. Explore the data using histogram, heatmaps.











2000

1000

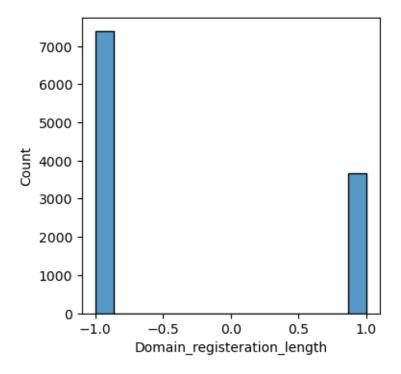
0

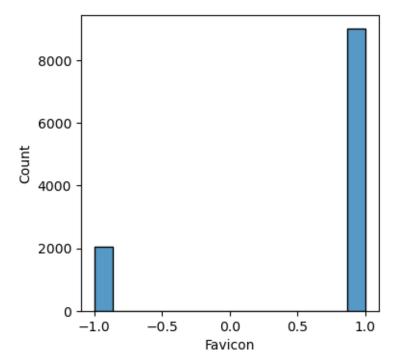
-1.0

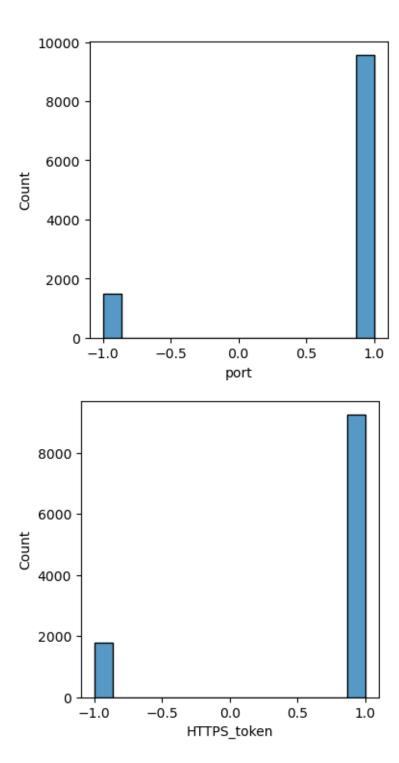
-0.5

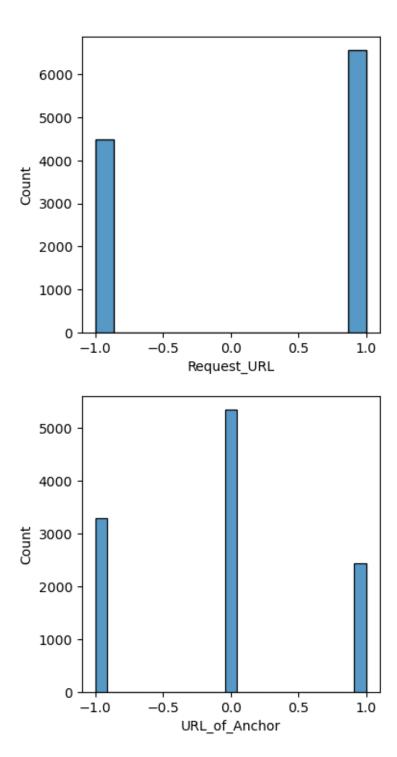
0.0 SSLfinal\_State 0.5

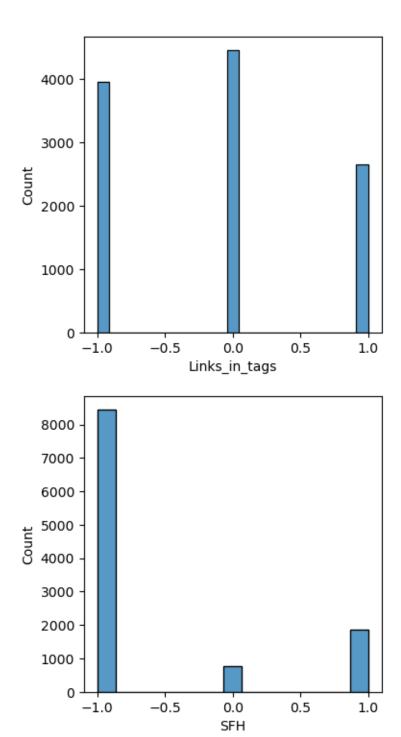
1.0



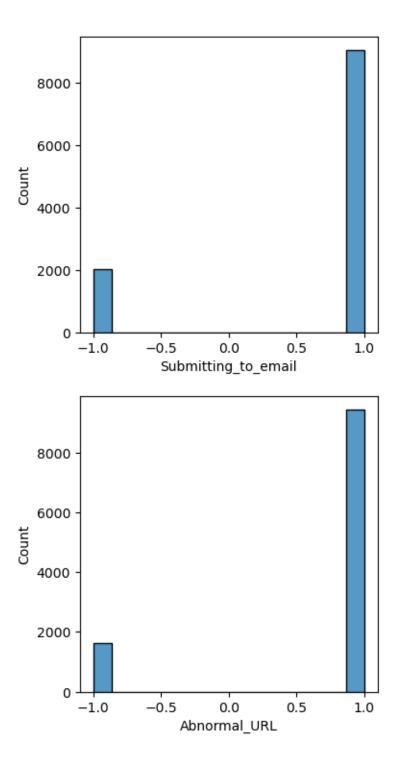


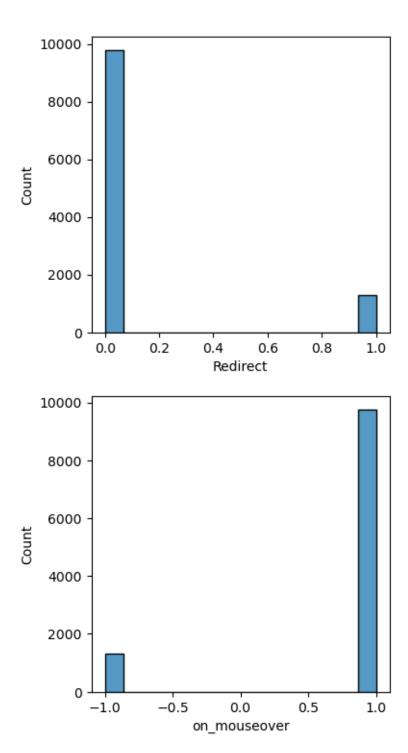


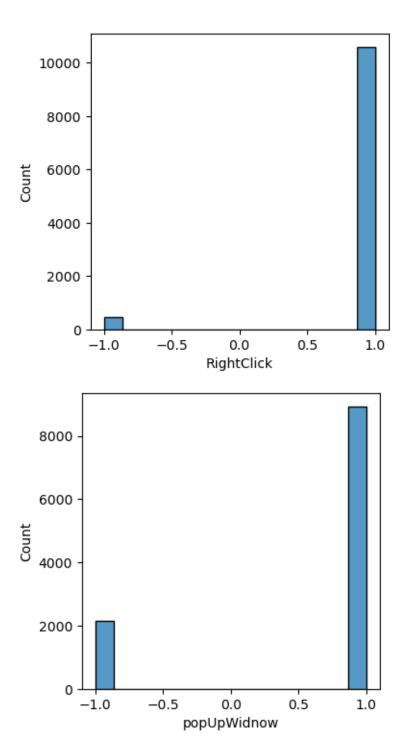


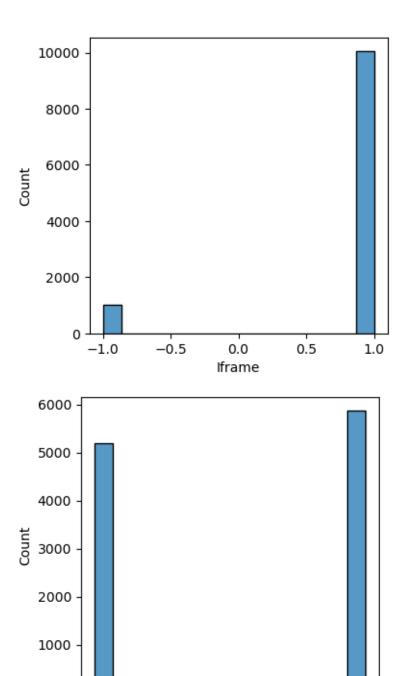


1.0









0

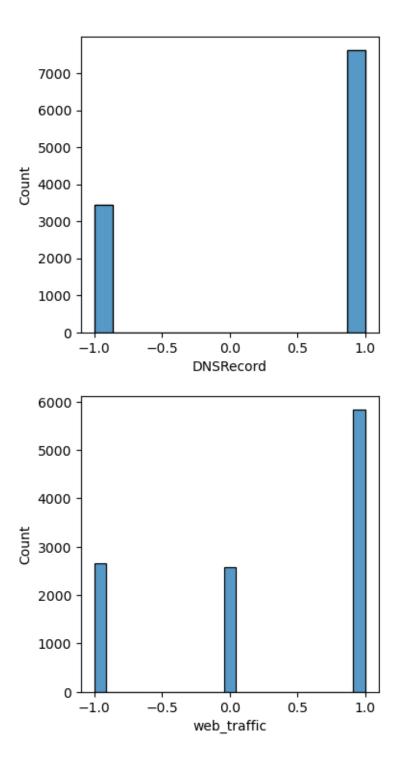
-1.0

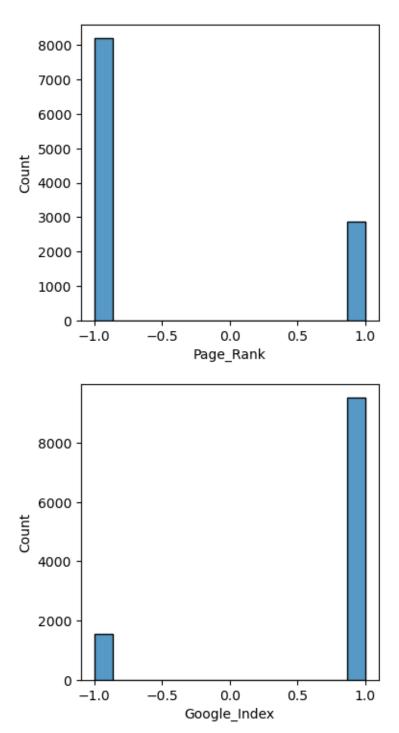
-0.5

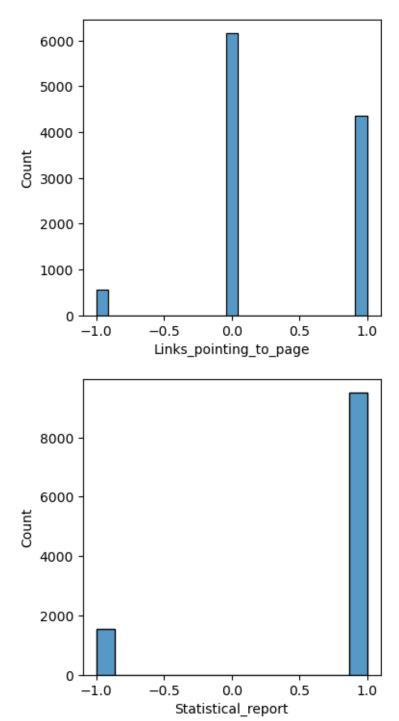
0.0 age\_of\_domain

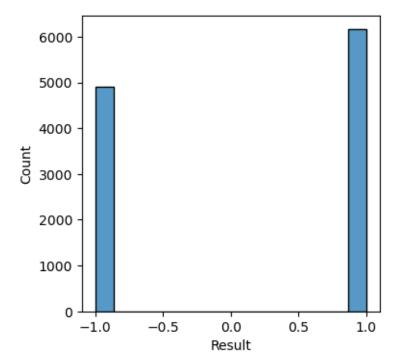
0.5

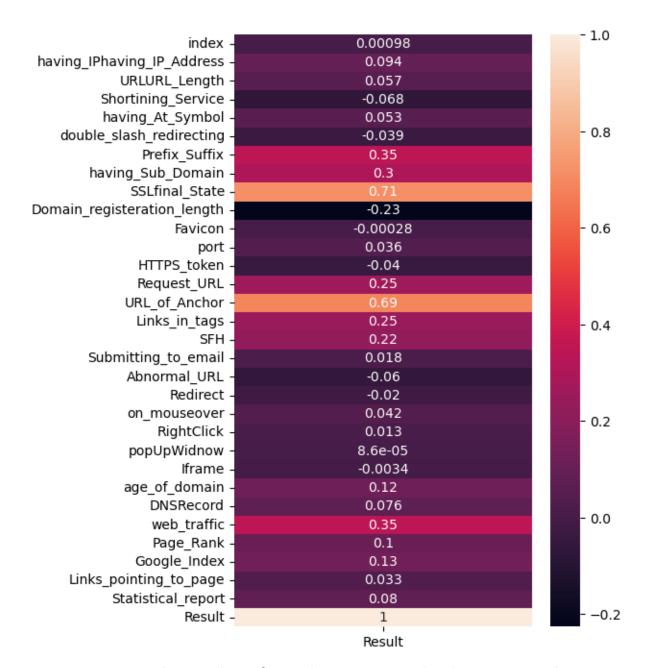
1.0











2. Determine the number of samples present in the data, unique elements in all the features.

df.shape (11055, 32)

	count	mean	std	min	25%	50%	75%	max	
index	11055.0	5528.000000	3191.447947	1.0	2764.5	5528.0	8291.5	11055.0	
