5_ML_Default_2018

June 17, 2024

1 Machine Learning Models on the IDS 2018

In this notebook, deicision tree and random forest based machine learning algorithms are applied to the ids2018 dataset. Several methods for resolving the class imbalance are tested. Decision tree algorithms were chosen for their effectiveness and the training time which were better than other machine learning models. RT and RF based algorithms performed better in the preliminary experiments

[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,␣
↪recall_score, f1_score, roc_auc_score
from notebook_utils import load_sample_dataset_2018
%matplotlib inline
%load_ext autoreload
%autoreload 2

file_path = r"..\CIC-IDS-2018\Processed Traffic Data for ML Algorithms"

attack_labels = {
    0: 'Benign',
    1: 'Bot',
    2: 'Brute Force -Web',
    3: 'Brute Force -XSS',
    4: 'DDOS attack-HOIC',
    5: 'DDOS attack-LOIC-UDP',
    6: 'DDoS attacks-LOIC-HTTP',
    7: 'DoS attacks-GoldenEye',
```

```
    8: 'DoS attacks-Hulk',
    9: 'DoS attacks-SlowHTTPTest',
    10: 'DoS attacks-Slowloris',
    11: 'FTP-BruteForce',
    12: 'Infilteration',
    13: 'SQL Injection',
    14: 'SSH-Bruteforce'
}

df = load_sample_dataset_2018(file_path)
```

```
Processed 1/10 files.
Processed 2/10 files.
Processed 3/10 files.
Processed 4/10 files.
Processed 5/10 files.
Processed 6/10 files.
Processed 7/10 files.
Processed 8/10 files.
Processed 9/10 files.
Processed 10/10 files.
Creating is_attack column…
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1623303 entries, 0 to 1623302
Data columns (total 81 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   dst_port            1623295 non-null  float64
 1   protocol            1623295 non-null  float64
 2   timestamp           0 non-null        float64
 3   flow_duration       1623295 non-null  float64
 4   tot_fwd_pkts        1623295 non-null  float64
 5   tot_bwd_pkts        1623295 non-null  float64
 6   totlen_fwd_pkts     1623295 non-null  float64
 7   totlen_bwd_pkts     1623295 non-null  float64
 8   fwd_pkt_len_max     1623295 non-null  float64
 9   fwd_pkt_len_min     1623295 non-null  float64
 10  fwd_pkt_len_mean    1623295 non-null  float64
 11  fwd_pkt_len_std     1623295 non-null  float64
 12  bwd_pkt_len_max     1623295 non-null  float64
 13  bwd_pkt_len_min     1623295 non-null  float64
 14  bwd_pkt_len_mean    1623295 non-null  float64
 15  bwd_pkt_len_std     1623295 non-null  float64
 16  flow_byts_s         1617377 non-null  float64
 17  flow_pkts_s         1623295 non-null  float64
 18  flow_iat_mean       1623295 non-null  float64
 19  flow_iat_std        1623295 non-null  float64
 20  flow_iat_max        1623295 non-null  float64
```

21	flow_iat_min	1623295	non-null	float64
22	fwd_iat_tot	1623295	non-null	float64
23	fwd_iat_mean	1623295	non-null	float64
24	fwd_iat_std	1623295	non-null	float64
25	fwd_iat_max	1623295	non-null	float64
26	fwd_iat_min	1623295	non-null	float64
27	bwd_iat_tot	1623295	non-null	float64
28	bwd_iat_mean	1623295	non-null	float64
29	bwd_iat_std	1623295	non-null	float64
30	bwd_iat_max	1623295	non-null	float64
31	bwd_iat_min	1623295	non-null	float64
32	fwd_psh_flags	1623295	non-null	float64
33	bwd_psh_flags	1623295	non-null	float64
34	fwd_urg_flags	1623295	non-null	float64
35	bwd_urg_flags	1623295	non-null	float64
36	fwd_header_len	1623295	non-null	float64
37	bwd_header_len	1623295	non-null	float64
38	fwd_pkts_s	1623295	non-null	float64
39	bwd_pkts_s	1623295	non-null	float64
40	pkt_len_min	1623295	non-null	float64
41	pkt_len_max	1623295	non-null	float64
42	pkt_len_mean	1623295	non-null	float64
43	pkt_len_std	1623295	non-null	float64
44	pkt_len_var	1623295	non-null	float64
45	fin_flag_cnt	1623295	non-null	float64
46	syn_flag_cnt	1623295	non-null	float64
47	rst_flag_cnt	1623295	non-null	float64
48	psh_flag_cnt	1623295	non-null	float64
49	ack_flag_cnt	1623295	non-null	float64
50	urg_flag_cnt	1623295	non-null	float64
51	cwe_flag_count	1623295	non-null	float64
52	ece_flag_cnt	1623295	non-null	float64
53	down_up_ratio	1623295	non-null	float64
54	pkt_size_avg	1623295	non-null	float64
55	fwd_seg_size_avg	1623295	non-null	float64
56	bwd_seg_size_avg	1623295	non-null	float64
57	fwd_byts_b_avg	1623295	non-null	float64
58	fwd_pkts_b_avg	1623295	non-null	float64
59	fwd_blk_rate_avg	1623295	non-null	float64
60	bwd_byts_b_avg	1623295	non-null	float64
61	bwd_pkts_b_avg	1623295	non-null	float64
62	bwd_blk_rate_avg	1623295	non-null	float64
63	subflow_fwd_pkts	1623295	non-null	float64
64	subflow_fwd_byts	1623295	non-null	float64
65	subflow_bwd_pkts	1623295	non-null	float64
66	subflow_bwd_byts	1623295	non-null	float64
67	init_fwd_win_byts	1623295	non-null	float64
68	init_bwd_win_byts	1623295	non-null	float64

```
 69  fwd_act_data_pkts  1623295 non-null  float64
 70  fwd_seg_size_min   1623295 non-null  float64
 71  active_mean        1623295 non-null  float64
 72  active_std         1623295 non-null  float64
 73  active_max         1623295 non-null  float64
 74  active_min         1623295 non-null  float64
 75  idle_mean          1623295 non-null  float64
 76  idle_std           1623295 non-null  float64
 77  idle_max           1623295 non-null  float64
 78  idle_min           1623295 non-null  float64
 79  label              1623303 non-null  category
 80  is_attack          1623303 non-null  int64
dtypes: category(1), float64(79), int64(1)
memory usage: 992.3 MB
None
```

1.1 Preparing the Dataset

1.1.1 Check for invalid values

[2]:
```
# Select only numeric columns
numeric_columns = df.select_dtypes(include=[np.number]).columns
# Identify columns with NaN, infinity, or negative values
nan_columns = df[numeric_columns].columns[df[numeric_columns].isna().any()]
inf_columns = df[numeric_columns].columns[np.isinf(df[numeric_columns]).any()]
neg_columns = df[numeric_columns].columns[(df[numeric_columns] < 0).any()]
print("Columns with NaN values:", nan_columns.tolist())
print("Columns with infinite values:", inf_columns.tolist())
print("Columns with negative values:", neg_columns.tolist())
# Calculate the percentage of NaN, infinite, and negative values
nan_percentage = df[nan_columns].isna().mean() * 100
# nan_percentage = nan_percentage[nan_percentage > 1]
inf_percentage = df[inf_columns].map(lambda x: np.isinf(x)).mean() * 100
neg_percentage = df[neg_columns].map(lambda x: x < 0).mean() * 100
print("Percentage of NaN values in each column:\n", nan_percentage)
print("Percentage of infinite values in each column:\n", inf_percentage)
print("Percentage of negative values in each column:\n", neg_percentage)
```

```
Columns with NaN values: ['dst_port', 'protocol', 'timestamp', 'flow_duration',
'tot_fwd_pkts', 'tot_bwd_pkts', 'totlen_fwd_pkts', 'totlen_bwd_pkts',
'fwd_pkt_len_max', 'fwd_pkt_len_min', 'fwd_pkt_len_mean', 'fwd_pkt_len_std',
'bwd_pkt_len_max', 'bwd_pkt_len_min', 'bwd_pkt_len_mean', 'bwd_pkt_len_std',
'flow_byts_s', 'flow_pkts_s', 'flow_iat_mean', 'flow_iat_std', 'flow_iat_max',
'flow_iat_min', 'fwd_iat_tot', 'fwd_iat_mean', 'fwd_iat_std', 'fwd_iat_max',
'fwd_iat_min', 'bwd_iat_tot', '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_len', 'bwd_header_len', 'fwd_pkts_s', 'bwd_pkts_s',
'pkt_len_min', 'pkt_len_max', 'pkt_len_mean', 'pkt_len_std', 'pkt_len_var',
'fin_flag_cnt', 'syn_flag_cnt', 'rst_flag_cnt', 'psh_flag_cnt', 'ack_flag_cnt',
```

```
'urg_flag_cnt', 'cwe_flag_count', 'ece_flag_cnt', 'down_up_ratio',
'pkt_size_avg', 'fwd_seg_size_avg', 'bwd_seg_size_avg', 'fwd_byts_b_avg',
'fwd_pkts_b_avg', 'fwd_blk_rate_avg', 'bwd_byts_b_avg', 'bwd_pkts_b_avg',
'bwd_blk_rate_avg', 'subflow_fwd_pkts', 'subflow_fwd_byts', 'subflow_bwd_pkts',
'subflow_bwd_byts', 'init_fwd_win_byts', 'init_bwd_win_byts',
'fwd_act_data_pkts', 'fwd_seg_size_min', 'active_mean', 'active_std',
'active_max', 'active_min', 'idle_mean', 'idle_std', 'idle_max', 'idle_min']
Columns with infinite values: ['flow_byts_s', 'flow_pkts_s']
Columns with negative values: ['flow_duration', 'flow_pkts_s', 'flow_iat_mean',
'flow_iat_min', 'fwd_iat_tot', 'fwd_iat_mean', 'fwd_iat_min',
'init_fwd_win_byts', 'init_bwd_win_byts']
Percentage of NaN values in each column:
 dst_port            0.000493
protocol            0.000493
timestamp         100.000000
flow_duration       0.000493
tot_fwd_pkts        0.000493
                      …
active_min          0.000493
idle_mean           0.000493
idle_std            0.000493
idle_max            0.000493
idle_min            0.000493
Length: 79, dtype: float64
Percentage of infinite values in each column:
 flow_byts_s    0.219182
flow_pkts_s    0.583746
dtype: float64
Percentage of negative values in each column:
 flow_duration         0.000123
flow_pkts_s           0.000123
flow_iat_mean         0.000123
flow_iat_min          0.000123
fwd_iat_tot           0.000123
fwd_iat_mean          0.000123
fwd_iat_min           0.000123
init_fwd_win_byts    27.295235
init_bwd_win_byts    50.867888
dtype: float64
```

For negative values, 2 columns have an extremely high percentage of negative values. We choose to drop the features “init_win_bytes_forward” and “init_win_bytes_backward” as the source of the negative sign is unknown. For the rest of relevant features, the percentages of negative, infinite or are low so the rows are dropped.

[3]:
```
def replace_invalid(df):
    # Select only numeric columns
    numeric_columns = df.select_dtypes(include=[np.number]).columns
```

```
    # Identify columns with NaN, infinite, or negative values
    nan_columns = df[numeric_columns].columns[df[numeric_columns].isna().any()]
    inf_columns = df[numeric_columns].columns[np.isinf(df[numeric_columns]).
 ↪any()]
    neg_columns = df[numeric_columns].columns[(df[numeric_columns] < 0).any()]
    # Drop rows with NaN values (low percentage of NaN values)
    # df = df.dropna(subset=nan_columns)
    # Drop rows with infinite values (assuming low percentage)
    for col in inf_columns:
        df = df[np.isfinite(df[col])]
    # Drop columns with a high percentage of negative values
    columns_to_drop = ['init_fwd_win_byts', 'init_bwd_win_byts']
    df = df.drop(columns=columns_to_drop)
    # Drop rows with negative values in the remaining columns
    remaining_neg_columns = [col for col in neg_columns if col not in␣
 ↪columns_to_drop]
    for col in remaining_neg_columns:
        df = df[df[col] >= 0]
    return df
```

[4]:
```
df = replace_invalid(df)
```

[5]:
```
X = df.iloc[:, 0:76]
Y = df[["label", "is_attack", "label_code"]]

X.info()
Y.info()
print(Y.label.value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1613823 entries, 0 to 1250804
Data columns (total 76 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   dst_port            1613823 non-null  float64
 1   protocol            1613823 non-null  float64
 2   timestamp           0 non-null        float64
 3   flow_duration       1613823 non-null  float64
 4   tot_fwd_pkts        1613823 non-null  float64
 5   tot_bwd_pkts        1613823 non-null  float64
 6   totlen_fwd_pkts     1613823 non-null  float64
 7   totlen_bwd_pkts     1613823 non-null  float64
 8   fwd_pkt_len_max     1613823 non-null  float64
 9   fwd_pkt_len_min     1613823 non-null  float64
 10  fwd_pkt_len_mean    1613823 non-null  float64
 11  fwd_pkt_len_std     1613823 non-null  float64
 12  bwd_pkt_len_max     1613823 non-null  float64
 13  bwd_pkt_len_min     1613823 non-null  float64
```

```
14  bwd_pkt_len_mean   1613823 non-null  float64
15  bwd_pkt_len_std    1613823 non-null  float64
16  flow_byts_s        1613823 non-null  float64
17  flow_pkts_s        1613823 non-null  float64
18  flow_iat_mean      1613823 non-null  float64
19  flow_iat_std       1613823 non-null  float64
20  flow_iat_max       1613823 non-null  float64
21  flow_iat_min       1613823 non-null  float64
22  fwd_iat_tot        1613823 non-null  float64
23  fwd_iat_mean       1613823 non-null  float64
24  fwd_iat_std        1613823 non-null  float64
25  fwd_iat_max        1613823 non-null  float64
26  fwd_iat_min        1613823 non-null  float64
27  bwd_iat_tot        1613823 non-null  float64
28  bwd_iat_mean       1613823 non-null  float64
29  bwd_iat_std        1613823 non-null  float64
30  bwd_iat_max        1613823 non-null  float64
31  bwd_iat_min        1613823 non-null  float64
32  fwd_psh_flags      1613823 non-null  float64
33  bwd_psh_flags      1613823 non-null  float64
34  fwd_urg_flags      1613823 non-null  float64
35  bwd_urg_flags      1613823 non-null  float64
36  fwd_header_len     1613823 non-null  float64
37  bwd_header_len     1613823 non-null  float64
38  fwd_pkts_s         1613823 non-null  float64
39  bwd_pkts_s         1613823 non-null  float64
40  pkt_len_min        1613823 non-null  float64
41  pkt_len_max        1613823 non-null  float64
42  pkt_len_mean       1613823 non-null  float64
43  pkt_len_std        1613823 non-null  float64
44  pkt_len_var        1613823 non-null  float64
45  fin_flag_cnt       1613823 non-null  float64
46  syn_flag_cnt       1613823 non-null  float64
47  rst_flag_cnt       1613823 non-null  float64
48  psh_flag_cnt       1613823 non-null  float64
49  ack_flag_cnt       1613823 non-null  float64
50  urg_flag_cnt       1613823 non-null  float64
51  cwe_flag_count     1613823 non-null  float64
52  ece_flag_cnt       1613823 non-null  float64
53  down_up_ratio      1613823 non-null  float64
54  pkt_size_avg       1613823 non-null  float64
55  fwd_seg_size_avg   1613823 non-null  float64
56  bwd_seg_size_avg   1613823 non-null  float64
57  fwd_byts_b_avg     1613823 non-null  float64
58  fwd_pkts_b_avg     1613823 non-null  float64
59  fwd_blk_rate_avg   1613823 non-null  float64
60  bwd_byts_b_avg     1613823 non-null  float64
61  bwd_pkts_b_avg     1613823 non-null  float64
```

```
 62  bwd_blk_rate_avg   1613823 non-null  float64
 63  subflow_fwd_pkts   1613823 non-null  float64
 64  subflow_fwd_byts   1613823 non-null  float64
 65  subflow_bwd_pkts   1613823 non-null  float64
 66  subflow_bwd_byts   1613823 non-null  float64
 67  fwd_act_data_pkts  1613823 non-null  float64
 68  fwd_seg_size_min   1613823 non-null  float64
 69  active_mean        1613823 non-null  float64
 70  active_std         1613823 non-null  float64
 71  active_max         1613823 non-null  float64
 72  active_min         1613823 non-null  float64
 73  idle_mean          1613823 non-null  float64
 74  idle_std           1613823 non-null  float64
 75  idle_max           1613823 non-null  float64
dtypes: float64(76)
memory usage: 948.1 MB
<class 'pandas.core.frame.DataFrame'>
Index: 1613823 entries, 0 to 1250804
Data columns (total 3 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   label       1613823 non-null  category
 1   is_attack   1613823 non-null  int64
 2   label_code  1613823 non-null  int32
dtypes: category(1), int32(1), int64(1)
memory usage: 32.3 MB
label
Benign                      1338596
DDOS attack-HOIC              68817
DDoS attacks-LOIC-HTTP        57678
DoS attacks-Hulk              46307
Bot                           28759
FTP-BruteForce                19396
SSH-Bruteforce                18759
Infilteration                 15952
DoS attacks-SlowHTTPTest      14029
DoS attacks-GoldenEye          4215
DoS attacks-Slowloris          1055
DDOS attack-LOIC-UDP            168
Brute Force -Web                 53
Brute Force -XSS                 27
SQL Injection                    12
Label                             0
Name: count, dtype: int64
```

1.2 Feature Selection

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

[6]:

