```
In [1]: import warnings
          warnings.filterwarnings('ignore')
 In [2]: import numpy as np
          import pandas as pd
          import os
          import matplotlib.pyplot as plt
          import seaborn as sns
 In [3]: data = pd.read_csv('SDN Dataset/dataset_sdn.csv')
 In [4]: | null_counts = data.isnull().sum()
         # Print the number of null values
         print(f"{null_counts.sum()} null entries have been found in the dataset\n")
         # Drop null values
         data.dropna(inplace=True)
                                              # or df_data = df_data.dropna()
          # Find and handle duplicates
         duplicate_count = data.duplicated().sum()
         # Print the number of duplicate entries
         print(f"{duplicate_count} duplicate entries have been found in the dataset\n")
         # Remove duplicates
         data.drop_duplicates(inplace=True) # or df_data = df_data.drop_duplicates()
         # Display relative message
          print(f"All duplicates have been removed\n")
          # Reset the indexes
         data.reset_index(drop=True, inplace=True)
         # Inspect the dataset for categorical columns
          print("Categorical columns:",data.select_dtypes(include=['object']).columns.tolist(),'\n')
          # Print the first 5 lines
          data.head()
          1012 null entries have been found in the dataset
          5091 duplicate entries have been found in the dataset
          All duplicates have been removed
          Categorical columns: ['src', 'dst', 'Protocol']
 Out[4]:
                             src
                                    dst pktcount bytecount dur dur_nsec
                                                                             tot_dur flows ... pktrate Pairflow Protocol port_no tx_bytes rx_bytes tx_kbps rx_kbps tot_kbps label
          0 11425
                      1 10.0.0.1 10.0.0.8
                                           45304 48294064 100 716000000 1.010000e+11
                                                                                                               UDP
                                                                                                                                        3917
                                                                                                                                                         0.0
                                                                                                                                                                  0.0
                                                                                                451
                                                                                                                         3 143928631
                                                                                                                                                                       0
          1 11605
                                          126395 134737070 280 734000000 2.810000e+11
                                                                                                               UDP
                                                                                                                                3842
                       1 10.0.0.1 10.0.0.8
                                                                                                451
                                                                                                                                        3520
                                                                                                                                                   0
                                                                                                                                                         0.0
                                                                                                                                                                  0.0
                                                                                                                                                                       0
                                                  96294978 200 744000000 2.010000e+11
                                                                                                               UDP
          2 11425
                       1 10.0.0.2 10.0.0.8
                                           90333
                                                                                                451
                                                                                                                                3795
                                                                                                                                         1242
                                                                                                                                                   0
                                                                                                                                                         0.0
                                                                                                                                                                  0.0
                                                                                                                                                                       0
          3 11425
                                           90333 96294978 200 744000000 2.010000e+11
                                                                                                               UDP
                                                                                                                                3688
                                                                                                                                        1492
                                                                                                                                                                  0.0
                       1 10.0.0.2 10.0.0.8
                                                                                               451
                                                                                                                                                   0
                                                                                                                                                         0.0
                                                                                                                                                                       0
          4 11425
                      1 10.0.0.2 10.0.0.8
                                          90333 96294978 200 744000000 2.010000e+11
                                                                                               451
                                                                                                               UDP
                                                                                                                                3413