having_IPhaving_IP_Address	11055.0	0.313795	0.949534	-1.0	-1.0	1.0	1.0	1.0	
URLURL_Length	11055.0	-0.633198	0.766095	-1.0	-1.0	-1.0	-1.0	1.0	
Shortining_Service	11055.0	0.738761	0.673998	-1.0	1.0	1.0	1.0	1.0	
having_At_Symbol	11055.0	0.700588	0.713598	-1.0	1.0	1.0	1.0	1.0	
double_slash_redirecting	11055.0	0.741474	0.671011	-1.0	1.0	1.0	1.0	1.0	
Prefix_Suffix	11055.0	-0.734962	0.678139	-1.0	-1.0	-1.0	-1.0	1.0	
having_Sub_Domain	11055.0	0.063953	0.817518	-1.0	-1.0	0.0	1.0	1.0	
SSLfinal_State	11055.0	0.250927	0.911892	-1.0	-1.0	1.0	1.0	1.0	
Domain_registeration_length	11055.0	-0.336771	0.941629	-1.0	-1.0	-1.0	1.0	1.0	
Favicon	11055.0	0.628584	0.777777	-1.0	1.0	1.0	1.0	1.0	
port	11055.0	0.728268	0.685324	-1.0	1.0	1.0	1.0	1.0	
HTTPS_token	11055.0	0.675079	0.737779	-1.0	1.0	1.0	1.0	1.0	
Request_URL	11055.0	0.186793	0.982444	-1.0	-1.0	1.0	1.0	1.0	
URL_of_Anchor	11055.0	-0.076526	0.715138	-1.0	-1.0	0.0	0.0	1.0	
Links_in_tags	11055.0	-0.118137	0.763973	-1.0	-1.0	0.0	0.0	1.0	
SFH	11055.0	-0.595749	0.75914	3 -1.	0 -1.	0 -	1.0 -	-1.0	•