```
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_byts_b_avg', 'fwd_pkts_b_avg',
'fwd_blk_rate_avg', 'bwd_byts_b_avg', 'bwd_pkts_b_avg', 'bwd_blk_rate_avg']
```

[7]:

```
X = X.drop(columns=features_no_var)
X = X.drop(columns=['dst_port', 'timestamp'])
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1613823 entries, 0 to 1250804
Data columns (total 66 columns):
 #   Column             Non-Null Count    Dtype
---  ------             --------------    -----
 0   protocol           1613823 non-null  float64
 1   flow_duration      1613823 non-null  float64
 2   tot_fwd_pkts       1613823 non-null  float64
 3   tot_bwd_pkts       1613823 non-null  float64
 4   totlen_fwd_pkts    1613823 non-null  float64
 5   totlen_bwd_pkts    1613823 non-null  float64
 6   fwd_pkt_len_max    1613823 non-null  float64
 7   fwd_pkt_len_min    1613823 non-null  float64
 8   fwd_pkt_len_mean   1613823 non-null  float64
 9   fwd_pkt_len_std    1613823 non-null  float64
 10  bwd_pkt_len_max    1613823 non-null  float64
 11  bwd_pkt_len_min    1613823 non-null  float64
 12  bwd_pkt_len_mean   1613823 non-null  float64
 13  bwd_pkt_len_std    1613823 non-null  float64
 14  flow_byts_s        1613823 non-null  float64
 15  flow_pkts_s        1613823 non-null  float64
 16  flow_iat_mean      1613823 non-null  float64
 17  flow_iat_std       1613823 non-null  float64
 18  flow_iat_max       1613823 non-null  float64
 19  flow_iat_min       1613823 non-null  float64
 20  fwd_iat_tot        1613823 non-null  float64
 21  fwd_iat_mean       1613823 non-null  float64
 22  fwd_iat_std        1613823 non-null  float64
 23  fwd_iat_max        1613823 non-null  float64
 24  fwd_iat_min        1613823 non-null  float64
 25  bwd_iat_tot        1613823 non-null  float64
 26  bwd_iat_mean       1613823 non-null  float64
```

```
 27   bwd_iat_std         1613823 non-null  float64
 28   bwd_iat_max         1613823 non-null  float64
 29   bwd_iat_min         1613823 non-null  float64
 30   fwd_psh_flags       1613823 non-null  float64
 31   fwd_urg_flags       1613823 non-null  float64
 32   fwd_header_len      1613823 non-null  float64
 33   bwd_header_len      1613823 non-null  float64
 34   fwd_pkts_s          1613823 non-null  float64
 35   bwd_pkts_s          1613823 non-null  float64
 36   pkt_len_min         1613823 non-null  float64
 37   pkt_len_max         1613823 non-null  float64
 38   pkt_len_mean        1613823 non-null  float64
 39   pkt_len_std         1613823 non-null  float64
 40   pkt_len_var         1613823 non-null  float64
 41   fin_flag_cnt        1613823 non-null  float64
 42   syn_flag_cnt        1613823 non-null  float64
 43   rst_flag_cnt        1613823 non-null  float64
 44   psh_flag_cnt        1613823 non-null  float64
 45   ack_flag_cnt        1613823 non-null  float64
 46   urg_flag_cnt        1613823 non-null  float64
 47   cwe_flag_count      1613823 non-null  float64
 48   ece_flag_cnt        1613823 non-null  float64
 49   down_up_ratio       1613823 non-null  float64
 50   pkt_size_avg        1613823 non-null  float64
 51   fwd_seg_size_avg    1613823 non-null  float64
 52   bwd_seg_size_avg    1613823 non-null  float64
 53   subflow_fwd_pkts    1613823 non-null  float64
 54   subflow_fwd_byts    1613823 non-null  float64
 55   subflow_bwd_pkts    1613823 non-null  float64
 56   subflow_bwd_byts    1613823 non-null  float64
 57   fwd_act_data_pkts   1613823 non-null  float64
 58   fwd_seg_size_min    1613823 non-null  float64
 59   active_mean         1613823 non-null  float64
 60   active_std          1613823 non-null  float64
 61   active_max          1613823 non-null  float64
 62   active_min          1613823 non-null  float64
 63   idle_mean           1613823 non-null  float64
 64   idle_std            1613823 non-null  float64
 65   idle_max            1613823 non-null  float64
dtypes: float64(66)
memory usage: 824.9 MB
```

1.2.1 Remove collinear variables

[8]:
```
def correlation_feature_selection(df, threshold=0.95):
    corr_matrix = df.corr().abs()
```

```
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).
↪astype(bool))
    to_drop = [column for column in upper.columns if any(upper[column] >␣
↪threshold)]
    return df.drop(columns=to_drop)
X = correlation_feature_selection(X)
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1613823 entries, 0 to 1250804
Data columns (total 41 columns):
 #   Column            Non-Null Count    Dtype
---  ------            --------------    -----
 0   protocol          1613823 non-null  float64
 1   flow_duration     1613823 non-null  float64
 2   tot_fwd_pkts      1613823 non-null  float64
 3   tot_bwd_pkts      1613823 non-null  float64
 4   fwd_pkt_len_max   1613823 non-null  float64
 5   fwd_pkt_len_min   1613823 non-null  float64
 6   fwd_pkt_len_mean  1613823 non-null  float64
 7   bwd_pkt_len_max   1613823 non-null  float64
 8   bwd_pkt_len_min   1613823 non-null  float64
 9   bwd_pkt_len_mean  1613823 non-null  float64
 10  flow_byts_s       1613823 non-null  float64
 11  flow_pkts_s       1613823 non-null  float64
 12  flow_iat_mean     1613823 non-null  float64
 13  flow_iat_std      1613823 non-null  float64
 14  flow_iat_max      1613823 non-null  float64
 15  fwd_iat_std       1613823 non-null  float64
 16  bwd_iat_tot       1613823 non-null  float64
 17  bwd_iat_mean      1613823 non-null  float64
 18  bwd_iat_std       1613823 non-null  float64
 19  bwd_iat_max       1613823 non-null  float64
 20  bwd_iat_min       1613823 non-null  float64
 21  fwd_psh_flags     1613823 non-null  float64
 22  fwd_urg_flags     1613823 non-null  float64
 23  fwd_pkts_s        1613823 non-null  float64
 24  bwd_pkts_s        1613823 non-null  float64
 25  pkt_len_min       1613823 non-null  float64
 26  pkt_len_mean      1613823 non-null  float64
 27  pkt_len_var       1613823 non-null  float64
 28  fin_flag_cnt      1613823 non-null  float64
 29  rst_flag_cnt      1613823 non-null  float64
 30  psh_flag_cnt      1613823 non-null  float64
 31  ack_flag_cnt      1613823 non-null  float64
 32  urg_flag_cnt      1613823 non-null  float64
 33  down_up_ratio     1613823 non-null  float64
```

```
 34  fwd_seg_size_min  1613823 non-null  float64
 35  active_mean       1613823 non-null  float64
 36  active_std        1613823 non-null  float64
 37  active_max        1613823 non-null  float64
 38  active_min        1613823 non-null  float64
 39  idle_mean         1613823 non-null  float64
 40  idle_std          1613823 non-null  float64
dtypes: float64(41)
memory usage: 517.1 MB
```

1.2.2 Information Gain Selection

[9]:

```
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler

def oversample_minority_classes(X, Y, sample_size=1000):
    y=Y["label_code"]
    ros = RandomOverSampler(random_state=42)
    X_resampled, y_resampled = ros.fit_resample(X, y)
    # Create a subset of the oversampled data
    X_sample, _, y_sample, _ = train_test_split(X_resampled, y_resampled,␣
↪train_size=sample_size, stratify=y_resampled, random_state=42)
    return X_sample, y_sample

def information_gain_feature_selection(X, Y, sample_size=1000):
    # Create an oversampled subset of the data
    X_sample, y_sample = oversample_minority_classes(X, Y, sample_size)
    # Create is_attack column based on label_code
    y_sample = (y_sample != 0).astype(int)
    # Perform feature selection on the oversampled subset
    info_gain = mutual_info_classif(X_sample, y_sample)
    info_gain_df = pd.DataFrame({'Feature': X.columns, 'Information Gain':␣
↪info_gain})
    info_gain_df = info_gain_df.sort_values(by='Information Gain',␣
↪ascending=False)
    print(info_gain_df)
    selected_features = info_gain_df[info_gain_df['Information Gain'] >␣
↪0]['Feature'].tolist()
    return selected_features

# Determine the selected features using the oversampled subset
selected_features = information_gain_feature_selection(X, Y)

# Apply the selected features to the main dataset
X = X[selected_features]
```

```python
# Display information about the selected features
X.info()
```

```
              Feature  Information Gain
7     bwd_pkt_len_max          0.098128
27        pkt_len_var          0.084071
4     fwd_pkt_len_max          0.079047
6    fwd_pkt_len_mean          0.075914
9    bwd_pkt_len_mean          0.064383
2        tot_fwd_pkts          0.051284
26       pkt_len_mean          0.050098
1       flow_duration          0.046261
24          bwd_pkts_s          0.045107
14       flow_iat_max          0.043121
13       flow_iat_std          0.040591
34   fwd_seg_size_min          0.040315
8     bwd_pkt_len_min          0.038632
10        flow_byts_s          0.035294
18        bwd_iat_std          0.032327
20        bwd_iat_min          0.030660
23          fwd_pkts_s          0.029708
5     fwd_pkt_len_min          0.027187
12      flow_iat_mean          0.026420
11        flow_pkts_s          0.025621
15        fwd_iat_std          0.023797
3        tot_bwd_pkts          0.022471
16        bwd_iat_tot          0.021173
25        pkt_len_min          0.019351
19        bwd_iat_max          0.015935
17       bwd_iat_mean          0.015099
38         active_min          0.012552
0            protocol          0.011281
37         active_max          0.005979
36         active_std          0.004185
32       urg_flag_cnt          0.001447
39          idle_mean          0.000311
35        active_mean          0.000158
28       fin_flag_cnt          0.000000
29       rst_flag_cnt          0.000000
30       psh_flag_cnt          0.000000
31       ack_flag_cnt          0.000000
33      down_up_ratio          0.000000
22      fwd_urg_flags          0.000000
21      fwd_psh_flags          0.000000
40           idle_std          0.000000
<class 'pandas.core.frame.DataFrame'>
Index: 1613823 entries, 0 to 1250804
Data columns (total 33 columns):
```

```
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   bwd_pkt_len_max  1613823 non-null  float64
 1   pkt_len_var      1613823 non-null  float64
 2   fwd_pkt_len_max  1613823 non-null  float64
 3   fwd_pkt_len_mean 1613823 non-null  float64
 4   bwd_pkt_len_mean 1613823 non-null  float64
 5   tot_fwd_pkts     1613823 non-null  float64
 6   pkt_len_mean     1613823 non-null  float64
 7   flow_duration    1613823 non-null  float64
 8   bwd_pkts_s       1613823 non-null  float64
 9   flow_iat_max     1613823 non-null  float64
 10  flow_iat_std     1613823 non-null  float64
 11  fwd_seg_size_min 1613823 non-null  float64
 12  bwd_pkt_len_min  1613823 non-null  float64
 13  flow_byts_s      1613823 non-null  float64
 14  bwd_iat_std      1613823 non-null  float64
 15  bwd_iat_min      1613823 non-null  float64
 16  fwd_pkts_s       1613823 non-null  float64
 17  fwd_pkt_len_min  1613823 non-null  float64
 18  flow_iat_mean    1613823 non-null  float64
 19  flow_pkts_s      1613823 non-null  float64
 20  fwd_iat_std      1613823 non-null  float64
 21  tot_bwd_pkts     1613823 non-null  float64
 22  bwd_iat_tot      1613823 non-null  float64
 23  pkt_len_min      1613823 non-null  float64
 24  bwd_iat_max      1613823 non-null  float64
 25  bwd_iat_mean     1613823 non-null  float64
 26  active_min       1613823 non-null  float64
 27  protocol         1613823 non-null  float64
 28  active_max       1613823 non-null  float64
 29  active_std       1613823 non-null  float64
 30  urg_flag_cnt     1613823 non-null  float64
 31  idle_mean        1613823 non-null  float64
 32  active_mean      1613823 non-null  float64
dtypes: float64(33)
memory usage: 418.6 MB
```

1.3 Split Dataset

The dataset is split into a training set and a testing set with a ratio of 0.8/0.2. The dataset is stratified according to the label to have an equal representation of all classes in the 2 subsets.

[10]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪stratify=Y.label)
```

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

[11]:
```
label
Benign                       1070876
DDOS attack-HOIC               55054
DDoS attacks-LOIC-HTTP         46142
DoS attacks-Hulk               37046
Bot                            23007
FTP-BruteForce                 15517
SSH-Bruteforce                 15007
Infilteration                  12762
DoS attacks-SlowHTTPTest       11223
DoS attacks-GoldenEye           3372
DoS attacks-Slowloris            844
DDOS attack-LOIC-UDP             134
Brute Force -Web                  42
Brute Force -XSS                  22
SQL Injection                     10
Label                              0
Name: count, dtype: int64
```

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

[12]:
```
label
Benign                      267720
DDOS attack-HOIC             13763
DDoS attacks-LOIC-HTTP       11536
DoS attacks-Hulk              9261
Bot                           5752
FTP-BruteForce                3879
SSH-Bruteforce                3752
Infilteration                 3190
DoS attacks-SlowHTTPTest      2806
DoS attacks-GoldenEye          843
DoS attacks-Slowloris          211
DDOS attack-LOIC-UDP            34
Brute Force -Web                11
Brute Force -XSS                 5
SQL Injection                    2
Label                            0
Name: count, dtype: int64
```

[13]:
```
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: 0.0000
is_attack
0    1070876
1     220182
```

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

1.4 Machine Learning Classifiers with Default Hyperparameters

1.4.1 Helper Functions

[14]:
```
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)
```

[15]:
```
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))
    accuracy = accuracy_score(y_true, y_predict)
    precision = precision_score(y_true, y_predict, average='weighted')
    recall = recall_score(y_true, y_predict, average='weighted')
    f1 = f1_score(y_true, y_predict, average='weighted')
    auc = roc_auc_score(y_true, y_predict)
    print("Accuracy:", accuracy)
    print("Precision:", precision)
    print("Recall:", recall)
    print("F1 Score:", f1)
    print("AUC:", auc)
    return {"accuracy": accuracy, "precision": precision, "recall": recall,␣
↪"f1": f1, "auc": auc}
```

```
def calculate_metrics_by_label(y_true, y_pred, labels):
    results = []
    unique_labels = labels.unique()
    for label in unique_labels:
        indices = labels == label
        accuracy = accuracy_score(y_true[indices], y_pred[indices])
        results.append({
            'Label': label,
            'Accuracy': accuracy,
        })
    return pd.DataFrame(results)
```

[16]:
```
def test_metrics(model_name, model, dataset_type, scaler):
    # Predict and evaluate on the test set
    print(f"{model_name} with {dataset_type} Test Set Performance")
    Y_pred = model.predict(scaler.transform(X_test))
    metrics = metrics_report(f"Test {model_name} ({dataset_type})", Y_test.
 ↪is_attack, Y_pred)
    plot_confusion_matrix(f"{model_name} ({dataset_type})", Y_test, Y_pred)
    # Calculate metrics by label
    metrics_by_label = calculate_metrics_by_label(Y_test.is_attack, Y_pred,␣
 ↪Y_test.label)
    metrics_by_label['Method'] = dataset_type
    print(f"Metrics by Label ({dataset_type}):")
    print(metrics_by_label)
    return metrics, metrics_by_label
```

[17]:
```
def plot_overall_accuracy(metrics):
    methods = ['original', 'random', 'smote', 'adasyn']
    overall_accuracies = []

    # Extract overall accuracy for each method
    for method in methods:
        overall_accuracies.append(metrics[method][0]['accuracy'])

    # Plotting the overall accuracies
    plt.figure(figsize=(10, 6))
    bars = plt.bar(methods, overall_accuracies, color=['blue', 'orange',␣
 ↪'green', 'red'])
    plt.title('Overall Accuracy by Method')
    plt.xlabel('Method')
    plt.ylabel('Accuracy')
    plt.ylim(0.9, 1)
    plt.grid(True)

    # Display the values on each bar
    for bar in bars:
```

```
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width() / 2.0, yval, f'{yval:.3f}',␣
 ↪ha='center', va='bottom')

    plt.show()
```