                                                                                                                                        3665
                                                                                                                                                   0
                                                                                                                                                         0.0
                                                                                                                                                                  0.0
                                                                                                                                                                       0
          5 rows × 23 columns
 In [5]: data.columns
 Out[5]: Index(['dt', 'switch', 'src', 'dst', 'pktcount', 'bytecount', 'dur',
                 'dur_nsec', 'tot_dur', 'flows', 'packetins', 'pktperflow',
                 'byteperflow', 'pktrate', 'Pairflow', 'Protocol', 'port_no', 'tx_bytes',
                 'rx_bytes', 'tx_kbps', 'rx_kbps', 'tot_kbps', 'label'],
                dtype='object')
 In [7]: data['label'].value_counts()
 Out[7]: 0 61022
         1 37726
          Name: label, dtype: int64
 In [9]: del data['src']
         del data['dst']
         del data['Protocol']
In [10]: #change_label(data)
In [11]: data.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 98748 entries, 0 to 98747
          Data columns (total 20 columns):
          # Column
                            Non-Null Count Dtype
                            -----
          ---
                            98748 non-null int64
              dt
          0
                            98748 non-null int64
          1 switch
              pktcount
                            98748 non-null int64
                            98748 non-null int64
              bytecount
                             98748 non-null int64
              dur
          4
                            98748 non-null int64
           5 dur_nsec
              tot_dur
                            98748 non-null float64
                            98748 non-null int64
          7 flows
              packetins 98748 non-null int64
              pktperflow 98748 non-null int64
           10 byteperflow 98748 non-null int64
           11 pktrate
                            98748 non-null int64
           12 Pairflow
                            98748 non-null int64
           13 port_no
                            98748 non-null int64
           14 tx_bytes
                            98748 non-null int64
                            98748 non-null int64
           15 rx_bytes
           16 tx_kbps
                            98748 non-null int64
                            98748 non-null float64
           17 rx_kbps
           18 tot_kbps
                           98748 non-null float64
                            98748 non-null int64
           19 label
          dtypes: float64(3), int64(17)
          memory usage: 15.1 MB
In [12]: sns.countplot(x='label',data=data, palette='hls')
         plt.show()
          #plt.savefig('count_plot') Labeling traffic as normal (0) or malicious (1).
              60000
              50000
              40000
           30000
g
m
              20000
              10000
                                                    label
In [13]: plt.figure(figsize = (10,5))
          sns.heatmap(data.corr(), annot = True, cmap="rainbow")
         plt.show()
                    dt - 1-0.0190.170.280.26-0.170.260.310.0240.220.290.22 0.7-0.010.0612.07-0.046.050.069.0
                         .01<mark>9 1-</mark>0.0530.160.030.078.0330.04<mark>0.19</mark>0.0280.10.020.079.0050.068.078.03<del>0</del>.040.060.02
              pktcount -0.170.053 1 0.660.016.030.0160.250.290.480.290.480.000.00108038.03600040069.010.42
                                                                                                                   - 0.8
             bytecount -0.280.16<mark>0.66 1 0.040.0220.04</mark>0.230.110.330.530.33<mark>0.37</mark>0.010.024.025.064.072.0970.28
                   dur -0.260.030.0160.04 1 0.054 1 0.17-0.140.320.250.330.16.002 0.140.17-0.150.180.23-0
              dur_nsec -0.170.070.03D.0270.054 1 -0.0503.0063050.039.04D.0390.2.0.018.014.016.032.0390.050.02
                                                                                                                   - 0.6
               tot_dur -0.260.030.0160.04 1 -0.053 1 0.17-0.140.320.250.330.16.0020.140.17-0.150.180.23-0.
                 flows -0.31-0.040.250.230.1-0.0068.17 1 0.029-0.2-0.23-0.2 0.370.0380.150.180.150.180.23-0.1
             packetins 0.0240.190.290.110.140.0550.140.029 1 0.2-0.0870.2 0.25.005060930.110.030.0340.0450039
                                                                                                                   - 0.4
            pktperflow -0.2<del>2</del>0.02 0.48 0.33 0.32 0.32 0.32 0.2 0.2 1 0.81 1 -0.10,0000 0.040 0.04 0.11 0.13 0.18 0.11
           byteperflow -0.29-0.1 0.290.53-0.20.0410.250.230.0870.81 1 0.81-0.370.0150.040.0450.110.130.1-70.0042
               pktrate -0.220.02 0.480.33 0.30.03 0.33 -0.2 0.2 1 0.81 1 -0.15 0000 0.04 0.04 0.11 0.13 0.18 0.11
                                                                                                                   - 0.2
              Pairflow - 0.70.07-0.0690.370.16-0.210.160.370.25-0.150.370.15 1 -0.010.064.07-10.010.0055016.0
               port_no -0.0+0.006.800+03.0103.002020108.002020308.0905.60000010-050004701.01 1 0.0960.230.070.160.160.006
              tx_bytes 0.060.060.03B.0240.140.0140.140.150.093.0410.040.040.064.096 1 0.0940.44 0.110.270.04
                                                                                                                   - 0.0
              rx_bytes 0.07-0.070.036.0250.170.0160.170.180.110.049.049.040.0770.230.094 1 -0.120.390.160.0
               tx_kbps -0.046.030007040640.150.0320.150.150.030.110.110.110.010.070.440.12 1-0.0270.70.0021
               rx_kbps -0.050.0407006090720.180.0390.180.180.0340.130.130.1-10.0096.16-0.110.390.027 1 0.6-10.0024
                                                                                                                   - -0.2
              tot kbps -0.069.0610.010.0970.230.050.230.230.0450.180.170.180.0150.160.270.160.760.63 1-0.0031
                         .090.0290.420.28 - 0.10.028 - 0.1 - 0.10.0039.1 - 0.0040.110.02 - 0.000.040.050.0001000400
                                     bytecount
                                                          packetins
                                                              pktperflow
                                                                  byteperflow
                                                                         Pairflow
port_no
tx_bytes
                                         ą
                                                 tot_dur
                                                      flows
                                                                      pktrate
                                                                                       nx_bytes
                                                                                           tx_kbps
```

