Machine Learning for the Detection of Network Attacks

Analyse the machine learning algorithms on the [CICIDS 2017 Dataset] for clasification of network attacks. (https://www.unb.ca/cic/datasets/ids-2017.html):

- Support Vector Machine (Proposed Optimized Random Forest)
- Decision Tree
- Naive Bayes
- K Means Clustering
- K Nearest Neighbours

Import required libraries.

In [1]:
```
import glob
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sn
import time

from numpy import array

from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler

from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.neighbors import NearestNeighbors
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier

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

from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import completeness_score, homogeneity_score, v_measure_score

from sklearn.model_selection import train_test_split
```

Loading the dataset

The implemented attacks include Brute Force FTP, Brute Force SSH, DoS, Heartbleed, Web Attack, Infiltration, Botnet and DDoS.

Datasets is available in 8 different csv files.

- Monday-WorkingHours.pcap_ISCX.csv
- Tuesday-WorkingHours.pcap_ISCX.csv
- Wednesday-workingHours.pcap_ISCX.csv
- Thursday-WorkingHours-Morning-WebAttacks.pcap_ISCX.csv
- Thursday-WorkingHours-Afternoon-Infilteration.pcap_ISCX.csv
- Friday-WorkingHours-Morning.pcap_ISCX.csv
- Friday-WorkingHours-Afternoon-PortScan.pcap_ISCX.csv
- Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv

8 different csv files of cicids dataset needs to be concatenated into a single csv file.

In [2]:
```
# # path to the all 8 files of CICIDS dataset.
# path = './datasets'
# all_files = glob.glob(path + "/*.csv")

# # concatenate the 8 files into 1.
# dataset = pd.concat((pd.read_csv(f) for f in all_files))
```

In [3]:
```
# # saving the combined dataset to disk named cicids.csv
# dataset.to_csv('cicids')
```

In [4]:
```
dataset=pd.read_csv('cicids.csv')
```

In [5]:
```
# Dimenions of dataset.
print(dataset.shape)
```

```
(2827876, 79)
```

In [6]:
```
# column names as per dataset.

col_names = ["Destination_Port",
             "Flow_Duration",
             "Total_Fwd_Packets",
             "Total_Backward_Packets",
             "Total_Length_of_Fwd_Packets",
             "Total_Length_of_Bwd_Packets",
             "Fwd_Packet_Length_Max",
             "Fwd_Packet_Length_Min",
             "Fwd_Packet_Length_Mean",
             "Fwd_Packet_Length_Std",
             "Bwd_Packet_Length_Max",
             "Bwd_Packet_Length_Min",
             "Bwd_Packet_Length_Mean",
             "Bwd_Packet_Length_Std",
```

```
                "Flow_Bytes_s",
                "Flow_Packets_s",
                "Flow_IAT_Mean",
                "Flow_IAT_Std",
                "Flow_IAT_Max",
                "Flow_IAT_Min",
                "Fwd_IAT_Total",
                "Fwd_IAT_Mean",
                "Fwd_IAT_Std",
                "Fwd_IAT_Max",
                "Fwd_IAT_Min",
                "Bwd_IAT_Total",
                "Bwd_IAT_Mean",
                "Bwd_IAT_Std",
                "Bwd_IAT_Max",
                "Bwd_IAT_Min",
                "Fwd_PSH_Flags",
                "Bwd_PSH_Flags",
                "Fwd_URG_Flags",
                "Bwd_URG_Flags",
                "Fwd_Header_Length",
                "Bwd_Header_Length",
                "Fwd_Packets_s",
                "Bwd_Packets_s",
                "Min_Packet_Length",
                "Max_Packet_Length",
                "Packet_Length_Mean",
                "Packet_Length_Std",
                "Packet_Length_Variance",
                "FIN_Flag_Count",
                "SYN_Flag_Count",
                "RST_Flag_Count",
                "PSH_Flag_Count",
                "ACK_Flag_Count",
                "URG_Flag_Count",
                "CWE_Flag_Count",
                "ECE_Flag_Count",
                "Down_Up_Ratio",
                "Average_Packet_Size",
                "Avg_Fwd_Segment_Size",
                "Avg_Bwd_Segment_Size",
                "Fwd_Header_Length",
                "Fwd_Avg_Bytes_Bulk",
                "Fwd_Avg_Packets_Bulk",
                "Fwd_Avg_Bulk_Rate",
                "Bwd_Avg_Bytes_Bulk",
                "Bwd_Avg_Packets_Bulk",
                "Bwd_Avg_Bulk_Rate",
                "Subflow_Fwd_Packets",
                "Subflow_Fwd_Bytes",
                "Subflow_Bwd_Packets",
                "Subflow_Bwd_Bytes",
                "Init_Win_bytes_forward",
                "Init_Win_bytes_backward",
                "act_data_pkt_fwd",
                "min_seg_size_forward",
                "Active_Mean",
                "Active_Std",
                "Active_Max",
                "Active_Min",
                "Idle_Mean",
```

```
            "Idle_Std",
            "Idle_Max",
            "Idle_Min",
            "Label"
           ]
```

In [7]:
```
# Max rows and columnns to be shown in print console

pd.options.display.max_columns= 200
pd.options.display.max_rows= 200
```

In [8]:
```
# Assigning the column names.
dataset.columns = col_names

# first 5 records in the dataset.
dataset.head(5)
```

Out[8]:

	Destination_Port	Flow_Duration	Total_Fwd_Packets	Total_Backward_Packets	Total_Length_of_Fwd_Pacl
0	0	54865	3	2	
1	1	55054	109	1	
2	2	55055	52	1	
3	3	46236	34	1	
4	4	54863	3	2	

In [9]:
```
# check whether there is any categorical column are not if it is there it is to be enco
dataset.dtypes
```

