3_RT_Models

June 5, 2024

1 Machine Learning Models Applied to the IDS-2017

The purpose of this notebook is to experiment different machine learning on the IDS-2017 dataset generated by the CICFlowMeter on the recorder traffic which included benign and malicious flows

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import glob
import os
import xgboost as xgb
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, average_precision_score,␣
 ↪make_scorer, precision_score, accuracy_score, confusion_matrix
from notebook_utils import upsample_dataset
%matplotlib inline
%load_ext autoreload
%autoreload 2
file_path =␣
 ↪r"CIC-IDS-2017\CSVs\GeneratedLabelledFlows\TrafficLabelling\processed\ids2017_processed.
 ↪csv"

def replace_invalid(df):
    # Select only numeric columns
    numeric_columns = df.select_dtypes(include=[np.number]).columns

    # Identify columns with NaN, infinity, or negative values
    invalid_columns = df[numeric_columns].columns[df[numeric_columns].isna().
 ↪any() |
                                                  np.isinf(df[numeric_columns]).
 ↪any() |
                                                  (df[numeric_columns] < 0).
 ↪any()]
```

```
    print("Columns with NaN, infinity, or negative values:", invalid_columns.
 ↪tolist())

    # Replace invalid values with NaN and fill with column mean
    df[invalid_columns] = df[invalid_columns].replace([np.inf, -np.inf, -1], np.
 ↪nan)
    df[invalid_columns] = df[invalid_columns].fillna(df[invalid_columns].mean())

    return df

def load_dataset(file_path):
    df = pd.read_csv(file_path)
    convert_dict = {'label': 'category'}
    df = df.astype(convert_dict)
    replace_invalid(df)
    df.info()
    return df

attack_labels = {
    0: 'BENIGN',
    7: 'FTP-Patator',
    11: 'SSH-Patator',
    6: 'DoS slowloris',
    5: 'DoS Slowhttptest',
    4: 'DoS Hulk',
    3: 'DoS GoldenEye',
    8: 'Heartbleed',
    12: 'Web Attack - Brute Force',
    14: 'Web Attack - XSS',
    13: 'Web Attack - Sql Injection',
    9: 'Infiltration',
    1: 'Bot',
    10: 'PortScan',
    2: 'DDoS'
}
```

2 1. Preparing the Dataset

[2]:
```
df = load_dataset(file_path)
```

```
Columns with NaN, infinity, or negative values: ['flow_duration',
'flow_bytes_s', 'flow_packets_s', 'flow_iat_mean', 'flow_iat_max',
'flow_iat_min', 'fwd_iat_min', 'fwd_header_length', 'bwd_header_length',
'fwd_header_length_1', 'init_win_bytes_forward', 'init_win_bytes_backward',
'min_seg_size_forward']
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2830743 entries, 0 to 2830742
Data columns (total 96 columns):
 #   Column                       Dtype
---  ------                       -----
 0   destination_port             int64
 1   protocol                     int64
 2   flow_duration                float64
 3   total_fwd_packets            int64
 4   total_backward_packets       int64
 5   total_length_of_fwd_packets  float64
 6   total_length_of_bwd_packets  float64
 7   fwd_packet_length_max        float64
 8   fwd_packet_length_min        float64
 9   fwd_packet_length_mean       float64
 10  fwd_packet_length_std        float64
 11  bwd_packet_length_max        float64
 12  bwd_packet_length_min        float64
 13  bwd_packet_length_mean       float64
 14  bwd_packet_length_std        float64
 15  flow_bytes_s                 float64
 16  flow_packets_s               float64
 17  flow_iat_mean                float64
 18  flow_iat_std                 float64
 19  flow_iat_max                 float64
 20  flow_iat_min                 float64
 21  fwd_iat_total                float64
 22  fwd_iat_mean                 float64
 23  fwd_iat_std                  float64
 24  fwd_iat_max                  float64
 25  fwd_iat_min                  float64
 26  bwd_iat_total                float64
 27  bwd_iat_mean                 float64
 28  bwd_iat_std                  float64
 29  bwd_iat_max                  float64
 30  bwd_iat_min                  float64
 31  fwd_psh_flags                int64
 32  bwd_psh_flags                int64
 33  fwd_urg_flags                int64
 34  bwd_urg_flags                int64
 35  fwd_header_length            int64
 36  bwd_header_length            int64
 37  fwd_packets_s                float64
 38  bwd_packets_s                float64
 39  min_packet_length            float64
 40  max_packet_length            float64
 41  packet_length_mean           float64
 42  packet_length_std            float64
 43  packet_length_variance       float64
```

44	fin_flag_count	int64
45	syn_flag_count	int64
46	rst_flag_count	int64
47	psh_flag_count	int64
48	ack_flag_count	int64
49	urg_flag_count	int64
50	cwe_flag_count	int64
51	ece_flag_count	int64
52	down_up_ratio	float64
53	average_packet_size	float64
54	avg_fwd_segment_size	float64
55	avg_bwd_segment_size	float64
56	fwd_header_length_1	int64
57	fwd_avg_bytes_bulk	int64
58	fwd_avg_packets_bulk	int64
59	fwd_avg_bulk_rate	int64
60	bwd_avg_bytes_bulk	int64
61	bwd_avg_packets_bulk	int64
62	bwd_avg_bulk_rate	int64
63	subflow_fwd_packets	int64
64	subflow_fwd_bytes	int64
65	subflow_bwd_packets	int64
66	subflow_bwd_bytes	int64
67	init_win_bytes_forward	float64
68	init_win_bytes_backward	float64
69	act_data_pkt_fwd	int64
70	min_seg_size_forward	float64
71	active_mean	float64
72	active_std	float64
73	active_max	float64
74	active_min	float64
75	idle_mean	float64
76	idle_std	float64
77	idle_max	float64
78	idle_min	float64
79	label	category
80	is_attack	int64
81	label_code	int64
82	is_dos_hulk	int64
83	is_portscan	int64
84	is_ddos	int64
85	is_dos_goldeneye	int64
86	is_ftppatator	int64
87	is_sshpatator	int64
88	is_dos_slowloris	int64
89	is_dos_slowhttptest	int64
90	is_bot	int64
91	is_web_attack_brute_force	int64

```
 92  is_web_attack_xss           int64
 93  is_infiltration             int64
 94  is_web_attack_sql_injection int64
 95  is_heartbleed               int64
dtypes: category(1), float64(49), int64(46)
memory usage: 2.0 GB
```

[3]:

```
X = df.iloc[:, 0:79]
Y = df.iloc[:, 79:]
X.info()
Y.info()
print(Y.label.value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830743 entries, 0 to 2830742
Data columns (total 79 columns):
 #   Column                       Dtype
---  ------                       -----
 0   destination_port             int64
 1   protocol                     int64
 2   flow_duration                float64
 3   total_fwd_packets            int64
 4   total_backward_packets       int64
 5   total_length_of_fwd_packets  float64
 6   total_length_of_bwd_packets  float64
 7   fwd_packet_length_max        float64
 8   fwd_packet_length_min        float64
 9   fwd_packet_length_mean       float64
 10  fwd_packet_length_std        float64
 11  bwd_packet_length_max        float64
 12  bwd_packet_length_min        float64
 13  bwd_packet_length_mean       float64
 14  bwd_packet_length_std        float64
 15  flow_bytes_s                 float64
 16  flow_packets_s               float64
 17  flow_iat_mean                float64
 18  flow_iat_std                 float64
 19  flow_iat_max                 float64
 20  flow_iat_min                 float64
 21  fwd_iat_total                float64
 22  fwd_iat_mean                 float64
 23  fwd_iat_std                  float64
 24  fwd_iat_max                  float64
 25  fwd_iat_min                  float64
 26  bwd_iat_total                float64
 27  bwd_iat_mean                 float64
 28  bwd_iat_std                  float64
 29  bwd_iat_max                  float64
```

30	bwd_iat_min	float64
31	fwd_psh_flags	int64
32	bwd_psh_flags	int64
33	fwd_urg_flags	int64
34	bwd_urg_flags	int64
35	fwd_header_length	int64
36	bwd_header_length	int64
37	fwd_packets_s	float64
38	bwd_packets_s	float64
39	min_packet_length	float64
40	max_packet_length	float64
41	packet_length_mean	float64
42	packet_length_std	float64
43	packet_length_variance	float64
44	fin_flag_count	int64
45	syn_flag_count	int64
46	rst_flag_count	int64
47	psh_flag_count	int64
48	ack_flag_count	int64
49	urg_flag_count	int64
50	cwe_flag_count	int64
51	ece_flag_count	int64
52	down_up_ratio	float64
53	average_packet_size	float64
54	avg_fwd_segment_size	float64
55	avg_bwd_segment_size	float64
56	fwd_header_length_1	int64
57	fwd_avg_bytes_bulk	int64
58	fwd_avg_packets_bulk	int64
59	fwd_avg_bulk_rate	int64
60	bwd_avg_bytes_bulk	int64
61	bwd_avg_packets_bulk	int64
62	bwd_avg_bulk_rate	int64
63	subflow_fwd_packets	int64
64	subflow_fwd_bytes	int64
65	subflow_bwd_packets	int64
66	subflow_bwd_bytes	int64
67	init_win_bytes_forward	float64
68	init_win_bytes_backward	float64
69	act_data_pkt_fwd	int64
70	min_seg_size_forward	float64
71	active_mean	float64
72	active_std	float64
73	active_max	float64
74	active_min	float64
75	idle_mean	float64
76	idle_std	float64
77	idle_max	float64