1.4.2 Resampling methods

[18]:
```
from imblearn.over_sampling import RandomOverSampler, SMOTE, ADASYN

def resample_dataset(X, Y, min_samples, attack_labels, technique='smote'):
    Y = Y.drop(columns=['label'])
    combined = pd.concat([X, Y], axis=1)
    counts = Y['label_code'].value_counts()
    samples_number = {i: max(counts[i], min_samples) for i in np.
 ↪unique(Y['label_code'])}
    combined_array = combined.values
    y_array = Y['label_code'].values

    if technique == 'random':
        resampler = RandomOverSampler(random_state=42,␣
 ↪sampling_strategy=samples_number)
    elif technique == 'smote':
        resampler = SMOTE(random_state=42, sampling_strategy=samples_number,␣
 ↪k_neighbors=5)
    elif technique == 'adasyn':
        resampler = ADASYN(random_state=42, sampling_strategy=samples_number)
    else:
        raise ValueError("Invalid resampling technique. Choose 'random',␣
 ↪'smote', or 'adasyn'.")

    resampled_array, y_resampled = resampler.fit_resample(combined_array,␣
 ↪y_array)
    X_resampled = resampled_array[:, :-Y.shape[1]]
    Y_resampled = resampled_array[:, -Y.shape[1]:]
    X_resampled_df = pd.DataFrame(X_resampled, columns=X.columns)
    Y_resampled_df = pd.DataFrame(Y_resampled, columns=Y.columns)
    Y_resampled_df['label'] = Y_resampled_df['label_code'].map(attack_labels)
    Y_resampled_df['label'] = Y_resampled_df['label'].astype('category')
    return X_resampled_df, Y_resampled_df
```

[19]:
```
X_random_train, Y_random_train = resample_dataset(X_train, Y_train, 100000,␣
 ↪attack_labels, "random")
X_smote_train, Y_smote_train = resample_dataset(X_train, Y_train, 100000,␣
 ↪attack_labels, "smote")
```

```
X_adasyn_train, Y_adasyn_train = resample_dataset(X_train, Y_train, 100000,␣
↪attack_labels, "adasyn")
```

[20]:
```
Y_train.label.value_counts()
```

[20]:
```
label
Benign                      1070876
DDOS attack-HOIC              55054
DDoS attacks-LOIC-HTTP        46142
DoS attacks-Hulk              37046
Bot                           23007
FTP-BruteForce                15517
SSH-Bruteforce                15007
Infilteration                 12762
DoS attacks-SlowHTTPTest      11223
DoS attacks-GoldenEye          3372
DoS attacks-Slowloris           844
DDOS attack-LOIC-UDP            134
Brute Force -Web                 42
Brute Force -XSS                 22
SQL Injection                    10
Label                             0
Name: count, dtype: int64
```

[21]:
```
Y_random_train.label.value_counts()
```

[21]:
```
label
Benign                      1070876
Bot                          100000
Brute Force -Web             100000
Brute Force -XSS             100000
DDOS attack-HOIC             100000
DDOS attack-LOIC-UDP         100000
DDoS attacks-LOIC-HTTP       100000
DoS attacks-GoldenEye        100000
DoS attacks-Hulk             100000
DoS attacks-SlowHTTPTest     100000
DoS attacks-Slowloris        100000
FTP-BruteForce               100000
Infilteration                100000
SSH-Bruteforce               100000
Name: count, dtype: int64
```

[22]:
```
Y_smote_train.label.value_counts()
```

[22]:
```
label
Benign                      1070876
```

```
Bot                             100000
Brute Force -Web                100000
Brute Force -XSS                100000
DDOS attack-HOIC                100000
DDOS attack-LOIC-UDP            100000
DDoS attacks-LOIC-HTTP          100000
DoS attacks-GoldenEye           100000
DoS attacks-Hulk                100000
DoS attacks-SlowHTTPTest        100000
DoS attacks-Slowloris           100000
FTP-BruteForce                  100000
Infilteration                   100000
SSH-Bruteforce                  100000
Name: count, dtype: int64
```

[23]:
```
Y_adasyn_train.label.value_counts()
```

[23]:
```
label
Benign                         1070876
Infilteration                   102574
DoS attacks-GoldenEye           100245
DoS attacks-Slowloris           100008
Brute Force -XSS                100006
DDoS attacks-LOIC-HTTP          100003
SSH-Bruteforce                  100000
FTP-BruteForce                   99999
DDOS attack-LOIC-UDP             99998
DoS attacks-SlowHTTPTest         99997
Brute Force -Web                 99994
Bot                              99985
DDOS attack-HOIC                 99550
DoS attacks-Hulk                 98950
Name: count, dtype: int64
```

1.4.3 Scaling with the Standard Scaler

[24]:
```
# Original X_train
scaler = StandardScaler()
scaler.fit(X_train)
# Random Oversampling
scaler_random = StandardScaler()
scaler_random.fit(X_random_train)
# SMOTE
scaler_smote = StandardScaler()
scaler_smote.fit(X_smote_train)
# ADASYN
scaler_adasyn = StandardScaler()
```

```
scaler_adasyn.fit(X_adasyn_train)
```

[24]: StandardScaler()

1.4.4 Decision Tree

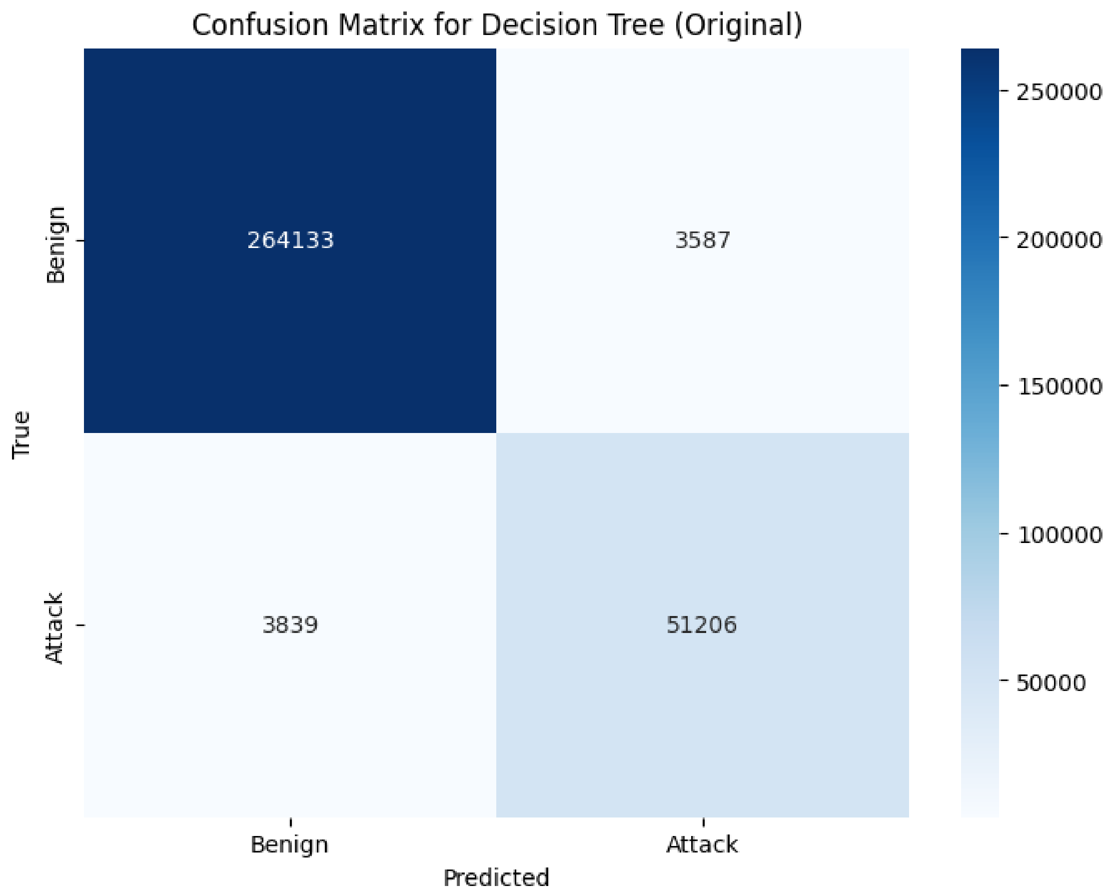
[25]:
```
dt_metrics = {}
```

[26]:
```
decision_tree_model = DecisionTreeClassifier()
decision_tree_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[26]: DecisionTreeClassifier()

[27]:
```
# Predict and evaluate on the test set
dt_metrics["original"] = test_metrics("Decision Tree", decision_tree_model,␣
↪"Original", scaler)
```

```
Decision Tree with Original Test Set Performance
Classification Report (Test Decision Tree (Original)):
              precision    recall  f1-score   support

           0     0.9857    0.9866    0.9861    267720
           1     0.9345    0.9303    0.9324     55045

    accuracy                         0.9770    322765
   macro avg     0.9601    0.9584    0.9593    322765
weighted avg     0.9770    0.9770    0.9770    322765

Accuracy: 0.9769925487583846
Precision: 0.9769526222247139
Recall: 0.9769925487583846
F1 Score: 0.976971567476951
AUC: 0.9584293678967986
```



Metrics by Label (Original):

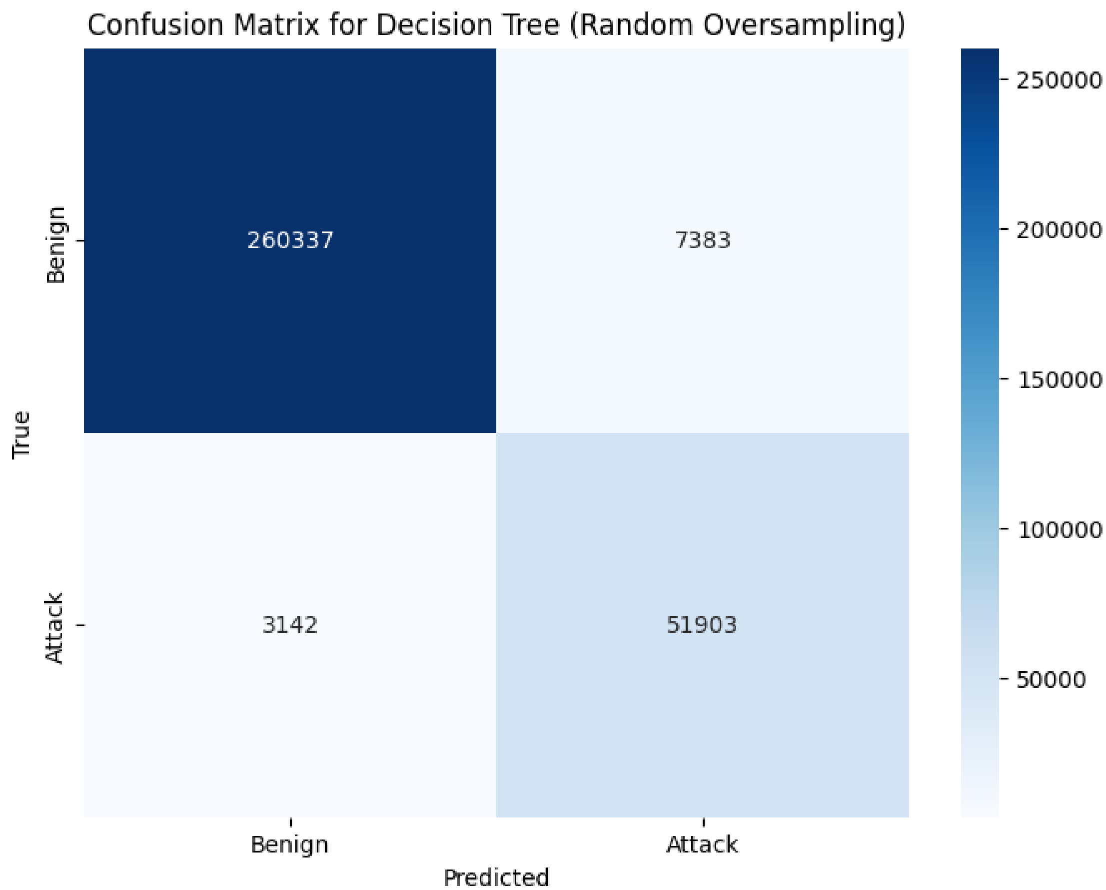
	Label	Accuracy	Method
0	Benign	0.986602	Original
1	DDOS attack-HOIC	0.951609	Original
2	DDoS attacks-LOIC-HTTP	0.981016	Original
3	DoS attacks-Hulk	0.995681	Original
4	DoS attacks-SlowHTTPTest	1.000000	Original
5	SSH-Bruteforce	0.999467	Original
6	FTP-BruteForce	1.000000	Original
7	Infilteration	0.101881	Original
8	DoS attacks-GoldenEye	0.998814	Original
9	Bot	0.994958	Original
10	DDOS attack-LOIC-UDP	1.000000	Original
11	DoS attacks-Slowloris	0.962085	Original
12	Brute Force -Web	0.545455	Original
13	Brute Force -XSS	0.400000	Original
14	SQL Injection	0.500000	Original

[28]:
```
decision_tree_model_random = DecisionTreeClassifier()
decision_tree_model_random.fit(scaler_random.transform(X_random_train),␣
↪Y_random_train.is_attack)
```

[28]: DecisionTreeClassifier()

[29]:
```
# Predict and evaluate on the test set
dt_metrics["random"] = test_metrics("Decision Tree",␣
↪decision_tree_model_random, "Random Oversampling", scaler_random)
```

```
Decision Tree with Random Oversampling Test Set Performance
Classification Report (Test Decision Tree (Random Oversampling)):
              precision    recall  f1-score   support

           0     0.9881    0.9724    0.9802    267720
           1     0.8755    0.9429    0.9079     55045

    accuracy                         0.9674    322765
   macro avg     0.9318    0.9577    0.9441    322765
weighted avg     0.9689    0.9674    0.9679    322765

Accuracy: 0.9673911359657955
Precision: 0.9688707442936672
Recall: 0.9673911359657955
F1 Score: 0.9678657616700608
AUC: 0.9576710549850029
```



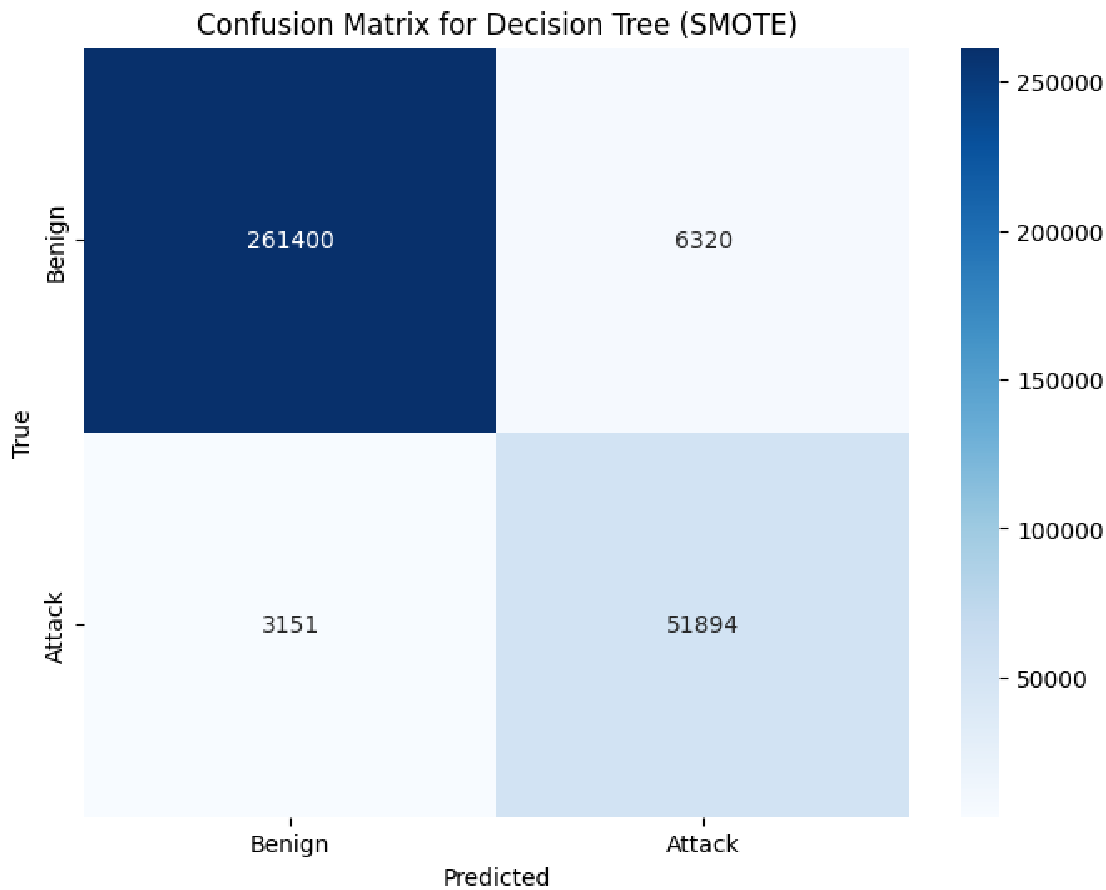

```
Metrics by Label (Random Oversampling):
                        Label  Accuracy             Method
0                      Benign  0.972423  Random Oversampling
1            DDOS attack-HOIC  0.967812  Random Oversampling
2      DDoS attacks-LOIC-HTTP  0.981276  Random Oversampling
3            DoS attacks-Hulk  0.997408  Random Oversampling
4    DoS attacks-SlowHTTPTest  1.000000  Random Oversampling
5              SSH-Bruteforce  0.999733  Random Oversampling
6              FTP-BruteForce  1.000000  Random Oversampling
7                Infilteration  0.239498  Random Oversampling
8       DoS attacks-GoldenEye  1.000000  Random Oversampling
9                         Bot  0.997392  Random Oversampling
10       DDOS attack-LOIC-UDP  1.000000  Random Oversampling
11      DoS attacks-Slowloris  0.952607  Random Oversampling
12           Brute Force -Web  0.545455  Random Oversampling
13           Brute Force -XSS  0.600000  Random Oversampling
14              SQL Injection  1.000000  Random Oversampling
```

[30]:
```
decision_tree_model_smote = DecisionTreeClassifier()
decision_tree_model_smote.fit(scaler_smote.transform(X_smote_train),
    Y_smote_train.is_attack)
```

[30]:
```
DecisionTreeClassifier()
```

[31]:
```
# Predict and evaluate on the test set
dt_metrics["smote"] = test_metrics("Decision Tree", decision_tree_model_smote,
    "SMOTE", scaler_smote)
```

