Phishing Detection using Supervised Learning

Importing

```
## Importing tools
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import sklearn
import pickle

%matplotlib inline

## model evaluation tools
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score,
f1_score,accuracy_score
from sklearn.metrics import roc_curve


## Importing Algoritms
from sklearn.linear_model import Ridge, Lasso, ElasticNet,
LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier, AdaBoostClassifier, ExtraTreesClassifier
from sklearn.svm import SVC, SVR
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis,
QuadraticDiscriminantAnalysis
```

Reading and exploring data

```
df=pd.read_csv("dataset_phishing.csv")
df.shape
```

```
(11430, 89)
```

```
df.head()
```

```
                                                 url  length_url  \
0              http://www.crestonwood.com/router.php          37
1  http://shadetreetechnology.com/V4/validation/a...          77
2  https://support-appleld.com.secureupdate.duila...         126
3                              http://rgipt.ac.in          18
4  http://www.iracing.com/tracks/gateway-motorspo...          55

   length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and
nb_or  ...  \
0               19   0        3           0      0      0       0
0  ...
1               23   1        1           0      0      0       0
0  ...
2               50   1        4           1      0      1       2
0  ...
3               11   0        2           0      0      0       0
0  ...
4               15   0        2           2      0      0       0
0  ...

   domain_in_title  domain_with_copyright  whois_registered_domain  \
0                0                      1                        0
1                1                      0                        0
2                1                      0                        0
3                1                      0                        0
4                0                      1                        0

   domain_registration_length  domain_age  web_traffic  dns_record  \
0                          45          -1            0           1
1                          77        5767            0           0
2                          14        4004      5828815           0
3                          62          -1       107721           0
4                         224        8175         8725           0

   google_index  page_rank      status
0             1          4  legitimate
1             1          2    phishing
2             1          0    phishing
3             0          3  legitimate
4             0          6  legitimate

[5 rows x 89 columns]
```

```
df=pd.DataFrame(df)
df.head()
```

```
                                                 url  length_url  \
0              http://www.crestonwood.com/router.php          37
1  http://shadetreetechnology.com/V4/validation/a...          77
2  https://support-appleld.com.secureupdate.duila...         126
```

```
3                                http://rgipt.ac.in          18
4  http://www.iracing.com/tracks/gateway-motorspo...          55

   length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and
nb_or  ...  \
0               19   0        3           0      0      0       0
0  ...
1               23   1        1           0      0      0       0
0  ...
2               50   1        4           1      0      1       2
0  ...
3               11   0        2           0      0      0       0
0  ...
4               15   0        2           2      0      0       0
0  ...

   domain_in_title  domain_with_copyright  whois_registered_domain  \
0                0                      1                        0
1                1                      0                        0
2                1                      0                        0
3                1                      0                        0
4                0                      1                        0

   domain_registration_length  domain_age  web_traffic  dns_record  \
0                          45          -1            0           1
1                          77        5767            0           0
2                          14        4004      5828815           0
3                          62          -1       107721           0
4                         224        8175         8725           0

   google_index  page_rank      status
0             1          4  legitimate
1             1          2    phishing
2             1          0    phishing
3             0          3  legitimate
4             0          6  legitimate

[5 rows x 89 columns]
```

```
print(df.dtypes) # all the data is int except status which needs to be
converted into int format
```

```
url                object
length_url          int64
length_hostname     int64
ip                  int64
nb_dots             int64
                    ...
web_traffic         int64
dns_record          int64
```

```
google_index        int64
page_rank           int64
status             object
Length: 89, dtype: object
```

```
df['status']
```

```
0        legitimate
1          phishing
2          phishing
3        legitimate
4        legitimate
            ...
11425    legitimate
11426      phishing
11427    legitimate
11428    legitimate
11429      phishing
Name: status, Length: 11430, dtype: object
```

```
labels,uniques=pd.factorize(df['status'])
```

```
df['status']=labels
```

```
uniques
```

```
Index(['legitimate', 'phishing'], dtype='object')
```

```
df.head()
```

```
                                                 url  length_url  \
0              http://www.crestonwood.com/router.php          37
1  http://shadetreetechnology.com/V4/validation/a...          77
2  https://support-appleld.com.secureupdate.duila...         126
3                                http://rgipt.ac.in          18
4  http://www.iracing.com/tracks/gateway-motorspo...          55

   length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and
nb_or  ...  \
0               19   0        3           0      0      0       0
0  ...
1               23   1        1           0      0      0       0
0  ...
2               50   1        4           1      0      1       2
0  ...
3               11   0        2           0      0      0       0
0  ...
4               15   0        2           2      0      0       0
0  ...

   domain_in_title  domain_with_copyright  whois_registered_domain  \
0                0                      1                        0
```

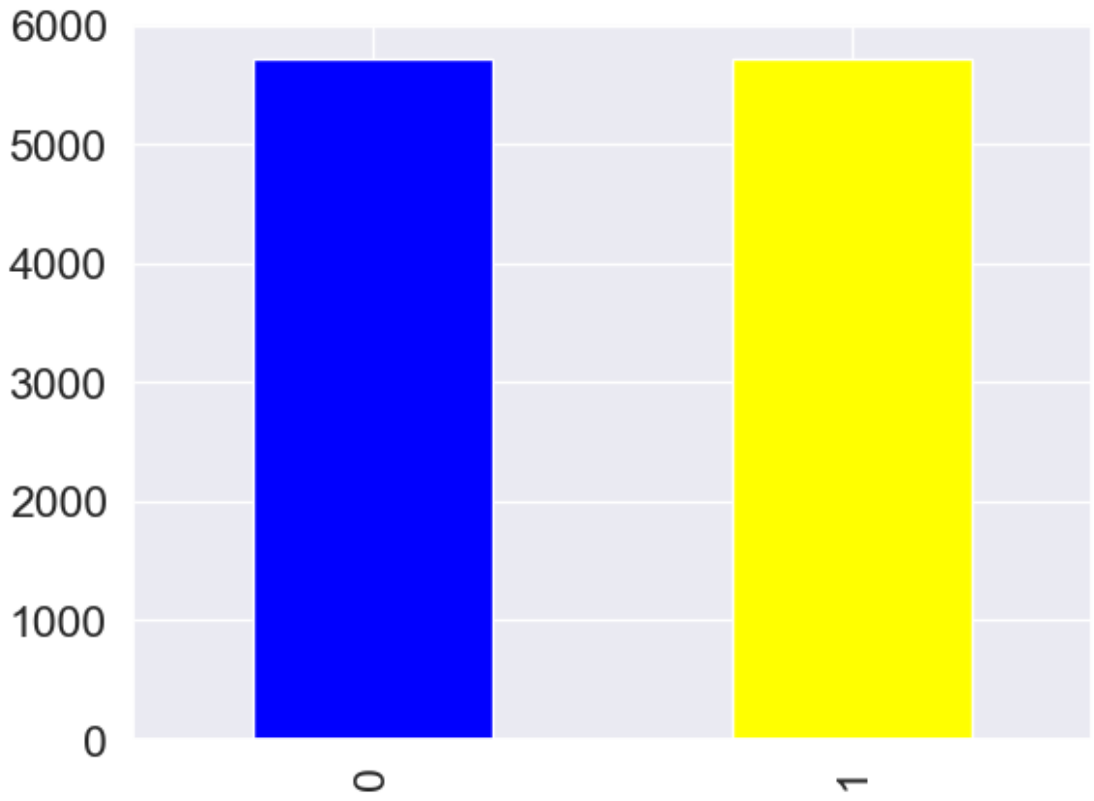
```
1                1                      0                         0
2                1                      0                         0
3                1                      0                         0
4                0                      1                         0

   domain_registration_length  domain_age  web_traffic  dns_record  \
0                          45          -1            0           1
1                          77        5767            0           0
2                          14        4004      5828815           0
3                          62          -1       107721           0
4                         224        8175         8725           0

   google_index  page_rank  status
0             1          4       0
1             1          2       1
2             1          0       1
3             0          3       0
4             0          6       0

[5 rows x 89 columns]
```

```
df['status'].value_counts()
```

```
0    5715
1    5715
Name: status, dtype: int64
```

```
df["status"].value_counts().plot(kind="bar",color=["blue","yellow"])
```

```
<Axes: >
```




```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11430 entries, 0 to 11429
Data columns (total 89 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   url                          11430 non-null  object
 1   length_url                   11430 non-null  int64
 2   length_hostname              11430 non-null  int64
 3   ip                           11430 non-null  int64
 4   nb_dots                      11430 non-null  int64
 5   nb_hyphens                   11430 non-null  int64
 6   nb_at                        11430 non-null  int64
 7   nb_qm                        11430 non-null  int64
 8   nb_and                       11430 non-null  int64
 9   nb_or                        11430 non-null  int64
 10  nb_eq                        11430 non-null  int64
 11  nb_underscore                11430 non-null  int64
 12  nb_tilde                     11430 non-null  int64
 13  nb_percent                   11430 non-null  int64
 14  nb_slash                     11430 non-null  int64
 15  nb_star                      11430 non-null  int64
 16  nb_colon                     11430 non-null  int64
 17  nb_comma                     11430 non-null  int64
 18  nb_semicolumn                11430 non-null  int64
```

