```
import numpy as np
import pandas as pd
import itertools
from sklearn.metrics import classification_report,confusion_matrix, accuracy_score
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import seaborn as sns
```

```
!pip install tld
```

```
Collecting tld
  Downloading tld-0.13-py2.py3-none-any.whl (263 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 263.8/263.8 kB 3.4 MB/s eta 0:00:00
Installing collected packages: tld
Successfully installed tld-0.13
```

```
!pip install googlesearch-python
```

```
Collecting googlesearch-python
  Downloading googlesearch-python-1.2.3.tar.gz (3.9 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: beautifulsoup4>=4.9 in /usr/local/lib/python3.10/dist-packages (from googlesearch-python) (4.11.2)
Requirement already satisfied: requests>=2.20 in /usr/local/lib/python3.10/dist-packages (from googlesearch-python) (2.31.0)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-packages (from beautifulsoup4>=4.9->googlesearch-python) (2.5)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.20->googlesearch-python) (3.3
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.20->googlesearch-python) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.20->googlesearch-python) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.20->googlesearch-python) (2023.11.1
Building wheels for collected packages: googlesearch-python
  Building wheel for googlesearch-python (setup.py) ... done
  Created wheel for googlesearch-python: filename=googlesearch_python-1.2.3-py3-none-any.whl size=4209 sha256=a33d009c1df93bf295bcde7628ec78510f75
  Stored in directory: /root/.cache/pip/wheels/98/24/e9/6c225502948c629b01cc895f86406819281ef0da385f3eb669
Successfully built googlesearch-python
Installing collected packages: googlesearch-python
Successfully installed googlesearch-python-1.2.3
```

```
df=pd.read_csv('/content/malicious_phish.csv')
```

```
print(df.shape)
df.head()
```

```
(651191, 2)
```

	url	type
0	br-icloud.com.br	phishing
1	mp3raid.com/music/krizz_kaliko.html	benign
2	bopsecrets.org/rexroth/cr/1.htm	benign
3	http://www.garage-pirenne.be/index.php?option=...	defacement
4	http://adventure-nicaragua.net/index.php?optio...	defacement

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 651191 entries, 0 to 651190
Data columns (total 2 columns):
 #   Column  Non-Null Count   Dtype 
---  ------  --------------   ----- 
 0   url     651191 non-null  object
 1   type    651191 non-null  object
dtypes: object(2)
memory usage: 9.9+ MB
```

```
df.nunique()
```

```
url     641119
type         4
dtype: int64
```

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

```
10066
```

```
df.drop_duplicates()
```

	url	type
0	br-icloud.com.br	phishing
1	mp3raid.com/music/krizz_kaliko.html	benign
2	bopsecrets.org/rexroth/cr/1.htm	benign
3	http://www.garage-pirenne.be/index.php?option=...	defacement
4	http://adventure-nicaragua.net/index.php?optio...	defacement
...	...	...
651186	xbox360.ign.com/objects/850/850402.html	phishing
651187	games.teamxbox.com/xbox-360/1860/Dead-Space/	phishing
651188	www.gamespot.com/xbox360/action/deadspace/	phishing
651189	en.wikipedia.org/wiki/Dead_Space_(video_game)	phishing
651190	www.angelfire.com/goth/devilmaycrytonite/	phishing

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

```
url     0
type    0
dtype: int64
```

```
df.type.value_counts()
```

```
benign        428103
defacement     96457
phishing       94111
malware        32520
Name: type, dtype: int64
```

```
df_filtered = df[df['type'].isin(['benign', 'phishing'])]
df_filtered.head()
```

	url	type
0	br-icloud.com.br	phishing
1	mp3raid.com/music/krizz_kaliko.html	benign
2	bopsecrets.org/rexroth/cr/1.htm	benign
5	http://buzzfil.net/m/show-art/ils-etaient-loin...	benign
6	espn.go.com/nba/player/_/id/3457/brandon-rush	benign

```
df = df_filtered
```

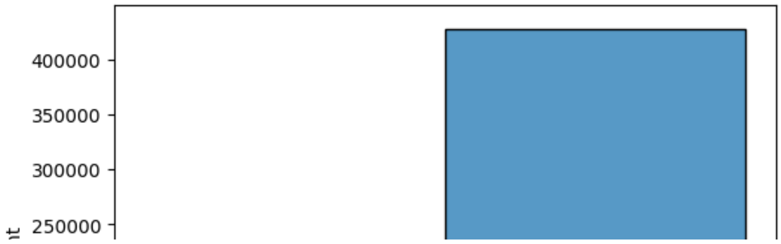
```
import re
from urllib.parse import urlparse
from googlesearch import search
!pip install tldextract
from tldextract import extract as get_tld
from tldextract import extract
```