```
Decision Tree with SMOTE Test Set Performance
Classification Report (Test Decision Tree (SMOTE)):
              precision    recall  f1-score   support

           0     0.9881    0.9764    0.9822    267720
           1     0.8914    0.9428    0.9164     55045

    accuracy                         0.9707    322765
   macro avg     0.9398    0.9596    0.9493    322765
weighted avg     0.9716    0.9707    0.9710    322765

Accuracy: 0.9706566697132589
Precision: 0.9716056485978953
Recall: 0.9706566697132589
F1 Score: 0.9709798334183373
AUC: 0.9595745868222374
```



Metrics by Label (SMOTE):

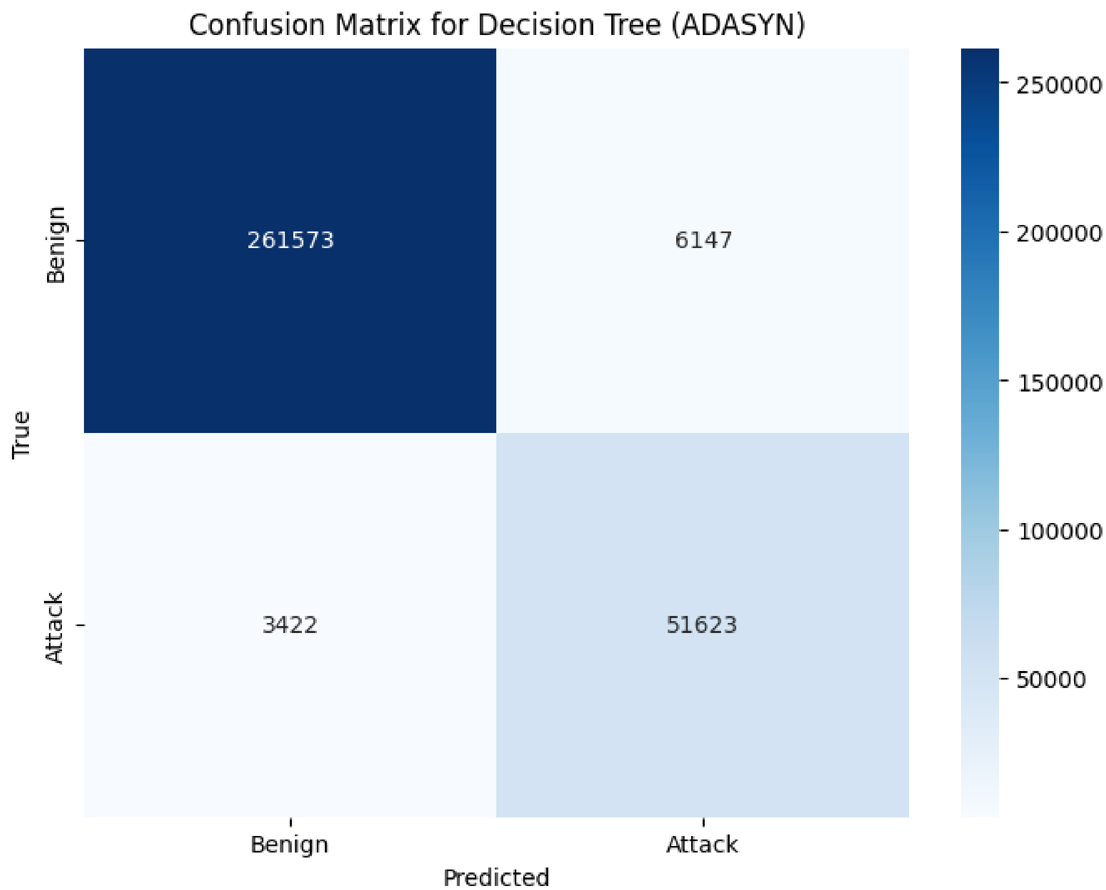
	Label	Accuracy	Method
0	Benign	0.976393	SMOTE
1	DDOS attack-HOIC	0.963017	SMOTE
2	DDoS attacks-LOIC-HTTP	0.984310	SMOTE
3	DoS attacks-Hulk	0.996869	SMOTE
4	DoS attacks-SlowHTTPTest	1.000000	SMOTE
5	SSH-Bruteforce	0.999467	SMOTE
6	FTP-BruteForce	1.000000	SMOTE
7	Infilteration	0.247962	SMOTE
8	DoS attacks-GoldenEye	0.998814	SMOTE
9	Bot	0.996349	SMOTE
10	DDOS attack-LOIC-UDP	1.000000	SMOTE
11	DoS attacks-Slowloris	0.981043	SMOTE
12	Brute Force -Web	0.636364	SMOTE
13	Brute Force -XSS	1.000000	SMOTE
14	SQL Injection	0.500000	SMOTE

[32]:
```
decision_tree_model_adasyn = DecisionTreeClassifier()
decision_tree_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train),␣
↪Y_adasyn_train.is_attack)
```

[32]:
```
DecisionTreeClassifier()
```

[33]:
```
# Predict and evaluate on the test set
dt_metrics["adasyn"] = test_metrics("Decision Tree",␣
↪decision_tree_model_adasyn, "ADASYN", scaler_adasyn)
```

```
Decision Tree with ADASYN Test Set Performance
Classification Report (Test Decision Tree (ADASYN)):
              precision    recall  f1-score   support

           0     0.9871    0.9770    0.9820    267720
           1     0.8936    0.9378    0.9152     55045

    accuracy                         0.9704    322765
   macro avg     0.9403    0.9574    0.9486    322765
weighted avg     0.9711    0.9704    0.9706    322765

Accuracy: 0.9703530432357907
Precision: 0.9711423595361217
Recall: 0.9703530432357907
F1 Score: 0.9706352716478273
AUC: 0.9574360632731159
```



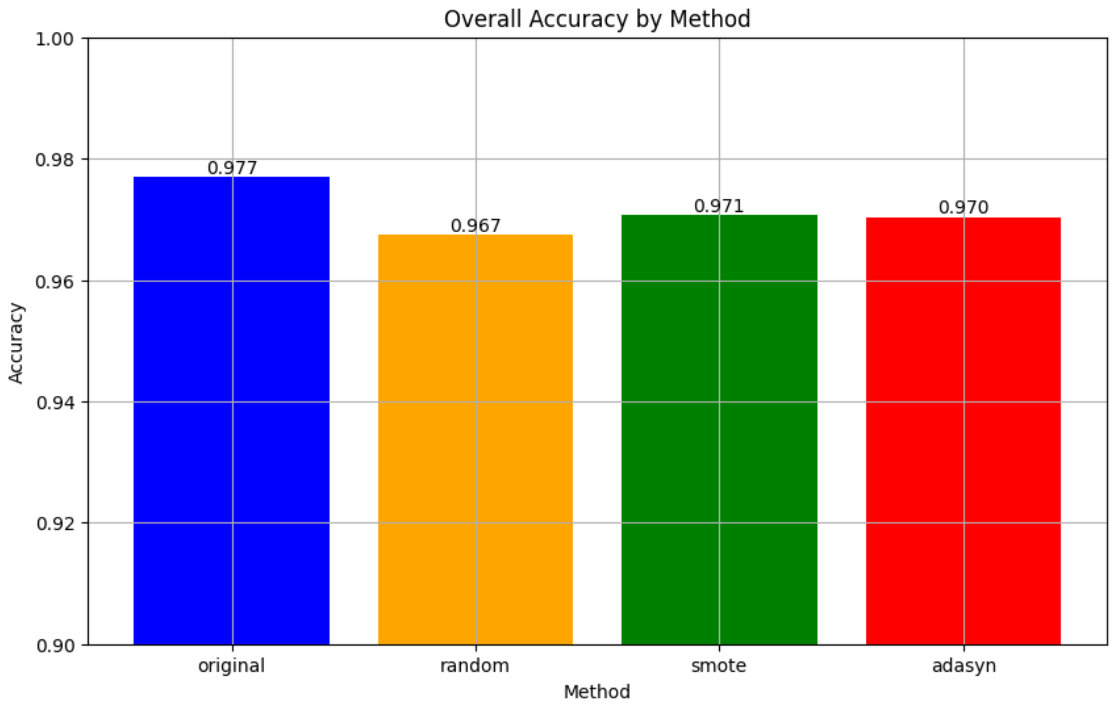
Metrics by Label (ADASYN):

	Label	Accuracy	Method
0	Benign	0.977039	ADASYN
1	DDOS attack-HOIC	0.965124	ADASYN
2	DDoS attacks-LOIC-HTTP	0.991505	ADASYN
3	DoS attacks-Hulk	0.997516	ADASYN
4	DoS attacks-SlowHTTPTest	1.000000	ADASYN
5	SSH-Bruteforce	0.999467	ADASYN
6	FTP-BruteForce	1.000000	ADASYN
7	Infilteration	0.124451	ADASYN
8	DoS attacks-GoldenEye	0.997628	ADASYN
9	Bot	0.998088	ADASYN
10	DDOS attack-LOIC-UDP	1.000000	ADASYN
11	DoS attacks-Slowloris	0.971564	ADASYN
12	Brute Force -Web	0.545455	ADASYN
13	Brute Force -XSS	0.800000	ADASYN
14	SQL Injection	0.500000	ADASYN

```
[34]: # Combine metrics into one DataFrame for Decision Tree
combined_metrics_dt = pd.concat([dt_metrics["adasyn"][1],␣
 ↪dt_metrics["original"][1], dt_metrics["random"][1], dt_metrics["smote"][1]])
# Pivot the table to get accuracy for each method as columns in the specified␣
 ↪order
accuracy_pivot_dt = combined_metrics_dt.pivot(index='Label', columns='Method',␣
 ↪values='Accuracy')
accuracy_pivot_dt = accuracy_pivot_dt[['Original', 'Random Oversampling',␣
 ↪'SMOTE', 'ADASYN']]
print("Accuracy by Label and Method (Decision Tree):")
print(accuracy_pivot_dt)
```

```
Accuracy by Label and Method (Decision Tree):
Method                    Original  Random Oversampling     SMOTE    ADASYN
Label
Benign                    0.986602             0.972423  0.976393  0.977039
Bot                       0.994958             0.997392  0.996349  0.998088
Brute Force -Web          0.545455             0.545455  0.636364  0.545455
Brute Force -XSS          0.400000             0.600000  1.000000  0.800000
DDOS attack-HOIC          0.951609             0.967812  0.963017  0.965124
DDOS attack-LOIC-UDP      1.000000             1.000000  1.000000  1.000000
DDoS attacks-LOIC-HTTP    0.981016             0.981276  0.984310  0.991505
DoS attacks-GoldenEye     0.998814             1.000000  0.998814  0.997628
DoS attacks-Hulk          0.995681             0.997408  0.996869  0.997516
DoS attacks-SlowHTTPTest  1.000000             1.000000  1.000000  1.000000
DoS attacks-Slowloris     0.962085             0.952607  0.981043  0.971564
FTP-BruteForce            1.000000             1.000000  1.000000  1.000000
Infilteration             0.101881             0.239498  0.247962  0.124451
SQL Injection             0.500000             1.000000  0.500000  0.500000
SSH-Bruteforce            0.999467             0.999733  0.999467  0.999467
```

```
[35]: plot_overall_accuracy(dt_metrics)
```



1.4.5 Random Forest

[36]:
```
rf_metrics = {}
```

[37]:
```
rf_model = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model.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:   22.7s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  1.3min finished
```

[37]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

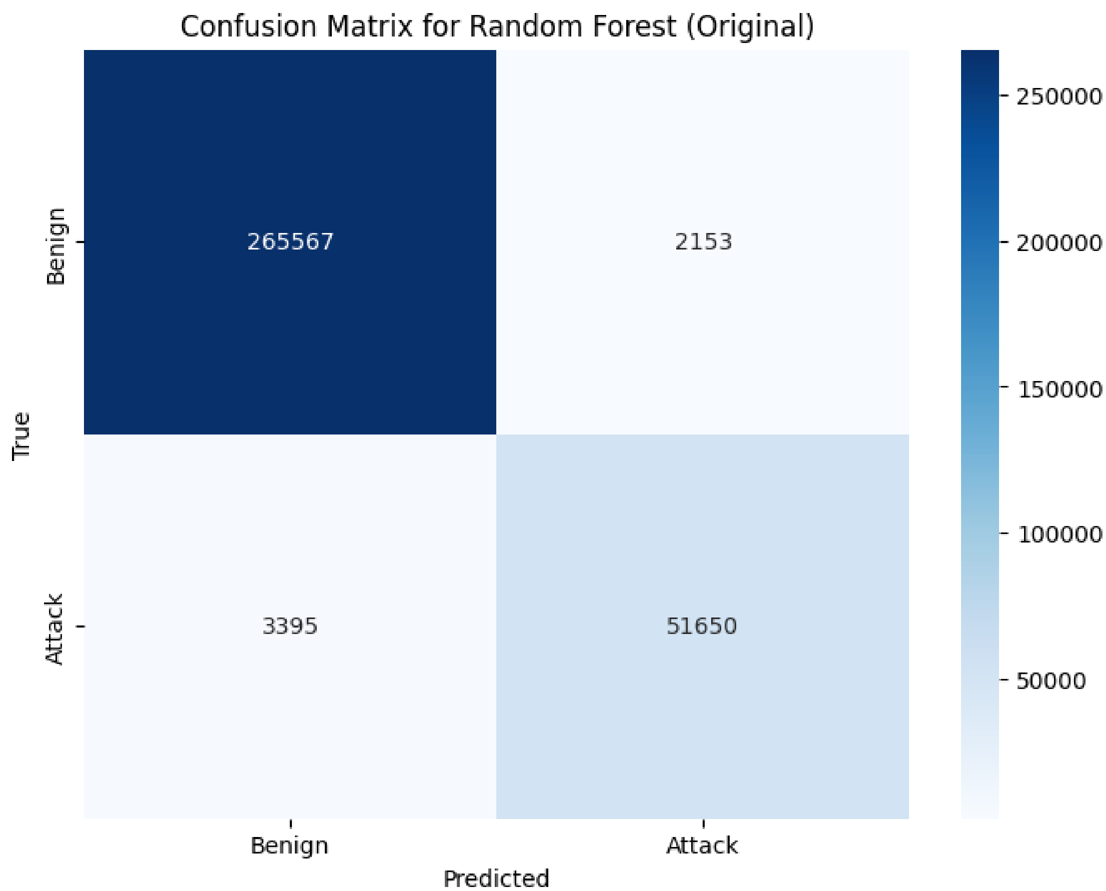
[38]:
```
# Predict and evaluate on the test set
rf_metrics["original"] = test_metrics("Random Forest", rf_model, "Original",␣
 ↪scaler)
```

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

```
Random Forest with Original Test Set Performance
```

```
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.1s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    0.6s finished
```

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

           0     0.9874    0.9920    0.9897    267720
           1     0.9600    0.9383    0.9490     55045

    accuracy                         0.9828    322765
   macro avg     0.9737    0.9651    0.9693    322765
weighted avg     0.9827    0.9828    0.9827    322765

Accuracy: 0.9828110235000697
Precision: 0.9827056123070539
Recall: 0.9828110235000697
F1 Score: 0.9827328464227976
AUC: 0.9651406029773095
```




```
Metrics by Label (Original):
                      Label  Accuracy    Method
0                    Benign  0.991958  Original
```

```
1            DDOS attack-HOIC  0.989029  Original
2       DDoS attacks-LOIC-HTTP  0.986997  Original
3             DoS attacks-Hulk  0.998056  Original
4    DoS attacks-SlowHTTPTest  1.000000  Original
5               SSH-Bruteforce  0.999467  Original
6               FTP-BruteForce  1.000000  Original
7                 Infilteration  0.044828  Original
8       DoS attacks-GoldenEye  1.000000  Original
9                          Bot  0.997914  Original
10       DDOS attack-LOIC-UDP  1.000000  Original
11      DoS attacks-Slowloris  0.971564  Original
12            Brute Force -Web  0.545455  Original
13            Brute Force -XSS  0.400000  Original
14               SQL Injection  0.500000  Original
```

[39]:
```
rf_model_random = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
 ↪is_attack)
```