Out[9]:
```
Destination_Port               int64
Flow_Duration                  int64
Total_Fwd_Packets              int64
Total_Backward_Packets         int64
Total_Length_of_Fwd_Packets    int64
Total_Length_of_Bwd_Packets    int64
Fwd_Packet_Length_Max          int64
Fwd_Packet_Length_Min          int64
Fwd_Packet_Length_Mean         int64
Fwd_Packet_Length_Std        float64
Bwd_Packet_Length_Max        float64
Bwd_Packet_Length_Min          int64
Bwd_Packet_Length_Mean         int64
Bwd_Packet_Length_Std        float64
Flow_Bytes_s                 float64
Flow_Packets_s               float64
Flow_IAT_Mean                float64
Flow_IAT_Std                 float64
Flow_IAT_Max                 float64
Flow_IAT_Min                   int64
Fwd_IAT_Total                  int64
Fwd_IAT_Mean                   int64
Fwd_IAT_Std                  float64
Fwd_IAT_Max                  float64
Fwd_IAT_Min                    int64
```

```
Bwd_IAT_Total                int64
Bwd_IAT_Mean                 int64
Bwd_IAT_Std                float64
Bwd_IAT_Max                float64
Bwd_IAT_Min                  int64
Fwd_PSH_Flags                int64
Bwd_PSH_Flags                int64
Fwd_URG_Flags                int64
Bwd_URG_Flags                int64
Fwd_Header_Length            int64
Bwd_Header_Length            int64
Fwd_Packets_s                int64
Bwd_Packets_s              float64
Min_Packet_Length          float64
Max_Packet_Length            int64
Packet_Length_Mean           int64
Packet_Length_Std          float64
Packet_Length_Variance     float64
FIN_Flag_Count             float64
SYN_Flag_Count               int64
RST_Flag_Count               int64
PSH_Flag_Count               int64
ACK_Flag_Count               int64
URG_Flag_Count               int64
CWE_Flag_Count               int64
ECE_Flag_Count               int64
Down_Up_Ratio                int64
Average_Packet_Size          int64
Avg_Fwd_Segment_Size       float64
Avg_Bwd_Segment_Size       float64
Fwd_Header_Length          float64
Fwd_Avg_Bytes_Bulk           int64
Fwd_Avg_Packets_Bulk         int64
Fwd_Avg_Bulk_Rate            int64
Bwd_Avg_Bytes_Bulk           int64
Bwd_Avg_Packets_Bulk         int64
Bwd_Avg_Bulk_Rate            int64
Subflow_Fwd_Packets          int64
Subflow_Fwd_Bytes            int64
Subflow_Bwd_Packets          int64
Subflow_Bwd_Bytes            int64
Init_Win_bytes_forward       int64
Init_Win_bytes_backward      int64
act_data_pkt_fwd             int64
min_seg_size_forward         int64
Active_Mean                float64
Active_Std                 float64
Active_Max                   int64
Active_Min                   int64
Idle_Mean                  float64
Idle_Std                   float64
Idle_Max                     int64
Idle_Min                     int64
Label                       object
dtype: object
```

Remove repeated columns, (NaN,Null,Infinite) values.

In [10]:

```
# Removing the duplicate columns (Header_length is repeated)
dataset = dataset.loc[:, ~dataset.columns.duplicated()]
```

```
dataset.shape
```

Out[10]: (2827876, 78)

In [11]:
```
# check if there are any Null values
dataset.isnull().any().any()
```

Out[11]: False

In [12]:
```
# Replace Inf values with NaN
dataset = dataset.replace([np.inf, -np.inf], np.nan)

# Drop all occurences of NaN
dataset = dataset.dropna()

# Double check these are all gone
dataset.isnull().any()
```

Out[12]:
```
Destination_Port              False
Flow_Duration                 False
Total_Fwd_Packets             False
Total_Backward_Packets        False
Total_Length_of_Fwd_Packets   False
Total_Length_of_Bwd_Packets   False
Fwd_Packet_Length_Max         False
Fwd_Packet_Length_Min         False
Fwd_Packet_Length_Mean        False
Fwd_Packet_Length_Std         False
Bwd_Packet_Length_Max         False
Bwd_Packet_Length_Min         False
Bwd_Packet_Length_Mean        False
Bwd_Packet_Length_Std         False
Flow_Bytes_s                  False
Flow_Packets_s                False
Flow_IAT_Mean                 False
Flow_IAT_Std                  False
Flow_IAT_Max                  False
Flow_IAT_Min                  False
Fwd_IAT_Total                 False
Fwd_IAT_Mean                  False
Fwd_IAT_Std                   False
Fwd_IAT_Max                   False
Fwd_IAT_Min                   False
Bwd_IAT_Total                 False
Bwd_IAT_Mean                  False
Bwd_IAT_Std                   False
Bwd_IAT_Max                   False
Bwd_IAT_Min                   False
Fwd_PSH_Flags                 False
Bwd_PSH_Flags                 False
Fwd_URG_Flags                 False
Bwd_URG_Flags                 False
Fwd_Header_Length             False
Bwd_Header_Length             False
Fwd_Packets_s                 False
Bwd_Packets_s                 False
Min_Packet_Length             False
Max_Packet_Length             False
Packet_Length_Mean            False
Packet_Length_Std             False
```

```
Packet_Length_Variance         False
FIN_Flag_Count                 False
SYN_Flag_Count                 False
RST_Flag_Count                 False
PSH_Flag_Count                 False
ACK_Flag_Count                 False
URG_Flag_Count                 False
CWE_Flag_Count                 False
ECE_Flag_Count                 False
Down_Up_Ratio                  False
Average_Packet_Size            False
Avg_Fwd_Segment_Size           False
Avg_Bwd_Segment_Size           False
Fwd_Avg_Bytes_Bulk             False
Fwd_Avg_Packets_Bulk           False
Fwd_Avg_Bulk_Rate              False
Bwd_Avg_Bytes_Bulk             False
Bwd_Avg_Packets_Bulk           False
Bwd_Avg_Bulk_Rate              False
Subflow_Fwd_Packets            False
Subflow_Fwd_Bytes              False
Subflow_Bwd_Packets            False
Subflow_Bwd_Bytes              False
Init_Win_bytes_forward         False
Init_Win_bytes_backward        False
act_data_pkt_fwd               False
min_seg_size_forward           False
Active_Mean                    False
Active_Std                     False
Active_Max                     False
Active_Min                     False
Idle_Mean                      False
Idle_Std                       False
Idle_Max                       False
Idle_Min                       False
Label                          False
dtype: bool
```