```
Collecting tldextract
  Downloading tldextract-5.1.1-py3-none-any.whl (97 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 97.7/97.7 kB 2.1 MB/s eta 0:00:00
Requirement already satisfied: idna in /usr/local/lib/python3.10/dist-packages (from tldextract) (3.6)
Requirement already satisfied: requests>=2.1.0 in /usr/local/lib/python3.10/dist-packages (from tldextract) (2.31.0)
Collecting requests-file>=1.4 (from tldextract)
  Downloading requests_file-1.5.1-py2.py3-none-any.whl (3.7 kB)
Requirement already satisfied: filelock>=3.0.8 in /usr/local/lib/python3.10/dist-packages (from tldextract) (3.13.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.1.0->tldextract) (3.3.2)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.1.0->tldextract) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.1.0->tldextract) (2023.11.17)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from requests-file>=1.4->tldextract) (1.16.0)
Installing collected packages: requests-file, tldextract
Successfully installed requests-file-1.5.1 tldextract-5.1.1
```

```
def having_ip_address(url):
    match = re.search(
        '(([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.'
        '([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\/)|'  # IPv4
        '((0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\/)' # IPv4 in hexadecimal
        '(?:[a-fA-F0-9]{1,4}:){7}[a-fA-F0-9]{1,4}', url)  # Ipv6
    if match:
        # print match.group()
        return 1
    else:
        # print 'No matching pattern found'
        return 0
df['use_of_ip'] = df['url'].apply(lambda i: having_ip_address(i))


def abnormal_url(url):
    hostname = urlparse(url).hostname
    hostname = str(hostname)
    match = re.search(hostname, url)
    if match:
        # print match.group()
        return 1
    else:
        # print 'No matching pattern found'
        return 0


df['abnormal_url'] = df['url'].apply(lambda i: abnormal_url(i))

#pip install googlesearch-python


def google_index(url):
    site = search(url, 5)
    return 1 if site else 0
df['google_index'] = df['url'].apply(lambda i: google_index(i))

def count_dot(url):
    count_dot = url.count('.')
    return count_dot

df['count.'] = df['url'].apply(lambda i: count_dot(i))

def count_www(url):
    url.count('www')
    return url.count('www')

df['count-www'] = df['url'].apply(lambda i: count_www(i))

def count_atrate(url):

    return url.count('@')

df['count@'] = df['url'].apply(lambda i: count_atrate(i))


def no_of_dir(url):
    urldir = urlparse(url).path
    return urldir.count('/')

df['count_dir'] = df['url'].apply(lambda i: no_of_dir(i))

def no_of_embed(url):
    urldir = urlparse(url).path
    return urldir.count('//')

df['count_embed_domian'] = df['url'].apply(lambda i: no_of_embed(i))


def shortening_service(url):
    match = re.search('bit\.ly|goo\.gl|shorte\.st|go2l\.ink|x\.co|ow\.ly|t\.co|tinyurl|tr\.im|is\.gd|cli\.gs|'
                      'yfrog\.com|migre\.me|ff\.im|tiny\.cc|url4\.eu|twit\.ac|su\.pr|twurl\.nl|snipurl\.com|'
                      'short\.to|BudURL\.com|ping\.fm|post\.ly|Just\.as|bkite\.com|snipr\.com|fic\.kr|loopt\.us|'
                      'doiop\.com|short\.ie|kl\.am|wp\.me|rubyurl\.com|om\.ly|to\.ly|bit\.do|t\.co|lnkd\.in|'
                      'db\.tt|qr\.ae|adf\.ly|goo\.gl|bitly\.com|cur\.lv|tinyurl\.com|ow\.ly|bit\.ly|ity\.im|'
                      'q\.gs|is\.gd|po\.st|bc\.vc|twitthis\.com|u\.to|j\.mp|buzurl\.com|cutt\.us|u\.bb|yourls\.org|'
                      'x\.co|prettylinkpro\.com|scrnch\.me|filoops\.info|vzturl\.com|qr\.net|1url\.com|tweez\.me|v\.gd|'
                      'tr\.im|link\.zip\.net',
                      url)
    if match:
        return 1
    else:
        return 0