19	nb_dollar	11430	non-null	int64
20	nb_space	11430	non-null	int64
21	nb_www	11430	non-null	int64
22	nb_com	11430	non-null	int64
23	nb_dslash	11430	non-null	int64
24	http_in_path	11430	non-null	int64
25	https_token	11430	non-null	int64
26	ratio_digits_url	11430	non-null	float64
27	ratio_digits_host	11430	non-null	float64
28	punycode	11430	non-null	int64
29	port	11430	non-null	int64
30	tld_in_path	11430	non-null	int64
31	tld_in_subdomain	11430	non-null	int64
32	abnormal_subdomain	11430	non-null	int64
33	nb_subdomains	11430	non-null	int64
34	prefix_suffix	11430	non-null	int64
35	random_domain	11430	non-null	int64
36	shortening_service	11430	non-null	int64
37	path_extension	11430	non-null	int64
38	nb_redirection	11430	non-null	int64
39	nb_external_redirection	11430	non-null	int64
40	length_words_raw	11430	non-null	int64
41	char_repeat	11430	non-null	int64
42	shortest_words_raw	11430	non-null	int64
43	shortest_word_host	11430	non-null	int64
44	shortest_word_path	11430	non-null	int64
45	longest_words_raw	11430	non-null	int64
46	longest_word_host	11430	non-null	int64
47	longest_word_path	11430	non-null	int64
48	avg_words_raw	11430	non-null	float64
49	avg_word_host	11430	non-null	float64
50	avg_word_path	11430	non-null	float64
51	phish_hints	11430	non-null	int64
52	domain_in_brand	11430	non-null	int64
53	brand_in_subdomain	11430	non-null	int64
54	brand_in_path	11430	non-null	int64
55	suspecious_tld	11430	non-null	int64
56	statistical_report	11430	non-null	int64
57	nb_hyperlinks	11430	non-null	int64
58	ratio_intHyperlinks	11430	non-null	float64
59	ratio_extHyperlinks	11430	non-null	float64
60	ratio_nullHyperlinks	11430	non-null	int64
61	nb_extCSS	11430	non-null	int64
62	ratio_intRedirection	11430	non-null	int64
63	ratio_extRedirection	11430	non-null	float64
64	ratio_intErrors	11430	non-null	int64
65	ratio_extErrors	11430	non-null	float64
66	login_form	11430	non-null	int64
67	external_favicon	11430	non-null	int64
68	links_in_tags	11430	non-null	float64

```
 69  submit_email                11430 non-null  int64
 70  ratio_intMedia              11430 non-null  float64
 71  ratio_extMedia              11430 non-null  float64
 72  sfh                         11430 non-null  int64
 73  iframe                      11430 non-null  int64
 74  popup_window                11430 non-null  int64
 75  safe_anchor                 11430 non-null  float64
 76  onmouseover                 11430 non-null  int64
 77  right_clic                  11430 non-null  int64
 78  empty_title                 11430 non-null  int64
 79  domain_in_title             11430 non-null  int64
 80  domain_with_copyright       11430 non-null  int64
 81  whois_registered_domain     11430 non-null  int64
 82  domain_registration_length  11430 non-null  int64
 83  domain_age                  11430 non-null  int64
 84  web_traffic                 11430 non-null  int64
 85  dns_record                  11430 non-null  int64
 86  google_index                11430 non-null  int64
 87  page_rank                   11430 non-null  int64
 88  status                      11430 non-null  int64
dtypes: float64(13), int64(75), object(1)
memory usage: 7.8+ MB
```

```
df.isna().sum()
```

```
url                0
length_url         0
length_hostname    0
ip                 0
nb_dots            0
                  ..
web_traffic        0
dns_record         0
google_index       0
page_rank          0
status             0
Length: 89, dtype: int64
```

```
## drop na code
```

```
df.describe() # to find the mean,median,std,min,max,etc.
```

```
         length_url  length_hostname            ip       nb_dots  \
count  11430.000000     11430.000000  11430.000000  11430.000000
mean      61.126684        21.090289      0.150569      2.480752
std       55.297318        10.777171      0.357644      1.369686
min       12.000000         4.000000      0.000000      1.000000
25%       33.000000        15.000000      0.000000      2.000000
50%       47.000000        19.000000      0.000000      2.000000
75%       71.000000        24.000000      0.000000      3.000000
max     1641.000000       214.000000      1.000000     24.000000
```

```
         nb_hyphens         nb_at         nb_qm        nb_and    nb_or
\
count  11430.000000  11430.000000  11430.000000  11430.000000  11430.0

mean       0.997550      0.022222      0.141207      0.162292      0.0

std        2.087087      0.155500      0.364456      0.821337      0.0

min        0.000000      0.000000      0.000000      0.000000      0.0

25%        0.000000      0.000000      0.000000      0.000000      0.0

50%        0.000000      0.000000      0.000000      0.000000      0.0

75%        1.000000      0.000000      0.000000      0.000000      0.0

max       43.000000      4.000000      3.000000     19.000000      0.0


              nb_eq  ...  domain_in_title  domain_with_copyright  \
count  11430.000000  ...     11430.000000           11430.000000
mean       0.293176  ...         0.775853               0.439545
std        0.998317  ...         0.417038               0.496353
min        0.000000  ...         0.000000               0.000000
25%        0.000000  ...         1.000000               0.000000
50%        0.000000  ...         1.000000               0.000000
75%        0.000000  ...         1.000000               1.000000
max       19.000000  ...         1.000000               1.000000

       whois_registered_domain  domain_registration_length
domain_age  \
count             11430.000000                11430.000000
11430.000000
mean                  0.072878                  492.532196
4062.543745
std                   0.259948                  814.769415
3107.784600
min                   0.000000                   -1.000000    -
12.000000
25%                   0.000000                   84.000000
972.250000
50%                   0.000000                  242.000000
3993.000000
75%                   0.000000                  449.000000
7026.750000
max                   1.000000                29829.000000
12874.000000
```

```
        web_traffic    dns_record  google_index     page_rank
status
count  1.143000e+04  11430.000000  11430.000000  11430.000000
11430.000000
mean   8.567566e+05      0.020122      0.533946      3.185739
0.500000
std    1.995606e+06      0.140425      0.498868      2.536955
0.500022
min    0.000000e+00      0.000000      0.000000      0.000000
0.000000
25%    0.000000e+00      0.000000      0.000000      1.000000
0.000000
50%    1.651000e+03      0.000000      1.000000      3.000000
0.500000
75%    3.738455e+05      0.000000      1.000000      5.000000
1.000000
max    1.076799e+07      1.000000      1.000000     10.000000
1.000000

[8 rows x 88 columns]
```

```
pd.crosstab(df.status,df.ip)
```

```
ip         0     1
status
0       5512   203
1       4197  1518
```

```
pd.crosstab(df.status,df.domain_with_copyright)
```

```
domain_with_copyright     0     1
status
0                      2712  3003
1                      3694  2021
```

```
pd.crosstab(df.status,df.port)
```

```
port       0   1
status
0       5704  11
1       5699  16
```

```
pd.crosstab(df.status,df.nb_redirection)
```

```
nb_redirection     0     1    2   3   4  5  6
status
0               3284  2002  362  54   9  4  0
1               3491  1825  300  74  22  2  1
```

```
pd.crosstab(df.status,df.google_index) # seems important
```

```
google_index     0     1
status
0             4748   967
1              579  5136
```

```
df.info()
```

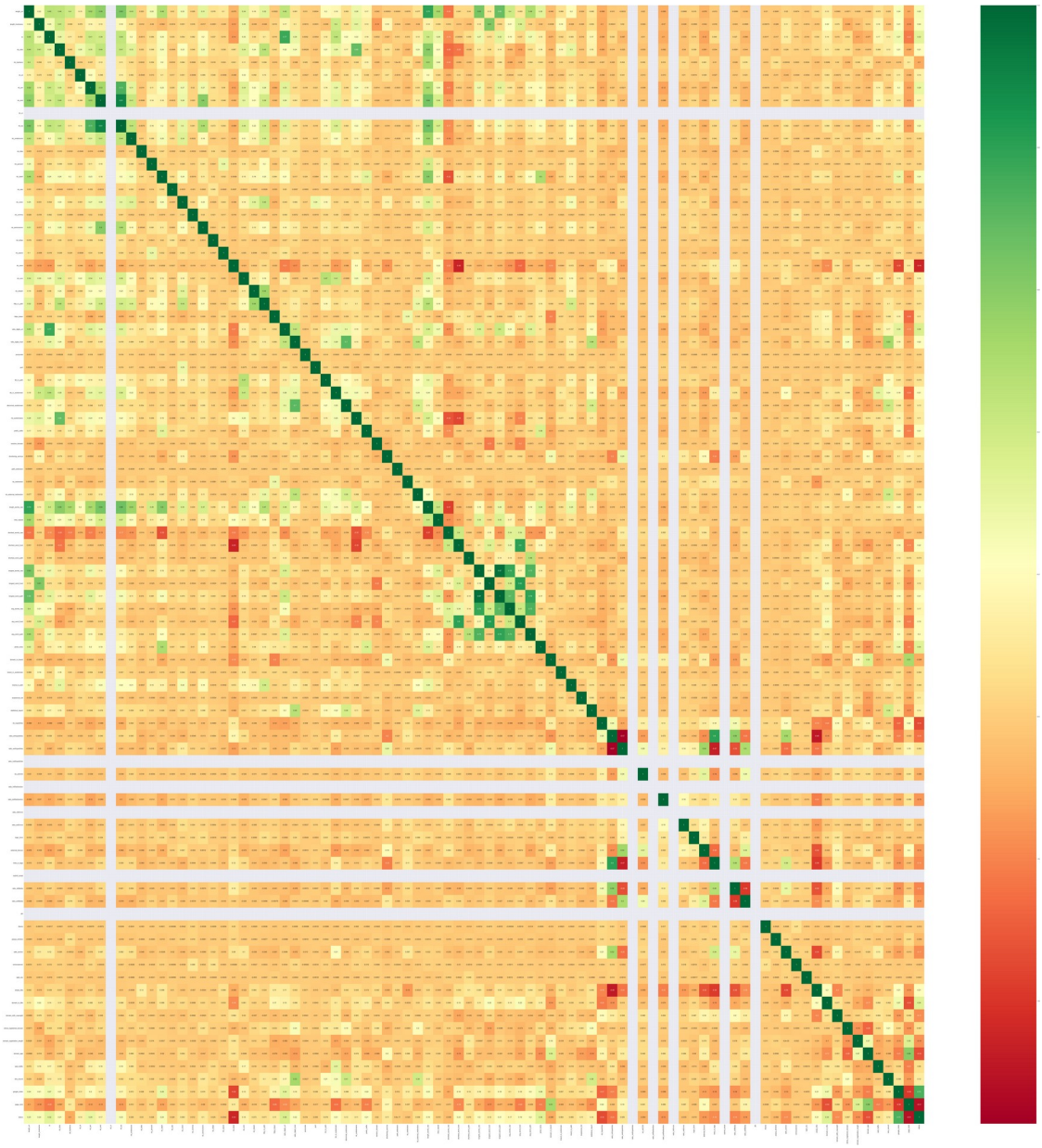
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11430 entries, 0 to 11429
Data columns (total 89 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   url                          11430 non-null  object
 1   length_url                   11430 non-null  int64
 2   length_hostname              11430 non-null  int64
 3   ip                           11430 non-null  int64
 4   nb_dots                      11430 non-null  int64
 5   nb_hyphens                   11430 non-null  int64
 6   nb_at                        11430 non-null  int64
 7   nb_qm                        11430 non-null  int64
 8   nb_and                       11430 non-null  int64
 9   nb_or                        11430 non-null  int64
 10  nb_eq                        11430 non-null  int64
 11  nb_underscore                11430 non-null  int64
 12  nb_tilde                     11430 non-null  int64
 13  nb_percent                   11430 non-null  int64
 14  nb_slash                     11430 non-null  int64
 15  nb_star                      11430 non-null  int64
 16  nb_colon                     11430 non-null  int64
 17  nb_comma                     11430 non-null  int64
 18  nb_semicolumn                11430 non-null  int64
 19  nb_dollar                    11430 non-null  int64
 20  nb_space                     11430 non-null  int64
 21  nb_www                       11430 non-null  int64
 22  nb_com                       11430 non-null  int64
 23  nb_dslash                    11430 non-null  int64
 24  http_in_path                 11430 non-null  int64
 25  https_token                  11430 non-null  int64
 26  ratio_digits_url             11430 non-null  float64
 27  ratio_digits_host            11430 non-null  float64
 28  punycode                     11430 non-null  int64
 29  port                         11430 non-null  int64
 30  tld_in_path                  11430 non-null  int64
 31  tld_in_subdomain             11430 non-null  int64
 32  abnormal_subdomain           11430 non-null  int64
 33  nb_subdomains                11430 non-null  int64
 34  prefix_suffix                11430 non-null  int64
 35  random_domain                11430 non-null  int64
 36  shortening_service           11430 non-null  int64
 37  path_extension               11430 non-null  int64
 38  nb_redirection               11430 non-null  int64
```

39	nb_external_redirection	11430	non-null	int64
40	length_words_raw	11430	non-null	int64
41	char_repeat	11430	non-null	int64
42	shortest_words_raw	11430	non-null	int64
43	shortest_word_host	11430	non-null	int64
44	shortest_word_path	11430	non-null	int64
45	longest_words_raw	11430	non-null	int64
46	longest_word_host	11430	non-null	int64
47	longest_word_path	11430	non-null	int64
48	avg_words_raw	11430	non-null	float64
49	avg_word_host	11430	non-null	float64
50	avg_word_path	11430	non-null	float64
51	phish_hints	11430	non-null	int64
52	domain_in_brand	11430	non-null	int64
53	brand_in_subdomain	11430	non-null	int64
54	brand_in_path	11430	non-null	int64
55	suspecious_tld	11430	non-null	int64
56	statistical_report	11430	non-null	int64
57	nb_hyperlinks	11430	non-null	int64
58	ratio_intHyperlinks	11430	non-null	float64
59	ratio_extHyperlinks	11430	non-null	float64
60	ratio_nullHyperlinks	11430	non-null	int64
61	nb_extCSS	11430	non-null	int64
62	ratio_intRedirection	11430	non-null	int64
63	ratio_extRedirection	11430	non-null	float64
64	ratio_intErrors	11430	non-null	int64
65	ratio_extErrors	11430	non-null	float64
66	login_form	11430	non-null	int64
67	external_favicon	11430	non-null	int64
68	links_in_tags	11430	non-null	float64
69	submit_email	11430	non-null	int64
70	ratio_intMedia	11430	non-null	float64
71	ratio_extMedia	11430	non-null	float64
72	sfh	11430	non-null	int64
73	iframe	11430	non-null	int64
74	popup_window	11430	non-null	int64
75	safe_anchor	11430	non-null	float64
76	onmouseover	11430	non-null	int64
77	right_clic	11430	non-null	int64
78	empty_title	11430	non-null	int64
79	domain_in_title	11430	non-null	int64
80	domain_with_copyright	11430	non-null	int64
81	whois_registered_domain	11430	non-null	int64
82	domain_registration_length	11430	non-null	int64
83	domain_age	11430	non-null	int64
84	web_traffic	11430	non-null	int64
85	dns_record	11430	non-null	int64
86	google_index	11430	non-null	int64
87	page_rank	11430	non-null	int64
88	status	11430	non-null	int64