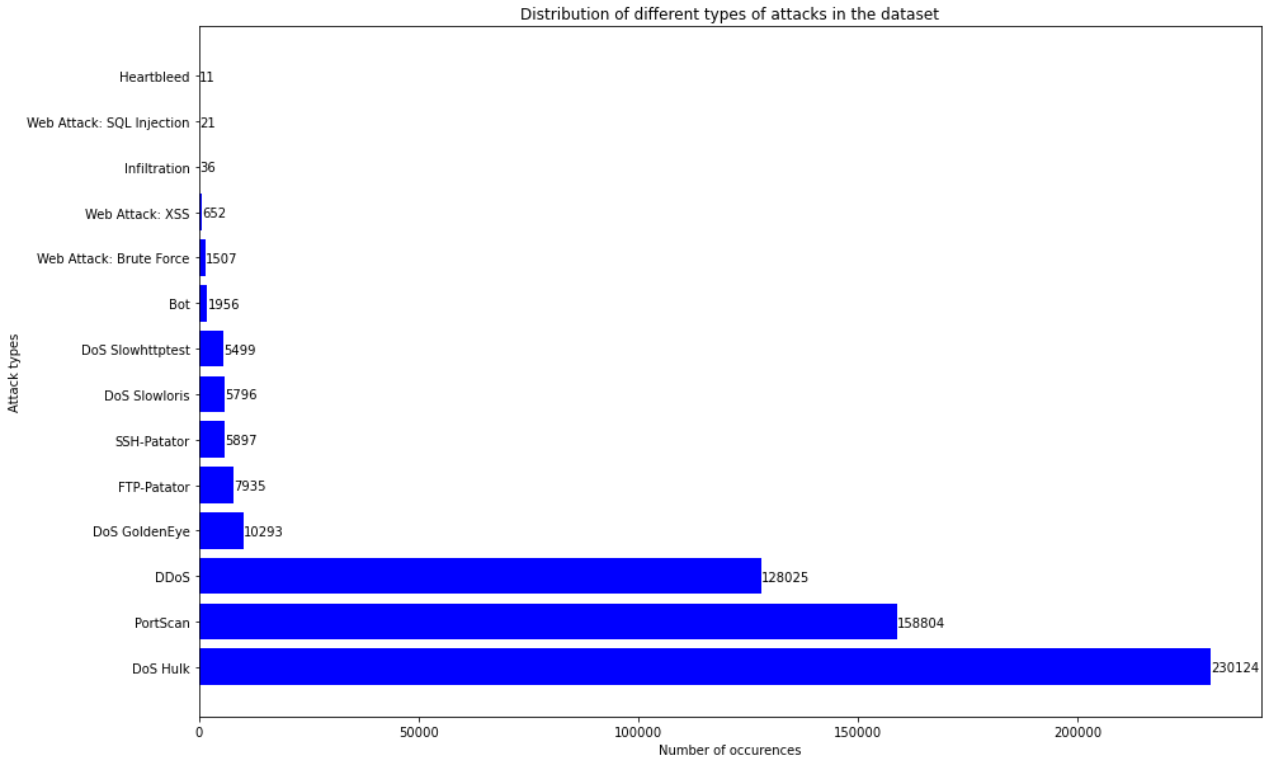
Analysing the attacks in dataset

In [13]:
```
# Distribution of Dataset
dataset['Label'].value_counts()
```

Out[13]:
```
BENIGN                        2271320
DoS Hulk                       230124
PortScan                       158804
DDoS                           128025
DoS GoldenEye                   10293
FTP-Patator                      7935
SSH-Patator                      5897
DoS slowloris                    5796
DoS Slowhttptest                 5499
Bot                              1956
Web Attack  Brute Force         1507
Web Attack  XSS                  652
Infiltration                      36
Web Attack  Sql Injection         21
Heartbleed                        11
Name: Label, dtype: int64
```

In [14]:
```
# Plotting the distribution of attacks in the dataset
```

```
plt.figure(figsize=(15,10))

attack = ('DoS Hulk', 'PortScan', 'DDoS', 'DoS GoldenEye', 'FTP-Patator', 'SSH-Patator'
          'DoS Slowhttptest', 'Bot', 'Web Attack: Brute Force', 'Web Attack: XSS', 'Inf
y_pos = np.arange(len(attack))
amount = dataset['Label'].value_counts()[1:]
plt.barh(y_pos, amount, align='center', color='blue' )
plt.yticks(y_pos, attack)
plt.title('Distribution of different types of attacks in the dataset')
plt.xlabel('Number of occurences')
plt.ylabel('Attack types')
for i, v in enumerate(amount):
    plt.text(v + 3, i-0.1 , str(v))

plt.show()
```



In [15]:

```
# There are only 11, 21, and 36 instances of Heartbleed, SQL injection and infiltration
# Remove 'Heartbleed', 'Web attack Sql Injection', 'Infiltration' as it's negligible.

dataset = dataset.replace(['Heartbleed', 'Web Attack \ufffd Sql Injection', 'Infiltration'],
dataset = dataset.dropna()
dataset['Label'].value_counts()
```