df['short_url'] = df['url'].apply(lambda i: shortening_service(i))
```

```
def count_https(url):
    return url.count('https')

def tld_length(url):
    tld_info = extract(url)
    tld = tld_info.suffix  # Use suffix attribute to get the Top-Level Domain
    try:
        return len(tld)
    except: TypeError


def suspicious_words(url):
    match = re.search('PayPal|login|signin|bank|account|update|free|lucky|service|bonus|ebayisapi|webscr',
                      url)
    if match:
        return 1
    else:
        return 0
df['sus_url'] = df['url'].apply(lambda i: suspicious_words(i))


def digit_count(url):
    digits = 0
    for i in url:
        if i.isnumeric():
            digits = digits + 1
    return digits


df['count-digits']= df['url'].apply(lambda i: digit_count(i))


def letter_count(url):
    letters = 0
    for i in url:
        if i.isalpha():
            letters = letters + 1
    return letters

df['count-letters']= df['url'].apply(lambda i: letter_count(i))


#First Directory Length
def fd_length(url):
    urlpath= urlparse(url).path
    try:
        return len(urlpath.split('/')[1])
    except:
        return 0

df['fd_length'] = df['url'].apply(lambda i: fd_length(i))

#Length of Top Level Domain
df['tld'] = df['url'].apply(lambda i: get_tld(i,tld_length(i)))


df['tld_length'] = df['url'].apply(lambda i: tld_length(i))


df["count-https"] = df["url"].apply(lambda i: i.count("https"))
df["count-http"] = df["url"].apply(lambda i: i.count("http"))
df["count%"] = df["url"].apply(lambda i: i.count("%"))
df["count?"] = df["url"].apply(lambda i: i.count("?"))
df["count-"] = df["url"].apply(lambda i: i.count("-"))
df["count="] = df["url"].apply(lambda i: i.count("="))
df["url_length"] = df["url"].apply(lambda i: len(str(i)))
df["hostname_length"] = df["url"].apply(lambda i: len(urlparse(i).netloc))


sns.histplot(df.type)
```

```
<Axes: xlabel='type', ylabel='Count'>
```




```
df.type.value_counts()
```

```
benign      428103
phishing     94111
Name: type, dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['type_code']=le.fit_transform(df['type'])
df['type_code'].value_counts()
```

```
1    10000
0    10000
Name: type_code, dtype: int64
```

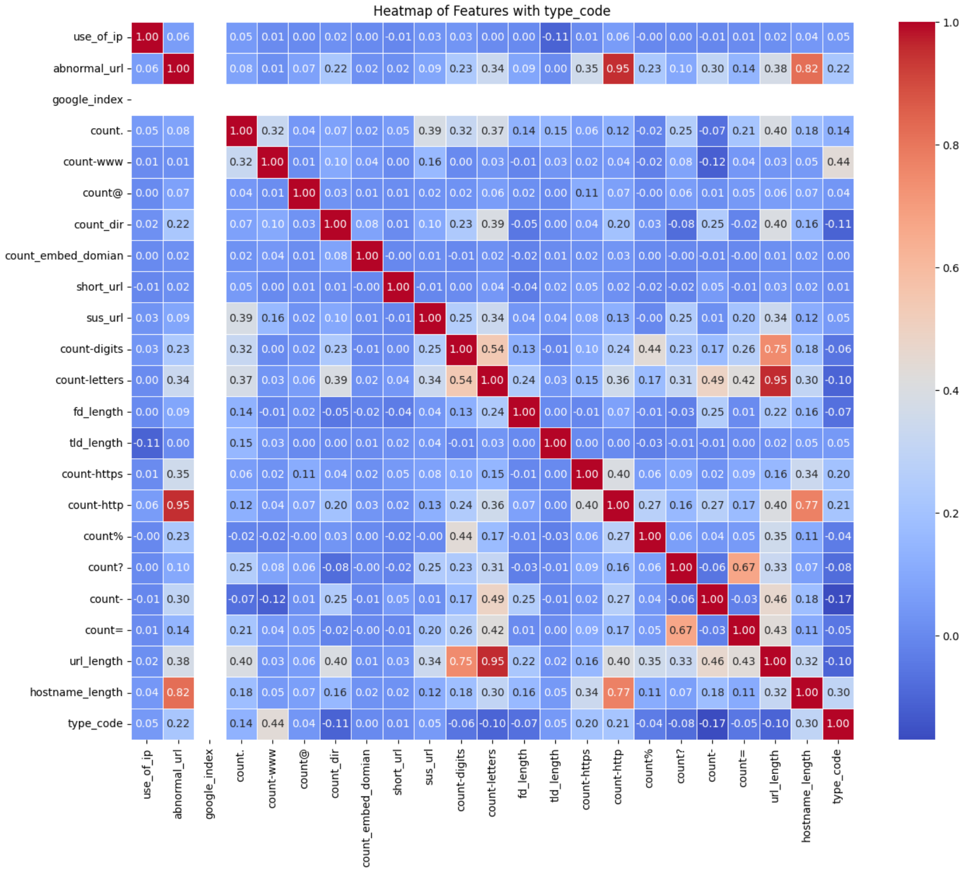
```
df.head()
```

	url	type	use_of_ip	abnormal_url	google_index	count.
0	br-icloud.com.br	phishing	0	0	1	2
1	mp3raid.com/music/krizz_kaliko.html	benign	0	0	1	2
2	bopsecrets.org/rexroth/cr/1.htm	benign	0	0	1	2
5	http://buzzfil.net/m/show-art/ils-etaient-loin...	benign	0	1	1	2
6	espn.go.com/nba/player/_/id/3457/brandon-rush	benign	0	0	1	2

5 rows × 26 columns