```
dtypes: float64(13), int64(75), object(1)
memory usage: 7.8+ MB
```

```
## add the plotting of the attributes selected by ayan and taniska
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(200,200))
#plot heat map
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

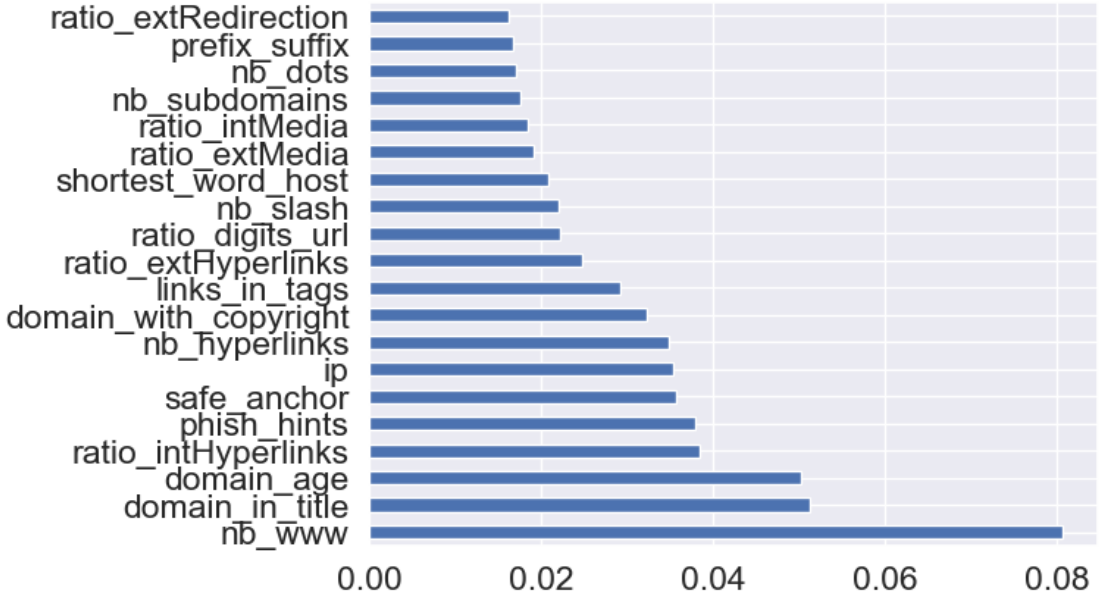
```
C:\Users\KIIT\AppData\Local\Temp\ipykernel_17968\1698413501.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  corrmat = df.corr()
```



```
## This code is used to find the most important attributes for us

X = df.iloc[:,1:86]  #independent columns
y = df['status']    #target column i.e price range
from sklearn.ensemble import ExtraTreesClassifier
import matplotlib.pyplot as plt
model = ExtraTreesClassifier()
model.fit(X,y)
print(model.feature_importances_) #use inbuilt class
feature_importances of tree based classifiers
#plot graph of feature importances for better visualization
feat_importances = pd.Series(model.feature_importances_,
index=X.columns)
```

```
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```

```
[1.44153933e-02 1.42731054e-02 3.53265094e-02 1.70128507e-02
 1.37772966e-02 2.87460449e-03 1.26223022e-02 2.70539230e-03
 0.00000000e+00 6.68384346e-03 5.52288568e-03 5.88851754e-04
 1.47621561e-03 2.20655713e-02 2.99668049e-05 9.74988980e-04
 1.76170300e-04 9.50304866e-04 1.89605761e-05 1.38024999e-03
 8.06978108e-02 3.04303673e-03 3.43864958e-04 8.74342079e-04
 9.42276304e-03 2.22589608e-02 1.19378380e-02 3.14568345e-05
 1.51649831e-04 2.10671782e-03 1.02197785e-02 2.53784850e-03
 1.75992312e-02 1.67694501e-02 3.73118504e-03 8.77103234e-03
 1.29807395e-04 1.03751390e-02 2.71106768e-05 1.50510959e-02
 1.24080168e-02 1.30013415e-02 2.08430197e-02 1.21470776e-02
 1.15417107e-02 9.85185802e-03 1.59194454e-02 1.04872755e-02
 1.16990753e-02 1.31014065e-02 3.80088481e-02 1.35850129e-02
 4.28825851e-04 6.70365271e-04 3.84088199e-03 4.22949671e-03
 3.48014331e-02 3.83817154e-02 2.48160640e-02 0.00000000e+00
 7.12791944e-03 0.00000000e+00 1.62079969e-02 0.00000000e+00
 1.02820984e-02 3.89271697e-03 1.21151536e-02 2.92761976e-02
 0.00000000e+00 1.84241498e-02 1.91224053e-02 0.00000000e+00
 2.52844216e-04 7.68668359e-04 3.56930022e-02 7.48186267e-05
 4.39684543e-04 1.47919392e-02 5.11884285e-02 3.22498174e-02
 4.28059062e-03 1.46889773e-02 5.03078715e-02 1.32353316e-02
 6.86093432e-03]
```




```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

X = df.iloc[:,1:44]  #independent columns
y = df['status']    #target column i.e price range
#apply SelectKBest class to extract top 10 best features
```

```
bestfeatures = SelectKBest(score_func=chi2, k=40)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Specs','Score']  #naming the dataframe
columns
print(featureScores.nlargest(20,'Score'))  #print 10 best features
```

```
                 Specs         Score
0           length_url  35328.039045
1      length_hostname   3574.909094
9                nb_eq   2116.254551
39    length_words_raw   2099.190649
42  shortest_word_host   1760.361475
7               nb_and   1381.779515
20              nb_www   1262.570425
2                   ip   1004.779198
6                nb_qm    931.273854
17       nb_semicolumn    704.022472
13            nb_slash    554.047400
4           nb_hyphens    500.135415
30    tld_in_subdomain    473.719023
33       prefix_suffix    420.136560
3              nb_dots    370.448986
21              nb_com    313.280246
5                nb_at    254.000000
25    ratio_digits_url    218.164314
26   ratio_digits_host    200.608193
31  abnormal_subdomain    183.680162
```

First we will Scale the data for the complete data set

```
from sklearn import preprocessing

df = df.drop('url',axis=1)

min_max_scaler = preprocessing.MinMaxScaler()
new_data = min_max_scaler.fit_transform(df)

# converting the scalled data to pandas DataFrame

new_data=pd.DataFrame(new_data)
new_data
```

```
             0         1    2         3         4     5         6
7   \
0      0.015347  0.071429  0.0  0.086957  0.000000  0.00  0.000000
0.000000
```

```
1      0.039902  0.090476  1.0  0.000000  0.000000  0.00  0.000000
0.000000
2      0.069982  0.219048  1.0  0.130435  0.023256  0.00  0.333333
0.105263
3      0.003683  0.033333  0.0  0.043478  0.000000  0.00  0.000000
0.000000
4      0.026397  0.052381  0.0  0.043478  0.046512  0.00  0.000000
0.000000
...         ...       ...  ...       ...       ...   ...       ...
...
11425  0.020258  0.061905  0.0  0.043478  0.000000  0.00  0.000000
0.000000
11426  0.044199  0.066667  0.0  0.173913  0.000000  0.25  0.333333
0.000000
11427  0.057090  0.057143  1.0  0.043478  0.139535  0.00  0.333333
0.000000
11428  0.015961  0.123810  0.0  0.043478  0.000000  0.00  0.000000
0.000000
11429  0.285451  0.047619  1.0  1.000000  0.000000  0.25  0.333333
0.473684

        8         9   ...   78   79   80        81        82
83  \
0      0.0  0.000000  ...  0.0  1.0  0.0  0.001542  0.000854
0.000000e+00
1      0.0  0.000000  ...  1.0  0.0  0.0  0.002615  0.448471
0.000000e+00
2      0.0  0.157895  ...  1.0  0.0  0.0  0.000503  0.311656
5.413097e-01
3      0.0  0.000000  ...  1.0  0.0  0.0  0.002112  0.000854
1.000382e-02
4      0.0  0.000000  ...  0.0  1.0  0.0  0.007543  0.635341
8.102722e-04
...    ...       ...  ...  ...  ...  ...       ...       ...
...
11425  0.0  0.000000  ...  0.0  0.0  0.0  0.015052  0.419680
3.696142e-04
11426  0.0  0.052632  ...  1.0  0.0  0.0  0.007107  0.523048
0.000000e+00
11427  0.0  0.052632  ...  0.0  0.0  0.0  0.094200  0.661726
7.429430e-07
11428  0.0  0.000000  ...  1.0  0.0  0.0  0.002883  0.221015
2.280364e-01
11429  0.0  0.473684  ...  1.0  1.0  1.0  0.000034  0.000854
0.000000e+00

        84   85   86   87
0      1.0  1.0  0.4  0.0
1      0.0  1.0  0.2  1.0
2      0.0  1.0  0.0  1.0
```

```
3      0.0  0.0  0.3  0.0
4      0.0  0.0  0.6  0.0
...    ...  ...  ...  ...
11425  0.0  0.0  0.6  0.0
11426  0.0  1.0  0.0  1.0
11427  0.0  1.0  1.0  0.0
11428  0.0  0.0  0.4  0.0
11429  1.0  1.0  0.0  1.0

[11430 rows x 88 columns]
```

```
# since the columns names were lost in scaling process so we restore
that

l=df.columns
j=0
for i in df.columns:
    new_data=new_data.rename(columns={j: i})
    j=j+1

new_data.head()
```

```
   length_url  length_hostname   ip   nb_dots  nb_hyphens  nb_at
nb_qm  \
0    0.015347         0.071429  0.0  0.086957    0.000000    0.0
0.000000
1    0.039902         0.090476  1.0  0.000000    0.000000    0.0
0.000000
2    0.069982         0.219048  1.0  0.130435    0.023256    0.0
0.333333
3    0.003683         0.033333  0.0  0.043478    0.000000    0.0
0.000000
4    0.026397         0.052381  0.0  0.043478    0.046512    0.0
0.000000

     nb_and  nb_or     nb_eq  ...  domain_in_title
domain_with_copyright  \
0  0.000000    0.0  0.000000  ...              0.0
1.0
1  0.000000    0.0  0.000000  ...              1.0
0.0
2  0.105263    0.0  0.157895  ...              1.0
0.0
3  0.000000    0.0  0.000000  ...              1.0
0.0
4  0.000000    0.0  0.000000  ...              0.0
1.0

   whois_registered_domain  domain_registration_length  domain_age  \
0                      0.0                    0.001542    0.000854
```

```
1                     0.0                    0.002615    0.448471
2                     0.0                    0.000503    0.311656
3                     0.0                    0.002112    0.000854
4                     0.0                    0.007543    0.635341

   web_traffic  dns_record  google_index  page_rank  status
0     0.000000         1.0           1.0        0.4     0.0
1     0.000000         0.0           1.0        0.2     1.0
2     0.541310         0.0           1.0        0.0     1.0
3     0.010004         0.0           0.0        0.3     0.0
4     0.000810         0.0           0.0        0.6     0.0

[5 rows x 88 columns]
```

```
status=pd.DataFrame()
status=new_data['status']
new_data=new_data.drop('status',axis=1)
```

```
# using the scalled data to analyse and identify most important
attributes

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

x = new_data.iloc[:,0:87]  #independent columns
y = status    #target column i.e status
#apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=chi2, k=5)
fit = bestfeatures.fit(x,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(x.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Specs','Score']  #naming the dataframe
columns
print(featureScores.nlargest(25,'Score'))  #print 20 best features
```

```
                   Specs         Score
85          google_index  2847.871702
2                     ip  1004.779198
20                nb_www   631.285213
86             page_rank   603.251699
30      tld_in_subdomain   473.719023
77           empty_title   428.838710
33         prefix_suffix   420.136560
6                  nb_qm   310.424618
25       ratio_digits_url   301.381630
78        domain_in_title   301.077582
50           phish_hints   278.507742
26     ratio_digits_host   250.760241
```

```
82             domain_age   231.578842
55     statistical_report   217.441435
69         ratio_intMedia   213.149404
79  domain_with_copyright   191.943471
31     abnormal_subdomain   183.680162
84             dns_record   167.026087
57    ratio_intHyperlinks   160.054949
70         ratio_extMedia   142.879750
74            safe_anchor   141.547931
66       external_favicon   136.965572
54         suspecious_tld   136.043902
67          links_in_tags   128.912288
35     shortening_service   112.828490
```