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```
#data[data.Label == 'Attack'].sample(n=50_00),
             #data[data.Label == 'Normal'].sample(n=50_00),
In [16]: # Import label encoder
         #from sklearn import preprocessing
         # label_encoder object knows
         # how to understand word labels.
         #label_encoder = preprocessing.LabelEncoder()
         # Encode labels in column 'species'.
         #data['Label']= label_encoder.fit_transform(data['Label'])
In [17]: | X = data.drop(["label"],axis =1)
         y = data["label"]
         FS
In [18]: from sklearn.feature_selection import SelectKBest, SelectPercentile, mutual_info_classif
In [24]: selector = SelectPercentile(mutual_info_classif, percentile=30)
         X_reduced = selector.fit_transform(X, y)
         #X_reduced.shape
In [25]: | cols = selector.get_support(indices=True)
         selected_columns = X.iloc[:,cols].columns.tolist()
         selected_columns
Out[25]: ['dt', 'pktcount', 'bytecount', 'pktperflow', 'byteperflow', 'pktrate']
In [26]: len(selected_columns)
Out[26]: 6
In [27]: df = data[['dt', 'pktcount', 'bytecount', 'pktperflow', 'byteperflow', 'pktrate', 'label']]
In [28]: df.columns
Out[28]: Index(['dt', 'pktcount', 'bytecount', 'pktperflow', 'byteperflow', 'pktrate',
                 'label'],
               dtype='object')
In [30]: | X = df.drop(["label"],axis =1)
         y = df["label"]
In [31]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 42)
         #X_train.shape, y_train.shape, X_test.shape, y_test.shape
In [32]: | from sklearn.metrics import accuracy_score # for calculating accuracy of model
         from sklearn.metrics import precision_score
         from sklearn.metrics import recall_score
         from sklearn.metrics import f1_score
In [33]: ML_Model = []
         accuracy = []
         precision = []
         recall = []
         f1score = []
         #function to call for storing the results
         def storeResults(model, a,b,c,d):
             ML_Model.append(model)
             accuracy.append(round(a, 3))
             precision.append(round(b, 3))
             recall.append(round(c, 3))
             f1score.append(round(d, 3))
```

BernoulliNB

In [15]: #print(data.info())

#data = pd.concat([