```
# Create a DataFrame with columns other than 'url'
features_df = df.drop(columns=['url', 'type'])

# Assuming 'type_code' is the column you want to predict
target_column = 'type_code'

# Add the target column to the features DataFrame
features_df[target_column] = df[target_column]

# Calculate the correlation matrix
correlation_matrix = features_df.corr()

# Set up the matplotlib figure
plt.figure(figsize=(15, 12))

# Create a heatmap using seaborn
heatmap = sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)

# Set the title of the heatmap
plt.title(f"Heatmap of Features with {target_column}")

# Show the plot
plt.show()
```

```
<ipython-input-36-683815e48689>:11: FutureWarning: The default value of numeric_only in DataFra
  correlation_matrix = features_df.corr()
```



```
from sklearn.preprocessing import LabelEncoder

lb_make = LabelEncoder()
df["type_code"] = lb_make.fit_transform(df["type"])
df["type_code"].value_counts()
```

```
1    10000
0    10000
Name: type_code, dtype: int64
```

```
X = df[['use_of_ip','abnormal_url', 'count.', 'count-www', 'count@',
       'count_dir', 'count_embed_domian', 'short_url', 'count-https',
       'count-http', 'count%', 'count?', 'count-', 'count=', 'url_length',
       'hostname_length', 'sus_url', 'fd_length', 'tld_length', 'count-digits',
       'count-letters']]

#Target Variable
y = df['type_code']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2,shuffle=True, random_state=5)
```

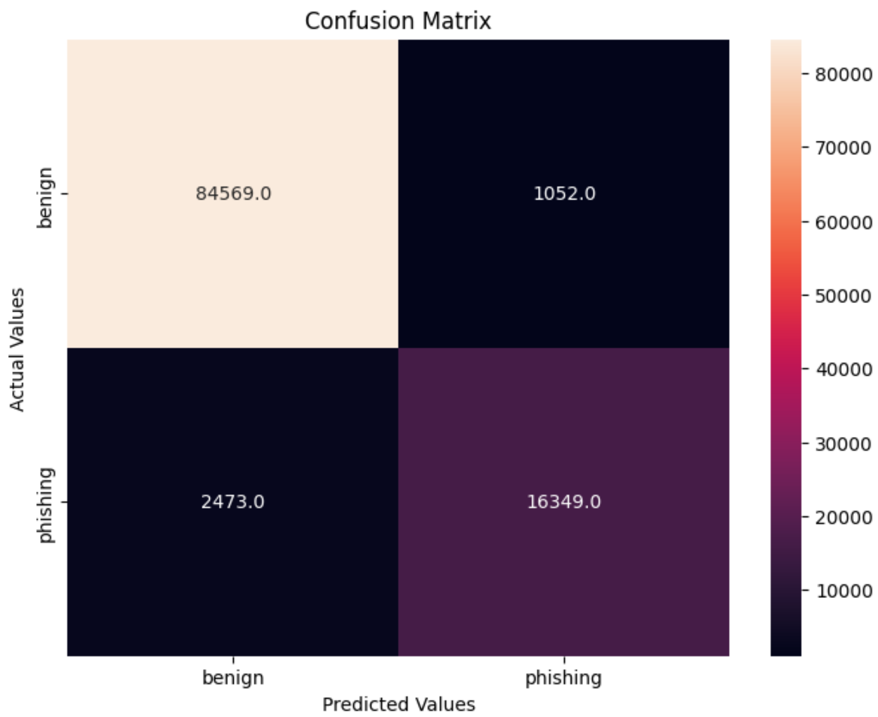
Since deep learning models like CNN, LSTM, CNN-LSTM are already been discussed in the paper, lets compare it with more classification models such as XGboost classifier, Light GBM classifier, Rnadom forest classifier

1) XGboost classifier

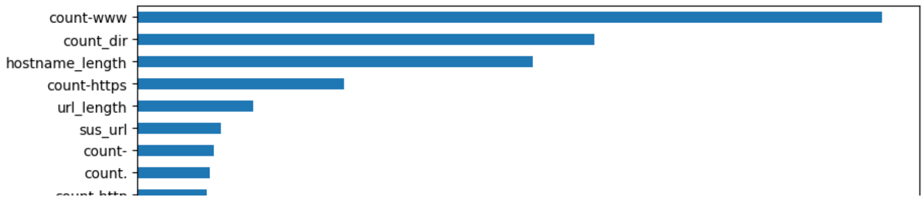
```
from sklearn import metrics
import xgboost as xgb
xgb_c = xgb.XGBClassifier(n_estimators= 100)
xgb_c.fit(X_train,y_train)
y_pred_x = xgb_c.predict(X_test)
print(classification_report(y_test,y_pred_x,target_names=['benign','phishing']))