```
dt=pd.DataFrame()

dt['google_index']=x['google_index']
dt['ip']=x['ip']
dt["nb_www"]=x['nb_www']
dt['page_rank']=x['page_rank']
dt['tld_in_subdomain']=x['tld_in_subdomain']
dt['empty_title']=x['empty_title']
dt['prefix_suffix']=x['prefix_suffix']
dt['nb_qm']=x['nb_qm']
dt['ratio_digits_url']=x['ratio_digits_url']
dt['domain_in_title']=x['domain_in_title']
dt['phish_hints']=x['phish_hints']
dt['ratio_digits_host']=x['ratio_digits_host']
dt['domain_age']=x['domain_age']
dt['statistical_report']=x['statistical_report']
dt['ratio_intMedia']=x['ratio_intMedia']
dt['domain_with_copyright']=x['domain_with_copyright']

## if necesary add attributes as much needed

dt.shape,status.shape
```

```
((11430, 16), (11430,))
```

```
tempsv=dt
tempsv['status']=status
tempsv.to_csv('filename.csv', index = False, encoding='utf-8')
```

Initial Modelling

```
models = {
          "Logistic Regression":LogisticRegression(),
          "KNN":KNeighborsClassifier(),
          "Random Forest":RandomForestClassifier(),
          "AdaBoostClassifier":AdaBoostClassifier(),
```

```
            "Ridge":Ridge(),
            "Lasso":Lasso(),
            "ElasticNet":ElasticNet(),
            "DecisionTreeClassifier":DecisionTreeClassifier(),
            "GradientBoostingClassifier":GradientBoostingClassifier(),
            "ExtraTreesClassifier":ExtraTreesClassifier(),
            "SVC":SVC(),
            "SVR":SVR(),
            "GaussianNB":GaussianNB(),
            "GaussianProcessClassifier":GaussianProcessClassifier(),
            "MLPClassifier":MLPClassifier(),
            "LinearDiscriminantAnalysis":LinearDiscriminantAnalysis(),

"QuadraticDiscriminantAnalysis":QuadraticDiscriminantAnalysis()
          }

# function to fit and score models
def fit_and_score(models,X_train,X_test,y_train,y_test):
    np.random.seed(108)

    # Make a dictionary to keep model scores
    model_scores = {}
    # loop through models
    for name, model in models.items():

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

        # saving the model
        pickle.dump(model,open("./Models/ "+name+".pkl","wb"))

        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test,y_test)
    return model_scores

# splitting the data
x = dt.drop('status',axis=1)
y = dt['status']
np.random.seed(108)

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

# finding the initial score for the model after fitting the models
model_scores = fit_and_score(models = models,
                             X_train = x_train,
                             X_test = x_test,
                             y_train = y_train,
                             y_test = y_test)
model_scores
```

```
C:\Users\KIIT\Desktop\Minor-Project\env\lib\site-packages\sklearn\
linear_model\_ridge.py:216: LinAlgWarning: Ill-conditioned matrix
(rcond=3.17788e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
C:\Users\KIIT\Desktop\Minor-Project\env\lib\site-packages\sklearn\
discriminant_analysis.py:926: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

```
{'Logistic Regression': 0.794692330125401,
 'KNN': 0.8428113152522602,
 'Random Forest': 0.9658792650918635,
 'AdaBoostClassifier': 0.9477981918926801,
 'Ridge': 0.7317558198848393,
 'Lasso': 0.30471890073780317,
 'ElasticNet': 0.3349877703960227,
 'DecisionTreeClassifier': 0.9329250510352872,
 'GradientBoostingClassifier': 0.958296879556722,
 'ExtraTreesClassifier': 0.9650043744531933,
 'SVC': 0.6071741032370953,
 'SVR': -0.17078884773116498,
 'GaussianNB': 0.7454068241469817,
 'GaussianProcessClassifier': 0.805191017789443,
 'MLPClassifier': 0.8404782735491397,
 'LinearDiscriminantAnalysis': 0.9285505978419364,
 'QuadraticDiscriminantAnalysis': 0.6827063283756197}
```

```
# after analysis we choose the best 7 algorithms for further
hypertuning
new_models={
          "Random Forest":RandomForestClassifier(),
          "ExtraTreesClassifier":ExtraTreesClassifier(),
          "GradientBoostingClassifier":GradientBoostingClassifier(),
          "AdaBoostClassifier":AdaBoostClassifier(),
          "DecisionTreeClassifier":DecisionTreeClassifier(),
          "MLPClassifier":MLPClassifier(),
          "Logistic Regression":LogisticRegression()
}
```

HyperTuning Different Algorithms with there Specific Parameters

1.Decision Tree Classifier

```
np.random.seed(108)

cf_grid={
    "criterion":["gini", "entropy", "log_loss"],
    "splitter":["best", "random"],
    "max_depth":[None,1,2,3,5,10],
    "min_samples_split":np.arange(0,50,10),
    "min_samples_split":np.arange(0,50,10),
```

```
    "min_samples_leaf":np.arange(1,50,5),
    "min_weight_fraction_leaf":np.arange(0,10,1)
}

grid = RandomizedSearchCV(DecisionTreeClassifier(),
                          param_distributions = cf_grid,
                          cv = 7,
                          verbose = True,
                          n_iter=100)
grid.fit(x_train,y_train)
pickle.dump(grid,open("DecisionTreeClassifier_HyperTuned.pkl","wb"))
print(grid.best_params_)
print(grid.best_score_)
```

2.MLP Classifier

```
np.random.seed(108)

cf_grid={
    "hidden_layer_sizes":[100,200],
    "activation":["identity", "logistic", "tanh", "relu"],
    "solver":["lbfgs", "sgd", "adam"],
    "alpha":[0.0001,0.0005],
    "batch_size":np.arange(0,50,10),
    "learning_rate":["constant", "invscaling", "adaptive"],
    "power_t":np.arange(0,10,2)
}

grid = RandomizedSearchCV(MLPClassifier(),
                          param_distributions = cf_grid,
                          cv = 7,
                          verbose = True)
grid.fit(x_train,y_train)
pickle.dump(grid,open("MLPClassifier_HyperTuned.pkl","wb"))
print(grid.best_params_)
print(grid.best_score_)
```

3.LogisticRegression

```
np.random.seed(108)

cf_grid={
    "penalty":['l1', 'l2', 'elasticnet', None],
    "dual":[True,False],
    "fit_intercept":[True,False],
    "intercept_scaling":np.arange(1,10,1),
    "class_weight":['dict','balanced'],
    "solver":['lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky',
'sag', 'saga'],
}
```

```
grid = RandomizedSearchCV(LogisticRegression(),
                          param_distributions = cf_grid,
                          cv = 7,
                          verbose = True)
grid.fit(x_train,y_train)
pickle.dump(grid,open("LogisticRegression_HyperTuned.pkl","wb"))
print(grid.best_params_)
print(grid.best_score_)
```

4.RandomForest Classifier

```
rf_grid = {"n_estimators":np.arange(10,300,50),
           "max_depth": [None,3,5,10,20,50,100],
           "min_samples_split":np.arange(2,30,2),
           "min_samples_leaf": np.arange(1,30,2)}


rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                          param_distributions = rf_grid,
                          cv = 10,
                          n_iter = 15,
                          verbose = True)

rs_rf.fit(x_train,y_train)

pickle.dump(rs_rf,open("RandomForest_HyperTuned.pkl","wb"))

rs_rf.score(x_test,y_test)
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits


KeyboardInterrupt
```

5.ExtraTrees Classifier

```
etc_grid = {"n_estimators":np.arange(10,3000,50),
           "max_depth": [None,3,5,10,20,50,100],
           "min_samples_split":np.arange(2,30,2),
           "min_samples_leaf": np.arange(1,30,2),
           }

rs_etc = RandomizedSearchCV(ExtraTreesClassifier(),
                          param_distributions = etc_grid,
                          cv = 10,
                          n_iter = 15,
                          verbose = True)


rs_etc.fit(x_train,y_train)
```

```
pickle.dump(rs_etc,open("ExtraTreesClassifier_HyperTuned.pkl","wb"))

rs_etc.score(x_test,y_test)
```

6.Gradient Boosting Classifier

```
GBC_grid = {"n_estimators":np.arange(10,300,50),
            "max_depth": [None,3,5,10,20,50,100],
            "min_samples_split":np.arange(2,30,2),
            "min_samples_leaf": np.arange(1,30,2),
            "random_state":np.arange(1,11,1),
            "learning_rate":[0.1,0.01,0.005]}

rs_GBC = RandomizedSearchCV(GradientBoostingClassifier(),
                            param_distributions = GBC_grid,
                            cv = 10,
                            n_iter = 15,
                            verbose = True)

rs_GBC.fit(x_train,y_train)

pickle.dump(rs_GBC,open("GradientBoostingClassifier_HyperTuned.pkl","w
b"))

rs_GBC.score(x_test,y_test)
```

7.AdaBoost Classifier

```
ABC_grid = {"n_estimators":np.arange(10,300,50),
            "random_state":np.arange(1,11,1),
            "learning_rate":[0.1,0.01,0.005]}

rs_ABC = RandomizedSearchCV(AdaBoostClassifier(),
                            param_distributions = ABC_grid,
                            cv = 10,
                            n_iter = 15,
                            verbose = True)

rs_ABC.fit(x_train,y_train)

pickle.dump(rs_ABC,open("AdaBoostClassifier_HyperTuned.pkl","wb"))

rs_ABC.score(x_test,y_test)
```

Metrics Analysis of the Algorithms

```
# return the metric precision,accuracy,recall & f1_score of the model
def metric_analysis(model):
    y_preds=model.predict(x_test)
```

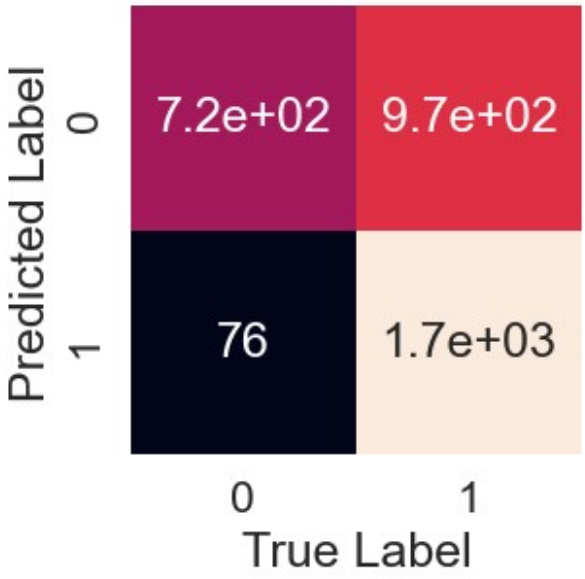
```
    precision=precision_score(y_test,y_preds)
    accuracy=accuracy_score(y_test,y_preds)
    recall=recall_score(y_test,y_preds)
    f1score=f1_score(y_test,y_preds)

    result={
        "precision":precision,
        "accuracy":accuracy,
        "recall":recall,
        "f1score":f1score
    }

    return result

# plots the Confusion Matrix TT,TF,FT & FF
sns.set(font_scale = 1.5)
def plot_conf_matrix(model):
    y_preds=model.predict(x_test)
    fig,ax  = plt.subplots(figsize=(3,3))
    ax = sns.heatmap(confusion_matrix(y_test,y_preds),
                     annot = True,
                     cbar = False)
    plt.xlabel("True Label")
    plt.ylabel("Predicted Label")

# Visualize cross-validated metrics
def cross_validated(model):
    result=metric_analysis(model)
    cv_metrics = pd.DataFrame({"Accuracy":result['accuracy'],
                               "Precision":result['precision'],
                               "Recall":result['recall'],
                               "F1":result['f1score']},
                              index = [0])
    cv_metrics.T.plot.bar(title="Cross-validated classification
metrics")

# prints the classification report consisting of macro average and
weighted average and accuracy
def classification_report_print(model):
    y_preds=model.predict(x_test)
    print(classification_report(y_test,y_preds))

# Plots the ROC(receiver operating characteristic curve) of the model
def plot_roc_curve(model):
    y_probs=model.predict_proba(x_test)

    y_probs_positive=y_probs[:,1]
    fpr,tpr,thresholds=roc_curve(y_test,y_probs_positive)

    plt.plot(fpr,tpr,color="orange",label="ROC")
    ##Customize the plot
```