Submitting_to_email	11055.0	0.635640	0.77202	1 -1.	0 1.	0	1.0	1.0	1
Abnormal_URL	11055.0	0.705292	0.70894	9 -1.	0 1.	0	1.0	1.0	1
Redirect	11055.0	0.115694	0.31987	2 0.	0 0.	0	0.0	0.0	1
on_mouseover	11055.0	0.762099	0.64749	0 -1.	0 1.	0	1.0	1.0	1
RightClick	11055.0	0.91388	0.40599	1 -1.	0 1.	0	1.0	1.0	1
popUpWidnow	11055.0	0.613388	0.78981	8 <b>-</b> 1.	0 1.	0	1.0	1.0	1
Iframe	11055.0	0.81691	0.57678	4 -1.	0 1.	0	1.0	1.0	1
age_of_domain	11055.0	0.061239	0.99816	8 -1.	0 -1.	0	1.0	1.0	1
DNSRecord							1.0	1.0	1
web_traffic	11055.0						1.0	1.0	1
Page_Rank	11055.0						1.0	1.0	1
Google Index							1.0	1.0	1
Links_pointing_to_page	11055.0						0.0	1.0	1
Statistical_report							1.0	1.0	1
Result	11055.0	0.11388	0.99353	9 -1.	0 -1.	0	1.0	1.0	

```
df['Result'].unique()
array([-1, 1], dtype=int64)
df['Result'].nunique()
for i in df.columns:
    print (i , ":", df[i].unique(),"\n len :",df[i].nunique())
    print ("\n")
{\tt having\_IPhaving\_IP\_Address} : \hbox{ $[-1$ 1]}
 len : 2
URLURL_Length : [ 1 0 -1]
 len : 3
Shortining_Service : [ 1 -1]