Out[15]:

```
BENIGN                      2271320
DoS Hulk                     230124
PortScan                     158804
DDoS                         128025
DoS GoldenEye                 10293
FTP-Patator                    7935
SSH-Patator                    5897
DoS slowloris                  5796
DoS Slowhttptest               5499
Bot                            1956
Web Attack \ufffd Brute Force    1507
```

```
Web Attack ? XSS                652
Name: Label, dtype: int64
```

In [16]:
```
# Labelling Web Attack ? Brute Force as Brute Force
# Labelling Web Attack ? XSS as XSS

dataset.loc[dataset.Label == 'Web Attack ? Brute Force', ['Label']] = 'Brute Force'
dataset.loc[dataset.Label == 'Web Attack ? XSS', ['Label']] = 'XSS'
```

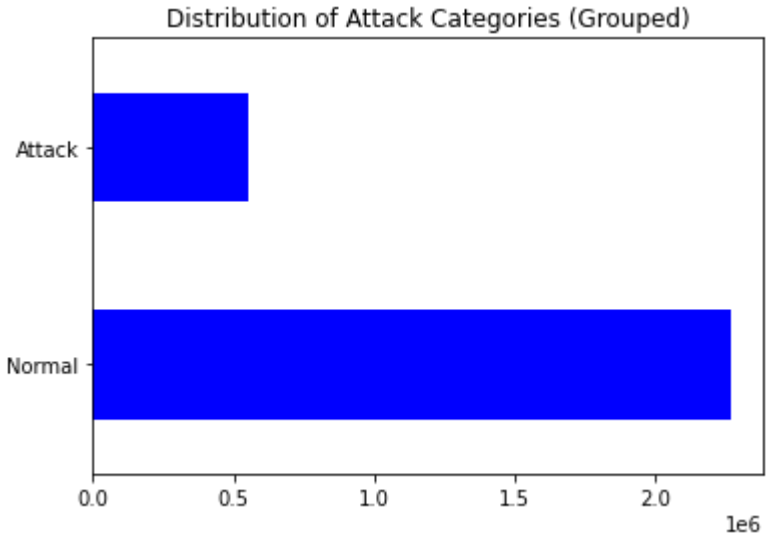
In [17]:
```
# Creating a attack column, containing binary labels for normal and attack to apply bin

dataset['Attack'] = np.where(dataset['Label'] == 'BENIGN','Normal' , 'Attack')
```

In [18]:
```
# Grouping attack labels in attack category as in dataset description for multi-class c

attack_group = {'BENIGN': 'benign',
                'DoS Hulk': 'dos',
                'PortScan': 'probe',
                'DDoS': 'ddos',
                'DoS GoldenEye': 'dos',
                'FTP-Patator': 'brute_force',
                'SSH-Patator': 'brute_force',
                'DoS slowloris': 'dos',
                'DoS Slowhttptest': 'dos',
                'Bot': 'botnet',
                'Brute Force': 'web_attack',
                'XSS': 'web_attack'}

# Create grouped label column

dataset['Label_Category'] = dataset['Label'].map(lambda x: attack_group[x])
dataset['Label_Category'].value_counts()
```

Out[18]:
```
benign         2271320
dos             251712
probe           158804
ddos            128025
brute_force      13832
web_attack        2159
botnet            1956
Name: Label_Category, dtype: int64
```

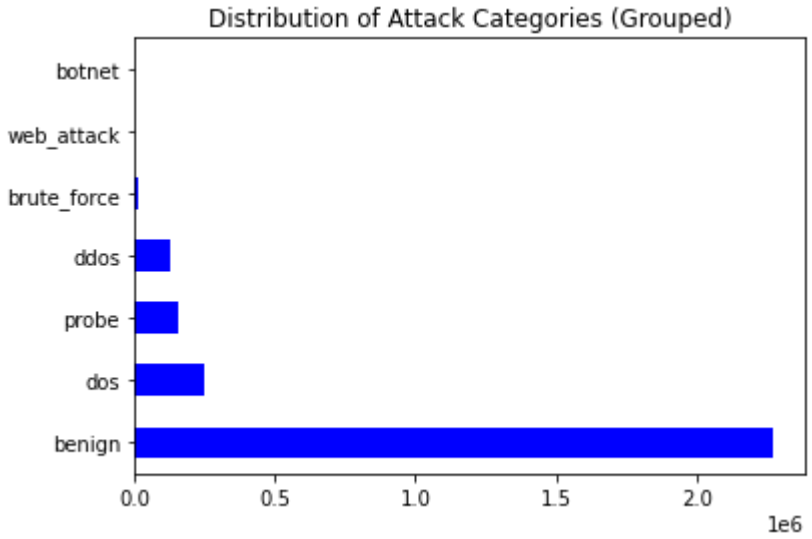
In [19]:
```
# Plotting binary grouped column Attack

train_attacks = dataset['Attack'].value_counts()
train_attacks.plot(kind='barh', color='blue')
plt.title('Distribution of Attack Categories (Grouped)')
```