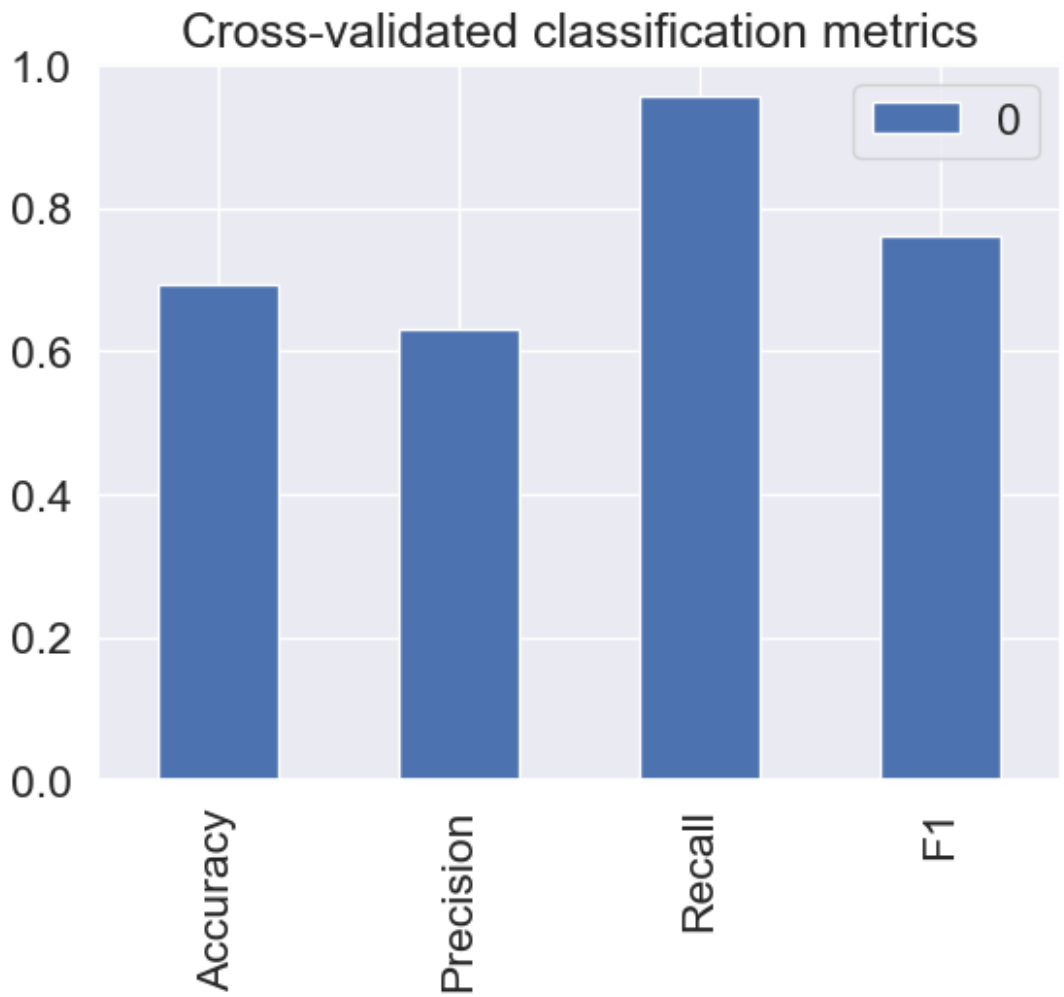
```
    plt.xlabel("False positive rate(fpr)")
    plt.ylabel("True positive rate(tpr)")
    plt.title("Receiver Operating Characterstic (ROC) Curve")
    plt.legend()
    plt.show()

# runs various metrics functions for a particular model
def metrics(model):
    plot_roc_curve(model)
    plot_conf_matrix(model)
    cross_validated(model)
    classification_report_print(model)
```

Analyzing Models By Calling Metric Function()

```
dtc=pickle.load(open("./hyper/
DecisionTreeClassifier_HyperTuned.pkl","rb"))
metrics(dtc)
```

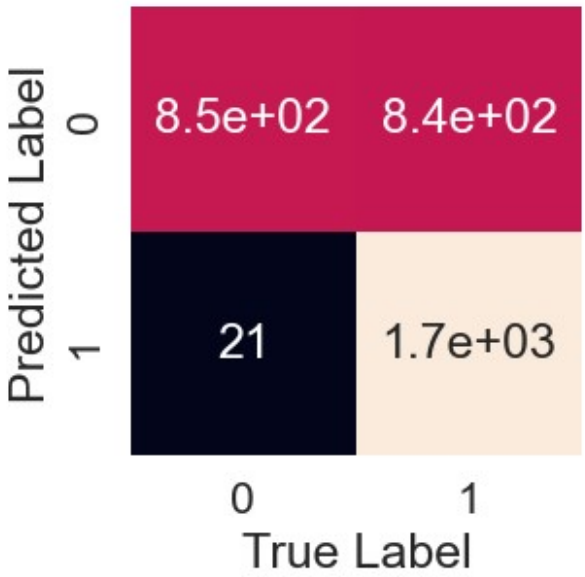
```
              precision    recall  f1-score   support

         0.0       0.90      0.43      0.58      1695
         1.0       0.63      0.96      0.76      1734

    accuracy                           0.69      3429
   macro avg       0.77      0.69      0.67      3429
weighted avg       0.77      0.69      0.67      3429
```

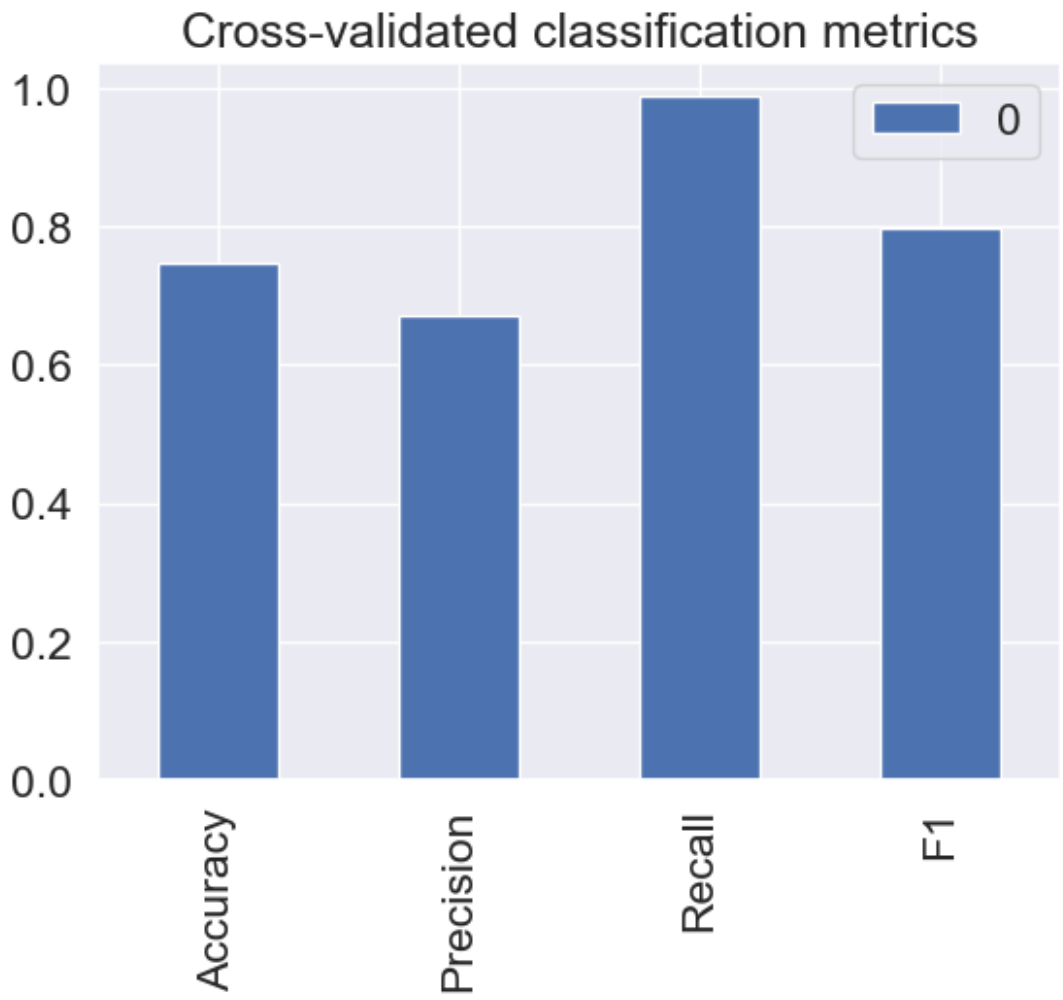




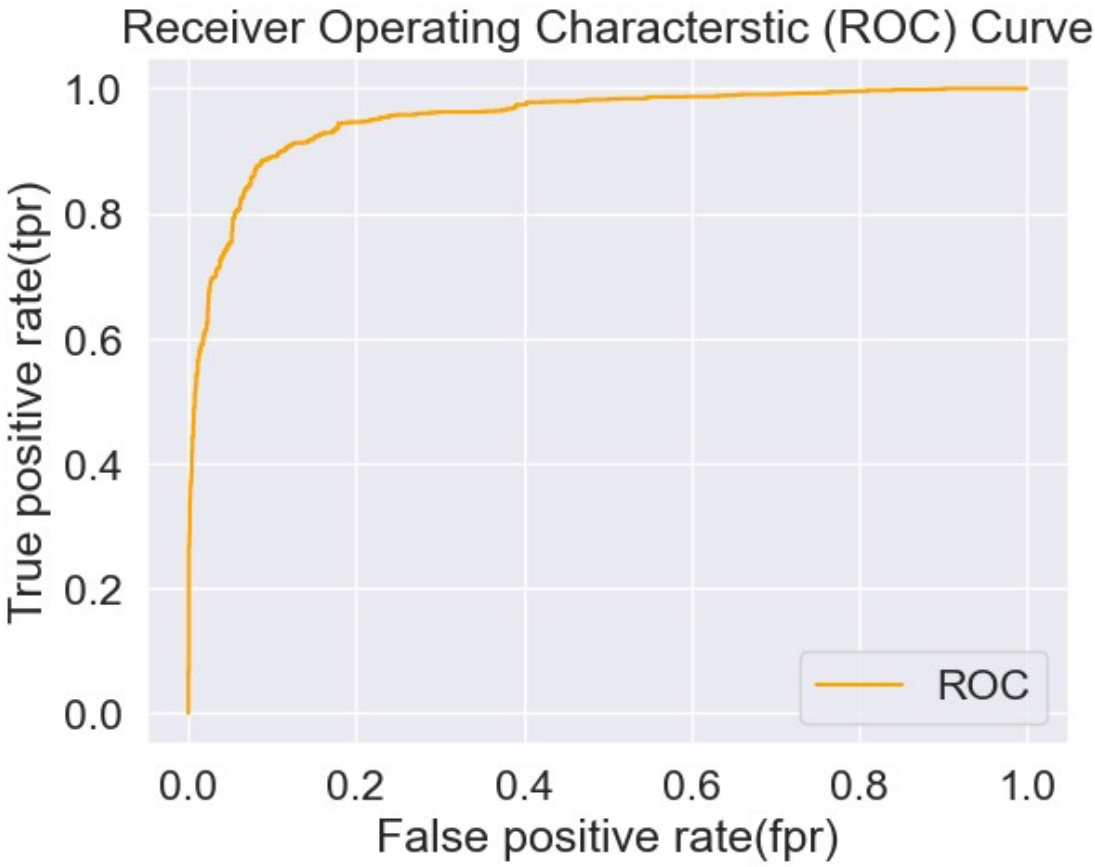

```
mlp=pickle.load(open("./hyper/MLPClassifier_HyperTuned.pkl","rb"))
metrics(mlp)
```

```
              precision    recall  f1-score   support

         0.0       0.98      0.50      0.66      1695
         1.0       0.67      0.99      0.80      1734

    accuracy                           0.75      3429
   macro avg       0.82      0.75      0.73      3429
weighted avg       0.82      0.75      0.73      3429
```