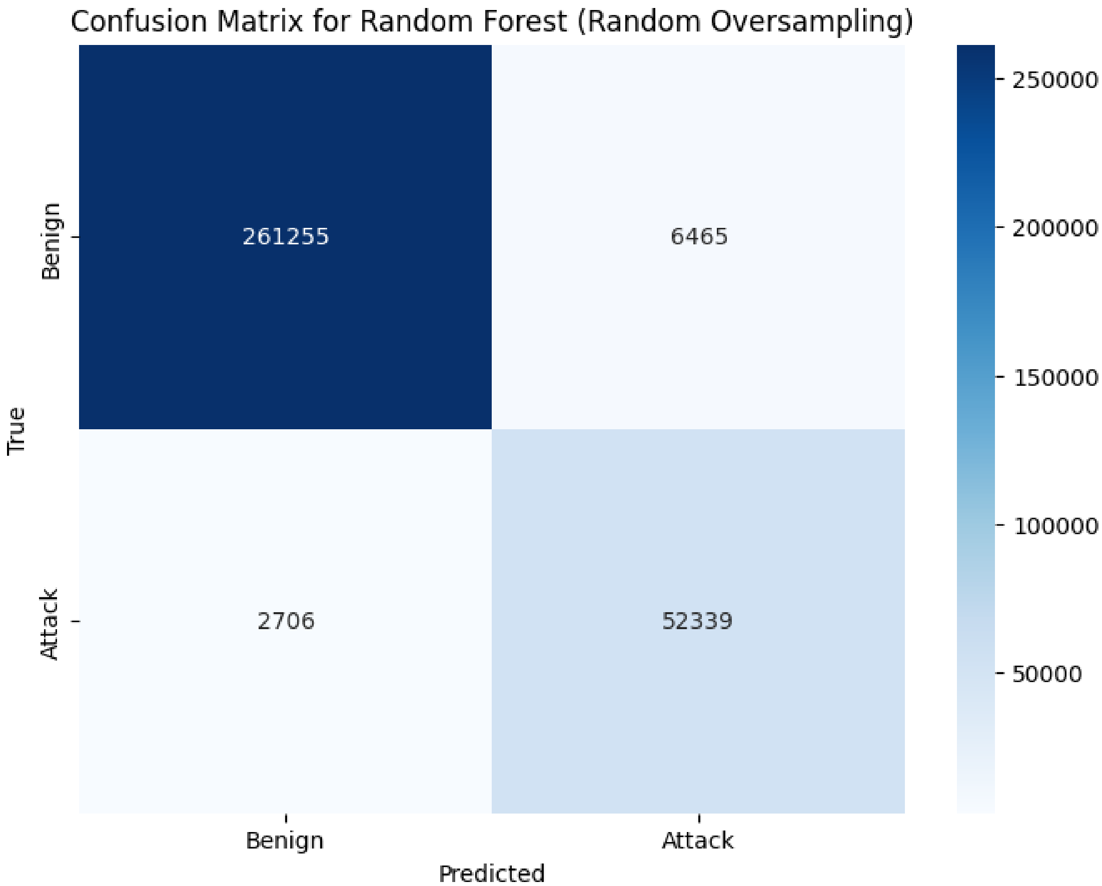
```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   35.1s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.0min finished
```

[39]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[40]:
```
# Predict and evaluate on the test set
rf_metrics["random"] = test_metrics("Random Forest", rf_model_random, "Random␣
 ↪Oversampling", scaler_random)
```

```
Random Forest with Random Oversampling Test Set Performance

[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.1s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    0.6s finished

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

           0     0.9897    0.9759    0.9828    267720
           1     0.8901    0.9508    0.9194     55045

    accuracy                         0.9716    322765
   macro avg     0.9399    0.9633    0.9511    322765
weighted avg     0.9727    0.9716    0.9720    322765

Accuracy: 0.9715861385218347
Precision: 0.972747152441986
Recall: 0.9715861385218347
```

```
F1 Score: 0.9719547712798587
AUC: 0.9633459288372468
```




```
Metrics by Label (Random Oversampling):
                       Label  Accuracy               Method
0                     Benign  0.975852  Random Oversampling
1           DDOS attack-HOIC  0.993388  Random Oversampling
2      DDoS attacks-LOIC-HTTP  0.988211  Random Oversampling
3            DoS attacks-Hulk  0.998380  Random Oversampling
4    DoS attacks-SlowHTTPTest  1.000000  Random Oversampling
5              SSH-Bruteforce  0.999467  Random Oversampling
6              FTP-BruteForce  1.000000  Random Oversampling
7                Infilteration  0.232915  Random Oversampling
8       DoS attacks-GoldenEye  1.000000  Random Oversampling
9                         Bot  0.999478  Random Oversampling
10         DDOS attack-LOIC-UDP  1.000000  Random Oversampling
11      DoS attacks-Slowloris  0.976303  Random Oversampling
12            Brute Force -Web  0.545455  Random Oversampling
13            Brute Force -XSS  0.600000  Random Oversampling
```

```
14             SQL Injection  1.000000  Random Oversampling
```

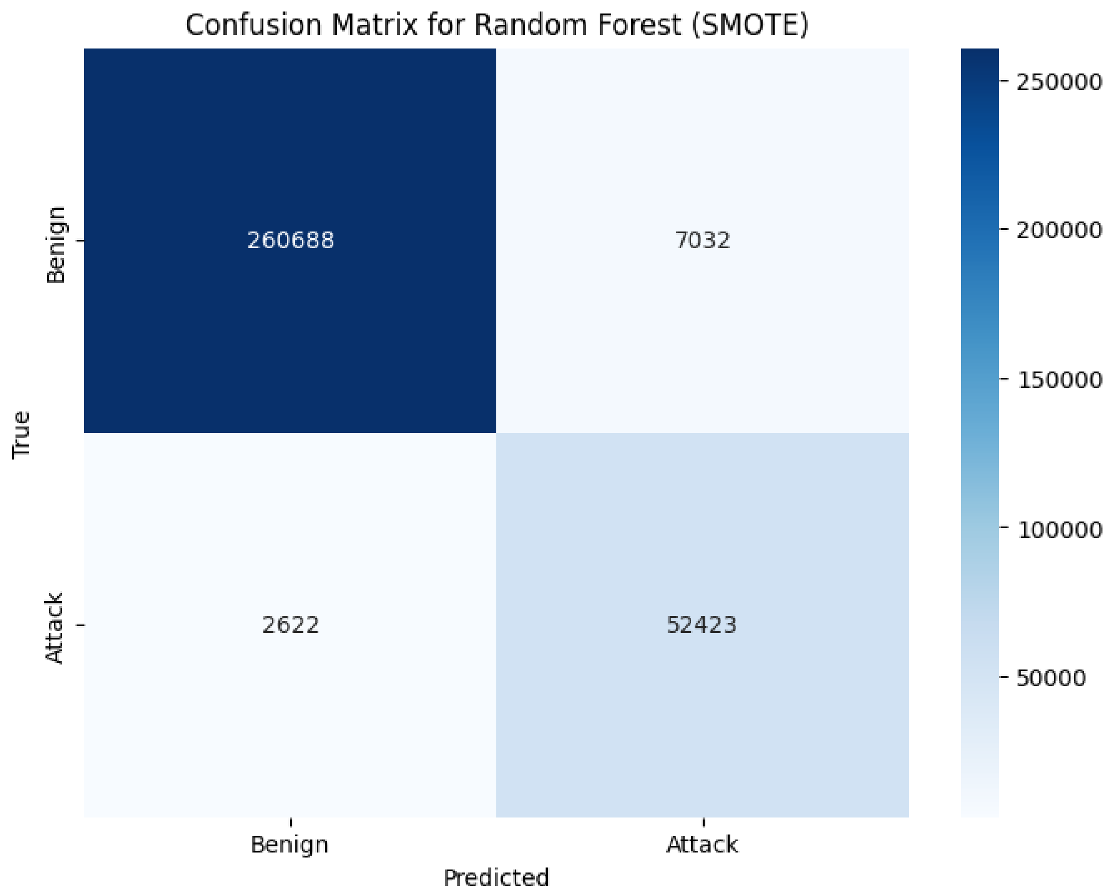
[41]:
```python
rf_model_smote = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
 ↪is_attack)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   37.0s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.1min finished
```

[41]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[42]:
```python
# Predict and evaluate on the test set
rf_metrics["smote"] = test_metrics("Random Forest", rf_model_smote, "SMOTE",␣
 ↪scaler_smote)
```

```
Random Forest with SMOTE 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:    0.8s finished

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

           0     0.9900    0.9737    0.9818    267720
           1     0.8817    0.9524    0.9157     55045

    accuracy                         0.9701    322765
   macro avg     0.9359    0.9630    0.9488    322765
weighted avg     0.9716    0.9701    0.9705    322765


Accuracy: 0.9700896937400276
Precision: 0.9715696425576648
Recall: 0.9700896937400276
F1 Score: 0.9705414989103793
AUC: 0.9630499987398763
```



Metrics by Label (SMOTE):

	Label	Accuracy	Method
0	Benign	0.973734	SMOTE
1	DDOS attack-HOIC	0.994623	SMOTE
2	DDoS attacks-LOIC-HTTP	0.989511	SMOTE
3	DoS attacks-Hulk	0.998596	SMOTE
4	DoS attacks-SlowHTTPTest	1.000000	SMOTE
5	SSH-Bruteforce	0.999467	SMOTE
6	FTP-BruteForce	1.000000	SMOTE
7	Infilteration	0.247962	SMOTE
8	DoS attacks-GoldenEye	1.000000	SMOTE
9	Bot	0.999478	SMOTE
10	DDOS attack-LOIC-UDP	1.000000	SMOTE
11	DoS attacks-Slowloris	0.981043	SMOTE
12	Brute Force -Web	0.727273	SMOTE
13	Brute Force -XSS	0.600000	SMOTE
14	SQL Injection	0.500000	SMOTE

[43]:
```
rf_model_adasyn = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
 ↪is_attack)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   37.5s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.1min finished
```

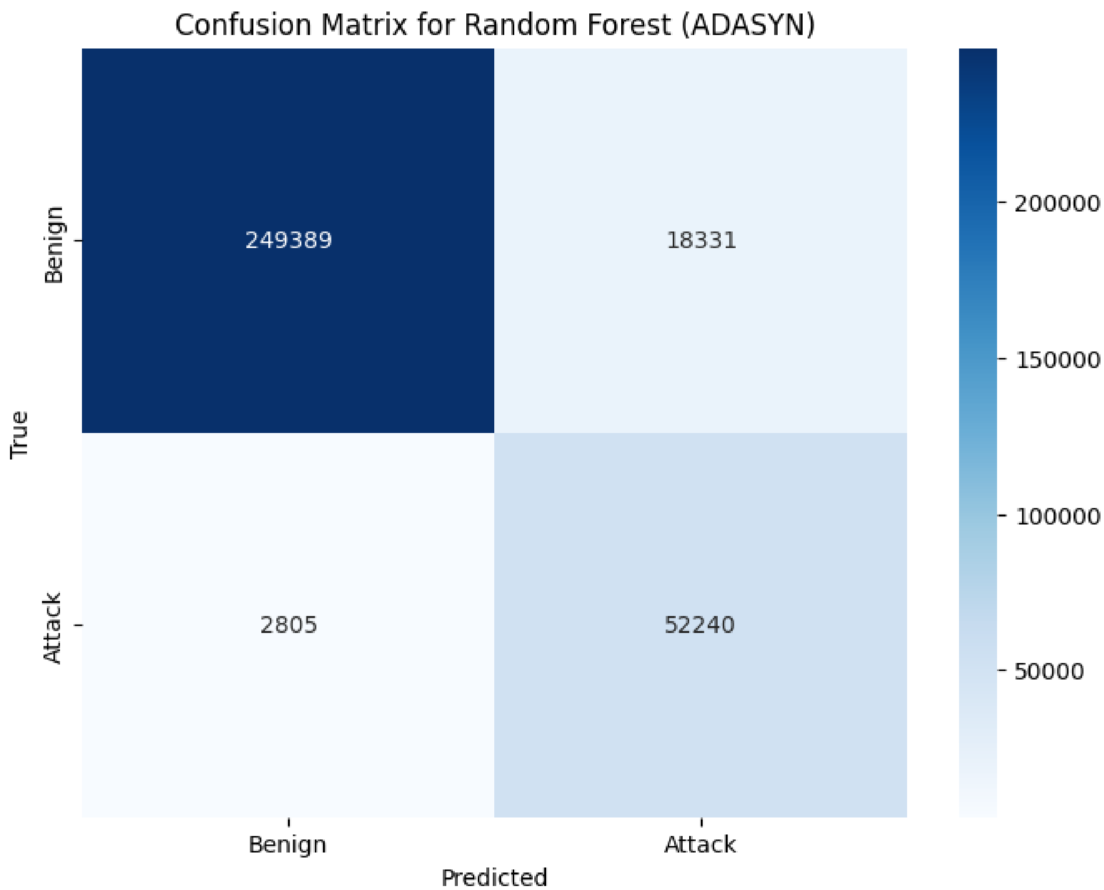
[43]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[44]:
```
# Predict and evaluate on the test set
rf_metrics["adasyn"] = test_metrics("Random Forest", rf_model_adasyn, "ADASYN",␣
 ↪scaler_adasyn)
```

```
Random Forest with ADASYN Test Set Performance
```

```
[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:    0.1s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    0.7s finished
```

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

           0     0.9889    0.9315    0.9593    267720
           1     0.7402    0.9490    0.8317     55045

    accuracy                         0.9345    322765
   macro avg     0.8646    0.9403    0.8955    322765
weighted avg     0.9465    0.9345    0.9376    322765

Accuracy: 0.934515824206466
Precision: 0.9464757098207695
Recall: 0.934515824206466
F1 Score: 0.9375849455115585
AUC: 0.9402854513910675
```



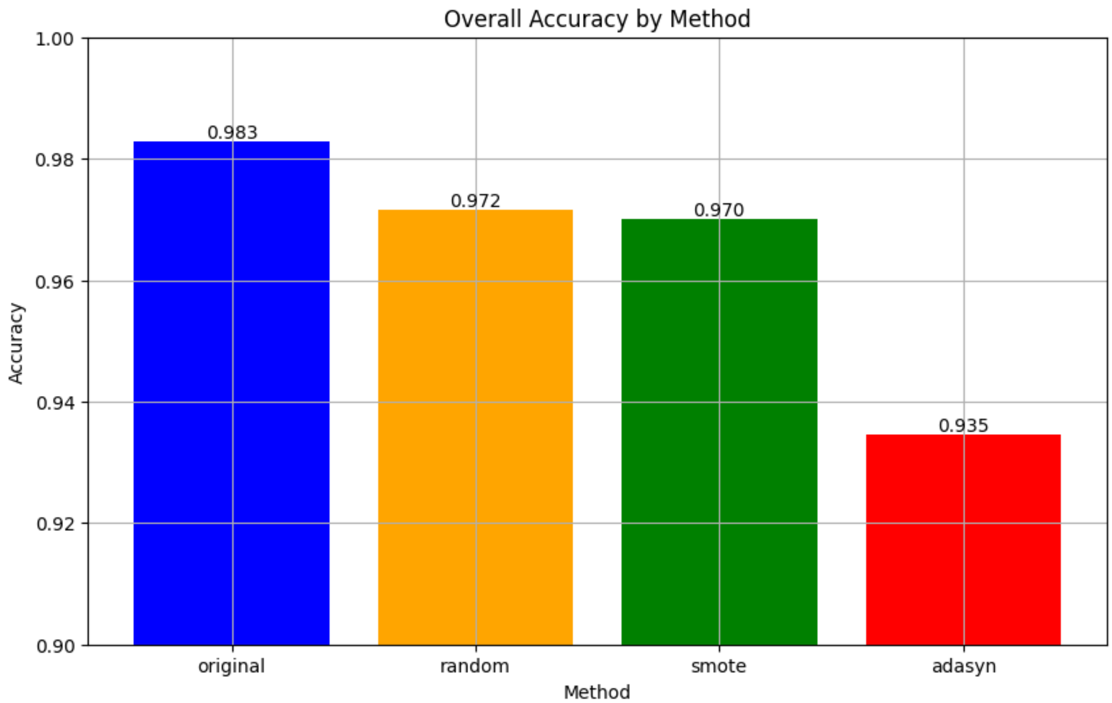
Metrics by Label (ADASYN):

	Label	Accuracy	Method
0	Benign	0.931529	ADASYN
1	DDOS attack-HOIC	0.997748	ADASYN
2	DDoS attacks-LOIC-HTTP	0.995232	ADASYN
3	DoS attacks-Hulk	0.999568	ADASYN
4	DoS attacks-SlowHTTPTest	1.000000	ADASYN
5	SSH-Bruteforce	0.999733	ADASYN
6	FTP-BruteForce	1.000000	ADASYN
7	Infilteration	0.151411	ADASYN
8	DoS attacks-GoldenEye	1.000000	ADASYN
9	Bot	0.999478	ADASYN
10	DDOS attack-LOIC-UDP	1.000000	ADASYN
11	DoS attacks-Slowloris	0.990521	ADASYN
12	Brute Force -Web	0.909091	ADASYN
13	Brute Force -XSS	0.800000	ADASYN
14	SQL Injection	1.000000	ADASYN

[45]:
```
# Combine metrics into one DataFrame
combined_metrics_rf = pd.concat([rf_metrics["adasyn"][1],␣
↪rf_metrics["original"][1], rf_metrics["random"][1], rf_metrics["smote"][1]])
# Pivot the table to get accuracy for each method as columns in the specified␣
↪order
accuracy_pivot_rf = combined_metrics_rf.pivot(index='Label', columns='Method',␣
↪values='Accuracy')
accuracy_pivot_rf = accuracy_pivot_rf[['Original', 'Random Oversampling',␣
↪'SMOTE', 'ADASYN']]
print("Accuracy by Label and Method:")
print(accuracy_pivot_rf)
```