score = metrics.accuracy_score(y_test, y_pred_x)
print("accuracy:   %4.2f" % score)
```

```
                  precision    recall  f1-score   support

          benign       0.97      0.99      0.98     85621
        phishing       0.94      0.87      0.90     18822

        accuracy                           0.97    104443
       macro avg       0.96      0.93      0.94    104443
    weighted avg       0.97      0.97      0.97    104443

    accuracy:   0.97
```

```
cm = confusion_matrix(y_test, y_pred_x)
cm_df = pd.DataFrame(cm,
                     index = ['benign','phishing'],
                     columns = ['benign','phishing'])
plt.figure(figsize=(8,6))
sns.heatmap(cm_df, annot=True,fmt=".1f")
plt.title('Confusion Matrix')
plt.ylabel('Actual Values')
plt.xlabel('Predicted Values')
plt.show()
```




```
feat_importances = pd.Series(xgb_c.feature_importances_, index=X_train.columns)
feat_importances.sort_values().plot(kind="barh",figsize=(10, 6))
plt.show()
```



The above figure shows the importance of each of the features in the trained XGboost model.

2) Light GBM model

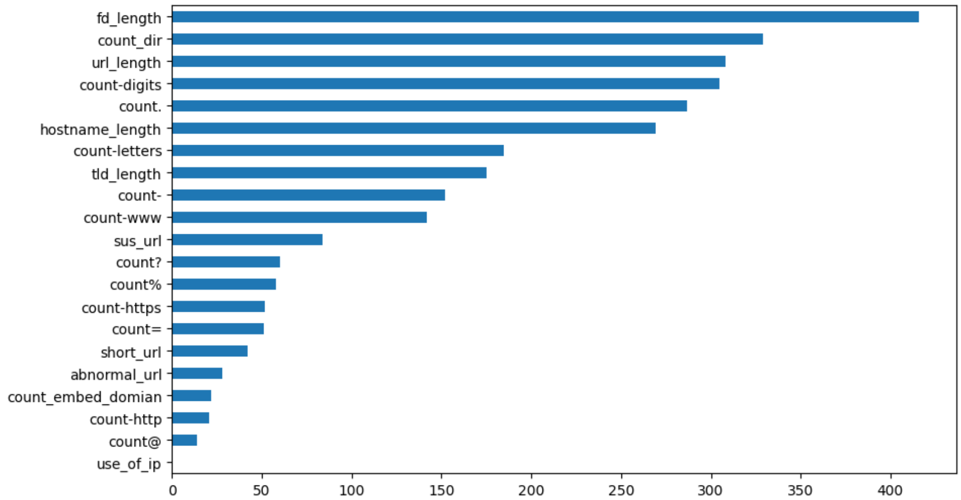
```
from lightgbm import LGBMClassifier

lgb = LGBMClassifier(boosting_type='gbdt', n_jobs=5, silent=True, random_state=5)
LGB_C = lgb.fit(X_train, y_train)

y_pred_lgb = LGB_C.predict(X_test)
print(classification_report(y_test, y_pred_lgb, target_names=['benign', 'phishing']))

accuracy = accuracy_score(y_test, y_pred_lgb)
print("Accuracy: %4.2f" % accuracy)
```

