2_ML_Default_IDS2017

June 16, 2024

1 Machine Learning Models on the IDS 2017

In this notebook, random tree and random forest based machine learning algorithms are applied to the ids2017 dataset. Several methods for resolving the class imbalance are tested. Random 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 upsample_dataset
%matplotlib inline
%load_ext autoreload
%autoreload 2
file_path = r"..
 ↪\CIC-IDS-2017\CSVs\GeneratedLabelledFlows\TrafficLabelling\processed\ids2017_processed.
 ↪csv"

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

1.1 1. Preparing the Dataset

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

```
<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                int64
 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	int64
68	init_win_bytes_backward	int64
69	act_data_pkt_fwd	int64

```
 70  min_seg_size_forward          int64
 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(45), int64(50)
memory usage: 2.0 GB
```

Check for invalid values

[3]:
```python
# 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
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: ['flow_bytes_s']
Columns with infinite values: ['flow_bytes_s', 'flow_packets_s']
Columns with 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']
Percentage of NaN values in each column:
 flow_bytes_s    0.047973
dtype: float64
Percentage of infinite values in each column:
 flow_bytes_s      0.053308
flow_packets_s    0.101281
dtype: float64
Percentage of negative values in each column:
 flow_duration              0.004063
flow_bytes_s               0.003003
flow_packets_s             0.004063
flow_iat_mean              0.004063
flow_iat_max               0.004063
flow_iat_min               0.102129
fwd_iat_min                0.000601
fwd_header_length          0.001236
bwd_header_length          0.000777
fwd_header_length_1        0.001236
init_win_bytes_forward    35.368417
init_win_bytes_backward   50.924863
min_seg_size_forward       0.001236
dtype: float64
```

Given the low percentage of null values in only one column (0.4%), it is safe to drop the rows with NaN values. The same applies to th infinite values. 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 the features, the percentages are low so the rows with negative values are dropped.

[4]:
```
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_win_bytes_forward', 'init_win_bytes_backward']
    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
```

[5]:
```
df = replace_invalid(df)
```

[6]:
```
X = df.iloc[:, 0:77]
Y = df.iloc[:, 77:]
X.info()
Y.info()
print(Y.label.value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2824951 entries, 0 to 2830742
Data columns (total 77 columns):
 #   Column                       Dtype
---  ------                       -----
 0   destination_port             int64
 1   protocol                     int64
 2   flow_duration                int64
 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  act_data_pkt_fwd             int64
 68  min_seg_size_forward         int64
 69  active_mean                  float64
 70  active_std                   float64
 71  active_max                   float64
 72  active_min                   float64
 73  idle_mean                    float64
 74  idle_std                     float64
 75  idle_max                     float64
 76  idle_min                     float64
dtypes: float64(45), int64(32)
memory usage: 1.6 GB
<class 'pandas.core.frame.DataFrame'>
Index: 2824951 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: 369.1 MB
label
BENIGN                    2268589
DoS Hulk                   229965
PortScan                   158804
DDoS                       128006
DoS GoldenEye               10288
FTP-Patator                  7931
```

```
SSH-Patator                       5895
DoS slowloris                     5796
DoS Slowhttptest                  5499
Bot                               1956
Web Attack - Brute Force          1507
Web Attack - XSS                   652
Infiltration                        35
Web Attack - Sql Injection          21
Heartbleed                           7
Name: count, dtype: int64
```

1.2 2. Feature Selection

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

[7]:
```
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

[8]:
```
X = X.drop(columns=features_no_var)
X = X.drop(columns=['destination_port'])
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2824951 entries, 0 to 2830742
Data columns (total 68 columns):
 #   Column                       Dtype
---  ------                       -----
 0   protocol                     int64
 1   flow_duration                int64
 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   act_data_pkt_fwd             int64
 59   min_seg_size_forward         int64
 60   active_mean                  float64
 61   active_std                   float64
 62   active_max                   float64
 63   active_min                   float64
 64   idle_mean                    float64
 65   idle_std                     float64
 66   idle_max                     float64
 67   idle_min                     float64
dtypes: float64(45), int64(23)
memory usage: 1.5 GB
```

1.2.1 Remove collinear variables

[9]:
```
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: 2824951 entries, 0 to 2830742
Data columns (total 42 columns):
 #    Column                       Dtype
---   ------                       -----
 0    protocol                     int64
 1    flow_duration                int64
 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_max                 float64
 14   flow_iat_min                 float64
 15   fwd_iat_mean                 float64
 16   fwd_iat_std                  float64
```

```
 17  fwd_iat_min                 float64
 18  bwd_iat_total               float64
 19  bwd_iat_mean                float64
 20  bwd_iat_std                 float64
 21  bwd_iat_max                 float64
 22  bwd_iat_min                 float64
 23  fwd_psh_flags               int64
 24  fwd_urg_flags               int64
 25  bwd_packets_s               float64
 26  min_packet_length           float64
 27  max_packet_length           float64
 28  packet_length_mean          float64
 29  packet_length_variance      float64
 30  fin_flag_count              int64
 31  rst_flag_count              int64
 32  psh_flag_count              int64
 33  ack_flag_count              int64
 34  urg_flag_count              int64
 35  down_up_ratio               float64
 36  min_seg_size_forward        int64
 37  active_mean                 float64
 38  active_std                  float64
 39  active_max                  float64
 40  active_min                  float64
 41  idle_std                    float64
dtypes: float64(31), int64(11)
memory usage: 926.8 MB
```

1.2.2 Information gain selection

[10]:
```python
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler
import pandas as pd

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)
```

```python
    # 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]

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

```
                        Feature  Information Gain
7          bwd_packet_length_max          0.115228
4          fwd_packet_length_max          0.112826
27             max_packet_length          0.096413
0                       protocol          0.093959
5          fwd_packet_length_min          0.090742
3    total_length_of_fwd_packets          0.086306
29        packet_length_variance          0.084187
26             min_packet_length          0.083318
8          bwd_packet_length_min          0.081439
14                  flow_iat_min          0.070721
28            packet_length_mean          0.070513
18                 bwd_iat_total          0.060881
21                   bwd_iat_max          0.059818
13                  flow_iat_max          0.059632
1                  flow_duration          0.058154
19                  bwd_iat_mean          0.056881
6         fwd_packet_length_mean          0.055221
12                  flow_iat_std          0.051438
9                   flow_bytes_s          0.050484
22                   bwd_iat_min          0.048492
15                  fwd_iat_mean          0.046317
16                   fwd_iat_std          0.041332
11                 flow_iat_mean          0.038977
25                 bwd_packets_s          0.037749
```

```
10              flow_packets_s         0.037578
17                 fwd_iat_min         0.035224
39                  active_max         0.034494
2             total_fwd_packets        0.029691
40                  active_min         0.029512
37                 active_mean         0.028532
34               urg_flag_count        0.018526
23                fwd_psh_flags        0.016270
41                    idle_std         0.012641
20                 bwd_iat_std         0.011882
36          min_seg_size_forward       0.011519
32               psh_flag_count        0.011453
31               rst_flag_count        0.000013
33               ack_flag_count        0.000000
35                down_up_ratio        0.000000
38                  active_std         0.000000
24                fwd_urg_flags        0.000000
30               fin_flag_count        0.000000
<class 'pandas.core.frame.DataFrame'>
Index: 2824951 entries, 0 to 2830742
Data columns (total 37 columns):
 #   Column                       Dtype
---  ------                       -----
 0   bwd_packet_length_max        float64
 1   fwd_packet_length_max        float64
 2   max_packet_length            float64
 3   protocol                     int64
 4   fwd_packet_length_min        float64
 5   total_length_of_fwd_packets  float64
 6   packet_length_variance       float64
 7   min_packet_length            float64
 8   bwd_packet_length_min        float64
 9   flow_iat_min                 float64
 10  packet_length_mean           float64
 11  bwd_iat_total                float64
 12  bwd_iat_max                  float64
 13  flow_iat_max                 float64
 14  flow_duration                int64
 15  bwd_iat_mean                 float64
 16  fwd_packet_length_mean       float64
 17  flow_iat_std                 float64
 18  flow_bytes_s                 float64
 19  bwd_iat_min                  float64
 20  fwd_iat_mean                 float64
 21  fwd_iat_std                  float64
 22  flow_iat_mean                float64
 23  bwd_packets_s                float64
 24  flow_packets_s               float64
```

```
 25   fwd_iat_min                 float64
 26   active_max                  float64
 27   total_fwd_packets           int64
 28   active_min                  float64
 29   active_mean                 float64
 30   urg_flag_count              int64
 31   fwd_psh_flags               int64
 32   idle_std                    float64
 33   bwd_iat_std                 float64
 34   min_seg_size_forward        int64
 35   psh_flag_count              int64
 36   rst_flag_count              int64
dtypes: float64(29), int64(8)
memory usage: 819.0 MB
```

1.3 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.

[11]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪stratify=Y.label_code)
```

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

[12]:
```
label
BENIGN                        1814870
DoS Hulk                       183972
PortScan                       127043
DDoS                           102405
DoS GoldenEye                    8230
FTP-Patator                      6345
SSH-Patator                      4716
DoS slowloris                    4637
DoS Slowhttptest                 4399
Bot                              1565
Web Attack - Brute Force         1205
Web Attack - XSS                  522
Infiltration                       28
Web Attack - Sql Injection         17
Heartbleed                          6
Name: count, dtype: int64
```

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

[13]:
```
label
BENIGN                        453719
DoS Hulk                       45993
```

```
PortScan                       31761
DDoS                           25601
DoS GoldenEye                   2058
FTP-Patator                     1586
SSH-Patator                     1179
DoS slowloris                   1159
DoS Slowhttptest                1100
Bot                              391
Web Attack - Brute Force         302
Web Attack - XSS                 130
Infiltration                       7
Web Attack - Sql Injection         4
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: 0.8031
is_attack
0    1814870
1     445090
Name: count, dtype: int64
```

1.4 4. Machine Learning Classifiers with Default Hyperparameters

1.4.1 Helper functions

[15]:
```
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)
```

[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))
    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)
```

[17]:
```
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
```

[18]:
```
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

[19]:
```
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)
    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
```

[20]:
```
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")
```

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

[21]:
```
label
BENIGN                        1814870
DoS Hulk                       183972
PortScan                       127043
DDoS                           102405
DoS GoldenEye                    8230
FTP-Patator                      6345
SSH-Patator                      4716
DoS slowloris                    4637
DoS Slowhttptest                 4399
Bot                              1565
Web Attack - Brute Force         1205
Web Attack - XSS                  522
Infiltration                       28
Web Attack - Sql Injection         17
Heartbleed                          6
Name: count, dtype: int64
```

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

[22]:
```
label
BENIGN                        1814870
DoS Hulk                       183972
PortScan                       127043
DDoS                           102405
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
```

[23]:
```python
Y_smote_train.label.value_counts()
```

[23]:
```
label
BENIGN                        1814870
DoS Hulk                       183972
PortScan                       127043
DDoS                           102405
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
```

[24]:
```python
Y_adasyn_train.label.value_counts()
```

[24]:
```
label
BENIGN                        1814870
DoS Hulk                       183972
PortScan                       127043
DDoS                           102405
Web Attack - XSS               100019
Bot                            100007
```

```
FTP-Patator                   100005
Web Attack - Sql Injection    100001
Infiltration                   99999
Heartbleed                     99998
SSH-Patator                    99972
DoS slowloris                  99949
DoS GoldenEye                  99914
Web Attack - Brute Force       99912
DoS Slowhttptest               99868
Name: count, dtype: int64
```