 len : 2
having_IPhaving_IP_Address : [-1 1]
len : 2
URLURL_Length : [ 1 0 -1]
len : 3
Shortining_Service : [ 1 -1]
len : 2
having_At_Symbol : [ 1 -1]
len : 2
double_slash_redirecting : [-1 1]
len : 2
Prefix_Suffix : [-1 1]
len : 2
having_Sub_Domain : [-1 0 1]
```

```
SSLfinal_State : [-1 1 0]
len : 3
Domain_registeration_length : [-1 1]
len : 2
Favicon : [ 1 -1]
len : 2
port : [ 1 -1]
len : 2
HTTPS_token : [-1 1]
len : 2
Request_URL : [ 1 -1]
len : 2
URL_of_Anchor : [-1 0 1]
len : 3
Links_in_tags : [ 1 -1 0]
len : 3
SFH : [-1 1 0]
len : 3
Submitting_to_email : [-1 1]
len : 2
Abnormal_URL : [-1 1]
len : 2
Redirect : [0 1]
len : 2
on_mouseover : [ 1 -1]
len : 2
RightClick : [ 1 -1]
len : 2
```

```
popUpWidnow : [ 1 -1]
 Iframe : [ 1 -1]
  len : 2
 age_of_domain : [-1 1]
  len : 2
 DNSRecord : [-1 1]
 len : 2
 web_traffic : [-1 0 1]
 len : 3
 Page_Rank : [-1 1]
 len : 2
 Google_Index : [ 1 -1]
  len : 2
Links_pointing_to_page : [ 1 0 -1]
len : 3
Statistical_report : [-1 1]
Result : [-1 1]
len : 2
```