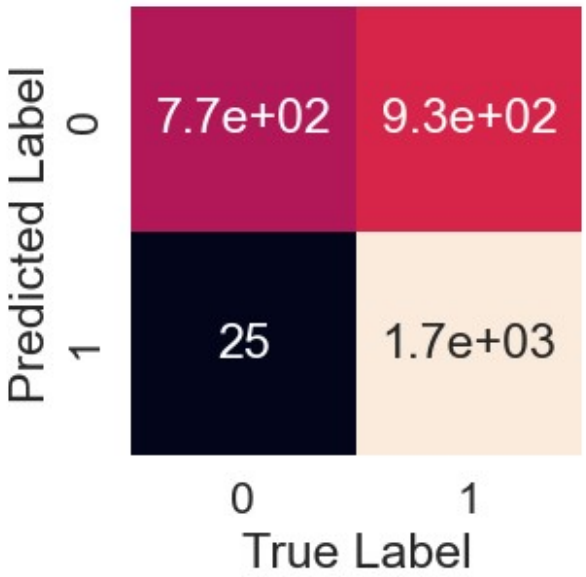

Predicted Label
0
1
8.5e+02
8.4e+02
21
1.7e+03
0
1
True Label

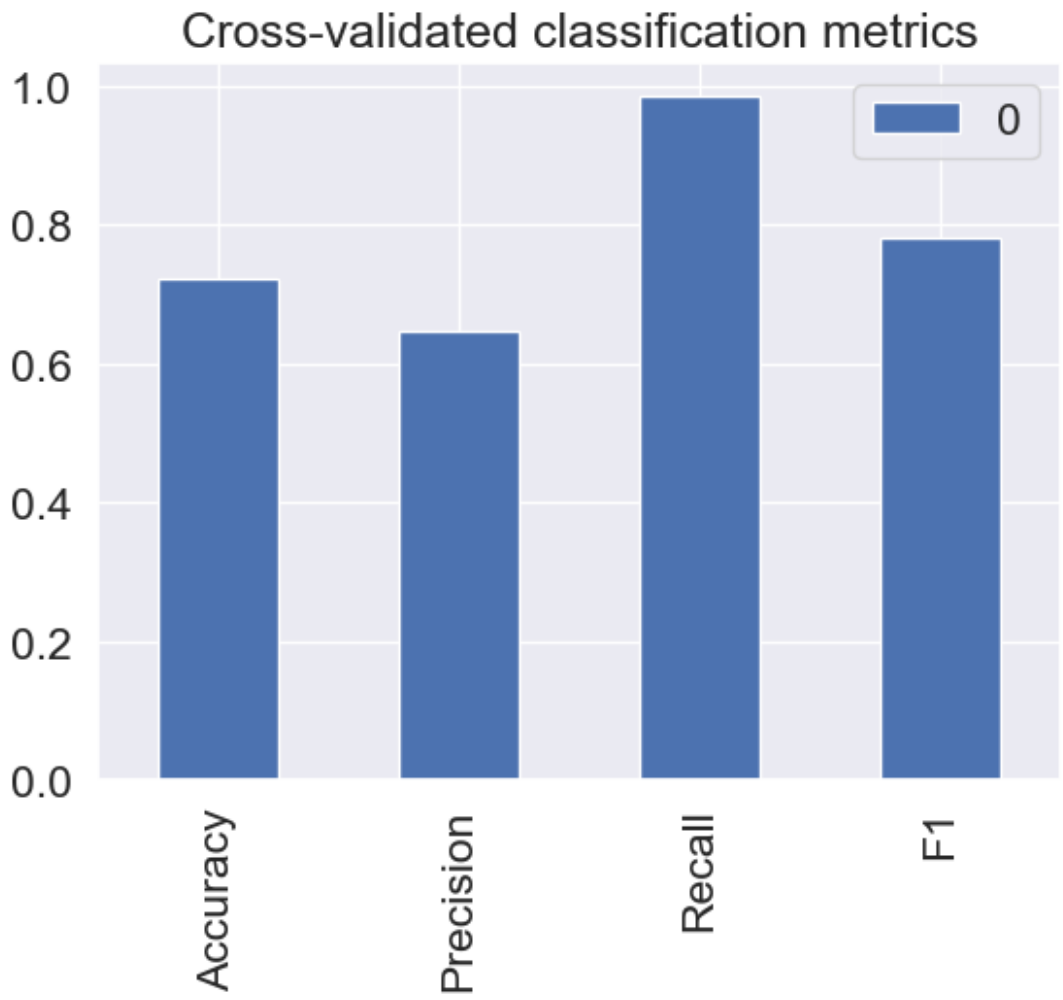

Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
lr=pickle.load(open("./hyper/LogisticRegression_HyperTuned.pkl","rb"))
metrics(lr)
```

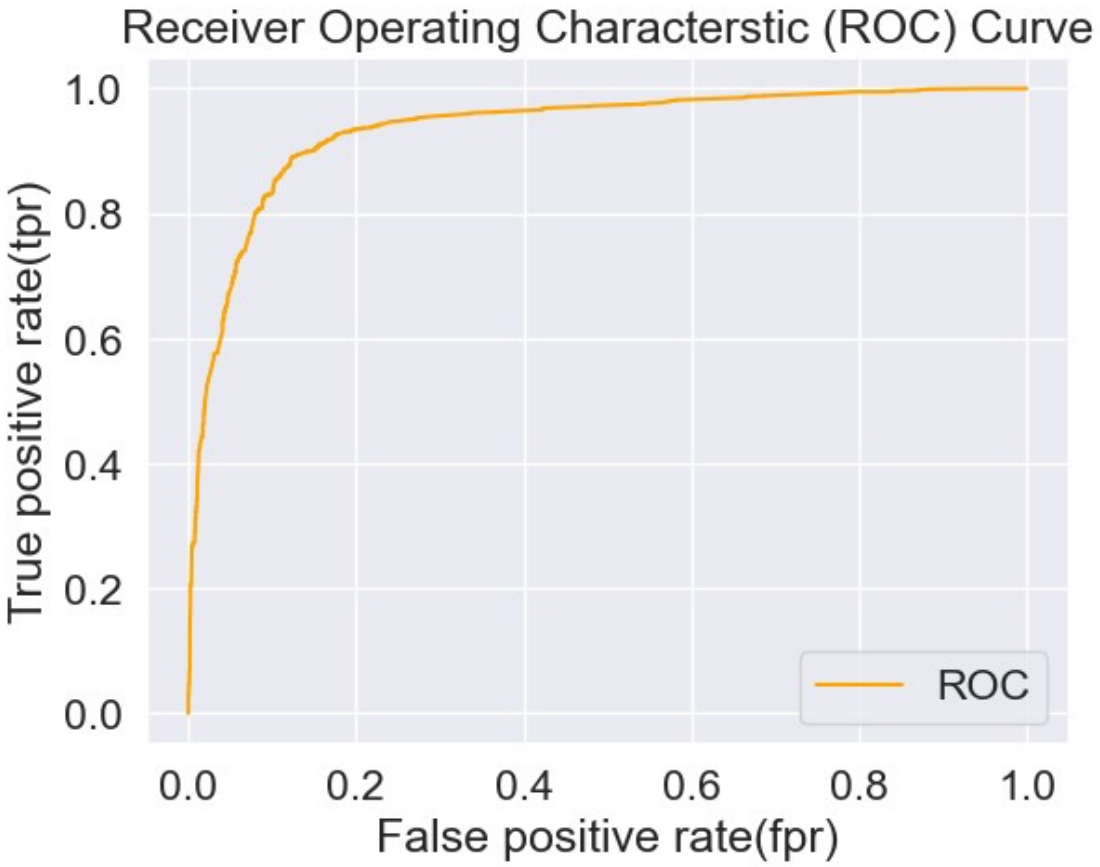


	precision	recall	f1-score	support
0.0	0.97	0.45	0.62	1695
1.0	0.65	0.99	0.78	1734
accuracy			0.72	3429
macro avg	0.81	0.72	0.70	3429
weighted avg	0.81	0.72	0.70	3429

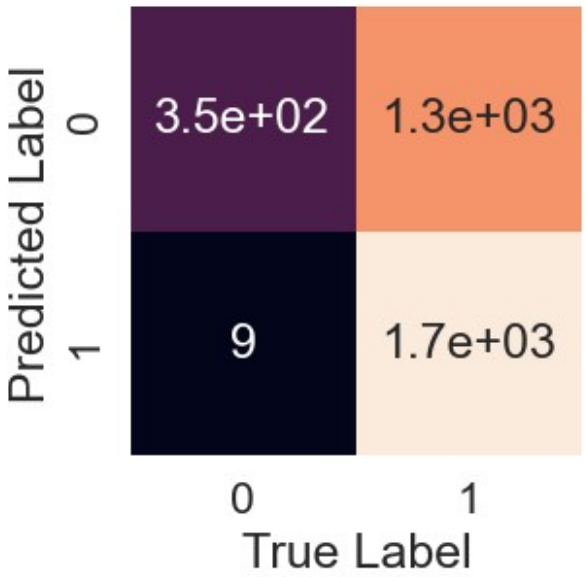

Predicted Label
0
1
7.7e+02
9.3e+02
25
1.7e+03
0
1
True Label

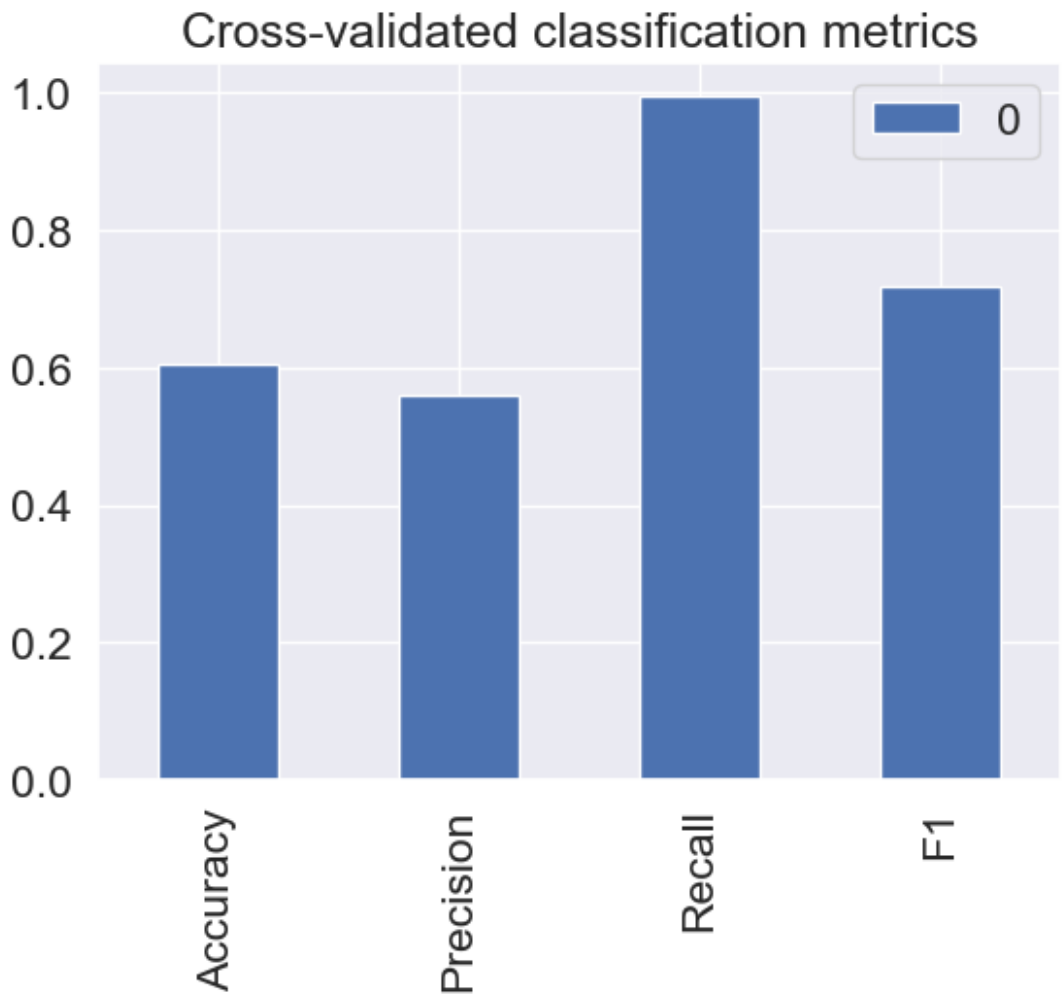

Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
rf=pickle.load(open("./hyper/RandomForest_Hypertuned.pkl","rb"))
metrics(rf)
```