```
Accuracy by Label and Method:
Method                   Original  Random Oversampling     SMOTE    ADASYN
Label
Benign                   0.991958             0.975852  0.973734  0.931529
Bot                      0.997914             0.999478  0.999478  0.999478
Brute Force -Web         0.545455             0.545455  0.727273  0.909091
Brute Force -XSS         0.400000             0.600000  0.600000  0.800000
DDOS attack-HOIC         0.989029             0.993388  0.994623  0.997748
DDOS attack-LOIC-UDP     1.000000             1.000000  1.000000  1.000000
DDoS attacks-LOIC-HTTP   0.986997             0.988211  0.989511  0.995232
DoS attacks-GoldenEye    1.000000             1.000000  1.000000  1.000000
DoS attacks-Hulk         0.998056             0.998380  0.998596  0.999568
DoS attacks-SlowHTTPTest 1.000000             1.000000  1.000000  1.000000
DoS attacks-Slowloris    0.971564             0.976303  0.981043  0.990521
FTP-BruteForce           1.000000             1.000000  1.000000  1.000000
Infilteration            0.044828             0.232915  0.247962  0.151411
SQL Injection            0.500000             1.000000  0.500000  1.000000
SSH-Bruteforce           0.999467             0.999467  0.999467  0.999733
```

[46]:
```
plot_overall_accuracy(rf_metrics)
```



1.4.6 Adaboost

[47]:
```
ada_metrics = {}
```

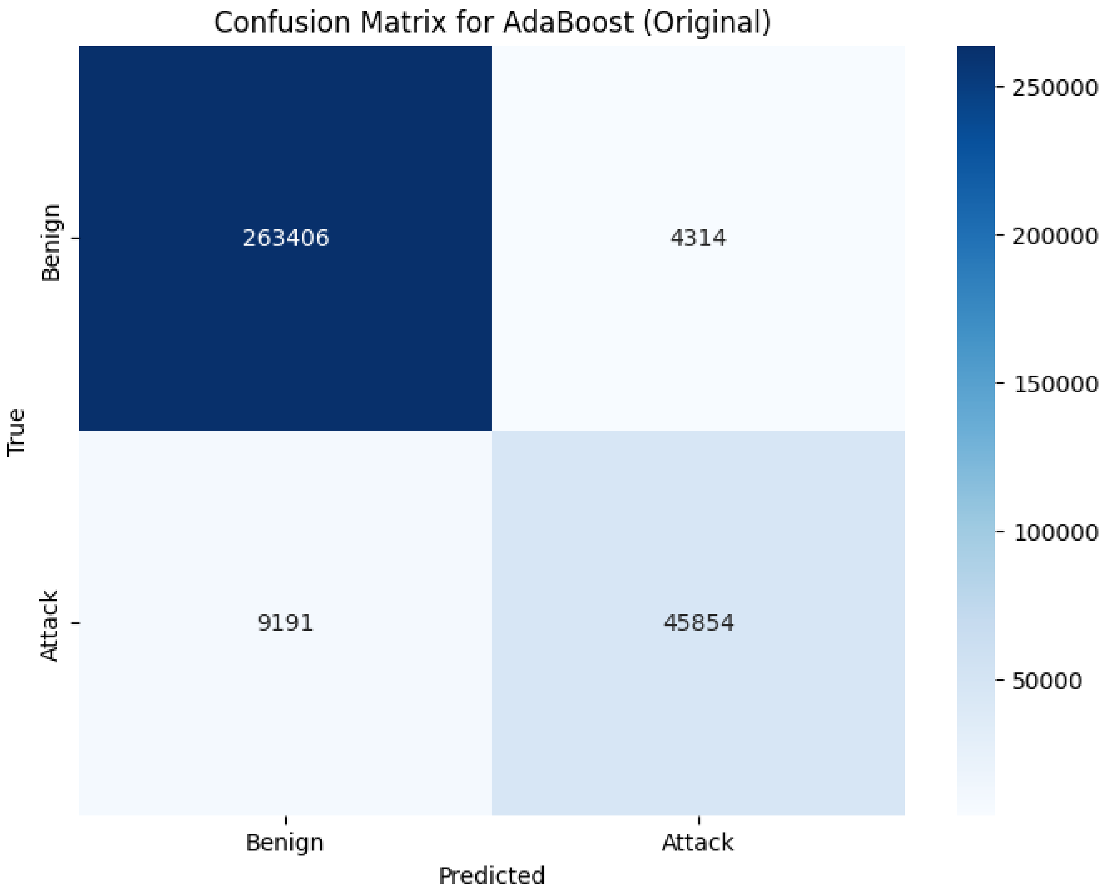
[48]:
```
from sklearn.ensemble import AdaBoostClassifier

ada_model = AdaBoostClassifier(algorithm='SAMME')
ada_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[48]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[49]:
```
# Predict and evaluate on the test set
ada_metrics["original"] = test_metrics("AdaBoost", ada_model, "Original",␣
↪scaler)
```

```
AdaBoost with Original Test Set Performance
Classification Report (Test AdaBoost (Original)):
              precision    recall  f1-score   support

           0     0.9663    0.9839    0.9750    267720
           1     0.9140    0.8330    0.8716     55045

    accuracy                         0.9582    322765
   macro avg     0.9401    0.9085    0.9233    322765
weighted avg     0.9574    0.9582    0.9574    322765
```

```
Accuracy: 0.958158412467275
Precision: 0.9573685394091846
Recall: 0.958158412467275
F1 Score: 0.9573774935315756
AUC: 0.9084568363222154
```




```
Metrics by Label (Original):
                       Label  Accuracy    Method
0                     Benign  0.983886  Original
1           DDOS attack-HOIC  0.957640  Original
2      DDoS attacks-LOIC-HTTP  0.923544  Original
3           DoS attacks-Hulk  0.974949  Original
4    DoS attacks-SlowHTTPTest  0.869922  Original
5             SSH-Bruteforce  0.980011  Original
6             FTP-BruteForce  0.874452  Original
7               Infilteration  0.036991  Original
8      DoS attacks-GoldenEye  0.501779  Original
9                        Bot  0.492524  Original
```

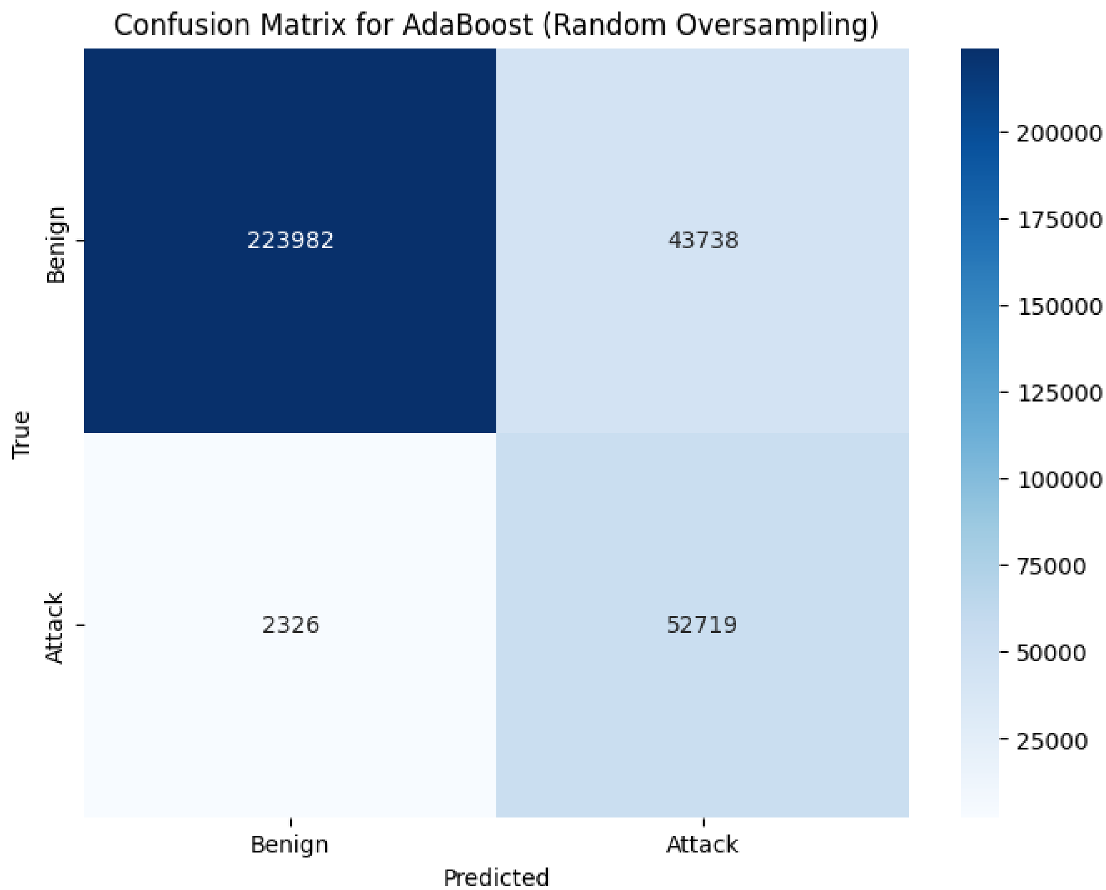
```
10      DDOS attack-LOIC-UDP  0.000000  Original
11     DoS attacks-Slowloris  0.497630  Original
12          Brute Force -Web  0.090909  Original
13          Brute Force -XSS  0.200000  Original
14             SQL Injection  0.000000  Original
```

[50]:
```
ada_model_random = AdaBoostClassifier(algorithm='SAMME')
ada_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
 ↪is_attack)
```

[50]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[51]:
```
# Predict and evaluate on the test set
ada_metrics["random"] = test_metrics("AdaBoost", ada_model_random, "Random␣
 ↪Oversampling", scaler_random)
```

```
AdaBoost with Random Oversampling Test Set Performance
Classification Report (Test AdaBoost (Random Oversampling)):
              precision    recall  f1-score   support

           0     0.9897    0.8366    0.9068    267720
           1     0.5466    0.9577    0.6960     55045

    accuracy                         0.8573    322765
   macro avg     0.7681    0.8972    0.8014    322765
weighted avg     0.9141    0.8573    0.8708    322765

Accuracy: 0.8572831626725327
Precision: 0.9141432761392969
Recall: 0.8572831626725327
F1 Score: 0.8708068473290808
AUC: 0.8971857421926237
```



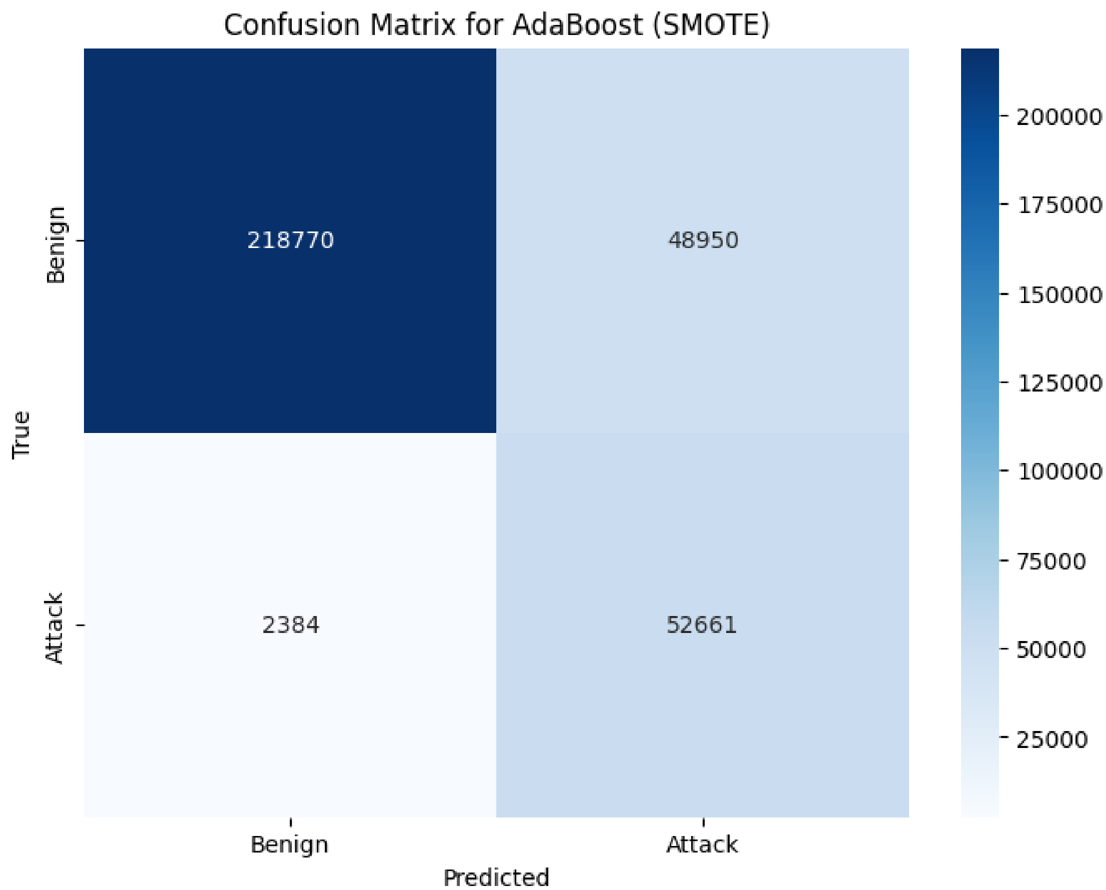

```
Metrics by Label (Random Oversampling):
                      Label  Accuracy              Method
0                    Benign  0.836628  Random Oversampling
1          DDOS attack-HOIC  1.000000  Random Oversampling
2      DDoS attacks-LOIC-HTTP  0.986304  Random Oversampling
3          DoS attacks-Hulk  0.999136  Random Oversampling
4    DoS attacks-SlowHTTPTest  1.000000  Random Oversampling
5             SSH-Bruteforce  1.000000  Random Oversampling
6             FTP-BruteForce  1.000000  Random Oversampling
7              Infilteration  0.331034  Random Oversampling
8       DoS attacks-GoldenEye  1.000000  Random Oversampling
9                       Bot  0.995480  Random Oversampling
10       DDOS attack-LOIC-UDP  1.000000  Random Oversampling
11      DoS attacks-Slowloris  1.000000  Random Oversampling
12          Brute Force -Web  1.000000  Random Oversampling
13          Brute Force -XSS  1.000000  Random Oversampling
14             SQL Injection  1.000000  Random Oversampling
```

[52]:
```
ada_model_smote = AdaBoostClassifier(algorithm='SAMME')
ada_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
 ↪is_attack)
```

[52]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[53]:
```
# Predict and evaluate on the test set
ada_metrics["smote"] = test_metrics("AdaBoost", ada_model_smote, "SMOTE",␣
 ↪scaler_smote)
```

```
AdaBoost with SMOTE Test Set Performance
Classification Report (Test AdaBoost (SMOTE)):
              precision    recall  f1-score   support

           0     0.9892    0.8172    0.8950    267720
           1     0.5183    0.9567    0.6723     55045

    accuracy                         0.8410    322765
   macro avg     0.7537    0.8869    0.7837    322765
weighted avg     0.9089    0.8410    0.8570    322765

Accuracy: 0.8409554939352161
Precision: 0.9089018131038703
Recall: 0.8409554939352161
F1 Score: 0.8570188688361758
AUC: 0.8869248500171077
```



Metrics by Label (SMOTE):

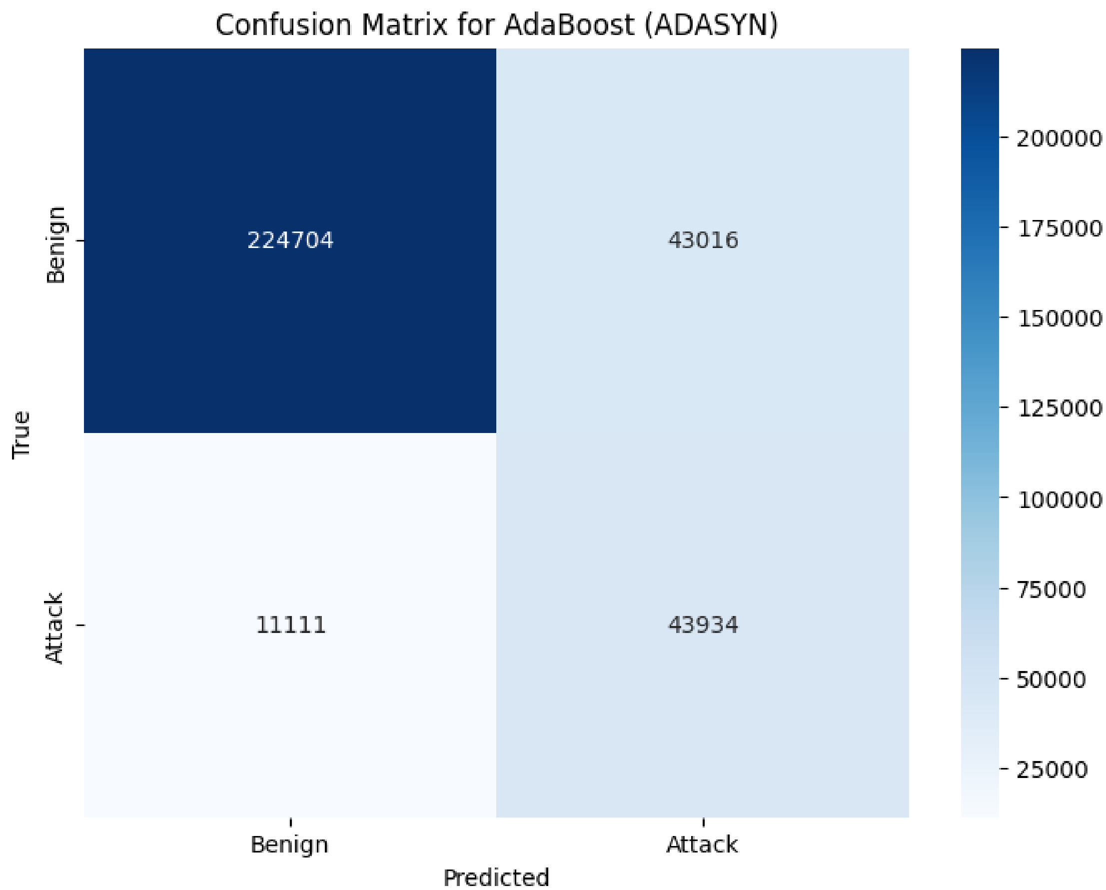
	Label	Accuracy	Method
0	Benign	0.817160	SMOTE
1	DDOS attack-HOIC	1.000000	SMOTE
2	DDoS attacks-LOIC-HTTP	0.986564	SMOTE
3	DoS attacks-Hulk	0.999784	SMOTE
4	DoS attacks-SlowHTTPTest	1.000000	SMOTE
5	SSH-Bruteforce	1.000000	SMOTE
6	FTP-BruteForce	1.000000	SMOTE
7	Infilteration	0.334483	SMOTE
8	DoS attacks-GoldenEye	1.000000	SMOTE
9	Bot	0.981919	SMOTE
10	DDOS attack-LOIC-UDP	1.000000	SMOTE
11	DoS attacks-Slowloris	1.000000	SMOTE
12	Brute Force -Web	1.000000	SMOTE
13	Brute Force -XSS	1.000000	SMOTE
14	SQL Injection	1.000000	SMOTE