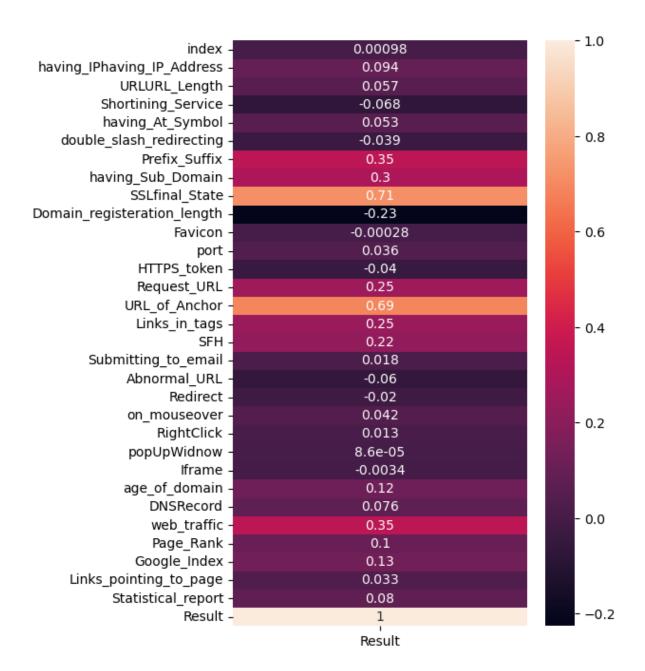
## 3. Check if there is any null value in any features.

```
index
having_IPhaving_IP_Address
URLURL_Length
                            0
Shortining_Service
having_At_Symbol
                            0
double_slash_redirecting
Prefix_Suffix
having_Sub_Domain
SSLfinal_State
                            0
Domain_registeration_length
Favicon
                            0
port
HTTPS_token
                            0
Request_URL
URL_of_Anchor
Links_in_tags
Submitting_to_email
Abnormal_URL
                            0
Redirect
on_mouseover
                            0
RightClick
                            0
popUpWidnow
                            0
Iframe
age_of_domain
DNSRecord
```

```
web_traffic 0
Page_Rank 0
Google_Index 0
Links_pointing_to_page 0
Statistical_report 0
Result 0
dtype: int64
```

4.Next, we have to find if there are any correlated features present in the data. Remove the feature which might be correlated with some threshold.