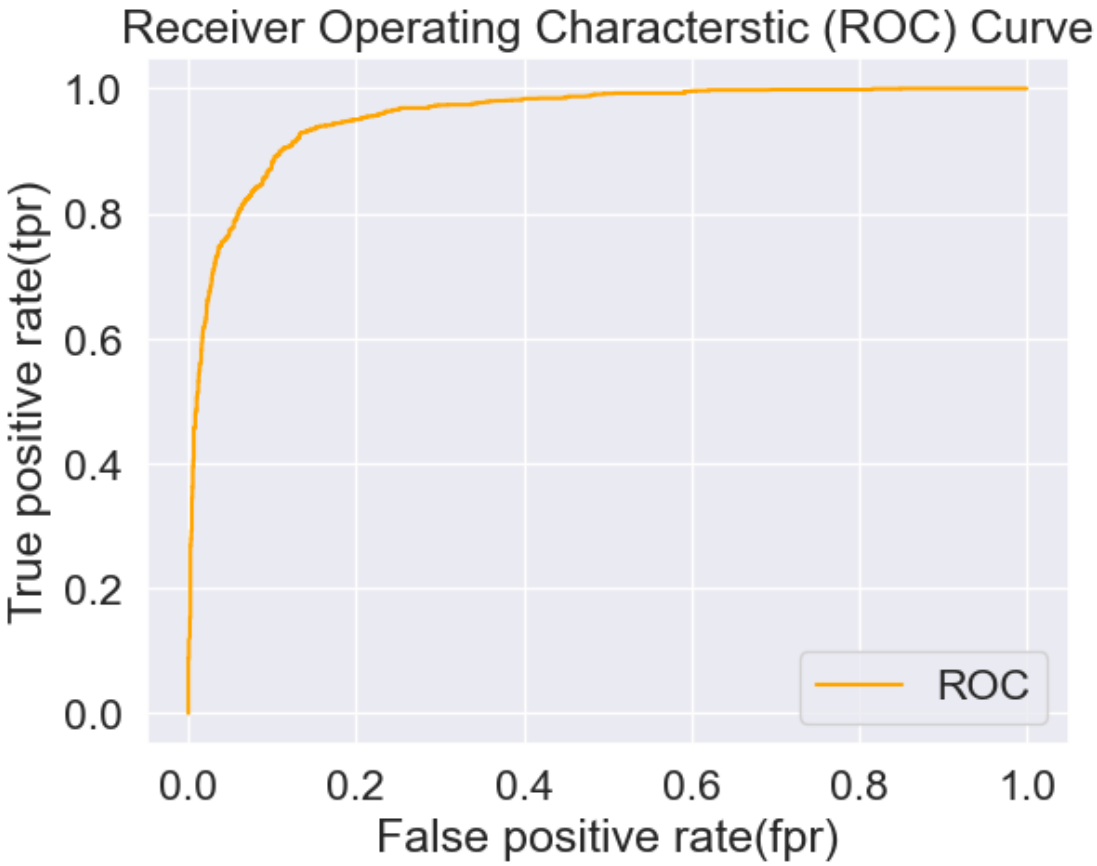


	precision	recall	f1-score	support
0.0	0.97	0.20	0.34	1695
1.0	0.56	0.99	0.72	1734
accuracy			0.60	3429
macro avg	0.77	0.60	0.53	3429
weighted avg	0.77	0.60	0.53	3429

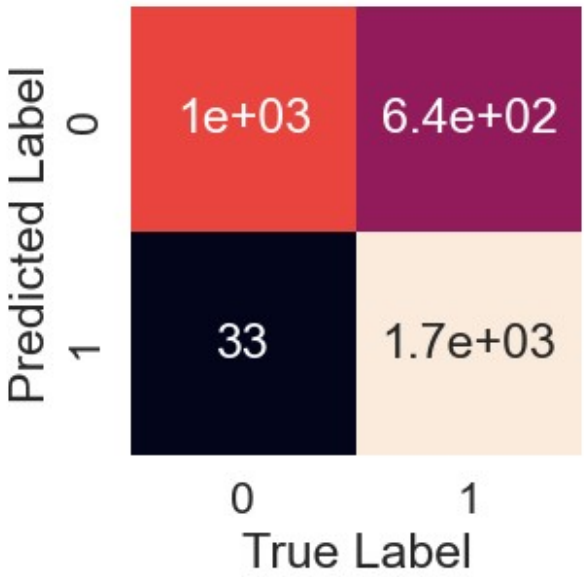

Predicted Label
0
1
3.5e+02
1.3e+03
9
1.7e+03
0
1
True Label

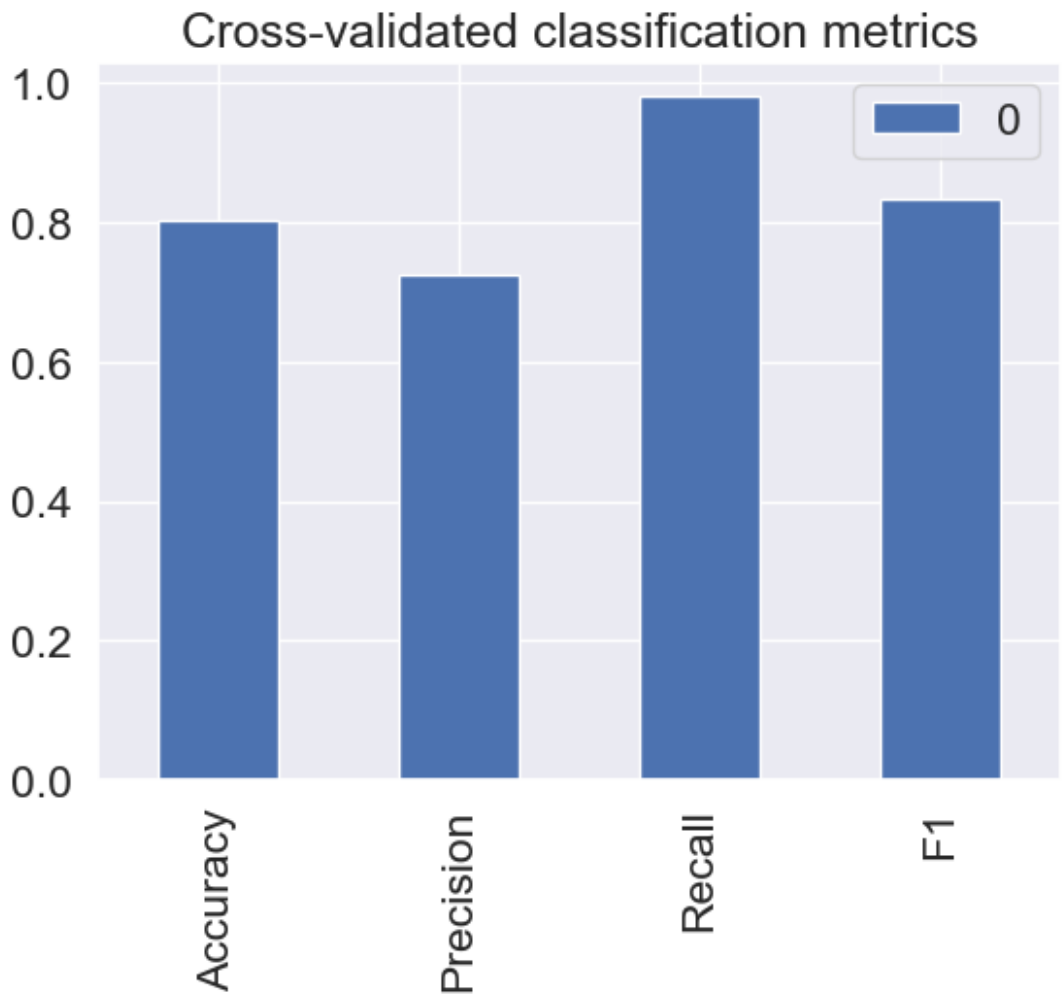

Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
rf=pickle.load(open("./hyper/
ExtraTreesClassifier_Hypertuned.pkl","rb"))
metrics(rf)
```

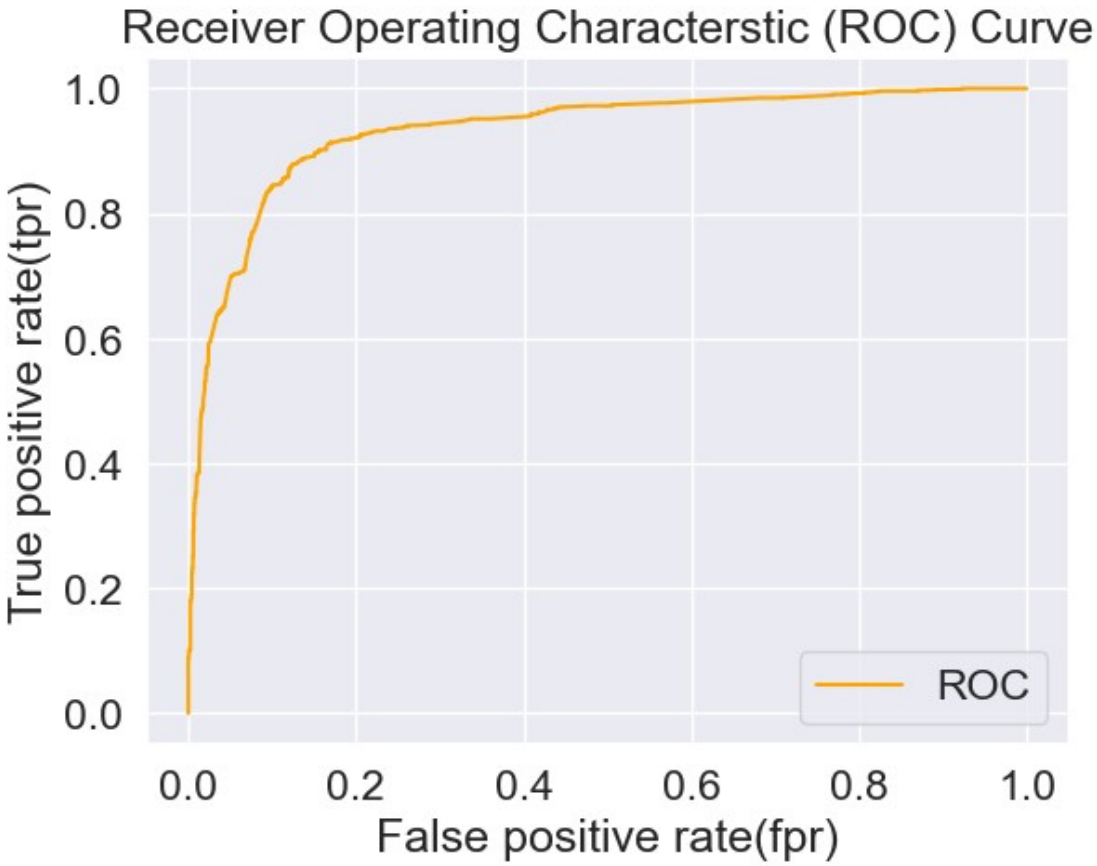


	precision	recall	f1-score	support
0.0	0.97	0.62	0.76	1695
1.0	0.73	0.98	0.83	1734
accuracy			0.80	3429
macro avg	0.85	0.80	0.79	3429
weighted avg	0.85	0.80	0.80	3429

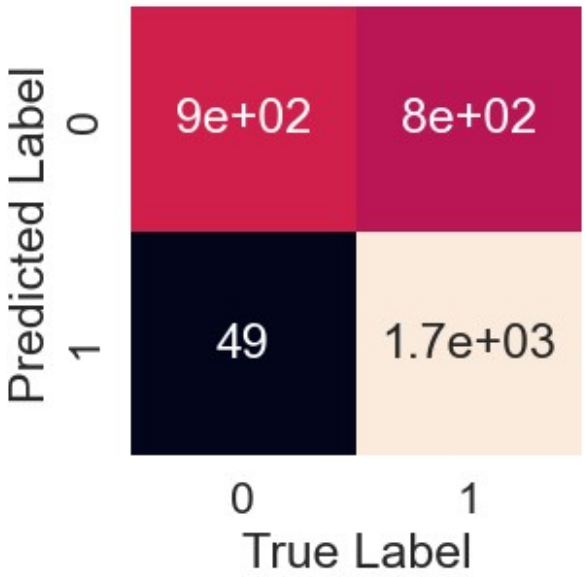

Predicted Label
0
1
1e+03
6.4e+02
33
1.7e+03
0
1
True Label

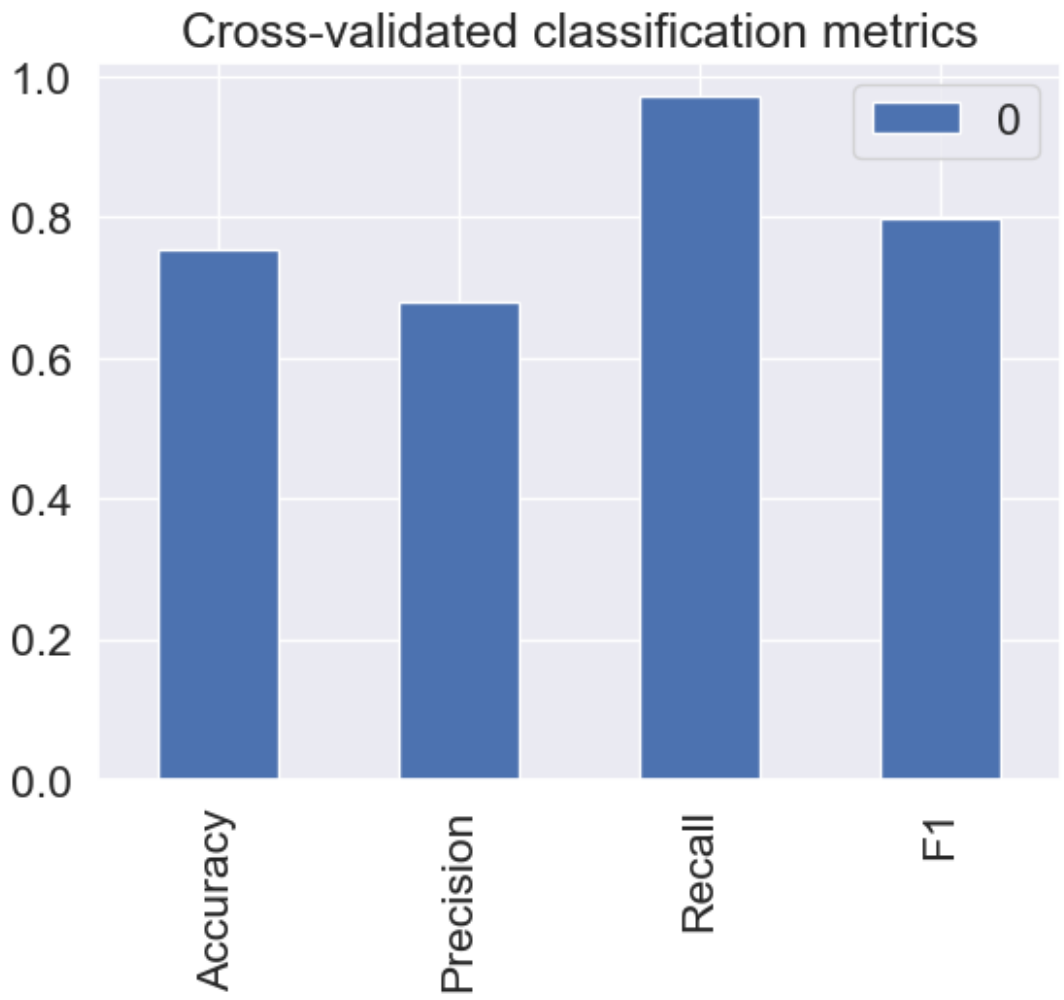

Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
gbc=pickle.load(open("./hyper/
GradientBoostingClassifier_Hypertuned.pkl","rb"))
metrics(gbc)
```