[54]:
```python
ada_model_adasyn = AdaBoostClassifier(algorithm='SAMME')
ada_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
    ↪is_attack)
```

[54]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[55]:
```python
# Predict and evaluate on the test set
ada_metrics["adasyn"] = test_metrics("AdaBoost", ada_model_adasyn, "ADASYN",␣
    ↪scaler_adasyn)
```

```
AdaBoost with ADASYN Test Set Performance
Classification Report (Test AdaBoost (ADASYN)):
              precision    recall  f1-score   support

           0     0.9529    0.8393    0.8925    267720
           1     0.5053    0.7981    0.6188     55045

    accuracy                         0.8323    322765
   macro avg     0.7291    0.8187    0.7557    322765
weighted avg     0.8765    0.8323    0.8458    322765

Accuracy: 0.8323021393273744
Precision: 0.876547317034483
Recall: 0.8323021393273744
F1 Score: 0.8458294017160278
AUC: 0.8187358191117472
```




```
Metrics by Label (ADASYN):
                        Label  Accuracy  Method
0                      Benign  0.839325  ADASYN
1            DDOS attack-HOIC  0.999419  ADASYN
2       DDoS attacks-LOIC-HTTP  0.481276  ADASYN
3            DoS attacks-Hulk  0.996977  ADASYN
4    DoS attacks-SlowHTTPTest  1.000000  ADASYN
5              SSH-Bruteforce  1.000000  ADASYN
6              FTP-BruteForce  1.000000  ADASYN
7               Infilteration  0.318495  ADASYN
8       DoS attacks-GoldenEye  1.000000  ADASYN
9                         Bot  0.493220  ADASYN
10        DDOS attack-LOIC-UDP  1.000000  ADASYN
11      DoS attacks-Slowloris  1.000000  ADASYN
12           Brute Force -Web  0.818182  ADASYN
13           Brute Force -XSS  1.000000  ADASYN
14              SQL Injection  1.000000  ADASYN
```

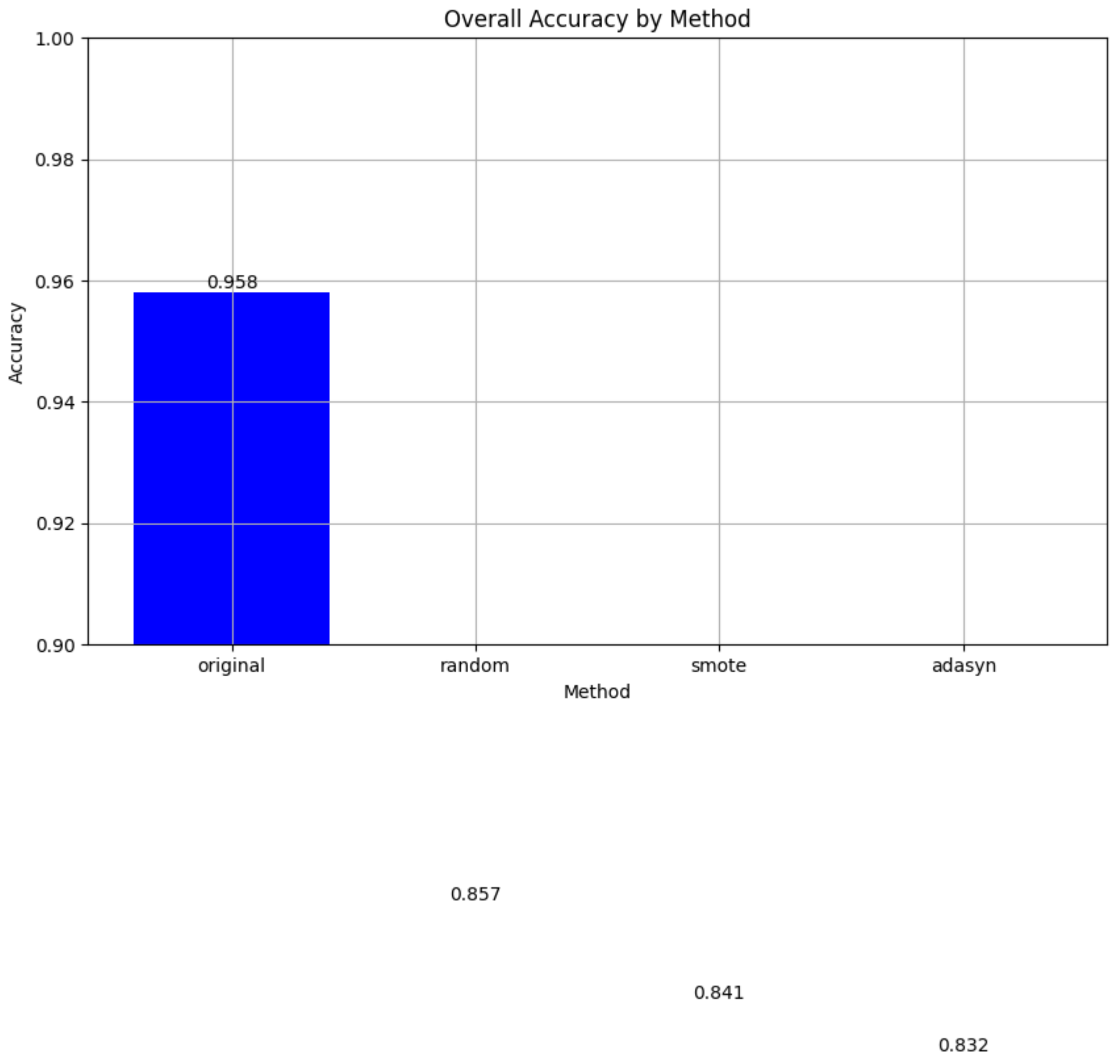
[56]:

```
# Combine metrics into one DataFrame
combined_metrics_ada = pd.concat([ada_metrics["adasyn"][1],␣
 ↪ada_metrics["original"][1], ada_metrics["random"][1],␣
 ↪ada_metrics["smote"][1]])

# Pivot the table to get accuracy for each method as columns in the specified␣
 ↪order
accuracy_pivot_ada = combined_metrics_ada.pivot(index='Label',␣
 ↪columns='Method', values='Accuracy')
accuracy_pivot_ada = accuracy_pivot_ada[['Original', 'Random Oversampling',␣
 ↪'SMOTE', 'ADASYN']]
print("Accuracy by Label and Method (AdaBoost):")
print(accuracy_pivot_ada)
```

```
Accuracy by Label and Method (AdaBoost):
Method                    Original  Random Oversampling     SMOTE    ADASYN
Label
Benign                    0.983886             0.836628  0.817160  0.839325
Bot                       0.492524             0.995480  0.981919  0.493220
Brute Force -Web          0.090909             1.000000  1.000000  0.818182
Brute Force -XSS          0.200000             1.000000  1.000000  1.000000
DDOS attack-HOIC          0.957640             1.000000  1.000000  0.999419
DDOS attack-LOIC-UDP      0.000000             1.000000  1.000000  1.000000
DDoS attacks-LOIC-HTTP    0.923544             0.986304  0.986564  0.481276
DoS attacks-GoldenEye     0.501779             1.000000  1.000000  1.000000
DoS attacks-Hulk          0.974949             0.999136  0.999784  0.996977
DoS attacks-SlowHTTPTest  0.869922             1.000000  1.000000  1.000000
DoS attacks-Slowloris     0.497630             1.000000  1.000000  1.000000
FTP-BruteForce            0.874452             1.000000  1.000000  1.000000
Infilteration             0.036991             0.331034  0.334483  0.318495
SQL Injection             0.000000             1.000000  1.000000  1.000000
SSH-Bruteforce            0.980011             1.000000  1.000000  1.000000
```

[57]:

```
plot_overall_accuracy(ada_metrics)
```



1.4.7 XGBoost

[58]:
```
xgb_metrics = {}
```

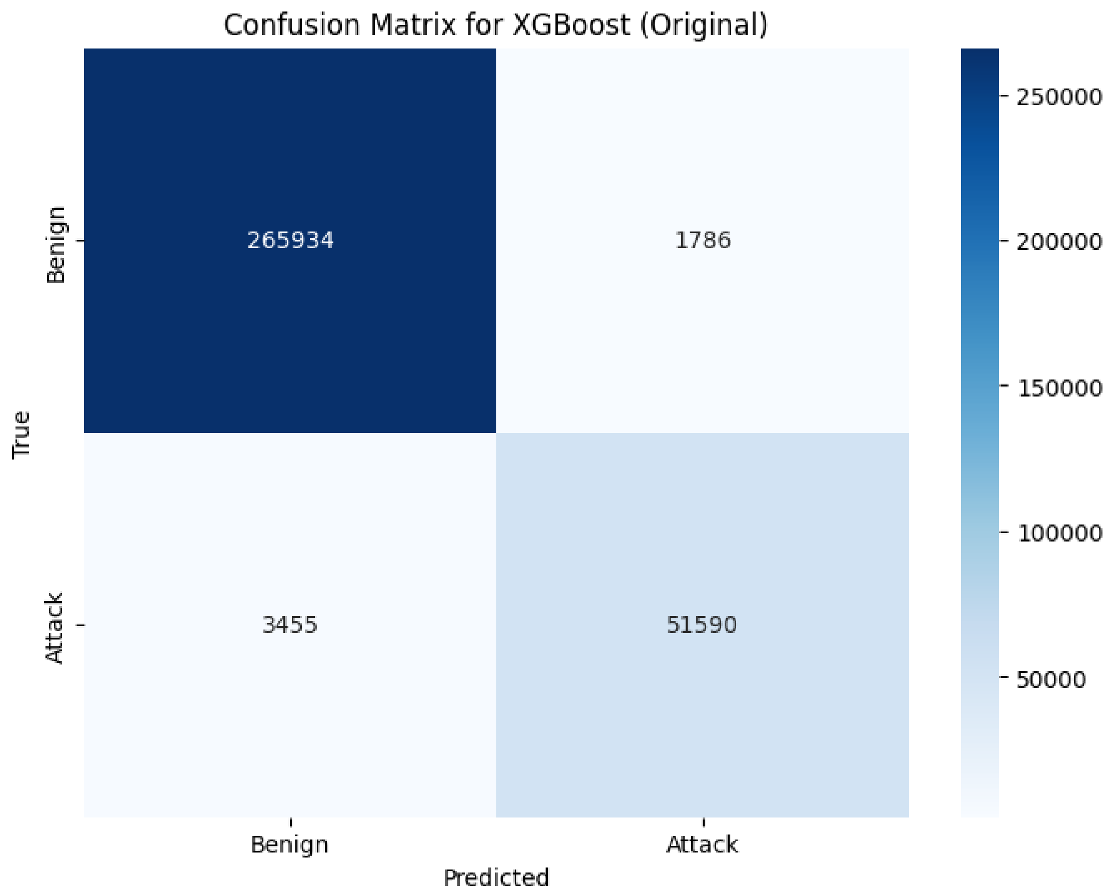
[59]:
```
import xgboost as xgb

xgb_model = xgb.XGBClassifier(n_jobs=-1)
xgb_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[59]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
```

```
                 interaction_constraints=None, learning_rate=None, max_bin=None,
                 max_cat_threshold=None, max_cat_to_onehot=None,
                 max_delta_step=None, max_depth=None, max_leaves=None,
                 min_child_weight=None, missing=nan, monotone_constraints=None,
                 multi_strategy=None, n_estimators=None, n_jobs=-1,
                 num_parallel_tree=None, random_state=None, …)
```

[60]:
```python
# Predict and evaluate on the test set
# Original Dataset
xgb_metrics["original"] = test_metrics("XGBoost", xgb_model, "Original", scaler)
```

```
XGBoost with Original Test Set Performance
Classification Report (Test XGBoost (Original)):
              precision    recall  f1-score   support

           0     0.9872    0.9933    0.9902    267720
           1     0.9665    0.9372    0.9517     55045

    accuracy                         0.9838    322765
   macro avg     0.9769    0.9653    0.9710    322765
weighted avg     0.9837    0.9838    0.9837    322765

Accuracy: 0.983762179914179
Precision: 0.983655475338238
Recall: 0.983762179914179
F1 Score: 0.9836624283867066
AUC: 0.9652810119484841
```



Metrics by Label (Original):

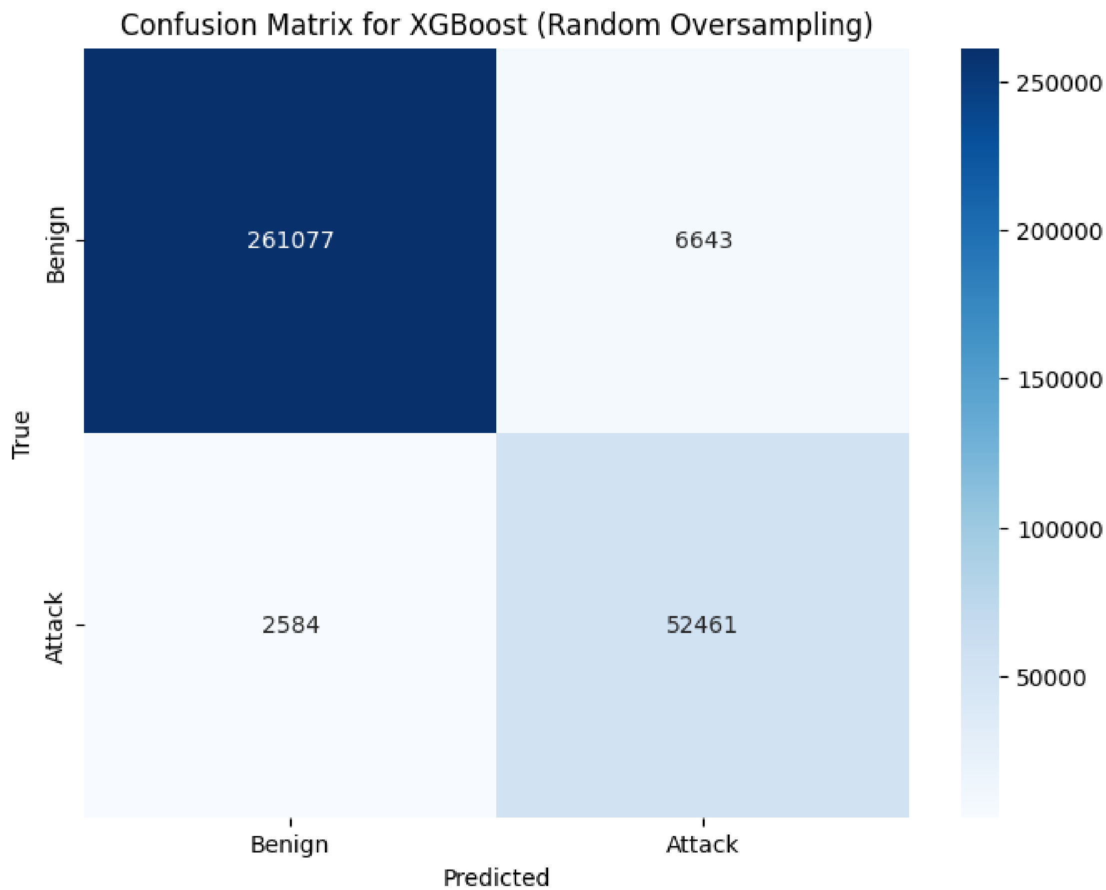
	Label	Accuracy	Method
0	Benign	0.993329	Original
1	DDOS attack-HOIC	0.996440	Original
2	DDoS attacks-LOIC-HTTP	0.979282	Original
3	DoS attacks-Hulk	0.999676	Original
4	DoS attacks-SlowHTTPTest	1.000000	Original
5	SSH-Bruteforce	1.000000	Original
6	FTP-BruteForce	1.000000	Original
7	Infilteration	0.023511	Original
8	DoS attacks-GoldenEye	0.998814	Original
9	Bot	0.996871	Original
10	DDOS attack-LOIC-UDP	1.000000	Original
11	DoS attacks-Slowloris	0.914692	Original
12	Brute Force -Web	0.363636	Original
13	Brute Force -XSS	0.400000	Original
14	SQL Injection	0.000000	Original