Scaling using the standard scaler

[25]:
```python
# 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)
```

[25]:
```
StandardScaler()
```

1.4.3 Random Forest

[26]:
```python
rf_metrics = {}
```

Without resampling

[27]:
```python
rf_model = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

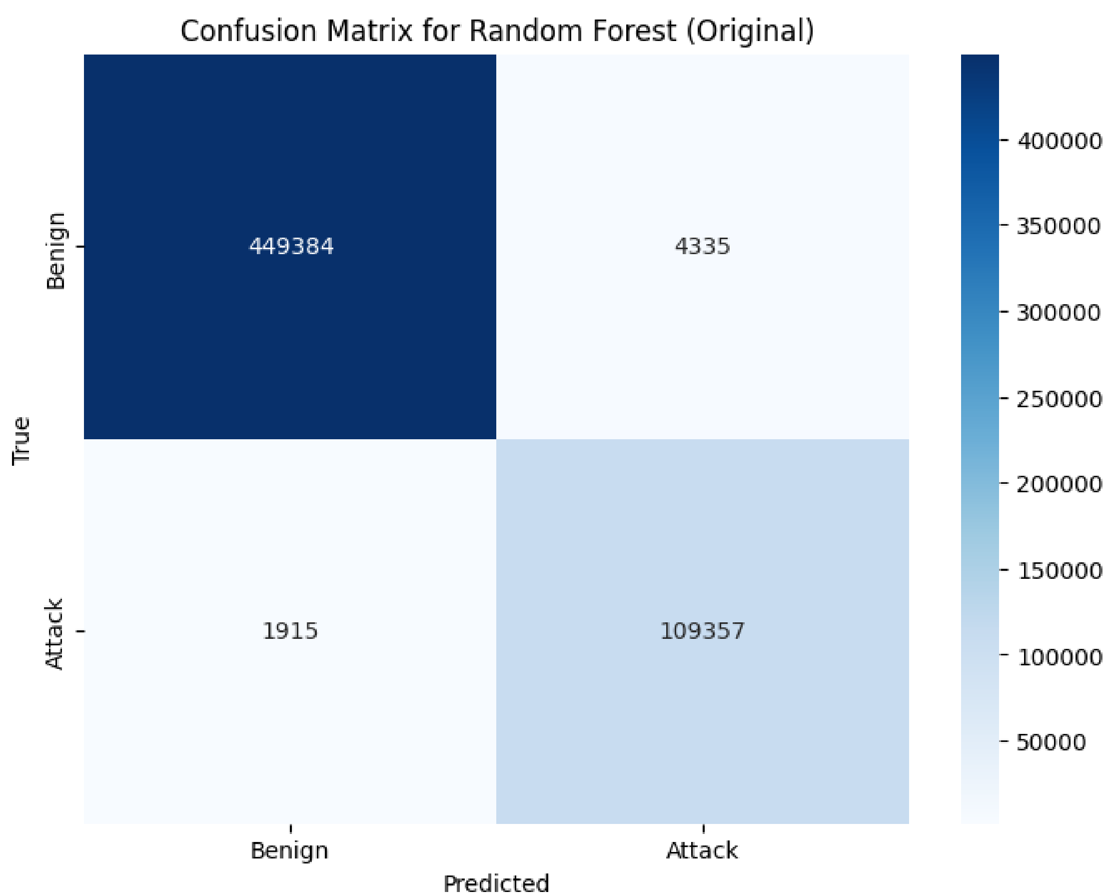
```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   36.5s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.3min finished
```

[27]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[28]:
```python
# Predict and evaluate on the test set
rf_metrics["original"] = test_metrics("Random Forest", rf_model, "Original",␣
↪scaler)
```

```
Random Forest with Original 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 (Original)):
              precision    recall  f1-score   support

           0     0.9958    0.9904    0.9931    453719
           1     0.9619    0.9828    0.9722    111272

    accuracy                         0.9889    564991
   macro avg     0.9788    0.9866    0.9827    564991
weighted avg     0.9891    0.9889    0.9890    564991

Accuracy: 0.9889378768865345
Precision: 0.9890830193424515
Recall: 0.9889378768865345
F1 Score: 0.9889825860984667
AUC: 0.9866177742184126
```



```
Metrics by Label (Original):
                          Label  Accuracy    Method
0                        BENIGN  0.990446  Original
1                      DoS Hulk  0.978127  Original
2                          DDoS  0.998750  Original
3                      PortScan  1.000000  Original
4              DoS Slowhttptest  0.992727  Original
5                   FTP-Patator  0.984868  Original
6                 DoS GoldenEye  0.990282  Original
7                           Bot  0.457801  Original
8                 DoS slowloris  0.993960  Original
9                   SSH-Patator  0.525869  Original
10     Web Attack - Brute Force  0.880795  Original
11             Web Attack - XSS  0.961538  Original
12  Web Attack - Sql Injection  0.500000  Original
13                 Infiltration  0.428571  Original
14                   Heartbleed  1.000000  Original
```

With random oversampler

[29]:
```
rf_model_random = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
  ↪is_attack)
```

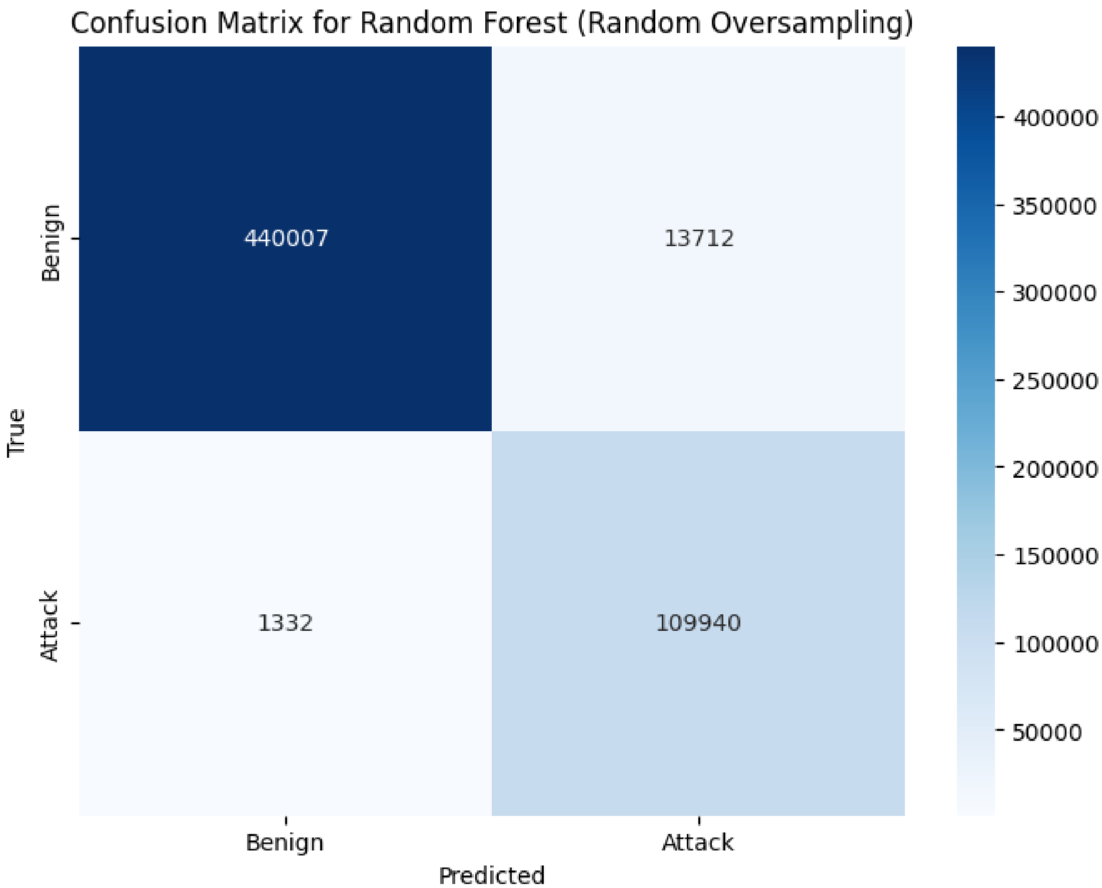
```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   49.0s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.9min finished
```

[29]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[30]:
```
# 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:    0.0s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    0.5s finished

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

           0     0.9970    0.9698    0.9832    453719
           1     0.8891    0.9880    0.9360    111272

    accuracy                         0.9734    564991
```

```
   macro avg     0.9430    0.9789    0.9596    564991
weighted avg     0.9757    0.9734    0.9739    564991

Accuracy: 0.973373027180964
Precision: 0.9757367414142306
Recall: 0.973373027180964
F1 Score: 0.9738904743080002
AUC: 0.9789039925346467
```




```
Metrics by Label (Random Oversampling):
                         Label  Accuracy               Method
0                       BENIGN  0.969779  Random Oversampling
1                     DoS Hulk  0.978388  Random Oversampling
2                         DDoS  0.998633  Random Oversampling
3                     PortScan  1.000000  Random Oversampling
4             DoS Slowhttptest  0.994545  Random Oversampling
5                  FTP-Patator  0.998108  Random Oversampling
6                DoS GoldenEye  0.991254  Random Oversampling
7                          Bot  0.749361  Random Oversampling
```

```
8                 DoS slowloris  0.993960  Random Oversampling
9                   SSH-Patator  0.882952  Random Oversampling
10     Web Attack - Brute Force  0.920530  Random Oversampling
11             Web Attack - XSS  0.961538  Random Oversampling
12   Web Attack - Sql Injection  0.750000  Random Oversampling
13                 Infiltration  0.571429  Random Oversampling
14                   Heartbleed  1.000000  Random Oversampling
```

With SMOTE

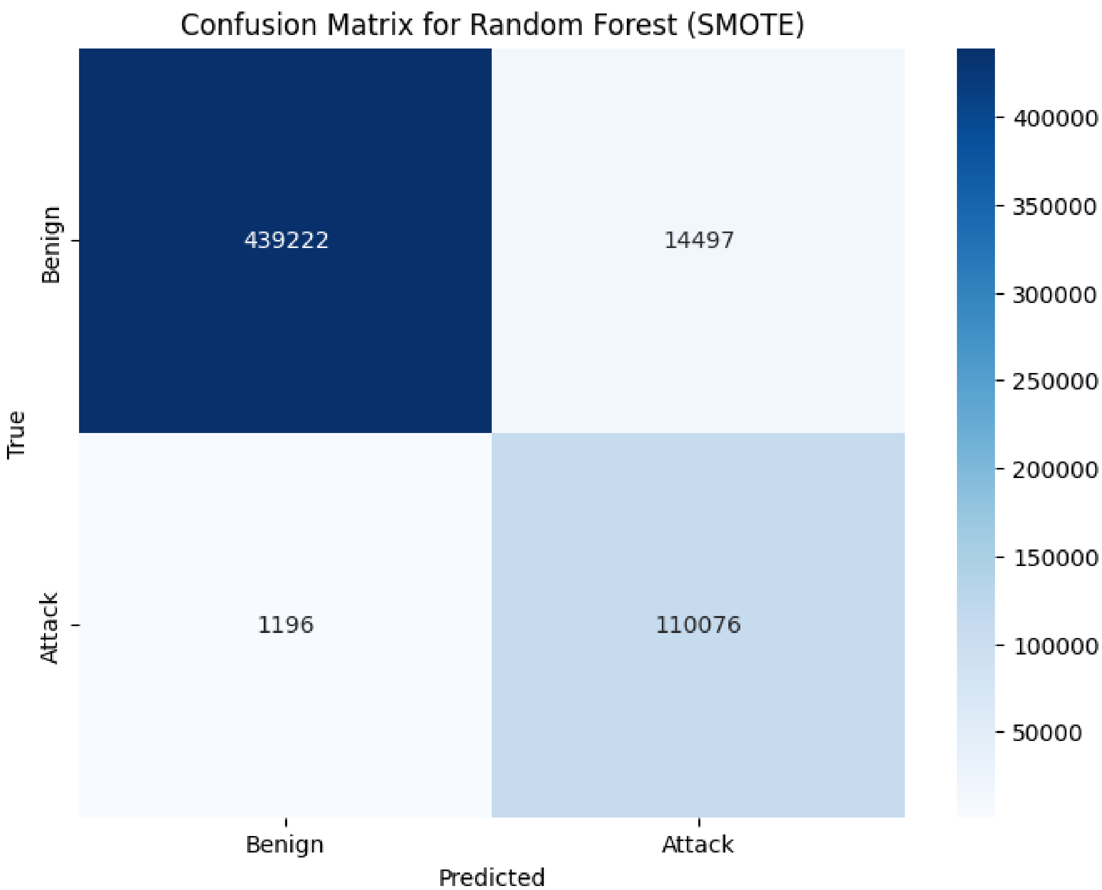
[31]:
```
rf_model_smote = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
 ↪is_attack)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   55.1s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  3.1min finished
```

[31]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[32]:
```
# 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:    0.1s
[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:    0.5s finished

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

           0     0.9973    0.9680    0.9824    453719
           1     0.8836    0.9893    0.9335    111272

    accuracy                         0.9722    564991
   macro avg     0.9405    0.9787    0.9580    564991
weighted avg     0.9749    0.9722    0.9728    564991