```
[LightGBM] [Warning] Unknown parameter: silent
[LightGBM] [Warning] Unknown parameter: silent
[LightGBM] [Info] Number of positive: 75289, number of negative: 342482
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.092505 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1165
[LightGBM] [Info] Number of data points in the train set: 417771, number of used features: 21
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.180216 -> initscore=-1.514885
[LightGBM] [Info] Start training from score -1.514885
[LightGBM] [Warning] Unknown parameter: silent
              precision    recall  f1-score   support

      benign       0.97      0.99      0.98     85621
    phishing       0.94      0.86      0.90     18822

    accuracy                           0.96    104443
   macro avg       0.95      0.92      0.94    104443
weighted avg       0.96      0.96      0.96    104443

Accuracy: 0.96
```

```
cm = confusion_matrix(y_test, y_pred_lgb)
cm_df = pd.DataFrame(cm,
                     index = ['benign','phishing'],
                     columns = ['benign','phishing'])
plt.figure(figsize=(8,6))
sns.heatmap(cm_df, annot=True,fmt=".1f")
plt.title('Confusion Matrix')
plt.ylabel('Actual Values')
plt.xlabel('Predicted Values')
plt.show()
```

Confusion Matrix

```
feat_importances = pd.Series(lgb.feature_importances_, index=X_train.columns)
feat_importances.sort_values().plot(kind="barh",figsize=(10, 6))
plt.show()
```



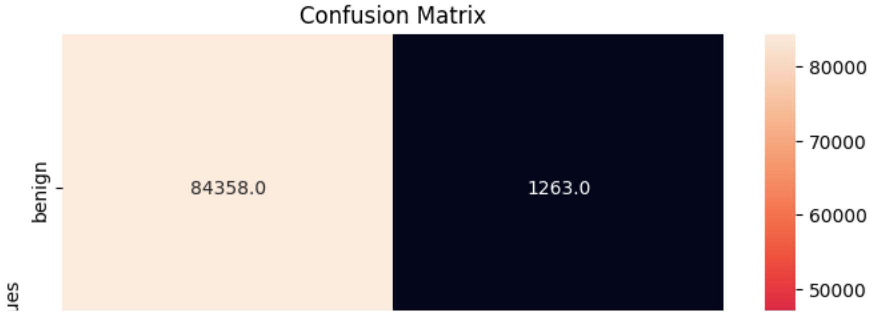
As you can see there is no importance for use_of_ip feature for building the model.

3) Random Forest model

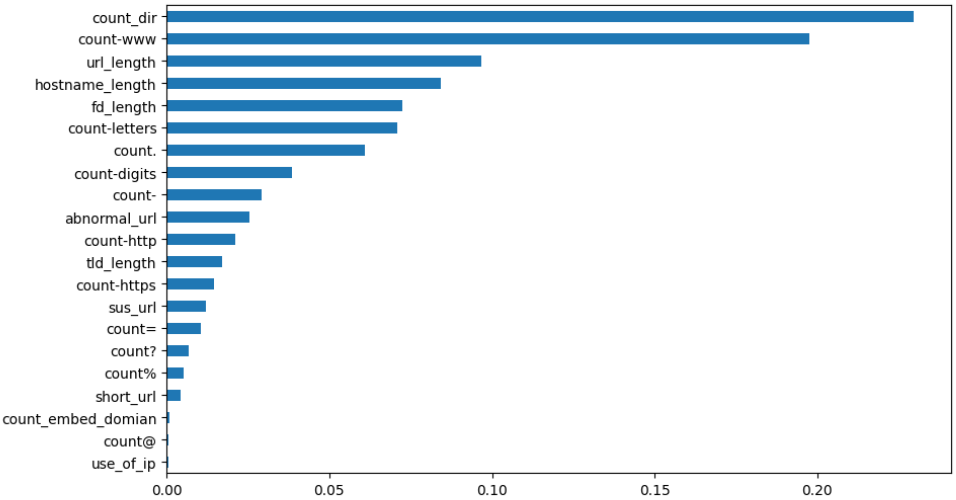
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=100,max_features='sqrt')
rf.fit(X_train,y_train)
y_pred_rf = rf.predict(X_test)
print(classification_report(y_test,y_pred_rf,target_names=['benign','phishing']))

score = metrics.accuracy_score(y_test, y_pred_rf)
print("accuracy:   %4.3f" % score)
```

```
              precision    recall  f1-score   support

      benign       0.98      0.99      0.98     85621
    phishing       0.93      0.89      0.91     18822

    accuracy                           0.97    104443
   macro avg       0.95      0.94      0.94    104443
weighted avg       0.97      0.97      0.97    104443

accuracy:   0.968
```

```
cm = confusion_matrix(y_test, y_pred_rf)
cm_df = pd.DataFrame(cm, index = ['benign','phishing'], columns = ['benign','phishing'])
plt.figure(figsize=(8,6))
sns.heatmap(cm_df, annot=True,fmt=".1f")
plt.title('Confusion Matrix')
plt.ylabel('Actual Values')
plt.xlabel('Predicted Values')
plt.show()
```




```
feat_importances = pd.Series(rf.feature_importances_, index=X_train.columns)
feat_importances.sort_values().plot(kind="barh",figsize=(10, 6))
plt.show()
```