[61]:
```
xgb_model_random = xgb.XGBClassifier(n_jobs=-1)
xgb_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
 ↪is_attack)
```

[61]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=-1,
              num_parallel_tree=None, random_state=None, …)
```

[62]:
```
# Predict and evaluate on the test set
# Random Oversampling
xgb_metrics["random"] = test_metrics("XGBoost", xgb_model_random, "Random␣
 ↪Oversampling", scaler_random)
```

```
XGBoost with Random Oversampling Test Set Performance
Classification Report (Test XGBoost (Random Oversampling)):
              precision    recall  f1-score   support

           0     0.9902    0.9752    0.9826    267720
           1     0.8876    0.9531    0.9192     55045

    accuracy                         0.9714    322765
   macro avg     0.9389    0.9641    0.9509    322765
weighted avg     0.9727    0.9714    0.9718    322765

Accuracy: 0.9714126376775672
Precision: 0.9727028383818523
Recall: 0.9714126376775672
F1 Score: 0.9718117201171353
AUC: 0.9641216761758172
```



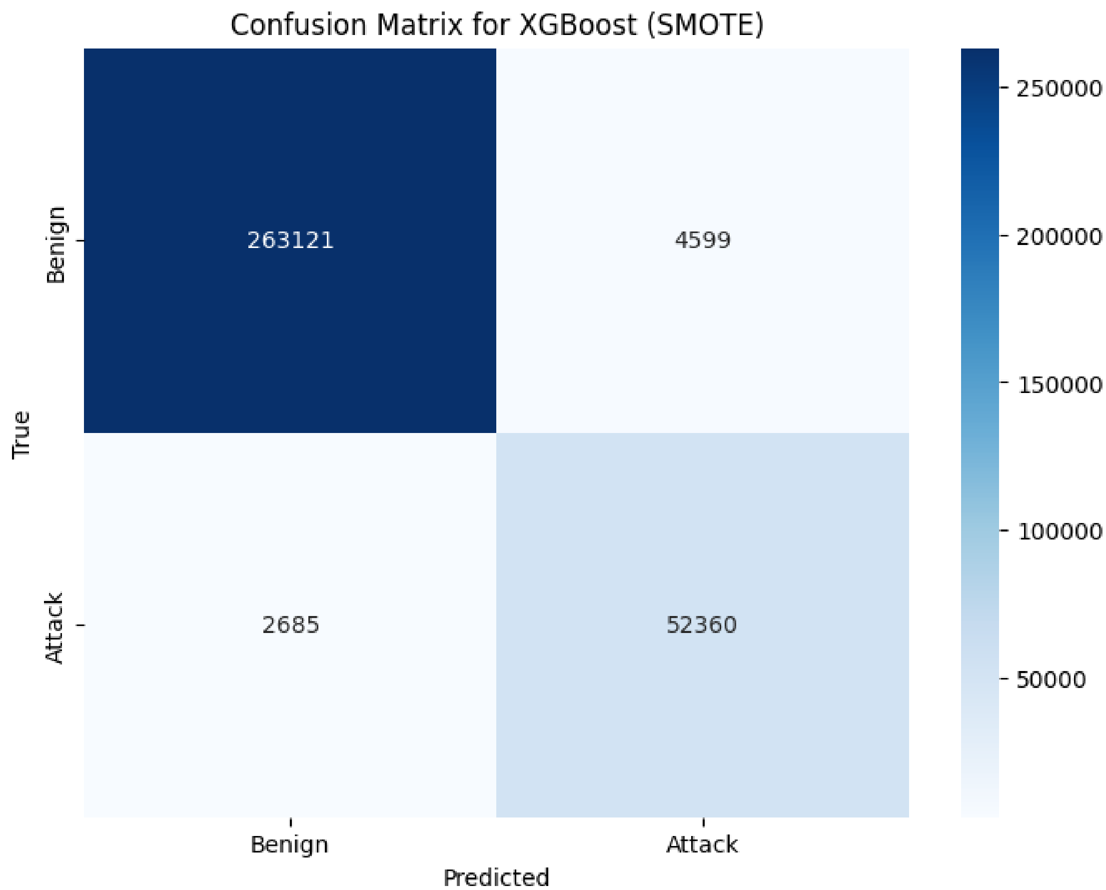

```
Metrics by Label (Random Oversampling):
                       Label  Accuracy              Method
0                     Benign  0.975187  Random Oversampling
1           DDOS attack-HOIC  0.998329  Random Oversampling
2      DDoS attacks-LOIC-HTTP  0.985697  Random Oversampling
3           DoS attacks-Hulk  0.999784  Random Oversampling
4    DoS attacks-SlowHTTPTest  1.000000  Random Oversampling
5              SSH-Bruteforce  1.000000  Random Oversampling
6              FTP-BruteForce  1.000000  Random Oversampling
7                Infilteration  0.254859  Random Oversampling
8       DoS attacks-GoldenEye  1.000000  Random Oversampling
9                         Bot  0.998435  Random Oversampling
10       DDOS attack-LOIC-UDP  1.000000  Random Oversampling
11      DoS attacks-Slowloris  0.985782  Random Oversampling
12           Brute Force -Web  0.636364  Random Oversampling
13           Brute Force -XSS  0.800000  Random Oversampling
14              SQL Injection  1.000000  Random Oversampling
```

[63]:
```
xgb_model_smote = xgb.XGBClassifier(n_jobs=-1)
xgb_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
  ↪is_attack)
```

[63]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=-1,
              num_parallel_tree=None, random_state=None, …)
```

[64]:
```
# Predict and evaluate on the test set
# SMOTE
xgb_metrics["smote"] = test_metrics("XGBoost", xgb_model_smote, "SMOTE",␣
  ↪scaler_smote)
```

```
XGBoost with SMOTE Test Set Performance
Classification Report (Test XGBoost (SMOTE)):
              precision    recall  f1-score   support

           0     0.9899    0.9828    0.9863    267720
           1     0.9193    0.9512    0.9350     55045

    accuracy                         0.9774    322765
   macro avg     0.9546    0.9670    0.9607    322765
weighted avg     0.9779    0.9774    0.9776    322765

Accuracy: 0.9774324973277771
Precision: 0.9778513988563949
Recall: 0.9774324973277771
F1 Score: 0.9775848417524753
AUC: 0.9670216661694708
```



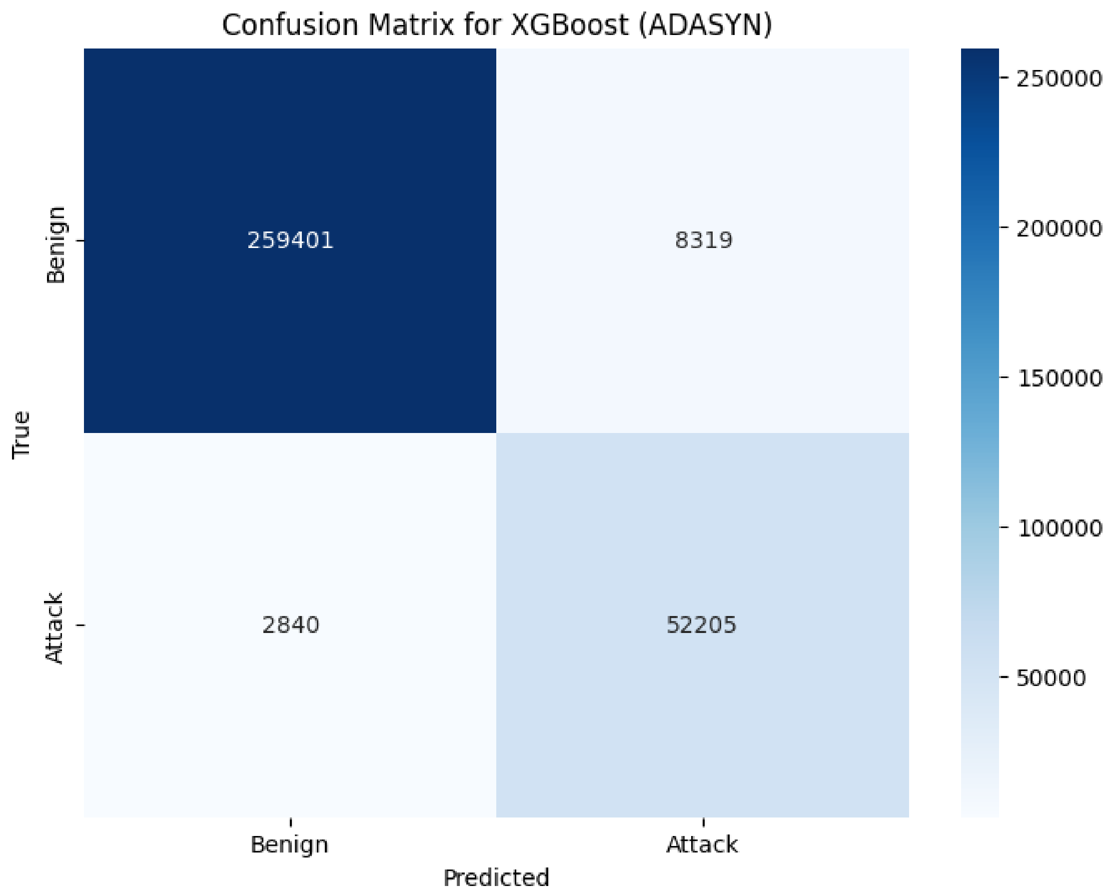

```
Metrics by Label (SMOTE):
                       Label  Accuracy Method
0                     Benign  0.982822  SMOTE
1          DDOS attack-HOIC  0.999055  SMOTE
2      DDoS attacks-LOIC-HTTP  0.982576  SMOTE
3           DoS attacks-Hulk  0.999784  SMOTE
4    DoS attacks-SlowHTTPTest  1.000000  SMOTE
5              SSH-Bruteforce  1.000000  SMOTE
6              FTP-BruteForce  1.000000  SMOTE
7               Infilteration  0.230721  SMOTE
8      DoS attacks-GoldenEye  1.000000  SMOTE
9                        Bot  0.998609  SMOTE
10       DDOS attack-LOIC-UDP  1.000000  SMOTE
11     DoS attacks-Slowloris  0.985782  SMOTE
12          Brute Force -Web  0.727273  SMOTE
13          Brute Force -XSS  1.000000  SMOTE
14             SQL Injection  0.500000  SMOTE
```

[65]:
```
xgb_model_adasyn = xgb.XGBClassifier(n_jobs=-1)
xgb_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
 ↪is_attack)
```

[65]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=-1,
              num_parallel_tree=None, random_state=None, …)
```

[66]:
```
# Predict and evaluate on the test set
# ADASYN
xgb_metrics["adasyn"] = test_metrics("XGBoost", xgb_model_adasyn, "ADASYN",␣
 ↪scaler_adasyn)
```

```
XGBoost with ADASYN Test Set Performance
Classification Report (Test XGBoost (ADASYN)):
              precision    recall  f1-score   support

           0     0.9892    0.9689    0.9789    267720
           1     0.8626    0.9484    0.9034     55045

    accuracy                         0.9654    322765
   macro avg     0.9259    0.9587    0.9412    322765
weighted avg     0.9676    0.9654    0.9661    322765

Accuracy: 0.9654268585503385
Precision: 0.9675762560643688
Recall: 0.9654268585503385
F1 Score: 0.966067678825433
AUC: 0.9586661700611769
```



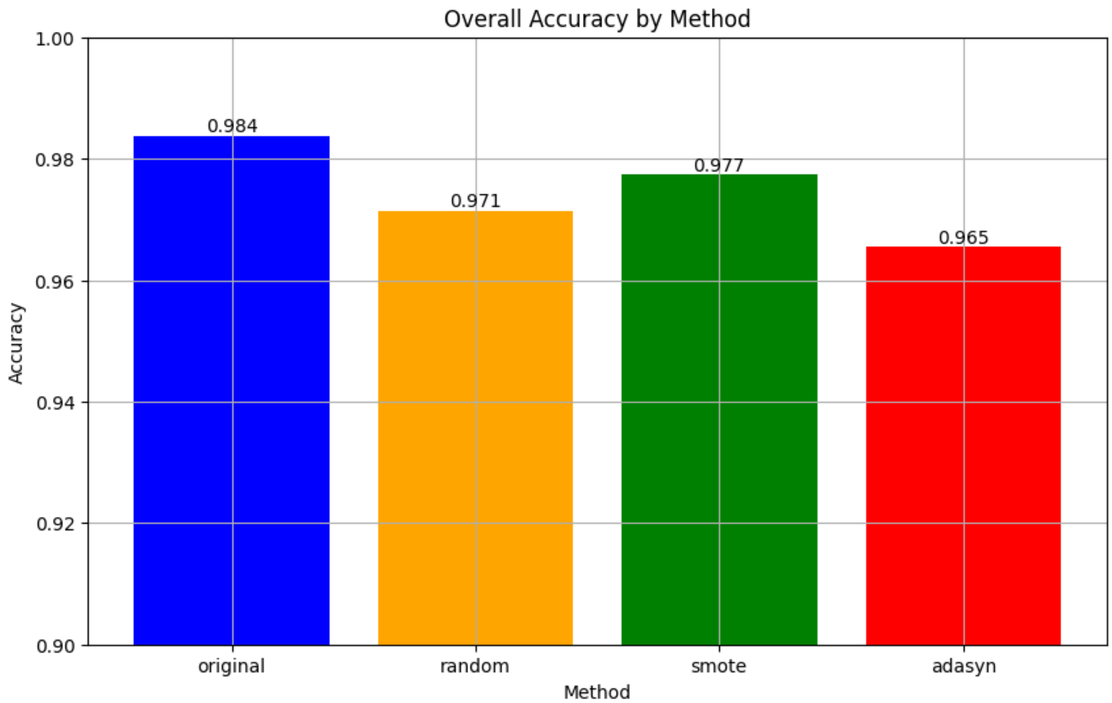
Metrics by Label (ADASYN):

	Label	Accuracy	Method
0	Benign	0.968926	ADASYN
1	DDOS attack-HOIC	0.999491	ADASYN
2	DDoS attacks-LOIC-HTTP	0.997053	ADASYN
3	DoS attacks-Hulk	1.000000	ADASYN
4	DoS attacks-SlowHTTPTest	1.000000	ADASYN
5	SSH-Bruteforce	1.000000	ADASYN
6	FTP-BruteForce	1.000000	ADASYN
7	Infilteration	0.125392	ADASYN
8	DoS attacks-GoldenEye	0.998814	ADASYN
9	Bot	0.999652	ADASYN
10	DDOS attack-LOIC-UDP	1.000000	ADASYN
11	DoS attacks-Slowloris	0.990521	ADASYN
12	Brute Force -Web	0.727273	ADASYN
13	Brute Force -XSS	1.000000	ADASYN
14	SQL Injection	0.500000	ADASYN

[67]:
```
# Combine metrics into one DataFrame
combined_metrics_xgb = pd.concat([xgb_metrics["adasyn"][1],␣
 ↪xgb_metrics["original"][1], xgb_metrics["random"][1],␣
 ↪xgb_metrics["smote"][1]])
# Pivot the table to get accuracy for each method as columns in the specified␣
 ↪order
accuracy_pivot_xgb = combined_metrics_xgb.pivot(index='Label',␣
 ↪columns='Method', values='Accuracy')
accuracy_pivot_xgb = accuracy_pivot_xgb[['Original', 'Random Oversampling',␣
 ↪'SMOTE', 'ADASYN']]
print("Accuracy by Label and Method:")
print(accuracy_pivot_xgb)
```

```
Accuracy by Label and Method:
Method                    Original  Random Oversampling     SMOTE    ADASYN
Label
Benign                    0.993329             0.975187  0.982822  0.968926
Bot                       0.996871             0.998435  0.998609  0.999652
Brute Force -Web          0.363636             0.636364  0.727273  0.727273
Brute Force -XSS          0.400000             0.800000  1.000000  1.000000
DDOS attack-HOIC          0.996440             0.998329  0.999055  0.999491
DDOS attack-LOIC-UDP      1.000000             1.000000  1.000000  1.000000
DDoS attacks-LOIC-HTTP    0.979282             0.985697  0.982576  0.997053
DoS attacks-GoldenEye     0.998814             1.000000  1.000000  0.998814
DoS attacks-Hulk          0.999676             0.999784  0.999784  1.000000
DoS attacks-SlowHTTPTest  1.000000             1.000000  1.000000  1.000000
DoS attacks-Slowloris     0.914692             0.985782  0.985782  0.990521
FTP-BruteForce            1.000000             1.000000  1.000000  1.000000
Infilteration             0.023511             0.254859  0.230721  0.125392
SQL Injection             0.000000             1.000000  0.500000  0.500000
SSH-Bruteforce            1.000000             1.000000  1.000000  1.000000
```

[68]:
```
plot_overall_accuracy(xgb_metrics)
```


Overall Accuracy by Method
1.00
0.98
0.96
0.94
0.92
0.90
Accuracy
0.984
0.971
0.977
0.965
original
random
smote
adasyn
Method