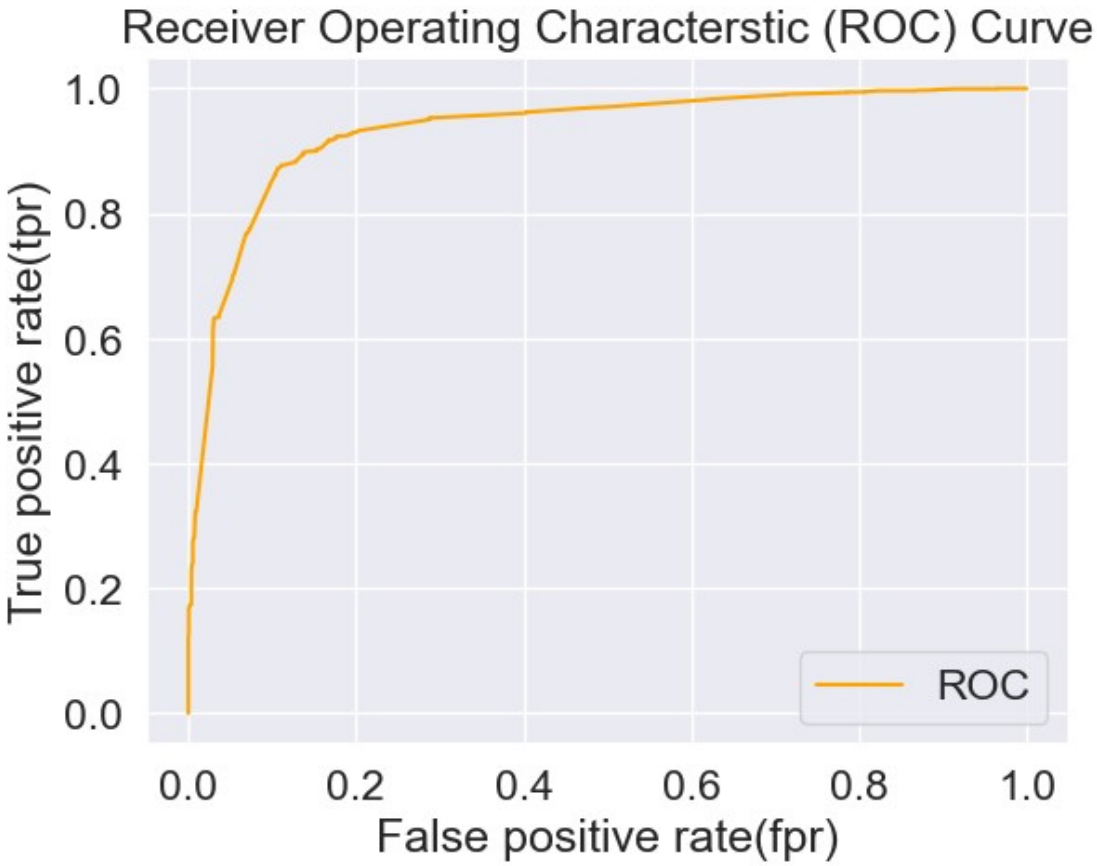


	precision	recall	f1-score	support
0.0	0.95	0.53	0.68	1695
1.0	0.68	0.97	0.80	1734
accuracy			0.75	3429
macro avg	0.81	0.75	0.74	3429
weighted avg	0.81	0.75	0.74	3429

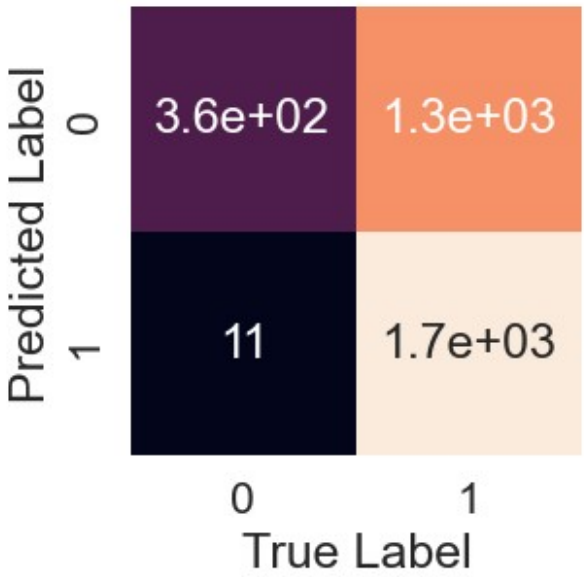

Predicted Label
0
1
9e+02
8e+02
49
1.7e+03
0
1
True Label

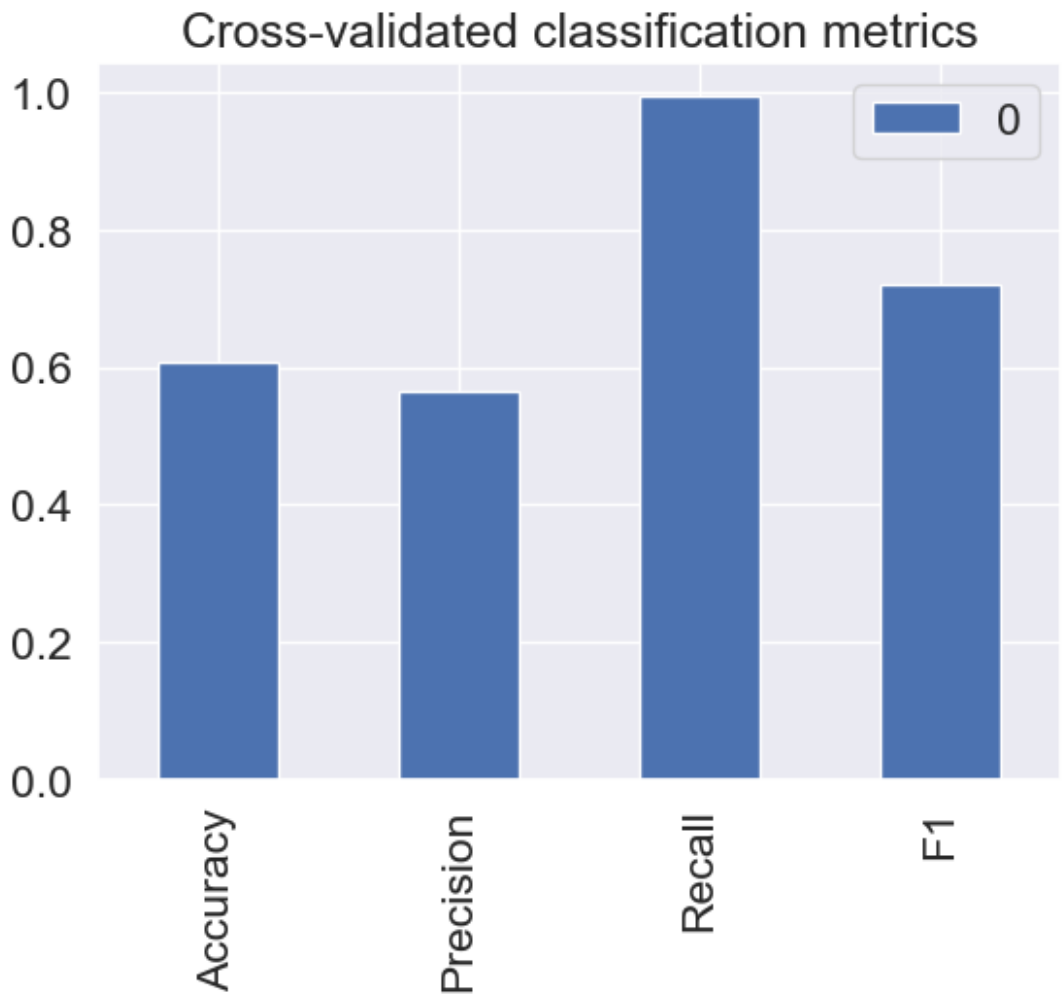

Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
ada=pickle.load(open("./hyper/
AdaBoostClassifier_Hypertuned.pkl","rb"))
metrics(ada)
```



	precision	recall	f1-score	support
0.0	0.97	0.21	0.35	1695
1.0	0.56	0.99	0.72	1734
accuracy			0.61	3429
macro avg	0.77	0.60	0.54	3429
weighted avg	0.76	0.61	0.54	3429


Predicted Label
0
1
3.6e+02
1.3e+03
11
1.7e+03
0
1
True Label


Cross-validated classification metrics
1.0
0.8
0.6
0.4
0.2
0.0
0
Accuracy
Precision
Recall
F1

```
## In conclusion we get to know that gridient boosting and random
forest classifier algorithms give the best accuracy in
## terms of the selected parameters and after our own customized
dataset using data engineering !!
```