df.corr()							
	index	having_IPhaving_IP_Address	URLURL_Length	Shortining_Service	having_At_Symbol	double_slash_redirecting	Prefix_Su
index	1.000000	-0.388317	0.006105	-0.006281	-0.169478	-0.003363	-0.007
having_IPhaving_IP_Address	-0.388317	1.000000	-0.052411	0.403461	0.158699	0.397389	-0.005
URLURL_Length	0.006105	-0.052411	1.000000	-0.097881	-0.075108	-0.081247	0.055
Shortining_Service	-0.006281	0.403461	-0.097881	1.000000	0.104447	0.842796	-0.080
having_At_Symbol	-0.169478	0.158699	-0.075108	0.104447	1.000000	0.086960	-0.011
double_slash_redirecting	-0.003363	0.397389	-0.081247	0.842796	0.086960	1.000000	-0.085
Prefix_Suffix	-0.007340	-0.005257	0.055247	-0.080471	-0.011726	-0.085590	1.000
having_Sub_Domain	0.234091	-0.080745	0.003997	-0.041916	-0.058976	-0.043079	0.087
SSLfinal_State	-0.006682	0.071414	0.048754	-0.061426	0.031220	-0.036200	0.261
Domain_registeration_length	-0.001180	-0.022739	-0.221892	0.060923	0.015522	0.047464	-0.096
Favicon	0.007293	0.087025	-0.042497	0.006101	0.304899	0.035100	-0.007
port	0.001656	0.060979	0.000323	0.002201	0.364891	0.025060	-0.022
HTTPS_token	0.002916	0.363534	-0.089383	0.757838	0.104561	0.760799	-0.070
Request_URL	-0.000862	0.029773	0.246348	-0.037235	0.027909	-0.026368	0.098

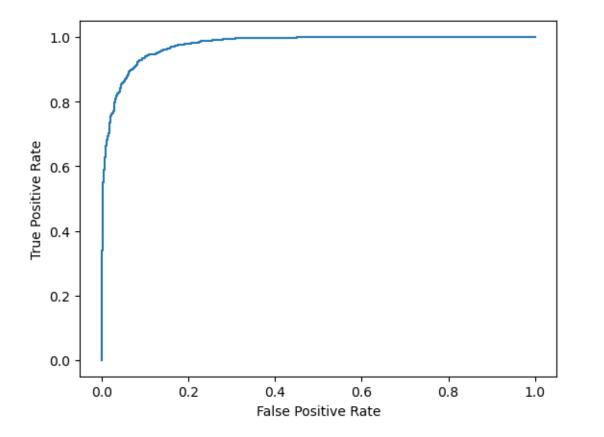


- 5. Finally, build a robust classification system that classifies whether the URL sample is a phishing site or not.
- Build classification models using a binary classifier to detect malicious or phishing URLs.

LogisticRegression
LogisticRegression()

```
[63]: #testing
      from sklearn.metrics import confusion_matrix, classification_report
      confusion_matrix(y_test, pred)
[63]: array([[1421, 144],
             [ 148, 1936]], dtype=int64)
[64]: print(classification_report(y_test, pred))
                    precision
                                 recall f1-score
                                                     support
                -1
                         0.91
                                    0.91
                                              0.91
                                                        1565
                 1
                         0.93
                                    0.93
                                              0.93
                                                        2084
          accuracy
                                              0.92
                                                        3649
         macro avg
                         0.92
                                    0.92
                                              0.92
                                                        3649
      weighted avg
                         0.92
                                    0.92
                                              0.92
                                                        3649
```

 Illustrate the diagnostic ability of this binary classifier by plotting the ROC curve.



• Validate the accuracy of data by the K-Fold cross-validation technique.

```
#view mean absolute error
mean(absolute(scores))

0.15413630301195455

# average absolute error between the model prediction and the actual observed data is 0.154

#view RMSE
sqrt(mean(absolute(scores)))

0.39260196511473877

# root mean squared error (RMSE) was 0.392
```

• The final output consists of the model, which will give maximum accuracy on the validation dataset with selected attributes.

precision recall f1-score support -1 0.91 0.91 0.91 1565 0.93 0.93 0.93 2084 0.92 3649 accuracy 0.92 0.92 0.92 macro avg 3649

0.92

0.92

3649

0.92

weighted avg