```
In [34]: from sklearn.naive_bayes import BernoulliNB

bnb = BernoulliNB(alpha=1.0, binarize=0.0, fit_prior=True, class_prior=None)

bnb.fit(X_train, y_train)

y_pred = bnb.predict(X_test)

bnb_acc = accuracy_score(y_pred, y_test)

bnb_prec = precision_score(y_pred, y_test, average='weighted')

bnb_prec = recall_score(y_pred, y_test, average='weighted')

bnb_f1 = f1_score(y_pred, y_test, average='weighted')
```

In [35]: storeResults('BernoulliNB',bnb_acc,bnb_prec,bnb_rec,bnb_f1)

Passive Aggressive

In [37]: storeResults('PassiveAggressive',pa_acc,pa_prec,pa_rec,pa_f1)

SGDClassifier

In [39]: storeResults('SGDClassifier',sgd_acc,sgd_prec,sgd_rec,sgd_f1)

MLP Classifier

Ensemble

```
In [42]: from sklearn.ensemble import VotingClassifier
         eclf1 = VotingClassifier(estimators=[('BNB', bnb),('PA', pa),('SGD', sgd),('MLP', mlp)], voting='hard')
         eclf1.fit(X_train, y_train)
         y_pred = eclf1.predict(X_test)
         stac_acc = accuracy_score(y_pred, y_test)
         stac_prec = precision_score(y_pred, y_test,average='weighted')
         stac_rec = recall_score(y_pred, y_test,average='weighted')
         stac_f1 = f1_score(y_pred, y_test,average='weighted')
In [43]: storeResults('Ensemble', stac_acc, stac_prec, stac_rec, stac_f1)
```

Extension

```
In [44]: from sklearn.ensemble import VotingClassifier, AdaBoostClassifier, RandomForestClassifier, BaggingClassifier
         from sklearn.tree import DecisionTreeClassifier
         brf = BaggingClassifier(RandomForestClassifier(),n_estimators=10, random_state=0,max_samples=1.0,max_features=1.0)
         bdt = AdaBoostClassifier(
             DecisionTreeClassifier(max_depth=1), algorithm="SAMME", n_estimators=200
         ext = VotingClassifier(estimators=[('BoostDT', bdt),('BagRF', brf)], voting='soft')
         ext.fit(X_train, y_train)
         y_pred = ext.predict(X_test)
         ml_acc = accuracy_score(y_pred, y_test)
         ml_prec = precision_score(y_pred, y_test,average='weighted')
         ml_rec = recall_score(y_pred, y_test,average='weighted')
         ml_f1 = f1_score(y_pred, y_test,average='weighted')
```

In [45]: storeResults('Extension',ml_acc,ml_prec,ml_rec,ml_f1)

Comparison

```
In [46]: #creating dataframe
         result = pd.DataFrame({ 'ML Model' : ML_Model,
                                 'Accuracy' : accuracy,
                                'Precision': precision,
                                'Recall' : recall,
                                'F1_score' : f1score
                               })
```

In [47]: result

```
Out[47]:
                    ML Model Accuracy Precision Recall F1_score
                   BernoulliNB
                                 0.633
                                          0.920 0.633
                                                          0.732
           1 PassiveAggressive
                                 0.587
                                           0.654 0.587
                                                           0.611
                 SGDClassifier
                                 0.688
                                          0.706 0.688
                                                          0.684
                  MLPClassifier
                                 0.697
                                           0.845 0.697
                                                          0.704
                                 0.737
                                          0.735 0.737
                                                          0.734
                     Ensemble
                                 1.000
                                           1.000 1.000
                                                          1.000
                     Extension
```

Modelling