Accuracy: 0.9722243363168617
Precision: 0.9749000676591014
Recall: 0.9722243363168617
F1 Score: 0.9728009787266748
AUC: 0.9786500347644719
```



Metrics by Label (SMOTE):

	Label	Accuracy	Method
0	BENIGN	0.968049	SMOTE
1	DoS Hulk	0.980106	SMOTE
2	DDoS	0.998594	SMOTE
3	PortScan	1.000000	SMOTE
4	DoS Slowhttptest	0.995455	SMOTE
5	FTP-Patator	0.999369	SMOTE
6	DoS GoldenEye	0.991740	SMOTE
7	Bot	0.790281	SMOTE
8	DoS slowloris	0.995686	SMOTE
9	SSH-Patator	0.905852	SMOTE
10	Web Attack - Brute Force	0.943709	SMOTE
11	Web Attack - XSS	0.976923	SMOTE
12	Web Attack - Sql Injection	0.750000	SMOTE
13	Infiltration	0.571429	SMOTE
14	Heartbleed	1.000000	SMOTE

With ADASYN

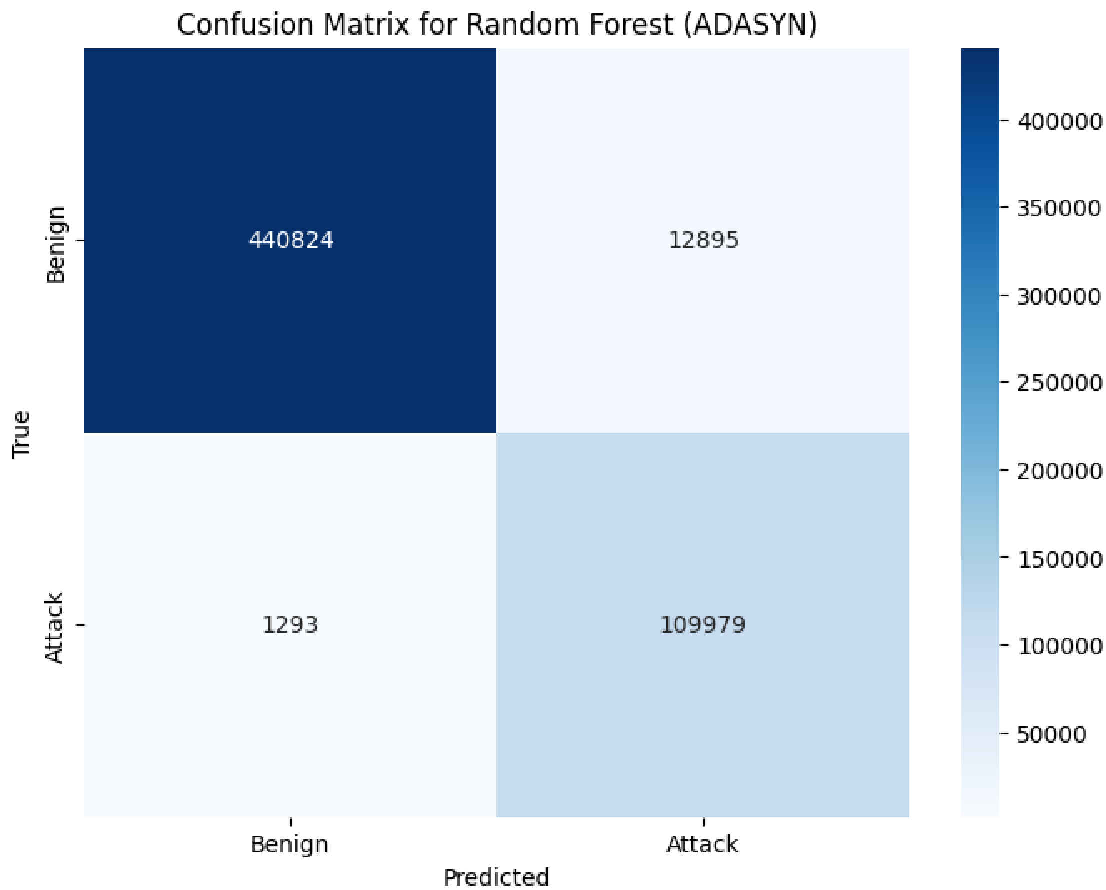
[33]:
```python
rf_model_adasyn = RandomForestClassifier(verbose=1, n_jobs=-1)
rf_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
 ↪is_attack)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   49.2s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.8min finished
```

[33]:
```
RandomForestClassifier(n_jobs=-1, verbose=1)
```

[34]:
```python
# 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:    0.5s finished

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

           0     0.9971    0.9716    0.9842    453719
           1     0.8951    0.9884    0.9394    111272

    accuracy                         0.9749    564991
   macro avg     0.9461    0.9800    0.9618    564991
weighted avg     0.9770    0.9749    0.9753    564991

Accuracy: 0.9748880955625842
Precision: 0.9769830669123931
Recall: 0.9748880955625842
F1 Score: 0.9753476339890228
AUC: 0.9799795757708064
```




```
Metrics by Label (ADASYN):
                         Label  Accuracy  Method
0                       BENIGN  0.971579  ADASYN
1                     DoS Hulk  0.980693  ADASYN
2                         DDoS  0.998711  ADASYN
3                     PortScan  1.000000  ADASYN
4             DoS Slowhttptest  0.997273  ADASYN
5                  FTP-Patator  0.987390  ADASYN
6                DoS GoldenEye  0.992711  ADASYN
7                          Bot  0.639386  ADASYN
8                DoS slowloris  0.995686  ADASYN
9                  SSH-Patator  0.862595  ADASYN
10    Web Attack - Brute Force  0.930464  ADASYN
11            Web Attack - XSS  0.992308  ADASYN
12  Web Attack - Sql Injection  0.750000  ADASYN
13                Infiltration  0.571429  ADASYN
14                  Heartbleed  1.000000  ADASYN
```

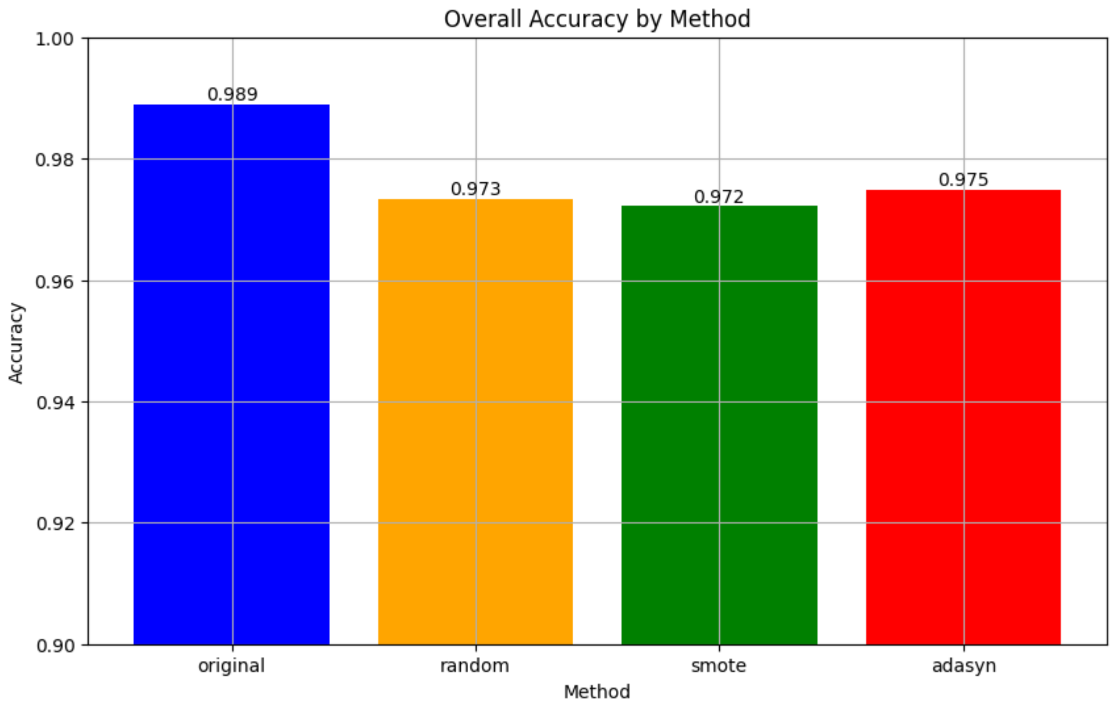
[35]:

```
# 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                      0.990446             0.969779  0.968049  0.971579
Bot                         0.457801             0.749361  0.790281  0.639386
DDoS                        0.998750             0.998633  0.998594  0.998711
DoS GoldenEye               0.990282             0.991254  0.991740  0.992711
DoS Hulk                    0.978127             0.978388  0.980106  0.980693
DoS Slowhttptest            0.992727             0.994545  0.995455  0.997273
DoS slowloris               0.993960             0.993960  0.995686  0.995686
FTP-Patator                 0.984868             0.998108  0.999369  0.987390
Heartbleed                  1.000000             1.000000  1.000000  1.000000
Infiltration                0.428571             0.571429  0.571429  0.571429
PortScan                    1.000000             1.000000  1.000000  1.000000
SSH-Patator                 0.525869             0.882952  0.905852  0.862595
Web Attack - Brute Force    0.880795             0.920530  0.943709  0.930464
Web Attack - Sql Injection  0.500000             0.750000  0.750000  0.750000
Web Attack - XSS            0.961538             0.961538  0.976923  0.992308
```

[36]:

```
plot_overall_accuracy(rf_metrics)
```



1.4.4 Gradient Boost (XGB)

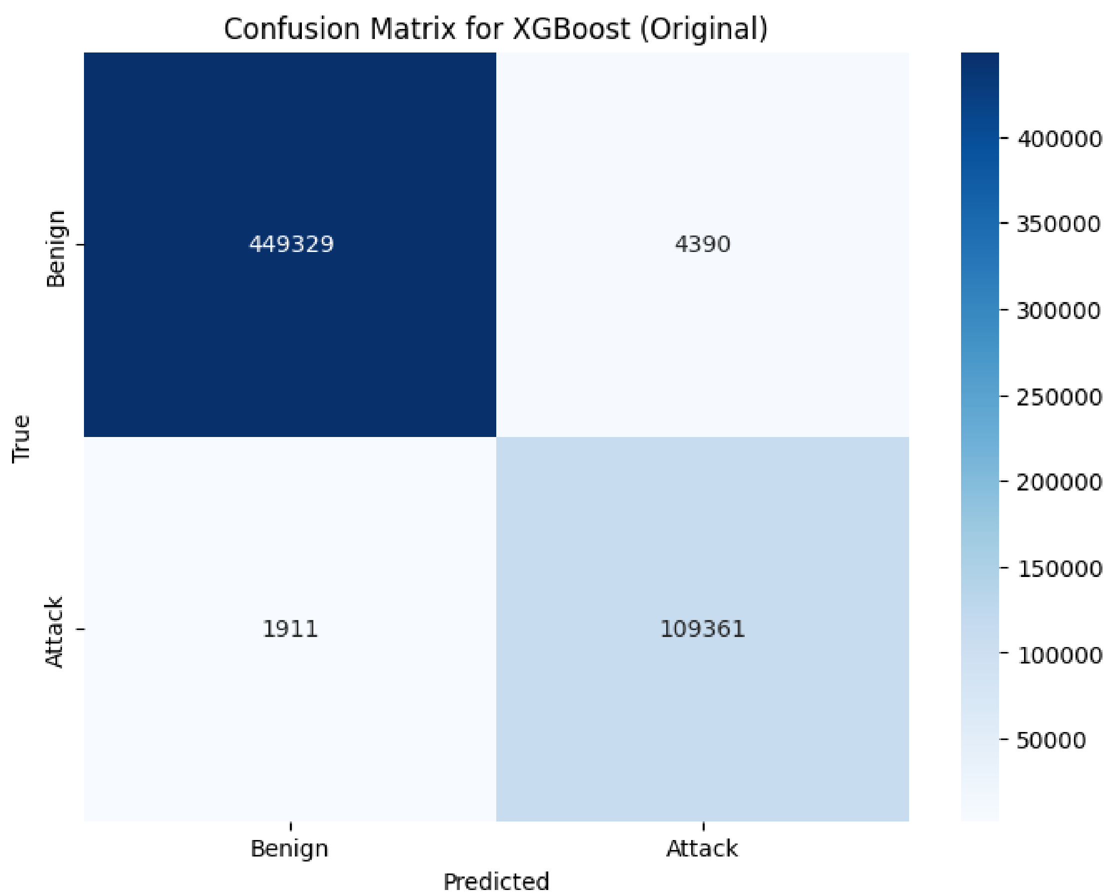
[37]:
```
xgb_metrics = {}
```

[38]:
```
import xgboost as xgb

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

[38]:
```
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, …)
```

[39]:
```
# 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     0.9958    0.9903    0.9930    453719
           1     0.9614    0.9828    0.9720    111272

    accuracy                         0.9888    564991
   macro avg     0.9786    0.9866    0.9825    564991
weighted avg     0.9890    0.9888    0.9889    564991

Accuracy: 0.9888476099619286
Precision: 0.9889983621979145
Recall: 0.9888476099619286
F1 Score: 0.9888937658065841
AUC: 0.9865751379906303
```




```
Metrics by Label (Original):
                          Label  Accuracy    Method
```

```
0                      BENIGN  0.990324  Original
1                    DoS Hulk  0.978388  Original
2                        DDoS  0.998633  Original
3                    PortScan  1.000000  Original
4            DoS Slowhttptest  0.996364  Original
5                 FTP-Patator  0.985498  Original
6               DoS GoldenEye  0.997570  Original
7                         Bot  0.398977  Original
8               DoS slowloris  0.993097  Original
9                 SSH-Patator  0.525869  Original
10   Web Attack - Brute Force  0.880795  Original
11           Web Attack - XSS  0.961538  Original
12  Web Attack - Sql Injection  0.500000  Original
13               Infiltration  0.285714  Original
14                 Heartbleed  1.000000  Original
```

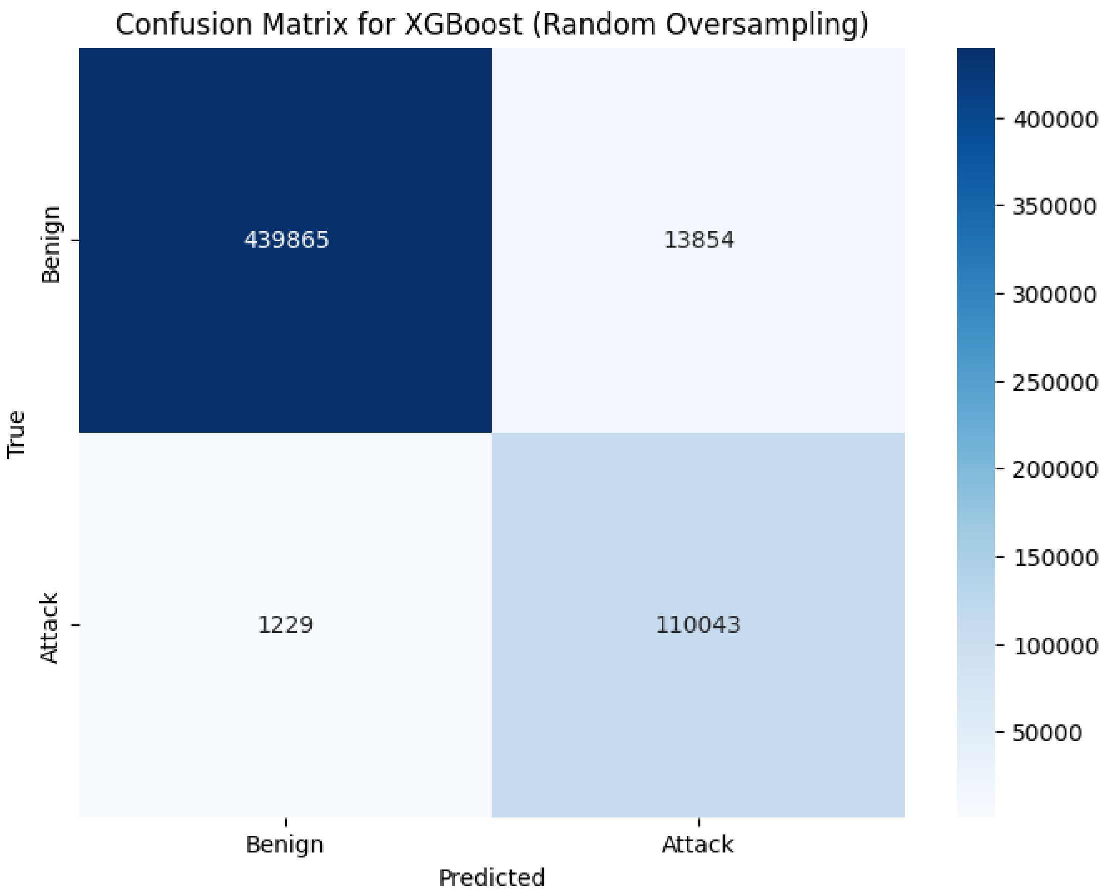
[40]:
```
xgb_model_random = xgb.XGBClassifier(n_jobs=-1)
xgb_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
 ↪is_attack)
```

[40]:
```
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, …)
```

[41]:
```
# 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     0.9972    0.9695    0.9831    453719
           1     0.8882    0.9890    0.9359    111272

    accuracy                         0.9733    564991
   macro avg     0.9427    0.9792    0.9595    564991
weighted avg     0.9757    0.9733    0.9738    564991
```

```
Accuracy: 0.9733039995327359
Precision: 0.9757403825518012
Recall: 0.9733039995327359
F1 Score: 0.9738322560350485
AUC: 0.9792103378369093
```



Metrics by Label (Random Oversampling):

	Label	Accuracy	Method
0	BENIGN	0.969466	Random Oversampling
1	DoS Hulk	0.979301	Random Oversampling
2	DDoS	0.998477	Random Oversampling
3	PortScan	0.999969	Random Oversampling
4	DoS Slowhttptest	0.998182	Random Oversampling
5	FTP-Patator	0.998108	Random Oversampling
6	DoS GoldenEye	0.998056	Random Oversampling
7	Bot	0.846547	Random Oversampling
8	DoS slowloris	0.995686	Random Oversampling
9	SSH-Patator	0.883800	Random Oversampling
10	Web Attack - Brute Force	0.940397	Random Oversampling

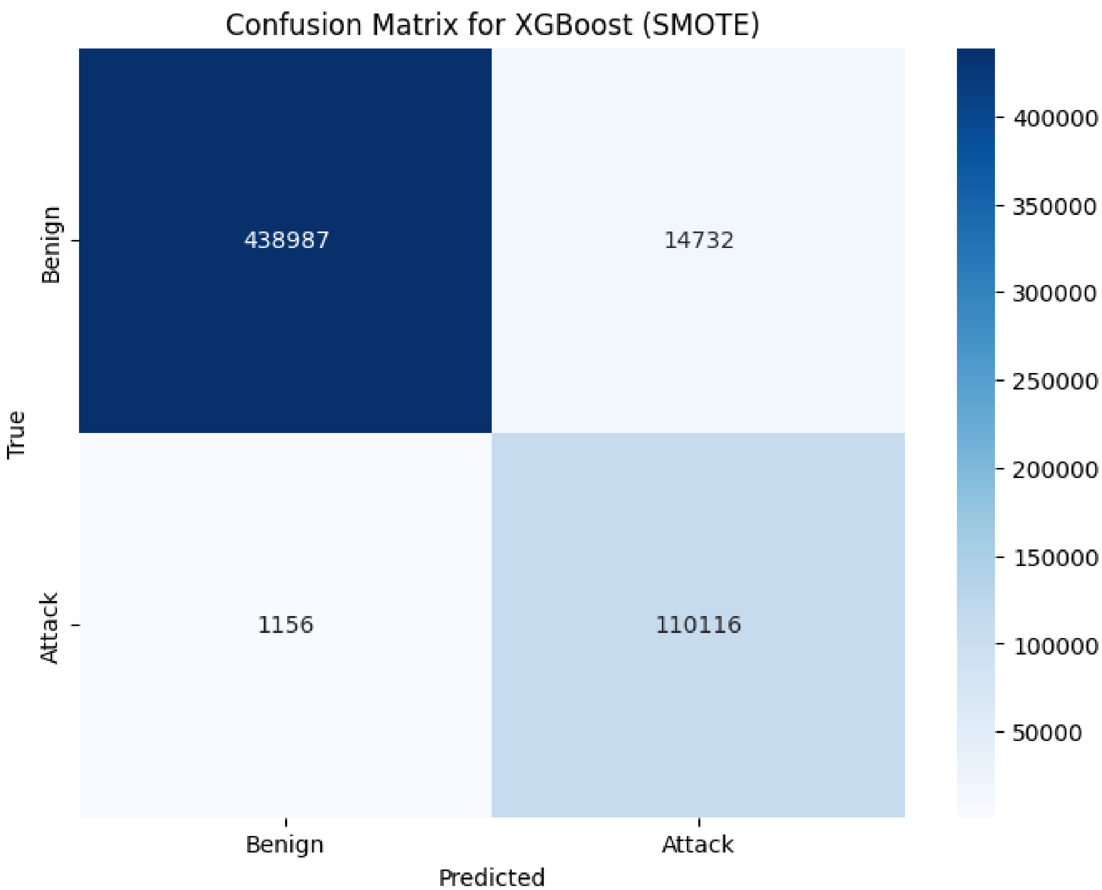
```
11             Web Attack - XSS  0.969231  Random Oversampling
12  Web Attack - Sql Injection  0.750000  Random Oversampling
13                Infiltration  0.571429  Random Oversampling
14                  Heartbleed  1.000000  Random Oversampling
```

[42]:
```python
xgb_model_smote = xgb.XGBClassifier(n_jobs=-1)
xgb_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
 ↪is_attack)
```

[42]:
```
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, …)
```

[43]:
```python
# 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     0.9974    0.9675    0.9822    453719
           1     0.8820    0.9896    0.9327    111272

    accuracy                         0.9719    564991
   macro avg     0.9397    0.9786    0.9575    564991
weighted avg     0.9747    0.9719    0.9725    564991

Accuracy: 0.9718791980757215
Precision: 0.9746514630752818
Recall: 0.9718791980757215
F1 Score: 0.9724740677916712
AUC: 0.9785708036405139
```



Metrics by Label (SMOTE):

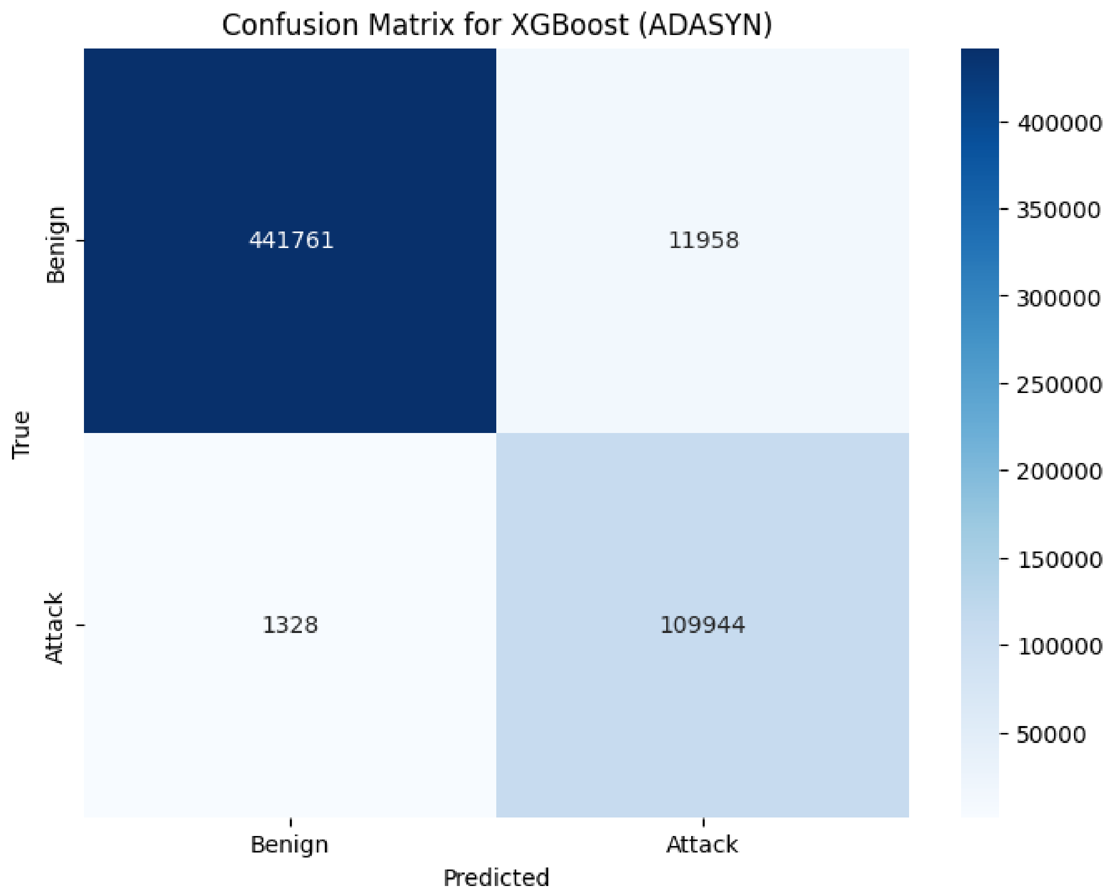
	Label	Accuracy	Method
0	BENIGN	0.967531	SMOTE
1	DoS Hulk	0.980258	SMOTE
2	DDoS	0.998516	SMOTE
3	PortScan	1.000000	SMOTE
4	DoS Slowhttptest	0.996364	SMOTE
5	FTP-Patator	0.998108	SMOTE
6	DoS GoldenEye	0.998056	SMOTE
7	Bot	0.820972	SMOTE
8	DoS slowloris	0.995686	SMOTE
9	SSH-Patator	0.911790	SMOTE
10	Web Attack - Brute Force	0.953642	SMOTE
11	Web Attack - XSS	0.984615	SMOTE
12	Web Attack - Sql Injection	0.750000	SMOTE
13	Infiltration	0.571429	SMOTE
14	Heartbleed	1.000000	SMOTE

[44]:
```
xgb_model_adasyn = xgb.XGBClassifier(n_jobs=-1)
xgb_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
 ↪is_attack)
```

[44]:
```
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, …)
```

[45]:
```
# 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     0.9970    0.9736    0.9852    453719
           1     0.9019    0.9881    0.9430    111272

    accuracy                         0.9765    564991
   macro avg     0.9495    0.9809    0.9641    564991
weighted avg     0.9783    0.9765    0.9769    564991

Accuracy: 0.9764845811703196
Precision: 0.978273799545184
Recall: 0.9764845811703196
F1 Score: 0.9768812289418751
AUC: 0.9808548809333403
```



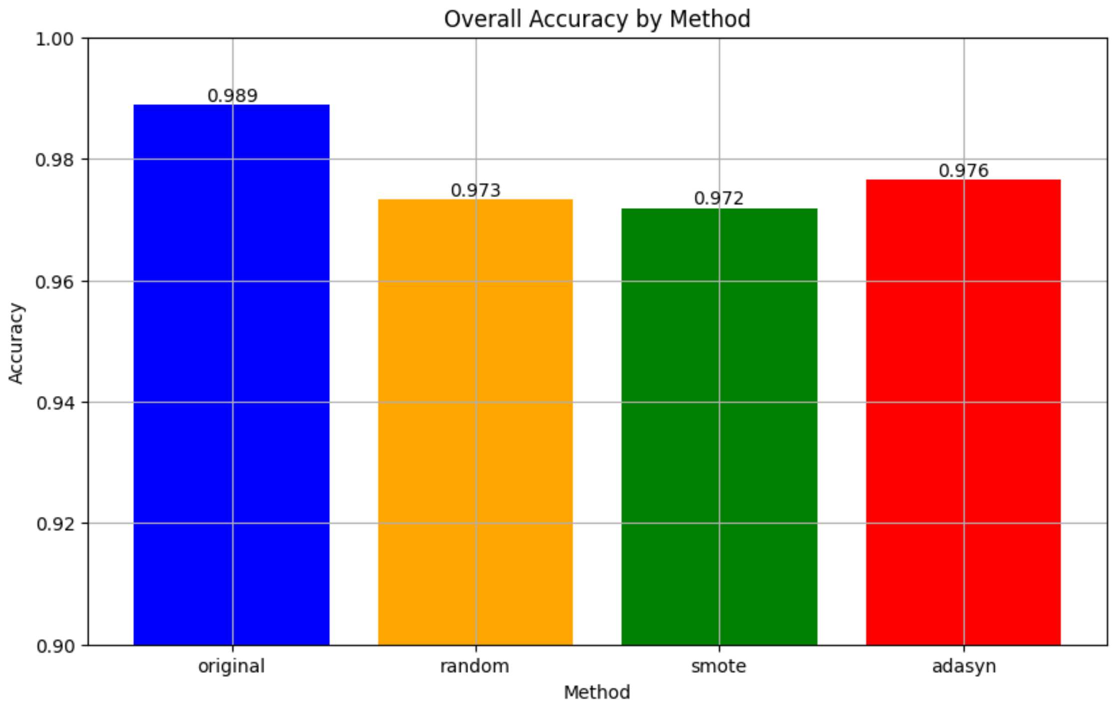
Metrics by Label (ADASYN):

	Label	Accuracy	Method
0	BENIGN	0.973644	ADASYN
1	DoS Hulk	0.980106	ADASYN
2	DDoS	0.998555	ADASYN
3	PortScan	1.000000	ADASYN
4	DoS Slowhttptest	0.997273	ADASYN
5	FTP-Patator	0.987390	ADASYN
6	DoS GoldenEye	0.999514	ADASYN
7	Bot	0.685422	ADASYN
8	DoS slowloris	0.996549	ADASYN
9	SSH-Patator	0.832061	ADASYN
10	Web Attack - Brute Force	0.927152	ADASYN
11	Web Attack - XSS	0.992308	ADASYN
12	Web Attack - Sql Injection	0.750000	ADASYN
13	Infiltration	0.571429	ADASYN
14	Heartbleed	1.000000	ADASYN

[46]:
```
# 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                      0.990324             0.969466  0.967531  0.973644
Bot                         0.398977             0.846547  0.820972  0.685422
DDoS                        0.998633             0.998477  0.998516  0.998555
DoS GoldenEye               0.997570             0.998056  0.998056  0.999514
DoS Hulk                    0.978388             0.979301  0.980258  0.980106
DoS Slowhttptest            0.996364             0.998182  0.996364  0.997273
DoS slowloris               0.993097             0.995686  0.995686  0.996549
FTP-Patator                 0.985498             0.998108  0.998108  0.987390
Heartbleed                  1.000000             1.000000  1.000000  1.000000
Infiltration                0.285714             0.571429  0.571429  0.571429
PortScan                    1.000000             0.999969  1.000000  1.000000
SSH-Patator                 0.525869             0.883800  0.911790  0.832061
Web Attack - Brute Force    0.880795             0.940397  0.953642  0.927152
Web Attack - Sql Injection  0.500000             0.750000  0.750000  0.750000
Web Attack - XSS            0.961538             0.969231  0.984615  0.992308
```

[47]:
```
plot_overall_accuracy(xgb_metrics)
```



1.4.5 AdaBoost

[48]:
```
ada_metrics = {}
```

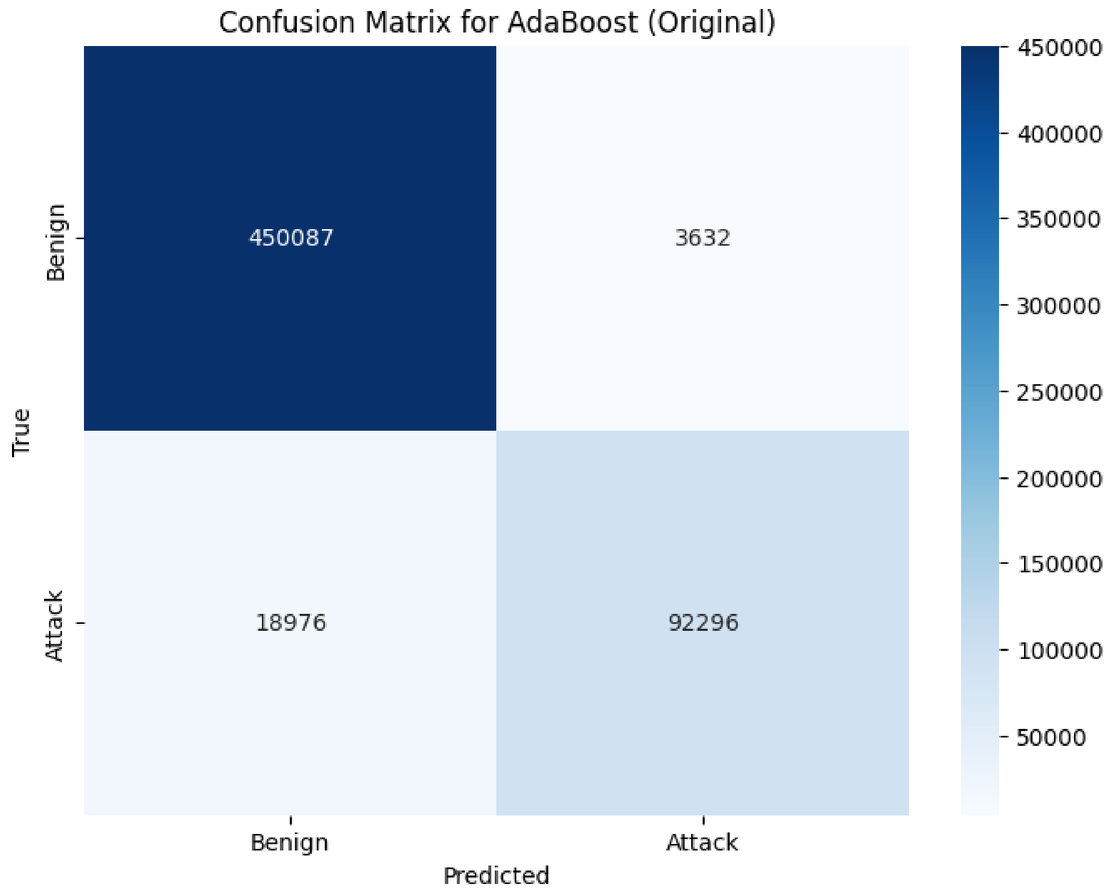
[49]:
```
from sklearn.ensemble import AdaBoostClassifier

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

[49]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[50]:
```
# 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     0.9595    0.9920    0.9755    453719
           1     0.9621    0.8295    0.8909    111272

    accuracy                         0.9600    564991
   macro avg     0.9608    0.9107    0.9332    564991
weighted avg     0.9601    0.9600    0.9588    564991
```

```
Accuracy: 0.9599852033041234
Precision: 0.9600556344851168
Recall: 0.9599852033041234
F1 Score: 0.9588362569510817
AUC: 0.9107289915288951
```




```
Metrics by Label (Original):
                     Label  Accuracy    Method
0                   BENIGN  0.991995  Original
1                 DoS Hulk  0.709956  Original
2                     DDoS  0.967501  Original
3                 PortScan  0.993892  Original
4        DoS Slowhttptest  0.565455  Original
5               FTP-Patator  0.425599  Original
6            DoS GoldenEye  0.488338  Original
7                      Bot  0.258312  Original
8            DoS slowloris  0.477135  Original
9              SSH-Patator  0.000848  Original
```

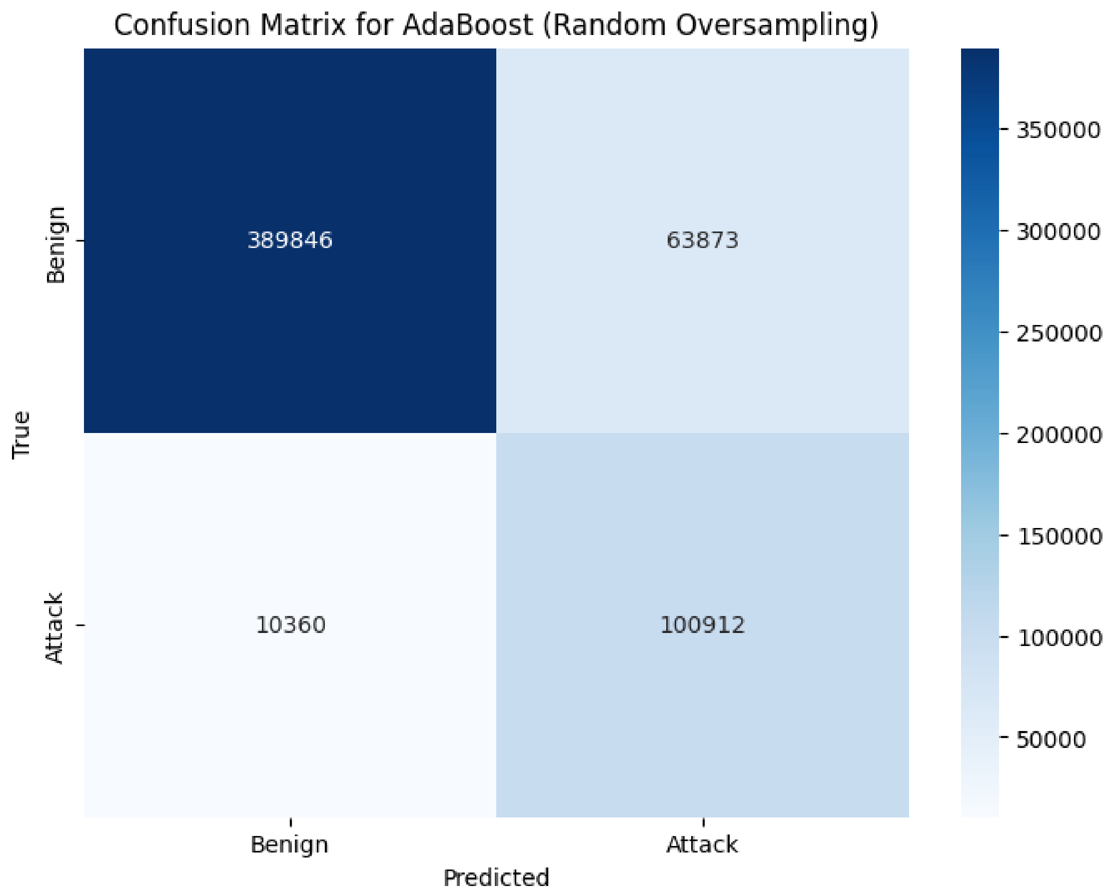
```
10    Web Attack - Brute Force  0.758278  Original
11            Web Attack - XSS  0.923077  Original
12  Web Attack - Sql Injection  0.000000  Original
13                Infiltration  0.000000  Original
14                  Heartbleed  1.000000  Original
```

[51]:
```python
ada_model_random = AdaBoostClassifier(algorithm='SAMME')
ada_model_random.fit(scaler_random.transform(X_random_train), Y_random_train.
 ↪is_attack)
```

[51]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[52]:
```python
# 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     0.9741    0.8592    0.9131    453719
           1     0.6124    0.9069    0.7311    111272

    accuracy                         0.8686    564991
   macro avg     0.7932    0.8831    0.8221    564991
weighted avg     0.9029    0.8686    0.8772    564991

Accuracy: 0.8686120663868983
Precision: 0.9028730076569125
Recall: 0.8686120663868983
F1 Score: 0.8772298371729309
AUC: 0.8830591281823519
```



Metrics by Label (Random Oversampling):

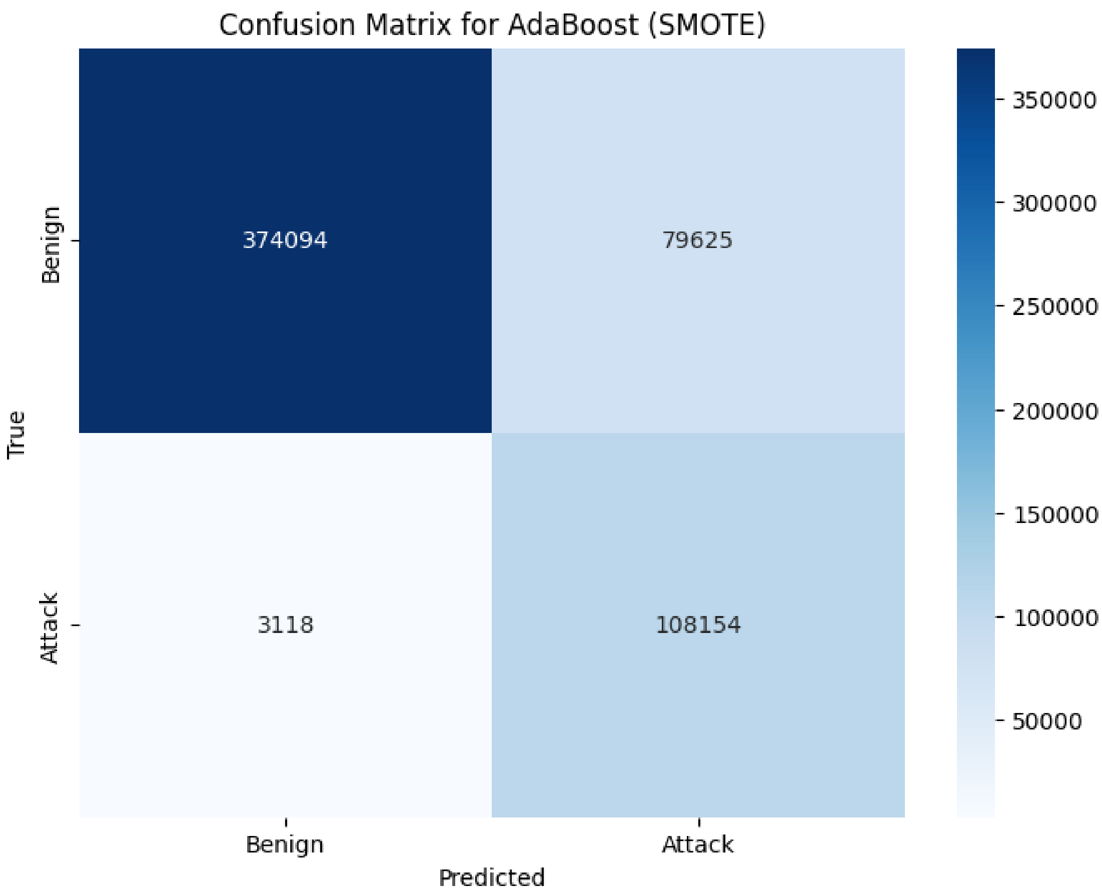
	Label	Accuracy	Method
0	BENIGN	0.859223	Random Oversampling
1	DoS Hulk	0.800818	Random Oversampling
2	DDoS	0.977267	Random Oversampling
3	PortScan	0.996033	Random Oversampling
4	DoS Slowhttptest	0.880000	Random Oversampling
5	FTP-Patator	0.996847	Random Oversampling
6	DoS GoldenEye	0.987366	Random Oversampling
7	Bot	0.258312	Random Oversampling
8	DoS slowloris	0.972390	Random Oversampling
9	SSH-Patator	0.997455	Random Oversampling
10	Web Attack - Brute Force	1.000000	Random Oversampling
11	Web Attack - XSS	1.000000	Random Oversampling
12	Web Attack - Sql Injection	1.000000	Random Oversampling
13	Infiltration	0.571429	Random Oversampling
14	Heartbleed	1.000000	Random Oversampling

[53]:
```
ada_model_smote = AdaBoostClassifier(algorithm='SAMME')
ada_model_smote.fit(scaler_smote.transform(X_smote_train), Y_smote_train.
 ↪is_attack)
```

[53]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[54]:
```
# 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     0.9917    0.8245    0.9004    453719
           1     0.5760    0.9720    0.7233    111272

    accuracy                         0.8535    564991
   macro avg     0.7838    0.8982    0.8119    564991
weighted avg     0.9099    0.8535    0.8655    564991

Accuracy: 0.8535498795556036
Precision: 0.9098504215667096
Recall: 0.8535498795556036
F1 Score: 0.8655411265765997
AUC: 0.8982422458405165
```



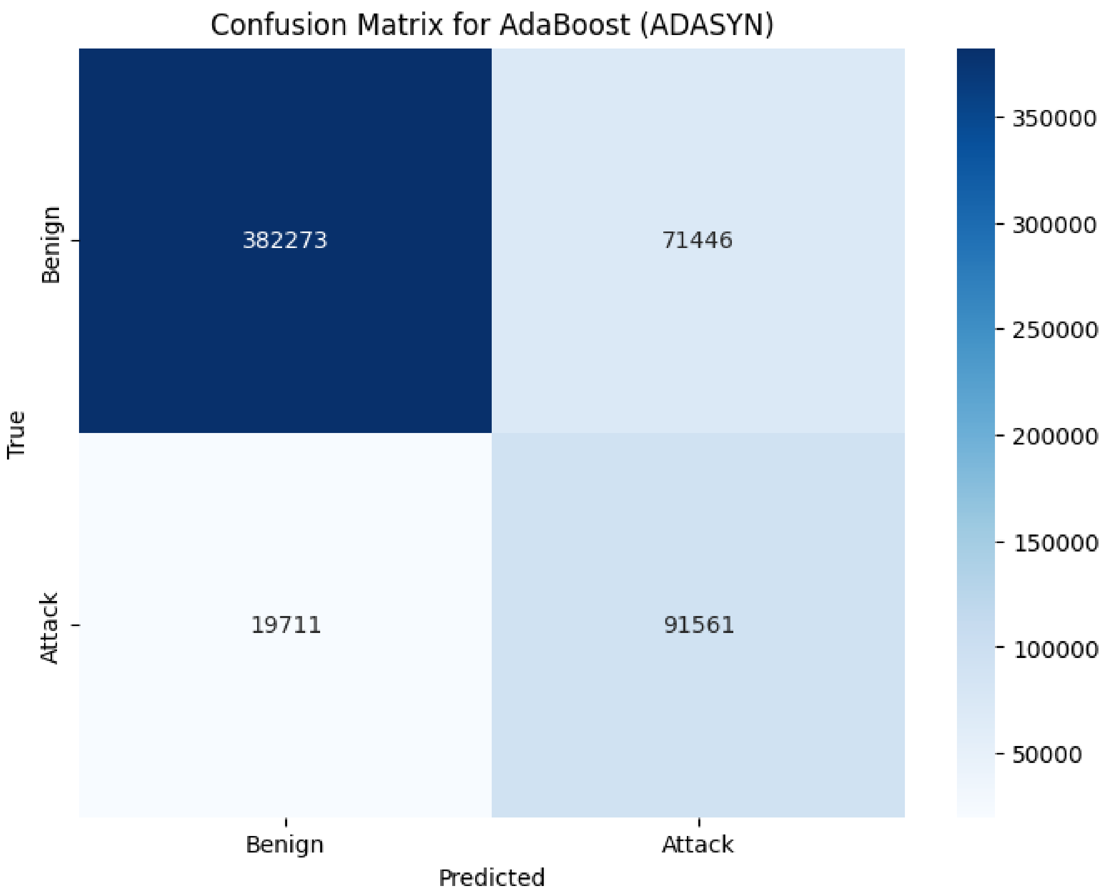

```
Metrics by Label (SMOTE):
                        Label  Accuracy Method
0                      BENIGN  0.824506  SMOTE
1                    DoS Hulk  0.955385  SMOTE
2                        DDoS  0.978946  SMOTE
3                    PortScan  0.997166  SMOTE
4            DoS Slowhttptest  0.934545  SMOTE
5                 FTP-Patator  0.996847  SMOTE
6               DoS GoldenEye  0.987852  SMOTE
7                         Bot  0.258312  SMOTE
8               DoS slowloris  0.964625  SMOTE
9                 SSH-Patator  0.998304  SMOTE
10     Web Attack - Brute Force  1.000000  SMOTE
11           Web Attack - XSS  1.000000  SMOTE
12  Web Attack - Sql Injection  1.000000  SMOTE
13               Infiltration  0.714286  SMOTE
14                 Heartbleed  1.000000  SMOTE
```

[55]:
```
ada_model_adasyn = AdaBoostClassifier(algorithm='SAMME')
ada_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train), Y_adasyn_train.
    ↪is_attack)
```

[55]:
```
AdaBoostClassifier(algorithm='SAMME')
```

[56]:
```
# 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     0.9510    0.8425    0.8935    453719
           1     0.5617    0.8229    0.6676    111272

    accuracy                         0.8387    564991
   macro avg     0.7563    0.8327    0.7806    564991
weighted avg     0.8743    0.8387    0.8490    564991

Accuracy: 0.8386576069353318
Precision: 0.874301841330705
Recall: 0.8386576069353318
F1 Score: 0.8489966488171201
AUC: 0.832694997457311
```

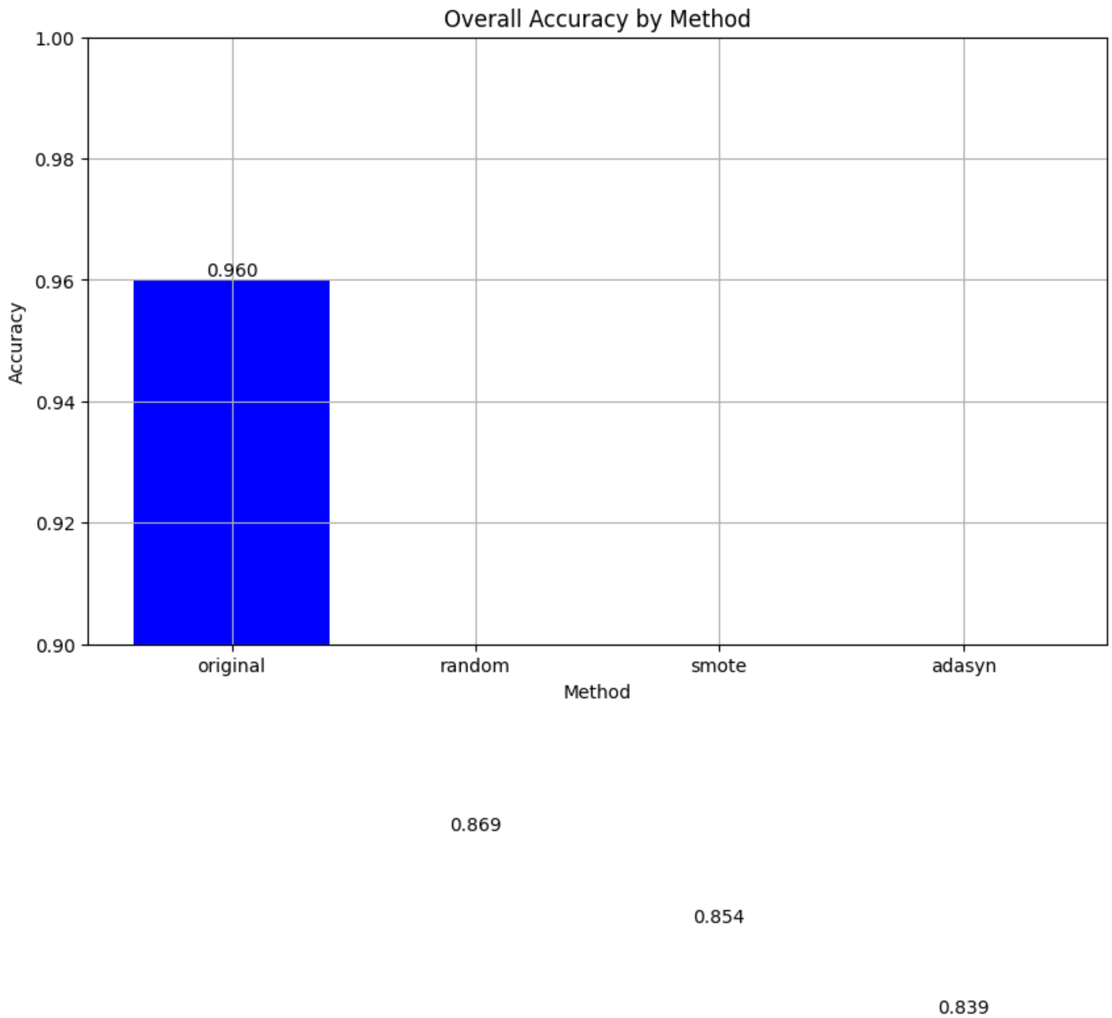



```
Metrics by Label (ADASYN):
                        Label  Accuracy  Method
0                      BENIGN  0.842532  ADASYN
1                    DoS Hulk  0.770552  ADASYN
2                        DDoS  0.668919  ADASYN
3                    PortScan  0.991656  ADASYN
4            DoS Slowhttptest  0.937273  ADASYN
5                 FTP-Patator  1.000000  ADASYN
6               DoS GoldenEye  0.977162  ADASYN
7                         Bot  0.286445  ADASYN
8               DoS slowloris  0.986195  ADASYN
9                 SSH-Patator  0.998304  ADASYN
10     Web Attack - Brute Force  1.000000  ADASYN
11           Web Attack - XSS  0.992308  ADASYN
12  Web Attack - Sql Injection  1.000000  ADASYN
13               Infiltration  0.571429  ADASYN
14                 Heartbleed  1.000000  ADASYN
```

[57]:
```
# 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                      0.991995             0.859223  0.824506  0.842532
Bot                         0.258312             0.258312  0.258312  0.286445
DDoS                        0.967501             0.977267  0.978946  0.668919
DoS GoldenEye               0.488338             0.987366  0.987852  0.977162
DoS Hulk                    0.709956             0.800818  0.955385  0.770552
DoS Slowhttptest            0.565455             0.880000  0.934545  0.937273
DoS slowloris               0.477135             0.972390  0.964625  0.986195
FTP-Patator                 0.425599             0.996847  0.996847  1.000000
Heartbleed                  1.000000             1.000000  1.000000  1.000000
Infiltration                0.000000             0.571429  0.714286  0.571429
PortScan                    0.993892             0.996033  0.997166  0.991656
SSH-Patator                 0.000848             0.997455  0.998304  0.998304
Web Attack - Brute Force    0.758278             1.000000  1.000000  1.000000
Web Attack - Sql Injection  0.000000             1.000000  1.000000  1.000000
Web Attack - XSS            0.923077             1.000000  1.000000  0.992308
```

[58]:
```
plot_overall_accuracy(ada_metrics)
```



1.4.6 Decision Tree

[59]:
```
dt_metrics = {}
```

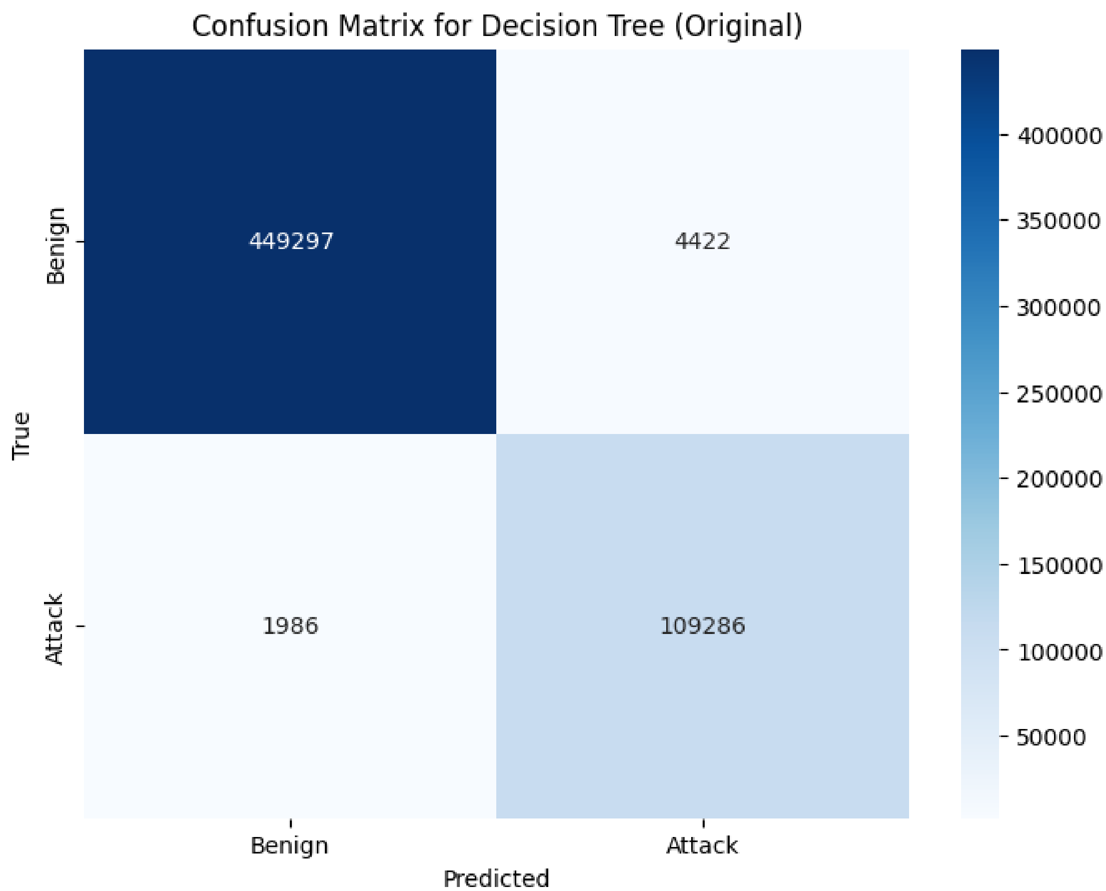
[60]:
```
decision_tree_model = DecisionTreeClassifier()
decision_tree_model.fit(scaler.transform(X_train), Y_train.is_attack)
```

[60]:
```
DecisionTreeClassifier()
```

[61]:
```
# 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     0.9956    0.9903    0.9929    453719
           1     0.9611    0.9822    0.9715    111272

    accuracy                         0.9887    564991
   macro avg     0.9784    0.9862    0.9822    564991
weighted avg     0.9888    0.9887    0.9887    564991

Accuracy: 0.9886582264142261
Precision: 0.9888069252328201
Recall: 0.9886582264142261
F1 Score: 0.9887043643089077
AUC: 0.9862028618667981
```




```
Metrics by Label (Original):
                         Label  Accuracy    Method
0                       BENIGN  0.990254  Original
1                     DoS Hulk  0.977584  Original
2                         DDoS  0.998555  Original
```

```
3                   PortScan  0.999969  Original
4             DoS Slowhttptest  0.957273  Original
5                 FTP-Patator  0.984868  Original
6               DoS GoldenEye  0.985909  Original
7                         Bot  0.480818  Original
8               DoS slowloris  0.994823  Original
9                 SSH-Patator  0.525021  Original
10    Web Attack - Brute Force  0.877483  Original
11            Web Attack - XSS  0.969231  Original
12  Web Attack - Sql Injection  0.250000  Original
13               Infiltration  0.428571  Original
14                 Heartbleed  1.000000  Original
```

[62]:

```
decision_tree_model_random = DecisionTreeClassifier()
decision_tree_model_random.fit(scaler_random.transform(X_random_train),
    Y_random_train.is_attack)
```

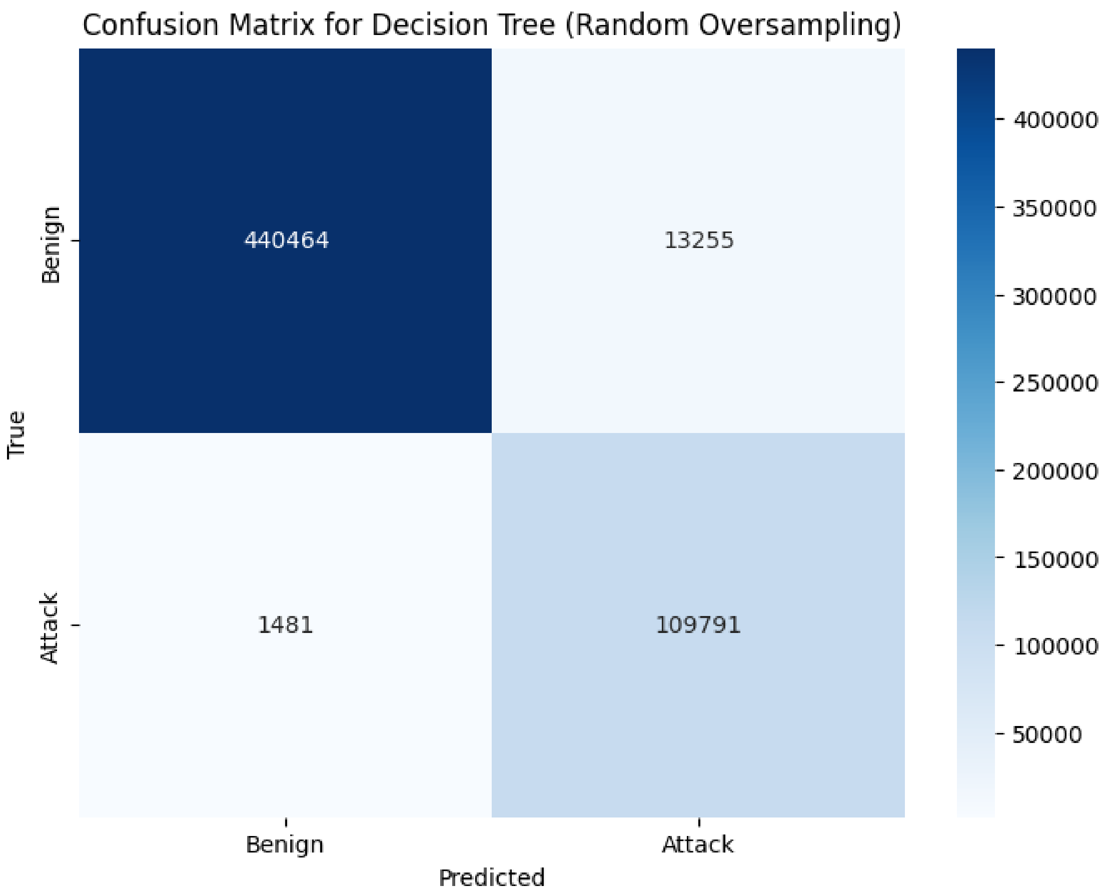
[62]:

```
DecisionTreeClassifier()
```

[63]:

```
# 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     0.9966    0.9708    0.9835    453719
           1     0.8923    0.9867    0.9371    111272

    accuracy                         0.9739    564991
   macro avg     0.9445    0.9787    0.9603    564991
weighted avg     0.9761    0.9739    0.9744    564991

Accuracy: 0.9739181686079955
Precision: 0.9760932225044914
Recall: 0.9739181686079955
F1 Score: 0.974402017866161
AUC: 0.978738077688858
```



Metrics by Label (Random Oversampling):

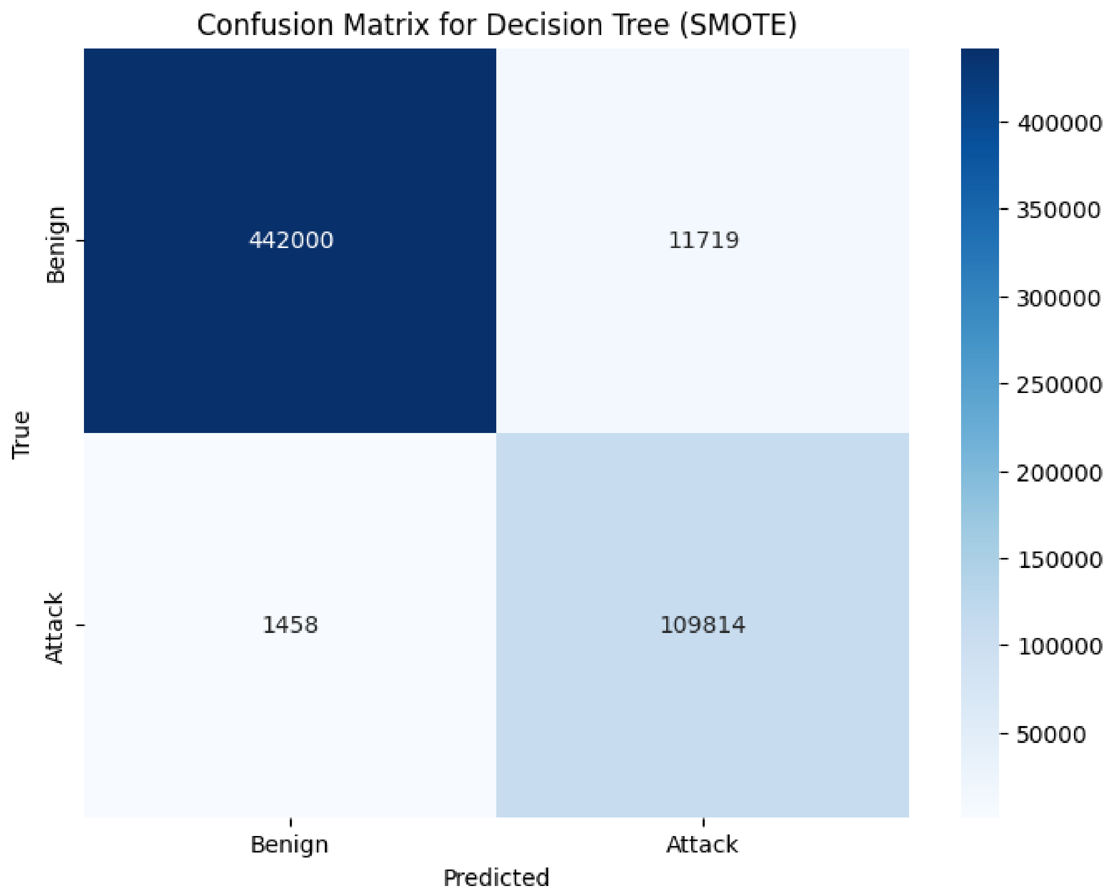
	Label	Accuracy	Method
0	BENIGN	0.970786	Random Oversampling
1	DoS Hulk	0.977649	Random Oversampling
2	DDoS	0.998086	Random Oversampling
3	PortScan	0.999969	Random Oversampling
4	DoS Slowhttptest	0.963636	Random Oversampling
5	FTP-Patator	0.998108	Random Oversampling
6	DoS GoldenEye	0.983965	Random Oversampling
7	Bot	0.672634	Random Oversampling
8	DoS slowloris	0.991372	Random Oversampling
9	SSH-Patator	0.865988	Random Oversampling
10	Web Attack - Brute Force	0.927152	Random Oversampling
11	Web Attack - XSS	0.961538	Random Oversampling
12	Web Attack - Sql Injection	0.750000	Random Oversampling
13	Infiltration	0.571429	Random Oversampling
14	Heartbleed	1.000000	Random Oversampling

[64]:
```
decision_tree_model_smote = DecisionTreeClassifier()
decision_tree_model_smote.fit(scaler_smote.transform(X_smote_train),
↪Y_smote_train.is_attack)
```

[64]:
```
DecisionTreeClassifier()
```

[65]:
```
# 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     0.9967    0.9742    0.9853    453719
           1     0.9036    0.9869    0.9434    111272

    accuracy                         0.9767    564991
   macro avg     0.9501    0.9805    0.9644    564991
weighted avg     0.9784    0.9767    0.9771    564991

Accuracy: 0.9766775045974183
Precision: 0.97836902901942
Recall: 0.9766775045974183
F1 Score: 0.977058110565439
AUC: 0.9805341056640133
```



Metrics by Label (SMOTE):

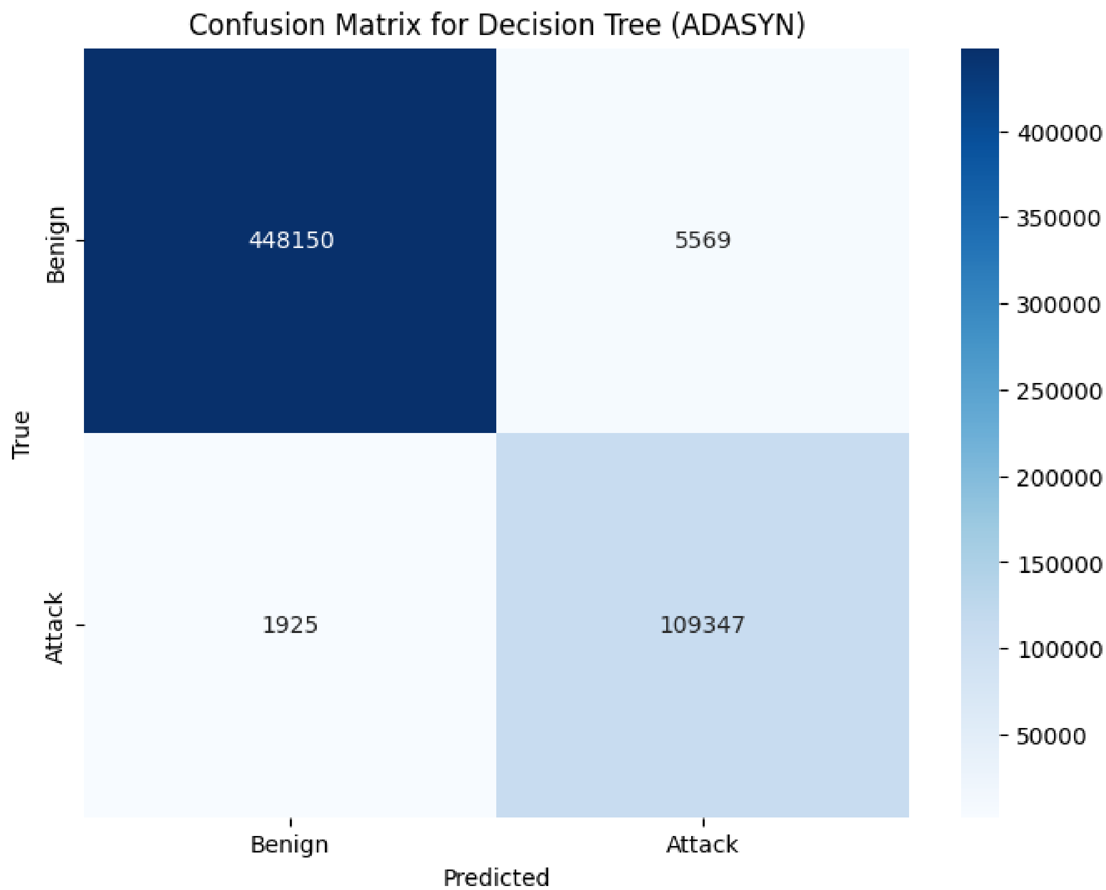
	Label	Accuracy	Method
0	BENIGN	0.974171	SMOTE
1	DoS Hulk	0.977627	SMOTE
2	DDoS	0.998516	SMOTE
3	PortScan	0.999969	SMOTE
4	DoS Slowhttptest	0.986364	SMOTE
5	FTP-Patator	0.997478	SMOTE
6	DoS GoldenEye	0.986395	SMOTE
7	Bot	0.705882	SMOTE
8	DoS slowloris	0.993960	SMOTE
9	SSH-Patator	0.838846	SMOTE
10	Web Attack - Brute Force	0.923841	SMOTE
11	Web Attack - XSS	0.961538	SMOTE
12	Web Attack - Sql Injection	0.750000	SMOTE
13	Infiltration	0.714286	SMOTE
14	Heartbleed	1.000000	SMOTE

[66]:
```
decision_tree_model_adasyn = DecisionTreeClassifier()
decision_tree_model_adasyn.fit(scaler_adasyn.transform(X_adasyn_train),␣
↪Y_adasyn_train.is_attack)
```

[66]: DecisionTreeClassifier()

[67]:
```
# 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     0.9957    0.9877    0.9917    453719
           1     0.9515    0.9827    0.9669    111272

    accuracy                         0.9867    564991
   macro avg     0.9736    0.9852    0.9793    564991
weighted avg     0.9870    0.9867    0.9868    564991

Accuracy: 0.9867360719020303
Precision: 0.987021046399671
Recall: 0.9867360719020303
F1 Score: 0.9868161767425531
AUC: 0.9852129667639811
```




```
Metrics by Label (ADASYN):
                          Label  Accuracy  Method
0                        BENIGN  0.987726  ADASYN
1                      DoS Hulk  0.977453  ADASYN
2                          DDoS  0.998359  ADASYN
3                      PortScan  0.999906  ADASYN
4              DoS Slowhttptest  0.978182  ADASYN
5                   FTP-Patator  0.986129  ADASYN
6                 DoS GoldenEye  0.984937  ADASYN
7                           Bot  0.526854  ADASYN
8                 DoS slowloris  0.993097  ADASYN
9                   SSH-Patator  0.551315  ADASYN
10     Web Attack - Brute Force  0.890728  ADASYN
11             Web Attack - XSS  0.953846  ADASYN
12   Web Attack - Sql Injection  0.500000  ADASYN
13                 Infiltration  0.571429  ADASYN
14                   Heartbleed  1.000000  ADASYN
```

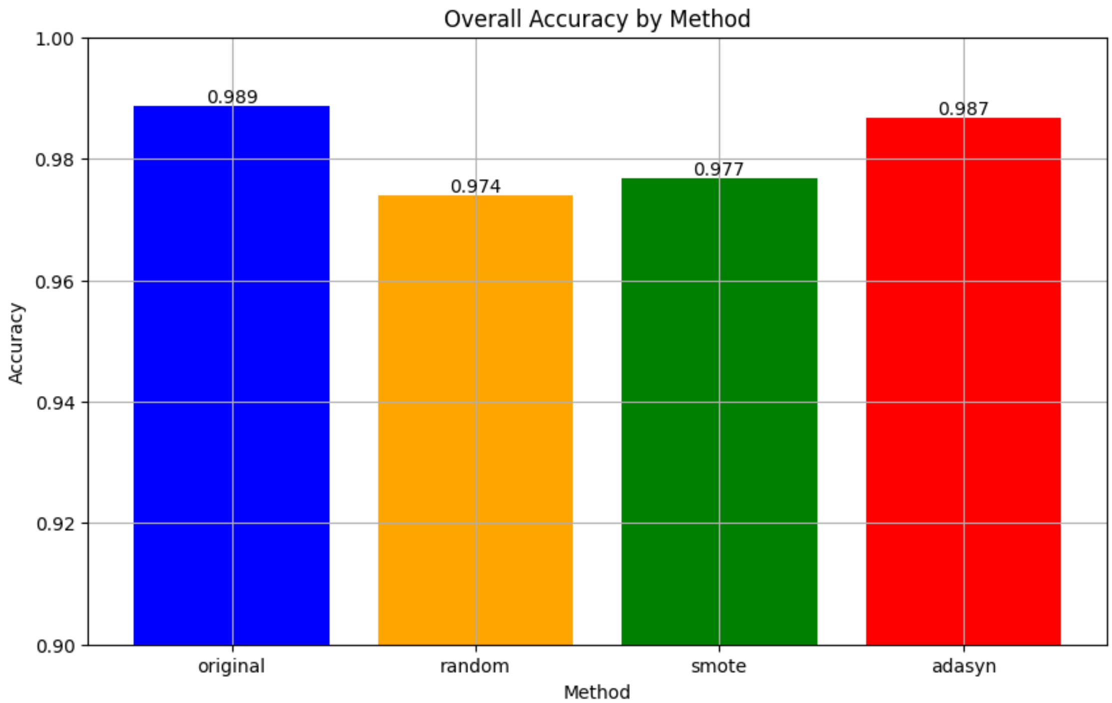
[68]:

```
# 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                      0.990254             0.970786  0.974171  0.987726
Bot                         0.480818             0.672634  0.705882  0.526854
DDoS                        0.998555             0.998086  0.998516  0.998359
DoS GoldenEye               0.985909             0.983965  0.986395  0.984937
DoS Hulk                    0.977584             0.977649  0.977627  0.977453
DoS Slowhttptest            0.957273             0.963636  0.986364  0.978182
DoS slowloris               0.994823             0.991372  0.993960  0.993097
FTP-Patator                 0.984868             0.998108  0.997478  0.986129
Heartbleed                  1.000000             1.000000  1.000000  1.000000
Infiltration                0.428571             0.571429  0.714286  0.571429
PortScan                    0.999969             0.999969  0.999969  0.999906
SSH-Patator                 0.525021             0.865988  0.838846  0.551315
Web Attack - Brute Force    0.877483             0.927152  0.923841  0.890728
Web Attack - Sql Injection  0.250000             0.750000  0.750000  0.500000
Web Attack - XSS            0.969231             0.961538  0.961538  0.953846
```

[69]:

```
plot_overall_accuracy(dt_metrics)
```


Overall Accuracy by Method
1.00
0.98
0.96
0.94
0.92
0.90
Accuracy
0.989
0.974
0.977
0.987
original
random
smote
adasyn
Method