Out[19]:
```
Text(0.5, 1.0, 'Distribution of Attack Categories (Grouped)')
```



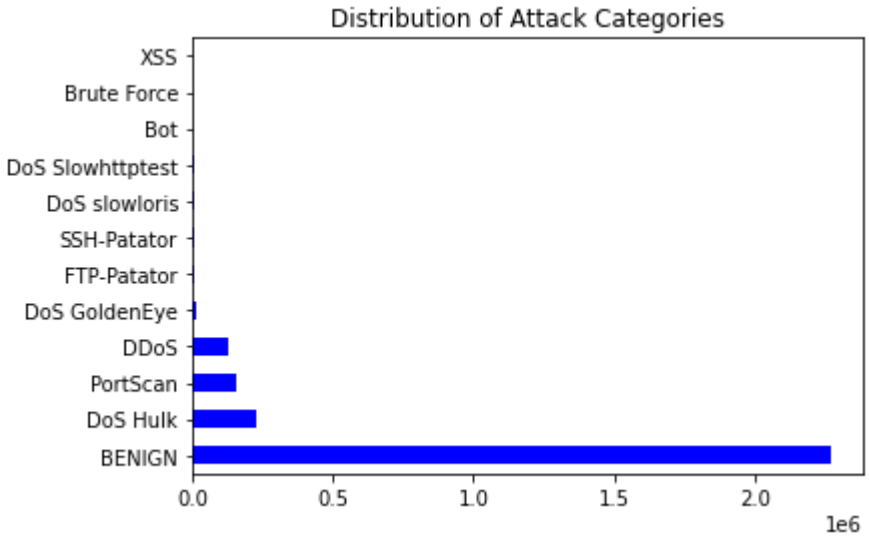
In [20]:
```
# Plotting multi-class grouped column Label_Category

train_attacks = dataset['Label_Category'].value_counts()
train_attacks.plot(kind='barh', color='blue')
plt.title('Distribution of Attack Categories (Grouped)')
```

Out[20]: Text(0.5, 1.0, 'Distribution of Attack Categories (Grouped)')



In [21]:
```
# Plotting multi-label column Label

train_attacks = dataset['Label'].value_counts()
train_attacks.plot(kind='barh', color='blue')
plt.title('Distribution of Attack Categories')
```

Out[21]: Text(0.5, 1.0, 'Distribution of Attack Categories')



In [22]:
```
print('Total number of all attack classes :',len(dataset.Label.unique()))
print('Total number of attack categories :',len(dataset.Label_Category.unique()))
```

```
Total number of all attack classes : 12
Total number of attack categories : 7
```

Splitting the dataset

Splitting dataset in 60:20:20 ratio, for training, testing and validation dataset. By stratifying with y label proportions of attacks remain the same throughout the 3 sets.

In [23]:
```
# 3 Different labeling options
attacks = ['Label', 'Label_Category', 'Attack']

# xs=feature vectors, ys=labels
xs = dataset.drop(attacks, axis=1)
ys = dataset[attacks]

# split dataset - stratified
x_train, x_test, y_train, y_test = train_test_split(xs, ys, test_size=0.3, random_state
```

Removing the columns with single unique values as it has no contribution in classification

In [24]:
```
column_names = np.array(list(x_train))
to_drop = []
for x in column_names:
    size = x_train.groupby([x]).size()
    # check for columns that only take one value
    if (len(size.unique()) == 1):
        to_drop.append(x)
to_drop
```

Out[24]:
```
['Fwd_URG_Flags',
 'Fwd_Header_Length',
```

```
'Fwd_Avg_Bytes_Bulk',
'Fwd_Avg_Packets_Bulk',
'Fwd_Avg_Bulk_Rate',
'Bwd_Avg_Bytes_Bulk',
'Bwd_Avg_Packets_Bulk',
'Bwd_Avg_Bulk_Rate']
```

In [25]:
```
x_train = x_train.drop(to_drop, axis=1)
x_test = x_test.drop(to_drop, axis=1)
dataset_copy = dataset.drop(to_drop, axis=1)
```

In [26]:
```
x_train.shape
```

Out[26]: (1979465, 69)

Data Normalization

Min-max normalization technique is used to normalize the numerical values in dataset.

In [27]:
```
# Normalise
min_max_scaler = MinMaxScaler().fit(x_train)

# Apply normalisation to dataset
x_train = min_max_scaler.transform(x_train)
x_test = min_max_scaler.transform(x_test)
```

Feature Selection

Selecting K-best features by using chi2 scoring function for features

In [28]:
```
features = SelectKBest(score_func=chi2, k=x_train.shape[1])

#fit features to the training dataset
fit = features.fit(x_train, y_train.Label)
```

In [29]:
```
# perform selectkbest with k=40

features = SelectKBest(score_func=chi2, k=40)
fit = features.fit(x_train, y_train.Label)

x_train = fit.transform(x_train)
x_test = fit.transform(x_test)
```

In [30]:
```
new_features = dataset_copy.columns[features.get_support(indices=True)]
```

In [31]:
```
print('Number of features selected :',len(new_features))
new_features
```

```
Number of features selected : 40
```

Out[31]:
```
Index(['Destination_Port', 'Flow_Duration', 'Total_Fwd_Packets',
       'Bwd_Packet_Length_Min', 'Bwd_Packet_Length_Mean',
       'Bwd_Packet_Length_Std', 'Flow_Bytes_s', 'Flow_IAT_Std', 'Flow_IAT_Max',
       'Flow_IAT_Min', 'Fwd_IAT_Total', 'Fwd_IAT_Mean', 'Fwd_IAT_Std',
       'Fwd_IAT_Max', 'Fwd_IAT_Min', 'Bwd_IAT_Total', 'Bwd_IAT_Mean',
       'Bwd_IAT_Std', 'Bwd_IAT_Max', 'Bwd_IAT_Min', 'Fwd_PSH_Flags',
       'Bwd_PSH_Flags', 'Bwd_Packets_s', 'Packet_Length_Mean',
       'Packet_Length_Std', 'Packet_Length_Variance', 'FIN_Flag_Count',
       'SYN_Flag_Count', 'RST_Flag_Count', 'ACK_Flag_Count', 'URG_Flag_Count',
       'CWE_Flag_Count', 'Avg_Fwd_Segment_Size', 'Init_Win_bytes_forward',
       'Init_Win_bytes_backward', 'Active_Min', 'Idle_Mean', 'Idle_Std',
       'Idle_Max', 'Idle_Min'],
      dtype='object')
```

In [32]:
```
attack = np.array(['BENIGN', 'Bot', 'Brute Force', 'DDoS', 'DoS GoldenEye', 'DoS Hulk',
                   'DoS slowloris', 'FTP-Patator', 'PortScan', 'SSH-Patator', 'XSS'])
attack_groups = np.array(['benign', 'botnet', 'brute_force', 'ddos', 'dos', 'probe', 'w
```

In [ ]:

In [ ]:

In [ ]:

Applying Machine Learning classifier models

Each machine learning algorithm is applied in three different categories :

1. On all attack labels (12).
2. Binary Classifier (2).
3. Multi-class Classifier (7).

And then evaluate performance of each algorithm by confusion matrix plot. Evaluate Accuracy, Precision, Recall, F1-score.

Optimizing the best performed Algorithm

Find the number of estimators value we should use

In [57]:
```
# n estimators is the number of decision trees we consider in the ensemble
n_estimators = [12, 25, 50, 100, 200]
results = []
time_results = []
```

In [34]:
```
# note: takes a long time
for estimator in n_estimators:
    # fit model with n_estimators parameter
    classifier =  RandomForestClassifier(n_estimators=estimator)
    classifier.fit(x_train, y_train.Label)
```

```
    # predict validation
    start = time.time()
    y_pred = classifier.predict(x_test)
    end = time.time()

    # calculate metrics
    p, r, f1, n = score(y_test.Label, y_pred, average = 'macro')

    # append f1 and time to results array
    results.append(f1)
    time_results.append(end-start)
```

In [35]:

```
# plot classification time for n_estimators
plt.plot(n_estimators, time_results)
plt.xlabel('n_estimators')
plt.ylabel('Classification Time (s)')
plt.title('How n_estimators value changes classification time')
plt.savefig('n_estimators-time.png')
```

In [36]:

```
# plot f1 score for n estimators
plt.plot(n_estimators, results)
plt.xlabel('n_estimators')
plt.ylabel('F1 Score')
plt.title('How n_estimators value changes F1 score for the validation dataset')
plt.savefig('n_estimators.png')
```

Although n_estimators=800 was highest, that many number of estimators is not realistic in terms of classificaiton times. We go with the second peak - n_estimators = 25

In [37]:

```
from sklearn.model_selection import RandomizedSearchCV

max_features = [int(x) for x in np.linspace(2, 40, num = 20)] # from 2 to 40 (max numbe
max_features.append('auto')
max_depth = [int(x) for x in np.linspace(10, 200, num = 10)] # 10 values for max depth
max_depth.append(None) # also have option for no max depth
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 4]
bootstrap = [True, False]

random_grid = {'n_estimators': [25], # chosen n_estimator
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

In [38]:

```
# Use the random grid to search for best hyperparameters

rf = RandomForestClassifier()

rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_ite
rf_random.fit(x_train, y_train['Label'])
```

In [39]:
```
rf_random.best_params_
```

In [ ]:

In [ ]:

In [ ]:

7. Proposed - Optimized Random forest method

In [40]:
```
classifier =  RandomForestClassifier(n_estimators=25, max_depth=200, min_samples_split=
                                     bootstrap=True)
```

1. a) On all attack labels.

In [41]:
```
# fit the model

start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

print("Model Training Time is : ", training_time)
```

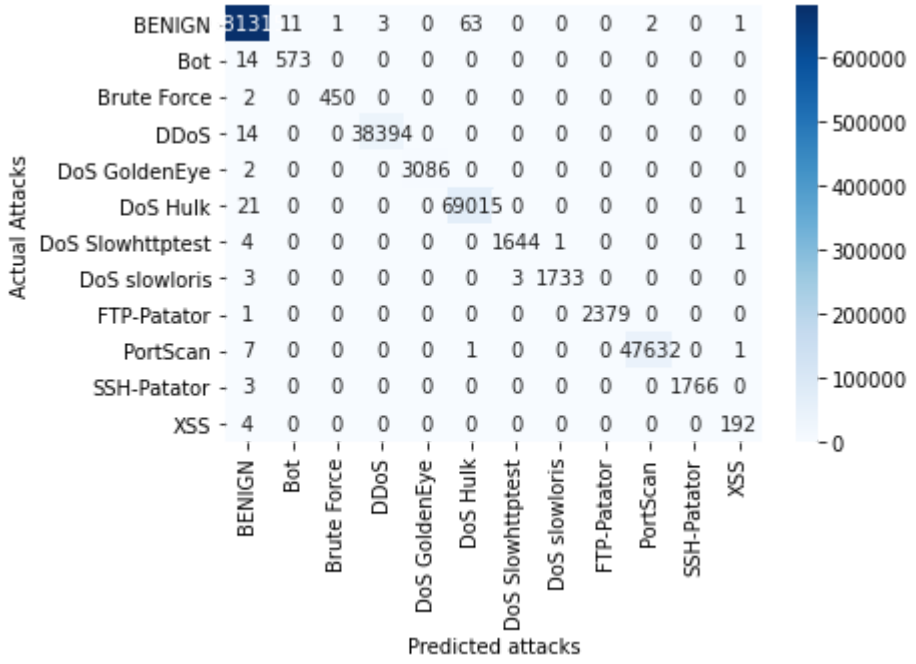
```
Model Training Time is :  1023.3599278926849
```

In [42]:
```
# predicting test results of Proposed Optimized Random Forest classifier on all labels.

start = time.time()
y_predict = classifier.predict(x_test)
end = time.time()
testing_time = end  - start

print("Model Testing Time is : ", testing_time)
```

```
Model Testing Time is :  3.261446952819824
```

In [43]:
```
# Creating confusion matrix for Proposed Optimized Random Forest classifier on all labe

confusion_rf_proposed_1 = pd.crosstab(y_test.Label, y_predict, rownames=['Actual Attack

print("Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on all

sn.heatmap(confusion_rf_proposed_1, annot=True, cmap= 'Blues', fmt='d')
plt.show()
confusion_rf_proposed_1
```

```
Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on all Labels
```



Out[43]:

Predicted attacks / Actual Attacks	BENIGN	Bot	Brute Force	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator	PortScan
BENIGN	681315	11	1	3	0	63	0	0	0	2
Bot	14	573	0	0	0	0	0	0	0	0
Brute Force	2	0	450	0	0	0	0	0	0	0
DDoS	14	0	0	38394	0	0	0	0	0	0
DoS GoldenEye	2	0	0	0	3086	0	0	0	0	0
DoS Hulk	21	0	0	0	0	69015	0	0	0	0
DoS Slowhttptest	4	0	0	0	0	0	1644	1	0	0
DoS slowloris	3	0	0	0	0	0	3	1733	0	0
FTP-Patator	1	0	0	0	0	0	0	0	2379	0
PortScan	7	0	0	0	0	1	0	0	0	47632
SSH-Patator	3	0	0	0	0	0	0	0	0	0
XSS	4	0	0	0	0	0	0	0	0	0

In [44]:

```
# Precision,Recall,F1-score for Proposed Optimized Random Forest classifier on all labe

precision, recall, fscore, support = score(y_test.Label, y_predict)

d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
```

```
results = pd.DataFrame(data=d)
results
```

Out[44]:

	attack	precision	recall	fscore
0	BENIGN	0.999890	0.999881	0.999886
1	Bot	0.981164	0.976150	0.978651
2	Brute Force	0.997783	0.995575	0.996678
3	DDoS	0.999922	0.999635	0.999779
4	DoS GoldenEye	1.000000	0.999352	0.999676
5	DoS Hulk	0.999074	0.999681	0.999377
6	DoS Slowhttptest	0.998179	0.996364	0.997270
7	DoS slowloris	0.999423	0.996550	0.997984
8	FTP-Patator	1.000000	0.999580	0.999790
9	PortScan	0.999958	0.999811	0.999885
10	SSH-Patator	1.000000	0.998304	0.999151
11	XSS	0.979592	0.979592	0.979592

In [45]:

```
# Average Accuracy,Precision,Recall,F1-score for Proposed Optimized Random Forest class

precision_rf_proposed_1, recall_rf_proposed_1, fscore_rf_proposed_1, support = score(y_
accuracy_rf_proposed_1 = accuracy_score(y_test.Label, y_predict)
print("Accuracy of Proposed Optimized Random Forest classifier on all labels : ", accur
```

```
Accuracy of Proposed Optimized Random Forest classifier on all labels :  0.9998066819670
817
```

In [ ]:

In [ ]:

1. b) Binary Classifier.

In [46]:

```
# fit the model

start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

print("Model Training Time is : ", training_time)
```

```
Model Training Time is :  984.4215383529663
```

In [47]:

```
# predicting test results of Proposed Optimized Random Forest classifier on binary labe
```

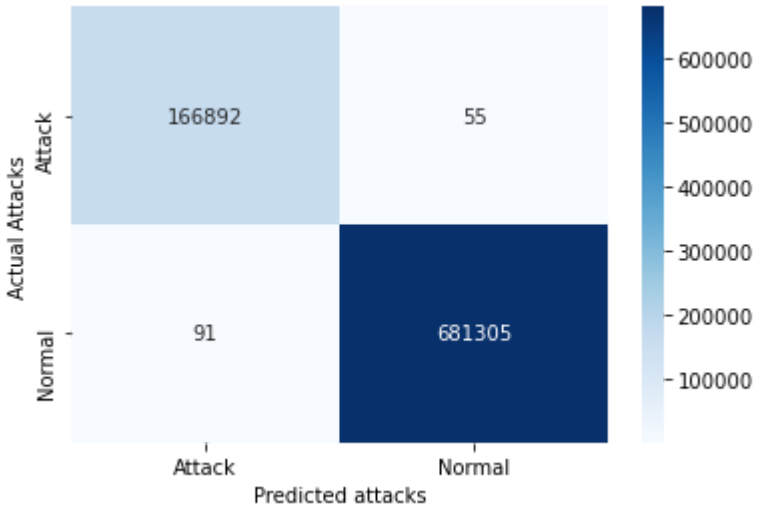
```
start = time.time()
y_predict = classifier.predict(x_test)
end = time.time()
testing_time = end  - start

print("Model Testing Time is : ", testing_time)
```

```
Model Testing Time is :  2.336059093475342
```

In [48]:

```
# Creating confusion matrix for Proposed Optimized Random Forest classifier on binary l

confusion_rf_proposed_2 = pd.crosstab(y_test.Attack, y_predict, rownames=['Actual Attac

print("Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on bina

sn.heatmap(confusion_rf_proposed_2, annot=True, cmap= 'Blues', fmt='d')
plt.show()
confusion_rf_proposed_2
```

```
Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on binary Label
s
```



Out[48]:

Predicted attacks	Attack	Normal
Actual Attacks		
Attack	166892	55
Normal	91	681305

In [49]:

```
# Precision,Recall,F1-score for Proposed Optimized Random Forest classifier on binary l

precision, recall, fscore, support = score(y_test.Attack, y_predict)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[49]:

	attack	precision	recall	fscore
0	0	0.999455	0.999671	0.999563
1	1	0.999919	0.999866	0.999893

In [50]:
```
# Average Accuracy,Precision,Recall,F1-score for Proposed Optimized Random Forest class

precision_rf_proposed_2, recall_rf_proposed_2, fscore_rf_proposed_2, n = score(y_test.A
accuracy_rf_proposed_2 = accuracy_score(y_test.Attack, y_predict)
print("Accuracy of Proposed Optimized Random Forest classifier on binary labels : ", ac
```

```
Accuracy of Proposed Optimized Random Forest classifier on binary labels :  0.9998278997
99963
```

In [ ]:
```

```

1. c) Multi-class Classifier.

In [51]:
```
# fit the model

start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

print("Model Training Time is : ", training_time)
```

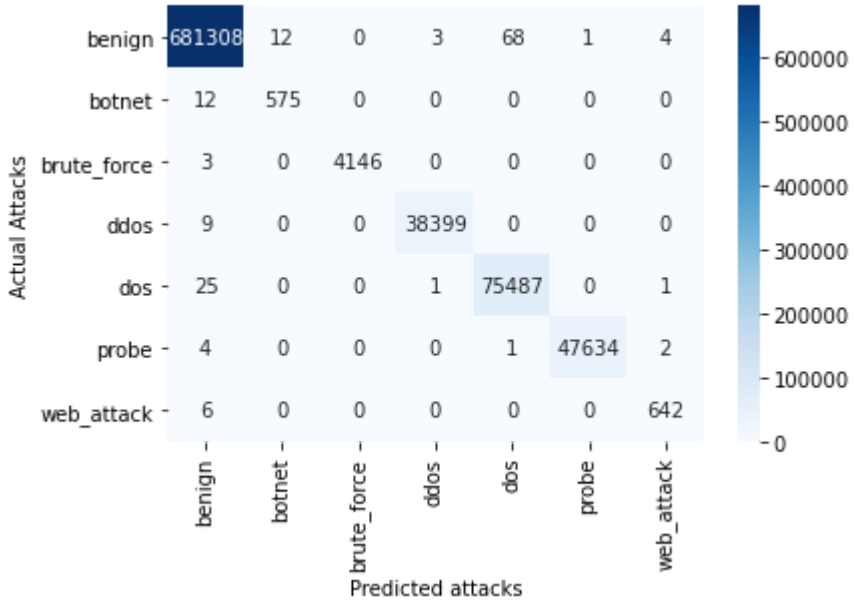
```
Model Training Time is :  1043.9241540431976
```

In [52]:
```
# predicting test results of Proposed Optimized Random Forest classifier on multi-class

start = time.time()
y_predict = classifier.predict(x_test)
end = time.time()
testing_time = end  - start

print("Model Testing Time is : ", testing_time)
```

```
Model Testing Time is :  2.8264429569244385
```

In [53]:
```
# Creating confusion matrix for Proposed Optimized Random Forest classifier on multi-cl

confusion_rf_proposed_3 = pd.crosstab(y_test.Label_Category, y_predict, rownames=['Actu

print("Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on mult

sn.heatmap(confusion_rf_proposed_3, annot=True, cmap= 'Blues', fmt='d')
plt.show()
confusion_rf_proposed_3
```

```
Plotting Confusion Matrix of Proposed Optimized Random Forest classifier on multi-class
Labels
```



Out[53]:

Predicted attacks	benign	botnet	brute_force	ddos	dos	probe	web_attack
Actual Attacks							
benign	681308	12	0	3	68	1	4
botnet	12	575	0	0	0	0	0
brute_force	3	0	4146	0	0	0	0
ddos	9	0	0	38399	0	0	0
dos	25	0	0	1	75487	0	1
probe	4	0	0	0	1	47634	2
web_attack	6	0	0	0	0	0	642

In [54]:

```
# Precision,Recall,F1-score for Proposed Optimized Random Forest classifier on multi-cl

precision, recall, fscore, support = score(y_test.Label_Category, y_predict)
d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fsco
results = pd.DataFrame(data=d)
results
```

Out[54]:

	attack	precision	recall	fscore
0	benign	0.999913	0.999871	0.999892
1	botnet	0.979557	0.979557	0.979557
2	brute_force	1.000000	0.999277	0.999638
3	ddos	0.999896	0.999766	0.999831
4	dos	0.999087	0.999642	0.999365
5	probe	0.999979	0.999853	0.999916
6	web_attack	0.989214	0.990741	0.989977

In [55]:
```
# Average Accuracy,Precision,Recall,F1-score for Proposed Optimized Random Forest class

precision_rf_proposed_3, recall_rf_proposed_3, fscore_rf_proposed_3, n = score(y_test.L
accuracy_rf_proposed_3 = accuracy_score(y_test.Label_Category, y_predict)
print("Accuracy of Proposed Optimized Random Forest classifier on multi-class labels :
```

```
Accuracy of Proposed Optimized Random Forest classifier on multi-class labels :  0.99982
08271890026
```

In [ ]:
```

```

Results for Proposed Optimized Random Forest:

In [56]:
```
print('Support Vector Machine: Precision / Recall / Fscore / Accuracy')

print('All Labels:', precision_rf_proposed_1, recall_rf_proposed_1, fscore_rf_proposed_
print('Binary Labels:', precision_rf_proposed_2, recall_rf_proposed_2, fscore_rf_propos
print('Multi-class Labels:', precision_rf_proposed_3, recall_rf_proposed_3, fscore_rf_p
```

```
Support Vector Machine: Precision / Recall / Fscore / Accuracy
All Labels: 0.9962486723312057 0.9950396397451962 0.9956431954712103 0.9998066819670817
Binary Labels: 0.9996871567168473 0.999768502383763 0.9997278233927755 0.999827899799963
Multi-class Labels: 0.9953780390642109 0.9955295414449206 0.9954536752329985 0.999820827
1890026
```

In [ ]:
```

```