```
In [48]: import joblib
         filename = 'models/model_sdn.sav'
         joblib.dump(ext, filename)
```

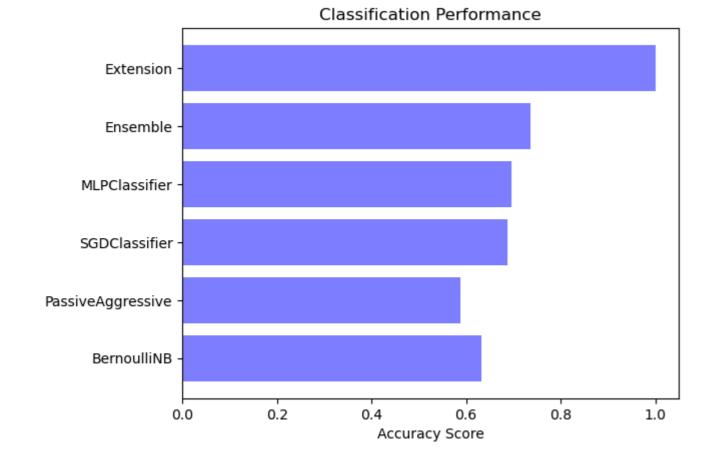
Out[48]: ['models/model_sdn.sav']

Graph

```
In [49]: | classifier = ML_Model
         y_pos = np.arange(len(classifier))
```

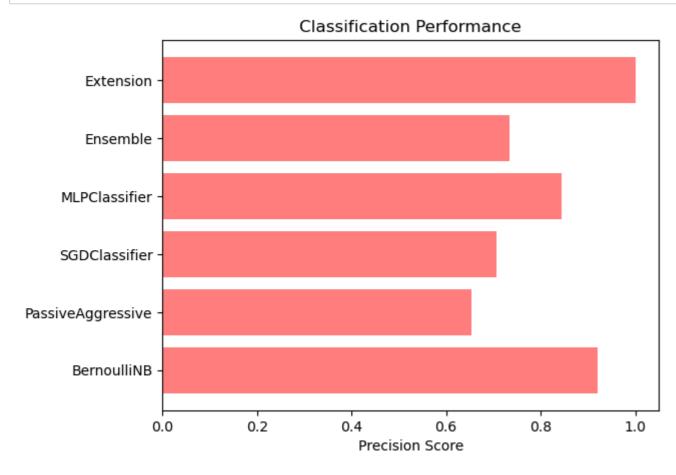
Accuracy

```
In [50]: import matplotlib.pyplot as plt2
         plt2.barh(y_pos, accuracy, align='center', alpha=0.5,color='blue')
         plt2.yticks(y_pos, classifier)
         plt2.xlabel('Accuracy Score')
         plt2.title('Classification Performance')
         plt2.show()
```



Precision

```
In [51]: plt2.barh(y_pos, precision, align='center', alpha=0.5,color='red')
         plt2.yticks(y_pos, classifier)
         plt2.xlabel('Precision Score')
         plt2.title('Classification Performance')
         plt2.show()
```

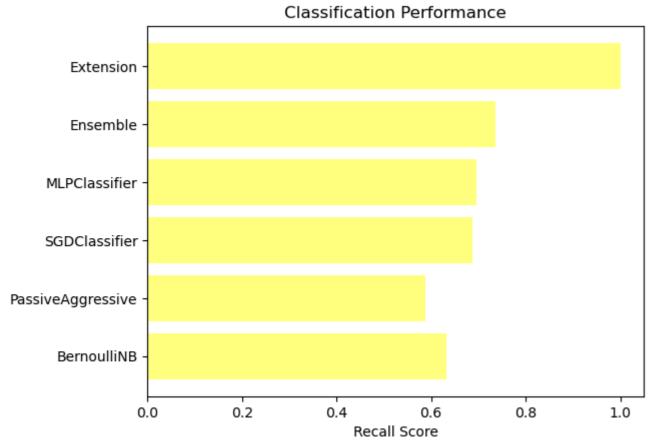


Recall

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```
In [52]: plt2.barh(y_pos, recall, align='center', alpha=0.5,color='yellow')
    plt2.yticks(y_pos, classifier)
    plt2.xlabel('Recall Score')
    plt2.title('Classification Performance')
    plt2.show()
```



F1 Score

In [53]:
 plt2.barh(y_pos, f1score, align='center', alpha=0.5,color='green')
 plt2.yticks(y_pos, classifier)
 plt2.xlabel('F1 Score')
 plt2.title('Classification Performance')
 plt2.show()



In []: