Classical_ML_Algorithm_IDS_IOT_MEDICAL

May 17, 2025

[1]:
```python
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report,␣
↪ConfusionMatrixDisplay, accuracy_score, recall_score, precision_score, f1_score
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier,␣
↪RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from imblearn.ensemble import BalancedRandomForestClassifier
import xgboost as xgb
```

[2]:
```python
# dataset used
# replace with Zach's df
df2 = pd.read_csv("0.05percent_2classes_processed.csv")
df8 = pd.read_csv("0.05percent_8classes_processed.csv")
df34 = pd.read_csv("0.05percent_34classes_processed.csv")
```

[3]:
```python
# creating dataframes to store result metrics
columns = ["Logistic Regression", "Adaboost", "Gradientboost", "KNN", "XGBoost",␣
↪"Random Forest", "Random Forest - Bagging"]
index = ["Accuracy", "Recall", "Precision", "F1-Score"]

metrics_2 = pd.DataFrame(index=index, columns=columns)
metrics_8 = pd.DataFrame(index=index, columns=columns)
metrics_34 = pd.DataFrame(index=index, columns=columns)
```

1 Processing and Splitting our dataset Function

80% Train 20% Test

[4]:
```python
# First, modify your split function to return the scaler
def split(df_name):
    if df_name == "df2":
        label = "benign"
        df = df2.sample(n=400000, random_state=42)
    else:
        label = "label"
        if df_name == "df8": df = df8.sample(n=400000, random_state=42)
        else: df = df34.sample(n=400000, random_state=42)

    # Sorting our dataset into features and target
    X = df.drop(label, axis = 1)
    y = df[label]

    # splitting out dataset to train and test
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪stratify=y)

    # scaling our features
    scaler = StandardScaler()
    scaled_X_train = scaler.fit_transform(X_train)
    scaled_X_test = scaler.transform(X_test)  # Note: should use transform, not␣
↪fit_transform here

    # encoding for XGBoost
    encoder = LabelEncoder()
    encoded_y_train = encoder.fit_transform(y_train)
    encoded_y_test = encoder.transform(y_test)  # Should use transform instead␣
↪of fit_transform

    return scaled_X_train, scaled_X_test, y_train, y_test, encoded_y_train,␣
↪encoded_y_test, scaler
```

2 Evaluation Functions

[5]:
```python
# displays the Classification Report and Confusion Matrix
# inserts the metrics of the model into the metrics dataframe
def evaluate(model, y_test, target_names, classes, model_name):
    pred = model.predict(scaled_X_test)

    accuracy = accuracy_score(y_test, pred)
    recall = recall_score(y_test, pred, average='macro')
    precision = precision_score(y_test, pred, average='macro')
    f1 = f1_score(y_test, pred, average='macro')
    insert_metrics(classes, model_name, [accuracy, recall, precision, f1])
```

```
    if model_name == "XGBoost":
        print(classification_report(y_test, pred, target_names = target_names,␣
↪digits = 3))

        if classes == 2 or classes == 8:
            plt.figure(figsize = (4, 2), dpi = 300)
            ConfusionMatrixDisplay(np.round(confusion_matrix(y_test, pred,␣
↪normalize="true"), 2),
                                   display_labels = target_names).plot()
            plt.xticks(rotation=90);
    else:
        print(classification_report(y_test, pred, digits = 3))

        if classes == 2 or classes == 8:
            plt.figure(figsize = (4, 2), dpi = 300)
            ConfusionMatrixDisplay(np.round(confusion_matrix(y_test, pred,␣
↪normalize="true"), 2),
                                   display_labels = target_names).plot()
            plt.xticks(rotation=90);
```

[6]:
```
# inserts the metrics of the model into the metrics dataframe
def insert_metrics(classes, model_name, metrics):
    if classes == 2:
        metrics_2.loc['Accuracy':'F1-Score', model_name] = metrics
    elif classes == 8:
        metrics_8.loc['Accuracy':'F1-Score', model_name] = metrics
    else:
        metrics_34.loc['Accuracy':'F1-Score', model_name] = metrics
```

[7]:
```
# inspired from Zach
def get_weights(y_train):
    import math

    # Get counts in log10
    y_train_count = y_train.value_counts()
    y_log = y_train_count.apply(lambda x: math.log10(x))

    # Find the factor needed to bring minority classes to majority
    y_log_max = y_log.max()
    y_log = y_log.apply(lambda x: math.pow(10,y_log_max - x))

    weight_dict = y_log.to_dict()

    return weight_dict
```

3 Save models

[8]:
```python
import os
import pickle

def save_model(model, model_name, class_type):
    """
    Save a trained model to disk based on classification type
    """
    # Create directory structure if it doesn't exist
    base_dir = os.path.join("saved_models", f"class_{class_type}")
    os.makedirs(base_dir, exist_ok=True)

    # Create file name with no spaces
    file_name = model_name.replace(" ", "_").lower() + ".pkl"
    file_path = os.path.join(base_dir, file_name)

    # Save the model using pickle
    with open(file_path, 'wb') as f:
        pickle.dump(model, f)

    print(f"Model '{model_name}' saved for {class_type}-class classification at:␣
 ↪{file_path}")

def save_scaler(scaler, class_type):
    """
    Save the fitted StandardScaler object
    """
    base_dir = os.path.join("saved_models", f"class_{class_type}")
    os.makedirs(base_dir, exist_ok=True)

    file_path = os.path.join(base_dir, "standard_scaler.pkl")

    with open(file_path, 'wb') as f:
        pickle.dump(scaler, f)

    print(f"Scaler saved for {class_type}-class classification at: {file_path}")

def load_model(model_name, class_type):
    """
    Load a saved model from disk
    """
    file_name = model_name.replace(" ", "_").lower() + ".pkl"
    file_path = os.path.join("saved_models", f"class_{class_type}", file_name)

    with open(file_path, 'rb') as f:
        model = pickle.load(f)
```

```python
    return model

def load_scaler(class_type):
    """
    Load a saved scaler from disk
    """
    file_path = os.path.join("saved_models", f"class_{class_type}",␣
↪"standard_scaler.pkl")

    with open(file_path, 'rb') as f:
        scaler = pickle.load(f)

    return scaler

# Example of how to save models after training
# For 2-class classification models
def save_models_for_class_2():
    # Save the scaler first
    # Make sure to get the scaler that was used to transform the training data
    save_scaler(scaler, 2)

    # Save all models
    save_model(logreg_model, "Logistic Regression", 2)
    save_model(clf, "Adaboost", 2)
    save_model(gbc, "Gradientboost", 2)
    save_model(knn, "KNN", 2)
    save_model(xgc, "XGBoost", 2)
    save_model(rfc, "Random Forest", 2)
    save_model(rfc, "Random Forest Bagging", 2)  # Make sure to rename variable

# Similar functions for 8-class and 34-class models
def save_models_for_class_8():
    save_scaler(scaler, 8)
    # Save all the 8-class models using the same pattern as above
    save_model(logreg_model, "Logistic Regression", 8)
    save_model(clf, "Adaboost", 8)
    save_model(gbc, "Gradientboost", 8)
    save_model(knn, "KNN", 8)
    save_model(xgc, "XGBoost", 8)
    save_model(rfc, "Random Forest", 8)
    save_model(rfcb, "Random Forest Bagging", 8)


def save_models_for_class_34():
    save_scaler(scaler, 34)
    # Save all the 34-class models using the same pattern as above
```

```python
    save_model(logreg_model, "Logistic Regression", 34)
    save_model(clf, "Adaboost", 34)
    save_model(gbc, "Gradientboost", 34)
    save_model(knn, "KNN", 34)
    save_model(xgc, "XGBoost", 34)
    save_model(rfc, "Random Forest", 34)
    save_model(rfcb, "Random Forest Bagging", 34)

# Example of how to load and use a saved model for prediction
def load_and_predict(model_name, class_type, X_new):
    """
    Load a model and scaler, and make predictions on new data

    Parameters:
    -----------
    model_name : str
        Name of the model to load
    class_type : int
        Classification type (2, 8, or 34)
    X_new : array-like
        New data to predict on

    Returns:
    --------
    predictions : array
        Predicted classes
    """
    # Load model and scaler
    model = load_model(model_name, class_type)
    scaler = load_scaler(class_type)

    # Scale the new data
    X_new_scaled = scaler.transform(X_new)

    # Make predictions
    predictions = model.predict(X_new_scaled)

    return predictions
```

4 1-Supervised learning

4.1 2 Classes

[9]:
```python
scaled_X_train, scaled_X_test, y_train, y_test, encoded_y_train, encoded_y_test,␣
↪scaler = split("df2")
```

[10]:
```
weight_dict = get_weights(y_train)
weight_dict
```

[10]: {False: 1.0, True: 41.6552919221541}

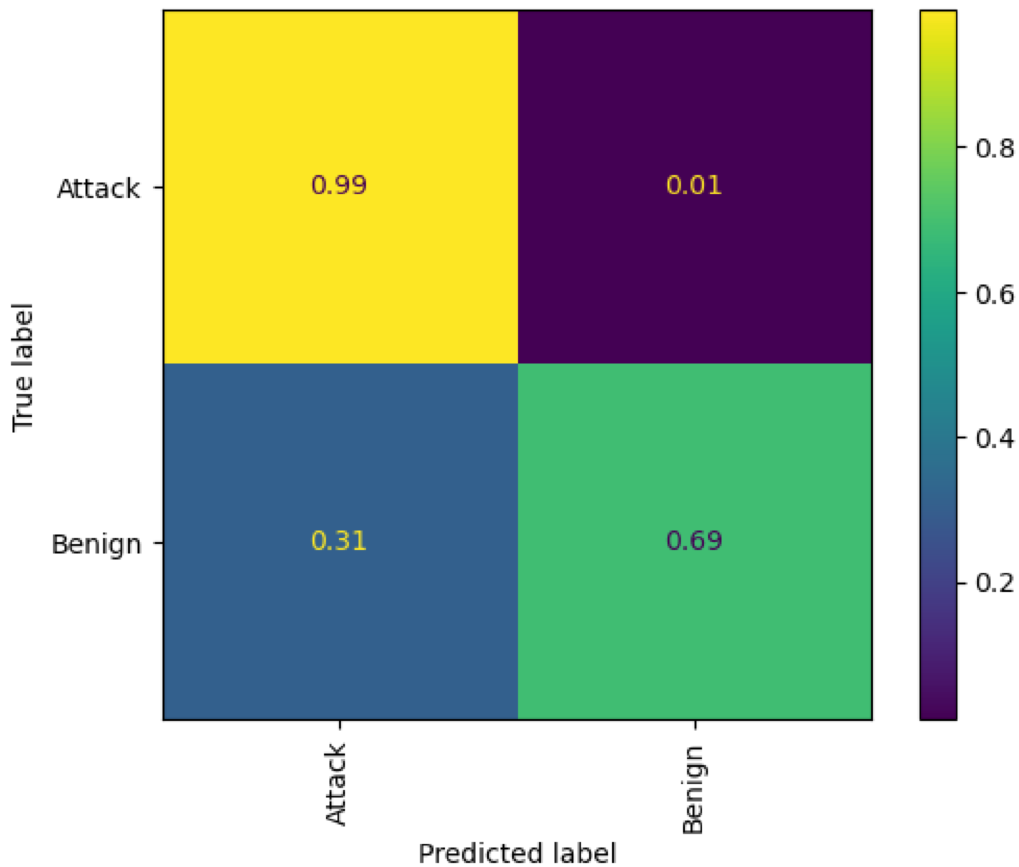
[11]:
```
# essential for XGBoost
target_names = ["Attack", "Benign"]
```

4.1.1 Logistic Regression

[12]:
```
logreg_model = LogisticRegression(C = 1, max_iter=500, solver='lbfgs',␣
 ↪penalty='l2', random_state=42)
logreg_model.fit(scaled_X_train, y_train)

evaluate(logreg_model, y_test, target_names, 2, "Logistic Regression")
```

```
              precision    recall  f1-score   support

       False      0.993     0.994     0.994     78124
        True      0.747     0.695     0.720      1876

    accuracy                          0.987     80000
   macro avg      0.870     0.844     0.857     80000
weighted avg      0.987     0.987     0.987     80000
```

```
<Figure size 1200x600 with 0 Axes>
```

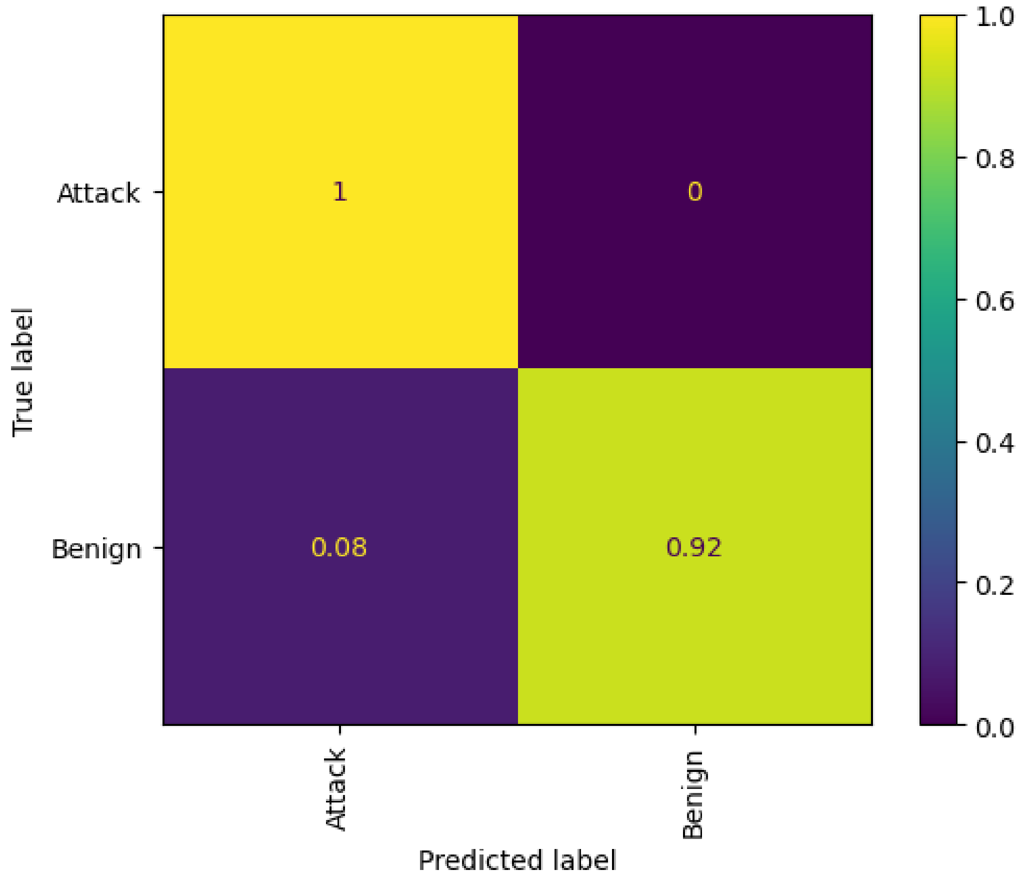


4.1.2 Adaboost

[13]:
```
clf = AdaBoostClassifier(n_estimators=100, learning_rate = 1, random_state=42)
clf.fit(scaled_X_train, y_train)

evaluate(clf, y_test, target_names, 2, "Adaboost")
```

```
              precision    recall  f1-score   support

       False      0.998     0.997     0.997     78124
        True      0.877     0.921     0.898      1876

    accuracy                          0.995     80000
   macro avg      0.937     0.959     0.948     80000
weighted avg      0.995     0.995     0.995     80000
```

```
<Figure size 1200x600 with 0 Axes>
```

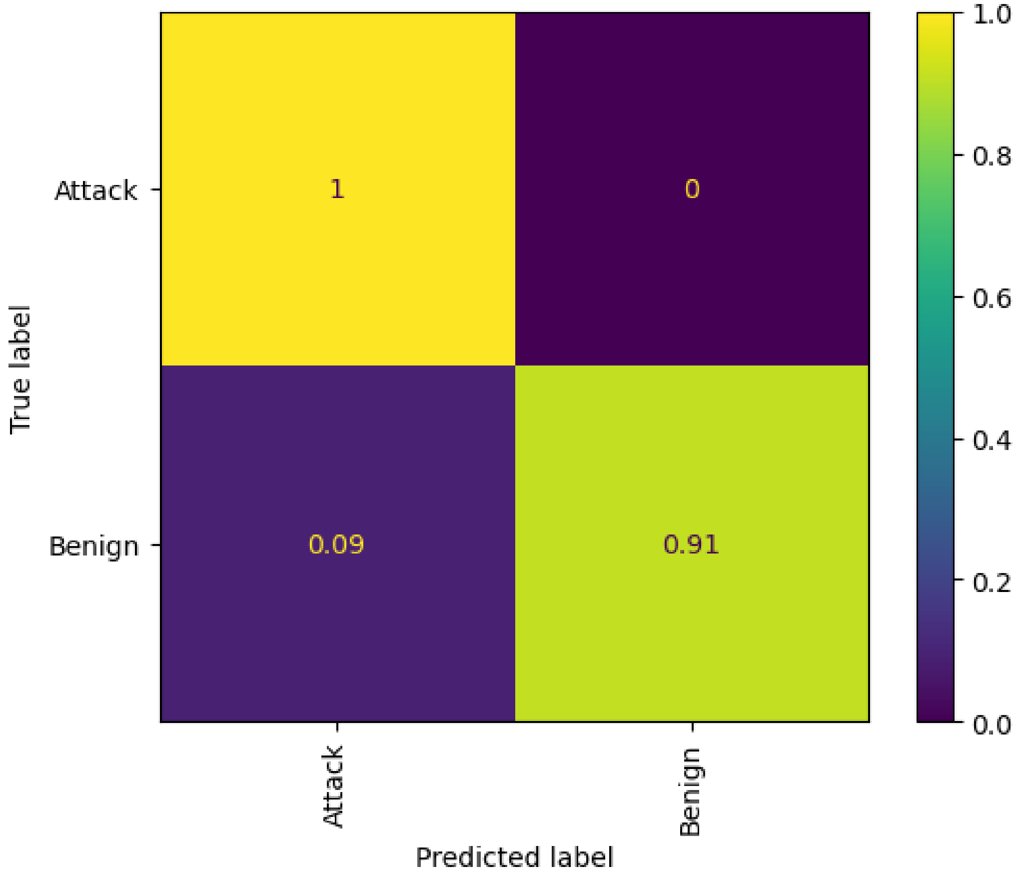


4.1.3 Gradientboost

[14]:
```
gbc = GradientBoostingClassifier(n_estimators = 100, learning_rate = 1,␣
↪max_depth = None)
gbc.fit(scaled_X_train, y_train)

evaluate(gbc, y_test, target_names, 2, "Gradientboost")
```

```
              precision    recall  f1-score   support

       False      0.998     0.998     0.998     78124
        True      0.907     0.912     0.910      1876

    accuracy                          0.996     80000
   macro avg      0.953     0.955     0.954     80000
weighted avg      0.996     0.996     0.996     80000
```

```
<Figure size 1200x600 with 0 Axes>
```

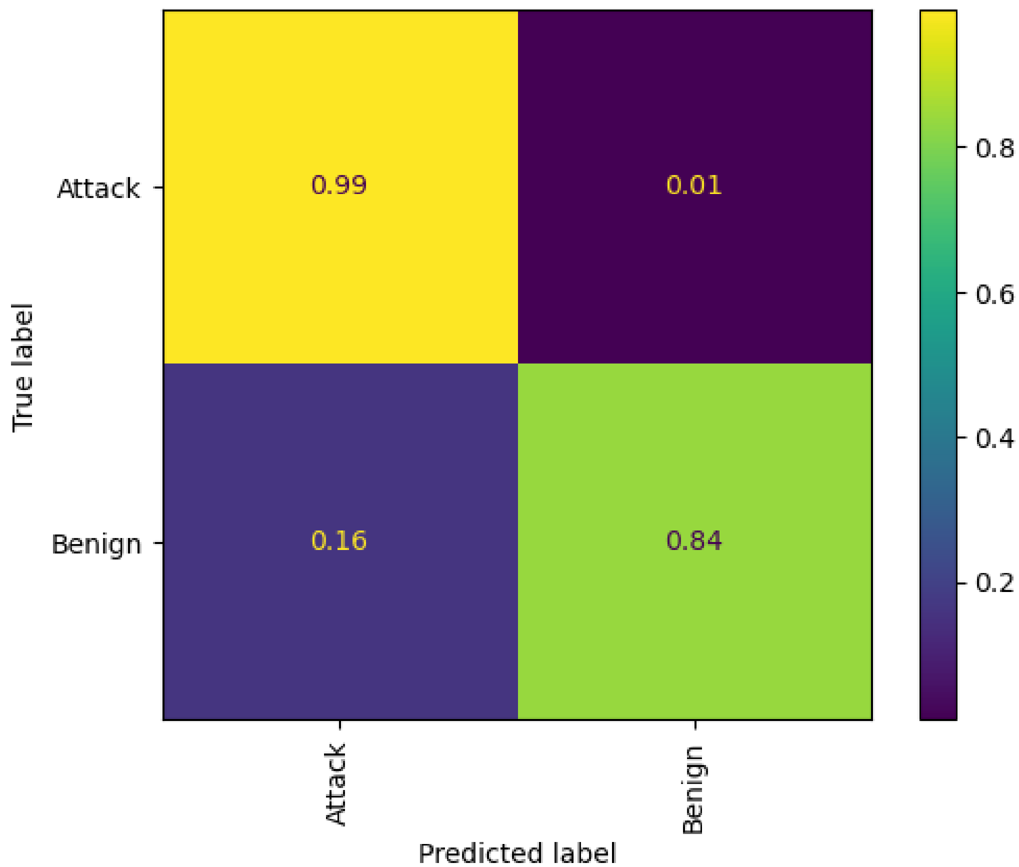


4.1.4 KNN

[15]:
```
knn = KNeighborsClassifier(n_neighbors = 8)
knn.fit(scaled_X_train, y_train)

evaluate(knn, y_test, target_names, 2, "KNN")
```

```
              precision    recall  f1-score   support

       False      0.996     0.994     0.995     78124
        True      0.783     0.840     0.810      1876

    accuracy                          0.991     80000
   macro avg      0.890     0.917     0.903     80000
weighted avg      0.991     0.991     0.991     80000
```

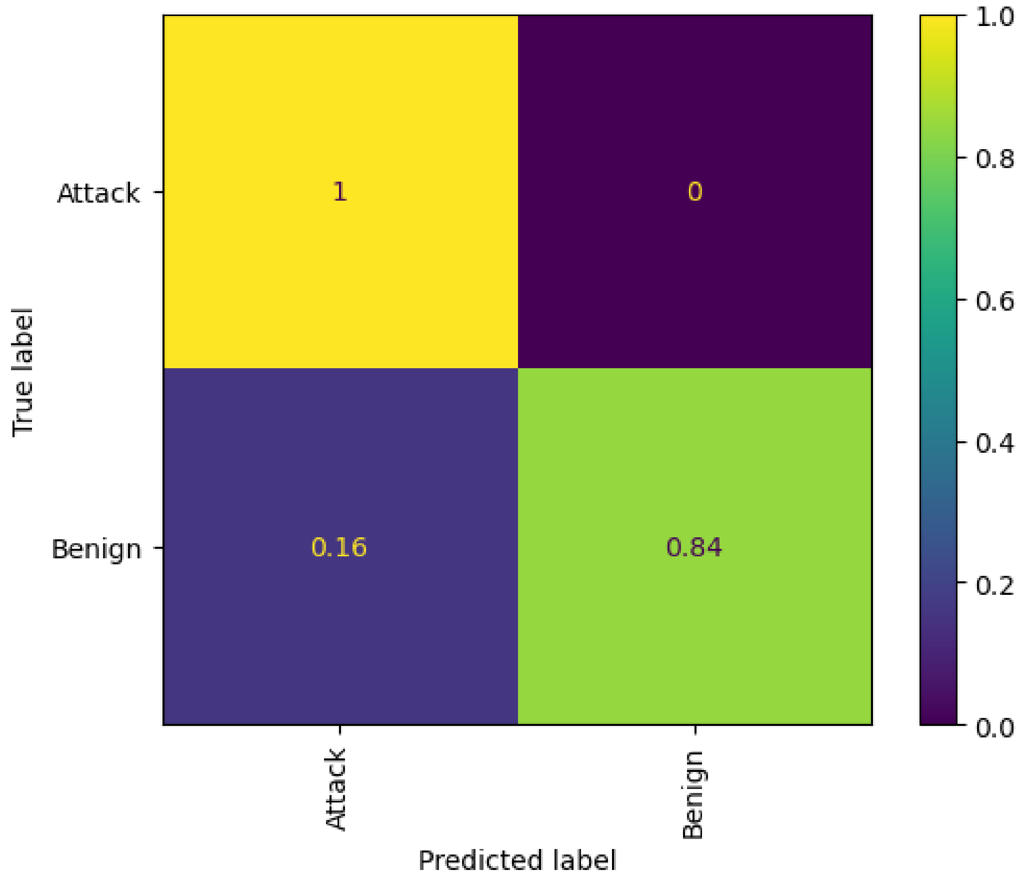
```
<Figure size 1200x600 with 0 Axes>
```



4.1.5 XGBoost

[16]:
```
xgc = xgb.XGBClassifier(n_estimators=100, learning_rate = 1, booster = "gbtree",␣
↪random_state = 42,
                        max_depth = 13,n_jobs=-1)
xgc.fit(scaled_X_train, encoded_y_train)

evaluate(xgc, encoded_y_test, target_names, 2, "XGBoost")
```

```
              precision    recall  f1-score   support

      Attack      0.996     0.996     0.996     78124
      Benign      0.839     0.836     0.837      1876

    accuracy                          0.992     80000
   macro avg      0.917     0.916     0.917     80000
weighted avg      0.992     0.992     0.992     80000


<Figure size 1200x600 with 0 Axes>
```

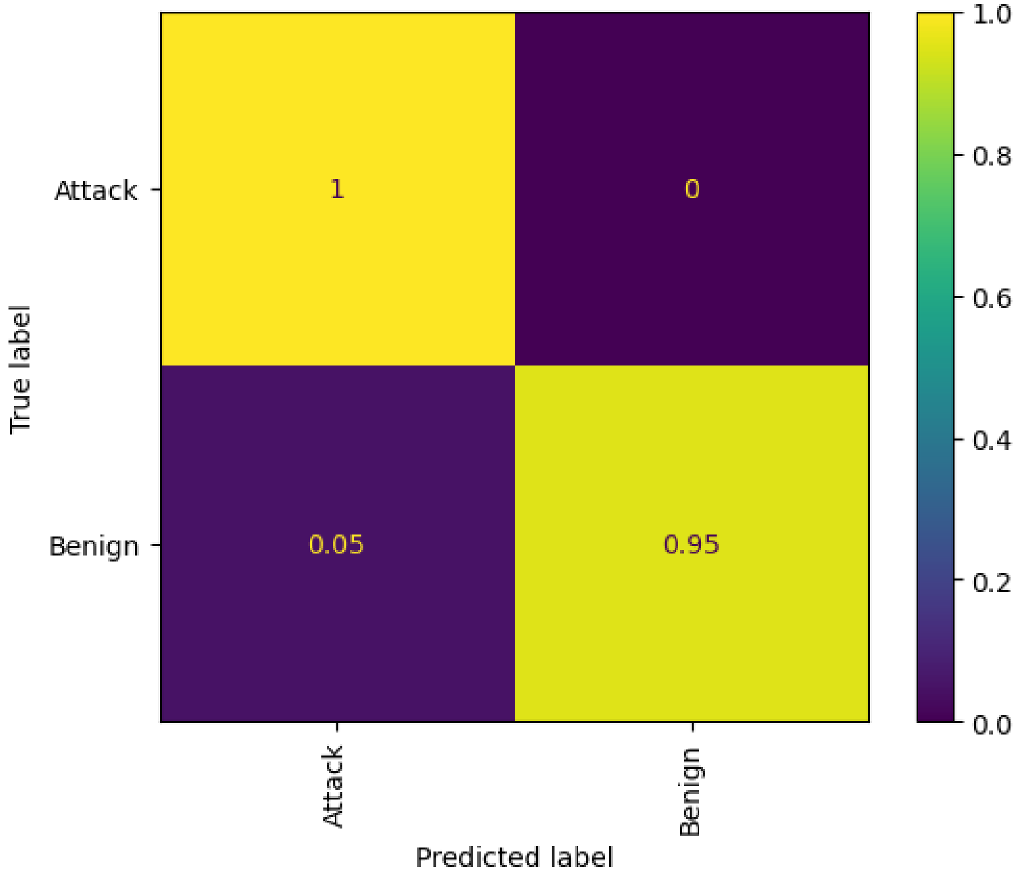


4.1.6 Random Forest

[17]:
```
# Base RF
rfc = RandomForestClassifier(n_estimators=100,n_jobs=-1)
rfc.fit(scaled_X_train, y_train)

evaluate(rfc, y_test, target_names, 2, "Random Forest")
```

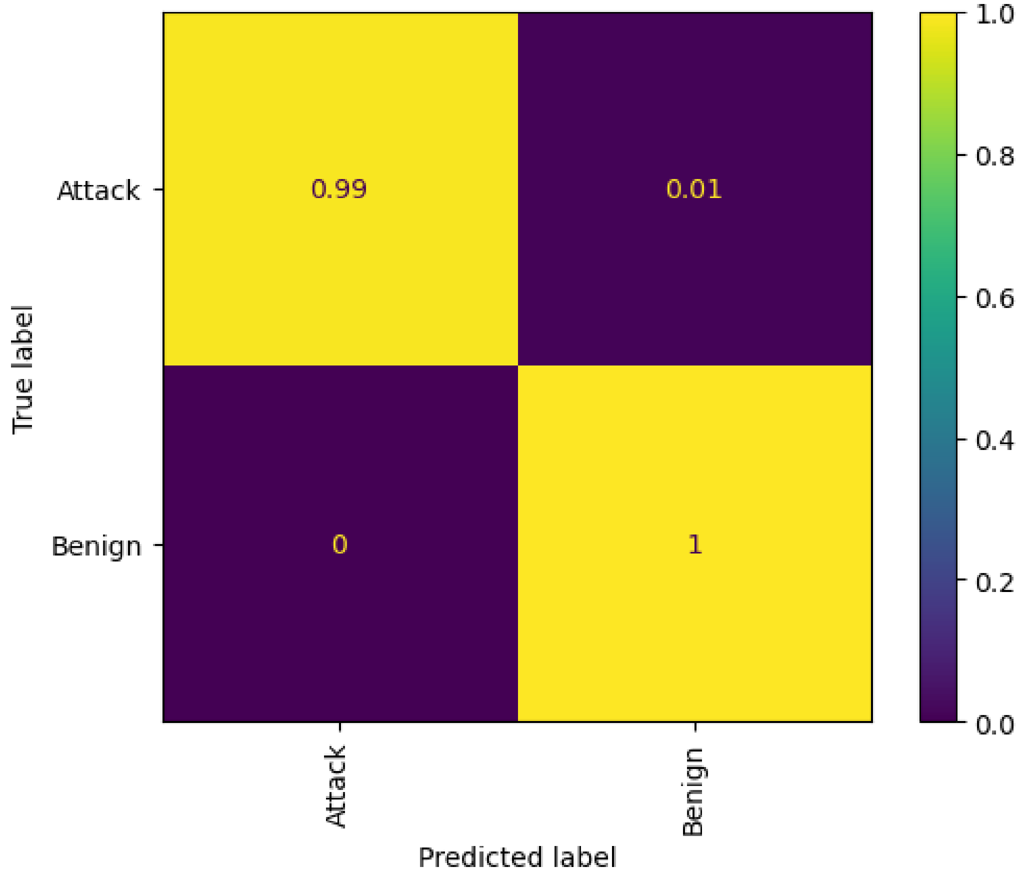
```
              precision    recall  f1-score   support

       False      0.999     0.998     0.998     78124
        True      0.925     0.949     0.937      1876

    accuracy                          0.997     80000
   macro avg      0.962     0.973     0.968     80000
weighted avg      0.997     0.997     0.997     80000
```

```
<Figure size 1200x600 with 0 Axes>
```



[18]:
```
# Bagging-balanced
rfc = BalancedRandomForestClassifier(n_estimators=100, sampling_strategy="all",␣
 ↪replacement=True)
rfc.fit(scaled_X_train, y_train)

evaluate(rfc, y_test, target_names, 2, "Random Forest - Bagging")
```

```
              precision    recall  f1-score   support

       False      1.000     0.989     0.995     78124
        True      0.688     0.999     0.815      1876

    accuracy                          0.989     80000
   macro avg      0.844     0.994     0.905     80000
weighted avg      0.993     0.989     0.990     80000


<Figure size 1200x600 with 0 Axes>
```



[19]:
```
# exporting and displaying the class 2 metrics
metrics_2.to_csv('metrics_2.csv', index=True)
metrics_2
# Add:
```

[19]:

	Logistic Regression	Adaboost	Gradientboost	KNN	XGBoost
Accuracy	0.987325	0.9951	0.99575	0.990788	0.992387
Recall	0.844459	0.958733	0.954903	0.916986	0.916244
Precision	0.869905	0.93737	0.952549	0.889666	0.91733
F1-Score	0.856703	0.947783	0.953723	0.902836	0.916786

	Random Forest	Random Forest - Bagging
Accuracy	0.996988	0.98935
Recall	0.973486	0.994027
Precision	0.961723	0.843967
F1-Score	0.967526	0.90465

[20]:
```
save_models_for_class_2()
```

```
Scaler saved for 2-class classification at:
saved_models/class_2/standard_scaler.pkl
Model 'Logistic Regression' saved for 2-class classification at:
saved_models/class_2/logistic_regression.pkl
Model 'Adaboost' saved for 2-class classification at:
saved_models/class_2/adaboost.pkl
Model 'Gradientboost' saved for 2-class classification at:
saved_models/class_2/gradientboost.pkl
Model 'KNN' saved for 2-class classification at: saved_models/class_2/knn.pkl
Model 'XGBoost' saved for 2-class classification at:
saved_models/class_2/xgboost.pkl
Model 'Random Forest' saved for 2-class classification at:
saved_models/class_2/random_forest.pkl
Model 'Random Forest Bagging' saved for 2-class classification at:
saved_models/class_2/random_forest_bagging.pkl
```

4.2 8 Classes

[21]:
```
scaled_X_train, scaled_X_test, y_train, y_test, encoded_y_train, encoded_y_test,␣
↪scaler  = split("df8")
```

[22]:
```
weight_dict = get_weights(y_train)
weight_dict
```

[22]:
```
{'DDoS': 1.0,
 'DoS': 4.217345664488805,
 'Mirai': 12.836500853853368,
 'Benign': 31.061183684350862,
 'Spoofing': 68.8392909896603,
 'Recon': 95.61797291752158,
 'Web': 1429.5766871165652,
 'BruteForce': 2709.5465116279092}
```

[23]:
```
y_test.value_counts()
```

[23]:
```
label
DDoS          58255
DoS           13813
Mirai          4538
Benign         1876
Spoofing        846
Recon           609
Web              41
BruteForce       22
Name: count, dtype: int64
```

[24]:
```
# essential for XGBoost
```

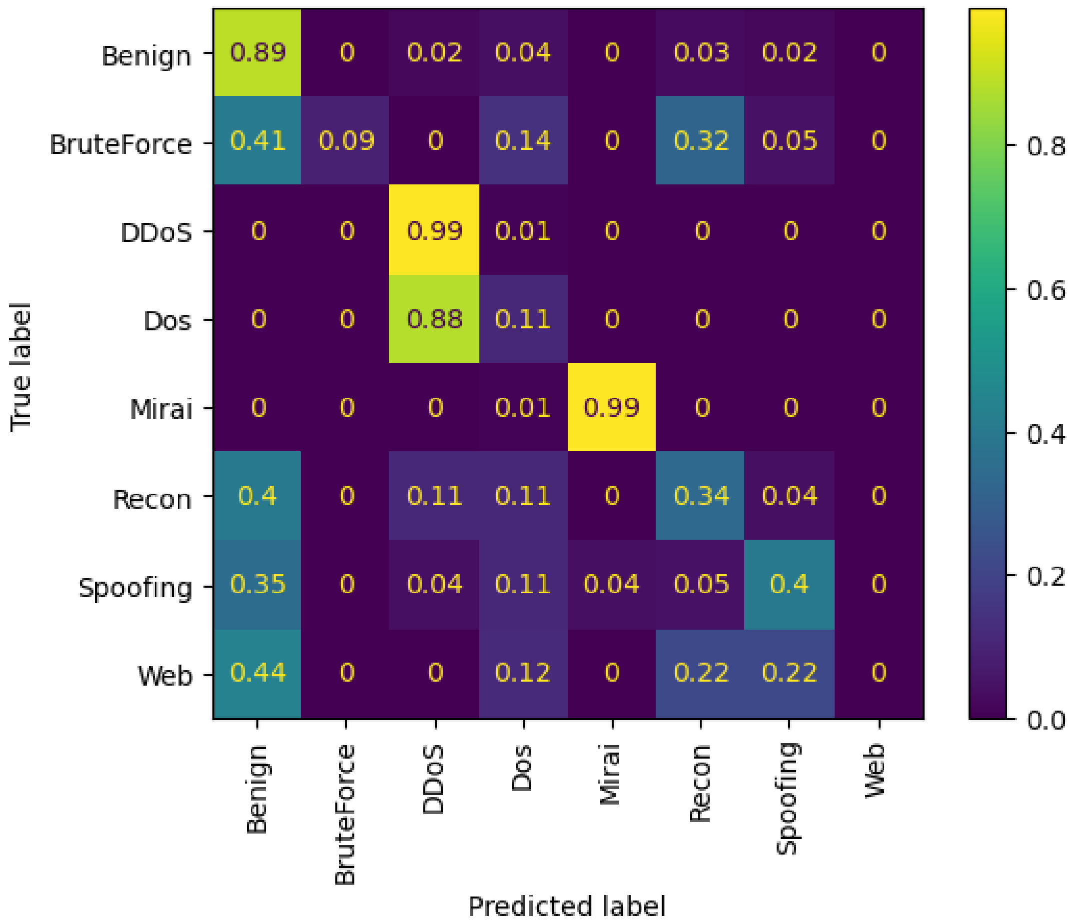
```
target_names = ["Benign", "BruteForce", "DDoS", "Dos", "Mirai", "Recon",␣
↪"Spoofing", "Web"]
```

4.2.1 Logistic Regression

[25]:
```
logreg_model = LogisticRegression(C = 1, max_iter=500, solver='lbfgs',␣
↪penalty='l2', random_state=42,n_jobs=-1)
logreg_model.fit(scaled_X_train, y_train)

evaluate(logreg_model, y_test, target_names, 8, "Logistic Regression")
```

```
              precision    recall  f1-score   support

      Benign      0.695     0.888     0.780      1876
  BruteForce      1.000     0.091     0.167        22
        DDoS      0.824     0.991     0.900     58255
         DoS      0.700     0.111     0.192     13813
       Mirai      0.991     0.987     0.989      4538
       Recon      0.573     0.340     0.427       609
    Spoofing      0.767     0.404     0.529       846
         Web      0.000     0.000     0.000        41

    accuracy                          0.825     80000
   macro avg      0.694     0.476     0.498     80000
weighted avg      0.806     0.825     0.772     80000
```

```
<Figure size 1200x600 with 0 Axes>
```



4.2.2 Adaboost

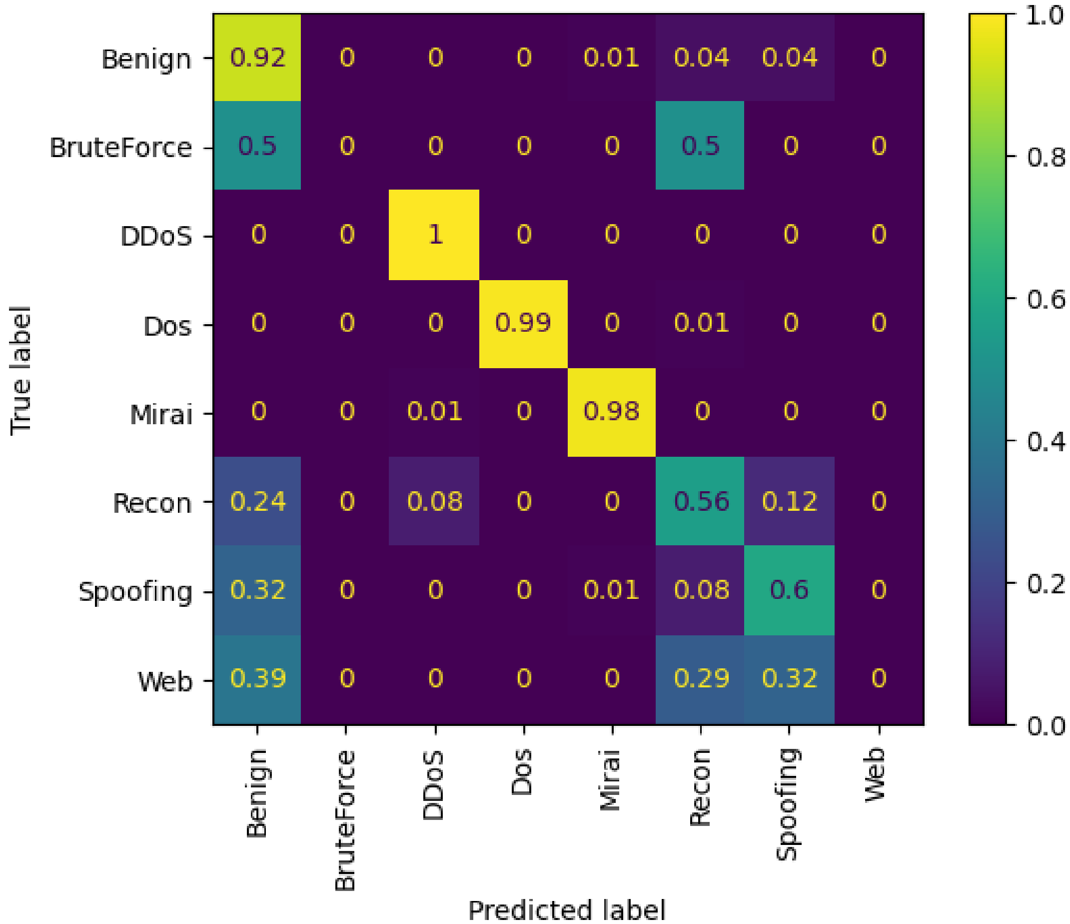
[26]:
```
clf = AdaBoostClassifier(n_estimators=100, learning_rate = 1, random_state=42)
clf.fit(scaled_X_train, y_train)

evaluate(clf, y_test, target_names, 8, "Adaboost")
```

	precision	recall	f1-score	support
Benign	0.767	0.916	0.835	1876
BruteForce	0.000	0.000	0.000	22
DDoS	0.998	0.997	0.998	58255
DoS	0.995	0.991	0.993	13813
Mirai	0.993	0.981	0.987	4538
Recon	0.521	0.558	0.539	609
Spoofing	0.754	0.597	0.666	846
Web	0.000	0.000	0.000	41

```
    accuracy                          0.985     80000
   macro avg      0.629     0.630     0.627     80000
weighted avg      0.985     0.985     0.985     80000
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
<Figure size 1200x600 with 0 Axes>
```

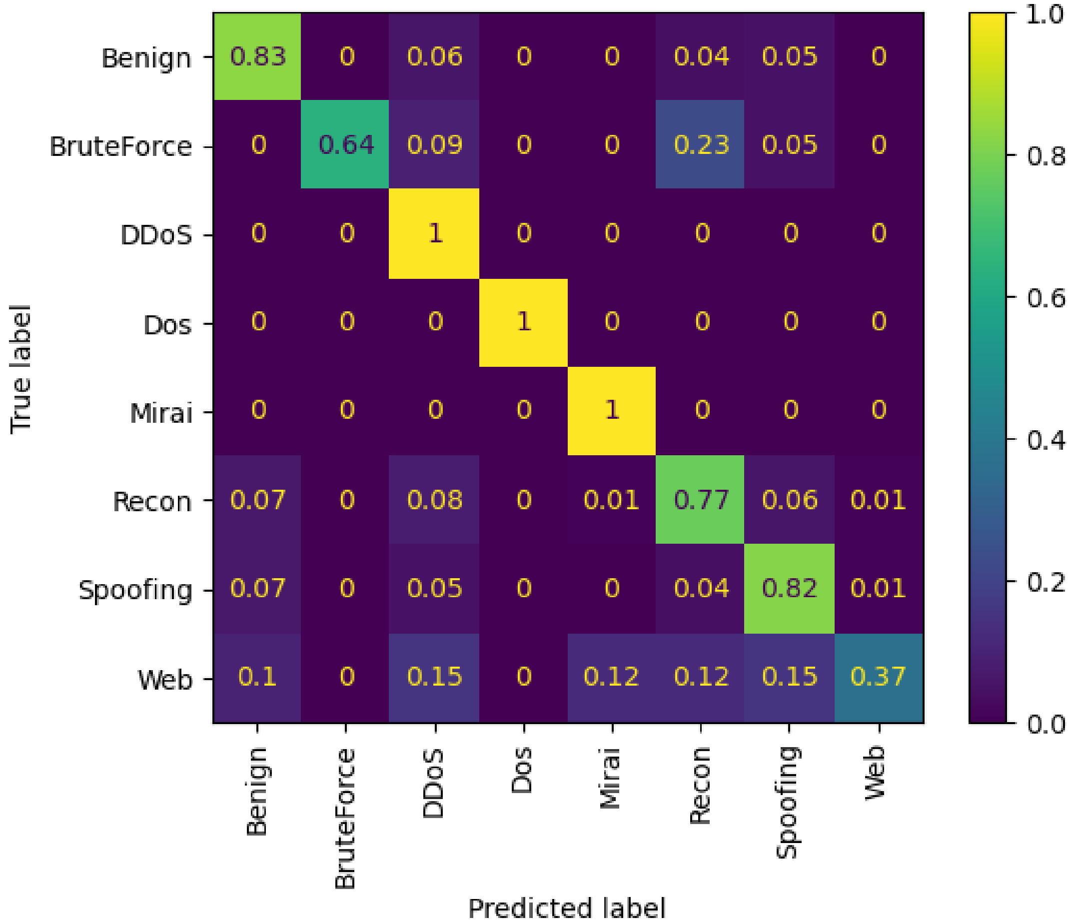


4.2.3 Gradientboost

[27]:
```
gbc = GradientBoostingClassifier(n_estimators=100, learning_rate = 1, max_depth␣
↪= None)
gbc.fit(scaled_X_train, y_train)


evaluate(gbc, y_test, target_names, 8, "Gradientboost")
```

```
              precision    recall  f1-score   support

      Benign      0.936     0.832     0.881      1876
  BruteForce      0.778     0.636     0.700        22
        DDoS      0.996     1.000     0.998     58255
         DoS      0.999     0.999     0.999     13813
       Mirai      0.996     0.999     0.998      4538
       Recon      0.785     0.772     0.778       609
    Spoofing      0.824     0.823     0.823       846
         Web      0.405     0.366     0.385        41

    accuracy                          0.992     80000
   macro avg      0.840     0.803     0.820     80000
weighted avg      0.991     0.992     0.992     80000
```

```
<Figure size 1200x600 with 0 Axes>
```

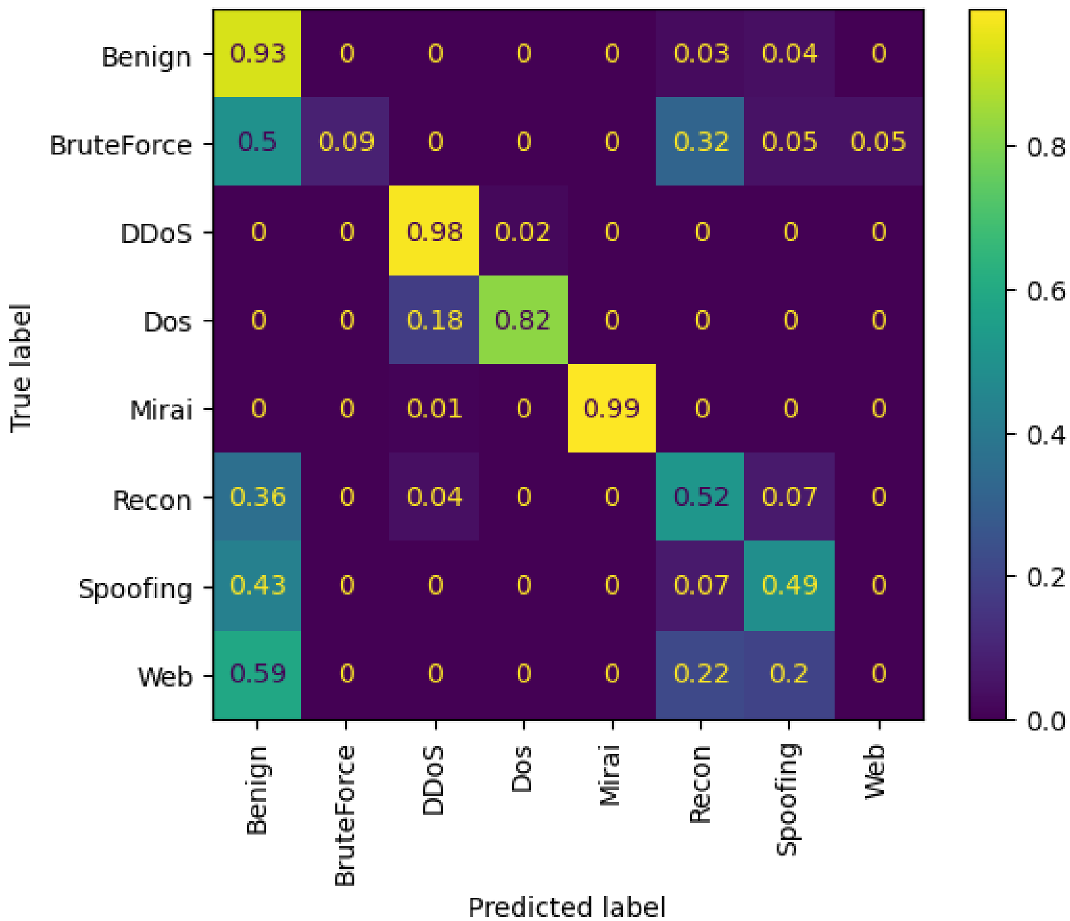


5 KNN

[28]:
```
knn = KNeighborsClassifier(n_neighbors = 8)
knn.fit(scaled_X_train, y_train)

evaluate(knn, y_test, target_names, 8, "KNN")
```

```
              precision    recall  f1-score   support

      Benign      0.736     0.927     0.820      1876
  BruteForce      1.000     0.091     0.167        22
        DDoS      0.958     0.985     0.971     58255
         DoS      0.928     0.822     0.872     13813
       Mirai      0.998     0.990     0.994      4538
       Recon      0.692     0.524     0.596       609
    Spoofing      0.744     0.491     0.591       846
         Web      0.000     0.000     0.000        41
```

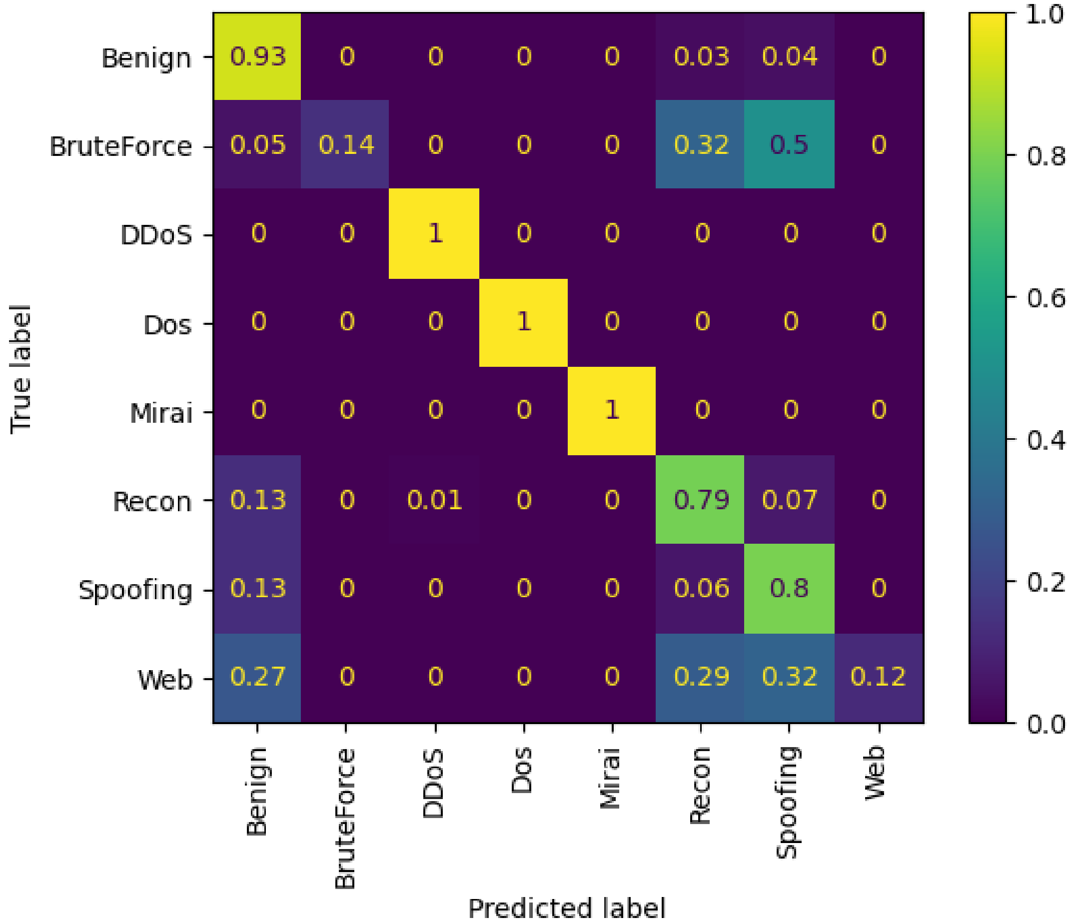
```
    accuracy                           0.946     80000
   macro avg      0.757     0.604     0.626     80000
weighted avg      0.945     0.946     0.944     80000


<Figure size 1200x600 with 0 Axes>
```



5.1 XGBoost

[29]:
```python
# Required to be trained on scaled_X_train, encoded_y_train
# evaluate parameter for y_test to be encoded y_test
xgc = xgb.XGBClassifier(n_estimators=100, learning_rate = 1, booster = "gbtree",␣
↪random_state = 42,
                         max_depth = 13, max_samples = 0.9 ,n_jobs=-1)
xgc.fit(scaled_X_train, encoded_y_train)

evaluate(xgc, encoded_y_test, target_names, 8, "XGBoost")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-packages/xgboost/training.py:183:
UserWarning: [14:28:30] WARNING: /workspace/src/learner.cc:738:
Parameters: { "max_samples" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
              precision    recall  f1-score   support

      Benign      0.896     0.933     0.914      1876
  BruteForce      1.000     0.136     0.240        22
        DDoS      1.000     1.000     1.000     58255
         Dos      0.999     0.999     0.999     13813
       Mirai      1.000     0.999     0.999      4538
       Recon      0.796     0.788     0.792       609
    Spoofing      0.822     0.798     0.810       846
         Web      0.357     0.122     0.182        41

    accuracy                          0.994     80000
   macro avg      0.859     0.722     0.742     80000
weighted avg      0.993     0.994     0.993     80000

<Figure size 1200x600 with 0 Axes>
```



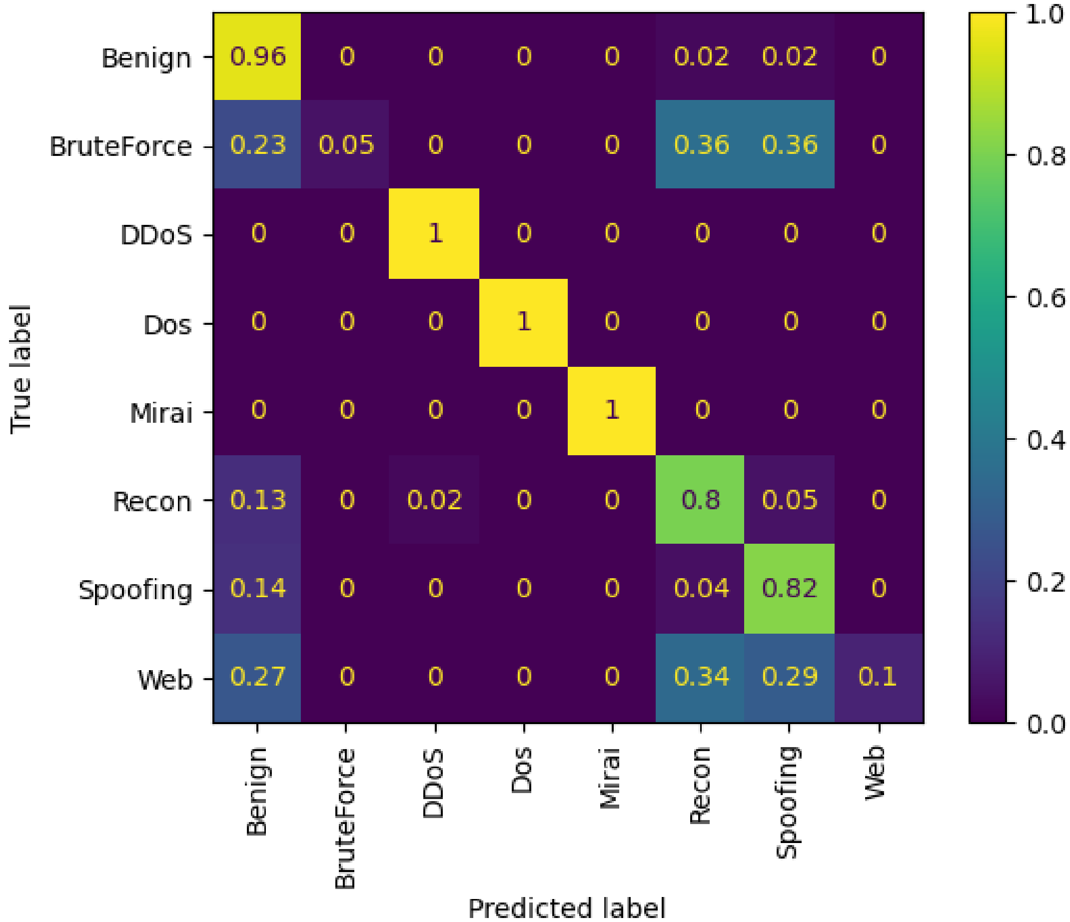
5.2 Random Forest

[30]:
```
# Base RF
rfc = RandomForestClassifier(n_estimators=100 ,n_jobs=-1)
rfc.fit(scaled_X_train, y_train)

evaluate(rfc, y_test, target_names, 8, "Random Forest")
```

```
              precision    recall  f1-score   support

      Benign      0.895     0.962     0.927      1876
  BruteForce      1.000     0.045     0.087        22
        DDoS      1.000     1.000     1.000     58255
         DoS      1.000     0.999     0.999     13813
       Mirai      1.000     1.000     1.000      4538
       Recon      0.827     0.801     0.814       609
    Spoofing      0.894     0.820     0.856       846
         Web      1.000     0.098     0.178        41
```

```
    accuracy                         0.995     80000
   macro avg      0.952     0.716     0.733     80000
weighted avg      0.995     0.995     0.994     80000
```

```
<Figure size 1200x600 with 0 Axes>
```

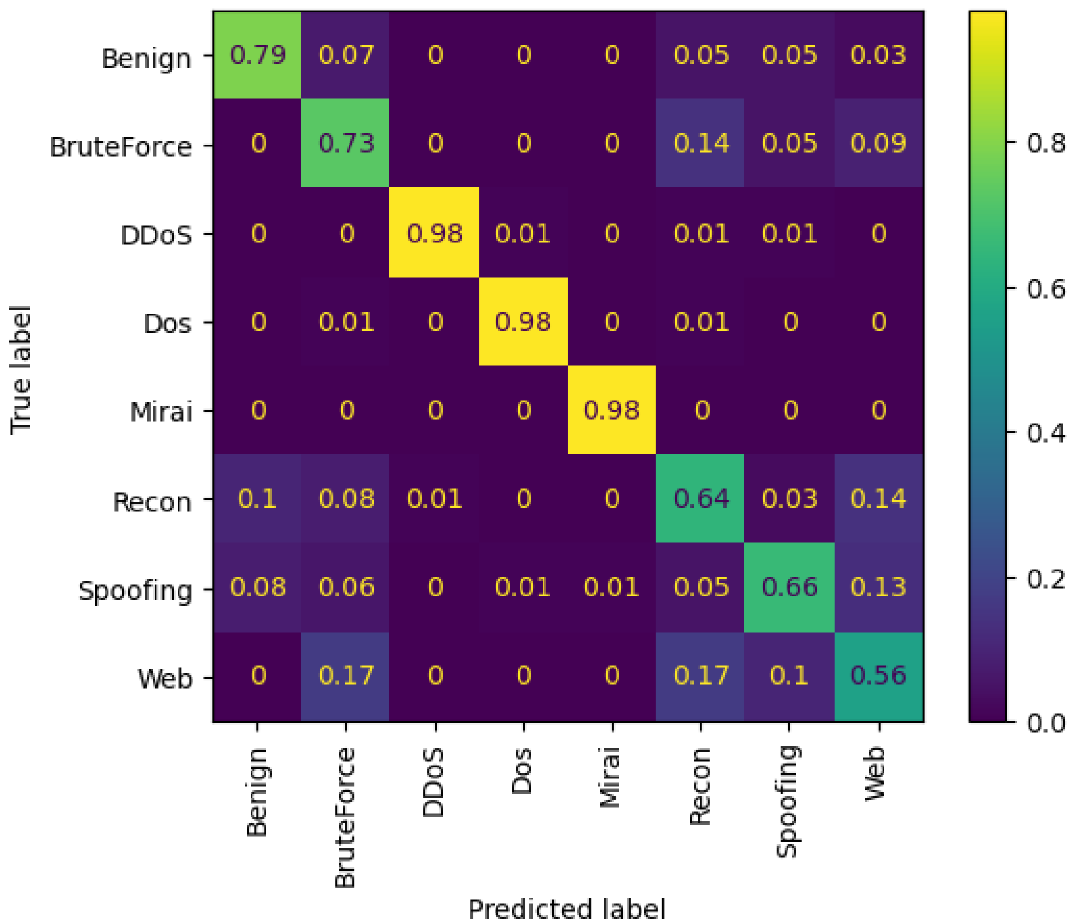


[31]:
```python
# Bagging-balanced
rfcb = BalancedRandomForestClassifier(n_estimators=100, sampling_strategy="all",␣
 ↪replacement=True ,n_jobs=-1)
rfcb.fit(scaled_X_train, y_train)

evaluate(rfcb, y_test, target_names, 8, "Random Forest - Bagging")
```

```
              precision    recall  f1-score   support
```

```
      Benign      0.896     0.792     0.841      1876
  BruteForce      0.039     0.727     0.074        22
        DDoS      1.000     0.976     0.987     58255
         DoS      0.954     0.980     0.967     13813
       Mirai      0.997     0.985     0.991      4538
       Recon      0.395     0.639     0.488       609
    Spoofing      0.509     0.661     0.575       846
         Web      0.067     0.561     0.120        41

    accuracy                          0.966     80000
   macro avg      0.607     0.790     0.630     80000
weighted avg      0.979     0.966     0.972     80000
```

```
<Figure size 1200x600 with 0 Axes>
```



[32]:
```python
# exporting and displaying the class 8 metrics
metrics_8.to_csv('metrics_8.csv', index=True)
```

```
metrics_8
```

[32]:

	Logistic Regression	Adaboost	Gradientboost	KNN	XGBoost
Accuracy	0.82475	0.985012	0.9917	0.946163	0.9936
Recall	0.476462	0.629999	0.80335	0.603714	0.721853
Precision	0.693832	0.628506	0.839952	0.756951	0.858733
F1-Score	0.497933	0.627205	0.820249	0.626488	0.741981

	Random Forest	Random Forest - Bagging
Accuracy	0.9947	0.966337
Recall	0.71562	0.789926
Precision	0.951963	0.607234
F1-Score	0.732571	0.630485

[33]:

```
save_models_for_class_8()
```

```
Scaler saved for 8-class classification at:
saved_models/class_8/standard_scaler.pkl
Model 'Logistic Regression' saved for 8-class classification at:
saved_models/class_8/logistic_regression.pkl
Model 'Adaboost' saved for 8-class classification at:
saved_models/class_8/adaboost.pkl
Model 'Gradientboost' saved for 8-class classification at:
saved_models/class_8/gradientboost.pkl
Model 'KNN' saved for 8-class classification at: saved_models/class_8/knn.pkl
Model 'XGBoost' saved for 8-class classification at:
saved_models/class_8/xgboost.pkl
Model 'Random Forest' saved for 8-class classification at:
saved_models/class_8/random_forest.pkl
Model 'Random Forest Bagging' saved for 8-class classification at:
saved_models/class_8/random_forest_bagging.pkl
```

6 34 Classes

[34]:

```
scaled_X_train, scaled_X_test, y_train, y_test, encoded_y_train, encoded_y_test,␣
↪scaler  = split("df34")
```

[35]:

```
weight_dict = get_weights(y_train)
weight_dict
```

[35]:

```
{'DDoS-ICMP_Flood': 1.0,
 'DDoS-UDP_Flood': 1.3327485222273208,
 'DDoS-TCP_Flood': 1.6057560975609746,
 'DDoS-PSHACK_Flood': 1.7570010319182976,
 'DDoS-SYN_Flood': 1.7736628470850218,
 'DDoS-RSTFINFlood': 1.7863680764082344,
 'DDoS-SynonymousIP_Flood': 1.9886825889081294,
```

```
 'DoS-UDP_Flood': 2.1790379523389207,
 'DoS-TCP_Flood': 2.6990816661200356,
 'DoS-SYN_Flood': 3.578302775563443,
 'BenignTraffic': 6.580967612954817,
 'Mirai-greeth_flood': 7.218859649122804,
 'Mirai-udpplain': 7.982056256062071,
 'Mirai-greip_flood': 9.630778232884722,
 'DDoS-ICMP_Fragmentation': 15.928064516129023,
 'MITM-ArpSpoofing': 23.291037735849052,
 'DDoS-UDP_Fragmentation': 24.299704724409448,
 'DDoS-ACK_Fragmentation': 25.452061855670088,
 'DNS_Spoofing': 39.03320158102764,
 'Recon-HostDiscovery': 52.58466453674118,
 'Recon-OSScan': 73.04289940828397,
 'Recon-PortScan': 87.85943060498215,
 'DoS-HTTP_Flood': 98.95190380761521,
 'VulnerabilityScan': 201.5387755102039,
 'DDoS-HTTP_Flood': 259.87894736842094,
 'DDoS-SlowLoris': 288.7543859649122,
 'DictionaryBruteForce': 574.1511627906976,
 'BrowserHijacking': 1097.2666666666653,
 'SqlInjection': 1204.317073170731,
 'CommandInjection': 1299.3947368421045,
 'XSS': 2244.4090909090896,
 'Backdoor_Malware': 3291.799999999997,
 'Recon-PingSweep': 3291.799999999997,
 'Uploading_Attack': 24688.49999999998}
```

[36]:
```
y_test.value_counts()
```

[36]:
```
label
DDoS-ICMP_Flood            12344
DDoS-UDP_Flood              9262
DDoS-TCP_Flood              7687
DDoS-PSHACK_Flood           7026
DDoS-SYN_Flood              6960
DDoS-RSTFINFlood            6910
DDoS-SynonymousIP_Flood     6207
DoS-UDP_Flood               5665
DoS-TCP_Flood               4574
DoS-SYN_Flood               3450
BenignTraffic               1875
Mirai-greeth_flood          1710
Mirai-udpplain              1546
Mirai-greip_flood           1282
DDoS-ICMP_Fragmentation      775
MITM-ArpSpoofing             530
```

```
DDoS-UDP_Fragmentation       508
DDoS-ACK_Fragmentation       485
DNS_Spoofing                 316
Recon-HostDiscovery          235
Recon-OSScan                 169
Recon-PortScan               140
DoS-HTTP_Flood               125
VulnerabilityScan             61
DDoS-HTTP_Flood               48
DDoS-SlowLoris                43
DictionaryBruteForce          22
BrowserHijacking              11
SqlInjection                  10
CommandInjection               9
XSS                            6
Backdoor_Malware               4
Recon-PingSweep                4
Uploading_Attack               1
Name: count, dtype: int64
```

[37]:

```
# essential for XGBoost
target_names = list(y_test.unique())
```

6.1 Logistic Regression

[38]:

```
logreg_model = LogisticRegression(C = 1, max_iter=500, solver='lbfgs',␣
↪penalty='l2', random_state=42, n_jobs=-1)
logreg_model.fit(scaled_X_train, y_train)

evaluate(logreg_model, y_test, target_names, 34, "Logistic Regression")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
```

```
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
                         precision    recall  f1-score   support

        Backdoor_Malware      0.000     0.000     0.000         4
           BenignTraffic      0.674     0.927     0.781      1875
        BrowserHijacking      0.000     0.000     0.000        11
        CommandInjection      0.000     0.000     0.000         9
  DDoS-ACK_Fragmentation      0.884     0.157     0.266       485
         DDoS-HTTP_Flood      0.327     0.375     0.350        48
         DDoS-ICMP_Flood      0.972     0.996     0.984     12344
 DDoS-ICMP_Fragmentation      0.612     0.981     0.754       775
       DDoS-PSHACK_Flood      0.999     0.983     0.991      7026
        DDoS-RSTFINFlood      0.999     0.999     0.999      6910
          DDoS-SYN_Flood      0.650     0.967     0.777      6960
          DDoS-SlowLoris      0.222     0.093     0.131        43
 DDoS-SynonymousIP_Flood      0.748     0.683     0.714      6207
          DDoS-TCP_Flood      0.620     0.945     0.748      7687
          DDoS-UDP_Flood      0.722     0.956     0.823      9262
  DDoS-UDP_Fragmentation      0.921     0.870     0.895       508
            DNS_Spoofing      0.327     0.114     0.169       316
    DictionaryBruteForce      1.000     0.045     0.087        22
           DoS-HTTP_Flood      0.595     0.600     0.598       125
            DoS-SYN_Flood      0.623     0.120     0.201      3450
            DoS-TCP_Flood      0.663     0.137     0.227      4574
            DoS-UDP_Flood      0.803     0.301     0.437      5665
          MITM-ArpSpoofing      0.740     0.472     0.576       530
       Mirai-greeth_flood      0.591     0.951     0.729      1710
        Mirai-greip_flood      0.536     0.117     0.192      1282
          Mirai-udpplain      0.995     0.957     0.976      1546
    Recon-HostDiscovery      0.466     0.345     0.396       235
            Recon-OSScan      0.128     0.036     0.056       169
         Recon-PingSweep      0.000     0.000     0.000         4
          Recon-PortScan      0.250     0.029     0.051       140
            SqlInjection      0.000     0.000     0.000        10
        Uploading_Attack      0.000     0.000     0.000         1
       VulnerabilityScan      0.000     0.000     0.000        61
                     XSS      0.000     0.000     0.000         6

                accuracy                          0.784     80000
               macro avg      0.502     0.416     0.409     80000
            weighted avg      0.786     0.784     0.745     80000

/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
```

```
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

6.2 Adaboost

[39]:
```python
clf = AdaBoostClassifier(n_estimators=100, learning_rate = 1, random_state=42 )
clf.fit(scaled_X_train, y_train)

evaluate(clf, y_test, target_names, 34, "Adaboost")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

	precision	recall	f1-score	support
Backdoor_Malware	0.000	0.000	0.000	4
BenignTraffic	0.546	0.946	0.693	1875
BrowserHijacking	0.000	0.000	0.000	11
CommandInjection	0.000	0.000	0.000	9
DDoS-ACK_Fragmentation	0.857	0.918	0.886	485
DDoS-HTTP_Flood	0.000	0.000	0.000	48
DDoS-ICMP_Flood	1.000	0.996	0.998	12344
DDoS-ICMP_Fragmentation	0.976	0.839	0.902	775
DDoS-PSHACK_Flood	1.000	0.980	0.990	7026
DDoS-RSTFINFlood	0.996	0.998	0.997	6910
DDoS-SYN_Flood	0.663	0.957	0.783	6960
DDoS-SlowLoris	0.000	0.000	0.000	43
DDoS-SynonymousIP_Flood	0.553	0.026	0.050	6207
DDoS-TCP_Flood	0.405	0.967	0.570	7687
DDoS-UDP_Flood	0.709	0.982	0.823	9262
DDoS-UDP_Fragmentation	0.950	0.941	0.946	508
DNS_Spoofing	0.000	0.000	0.000	316
DictionaryBruteForce	0.000	0.000	0.000	22
DoS-HTTP_Flood	0.000	0.000	0.000	125
DoS-SYN_Flood	1.000	0.008	0.016	3450

```
           DoS-TCP_Flood       0.494     0.037     0.070      4574
           DoS-UDP_Flood       0.700     0.321     0.440      5665
        MITM-ArpSpoofing       0.140     0.045     0.068       530
      Mirai-greeth_flood       0.590     0.926     0.721      1710
       Mirai-greip_flood       0.575     0.048     0.088      1282
          Mirai-udpplain       0.966     0.920     0.942      1546
     Recon-HostDiscovery       0.000     0.000     0.000       235
            Recon-OSScan       0.000     0.000     0.000       169
         Recon-PingSweep       0.000     0.000     0.000         4
          Recon-PortScan       0.000     0.000     0.000       140
            SqlInjection       0.000     0.000     0.000        10
        Uploading_Attack       0.000     0.000     0.000         1
       VulnerabilityScan       0.000     0.000     0.000        61
                     XSS       0.000     0.000     0.000         6

                accuracy                           0.724     80000
               macro avg       0.386     0.349     0.323     80000
            weighted avg       0.746     0.724     0.657     80000

/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

6.3 Gradientboost

[40]:
```python
gbc = GradientBoostingClassifier(n_estimators=100, learning_rate = 1, max_depth␣
 ↪= None)
gbc.fit(scaled_X_train, y_train)

evaluate(gbc, y_test, target_names, 34, "Gradientboost")
```

```
                       precision    recall  f1-score   support

         Backdoor_Malware       0.667     0.500     0.571         4
           BenignTraffic       0.941     0.862     0.900      1875
        BrowserHijacking       0.389     0.636     0.483        11
        CommandInjection       0.500     0.444     0.471         9
  DDoS-ACK_Fragmentation       0.996     0.990     0.993       485
          DDoS-HTTP_Flood       0.935     0.896     0.915        48
          DDoS-ICMP_Flood       0.998     1.000     0.999     12344
 DDoS-ICMP_Fragmentation       0.997     0.991     0.994       775
```

```
       DDoS-PSHACK_Flood      0.998     1.000     0.999      7026
        DDoS-RSTFINFlood      1.000     1.000     1.000      6910
          DDoS-SYN_Flood      0.999     1.000     0.999      6960
          DDoS-SlowLoris      1.000     0.953     0.976        43
DDoS-SynonymousIP_Flood      1.000     1.000     1.000      6207
          DDoS-TCP_Flood      0.992     1.000     0.996      7687
          DDoS-UDP_Flood      1.000     1.000     1.000      9262
 DDoS-UDP_Fragmentation      0.994     0.996     0.995       508
            DNS_Spoofing      0.683     0.668     0.675       316
   DictionaryBruteForce      0.630     0.773     0.694        22
          DoS-HTTP_Flood      0.909     0.960     0.934       125
           DoS-SYN_Flood      1.000     0.999     1.000      3450
           DoS-TCP_Flood      0.999     0.999     0.999      4574
           DoS-UDP_Flood      0.975     0.999     0.987      5665
         MITM-ArpSpoofing      0.830     0.753     0.789       530
      Mirai-greeth_flood      0.999     0.998     0.999      1710
       Mirai-greip_flood      0.999     0.998     0.999      1282
          Mirai-udpplain      1.000     0.998     0.999      1546
     Recon-HostDiscovery      0.787     0.753     0.770       235
            Recon-OSScan      0.635     0.586     0.609       169
         Recon-PingSweep      0.000     0.000     0.000         4
          Recon-PortScan      0.594     0.607     0.601       140
            SqlInjection      0.231     0.300     0.261        10
        Uploading_Attack      1.000     1.000     1.000         1
       VulnerabilityScan      1.000     0.902     0.948        61
                     XSS      0.500     0.167     0.250         6

                accuracy                          0.990     80000
               macro avg      0.829     0.816     0.818     80000
            weighted avg      0.990     0.990     0.990     80000
```

6.4 KNN

[41]:
```
knn = KNeighborsClassifier(n_neighbors = 8, n_jobs=-1)
knn.fit(scaled_X_train, y_train)

evaluate(knn, y_test, target_names, 34, "KNN")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
```

```
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
                         precision    recall  f1-score   support

        Backdoor_Malware      0.000     0.000     0.000         4
           BenignTraffic      0.714     0.958     0.818      1875
        BrowserHijacking      0.000     0.000     0.000        11
        CommandInjection      0.000     0.000     0.000         9
  DDoS-ACK_Fragmentation      0.690     0.625     0.656       485
         DDoS-HTTP_Flood      0.542     0.667     0.598        48
         DDoS-ICMP_Flood      0.988     0.993     0.991     12344
 DDoS-ICMP_Fragmentation      0.723     0.836     0.776       775
       DDoS-PSHACK_Flood      0.999     0.996     0.998      7026
        DDoS-RSTFINFlood      0.999     0.999     0.999      6910
          DDoS-SYN_Flood      0.901     0.964     0.931      6960
          DDoS-SlowLoris      0.686     0.558     0.615        43
 DDoS-SynonymousIP_Flood      0.957     0.944     0.951      6207
          DDoS-TCP_Flood      0.930     0.970     0.950      7687
          DDoS-UDP_Flood      0.899     0.953     0.925      9262
  DDoS-UDP_Fragmentation      0.962     0.858     0.907       508
            DNS_Spoofing      0.475     0.301     0.368       316
   DictionaryBruteForce      0.500     0.045     0.083        22
           DoS-HTTP_Flood      0.845     0.696     0.763       125
            DoS-SYN_Flood      0.907     0.802     0.851      3450
            DoS-TCP_Flood      0.952     0.876     0.912      4574
            DoS-UDP_Flood      0.902     0.812     0.855      5665
        MITM-ArpSpoofing      0.742     0.417     0.534       530
      Mirai-greeth_flood      0.937     0.950     0.943      1710
        Mirai-greip_flood      0.921     0.906     0.914      1282
          Mirai-udpplain      0.997     0.984     0.991      1546
     Recon-HostDiscovery      0.596     0.566     0.581       235
            Recon-OSScan      0.375     0.124     0.187       169
         Recon-PingSweep      0.000     0.000     0.000         4
          Recon-PortScan      0.457     0.150     0.226       140
            SqlInjection      0.000     0.000     0.000        10
        Uploading_Attack      0.000     0.000     0.000         1
      VulnerabilityScan      0.667     0.787     0.722        61
                     XSS      0.000     0.000     0.000         6

                accuracy                          0.932     80000
               macro avg      0.625     0.581     0.590     80000
            weighted avg      0.931     0.932     0.930     80000

/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

6.5 XGBoost

[42]:
```
xgc = xgb.XGBClassifier(n_estimators=100, learning_rate = 1, booster = "gbtree",␣
↪random_state = 42,
                        max_depth = 13, max_samples = 0.9 , n_jobs=-1)
xgc.fit(scaled_X_train, encoded_y_train)

evaluate(xgc, encoded_y_test, target_names, 34, "XGBoost")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-packages/xgboost/training.py:183:
UserWarning: [14:42:50] WARNING: /workspace/src/learner.cc:738:
Parameters: { "max_samples" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

	precision	recall	f1-score	support
BenignTraffic	0.000	0.000	0.000	4
DDoS-UDP_Flood	0.602	0.418	0.494	1875
DoS-UDP_Flood	0.000	0.000	0.000	11
DDoS-PSHACK_Flood	0.000	0.000	0.000	9
DDoS-SYN_Flood	0.000	0.000	0.000	485
DDoS-SynonymousIP_Flood	0.000	0.000	0.000	48
Recon-PortScan	0.961	0.510	0.666	12344
DDoS-ICMP_Flood	0.667	0.005	0.010	775
DDoS-TCP_Flood	0.931	0.849	0.888	7026
DDoS-RSTFINFlood	0.000	0.000	0.000	6910
DNS_Spoofing	0.122	0.217	0.156	6960
Mirai-greip_flood	0.000	0.000	0.000	43
DDoS-ICMP_Fragmentation	0.000	0.000	0.000	6207
DoS-SYN_Flood	0.139	0.876	0.241	7687
DoS-TCP_Flood	0.000	0.000	0.000	9262
Mirai-udpplain	0.000	0.000	0.000	508
DDoS-ACK_Fragmentation	0.000	0.000	0.000	316
Mirai-greeth_flood	0.000	0.000	0.000	22
DoS-HTTP_Flood	0.000	0.000	0.000	125
DDoS-UDP_Fragmentation	0.000	0.000	0.000	3450
MITM-ArpSpoofing	0.054	0.002	0.005	4574
Recon-HostDiscovery	0.072	0.054	0.062	5665
Recon-OSScan	0.000	0.000	0.000	530
SqlInjection	0.000	0.000	0.000	1710
DDoS-HTTP_Flood	0.000	0.000	0.000	1282
DDoS-SlowLoris	0.031	0.011	0.016	1546

```
   CommandInjection      0.263     0.021     0.039       235
  VulnerabilityScan      0.000     0.000     0.000       169
DictionaryBruteForce      0.000     0.000     0.000         4
    BrowserHijacking      0.000     0.000     0.000       140
                 XSS      0.000     0.000     0.000        10
     Backdoor_Malware      0.000     0.000     0.000         1
      Recon-PingSweep      0.000     0.000     0.000        61
     Uploading_Attack      0.000     0.000     0.000         6

             accuracy                          0.270     80000
            macro avg      0.113     0.087     0.076     80000
         weighted avg      0.284     0.270     0.234     80000
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

6.6 Random Forest

[43]:
```python
# Base RF
rfc = RandomForestClassifier(n_estimators=100 , n_jobs=-1)
rfc.fit(scaled_X_train, y_train)

evaluate(rfc, y_test, target_names, 34, "Random Forest")
```

```
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
```

```
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
                        precision    recall  f1-score   support

       Backdoor_Malware      0.000     0.000     0.000         4
          BenignTraffic      0.858     0.989     0.919      1875
       BrowserHijacking      0.000     0.000     0.000        11
       CommandInjection      0.000     0.000     0.000         9
 DDoS-ACK_Fragmentation      0.996     0.986     0.991       485
        DDoS-HTTP_Flood      1.000     0.958     0.979        48
        DDoS-ICMP_Flood      1.000     1.000     1.000     12344
DDoS-ICMP_Fragmentation      0.995     0.994     0.994       775
      DDoS-PSHACK_Flood      1.000     0.999     1.000      7026
       DDoS-RSTFINFlood      1.000     1.000     1.000      6910
         DDoS-SYN_Flood      0.999     0.999     0.999      6960
         DDoS-SlowLoris      0.741     0.930     0.825        43
DDoS-SynonymousIP_Flood      1.000     1.000     1.000      6207
         DDoS-TCP_Flood      1.000     0.999     1.000      7687
         DDoS-UDP_Flood      0.999     1.000     0.999      9262
 DDoS-UDP_Fragmentation      0.998     0.984     0.991       508
           DNS_Spoofing      0.765     0.671     0.715       316
   DictionaryBruteForce      1.000     0.091     0.167        22
          DoS-HTTP_Flood      0.976     0.976     0.976       125
          DoS-SYN_Flood      0.998     0.999     0.998      3450
          DoS-TCP_Flood      1.000     0.998     0.999      4574
          DoS-UDP_Flood      0.999     0.999     0.999      5665
        MITM-ArpSpoofing      0.885     0.811     0.846       530
      Mirai-greeth_flood      0.998     0.998     0.998      1710
       Mirai-greip_flood      0.996     0.995     0.996      1282
         Mirai-udpplain      0.999     0.999     0.999      1546
    Recon-HostDiscovery      0.827     0.774     0.800       235
           Recon-OSScan      0.874     0.533     0.662       169
        Recon-PingSweep      0.000     0.000     0.000         4
         Recon-PortScan      0.811     0.550     0.655       140
           SqlInjection      0.000     0.000     0.000        10
       Uploading_Attack      0.000     0.000     0.000         1
      VulnerabilityScan      0.951     0.951     0.951        61
                    XSS      0.000     0.000     0.000         6

               accuracy                          0.993     80000
              macro avg      0.755     0.711     0.719     80000
           weighted avg      0.992     0.993     0.992     80000

/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
```

```
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/faissalm/anaconda3/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

[44]:

```python
# Bagging-balanced
rfcb = BalancedRandomForestClassifier(n_estimators=100, sampling_strategy="all",␣
 ↪replacement=True)
rfcb.fit(scaled_X_train, y_train)
evaluate(rfcb, y_test, target_names, 34, "Random Forest - Bagging")
```

	precision	recall	f1-score	support
Backdoor_Malware	0.025	0.750	0.049	4
BenignTraffic	0.847	0.309	0.453	1875
BrowserHijacking	0.012	0.273	0.023	11
CommandInjection	0.045	0.444	0.082	9
DDoS-ACK_Fragmentation	0.807	0.930	0.864	485
DDoS-HTTP_Flood	0.221	0.708	0.337	48
DDoS-ICMP_Flood	0.974	0.993	0.984	12344
DDoS-ICMP_Fragmentation	0.997	0.899	0.946	775
DDoS-PSHACK_Flood	0.992	0.996	0.994	7026
DDoS-RSTFINFlood	0.999	0.998	0.998	6910
DDoS-SYN_Flood	0.953	0.949	0.951	6960
DDoS-SlowLoris	0.247	0.558	0.343	43
DDoS-SynonymousIP_Flood	0.975	0.948	0.961	6207
DDoS-TCP_Flood	0.985	0.985	0.985	7687
DDoS-UDP_Flood	0.775	0.996	0.872	9262
DDoS-UDP_Fragmentation	0.744	0.967	0.841	508
DNS_Spoofing	0.667	0.063	0.116	316
DictionaryBruteForce	0.000	0.000	0.000	22
DoS-HTTP_Flood	0.510	0.600	0.551	125
DoS-SYN_Flood	0.921	0.971	0.945	3450
DoS-TCP_Flood	0.903	0.991	0.945	4574
DoS-UDP_Flood	0.975	0.402	0.570	5665
MITM-ArpSpoofing	0.357	0.481	0.410	530
Mirai-greeth_flood	0.976	0.798	0.878	1710
Mirai-greip_flood	0.791	0.950	0.864	1282
Mirai-udpplain	0.968	0.993	0.980	1546
Recon-HostDiscovery	0.610	0.366	0.457	235
Recon-OSScan	0.132	0.101	0.114	169
Recon-PingSweep	0.006	0.250	0.012	4

```
  Recon-PortScan       0.123     0.064     0.085       140
    SqlInjection       0.019     0.200     0.034        10
 Uploading_Attack      0.006     1.000     0.012         1
VulnerabilityScan      0.229     0.787     0.354        61
             XSS       0.023     0.333     0.043         6

        accuracy                           0.907     80000
       macro avg       0.553     0.649     0.531     80000
    weighted avg       0.927     0.907     0.902     80000
```

[45]:
```
# exporting and displaying the class 34 metrics
metrics_34.to_csv('metrics_34.csv', index=True)
metrics_34
```

[45]:
```
          Logistic Regression  Adaboost Gradientboost       KNN   XGBoost  \
Accuracy             0.783575  0.723513       0.99035  0.932013  0.270375
Recall               0.416319  0.348667      0.815507  0.580547   0.08718
Precision            0.501909  0.385901      0.828673  0.625427  0.113056
F1-Score             0.409058  0.323045      0.817736  0.589563  0.075797

          Random Forest Random Forest - Bagging
Accuracy        0.99285                0.906525
Recall          0.71123                0.648675
Precision      0.754803                0.553339
F1-Score       0.719293                0.530971
```

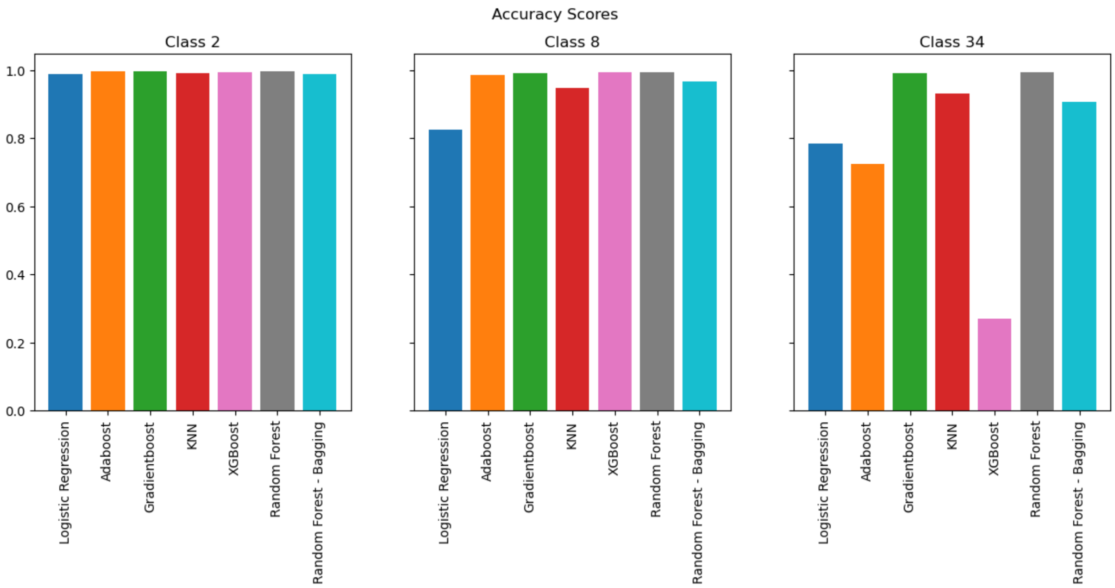
[46]:
```
save_models_for_class_34()
```

```
Scaler saved for 34-class classification at:
saved_models/class_34/standard_scaler.pkl
Model 'Logistic Regression' saved for 34-class classification at:
saved_models/class_34/logistic_regression.pkl
Model 'Adaboost' saved for 34-class classification at:
saved_models/class_34/adaboost.pkl
Model 'Gradientboost' saved for 34-class classification at:
saved_models/class_34/gradientboost.pkl
Model 'KNN' saved for 34-class classification at: saved_models/class_34/knn.pkl
Model 'XGBoost' saved for 34-class classification at:
saved_models/class_34/xgboost.pkl
Model 'Random Forest' saved for 34-class classification at:
saved_models/class_34/random_forest.pkl
Model 'Random Forest Bagging' saved for 34-class classification at:
saved_models/class_34/random_forest_bagging.pkl
```

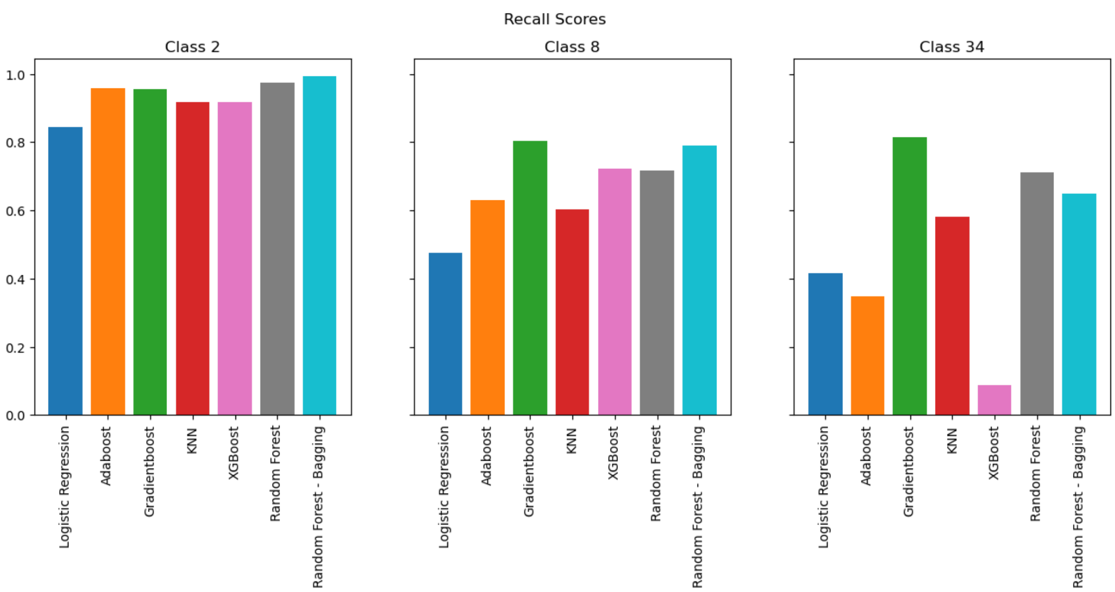
7 Metric Plot

[47]:
```python
# List of model names
model_names = ["Logistic Regression", "Adaboost", "Gradientboost", "KNN",␣
↪"XGBoost", "Random Forest", "Random Forest - Bagging"]

# List of dataframes
dataframes = [metrics_2, metrics_8, metrics_34]

# List of classes
classes = [2, 8, 34]

# List of metric names
metrics = ["Accuracy", "Recall", "Precision", "F1-Score"]

# Create a color mapping dictionary for each model
model_colors = {
    "Logistic Regression": 'tab:blue',
    "Adaboost": 'tab:orange',
    "Gradientboost": 'tab:green',
    "KNN": 'tab:red',
    "XGBoost": 'tab:pink',
    "Random Forest": 'tab:gray',
    "Random Forest - Bagging": 'tab:cyan'
}

# Creating subplots for each metric
for metric in metrics:
    fig, axs = plt.subplots(1, len(classes), figsize=(15, 5), sharey=True)
    fig.suptitle(f"{metric} Scores")

    for i, df in enumerate(dataframes):
        axs[i].set_title(f"Class {classes[i]}")

        # Plotting the respective metric score for each model with specified␣
↪color
        for model_name in model_names:
            color = model_colors[model_name]
            axs[i].bar(model_name, df.loc[metric, model_name], color=color)

        # Set x-axis ticks and labels, rotating labels by 90 degrees
        axs[i].set_xticks(range(len(model_names)))
        axs[i].set_xticklabels(model_names, rotation=90)

    # Save the figure
    plt.savefig(f'{metric}_scores.png', bbox_inches='tight')
```

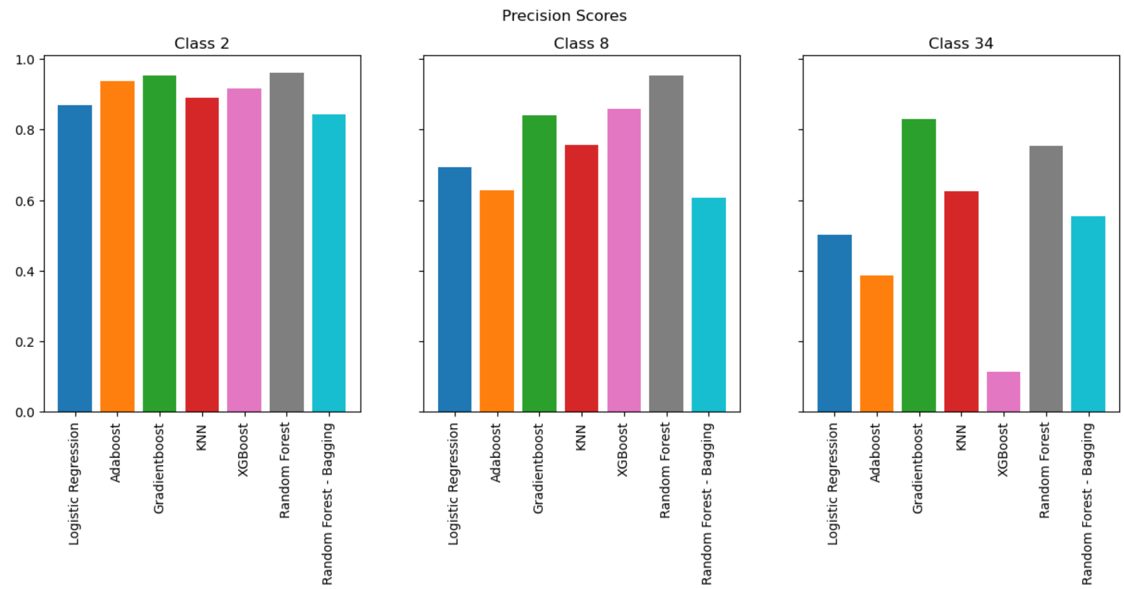
```
plt.show()
```

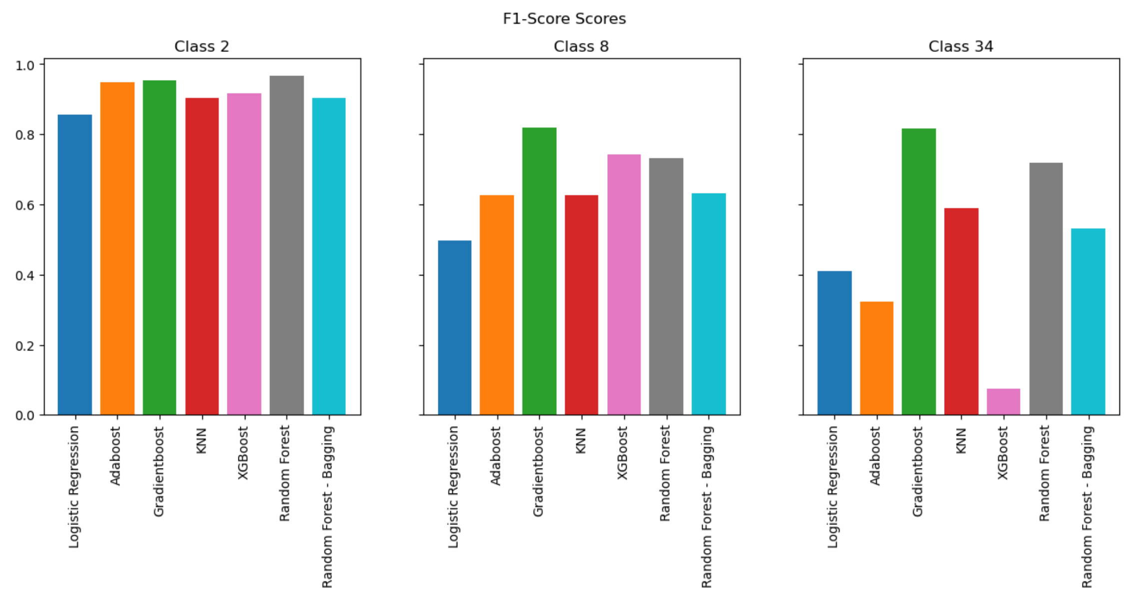


Accuracy Scores
Class 2
Class 8
Class 34
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
Adaboost
Gradientboost
KNN
XGBoost
Random Forest
Random Forest - Bagging



Recall Scores
Class 2
Class 8
Class 34
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
Adaboost
Gradientboost
KNN
XGBoost
Random Forest
Random Forest - Bagging





8 Metric Table

[48]:
```
# Concatenate them along rows
concatenated_data = pd.concat([metrics_2, metrics_8, metrics_34],␣
↪ignore_index=False)

# List of model names
```

```python
model_names = ["Logistic Regression", "Adaboost", "Gradientboost", "KNN",␣
 ↪"XGBoost", "Random Forest", "Random Forest - Bagging"]

# List of metric names
metrics = ["Accuracy", "Recall", "Precision", "F1-Score"]

# Create a DataFrame with the concatenated data
result_df = pd.DataFrame(concatenated_data.values,
                          pd.MultiIndex.from_product([["2 classes", "8 classes",␣
 ↪"34 classes"], metrics]),
                          columns=model_names)

# Display the result
result_df
```

[48]:

```
                      Logistic Regression  Adaboost Gradientboost       KNN  \
2 classes  Accuracy              0.987325    0.9951       0.99575  0.990788
           Recall                0.844459  0.958733      0.954903  0.916986
           Precision             0.869905   0.93737      0.952549  0.889666
           F1-Score              0.856703  0.947783      0.953723  0.902836
8 classes  Accuracy               0.82475  0.985012        0.9917  0.946163
           Recall                0.476462  0.629999       0.80335  0.603714
           Precision             0.693832  0.628506      0.839952  0.756951
           F1-Score              0.497933  0.627205      0.820249  0.626488
34 classes Accuracy              0.783575  0.723513       0.99035  0.932013
           Recall                0.416319  0.348667      0.815507  0.580547
           Precision             0.501909  0.385901      0.828673  0.625427
           F1-Score              0.409058  0.323045      0.817736  0.589563

                        XGBoost Random Forest Random Forest - Bagging
2 classes  Accuracy    0.992387      0.996988                 0.98935
           Recall      0.916244      0.973486                0.994027
           Precision    0.91733      0.961723                0.843967
           F1-Score    0.916786      0.967526                 0.90465
8 classes  Accuracy      0.9936        0.9947                0.966337
           Recall      0.721853       0.71562                0.789926
           Precision   0.858733      0.951963                0.607234
           F1-Score    0.741981      0.732571                0.630485
34 classes Accuracy    0.270375       0.99285                0.906525
           Recall       0.08718       0.71123                0.648675
           Precision   0.113056      0.754803                0.553339
           F1-Score    0.075797      0.719293                0.530971
```