```
 78  idle_min                     float64
dtypes: float64(49), int64(30)
memory usage: 1.7 GB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830743 entries, 0 to 2830742
Data columns (total 17 columns):
 #   Column                       Dtype
---  ------                       -----
 0   label                        category
 1   is_attack                    int64
 2   label_code                   int64
 3   is_dos_hulk                  int64
 4   is_portscan                  int64
 5   is_ddos                      int64
 6   is_dos_goldeneye             int64
 7   is_ftppatator                int64
 8   is_sshpatator                int64
 9   is_dos_slowloris             int64
 10  is_dos_slowhttptest          int64
 11  is_bot                       int64
 12  is_web_attack_brute_force    int64
 13  is_web_attack_xss            int64
 14  is_infiltration              int64
 15  is_web_attack_sql_injection  int64
 16  is_heartbleed                int64
dtypes: category(1), int64(16)
memory usage: 348.3 MB
label
BENIGN                        2273097
DoS Hulk                       231073
PortScan                       158930
DDoS                           128027
DoS GoldenEye                   10293
FTP-Patator                      7938
SSH-Patator                      5897
DoS slowloris                    5796
DoS Slowhttptest                 5499
Bot                              1966
Web Attack - Brute Force         1507
Web Attack - XSS                  652
Infiltration                       36
Web Attack - Sql Injection         21
Heartbleed                         11
Name: count, dtype: int64
```

3 2. Feature Selection

3.0.1 Correlation based feature selection

First, the columns with no variance are dropped as they have no impact on the target variables.

[4]:
```
stats = X.describe()
std = stats.loc["std"]
features_no_var = std[std == 0.0].index
# Exclude non-numeric columns (e.g., categorical columns) from the features␣
↪with zero variance
features_no_var_numeric = [col for col in features_no_var if col in X.
↪select_dtypes(include=[np.number]).columns]
print(features_no_var_numeric)
```

```
['bwd_psh_flags', 'bwd_urg_flags', 'fwd_avg_bytes_bulk', 'fwd_avg_packets_bulk',
'fwd_avg_bulk_rate', 'bwd_avg_bytes_bulk', 'bwd_avg_packets_bulk',
'bwd_avg_bulk_rate']
```

The destination port feature is dropped because it can act as a shortcut predictor and cause high overfitting for the training set as show in this paper

[5]:
```
X = X.drop(columns=features_no_var)
X = X.drop(columns=['destination_port'])
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830743 entries, 0 to 2830742
Data columns (total 70 columns):
 #   Column                       Dtype
---  ------                       -----
 0   protocol                     int64
 1   flow_duration                float64
 2   total_fwd_packets            int64
 3   total_backward_packets       int64
 4   total_length_of_fwd_packets  float64
 5   total_length_of_bwd_packets  float64
 6   fwd_packet_length_max        float64
 7   fwd_packet_length_min        float64
 8   fwd_packet_length_mean       float64
 9   fwd_packet_length_std        float64
 10  bwd_packet_length_max        float64
 11  bwd_packet_length_min        float64
 12  bwd_packet_length_mean       float64
 13  bwd_packet_length_std        float64
 14  flow_bytes_s                 float64
 15  flow_packets_s               float64
 16  flow_iat_mean                float64
 17  flow_iat_std                 float64
 18  flow_iat_max                 float64
```

19	flow_iat_min	float64
20	fwd_iat_total	float64
21	fwd_iat_mean	float64
22	fwd_iat_std	float64
23	fwd_iat_max	float64
24	fwd_iat_min	float64
25	bwd_iat_total	float64
26	bwd_iat_mean	float64
27	bwd_iat_std	float64
28	bwd_iat_max	float64
29	bwd_iat_min	float64
30	fwd_psh_flags	int64
31	fwd_urg_flags	int64
32	fwd_header_length	int64
33	bwd_header_length	int64
34	fwd_packets_s	float64
35	bwd_packets_s	float64
36	min_packet_length	float64
37	max_packet_length	float64
38	packet_length_mean	float64
39	packet_length_std	float64
40	packet_length_variance	float64
41	fin_flag_count	int64
42	syn_flag_count	int64
43	rst_flag_count	int64
44	psh_flag_count	int64
45	ack_flag_count	int64
46	urg_flag_count	int64
47	cwe_flag_count	int64
48	ece_flag_count	int64
49	down_up_ratio	float64
50	average_packet_size	float64
51	avg_fwd_segment_size	float64
52	avg_bwd_segment_size	float64
53	fwd_header_length_1	int64
54	subflow_fwd_packets	int64
55	subflow_fwd_bytes	int64
56	subflow_bwd_packets	int64
57	subflow_bwd_bytes	int64
58	init_win_bytes_forward	float64
59	init_win_bytes_backward	float64
60	act_data_pkt_fwd	int64
61	min_seg_size_forward	float64
62	active_mean	float64
63	active_std	float64
64	active_max	float64
65	active_min	float64
66	idle_mean	float64

```
 67   idle_std                    float64
 68   idle_max                    float64
 69   idle_min                    float64
dtypes: float64(49), int64(21)
memory usage: 1.5 GB
```

3.0.2 Remove collinear variables

[6]:
```
threshold = 0.9
corr_matrix = X.corr().abs()
corr_matrix.head()
```

[6]:
```
                           protocol  flow_duration  total_fwd_packets  \
protocol                   1.000000       0.265288           0.007272
flow_duration              0.265288       1.000000           0.020857
total_fwd_packets          0.007272       0.020857           1.000000
total_backward_packets     0.006361       0.019669           0.999070
total_length_of_fwd_packets 0.033234      0.065456           0.365508

                           total_backward_packets  \
protocol                                 0.006361
flow_duration                            0.019669
total_fwd_packets                        0.999070
total_backward_packets                   1.000000
total_length_of_fwd_packets              0.359451

                           total_length_of_fwd_packets  \
protocol                                      0.033234
flow_duration                                 0.065456
total_fwd_packets                             0.365508
total_backward_packets                        0.359451
total_length_of_fwd_packets                   1.000000

                           total_length_of_bwd_packets  \
protocol                                      0.005191
flow_duration                                 0.016186
total_fwd_packets                             0.996993
total_backward_packets                        0.994429
total_length_of_fwd_packets                   0.353762

                           fwd_packet_length_max  fwd_packet_length_min  \
protocol                                0.166066               0.315250
flow_duration                           0.273304               0.105235
total_fwd_packets                       0.009358               0.002989
total_backward_packets                  0.009039               0.002600
total_length_of_fwd_packets             0.197030               0.000275

                           fwd_packet_length_mean  fwd_packet_length_std  \
```

```
protocol                                   0.052344                0.178832
flow_duration                              0.143685                0.234434
total_fwd_packets                          0.000032                0.001403
total_backward_packets                     0.000333                0.001026
total_length_of_fwd_packets                0.185262                0.159787

                             …  act_data_pkt_fwd  min_seg_size_forward  \
protocol                     …          0.005043              0.003451
flow_duration                …          0.015942              0.001357
total_fwd_packets            …          0.887387              0.000184
total_backward_packets       …          0.882566              0.000018
total_length_of_fwd_packets  …          0.407448              0.001209

                             active_mean  active_std  active_max  active_min  \
protocol                        0.085598    0.081018    0.109356    0.063663
flow_duration                   0.189298    0.241059    0.294033    0.121169
total_fwd_packets               0.039937    0.008329    0.030459    0.041283
total_backward_packets          0.038963    0.006437    0.028602    0.041278
total_length_of_fwd_packets     0.101084    0.103326    0.126493    0.068325

                             idle_mean  idle_std  idle_max  idle_min
protocol                      0.179676  0.071305  0.184514  0.170531
flow_duration                 0.768031  0.243153  0.779524  0.738325
total_fwd_packets             0.001820  0.000809  0.001906  0.001670
total_backward_packets        0.001425  0.000492  0.001456  0.001330
total_length_of_fwd_packets   0.022660  0.027064  0.026079  0.018634

[5 rows x 70 columns]
```

[7]:
```python
# Upper triangle of correlations
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
upper.head()
```

[7]:
```
                             protocol  flow_duration  total_fwd_packets  \
protocol                          NaN       0.265288           0.007272
flow_duration                     NaN            NaN           0.020857
total_fwd_packets                 NaN            NaN                NaN
total_backward_packets            NaN            NaN                NaN
total_length_of_fwd_packets       NaN            NaN                NaN

                             total_backward_packets  \
protocol                                   0.006361
flow_duration                              0.019669
total_fwd_packets                          0.999070
total_backward_packets                          NaN
total_length_of_fwd_packets                     NaN
```

```
                              total_length_of_fwd_packets  \
protocol                                         0.033234
flow_duration                                    0.065456
total_fwd_packets                                0.365508
total_backward_packets                           0.359451
total_length_of_fwd_packets                           NaN

                              total_length_of_bwd_packets  \
protocol                                         0.005191
flow_duration                                    0.016186
total_fwd_packets                                0.996993
total_backward_packets                           0.994429
total_length_of_fwd_packets                      0.353762

                              fwd_packet_length_max  fwd_packet_length_min  \
protocol                                   0.166066               0.315250
flow_duration                              0.273304               0.105235
total_fwd_packets                          0.009358               0.002989
total_backward_packets                     0.009039               0.002600
total_length_of_fwd_packets                0.197030               0.000275

                              fwd_packet_length_mean  fwd_packet_length_std  \
protocol                                    0.052344               0.178832
flow_duration                               0.143685               0.234434
total_fwd_packets                           0.000032               0.001403
total_backward_packets                      0.000333               0.001026
total_length_of_fwd_packets                 0.185262               0.159787

                              …  act_data_pkt_fwd  min_seg_size_forward  \
protocol                      …          0.005043              0.003451
flow_duration                 …          0.015942              0.001357
total_fwd_packets             …          0.887387              0.000184
total_backward_packets        …          0.882566              0.000018
total_length_of_fwd_packets   …          0.407448              0.001209

                              active_mean  active_std  active_max  active_min  \
protocol                         0.085598    0.081018    0.109356    0.063663
flow_duration                    0.189298    0.241059    0.294033    0.121169
total_fwd_packets                0.039937    0.008329    0.030459    0.041283
total_backward_packets           0.038963    0.006437    0.028602    0.041278
total_length_of_fwd_packets      0.101084    0.103326    0.126493    0.068325

                              idle_mean  idle_std  idle_max  idle_min
protocol                       0.179676  0.071305  0.184514  0.170531
flow_duration                  0.768031  0.243153  0.779524  0.738325
total_fwd_packets              0.001820  0.000809  0.001906  0.001670
total_backward_packets         0.001425  0.000492  0.001456  0.001330
```

```
total_length_of_fwd_packets   0.022660  0.027064  0.026079  0.018634

[5 rows x 70 columns]
```

[8]:
```python
to_drop = [column for column in upper.columns if any(upper[column] > threshold)]
to_keep = [
    'Destination Port', 'Fwd Packet Length Std', 'Min Packet Length',
    'Packet Length Variance', 'PSH Flag Count', 'Active Max'
]
to_drop = [column for column in to_drop if column not in to_keep]
print('There are %d columns to remove.' % (len(to_drop)))
X = X.drop(columns=to_drop)
X.info()
```

```
There are 31 columns to remove.
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830743 entries, 0 to 2830742
Data columns (total 39 columns):
 #   Column                       Dtype
---  ------                       -----
 0   protocol                     int64
 1   flow_duration                float64
 2   total_fwd_packets            int64
 3   total_length_of_fwd_packets  float64
 4   fwd_packet_length_max        float64
 5   fwd_packet_length_min        float64
 6   fwd_packet_length_mean       float64
 7   bwd_packet_length_max        float64
 8   bwd_packet_length_min        float64
 9   flow_bytes_s                 float64
 10  flow_packets_s               float64
 11  flow_iat_mean                float64
 12  flow_iat_std                 float64
 13  flow_iat_min                 float64
 14  fwd_iat_min                  float64
 15  bwd_iat_total                float64
 16  bwd_iat_mean                 float64
 17  bwd_iat_std                  float64
 18  bwd_iat_max                  float64
 19  fwd_psh_flags                int64
 20  fwd_urg_flags                int64
 21  fwd_header_length            int64
 22  bwd_header_length            int64
 23  bwd_packets_s                float64
 24  min_packet_length            float64
 25  fin_flag_count               int64
 26  rst_flag_count               int64
 27  psh_flag_count               int64
```

```
 28   ack_flag_count               int64
 29   urg_flag_count               int64
 30   down_up_ratio                float64
 31   init_win_bytes_forward       float64
 32   init_win_bytes_backward      float64
 33   act_data_pkt_fwd             int64
 34   min_seg_size_forward         float64
 35   active_mean                  float64
 36   active_std                   float64
 37   active_max                   float64
 38   idle_std                     float64
dtypes: float64(27), int64(12)
memory usage: 842.3 MB
```

3.0.3 3. Split Dataset

The dataset is split into a train, cross-validation and evaluation sets with a ratio of 0.8/0.1/0.1. The dataset is stratified according to the label to have an equal representation of all classes in the 3 subsets.

[9]:
```
X_train, X_temp, Y_train, Y_temp = train_test_split(X, Y, test_size=0.2,␣
 ↪stratify=Y.label_code)
X_eval, X_test, Y_eval, Y_test = train_test_split(X_temp, Y_temp, test_size=0.
 ↪5, stratify=Y_temp.label_code)
```

Upsampling is used to generate artificial samples for types of attacks that are underrepresented in the dataset.

[10]:
```
X_train, Y_train = upsample_dataset(X, Y, 100000, attack_labels)
```

[11]:
```
Y_train.label.value_counts()
```

[11]:
```
label
BENIGN                        2273097
DoS Hulk                       231073
PortScan                       158930
DDoS                           128027
Bot                            100000
DoS GoldenEye                  100000
DoS Slowhttptest               100000
DoS slowloris                  100000
FTP-Patator                    100000
Heartbleed                     100000
Infiltration                   100000
SSH-Patator                    100000
Web Attack - Brute Force       100000
Web Attack - Sql Injection     100000
Web Attack - XSS               100000
```

```
Name: count, dtype: int64
```

[12]:
```
Y_eval.label.value_counts()
```

[12]:
```
label
BENIGN                        227310
DoS Hulk                       23107
PortScan                       15893
DDoS                           12803
DoS GoldenEye                   1029
FTP-Patator                      794
SSH-Patator                      589
DoS slowloris                    579
DoS Slowhttptest                 550
Bot                              197
Web Attack - Brute Force         151
Web Attack - XSS                  65
Infiltration                       4
Web Attack - Sql Injection         2
Heartbleed                         1
Name: count, dtype: int64
```

[13]:
```
Y_test.label.value_counts()
```

[13]:
```
label
BENIGN                        227310
DoS Hulk                       23108
PortScan                       15893
DDoS                           12803
DoS GoldenEye                   1030
FTP-Patator                      794
SSH-Patator                      590
DoS slowloris                    580
DoS Slowhttptest                 550
Bot                              196
Web Attack - Brute Force         150
Web Attack - XSS                  65
Infiltration                       3
Web Attack - Sql Injection         2
Heartbleed                         1
Name: count, dtype: int64
```

Statistics for the training set

[14]:
```
benign_percentage = len(Y_train.label[Y_train["label"]=="BENIGN"])/len(Y_train)
print('Percentage of benign samples: %.4f' % benign_percentage)
print(Y_train.is_attack.value_counts())
```

```
Percentage of benign samples: 0.5842
```

```
is_attack
0.0    2273097
1.0    1618030
Name: count, dtype: int64
```

4 3. Machine Learning Classifiers

In this section, different machine learning models are applied to classify network traffic. The metrics used to evaluate the models are primarily accuracy, precision, recall and the F1 score.

[15]:
```
scaler = StandardScaler()
scaler.fit(X_train)
```

[15]:
```
StandardScaler()
```

[16]:
```
def plot_confusion_matrix(model_name, Y_true, Y_pred, labels=["Benign",␣
↪"Attack"]):
    matrix = confusion_matrix(Y_true.is_attack, Y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(matrix, annot=True, cmap='Blues', fmt='d', xticklabels=labels,␣
↪yticklabels=labels)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title(f'Confusion Matrix for {model_name}')
    plt.show()

def metrics_report(dataset_type, y_true, y_predict, print_avg=True):
    print(f"Classification Report ({dataset_type}):")
    print(classification_report(y_true, y_predict, digits=4))
    if print_avg:
        print(f"Avg Precision Score: {average_precision_score(y_true,␣
↪y_predict, average='weighted')}")
    print("Accuracy:",accuracy_score(y_true, y_predict))
    res = classification_report(y_true, y_predict, digits=4, output_dict = True)
    res["accuracy"] = accuracy_score(y_true, y_predict)
    return res
```

[17]:
```
performance_models = {}
```

Functions for saving and loading modules

[18]:
```
import joblib

def save_model(model, model_name):
    file_path = f'models/{model_name}.pkl'
    joblib.dump(model, file_path)
    print(f'Model saved to {file_path}')
```

```
def load_model(model_name):
    file_path = f'models/{model_name}.pkl'
    model = joblib.load(file_path)
    print(f'Model loaded from {file_path}')
    return model

os.makedirs('models', exist_ok=True)
```

4.1 3.1 Decision Trees/Ensembles Algorithms

4.1.1 3.1.1 Regression Forest

Binary Classification

[19]:
```
rf_model_binary = RandomForestClassifier(verbose=1, n_jobs=-1,␣
 ↪class_weight='balanced', criterion="entropy", n_estimators = 300, bootstrap␣
 ↪= True, max_features=None)
rf_model_binary.fit(scaler.transform(X_train), Y_train.is_attack)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:  4.8min
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed: 27.4min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 46.3min finished
```

[19]:
```
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_features=None, n_estimators=300, n_jobs=-1,
                       verbose=1)
```

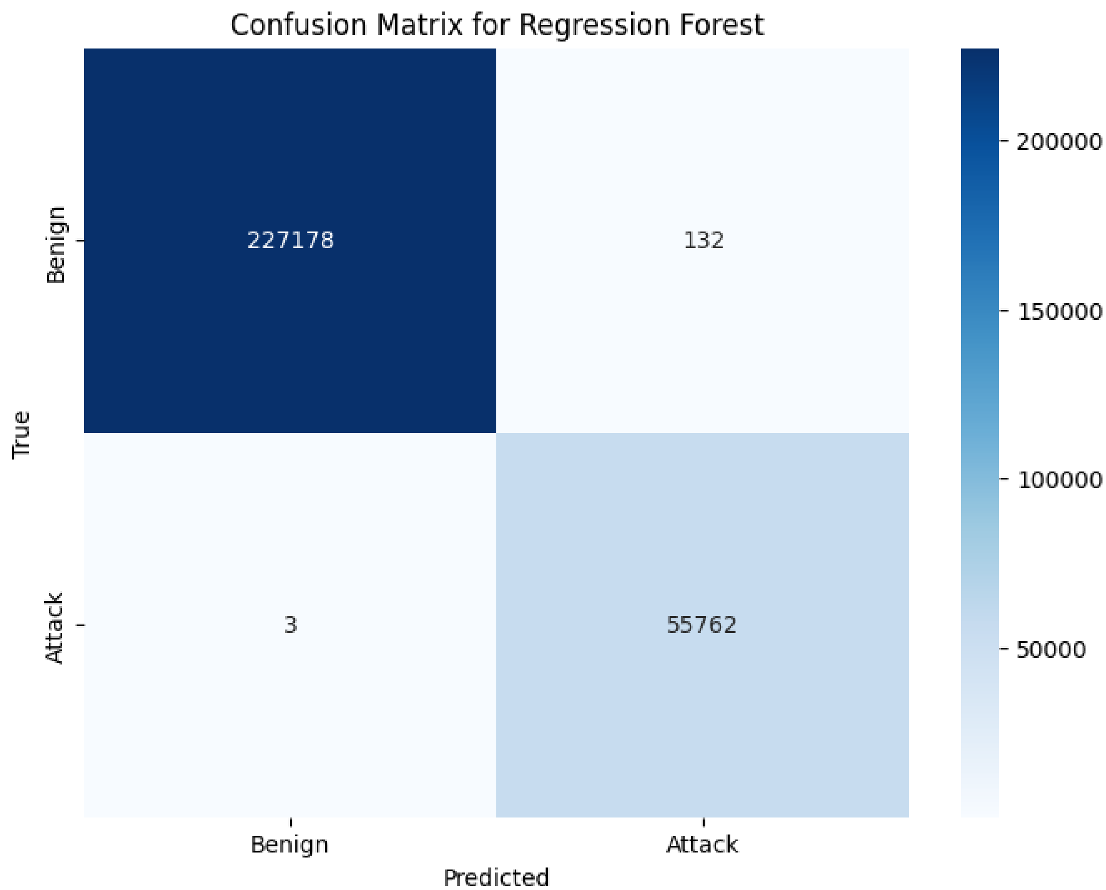
[20]:
```
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.is_attack, rf_model_binary.predict(scaler.
 ↪transform(X_eval)))
# Predict and evaluate on the test set
print("Test Set Performance")
Y_pred = rf_model_binary.predict(scaler.transform(X_test))
performance_models["rf"] = metrics_report("Test", Y_test.is_attack, Y_pred)
plot_confusion_matrix("Regression Forest", Y_test, Y_pred)
```

```
Evaluation Set Performance

[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.0s
[Parallel(n_jobs=16)]: Done 168 tasks      | elapsed:    0.3s
[Parallel(n_jobs=16)]: Done 300 out of 300 | elapsed:    0.7s finished

Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     1.0000    0.9995    0.9997    227310
           1     0.9979    0.9999    0.9989     55764
```

```
    accuracy                         0.9996    283074
   macro avg     0.9989    0.9997    0.9993    283074
weighted avg     0.9996    0.9996    0.9996    283074

Avg Precision Score: 0.9978486651284253
Accuracy: 0.9995725499339395
Test Set Performance
```

```
[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.0s
[Parallel(n_jobs=16)]: Done 168 tasks      | elapsed:    0.4s
[Parallel(n_jobs=16)]: Done 300 out of 300 | elapsed:    0.7s finished
```

```
Classification Report (Test):
              precision    recall  f1-score   support

           0     1.0000    0.9994    0.9997    227310
           1     0.9976    0.9999    0.9988     55765

    accuracy                         0.9995    283075
   macro avg     0.9988    0.9997    0.9992    283075
weighted avg     0.9995    0.9995    0.9995    283075

Avg Precision Score: 0.9975953147083236
Accuracy: 0.9995230945862404
```



[21]:
```
save_model(rf_model_binary, 'random_forest')
```

Model saved to models/random_forest.pkl

Multi-class classifier

[22]:
```
rf_model_multiclass = RandomForestClassifier(verbose=1, n_jobs=-1,␣
↪class_weight='balanced')
rf_model_multiclass.fit(scaler.transform(X_train), Y_train.label_code)
# Predict and evaluate on the evaluation set
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.label_code, rf_model_multiclass.
↪predict(scaler.transform(X_eval)), print_avg=False)
# Predict and evaluate on the test set
print("Test Set Performance")
metrics_report("Test", Y_test.label_code, rf_model_multiclass.predict(scaler.
↪transform(X_test)), print_avg=False)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
```

```
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  3.5min finished
[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.

Evaluation Set Performance

[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.2s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    1.0s finished

Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     1.0000    0.9977    0.9988    227310
           1     0.3803    1.0000    0.5510       197
           2     0.9999    0.9998    0.9999     12803
           3     0.9990    1.0000    0.9995      1029
           4     0.9966    1.0000    0.9983     23107
           5     1.0000    1.0000    1.0000       550
           6     1.0000    0.9983    0.9991       579
           7     1.0000    1.0000    1.0000       794
           8     1.0000    1.0000    1.0000         1
           9     1.0000    1.0000    1.0000         4
          10     0.9943    0.9999    0.9971     15893
          11     1.0000    1.0000    1.0000       589
          12     0.7254    0.6821    0.7031       151
          13     0.6667    1.0000    0.8000         2
          14     0.5625    0.9692    0.7119        65

    accuracy                         0.9979    283074
   macro avg     0.8883    0.9765    0.9173    283074
weighted avg     0.9987    0.9979    0.9982    283074

Accuracy: 0.9979404678635269
Test Set Performance

[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.2s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    1.0s finished

Classification Report (Test):
              precision    recall  f1-score   support

           0     1.0000    0.9975    0.9988    227310
           1     0.3748    1.0000    0.5452       196
           2     0.9999    0.9999    0.9999     12803
           3     0.9990    1.0000    0.9995      1030
           4     0.9959    1.0000    0.9980     23108
           5     0.9964    0.9982    0.9973       550
```

```
           6     0.9983    1.0000    0.9991       580
           7     1.0000    1.0000    1.0000       794
           8     1.0000    1.0000    1.0000         1
           9     1.0000    1.0000    1.0000         3
          10     0.9931    0.9999    0.9965     15893
          11     1.0000    1.0000    1.0000       590
          12     0.8015    0.7000    0.7473       150
          13     1.0000    1.0000    1.0000         2
          14     0.5676    0.9692    0.7159        65

    accuracy                         0.9978    283075
   macro avg     0.9151    0.9777    0.9332    283075
weighted avg     0.9986    0.9978    0.9981    283075

Accuracy: 0.9978380287909565
```

[22]:

```
{'0': {'precision': 0.9999955898372209,
  'recall': 0.9975276054727025,
  'f1-score': 0.9987600730301569,
  'support': 227310.0},
 '1': {'precision': 0.37476099426386233,
  'recall': 1.0,
  'f1-score': 0.545201668984701,
  'support': 196.0},
 '2': {'precision': 0.9999218933062564,
  'recall': 0.9999218933062564,
  'f1-score': 0.9999218933062564,
  'support': 12803.0},
 '3': {'precision': 0.9990300678952473,
  'recall': 1.0,
  'f1-score': 0.9995147986414362,
  'support': 1030.0},
 '4': {'precision': 0.9959486251185242,
  'recall': 1.0,
  'f1-score': 0.9979702008205571,
  'support': 23108.0},
 '5': {'precision': 0.9963702359346642,
  'recall': 0.9981818181818182,
  'f1-score': 0.997275204359673,
  'support': 550.0},
 '6': {'precision': 0.9982788296041308,
  'recall': 1.0,
  'f1-score': 0.9991386735572783,
  'support': 580.0},
 '7': {'precision': 1.0, 'recall': 1.0, 'f1-score': 1.0, 'support': 794.0},
 '8': {'precision': 1.0, 'recall': 1.0, 'f1-score': 1.0, 'support': 1.0},
 '9': {'precision': 1.0, 'recall': 1.0, 'f1-score': 1.0, 'support': 3.0},
```

```
 '10': {'precision': 0.9930638005373993,
  'recall': 0.9999370792172655,
  'f1-score': 0.9964885879107098,
  'support': 15893.0},
 '11': {'precision': 1.0, 'recall': 1.0, 'f1-score': 1.0, 'support': 590.0},
 '12': {'precision': 0.8015267175572519,
  'recall': 0.7,
  'f1-score': 0.7473309608540926,
  'support': 150.0},
 '13': {'precision': 1.0, 'recall': 1.0, 'f1-score': 1.0, 'support': 2.0},
 '14': {'precision': 0.5675675675675675,
  'recall': 0.9692307692307692,
  'f1-score': 0.7159090909090909,
  'support': 65.0},
 'accuracy': 0.9978380287909565,
 'macro avg': {'precision': 0.915097621441475,
  'recall': 0.9776532776939207,
  'f1-score': 0.9331674101582635,
  'support': 283075.0},
 'weighted avg': {'precision': 0.9986212901610746,
  'recall': 0.9978380287909565,
  'f1-score': 0.9981151144627087,
  'support': 283075.0}}
```

Given that the dataset lacks many samples for some of the attack types, the multiclass classifier has low accuracy for several attack types, even after upsampling, which will cause overfitting in this case. It is better to test other machine learning algorithms for binary classifiers.

4.1.2 3.1.2 Gradient Boost (XGB)

[23]:
```python
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import make_scorer, precision_score

# Define the parameter grid for RandomizedSearchCV
param_grid = {
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7, 10],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0],
    'gamma': [0, 0.1, 0.2, 0.3],
    'reg_alpha': [0, 0.1, 0.5, 1],
    'reg_lambda': [0, 0.1, 0.5, 1]
}
```

```
# Initialize the XGBoost classifier
xgb_model_binary = xgb.XGBClassifier(objective='binary:logistic',␣
↪scale_pos_weight=1, n_jobs=-1)

# Define the scorer
scorer = make_scorer(precision_score)

# Initialize RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=xgb_model_binary,␣
↪param_distributions=param_grid, n_iter=20,
                                   scoring=scorer, n_jobs=-1, cv=2, verbose=2,␣
↪random_state=42)

# Fit the model on the training data
random_search.fit(scaler.transform(X_train.astype('float32')), Y_train.
↪is_attack)

# Get the best model
best_xgb_model = random_search.best_estimator_

# Print the best hyperparameters
print("Best Hyperparameters:", random_search.best_params_)
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
Best Hyperparameters: {'subsample': 1.0, 'reg_lambda': 0.1, 'reg_alpha': 0.5,
'n_estimators': 300, 'min_child_weight': 1, 'max_depth': 7, 'learning_rate':
0.05, 'gamma': 0.1, 'colsample_bytree': 1.0}
```

Best Hyperparameters: {'subsample': 1.0, 'reg_lambda': 0, 'reg_alpha': 0.5, 'n_estimators': 100, 'min_child_weight': 3, 'max_depth': 10, 'learning_rate': 0.1, 'gamma': 0.3, 'colsample_bytree': 0.6}

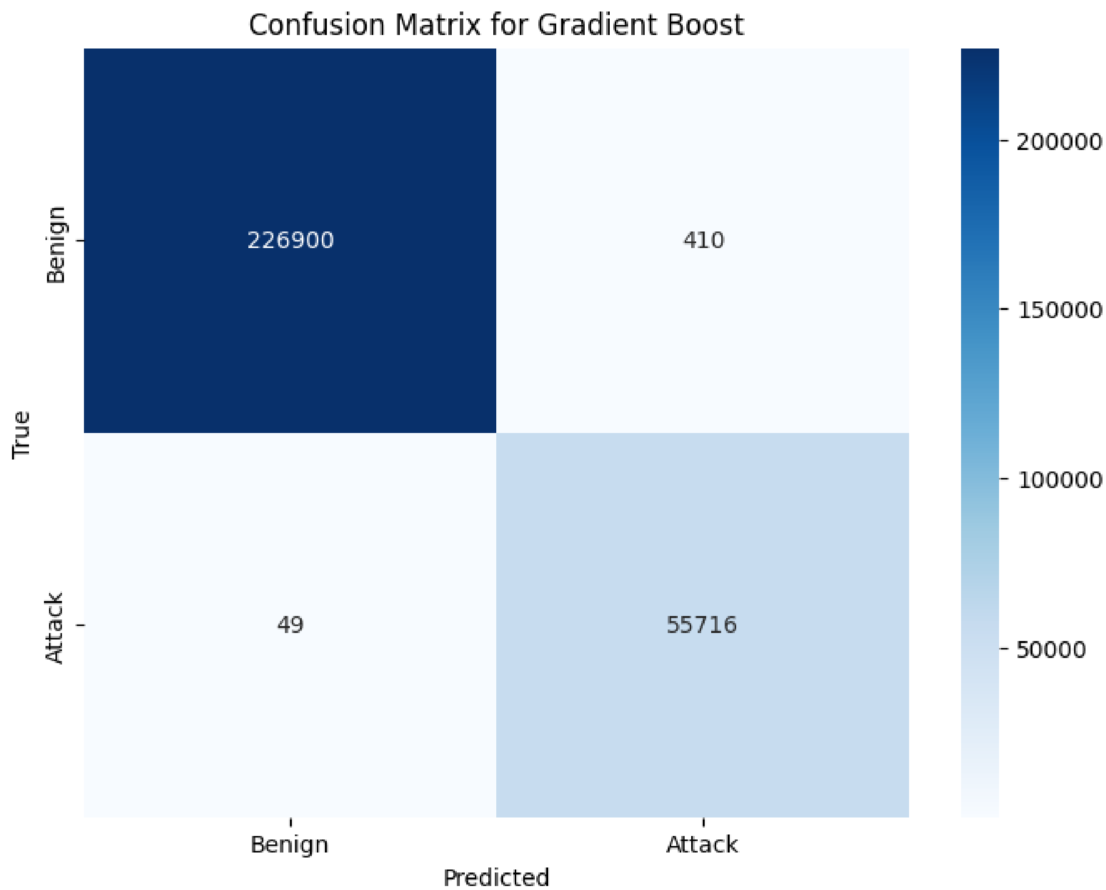
[24]:
```
best_params = random_search.best_params_

best_xgb_model = xgb.XGBClassifier(
    objective='binary:logistic',
    scale_pos_weight=1,
    n_jobs=-1,
    **best_params
)

# Fit the model on the training data
best_xgb_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[24]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=1.0, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
```

```
                   gamma=0.1, grow_policy=None, importance_type=None,
                   interaction_constraints=None, learning_rate=0.05, max_bin=None,
                   max_cat_threshold=None, max_cat_to_onehot=None,
                   max_delta_step=None, max_depth=7, max_leaves=None,
                   min_child_weight=1, missing=nan, monotone_constraints=None,
                   multi_strategy=None, n_estimators=300, n_jobs=-1,
                   num_parallel_tree=None, random_state=None, …)
```

[25]:
```
# Predict and evaluate on the evaluation set
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.is_attack, best_xgb_model.predict(scaler.
 ↪transform(X_eval)), print_avg=False)
# Predict and evaluate on the test set
print("Test Set Performance")
Y_pred = best_xgb_model.predict(scaler.transform(X_test))
performance_models["xgb"] = metrics_report("Test", Y_test.is_attack, Y_pred,␣
 ↪print_avg=False)
plot_confusion_matrix("Gradient Boost", Y_test, Y_pred)
```

```
Evaluation Set Performance
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9998    0.9983    0.9990    227310
           1     0.9930    0.9991    0.9960     55764

    accuracy                         0.9984    283074
   macro avg     0.9964    0.9987    0.9975    283074
weighted avg     0.9984    0.9984    0.9984    283074

Accuracy: 0.9984279728975463
Test Set Performance
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9998    0.9982    0.9990    227310
           1     0.9927    0.9991    0.9959     55765

    accuracy                         0.9984    283075
   macro avg     0.9962    0.9987    0.9974    283075
weighted avg     0.9984    0.9984    0.9984    283075

Accuracy: 0.9983785215932174
```



[26]:
```
save_model(best_xgb_model, 'xgb_model')
```

```
Model saved to models/xgb_model.pkl
```

4.1.3 3.1.3 ADABoost

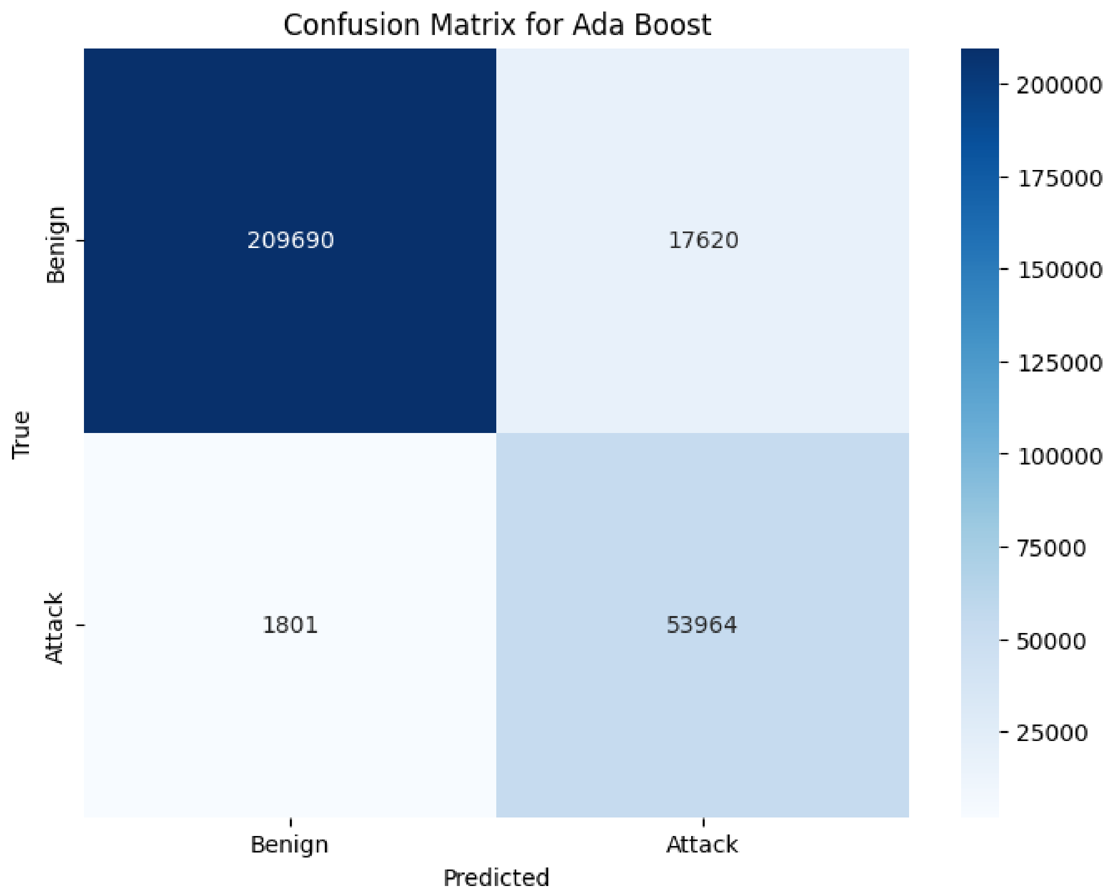
[27]:
```
from sklearn.ensemble import AdaBoostClassifier
ada_boost_model = AdaBoostClassifier(
    n_estimators=50,  # Number of weak learners
    learning_rate=1.0,  # Learning rate (contribution of each weak learner)
    algorithm='SAMME',  # SAMME.R is recommended for probability estimates
    random_state=42
)

# Fit the model on the training data
ada_boost_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[27]:
```
AdaBoostClassifier(algorithm='SAMME', random_state=42)
```

[28]:

```python
# Predict and evaluate on the evaluation set
y_pred_eval = ada_boost_model.predict(scaler.transform(X_eval))
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test = ada_boost_model.predict(scaler.transform(X_test))
performance_models["adaboost"] = metrics_report("Test", Y_test.is_attack,␣
 ↪y_pred_test, print_avg=False)
plot_confusion_matrix("Ada Boost", Y_test, y_pred_test)
```

```
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9910    0.9221    0.9553    227310
           1     0.7525    0.9657    0.8459     55764

    accuracy                         0.9307    283074
   macro avg     0.8718    0.9439    0.9006    283074
weighted avg     0.9440    0.9307    0.9337    283074

Accuracy: 0.9306930343302457
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9915    0.9225    0.9557    227310
           1     0.7539    0.9677    0.8475     55765

    accuracy                         0.9314    283075
   macro avg     0.8727    0.9451    0.9016    283075
weighted avg     0.9447    0.9314    0.9344    283075

Accuracy: 0.9313927404398128
```



[29]:
```
save_model(ada_boost_model, 'ada_boost_model')
```

```
Model saved to models/ada_boost_model.pkl
```

4.1.4 3.1.4 ID3

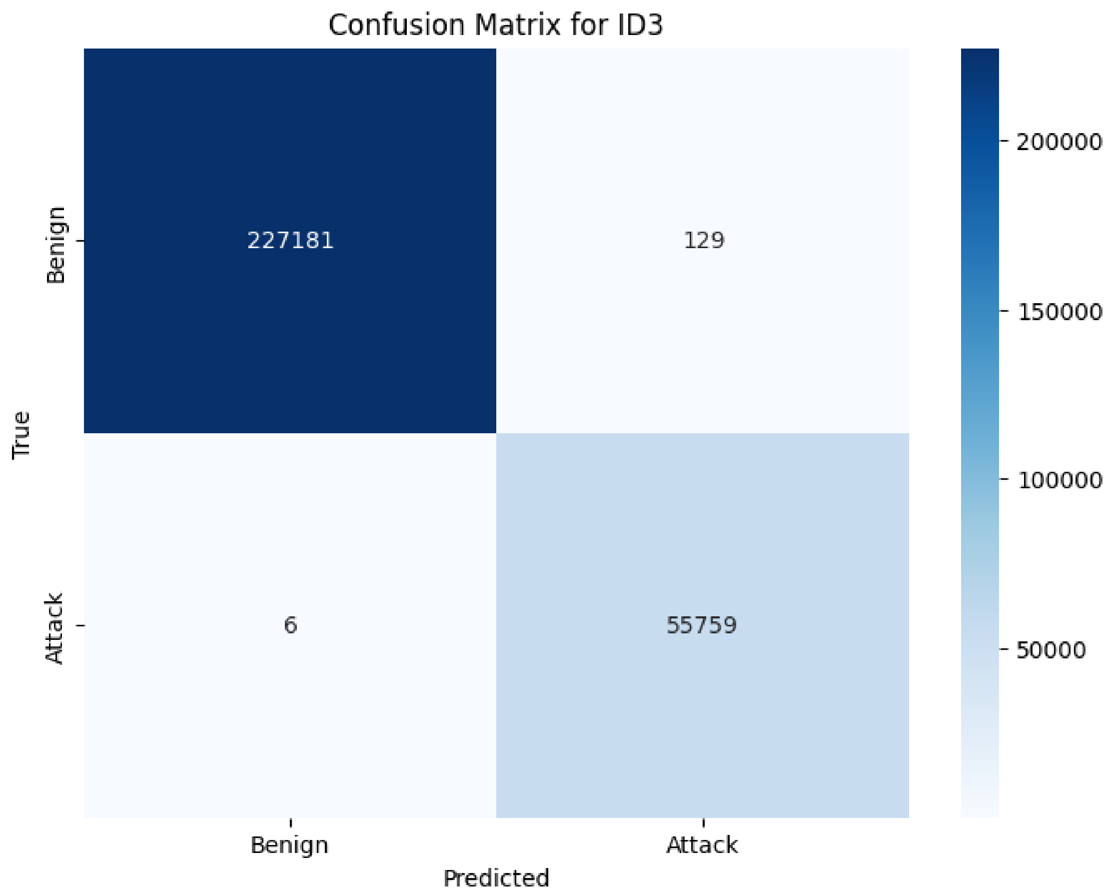
[30]:
```
id3_model = DecisionTreeClassifier(
    criterion='entropy',  # Use entropy for ID3-like behavior
    max_depth=None,  # Unlimited depth (ID3 doesn't prune trees)
    random_state=42
)

# Fit the model on the training data
id3_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[30]:
```
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

[31]:
```
y_pred_eval = id3_model.predict(scaler.transform(X_eval))
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)
```

```python
# Predict and evaluate on the test set
y_pred_test = id3_model.predict(scaler.transform(X_test))
performance_models["id3"] = metrics_report("Test", Y_test.is_attack,␣
↪y_pred_test, print_avg=False)
plot_confusion_matrix("ID3", Y_test, y_pred_test)
```

```
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     1.0000    0.9995    0.9997    227310
           1     0.9980    0.9999    0.9989     55764

    accuracy                         0.9996    283074
   macro avg     0.9990    0.9997    0.9993    283074
weighted avg     0.9996    0.9996    0.9996    283074

Accuracy: 0.9995760825791136
Classification Report (Test):
              precision    recall  f1-score   support

           0     1.0000    0.9994    0.9997    227310
           1     0.9977    0.9999    0.9988     55765

    accuracy                         0.9995    283075
   macro avg     0.9988    0.9997    0.9992    283075
weighted avg     0.9995    0.9995    0.9995    283075

Accuracy: 0.9995230945862404
```




```
[32]: save_model(id3_model, 'id3_model')
```

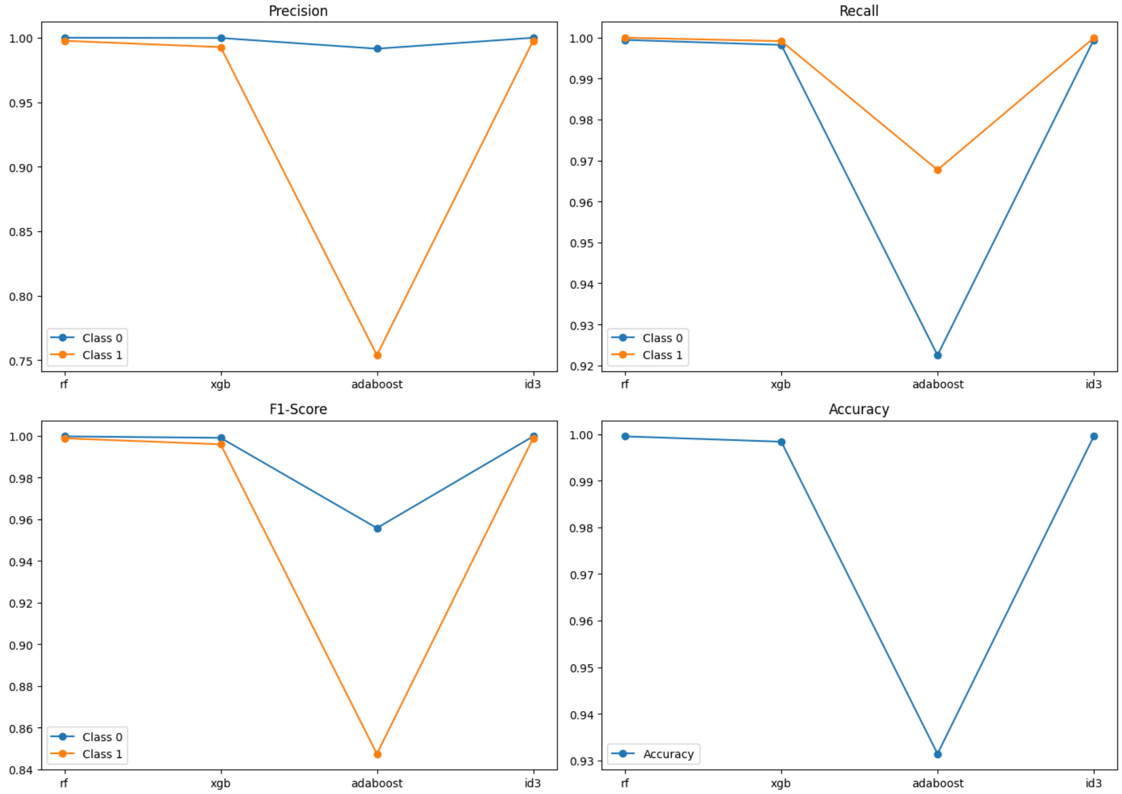
Model saved to models/id3_model.pkl

4.1.5 Conclusion

```
[33]: def extract_and_plot_metrics(metrics_dict):
          # Initialize dictionaries to store the metrics for plotting
          precision_dict = {'0': [], '1': [], 'model': []}
          recall_dict = {'0': [], '1': [], 'model': []}
          f1_score_dict = {'0': [], '1': [], 'model': []}
          accuracy_list = []

          # Iterate over the models in the metrics dictionary
          for model_name, metrics in metrics_dict.items():
              precision_dict['0'].append(metrics['0']['precision'])
              precision_dict['1'].append(metrics['1']['precision'])
              recall_dict['0'].append(metrics['0']['recall'])
              recall_dict['1'].append(metrics['1']['recall'])
```

```
        f1_score_dict['0'].append(metrics['0']['f1-score'])
        f1_score_dict['1'].append(metrics['1']['f1-score'])
        accuracy_list.append(metrics['accuracy'])
        precision_dict['model'].append(model_name)
        recall_dict['model'].append(model_name)
        f1_score_dict['model'].append(model_name)

    # Plotting the metrics
    fig, axs = plt.subplots(2, 2, figsize=(14, 10))

    # Plot precision
    axs[0, 0].plot(precision_dict['model'], precision_dict['0'], label='Class␣
↪0', marker='o')
    axs[0, 0].plot(precision_dict['model'], precision_dict['1'], label='Class␣
↪1', marker='o')
    axs[0, 0].set_title('Precision')
    axs[0, 0].legend()

    # Plot recall
    axs[0, 1].plot(recall_dict['model'], recall_dict['0'], label='Class 0',␣
↪marker='o')
    axs[0, 1].plot(recall_dict['model'], recall_dict['1'], label='Class 1',␣
↪marker='o')
    axs[0, 1].set_title('Recall')
    axs[0, 1].legend()

    # Plot f1-score
    axs[1, 0].plot(f1_score_dict['model'], f1_score_dict['0'], label='Class 0',␣
↪marker='o')
    axs[1, 0].plot(f1_score_dict['model'], f1_score_dict['1'], label='Class 1',␣
↪marker='o')
    axs[1, 0].set_title('F1-Score')
    axs[1, 0].legend()

    # Plot accuracy
    print(accuracy_list)
    print(precision_dict['model'])
    axs[1, 1].plot(precision_dict['model'], accuracy_list, label='Accuracy',␣
↪marker='o')
    axs[1, 1].set_title('Accuracy')
    axs[1, 1].legend()

    plt.tight_layout()
    plt.show()

extract_and_plot_metrics(performance_models)
```

```
[0.9995230945862404, 0.9983785215932174, 0.9313927404398128, 0.9995230945862404]
['rf', 'xgb', 'adaboost', 'id3']
```



ID3 and Random Forest perform very well on the dataset while Adaboost is the worst model. To conclude, after finetuning the hyperparameters, random forest seems to be the best tree based algorithm to perform on the dataset.

4.2 3.2 Deep Neural Network

In this section, deep neural networks are used to create binary classifiers that distinguish between benign and malicious traffics. Hyperparameters are optimized to obtain the best results.

[34]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
```

[35]:
```
# Define the model architecture
model = keras.Sequential([
    keras.layers.Dense(128, activation='relu', input_shape=(scaler.
 ↪transform(X_train).shape[1],)),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation='relu'),
```

```
    keras.layers.Dropout(0.5),
    keras.layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Train the model
history = model.fit(scaler.transform(X_train), Y_train.is_attack, epochs=10,␣
 ↪batch_size=32, validation_split=0.2)
```

```
C:\Users\youss\AppData\Local\Programs\Python\Python312\Lib\site-
packages\keras\src\layers\core\dense.py:88: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

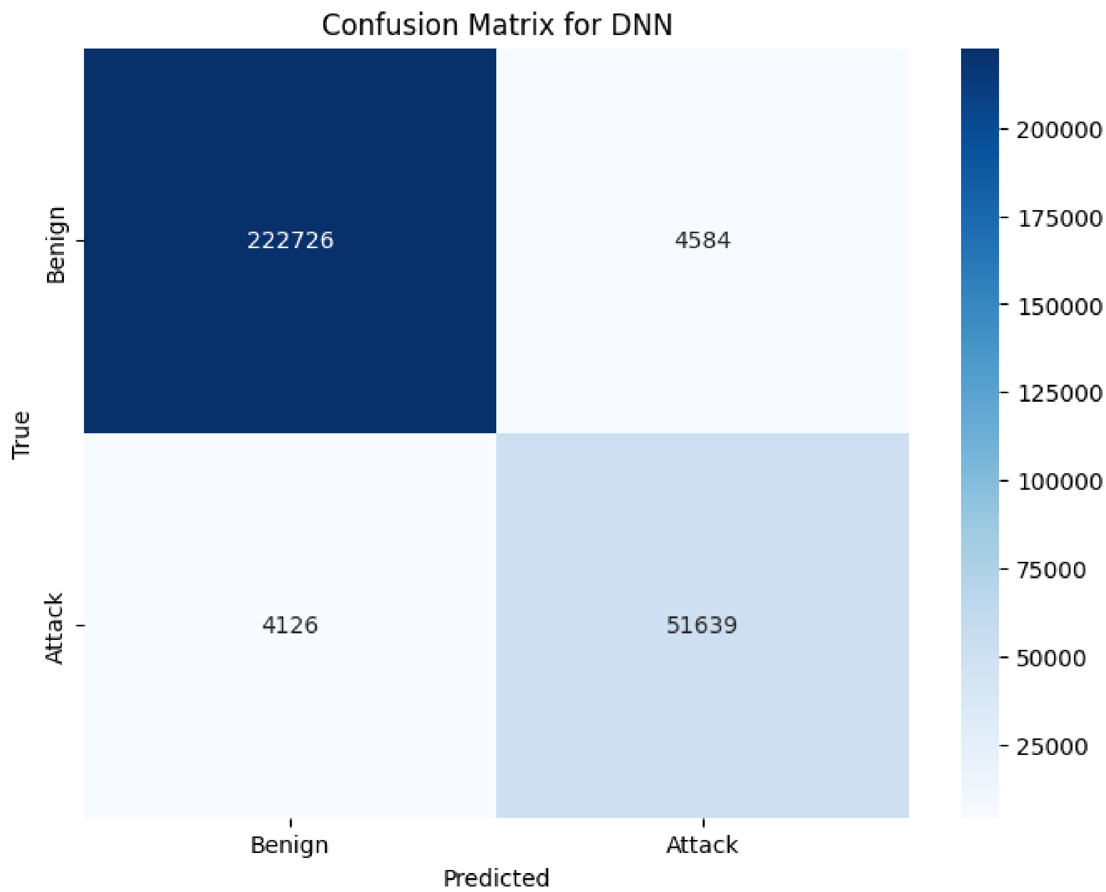
```
Epoch 1/10
97279/97279            66s
673us/step - accuracy: 0.9374 - loss: 0.1676 - val_accuracy: 0.2848 - val_loss:
8.9642
Epoch 2/10
97279/97279            66s
678us/step - accuracy: 0.9524 - loss: 0.1146 - val_accuracy: 0.2882 - val_loss:
7.4969
Epoch 3/10
97279/97279            65s
669us/step - accuracy: 0.9544 - loss: 0.1118 - val_accuracy: 0.2889 - val_loss:
4.7225
Epoch 4/10
97279/97279            65s
664us/step - accuracy: 0.9557 - loss: 0.1169 - val_accuracy: 0.2726 - val_loss:
10.9780
Epoch 5/10
97279/97279            64s
661us/step - accuracy: 0.9562 - loss: 0.1089 - val_accuracy: 0.3051 - val_loss:
6.2204
Epoch 6/10
97279/97279            65s
666us/step - accuracy: 0.9568 - loss: 0.1259 - val_accuracy: 0.3020 - val_loss:
9.3219
Epoch 7/10
97279/97279            65s
666us/step - accuracy: 0.9570 - loss: 0.1114 - val_accuracy: 0.2990 - val_loss:
11.0146
Epoch 8/10
97279/97279            65s
```

```
666us/step - accuracy: 0.9575 - loss: 0.1486 - val_accuracy: 0.3099 - val_loss:
5.7396
Epoch 9/10
97279/97279          65s
665us/step - accuracy: 0.9577 - loss: 0.1267 - val_accuracy: 0.3003 - val_loss:
9.3866
Epoch 10/10
97279/97279          65s
666us/step - accuracy: 0.9578 - loss: 0.1226 - val_accuracy: 0.3451 - val_loss:
8.2815
```

[36]:

```python
# Predict probabilities on the evaluation set
y_pred_eval_prob = model.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)

metrics_report("Test", Y_test.is_attack, y_pred_test, print_avg=False)
plot_confusion_matrix("DNN", Y_test, y_pred_test)
```

```
8847/8847          4s 420us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9813    0.9796    0.9805    227310
           1     0.9175    0.9239    0.9207     55764

    accuracy                         0.9686    283074
   macro avg     0.9494    0.9518    0.9506    283074
weighted avg     0.9687    0.9686    0.9687    283074

Accuracy: 0.9686477740802758
8847/8847          4s 433us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9818    0.9798    0.9808    227310
           1     0.9185    0.9260    0.9222     55765

    accuracy                         0.9692    283075
   macro avg     0.9501    0.9529    0.9515    283075
weighted avg     0.9693    0.9692    0.9693    283075

Accuracy: 0.9692307692307692
```



4.2.1 Hyperparameter Tuning

[37]:

```
def build_model(hp):
    model = Sequential()
    model.add(Dense(units=hp.Int('units_input', min_value=32, max_value=512,␣
↪step=32), activation='relu', input_shape=(X_train.shape[1],)))

    for i in range(hp.Int('num_layers', 1, 3)):
        model.add(Dense(units=hp.Int(f'units_{i}', min_value=32, max_value=512,␣
↪step=32), activation='relu'))
        model.add(Dropout(rate=hp.Float(f'dropout_{i}', min_value=0.0,␣
↪max_value=0.5, step=0.1)))

    model.add(Dense(1, activation='sigmoid'))

    model.compile(
```

```
        optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
 ↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='LOG',␣
 ↪default=1e-3)),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

[52]:
```
from keras_tuner import RandomSearch

directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning')
tuner = RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection'
)

tuner.search_space_summary()

# Perform the search
tuner.search(scaler.transform(X_train), Y_train.is_attack, epochs=10,␣
 ↪validation_split=0.2)
```

```
Reloading Tuner from G:\Other computers\My PC\stage\ML-
NIDS\Notebooks\hyperparam_tuning\intrusion_detection\tuner0.json
Search space summary
Default search space size: 9
units_input (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 1, 'max_value': 3, 'step': 1,
'sampling': 'linear'}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_0 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
```

```
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
```

[39]:

```
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print(best_hps)
model1 = build_model(best_hps)
history = model.fit(scaler.transform(X_train), Y_train.is_attack, epochs=20,
    validation_split=0.2, verbose=1)
```

```
<keras_tuner.src.engine.hyperparameters.hyperparameters.HyperParameters object
at 0x0000015161FA3830>
```

```
C:\Users\youss\AppData\Local\Programs\Python\Python312\Lib\site-
packages\keras\src\layers\core\dense.py:88: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/20
97279/97279            65s
667us/step - accuracy: 0.9579 - loss: 0.1334 - val_accuracy: 0.3554 - val_loss:
5.8488
Epoch 2/20
97279/97279            65s
668us/step - accuracy: 0.9580 - loss: 0.1261 - val_accuracy: 0.3384 - val_loss:
7.1888
Epoch 3/20
97279/97279            65s
670us/step - accuracy: 0.9584 - loss: 0.1040 - val_accuracy: 0.3418 - val_loss:
4.9406
Epoch 4/20
97279/97279            65s
668us/step - accuracy: 0.9583 - loss: 0.1237 - val_accuracy: 0.3384 - val_loss:
5.9503
Epoch 5/20
97279/97279            65s
668us/step - accuracy: 0.9586 - loss: 0.1698 - val_accuracy: 0.3462 - val_loss:
6.6066
Epoch 6/20
97279/97279            65s
666us/step - accuracy: 0.9587 - loss: 0.1062 - val_accuracy: 0.3664 - val_loss:
```

```
6.7357
Epoch 7/20
97279/97279            65s
668us/step - accuracy: 0.9586 - loss: 0.1191 - val_accuracy: 0.3445 - val_loss:
6.9325
Epoch 8/20
97279/97279            65s
667us/step - accuracy: 0.9586 - loss: 0.1078 - val_accuracy: 0.3645 - val_loss:
5.8693
Epoch 9/20
97279/97279            65s
667us/step - accuracy: 0.9586 - loss: 0.2841 - val_accuracy: 0.3554 - val_loss:
6.4449
Epoch 10/20
97279/97279            65s
665us/step - accuracy: 0.9589 - loss: 0.1272 - val_accuracy: 0.3623 - val_loss:
7.7536
Epoch 11/20
97279/97279            65s
665us/step - accuracy: 0.9591 - loss: 0.1058 - val_accuracy: 0.3481 - val_loss:
7.2022
Epoch 12/20
97279/97279            65s
671us/step - accuracy: 0.9593 - loss: 0.1060 - val_accuracy: 0.3884 - val_loss:
7.3497
Epoch 13/20
97279/97279            66s
675us/step - accuracy: 0.9587 - loss: 0.1452 - val_accuracy: 0.3858 - val_loss:
5.5309
Epoch 14/20
97279/97279            66s
676us/step - accuracy: 0.9594 - loss: 0.1067 - val_accuracy: 0.4324 - val_loss:
4.6448
Epoch 15/20
97279/97279            65s
667us/step - accuracy: 0.9589 - loss: 0.1081 - val_accuracy: 0.4341 - val_loss:
3.4974
Epoch 16/20
97279/97279            65s
667us/step - accuracy: 0.9595 - loss: 0.2097 - val_accuracy: 0.4070 - val_loss:
4.3750
Epoch 17/20
97279/97279            66s
673us/step - accuracy: 0.9593 - loss: 0.1092 - val_accuracy: 0.3577 - val_loss:
6.5637
Epoch 18/20
97279/97279            65s
665us/step - accuracy: 0.9596 - loss: 0.1057 - val_accuracy: 0.3408 - val_loss:
```

```
7.4742
Epoch 19/20
97279/97279          65s
669us/step - accuracy: 0.9595 - loss: 0.1479 - val_accuracy: 0.3792 - val_loss:
4.0979
Epoch 20/20
97279/97279          65s
668us/step - accuracy: 0.9592 - loss: 0.1318 - val_accuracy: 0.4012 - val_loss:
7.1979
```

[40]:
```
print(best_hps.values)
```

```
{'units_input': 480, 'num_layers': 2, 'units_0': 448, 'dropout_0':
0.30000000000000004, 'learning_rate': 0.00614260757976685, 'units_1': 224,
'dropout_1': 0.0, 'units_2': 256, 'dropout_2': 0.4}
```

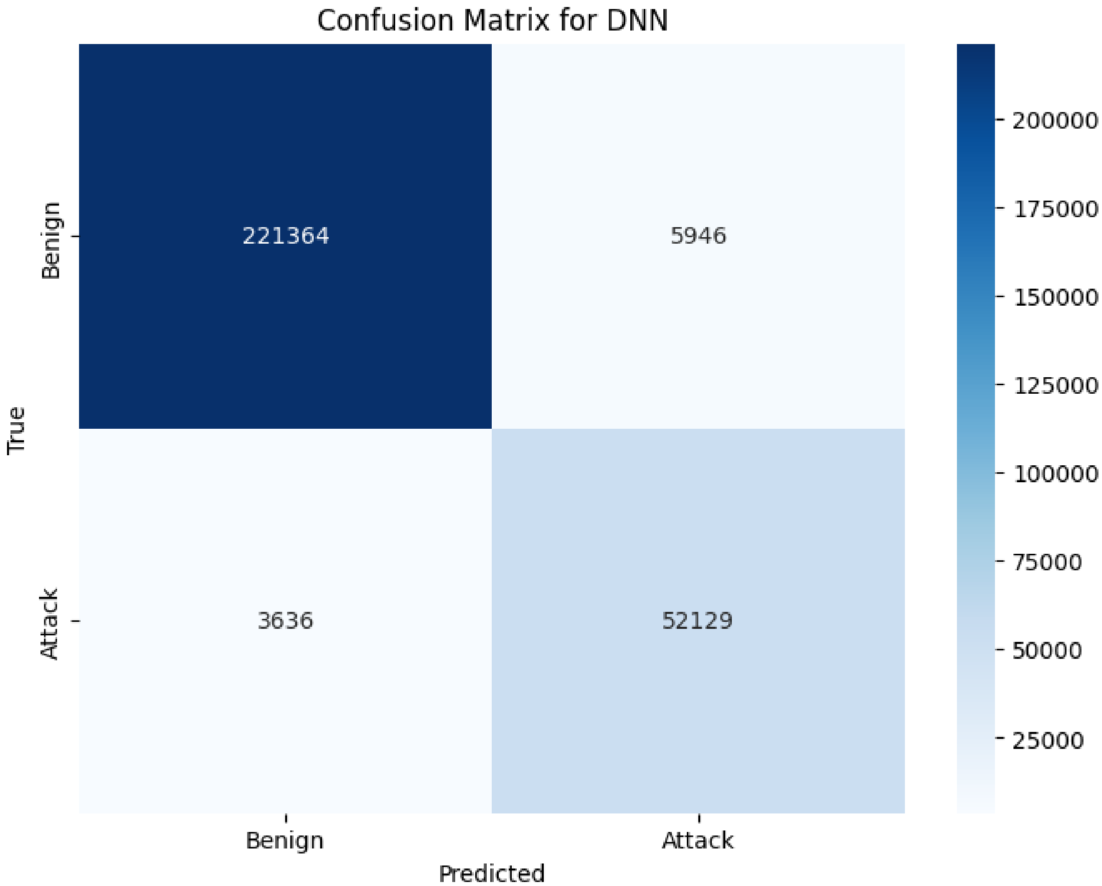
[41]:
```
from tensorflow.keras.models import save_model as save_model_keras

def save_keras_model(model, model_name):
    file_path = f'models/{model_name}.h5'
    save_model_keras(model, file_path)
    print(f'Model saved to {file_path}')

save_keras_model(model, 'DNN_model1')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.

Model saved to models/DNN_model1.h5
```

Best Hyperparameters {'units_input': 480, 'num_layers': 2, 'units_0': 448, 'dropout_0': 0.30000000000000004, 'learning_rate': 0.00614260757976685, 'units_1': 224, 'dropout_1': 0.0, 'units_2': 256, 'dropout_2': 0.4}

[42]:
```
# Predict probabilities on the evaluation set
y_pred_eval_prob = model.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)
# Predict and evaluate on the test set
y_pred_test_prob = model.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)

metrics_report("Test", Y_test.is_attack, y_pred_test, print_avg=False)
plot_confusion_matrix("DNN", Y_test, y_pred_test)
```

```
8847/8847              4s 424us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9833    0.9737    0.9785    227310
           1     0.8969    0.9326    0.9144     55764

    accuracy                         0.9656    283074
   macro avg     0.9401    0.9531    0.9464    283074
weighted avg     0.9663    0.9656    0.9658    283074

Accuracy: 0.9655920360047197
8847/8847              4s 446us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9838    0.9738    0.9788    227310
           1     0.8976    0.9348    0.9158     55765

    accuracy                         0.9662    283075
   macro avg     0.9407    0.9543    0.9473    283075
weighted avg     0.9669    0.9662    0.9664    283075

Accuracy: 0.9661503135211517
```


Confusion Matrix for DNN
221364
5946
3636
52129
True
Benign
Attack
Predicted
Benign
Attack
200000
175000
150000
125000
100000
75000
50000
25000