Lets try a custom Deep learning model for classification

```python
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.metrics import accuracy_score

# Define the custom neural network class
class CustomNN(nn.Module):
    def __init__(self, input_size, num_layers, dropout_rate, activation):
        super(CustomNN, self).__init__()
        layers = []
        for _ in range(num_layers):
            layers.append(nn.Linear(input_size, input_size))
            layers.append(nn.Dropout(dropout_rate))
            layers.append(activation)
        self.model = nn.Sequential(*layers)
        self.output_layer = nn.Linear(input_size, 2)  # Assuming binary classification

    def forward(self, x):
        x = self.model(x)
        x = self.output_layer(x)
        return x

# Assuming 'type_code' is the column you want to predict
target_column = 'type_code'

# Predictor Variables
X = df[['use_of_ip', 'abnormal_url', 'count.', 'count-www', 'count@',
        'count_dir', 'count_embed_domian', 'short_url', 'count-https',
        'count-http', 'count%', 'count?', 'count-', 'count=', 'url_length',
        'hostname_length', 'sus_url', 'fd_length', 'tld_length', 'count-digits',
        'count-letters']]

# Target Variable
y = df[target_column]

# Encode target variable
le = LabelEncoder()
y = le.fit_transform(y)

# Min-Max Scaling
scaler = MinMaxScaler()
X = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, shuffle=True, random_state=5)

# Convert data to PyTorch tensors
X_train_tensor = torch.FloatTensor(X_train)
y_train_tensor = torch.LongTensor(y_train)
X_test_tensor = torch.FloatTensor(X_test)
y_test_tensor = torch.LongTensor(y_test)

# Define hyperparameters
activation_functions = [nn.ReLU(), nn.Tanh(), nn.Sigmoid()]
epochs_list = [10, 20, 30, 40, 50, 60]
batch_sizes = [16, 32, 64, 100, 500, 1200, 1500]
optimizers = [optim.Adam, optim.SGD]
num_layers_list = [1, 2, 3]
dropout_rates = [0.1, 0.2, 0.3]

best_accuracy = 0.0
best_hyperparameters = {}

# Iterate over hyperparameters
for activation in activation_functions:
    for epochs in epochs_list:
        for batch_size in batch_sizes:
            for optimizer in optimizers:
                for num_layers in num_layers_list:
                    for dropout_rate in dropout_rates:
                        # Create the model
                        model = CustomNN(input_size=X_train_tensor.shape[1], num_layers=num_layers, dropout_rate=dropout_rate, activation=activation)

                        # Choose the optimizer
                        optimizer_instance = optimizer(model.parameters(), lr = 0.001)

                        # Loss function
                        criterion = nn.CrossEntropyLoss()

                        # Training loop
                        for epoch in range(epochs):
                            # Set model to training mode
```

```
                        model.train()

                        # Forward pass
                        y_pred = model(X_train_tensor)

                        # Compute the loss
                        loss = criterion(y_pred, y_train_tensor)

                        # Backward pass and optimization
                        optimizer_instance.zero_grad()
                        loss.backward()
                        optimizer_instance.step()

                    # Evaluate on the test set
                    with torch.no_grad():
                        model.eval()
                        y_pred = model(X_test_tensor)
                        _, predicted = torch.max(y_pred, 1)
                        accuracy = accuracy_score(y_test, predicted)

                    print(f"Activation: {activation.__class__.__name__}, Epochs: {epochs}, Batch Size: {batch_size}, Optimizer: {optimizer.__name_

                    # Check if this set of hyperparameters gives the best accuracy
                    if accuracy > best_accuracy:
                        best_accuracy = accuracy
                        print("************** New MAX ACCURACY **************")
                        best_hyperparameters = {
                            'activation': activation.__class__.__name__,
                            'epochs': epochs,
                            'batch_size': batch_size,
                            'optimizer': optimizer.__name__,
                            'num_layers': num_layers,
                            'dropout_rate': dropout_rate
                        }

print("Best Hyperparameters:", best_hyperparameters)
print("Best Accuracy:", best_accuracy*10.0)
```

```
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 2, Dropout: 0.1, Accuracy: 50.0
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 2, Dropout: 0.2, Accuracy: 50.0
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 2, Dropout: 0.3, Accuracy: 50.0
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 3, Dropout: 0.1, Accuracy: 50.0
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 3, Dropout: 0.2, Accuracy: 50.0
Activation: Sigmoid, Epochs: 60, Batch Size: 1500, Optimizer: SGD, Layers: 3, Dropout: 0.3, Accuracy: 50.0
Best Hyperparameters: {'activation': 'Sigmoid', 'epochs': 60, 'batch_size': 32, 'optimizer': 'Adam', 'num_layers': 1, 'dropout_rate': 0.1}
Best Accuracy: 9.175
```

Feature extraction using Bert and training it on our best model XGboost which gave 97% accuracy

```
!pip install -q autoviz
!pip install -q -U --pre pycaret
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 66.8/66.8 kB 1.6 MB/s eta 0:00:00
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  Preparing metadata (setup.py) ... done
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 106.8/106.8 kB 12.5 MB/s eta 0:00:00
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  Building wheel for pyod (setup.py) ... done
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the fol
lida 0.0.10 requires fastapi, which is not installed.
lida 0.0.10 requires python-multipart, which is not installed.
lida 0.0.10 requires uvicorn, which is not installed.
```

```
!pip -q install transformers
!pip -q install torch
```

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import cross_val_score
```

```
df = pd.read_csv('/content/malicious_phish.csv')

df_filtered = df[df['type'].isin(['benign', 'phishing'])]
df_benign = df_filtered[df_filtered['type'] == 'benign'].head(10000)
df_phishing = df_filtered[df_filtered['type'] == 'phishing'].head(10000)

df_result = pd.concat([df_benign, df_phishing])

df_result = df_result.sample(frac=1, random_state=42).reset_index(drop=True)
print(df_result)
df = df_result
```

```
                                                   url      type
0                                   secbusiness101.co.za  phishing
1                                 imdb.com/name/nm0159198/    benign
```

```
from sklearn.preprocessing import LabelEncoder

cat_cols = df.select_dtypes(include=['object']).columns.tolist()
le = LabelEncoder()
encoded_data = le.fit_transform(df['type'])
```

```
19998       uk.ask.com/wiki/Charles-Fran%C3%A7ois_Dupuis    benign
```

```
df['type'] = encoded_data
```

```
[20000 rows x 2 columns]
```

```
df.type.value_counts()
```

```
1    10000
0    10000
Name: type, dtype: int64
```

```
from transformers import BertModel, BertTokenizer
import torch

model = BertModel.from_pretrained('bert-base-uncased', output_hidden_states=True)
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
```

config.json: 100% 570/570 [00:00<00:00, 30.1kB/s]

model.safetensors: 100% 440M/440M [00:01<00:00, 273MB/s]

tokenizer_config.json: 100% 28.0/28.0 [00:00<00:00, 448B/s]

vocab.txt: 100% 232k/232k [00:00<00:00, 3.49MB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 10.4MB/s]

```
def extract_features(text):
    input_ids = torch.tensor([tokenizer.encode(text, add_special_tokens=True)])
    with torch.no_grad():
        outputs = model(input_ids)
        hidden_states = outputs[2]
    token_vecs = []
    for layer in range(-4, 0):
        token_vecs.append(hidden_states[layer][0])
    features = []
    for token in token_vecs:
        features.append(torch.mean(token, dim=0))
    return torch.stack(features)
```

```
features = []
for i in range(len(df)):
    features.append(extract_features(df.iloc[i]["url"]))
features = torch.cat(features).numpy()
```

```
types = df['type'].values
```

```
features_reshaped = features.reshape((20000, -1))
dataset = np.hstack((features_reshaped, types.reshape((-1, 1))))
```