Detecting Brute Force, DDoS, and DoS Attacks: A Supervised Learning Comparison

Participants

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Introduction

Network attacks have become a big threat in today's digital landscape, significantly impacting the security and availability of online services. Distributed Denial of Service (DDoS) attacks, Denial of Service (DoS) attacks, and brute force FTP attacks are all examples of the diverse range of threats that organizations face. DDoS attacks overwhelm services by flooding them with traffic from compromised devices, making them inaccessible to legitimate users. In 2016, for example, one of the most extensive instances of a DDoS attack was directed against the Domain Name System provider Dyn, creating a botnet composed of tens of millions of IP addresses. Major services, including Quora, Reddit, Amazon, SoundCloud, and the BBC, were entirely unavailable in North America and much of Europe for the duration of this attack, disrupting critical online activities such as e-commerce and voting.

Similarly, Denial of Service (DoS) attacks disrupt services by overwhelming them with traffic or exploiting vulnerabilities, but they originate from a single source rather than a distributed network. These attacks can cause significant downtime and resource exhaustion, further emphasizing the need for robust mitigation strategies. Brute force FTP attacks exploit weak passwords to gain unauthorized access to servers, highlighting the importance of strong authentication measures.

In our project, we will compare the effectiveness of various machine learning models such as Random Forest Trees, Naive Bayes, and Logistic Regression in detecting these different types of attacks. By evaluating how well each algorithm performs in detecting DDoS, DoS, and brute force FTP attacks, we will gain insights into their relative strengths and weaknesses, ultimately providing a comprehensive overview of their effectiveness in securing network infrastructures.

This research could help organizations understand which machine learning models are most effective in detecting and mitigating various network attacks, improving their ability to secure sensitive data and maintain service availability. Previous research in this area has primarily focused on evaluating machine learning models for attack detection, but such studies are often limited in scope, typically examining attacks from a single dataset.

Brute Force Attack

A brute force network attack is a technique that is used by attackers to gain unauthorized access to a system or network by repeatedly trying different combinations of usernames, passwords, or encryption keys until the correct one is found. It relies on sheer computational power and persistence rather than exploiting system vulnerabilities. This type of attack can be resource-intensive and time-consuming, but it is often effective against systems with weak passwords or poorly configured authentication mechanisms.

Distributed Denial of Service (DDoS) Attack

A Distributed Denial of Service (DDoS) attack is an attempt to disrupt the normal functioning of a server, network, or website by overwhelming it with a massive volume of traffic. This type of attack is “distributed” because it involves multiple compromised devices, often part of a botnet, which work together to flood the target with requests. The goal of a DDoS attack is to exhaust the target’s resources, such as bandwidth or server capacity, making it inaccessible to legitimate users. These attacks are usually launched by exploiting vulnerabilities in systems or by taking control of many devices to amplify the scale of the traffic.

Denial of Service (DoS) Attack

A Denial of Service (DoS) attack is an attempt to make a server, network, or service unavailable to its intended users by overwhelming it with a flood of traffic or sending data that exploits vulnerabilities in the system. Unlike a DDoS attack, a DoS attack is launched from a single source rather than multiple distributed devices. The goal is to exhaust the target’s resources, such as processing power or memory, so it cannot handle legitimate requests. This type of attack disrupts normal operations, causing inconvenience or financial loss to the target.

Data

The Canadian Institute for Cybersecurity Intrusion Detection System (CICIDS) datasets, collected by the University of New Brunswick, serve as a comprehensive resource for intrusion detection. These datasets include both benign traffic and a range of contemporary attacks, including DDoS, DoS, and brute force attacks, collected in packet capture (PCAP) files. To create these datasets, the researchers focused on generating realistic background traffic which resembles human interactions on the Internet for a capturing period of five days. During this period, various attacks were executed at different times. The researchers then aggregated the packet-level data into network flows, calculating a set of features which include both continuous variables (ie. flow duration, byte counts, packet counts, etc.) and categorical variables (source and destination ports, protocol types, etc.). The resulting dataset is both comprehensive and structured, allowing for supervised machine learning models to differentiate network traffic patterns and behavior.

For this project, we used two research datasets—CCIDS2017 and CCIDS2018—to analyze how machine learning detection systems respond to attacks which evolve over time. These datasets were chosen because they maintain consistency in the data collection methodology, with both relying on packet capture (PCAP) files aggregated into flow-level features. Additionally, both datasets include examples of the three attack types we are studying—DoS, DDoS, and brute force attacks —allowing for a comprehensive comparison of detection performance across different attack scenarios. By using these datasets, we were able to ensure a consistent evaluation framework while focusing on a broad range of network-based attacks.

Data Processing and Statistics

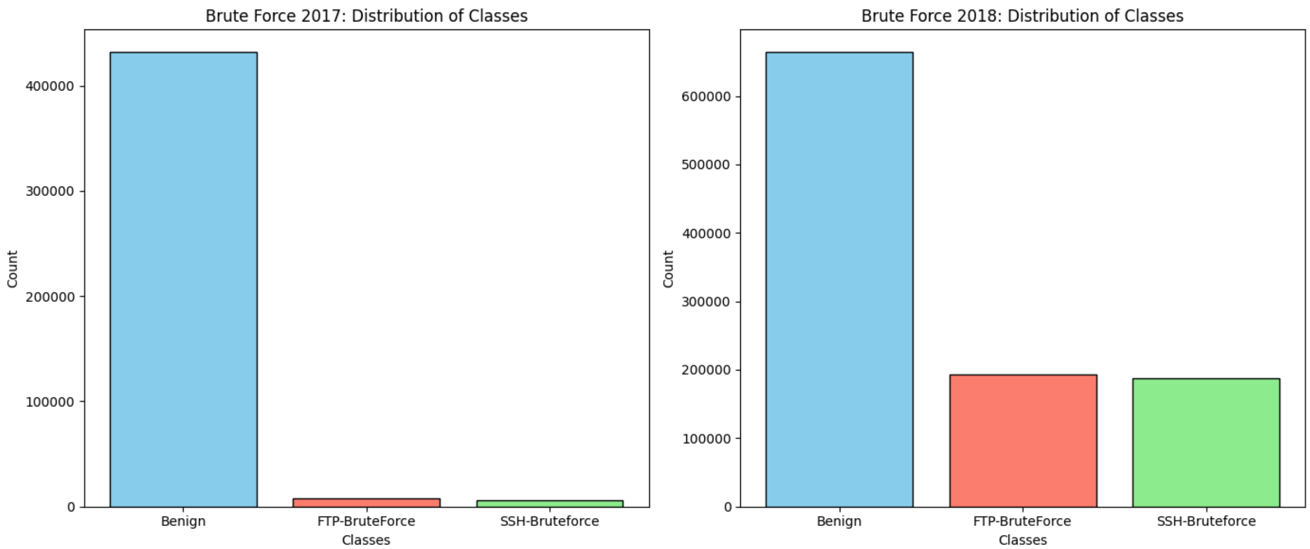
Cleaning Process

To clean the data for analysis, we followed a multi-step process to ensure consistency and relevance across both datasets. First and foremost, we removed any rows containing null or empty values, as these would interfere with model training and evaluation. We also filtered out examples that did not correspond to the attack types we were focusing on—DoS, DDoS, and brute force attacks. While both datasets included additional attack types, such as Heartbleed and various web attacks, these were not relevant to our research, so we excluded them. Next, we standardized the feature set between the two datasets. This was crucial because our machine learning models required a consistent feature vector. We started by removing features that only appeared in one of the datasets. For example, the 'Protocol' column was present in the CCIDS2018 dataset but not in the CCIDS2017 dataset, so we dropped it from the 2018 dataset to ensure uniformity. Additionally, we addressed discrepancies in column naming between the two datasets. Many columns in CCIDS2018 used abbreviated names (e.g., 'Bwd Header Len') that differed from the more descriptive names in CCIDS2017 (e.g., 'Bwd Header Length'). To resolve this, we mapped the column names between the two datasets using a predefined dictionary, ensuring that similar features were properly aligned. This allowed us to merge the datasets into a cohesive dataset that could be used for machine learning modeling.

Class Distributions

Brute Force

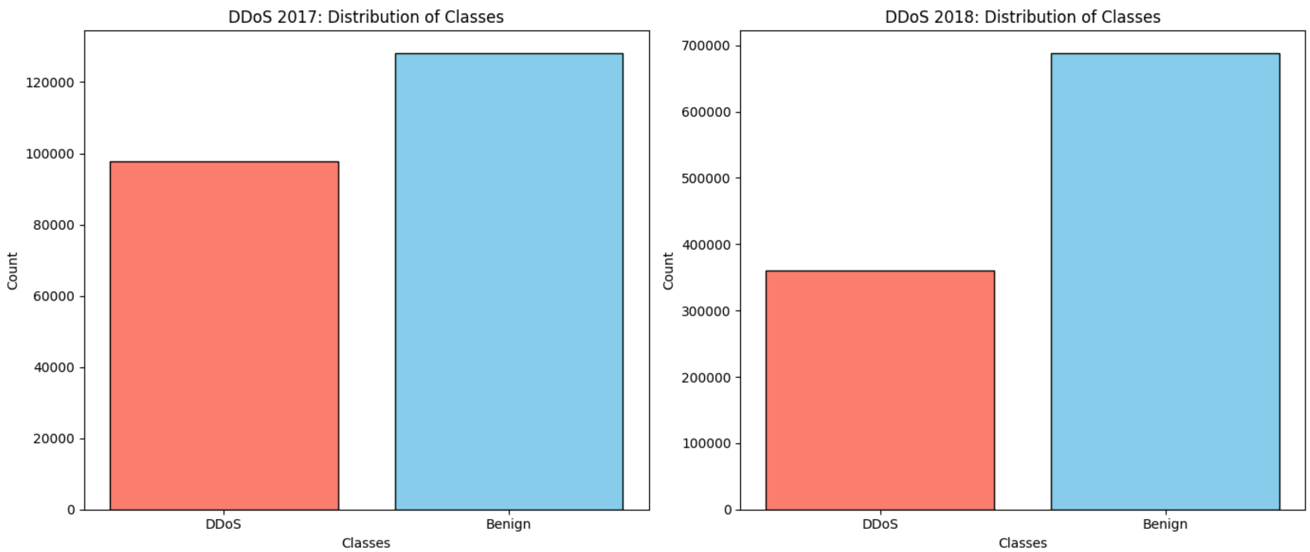
```
plot_paired_class_distributions(
    brute_force_2017_df, brute_force_2018_df,
    ['Benign', 'FTP-BruteForce', 'SSH-Bruteforce'],
    'Brute Force 2017: Distribution of Classes',
    'Brute Force 2018: Distribution of Classes'
)
```



These bar plots are showing the distribution of Benign, FTP-BruteForce, and SSH-BruteForce traffic for datasets from 2017 and 2018. In 2017, Benign traffic dominated the dataset, with very few instances of FTP and SSH brute force attacks. By 2018, the distribution becomes more balanced, with a noticeable increase in both FTP-BruteForce and SSH-BruteForce traffic, although Benign traffic still constitutes the majority. This suggests that there could be an increase in brute force attacks in 2018, or they made more of an active effort to collect less benign data.

DDoS

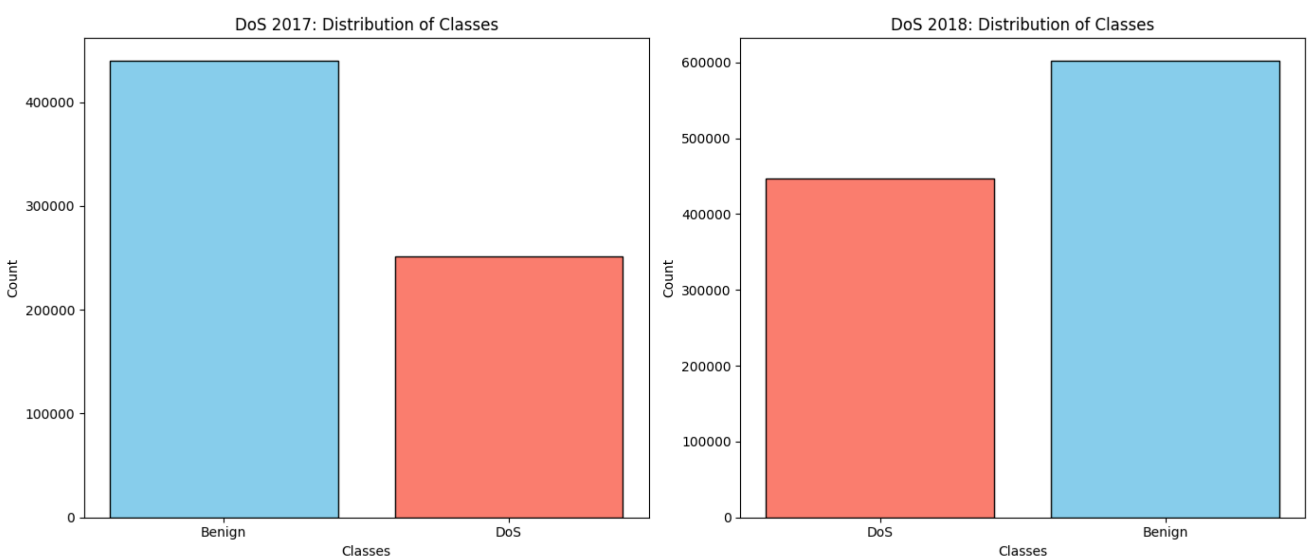
```
plot_paired_class_distributions(
    ddos_2017_df, ddos_2018_df,
    ['Benign', 'DDoS'],
    'DDoS 2017: Distribution of Classes',
    'DDoS 2018: Distribution of Classes'
)
```



These bar plots are showing the distribution of DDoS and Benign traffic in the 2017 and 2018 datasets. In 2017, there seems to be an imbalance with more Benign traffic compared to DDoS traffic, though the gap isn't as significant as in some other datasets. By 2018, the imbalance becomes much more pronounced, with Benign traffic far outweighing DDoS traffic. This most likely suggests that either fewer DDoS attacks were recorded in 2018, or the collection process favored capturing more Benign traffic.

DoS

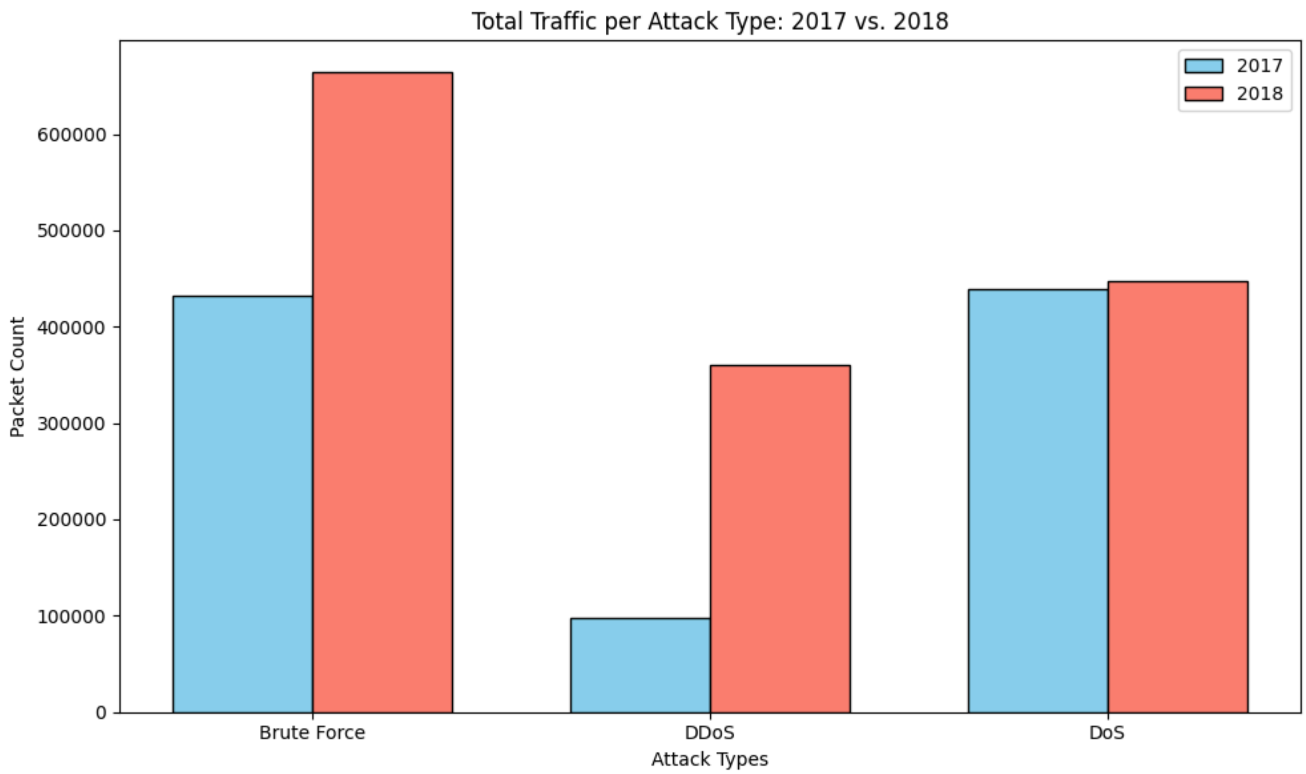
```
plot_paired_class_distributions(
    dos_2017_df, dos_2018_df,
    ['Benign', 'DoS'],
    'DoS 2017: Distribution of Classes',
    'DoS 2018: Distribution of Classes'
)
```



These bar plots are showing the distribution of Benign and DoS traffic for datasets from 2017 and 2018. In 2017, there's a clear imbalance, with much more Benign traffic than DoS traffic. However, in 2018, the trend reverses, with DoS traffic being more frequent than Benign traffic. This change reflects either an increase in DoS attack activity or differences in how the data was collected.

Packet Totals

```
plot_comparative_bar_chart(
    [brute_force_2017.get(0, 0), ddos_2017.get(0, 0), dos_2017.get(0, 0)],
    [brute_force_2018.get(0, 0), ddos_2018.get(0, 0), dos_2018.get(0, 0)],
    ['Brute Force', 'DDoS', 'DoS'],
    'Total Traffic per Attack Type: 2017 vs. 2018'
)
```



This bar plot is comparing the total traffic for Brute Force, DDoS, and DoS attacks in 2017 and 2018. For Brute Force attacks, there's a noticeable increase in traffic in 2018 compared to 2017, reflecting either a rise in attack activity or enhanced data collection. In contrast, DDoS traffic shows a dramatic increase from 2017 to 2018, suggesting either a surge in attack frequency or improved identification and recording of these events. DoS traffic remains relatively consistent across the two years, with only a minor increase in 2018.

Logistic Regression

Logistic regression is a statistical and machine learning algorithm used for binary and multi-class classification problems. It predicts the probability of an event belonging to a particular class by applying the logistic (sigmoid) function to a linear combination of input features. The sigmoid function ensures the output is a value between 0 and 1, which can be interpreted as a probability. Logistic regression is particularly effective for understanding the influence of independent variables on a binary dependent variable, making it a popular choice for tasks where the output involves two or more discrete classes. Its interpretability, simplicity, and ability to handle large datasets make it a practical model for identifying patterns in data associated with network attacks.

In the context of brute force, DDoS, and DoS attacks, logistic regression is especially useful due to its capacity to differentiate between normal and malicious network traffic based on key features like traffic volume, frequency of connection attempts, and packet characteristics. For brute force attacks, logistic regression can identify suspicious login attempts by analyzing patterns such as repeated access failures or unusually rapid login attempts. In the case of DDoS and DoS attacks, it can classify traffic based on abnormal volumes or irregular request patterns. Its efficiency in training and prediction makes it ideal for real-time detection systems, where quick decisions are crucial to mitigate the impact of these attacks. Moreover, the model's ability to provide probabilistic outputs allows security teams to set thresholds for alerts and prioritize responses to the most severe threats.

Logistic Regression Class Structure

```
class LogisticRegressionWorkflow:
    def __init__(self, X, y, class_names):
        """
        Initializes the workflow with data and class names.

        Parameters:
        X : DataFrame : The feature data.
        y : Series : The target labels.
        class_names : list : List of class names.
        """
        self.X = X
        self.y = y
        self.class_names = class_names
        self.X_train = None
        self.X_test = None
        self.y_train = None
        self.y_test = None
        self.best_model = None
        self.model = None
        self.y_pred = None
        self.y_pred_prob = None
        self.y_pred_new = None
        self.y_pred_prob_new = None
        self.report_df = None

    def train(self):
        """
        Splits the data, trains the model using GridSearchCV, and stores the best model.
        """
        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(
            self.X, self.y, test_size=0.2, random_state=42
        )

        pipeline = Pipeline([
            ('scaler', StandardScaler()),
            ('logreg', LogisticRegression(random_state=42, max_iter=1000))
        ])

        param_grid = {
            'logreg__C': [0.1, 10],
            'logreg__solver': ['lbfgs', 'liblinear']
        }

        grid_search = GridSearchCV(pipeline, param_grid, cv=3, n_jobs=-1, verbose=2)
        grid_search.fit(self.X_train, self.y_train)

        self.best_model = grid_search.best_estimator_
        self.model = self.best_model

    def predict(self):
        """
        Generates predictions for the test set and stores them as attributes.
        """
        if self.model is None:
            raise ValueError("The model is not trained. Run the train() method first.")
```

```
        self.y_pred = self.model.predict(self.X_test)
        self.y_pred_prob = self.model.predict_proba(self.X_test)

    def evaluate(self):
        """
        Generates the classification report and stores it as an attribute.
        """
        if self.y_test is None or self.y_pred is None:
            raise ValueError("Predictions have not been made. Ensure the model is trained
and predictions are generated before evaluation.")

        self.report_df = generate_classification_report(self.y_test, self.y_pred,
self.class_names)

    def plot_feature_importance(self):
        """
        Plots the feature importance based on the coefficients of the logistic regression
model.
        """
        coefficients = self.best_model.named_steps['logreg'].coef_[0]
        feature_names = self.X.columns
        importance = np.abs(coefficients)
        sorted_idx = importance.argsort()

        plt.figure(figsize=(10, 16))
        plt.barh(range(len(importance)), importance[sorted_idx], align='center',
color='purple')
        plt.yticks(range(len(importance)), [feature_names[i] for i in sorted_idx])
        plt.xlabel('Absolute Coefficient Value')
        plt.title('Feature Importances Based on Logistic Regression Coefficients')
        plt.tight_layout()
        plt.show()

    def plot_confusion_matrix(self):
        """
        Plots the confusion matrix for the test data.
        """
        plot_confusion_matrix(self.y_test, self.y_pred, self.class_names)

    def plot_roc_curve(self):
        """
        Plots the ROC curve for the test data.
        """
        plot_roc_curve(self.y_test, self.y_pred_prob, self.class_names)

    def predict_on_new_data(self, X_new, y_new):
        """
        Predicts the labels for new data and evaluates performance.

        Parameters:
        X_new : DataFrame : The new feature data (e.g., 2018 data).
        y_new : Series : The new target labels (e.g., 2018 labels).

        Returns:
        report_df : DataFrame : The classification report for the new data.
        """
        self.y_pred_new = self.best_model.predict(X_new)
        self.y_pred_prob_new = self.best_model.predict_proba(X_new)
        report_df = generate_classification_report(y_new, self.y_pred_new,
```

```
self.class_names)
        return report_df
```

Brute Force

2017 Data + Predictions

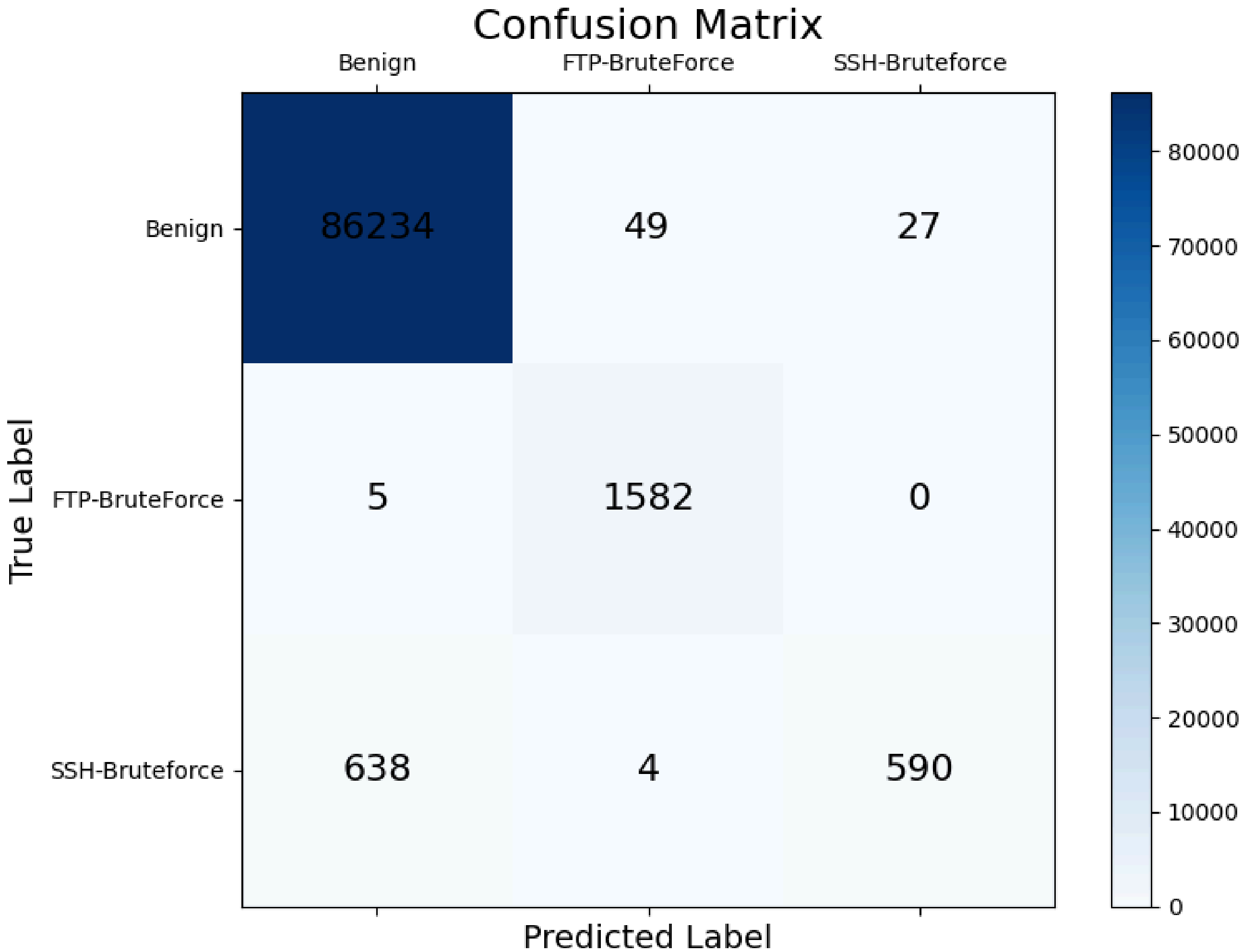
Classification Report

```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.992599	0.999119	0.995848	86310.000000
FTP-BruteForce	0.967584	0.996849	0.981999	1587.000000
SSH-Bruteforce	0.956240	0.478896	0.638183	1232.000000
Accuracy	0.991888	0.991888	0.991888	0.991888
Macro avg	0.972141	0.824955	0.872010	89129.000000
Weighted avg	0.991651	0.991888	0.990658	89129.000000

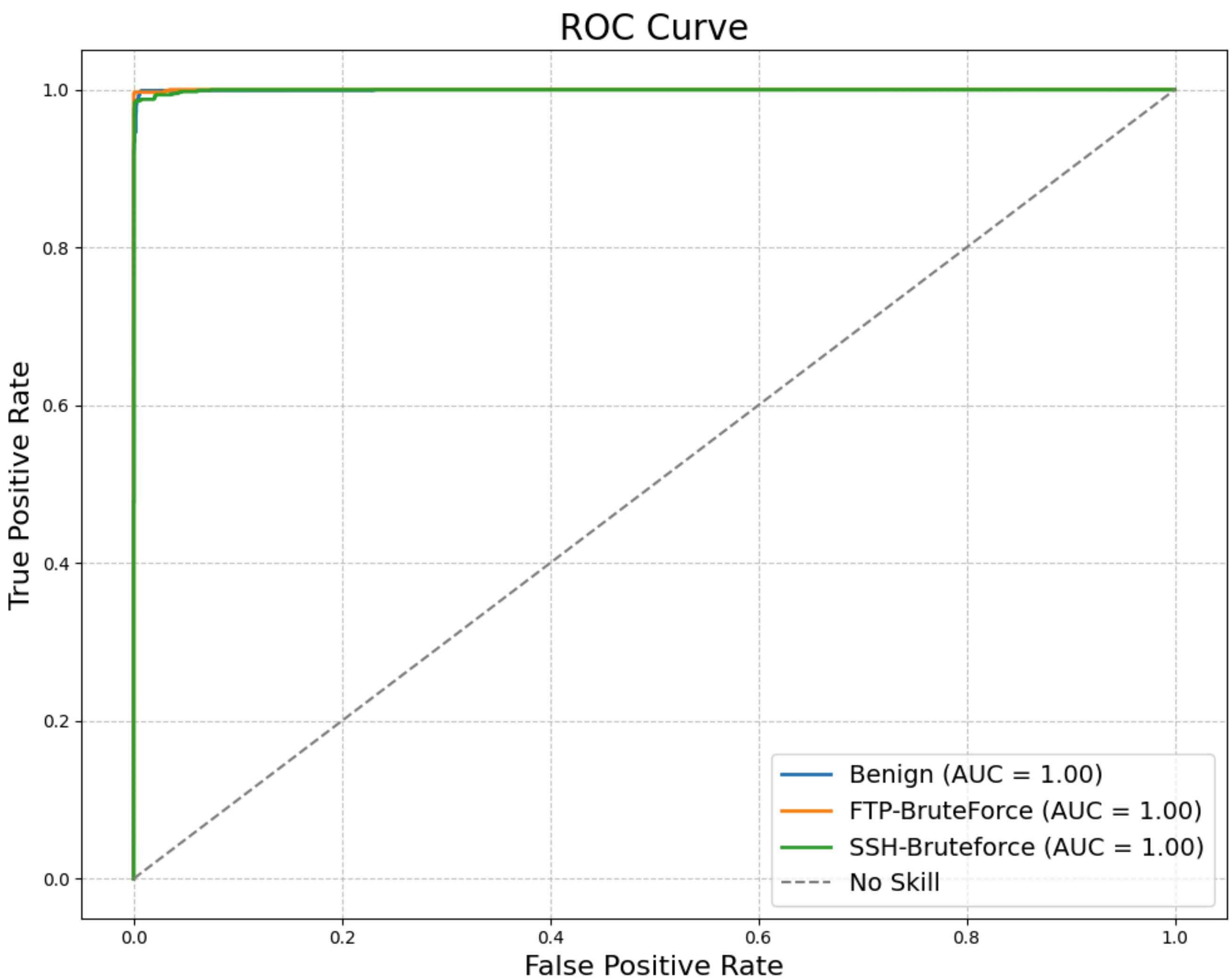
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

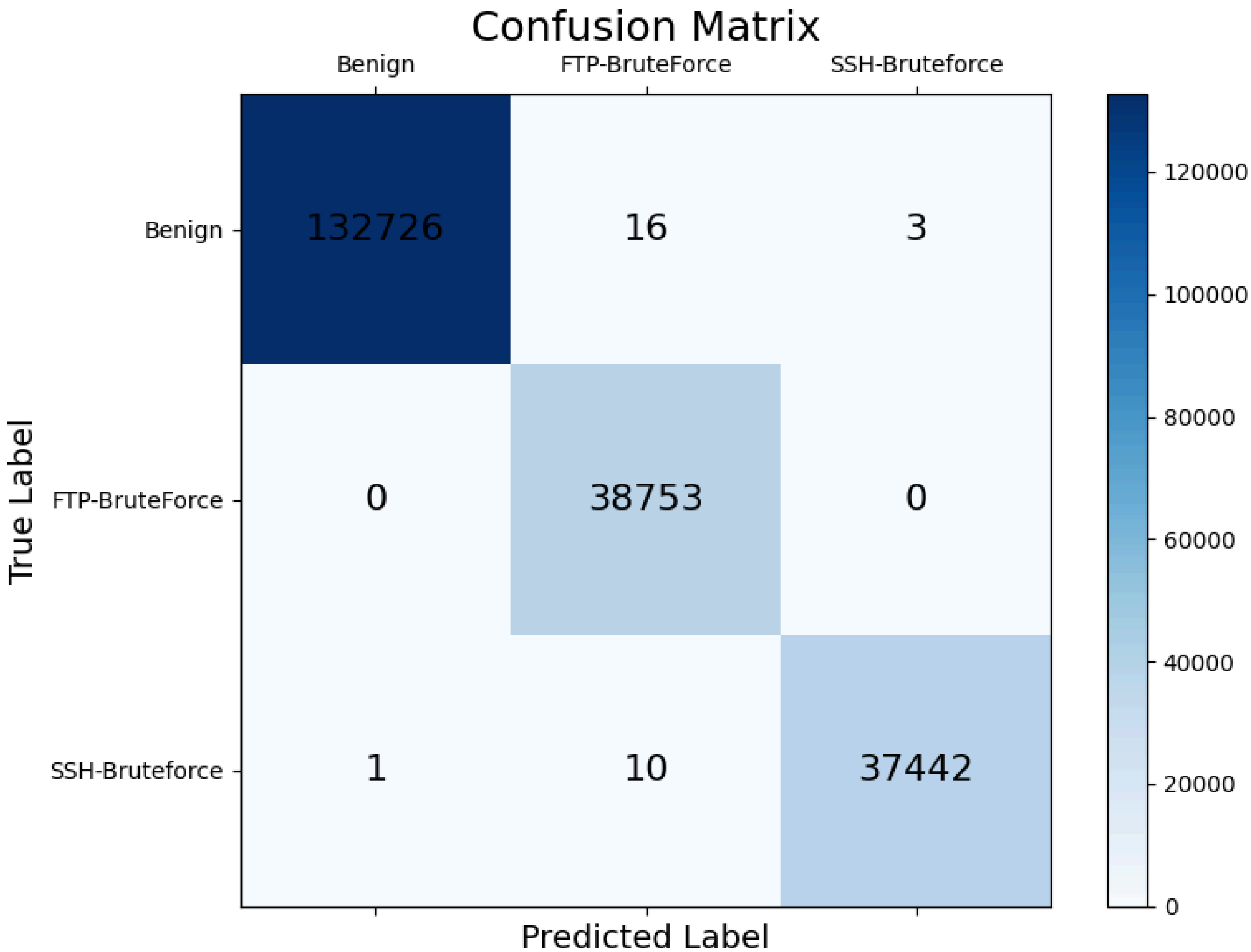
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	0.999992	0.999857	0.999925	132745.000000
FTP-BruteForce	0.999330	1.000000	0.999665	38753.000000
SSH-Bruteforce	0.999920	0.999706	0.999813	37453.000000
Accuracy	0.999856	0.999856	0.999856	0.999856
Macro avg	0.999747	0.999854	0.999801	208951.000000
Weighted avg	0.999857	0.999856	0.999856	208951.000000

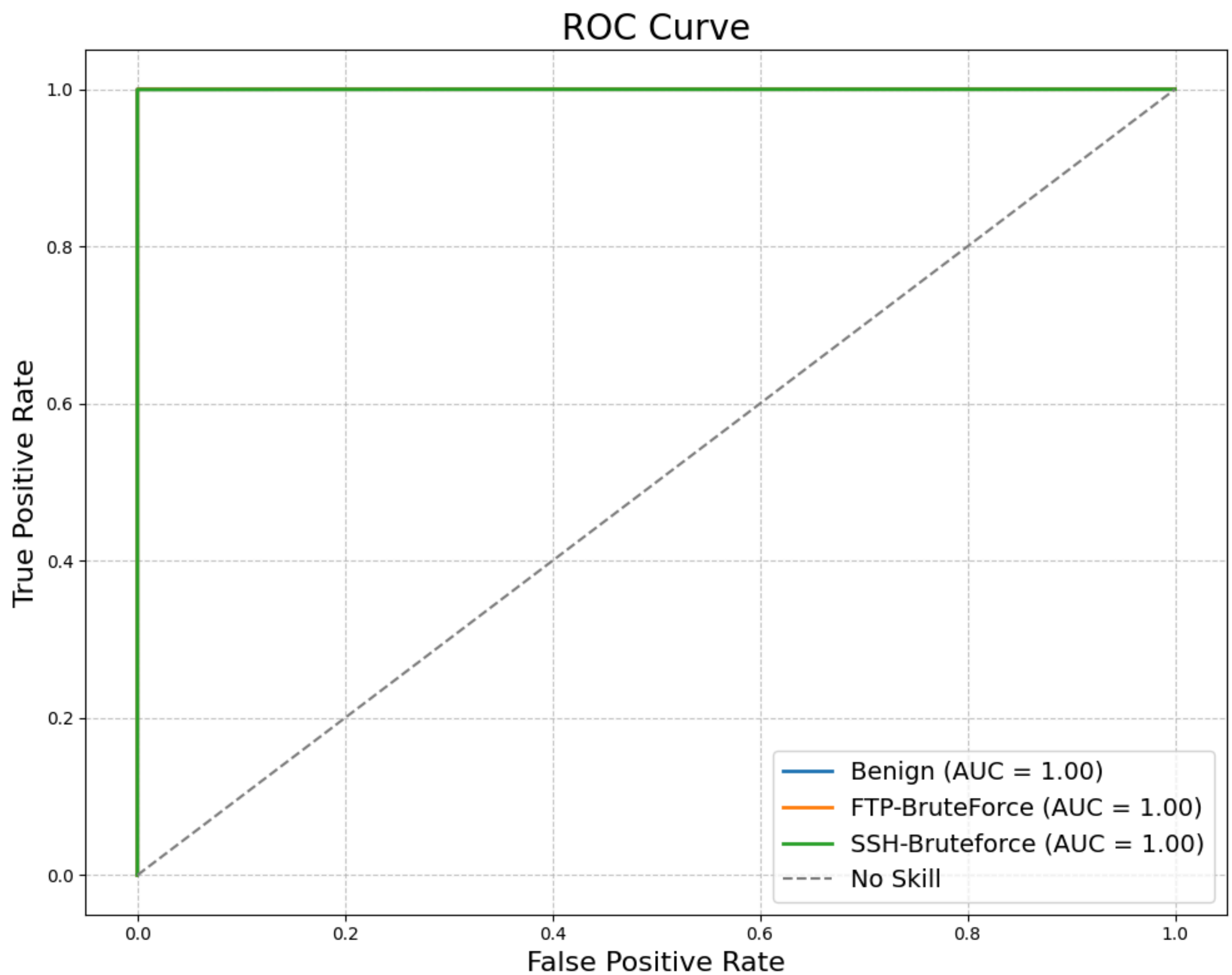
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



DDoS

2017 Data + Predictions

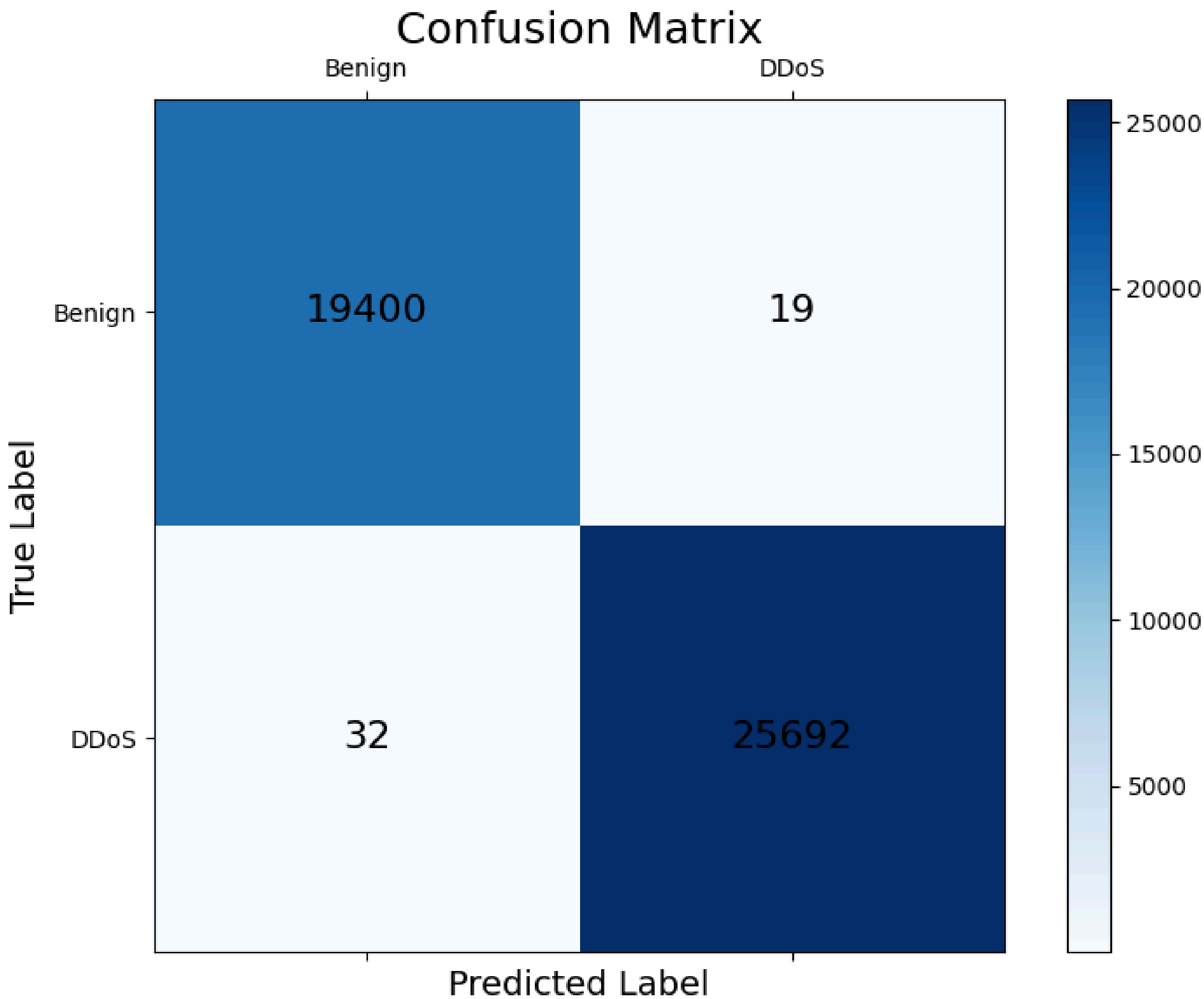
Classification Report

```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.998353	0.999022	0.998687	19419.00000
DDoS	0.999261	0.998756	0.999008	25724.00000
Accuracy	0.998870	0.998870	0.998870	0.99887
Macro avg	0.998807	0.998889	0.998848	45143.00000
Weighted avg	0.998871	0.998870	0.998870	45143.00000

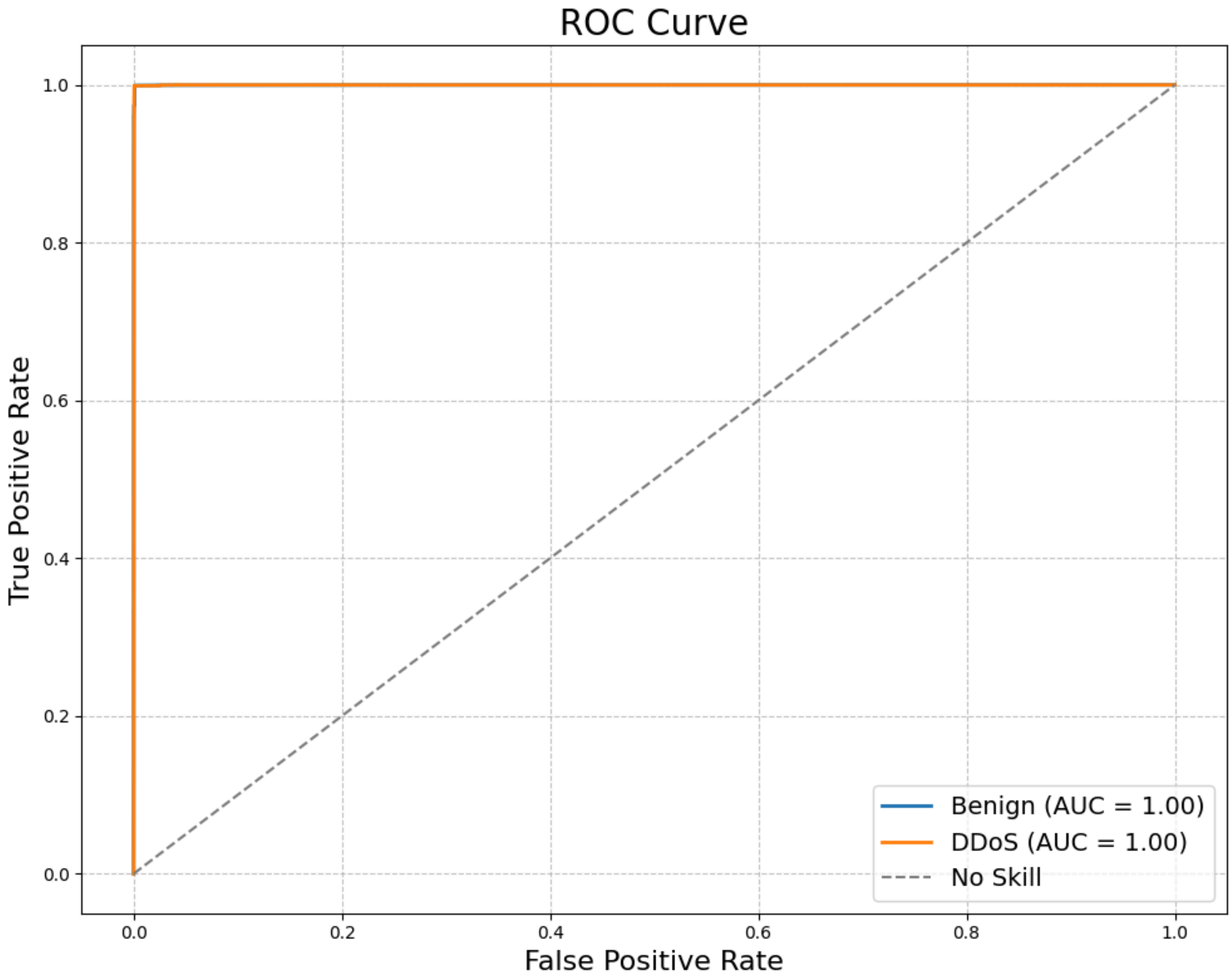
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

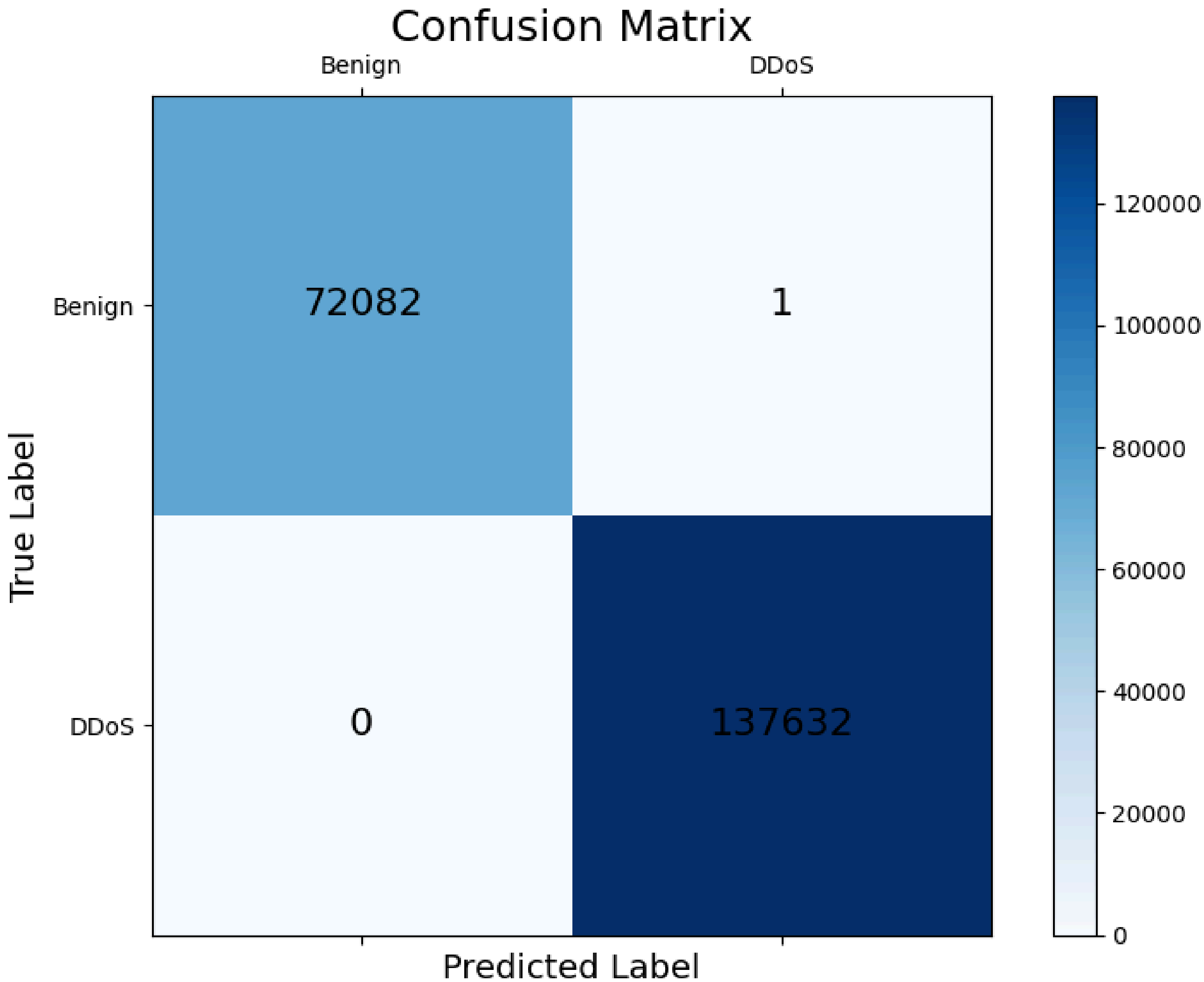
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.000000	0.999986	0.999993	72083.000000
DDoS	0.999993	1.000000	0.999996	137632.000000
Accuracy	0.999995	0.999995	0.999995	0.999995
Macro avg	0.999996	0.999993	0.999995	209715.000000
Weighted avg	0.999995	0.999995	0.999995	209715.000000

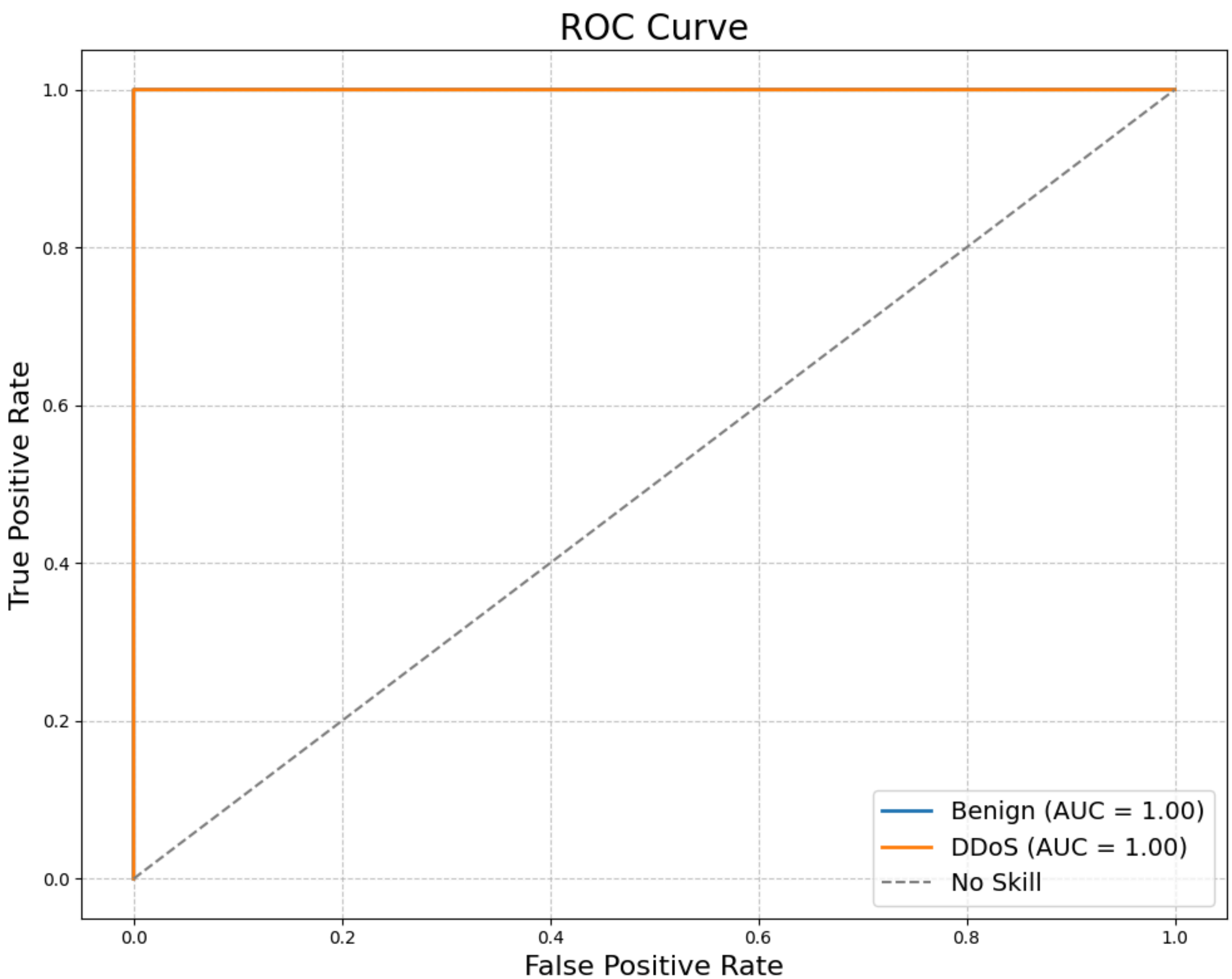
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



DoS

2017 Data + Predictions

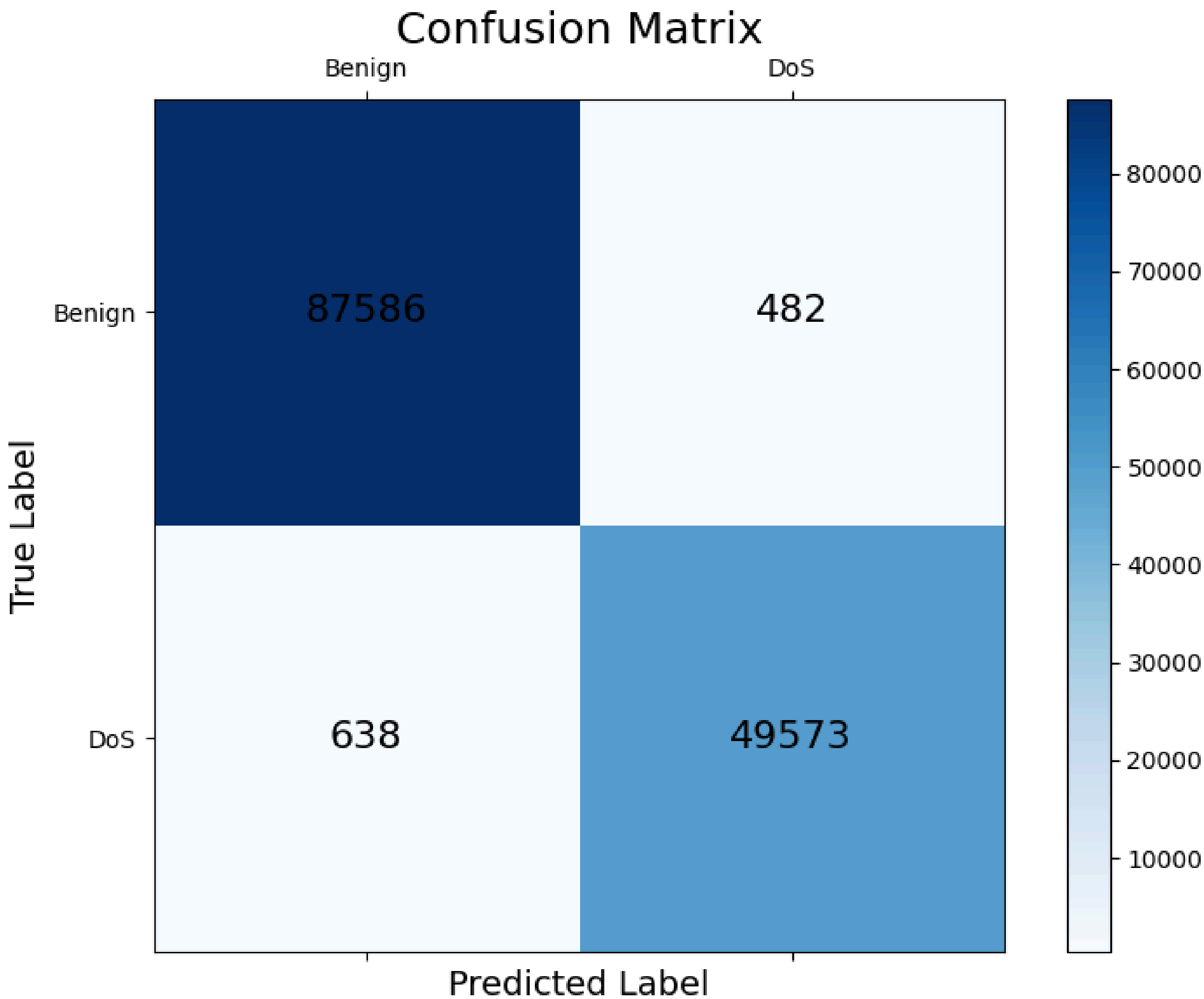
Classification Report

```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.992768	0.994527	0.993647	88068.0000
DoS	0.990371	0.987294	0.988830	50211.0000
Accuracy	0.991900	0.991900	0.991900	0.9919
Macro avg	0.991570	0.990910	0.991238	138279.0000
Weighted avg	0.991898	0.991900	0.991898	138279.0000

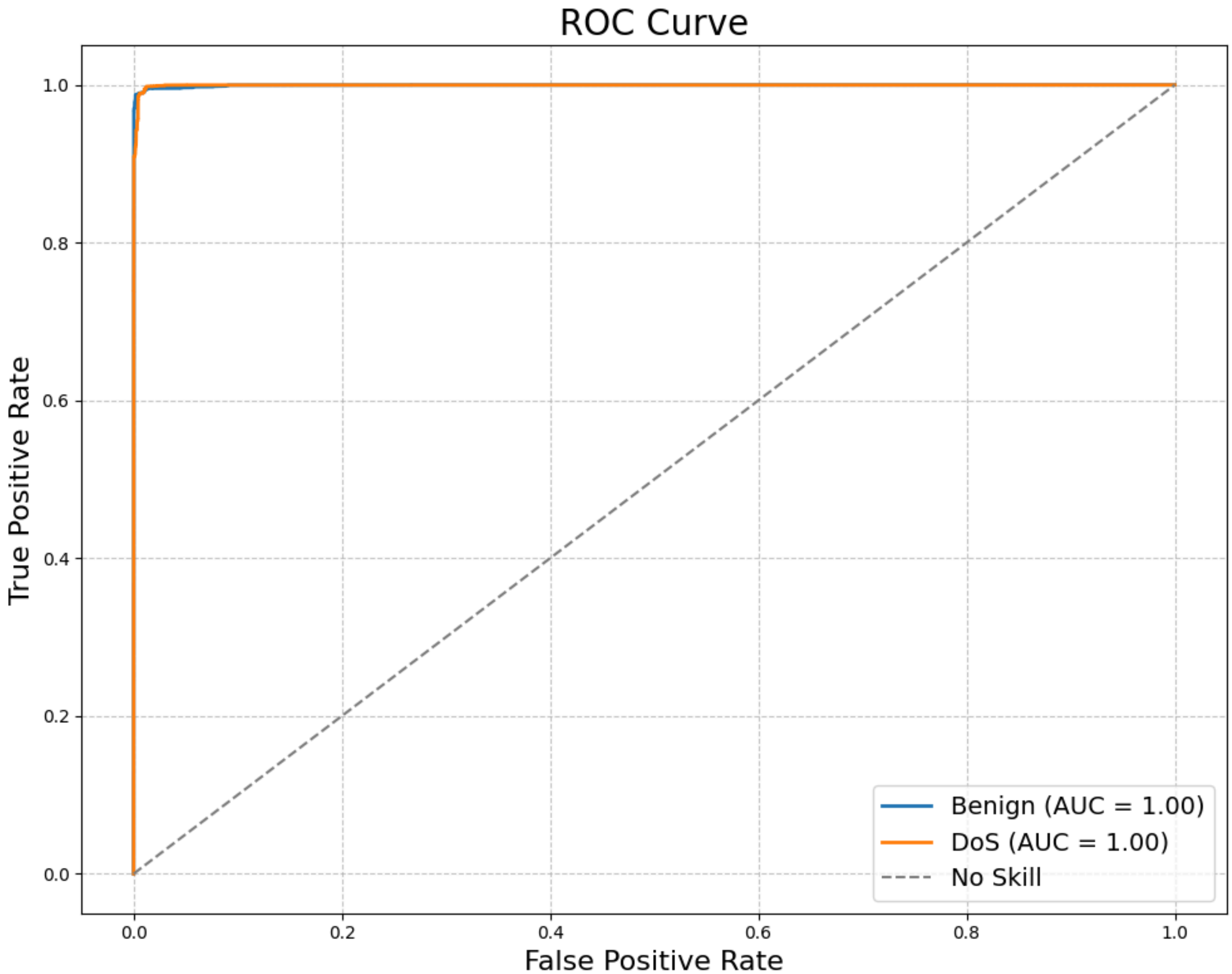
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

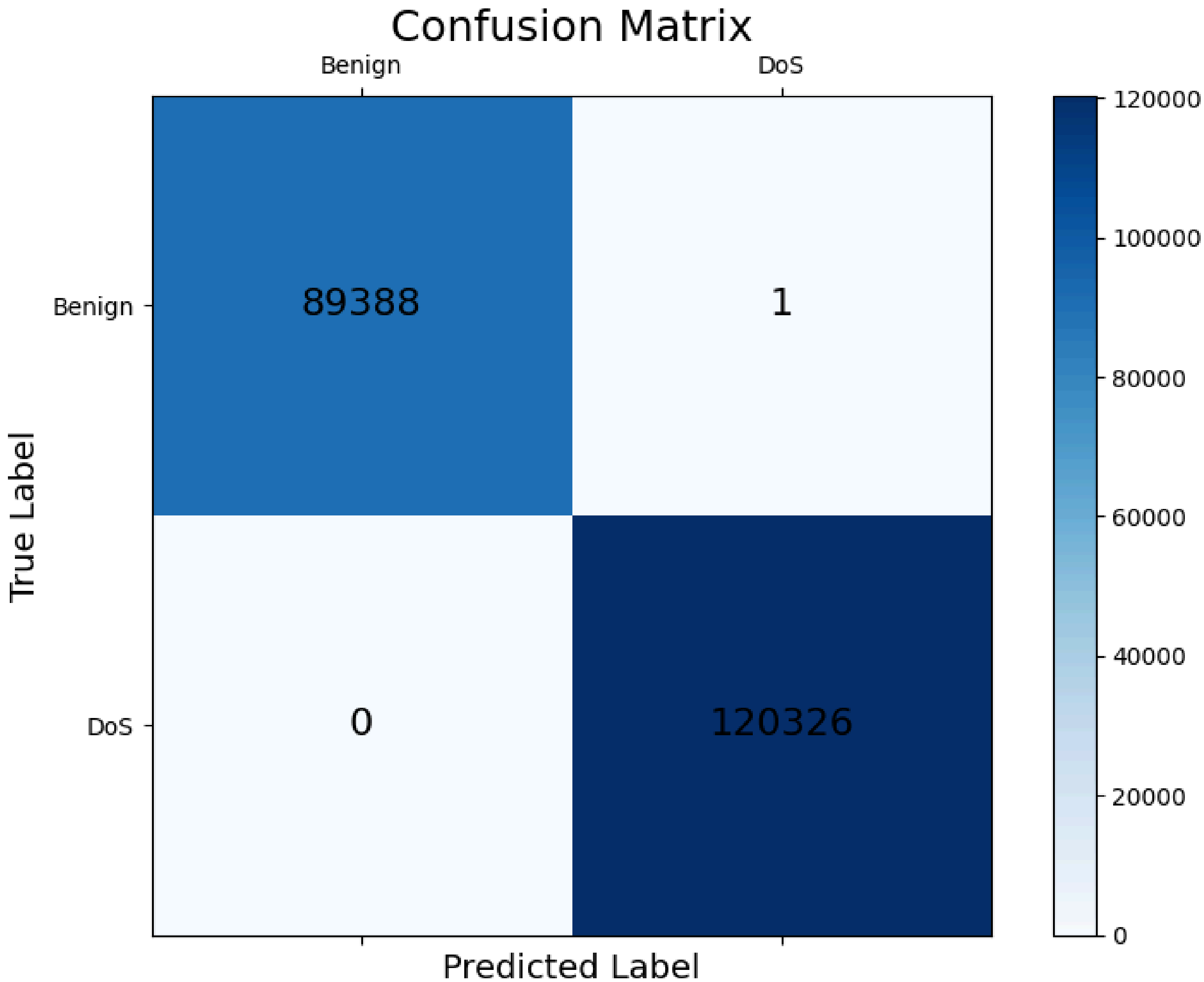
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.000000	0.999989	0.999994	89389.000000
DoS	0.999992	1.000000	0.999996	120326.000000
Accuracy	0.999995	0.999995	0.999995	0.999995
Macro avg	0.999996	0.999994	0.999995	209715.000000
Weighted avg	0.999995	0.999995	0.999995	209715.000000

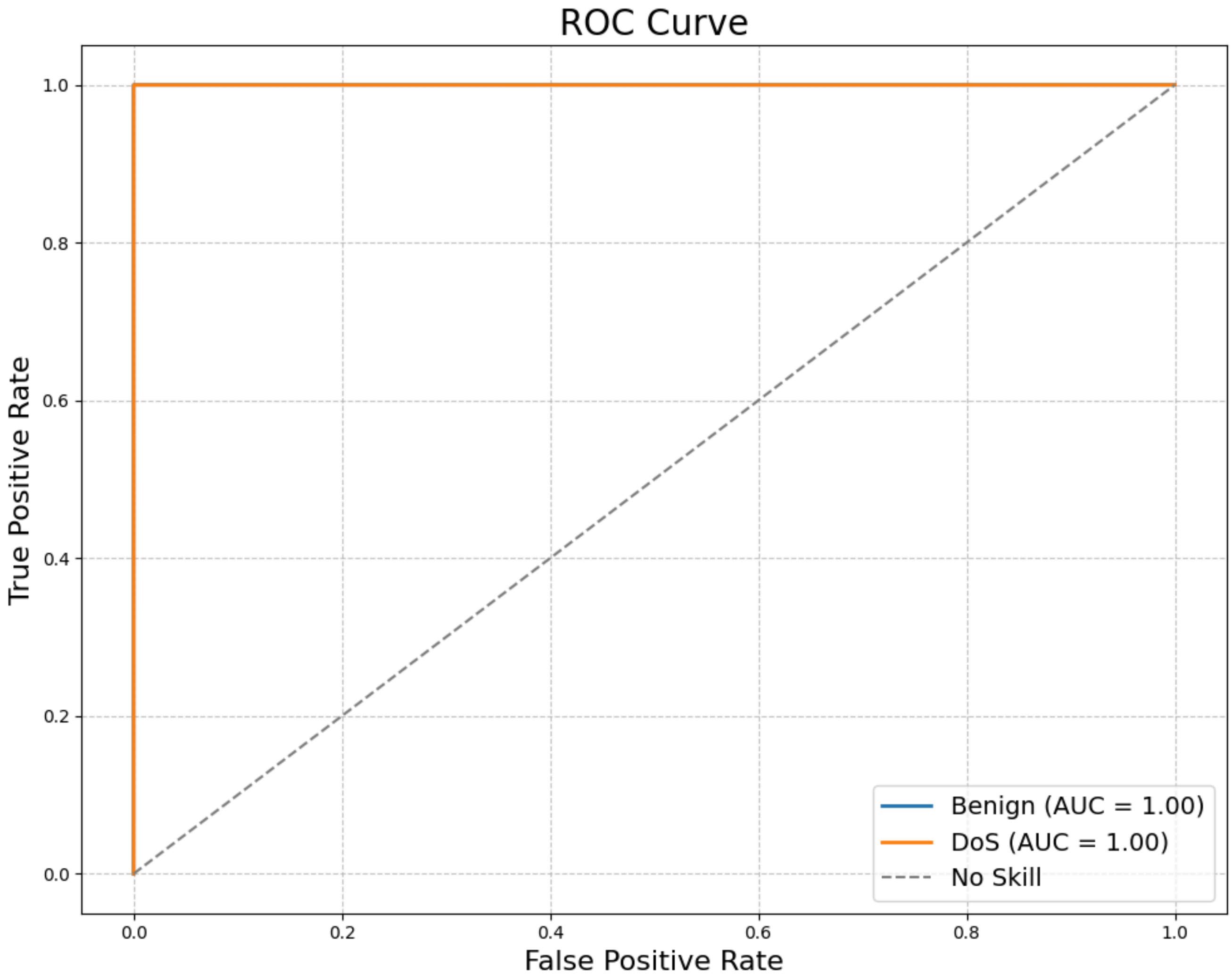
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



Random Forest

Random Forest is an ensemble machine learning algorithm that builds multiple decision trees during training and combines their outputs to improve classification or regression performance. Each tree in the forest is constructed using a random subset of the data and features, which introduces diversity and helps reduce overfitting. The final prediction is typically determined by averaging the outputs (in regression tasks) or by majority voting (in classification tasks). Random Forest is robust, can handle both categorical and numerical data, and is less sensitive to noise or outliers compared to individual decision trees. Its ability to rank feature importance also makes it valuable for identifying key variables contributing to a classification.

For detecting brute force, DDoS, and DoS attacks, Random Forest is particularly useful due to its flexibility and capability to model complex relationships between input features. In the case of brute force attacks, Random Forest can analyze intricate patterns such as repeated login attempts across multiple accounts or IP addresses, even if the data contains noise. For DDoS and DoS attacks, it excels at identifying anomalies in high-dimensional datasets, such as spikes in traffic volume, unusual packet sizes, or irregular request timings. Since it evaluates multiple decision trees, Random Forest provides a more reliable and accurate classification of network traffic, reducing the likelihood of false positives or negatives.

Random Forest Class Structure

```
class RandomForestWorkflow:
    """
    A class to manage the workflow of training, evaluating, and predicting with a Random
Forest model.
    """

    def __init__(self, X, y, class_names):
        """
        Initialize the workflow with data and class names.

        Parameters:
        X : DataFrame : The feature data.
        y : Series : The target labels.
        class_names : list : List of class names.
        """
        self.X = X
        self.y = y
        self.class_names = class_names
        self.best_model = None
        self.report_df = None
        self.y_pred = None
        self.y_pred_prob = None

    def train(self, test_size=0.2, random_state=42):
        """
        Train the Random Forest model with hyperparameter tuning.
        """
        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(
            self.X, self.y, test_size=test_size, random_state=random_state
        )
        self.best_model = self._tune_hyperparameters()

    def evaluate(self):
        """
        Evaluate the model on the test set and generate performance metrics.
        """
        if not self.best_model:
            raise ValueError("Model has not been trained. Call the train() method
first.")

        self.y_pred = self.best_model.predict(self.X_test)
        self.y_pred_prob = self.best_model.predict_proba(self.X_test)
        self.report_df = self._generate_classification_report(self.y_test, self.y_pred)

    def predict_on_new_data(self, X_new, y_new):
        """
        Predict on new data using the trained model.

        Parameters:
        X_new : DataFrame : New feature data.
        y_new : Series : New target labels.

        Returns:
        DataFrame : Classification report for the new data.
        """
        if not self.best_model:
```

```
            raise ValueError("Model has not been trained. Call the train() method
first.")

        self.y_new_pred = self.best_model.predict(X_new)
        self.y_new_pred_prob = self.best_model.predict_proba(X_new)
        return self._generate_classification_report(y_new, self.y_new_pred)

    def plot_confusion_matrix(self, y_true, y_pred):
        """
        Plot a confusion matrix.

        Parameters:
        y_true : Series : True labels.
        y_pred : Series : Predicted labels.
        """
        cm = confusion_matrix(y_true, y_pred)
        plt.figure(figsize=(8, 6))
        plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
        plt.title("Confusion Matrix")
        plt.colorbar()
        tick_marks = np.arange(len(self.class_names))
        plt.xticks(tick_marks, self.class_names, rotation=45)
        plt.yticks(tick_marks, self.class_names)

        for i in range(cm.shape[0]):
            for j in range(cm.shape[1]):
                plt.text(j, i, f"{cm[i, j]}", horizontalalignment="center",
                         color="white" if cm[i, j] > cm.max() / 2. else "black")

        plt.ylabel('True label')
        plt.xlabel('Predicted label')
        plt.tight_layout()
        plt.show()

    def plot_roc_curve(self, y_true, y_pred_prob):
        """
        Plot ROC curve and AUC for binary or multiclass classification.

        Parameters:
        y_true : array-like : True labels.
        y_pred_prob : ndarray : Predicted probabilities for each class.
        """
        plt.figure(figsize=(10, 8))
        n_classes = len(self.class_names)

        if n_classes == 2:
            fpr, tpr, _ = roc_curve(y_true, y_pred_prob[:, 1])
            roc_auc = auc(fpr, tpr)
            plt.plot(fpr, tpr, label=f"ROC curve (AUC = {roc_auc:.2f})",
color="darkorange")
        else:
            for i in range(n_classes):
                fpr, tpr, _ = roc_curve(y_true == i, y_pred_prob[:, i])
                roc_auc = auc(fpr, tpr)
                plt.plot(fpr, tpr, label=f"Class {self.class_names[i]} (AUC =
{roc_auc:.2f})")

        plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.05])
```

```
        plt.xlabel("False Positive Rate")
        plt.ylabel("True Positive Rate")
        plt.title("Receiver Operating Characteristic (ROC) Curve")
        plt.legend(loc="lower right")
        plt.tight_layout()
        plt.show()

    def _tune_hyperparameters(self):
        """
        Tune hyperparameters using GridSearchCV.

        Returns:
        Best estimator from the GridSearchCV.
        """
        param_grid = {
            'n_estimators': [50, 100],
            'max_depth': [None, 10],
            'min_samples_split': [2],
            'min_samples_leaf': [1],
            'bootstrap': [True]
        }
        grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,
cv=3, n_jobs=-1, verbose=2)
        grid_search.fit(self.X_train, self.y_train)
        return grid_search.best_estimator_

    def _generate_classification_report(self, y_true, y_pred):
        """
        Generate a classification report.

        Parameters:
        y_true : Series : True labels.
        y_pred : Series : Predicted labels.

        Returns:
        DataFrame : Classification report as a DataFrame.
        """
        report = classification_report(y_true, y_pred, target_names=self.class_names,
output_dict=True)
        return pd.DataFrame(report).transpose()

    def collect_metrics(report_df, model_type, algorithm):
      """
      Collect key metrics from the classification report DataFrame.
      """
      try:
          accuracy = report_df.loc['Accuracy', 'f1-score'] if 'Accuracy' in
report_df.index else None
          macro_f1 = report_df.loc['Macro avg', 'f1-score'] if 'Macro avg' in
report_df.index else None
          weighted_f1 = report_df.loc['Weighted avg', 'f1-score'] if 'Weighted avg' in
report_df.index else None

          return pd.DataFrame([{
              'Model': model_type,
              'Algorithm': algorithm,
              'Accuracy': accuracy,
              'Macro F1': macro_f1,
              'Weighted F1': weighted_f1
          }])
```

```python
    except KeyError as e:
        print(f"KeyError in collect_metrics: {e}")
        print("Available keys:", report_df.index)
        return pd.DataFrame([{
            'Model': model_type,
            'Algorithm': algorithm,
            'Accuracy': None,
            'Macro F1': None,
            'Weighted F1': None
        }])
```

Brute Force

2017 Data + Predictions

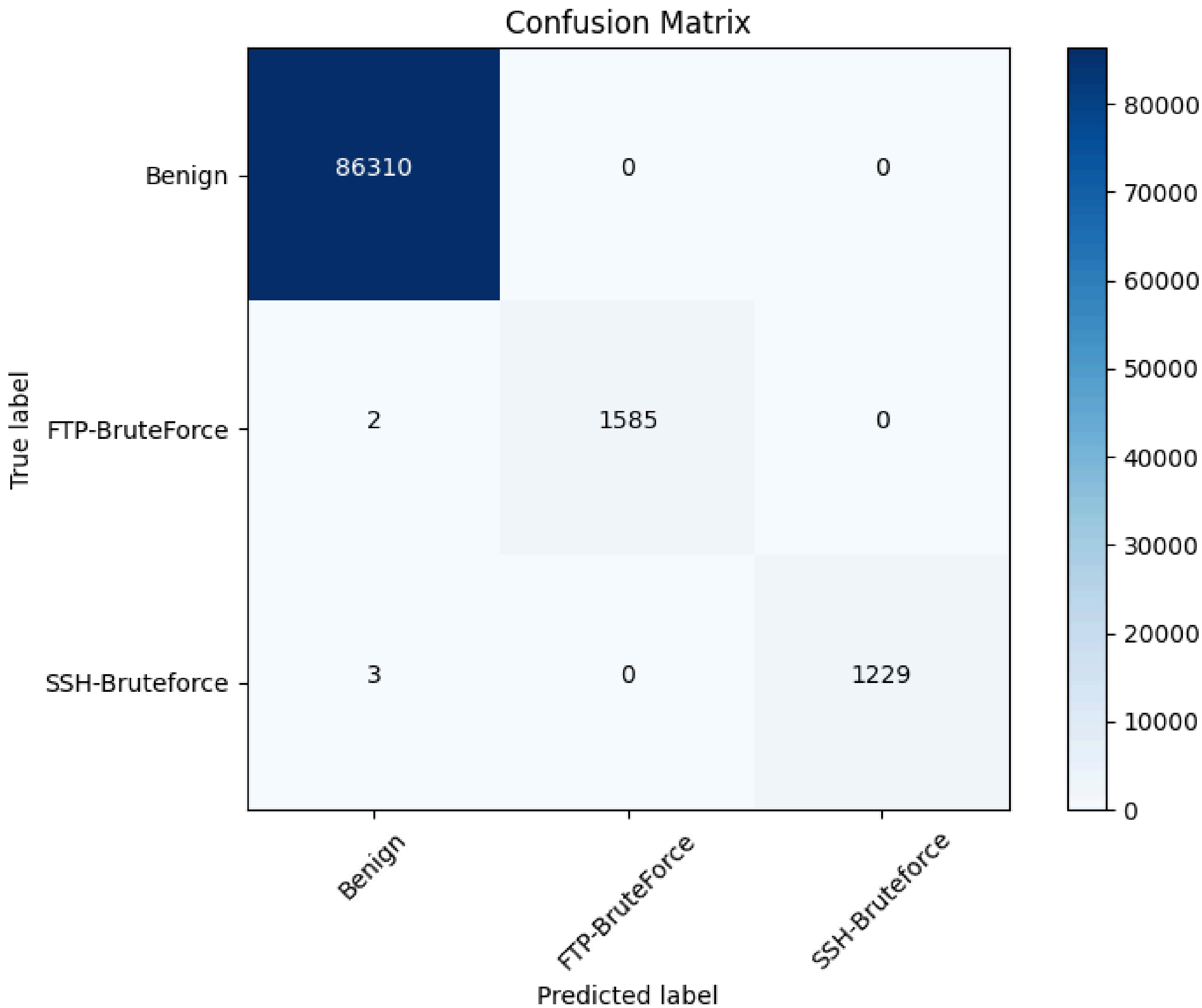
Classification Report

```python
brute_force_workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.999942	1.000000	0.999971	86310.000000
FTP-BruteForce	1.000000	0.998740	0.999369	1587.000000
SSH-Bruteforce	1.000000	0.997565	0.998781	1232.000000
Accuracy	0.999944	0.999944	0.999944	0.999944
Macro avg	0.999981	0.998768	0.999374	89129.000000
Weighted avg	0.999944	0.999944	0.999944	89129.000000

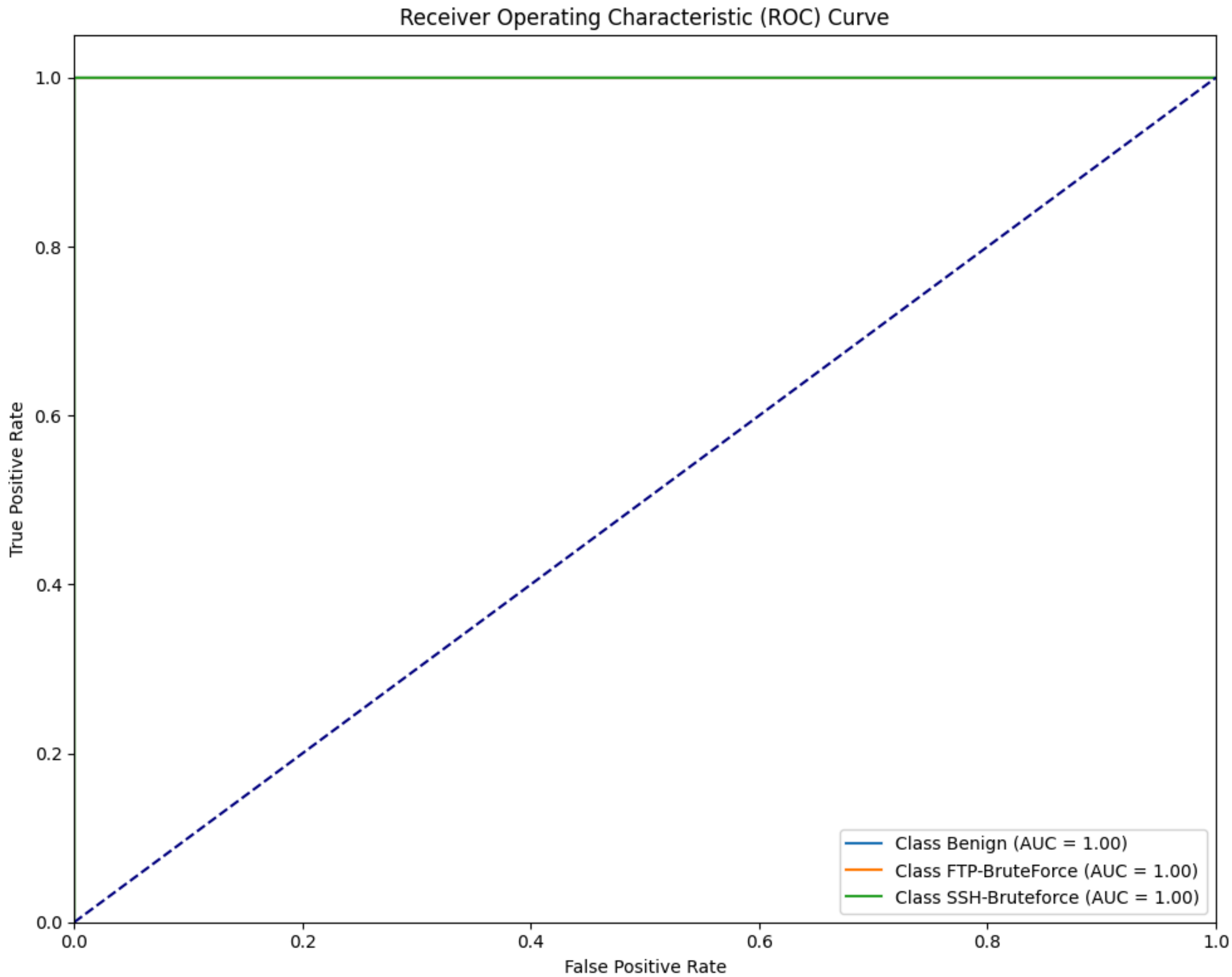
Confusion Matrix

```python
brute_force_workflow_2017.plot_confusion_matrix(
    brute_force_workflow_2017.y_test, brute_force_workflow_2017.y_pred
)
```



ROC Curve

```
brute_force_workflow_2017.plot_roc_curve(
    brute_force_workflow_2017.y_test, brute_force_workflow_2017.y_pred_prob
)
```



2018 Data + Predictions

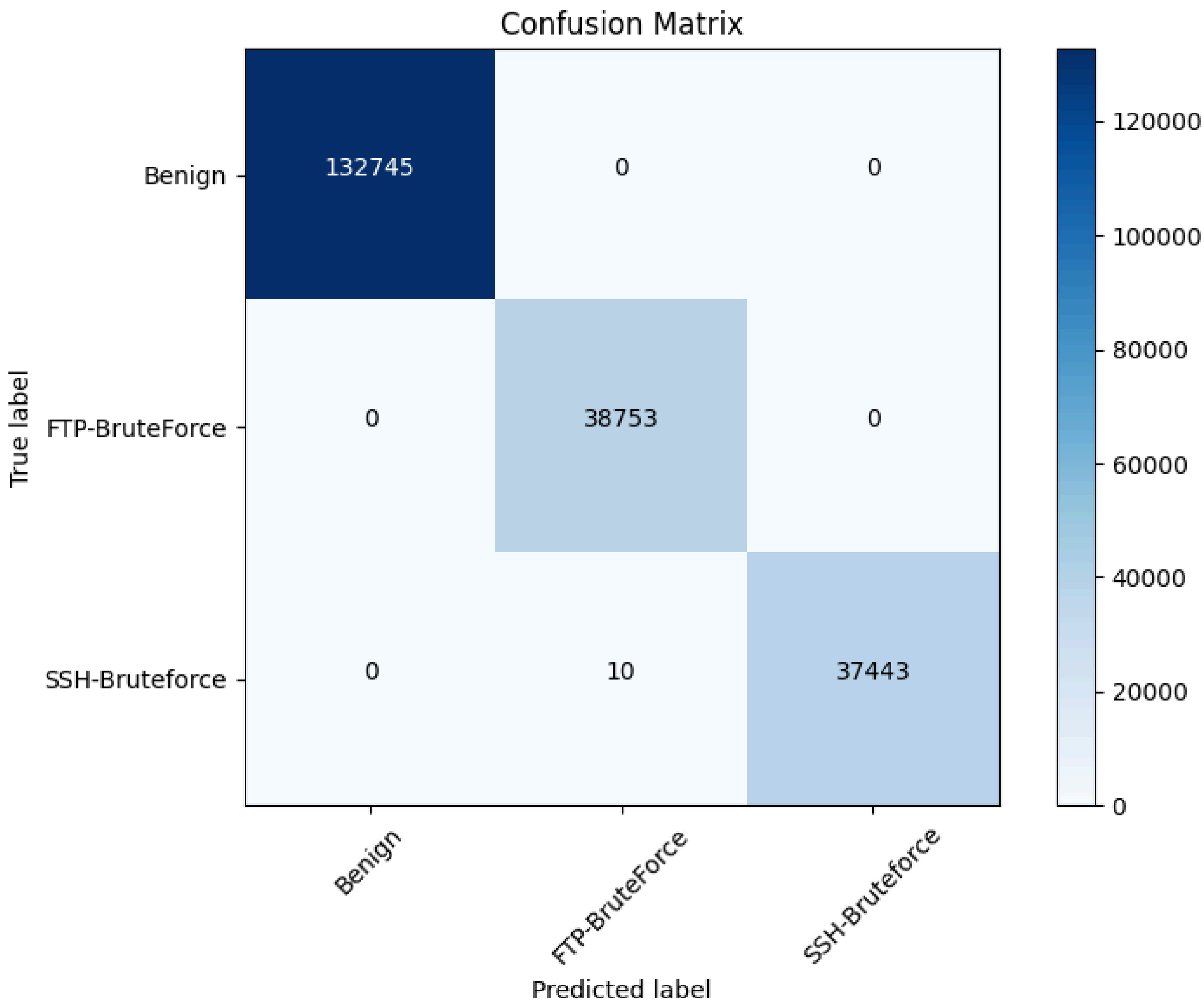
Classification Report

```
brute_force_workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.000000	1.000000	1.000000	132745.000000
FTP-BruteForce	0.999742	1.000000	0.999871	38753.000000
SSH-Bruteforce	1.000000	0.999733	0.999866	37453.000000
Accuracy	0.999952	0.999952	0.999952	0.999952
Macro avg	0.999914	0.999911	0.999912	208951.000000
Weighted avg	0.999952	0.999952	0.999952	208951.000000

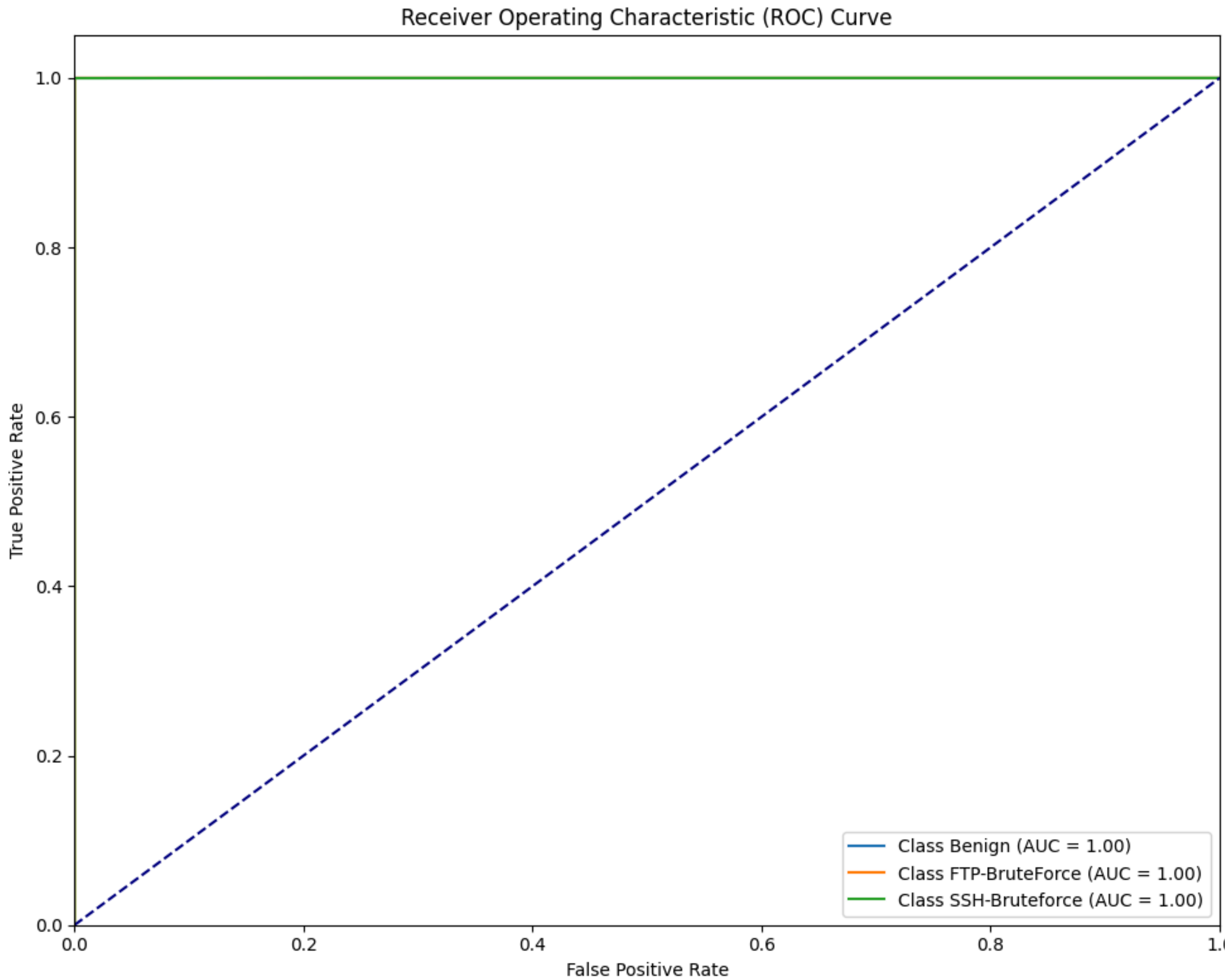
Confusion Matrix

```
brute_force_workflow_2018.plot_confusion_matrix(
    brute_force_workflow_2018.y_test, brute_force_workflow_2018.y_pred
)
```



ROC Curve

```
brute_force_workflow_2018.plot_roc_curve(
    brute_force_workflow_2018.y_test, brute_force_workflow_2018.y_pred_prob
)
```



DDoS

2017 Data + Predictions

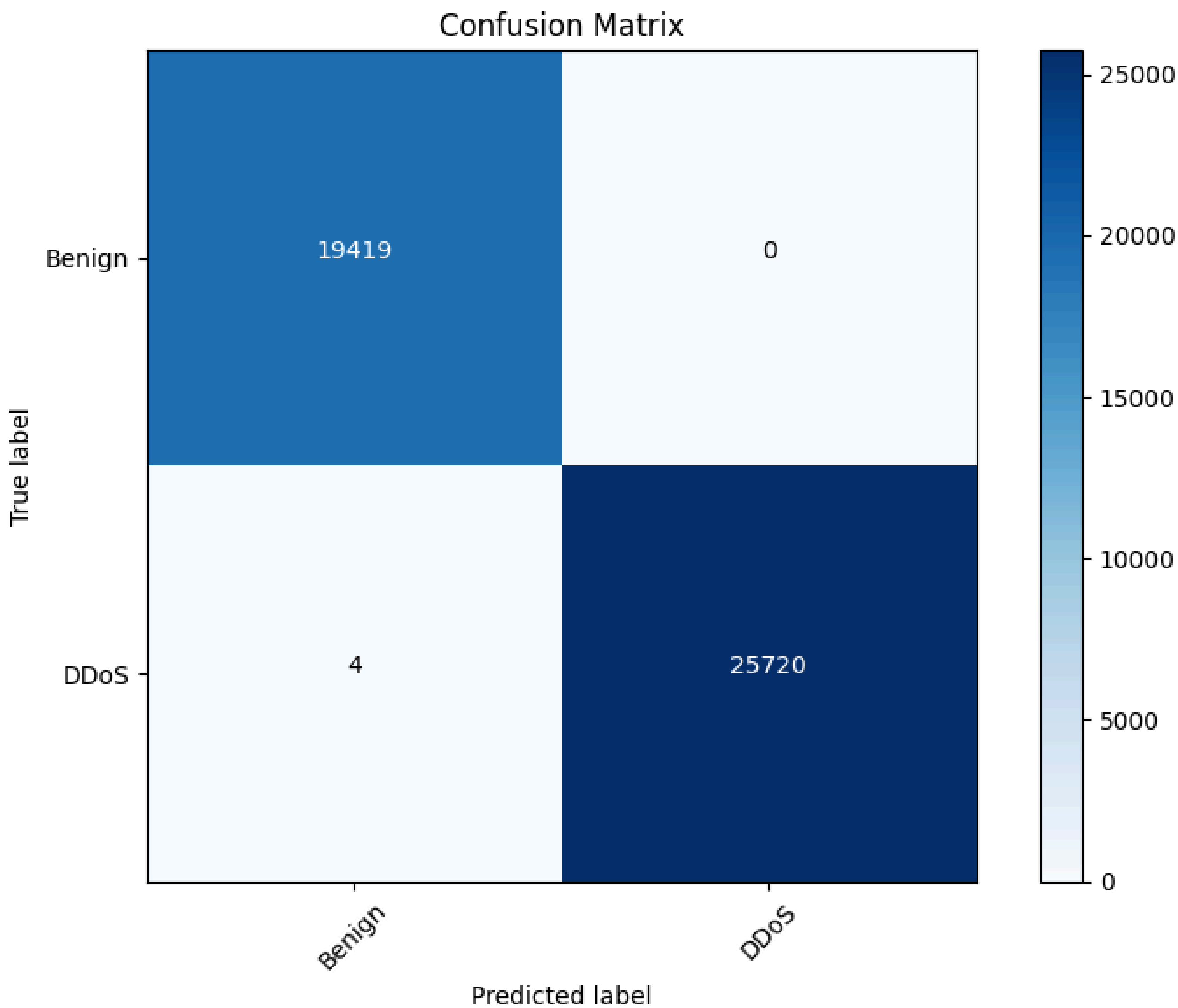
Classification Report

```
ddos_workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.999794	1.000000	0.999897	19419.000000
DDoS	1.000000	0.999845	0.999922	25724.000000
Accuracy	0.999911	0.999911	0.999911	0.999911
Macro avg	0.999897	0.999922	0.999910	45143.000000
Weighted avg	0.999911	0.999911	0.999911	45143.000000

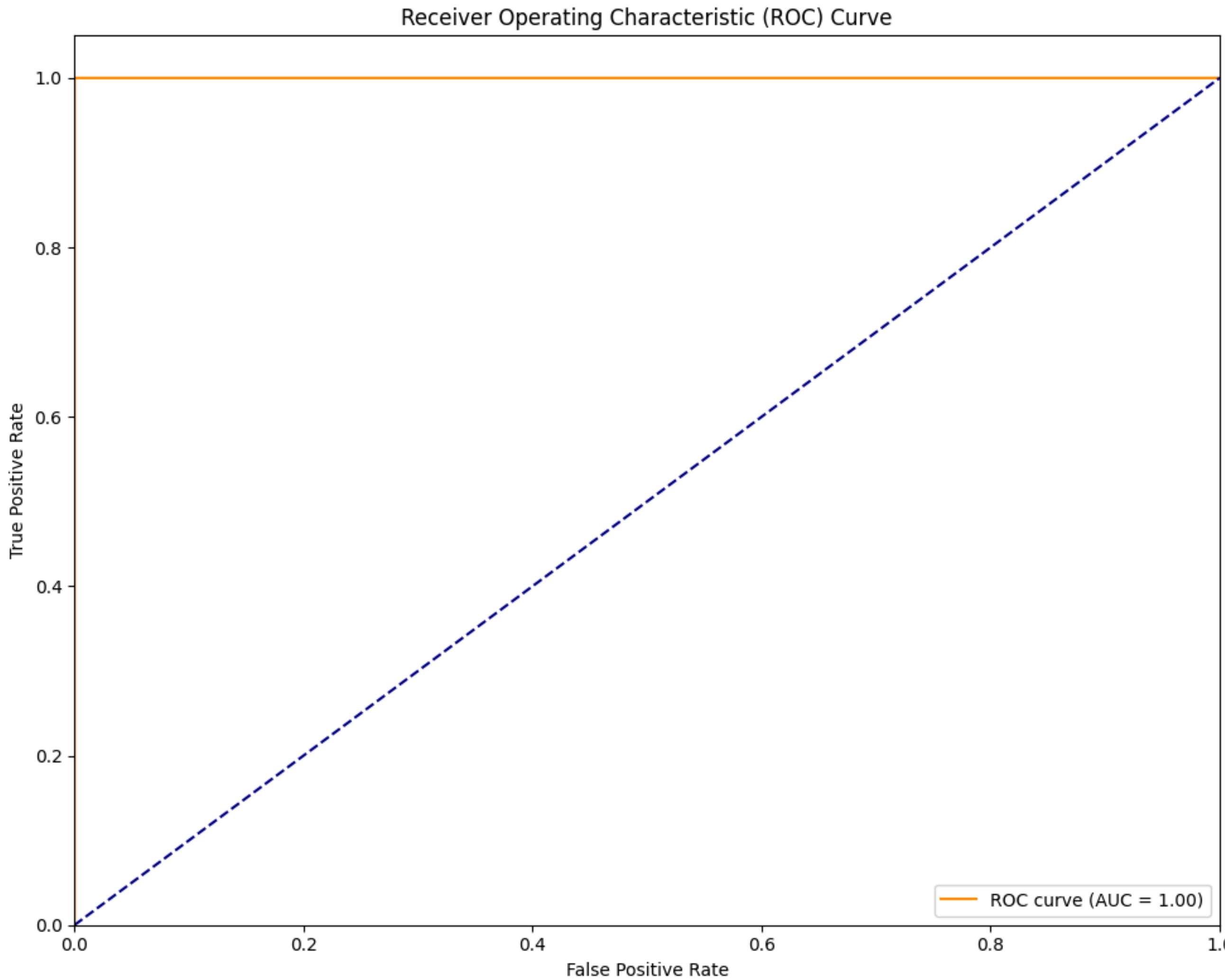
Confusion Matrix

```
ddos_workflow_2017.plot_confusion_matrix(ddos_workflow_2017.y_test,
ddos_workflow_2017.y_pred)
```



ROC Curve

```
ddos_workflow_2017.plot_roc_curve(ddos_workflow_2017.y_test,
ddos_workflow_2017.y_pred_prob)
```



2018 Data + Predictions

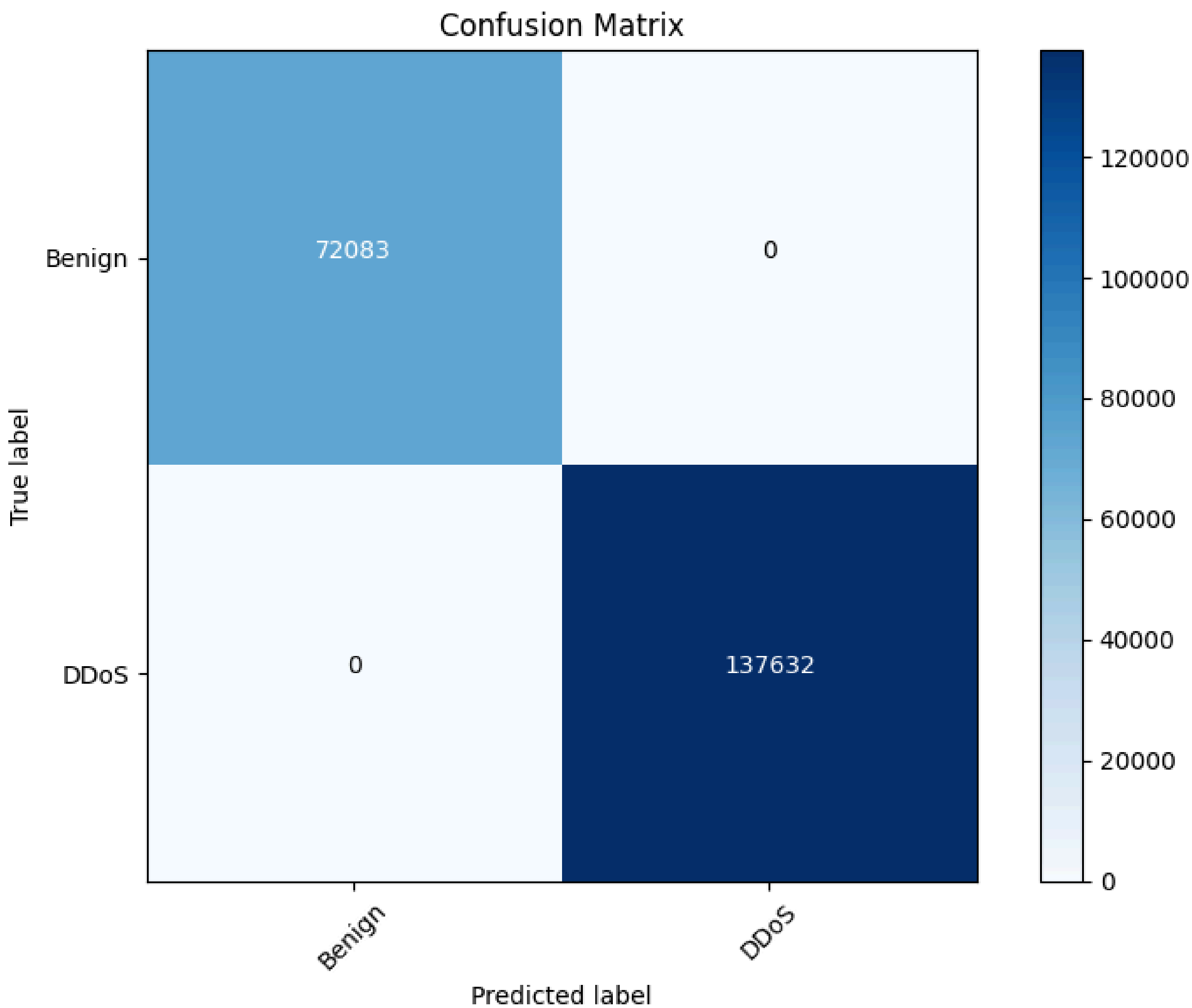
Classification Report

```
ddos_workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.0	1.0	1.0	72083.0
DDoS	1.0	1.0	1.0	137632.0
Accuracy	1.0	1.0	1.0	1.0
Macro avg	1.0	1.0	1.0	209715.0
Weighted avg	1.0	1.0	1.0	209715.0

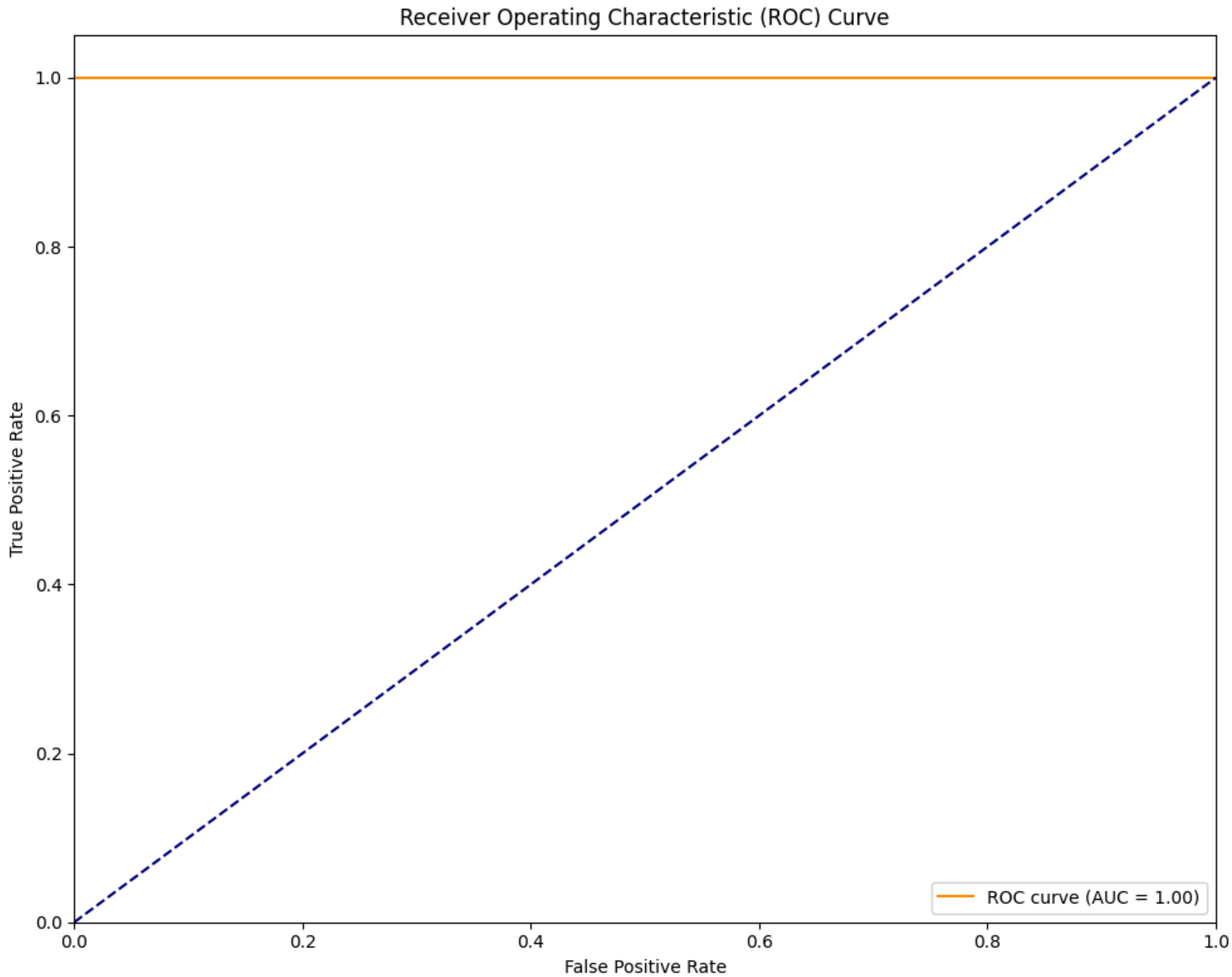
Confusion Matrix

```
ddos_workflow_2018.plot_confusion_matrix(ddos_workflow_2018.y_test,
ddos_workflow_2018.y_pred)
```



ROC Curve

```
ddos_workflow_2018.plot_roc_curve(ddos_workflow_2018.y_test,
ddos_workflow_2018.y_pred_prob)
```



DoS

2017 Data + Predictions

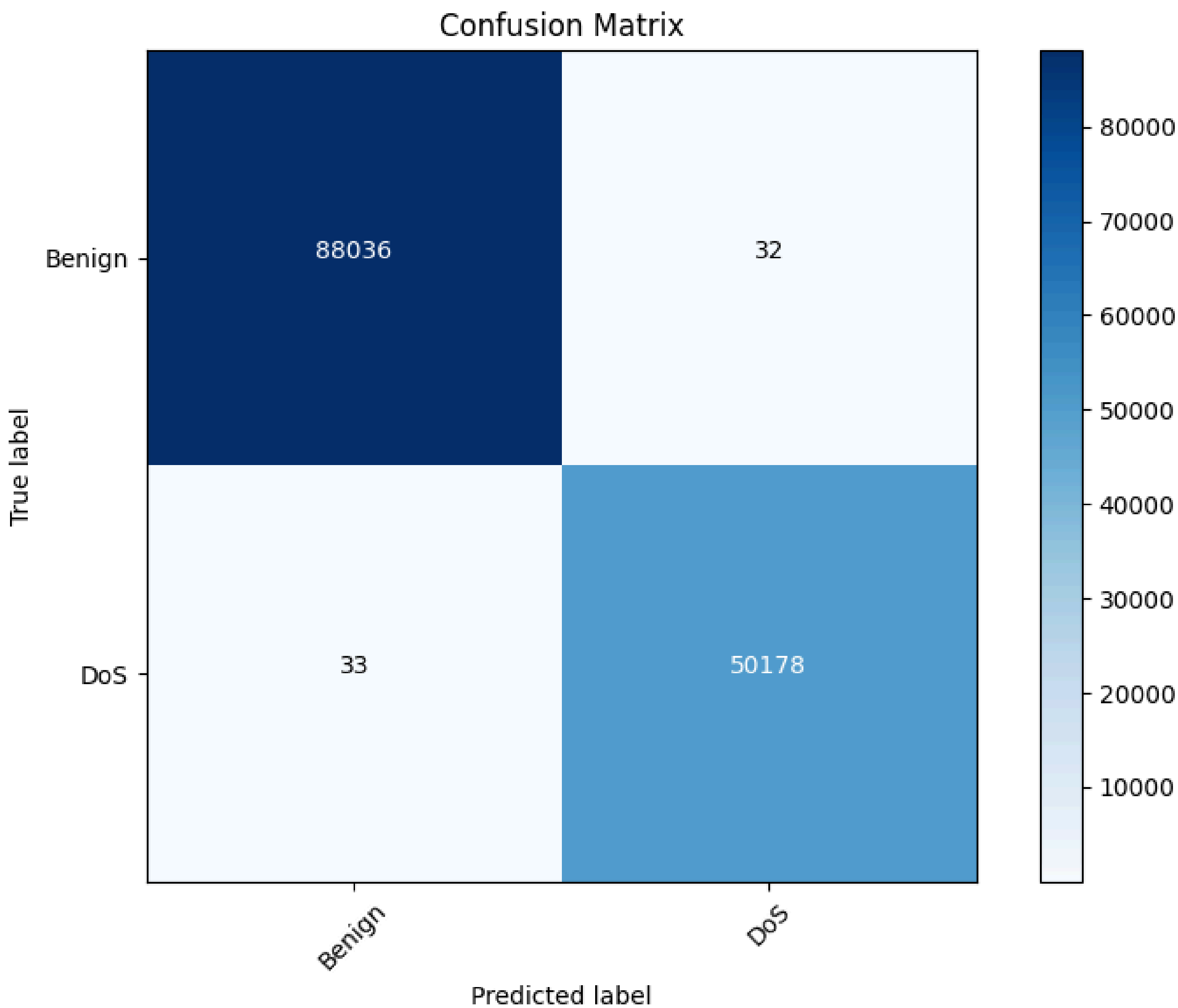
Classification Report

```
dos_workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.999625	0.999637	0.999631	88068.00000
DoS	0.999363	0.999343	0.999353	50211.00000
Accuracy	0.999530	0.999530	0.999530	0.99953
Macro avg	0.999494	0.999490	0.999492	138279.00000
Weighted avg	0.999530	0.999530	0.999530	138279.00000

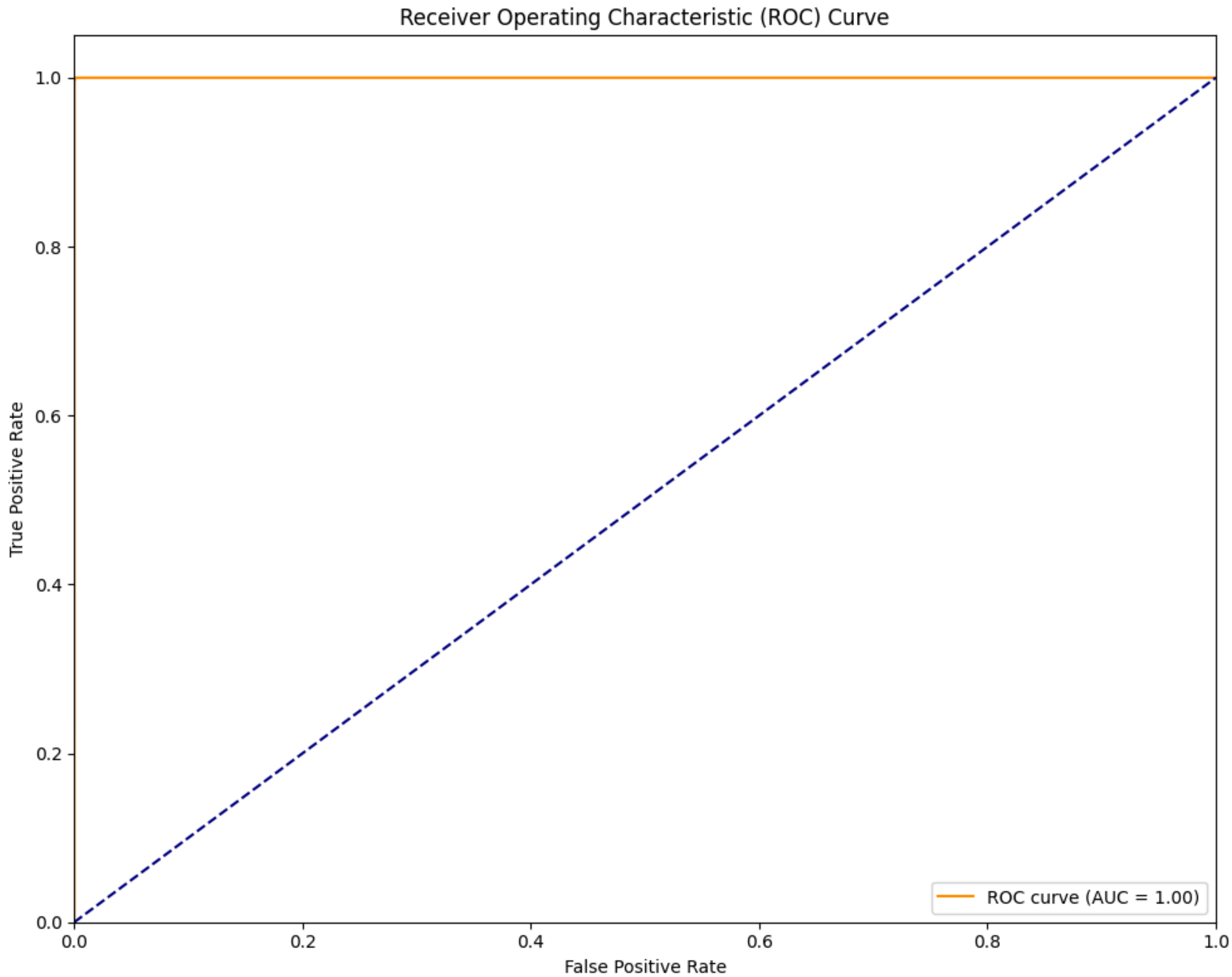
Confusion Matrix

```
dos_workflow_2017.plot_confusion_matrix(dos_workflow_2017.y_test,
dos_workflow_2017.y_pred)
```



ROC Curve

```
dos_workflow_2017.plot_roc_curve(dos_workflow_2017.y_test, dos_workflow_2017.y_pred_prob)
```



2018 Data + Predictions

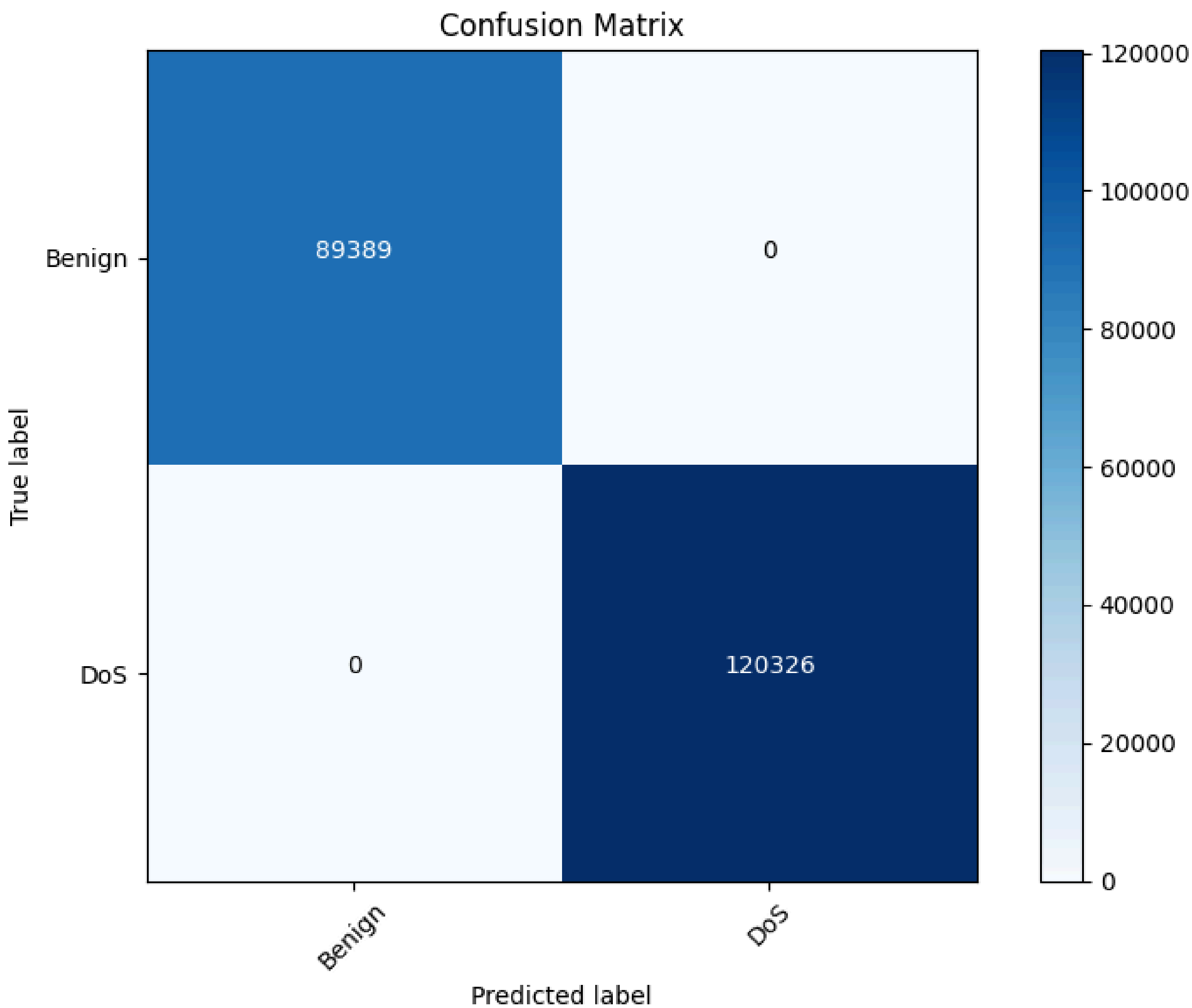
Classification Report

```
dos_workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.999625	0.999637	0.999631	88068.00000
DoS	0.999363	0.999343	0.999353	50211.00000
Accuracy	0.999530	0.999530	0.999530	0.99953
Macro avg	0.999494	0.999490	0.999492	138279.00000
Weighted avg	0.999530	0.999530	0.999530	138279.00000

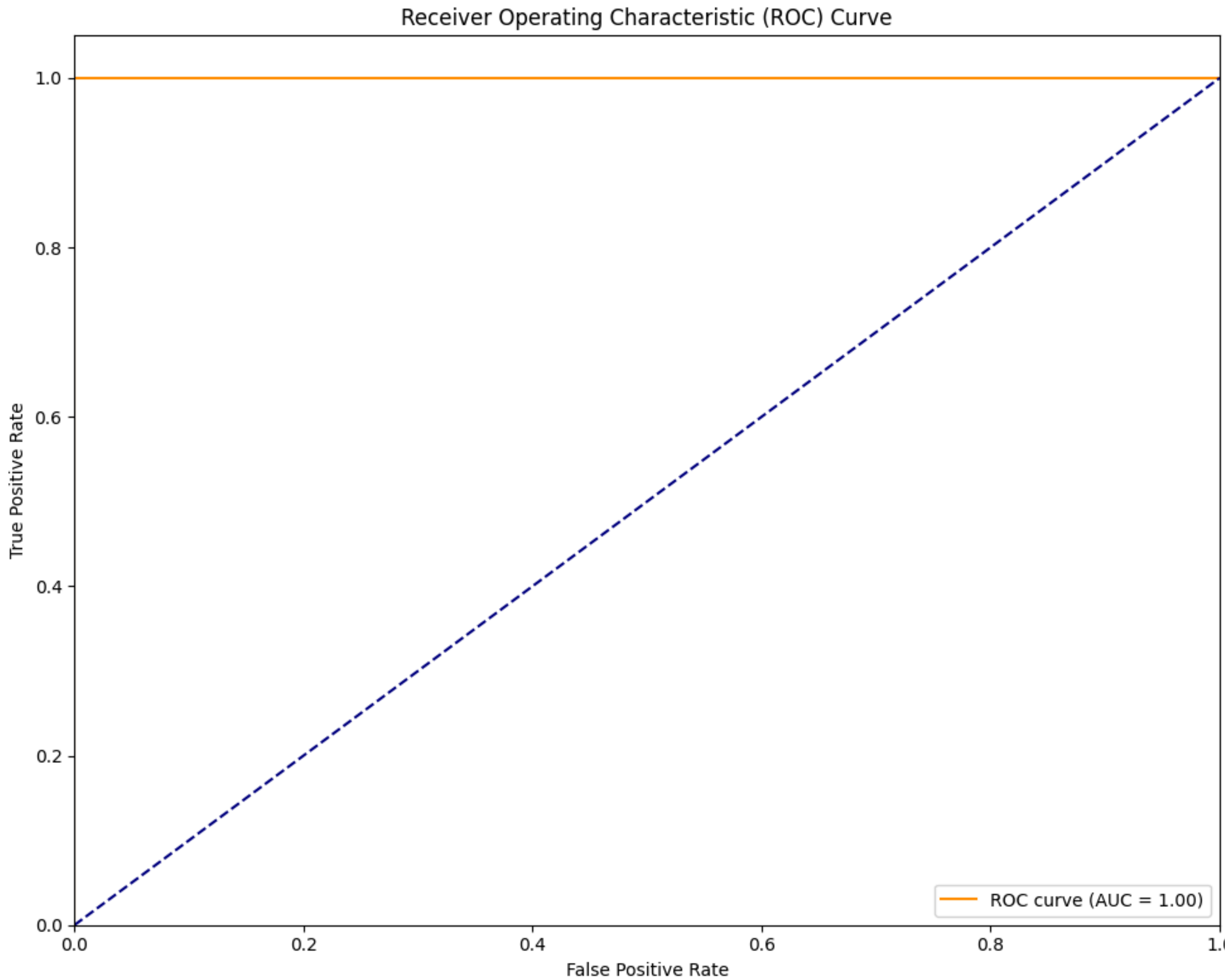
Confusion Matrix

```
dos_workflow_2017.plot_confusion_matrix(dos_workflow_2018.y_test,
dos_workflow_2018.y_pred)
```



ROC Curve

```
dos_workflow_2017.plot_roc_curve(dos_workflow_2018.y_test, dos_workflow_2018.y_pred_prob)
```



Naive Bayes

Naive Bayes is a probabilistic machine learning algorithm based on Bayes' Theorem, which calculates the likelihood of an event given prior knowledge of conditions related to the event. It is called "naive" because it assumes that all input features are independent of each other, an assumption that simplifies calculations but may not always hold true in real-world datasets. Despite this simplification, Naive Bayes is efficient, interpretable, and effective for many classification problems, especially when dealing with large datasets and categorical features. It is well-suited for tasks where speed and simplicity are critical.

In the context of detecting brute force, DDoS, and DoS attacks, Naive Bayes is particularly valuable for its ability to classify network traffic based on probabilistic patterns in the data. For brute force attacks, it can leverage features like the frequency of failed login attempts or unusual access patterns to assign probabilities to whether the behavior is normal or malicious. In the case of DDoS and DoS attacks, Naive Bayes can identify anomalies in network traffic by analyzing features such as traffic volume, packet sizes, and request intervals. Its probabilistic framework makes it adaptable to imbalanced datasets, where malicious traffic might be a small fraction of overall activity.

Naive Bayes Class Structure

```
class NaiveBayesWorkflow:
    """
    A class to manage the workflow of training, evaluating, and predicting with a Naive
Bayes model.
    """

    def __init__(self, X, y, class_names):
        """
        Initialize the workflow with data and class names.

        Parameters:
        X : DataFrame : The feature data.
        y : Series : The target labels.
        class_names : list : List of class names.
        """
        self.X = X
        self.y = y
        self.class_names = class_names
        self.X_train = None
        self.X_test = None
        self.y_train = None
        self.y_test = None
        self.model = None
        self.best_model = None
        self.y_pred = None
        self.y_pred_prob = None
        self.report_df = None

    def train(self):
        """
        Splits the data, trains the Naive Bayes model using GridSearchCV, and stores the
best model.
        """
        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(
            self.X, self.y, test_size=0.2, random_state=42
        )
        param_grid = {'var_smoothing': np.logspace(-9, 0, 10)}
        grid_search = GridSearchCV(GaussianNB(), param_grid, cv=3, n_jobs=-1, verbose=2)
        grid_search.fit(self.X_train, self.y_train)

        self.best_model = grid_search.best_estimator_
        self.model = self.best_model

    def predict(self):
        """
        Generates predictions for the test set and stores them as attributes.
        """
        if self.model is None:
            raise ValueError("The model is not trained. Run the train() method first.")

        self.y_pred = self.model.predict(self.X_test)
        self.y_pred_prob = self.model.predict_proba(self.X_test)

    def evaluate(self):
        """
        Generates the classification report and stores it as an attribute.
```

```
        """
        if self.y_test is None or self.y_pred is None:
            raise ValueError("Predictions have not been made. Ensure the model is trained
and predictions are generated before evaluation.")

        self.report_df = self._generate_classification_report(self.y_test, self.y_pred)

    def plot_confusion_matrix(self):
        """
        Plots the confusion matrix for the test data.
        """
        cm = confusion_matrix(self.y_test, self.y_pred)
        plt.figure(figsize=(8, 6))
        plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
        plt.title("Confusion Matrix")
        plt.colorbar()
        tick_marks = np.arange(len(self.class_names))
        plt.xticks(tick_marks, self.class_names, rotation=45)
        plt.yticks(tick_marks, self.class_names)

        for i in range(cm.shape[0]):
            for j in range(cm.shape[1]):
                plt.text(j, i, f"{cm[i, j]}",
                         horizontalalignment="center",
                         color="white" if cm[i, j] > cm.max() / 2. else "black")

        plt.ylabel('True label')
        plt.xlabel('Predicted label')
        plt.tight_layout()
        plt.show()

    def plot_roc_curve(self):
        """
        Plots the ROC curve for the test data.
        """
        fpr, tpr, roc_auc = {}, {}, {}

        for i, class_name in enumerate(self.class_names):
            fpr[class_name], tpr[class_name], _ = roc_curve(self.y_test == i,
self.y_pred_prob[:, i])
            roc_auc[class_name] = auc(fpr[class_name], tpr[class_name])

        plt.figure(figsize=(10, 8))
        for class_name in self.class_names:
            plt.plot(fpr[class_name], tpr[class_name], label=f'Class {class_name} (AUC =
{roc_auc[class_name]:.2f})')

        plt.plot([0, 1], [0, 1], 'k--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.05])
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Receiver Operating Characteristic (ROC) Curve')
        plt.legend(loc="lower right")
        plt.tight_layout()
        plt.show()

    def predict_on_new_data(self, X_new, y_new):
        """
        Predicts the labels for new data and evaluates performance.
```

```
        Parameters:
        X_new : DataFrame : The new feature data.
        y_new : Series : The new target labels.

        Returns:
        DataFrame : The classification report for the new data.
        """
        if self.model is None:
            raise ValueError("The model is not trained. Run the train() method first.")

        y_pred_new = self.best_model.predict(X_new)
        y_pred_prob_new = self.best_model.predict_proba(X_new)

        cm = confusion_matrix(y_new, y_pred_new)
        print("Confusion Matrix for New Data:")
        print(cm)

        return self._generate_classification_report(y_new, y_pred_new)

    def _generate_classification_report(self, y_true, y_pred):
        """
        Generate a classification report.

        Parameters:
        y_true : Series : True labels.
        y_pred : Series : Predicted labels.

        Returns:
        DataFrame : The classification report as a DataFrame.
        """
        report = classification_report(y_true, y_pred, target_names=self.class_names,
output_dict=True)
        return pd.DataFrame(report).transpose()
```

Brute Force

2017 Data + Predictions

Classification Report

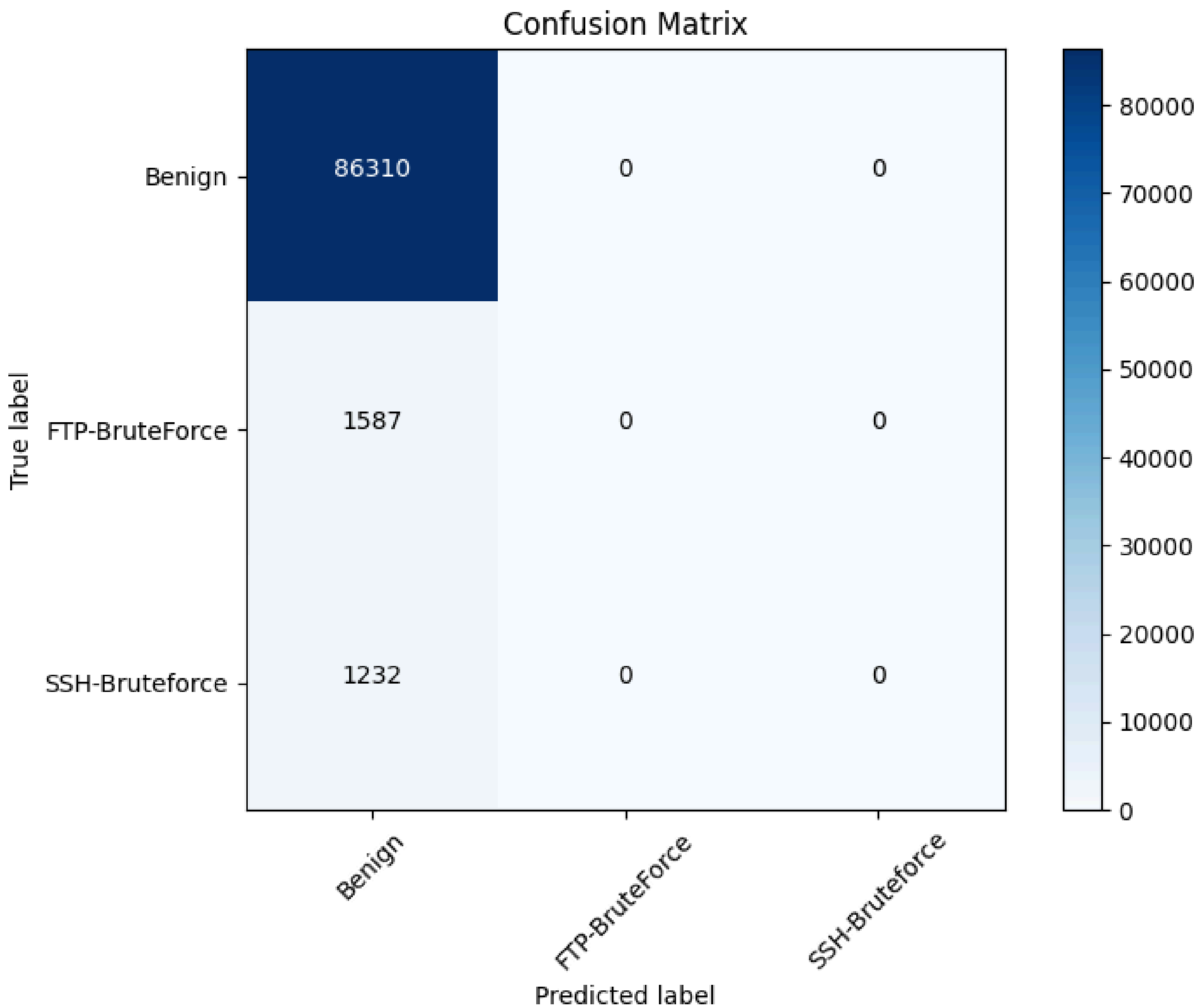
```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.968372	1.000000	0.983932	86310.000000
FTP-BruteForce	0.000000	0.000000	0.000000	1587.000000
SSH-Bruteforce	0.000000	0.000000	0.000000	1232.000000
Accuracy	0.968372	0.968372	0.968372	0.968372

	precision	recall	f1-score	support
Macro avg	0.322791	0.333333	0.327977	89129.000000
Weighted avg	0.937744	0.968372	0.952812	89129.000000

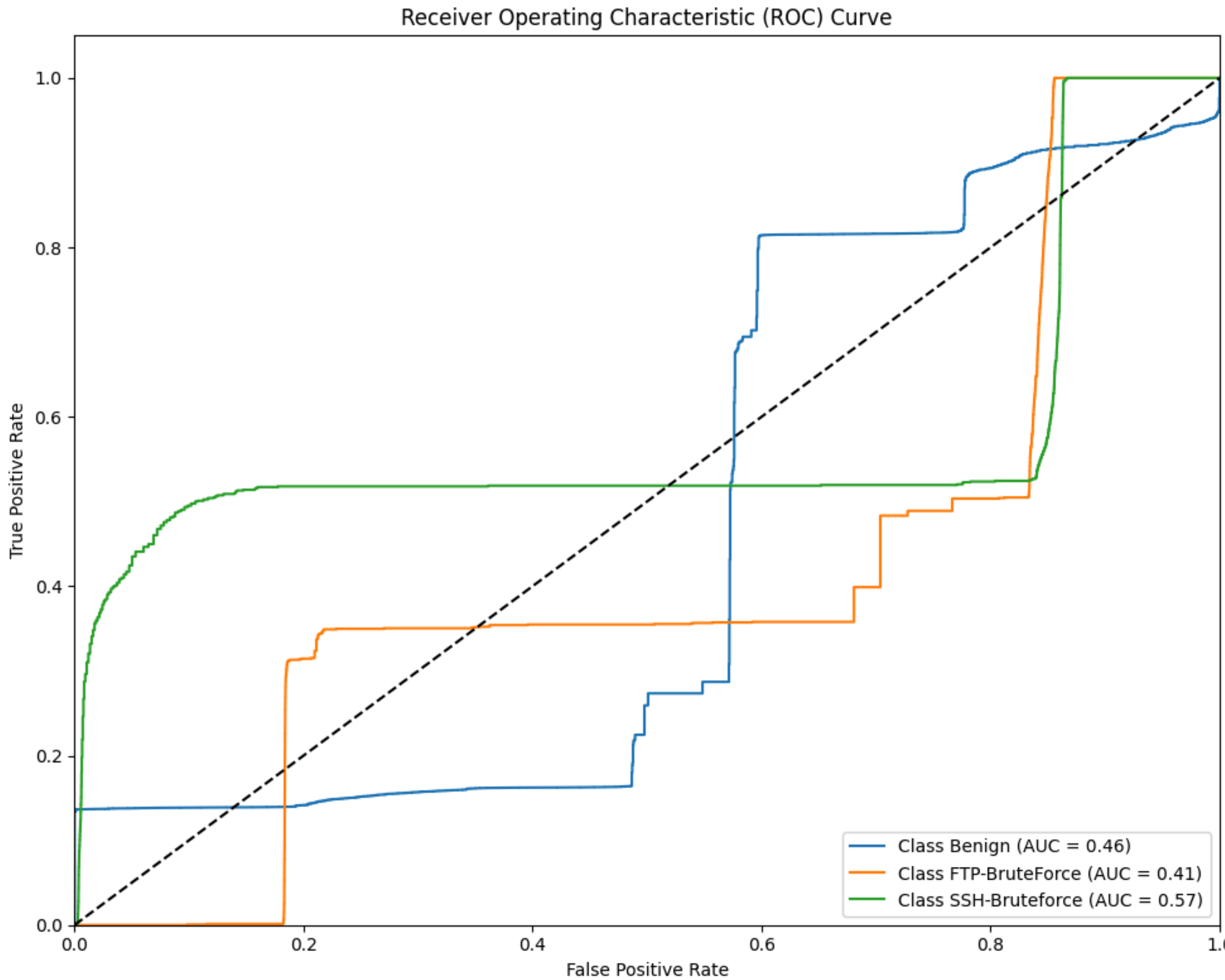
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

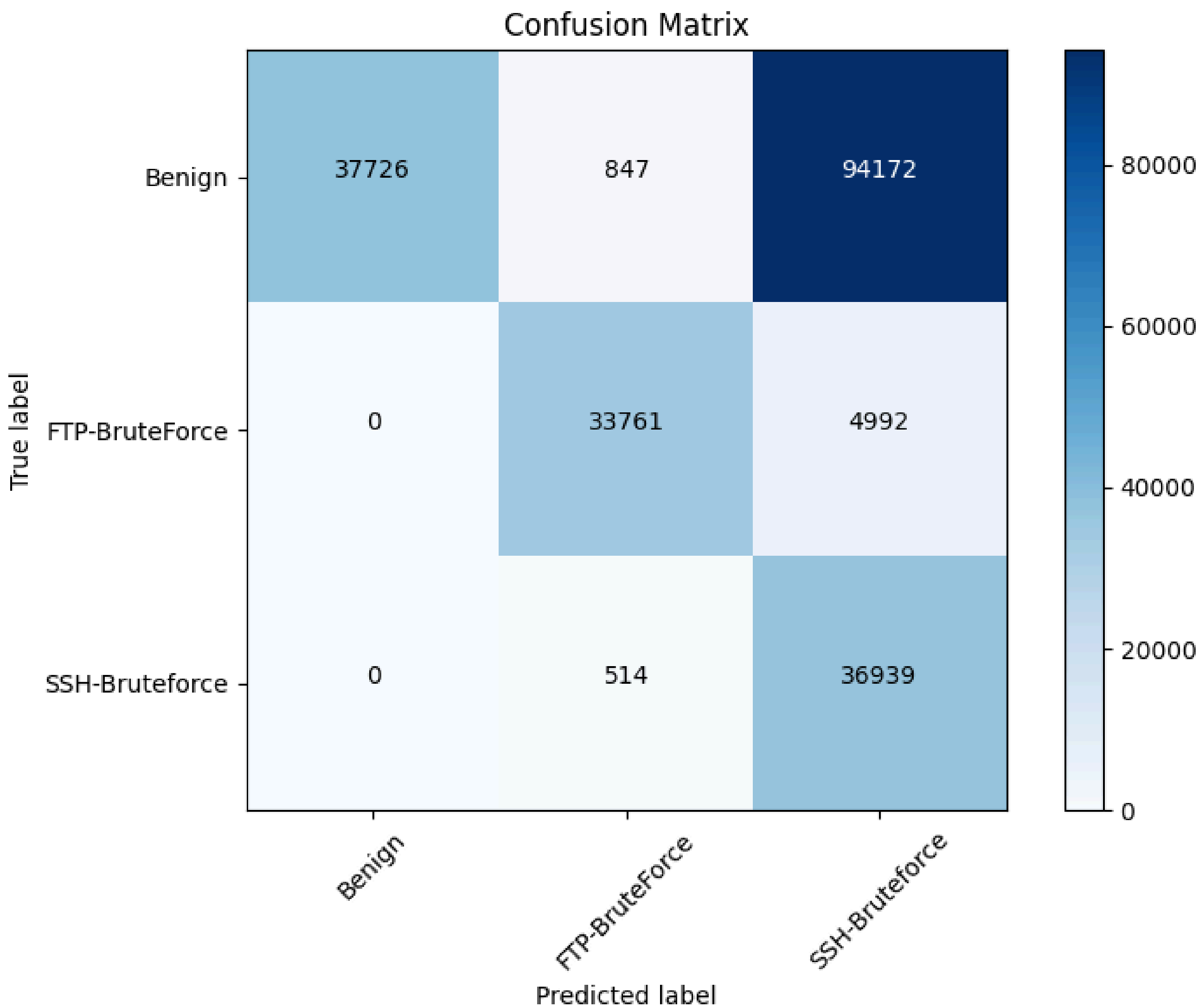
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.000000	0.284199	0.442609	132745.000000
FTP-BruteForce	0.961249	0.871184	0.914003	38753.000000
SSH-Bruteforce	0.271405	0.986276	0.425672	37453.000000
Accuracy	0.518906	0.518906	0.518906	0.518906
Macro avg	0.744218	0.713886	0.594095	208951.000000
Weighted avg	0.862218	0.518906	0.527000	208951.000000

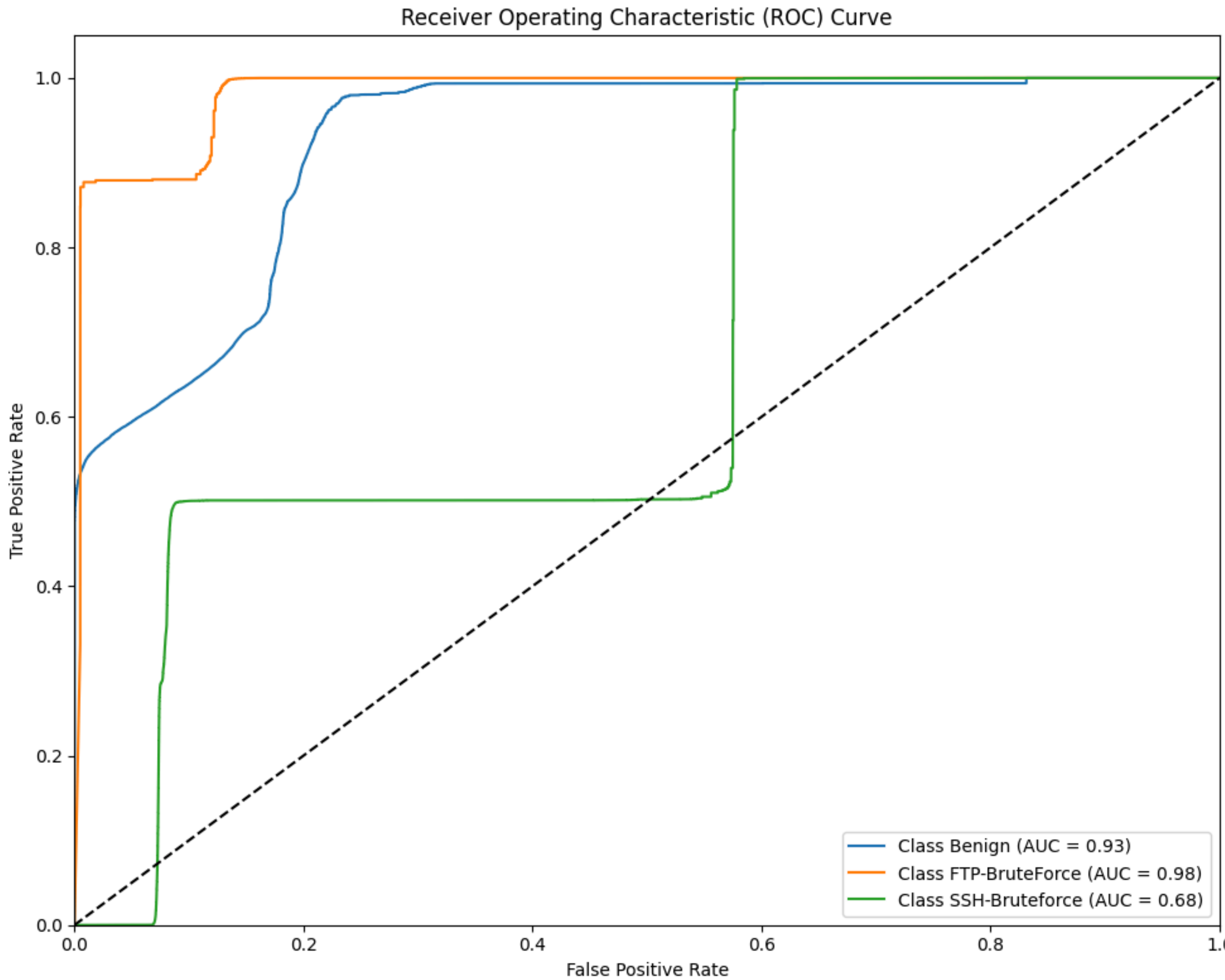
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



DDoS

2017 Data + Predictions

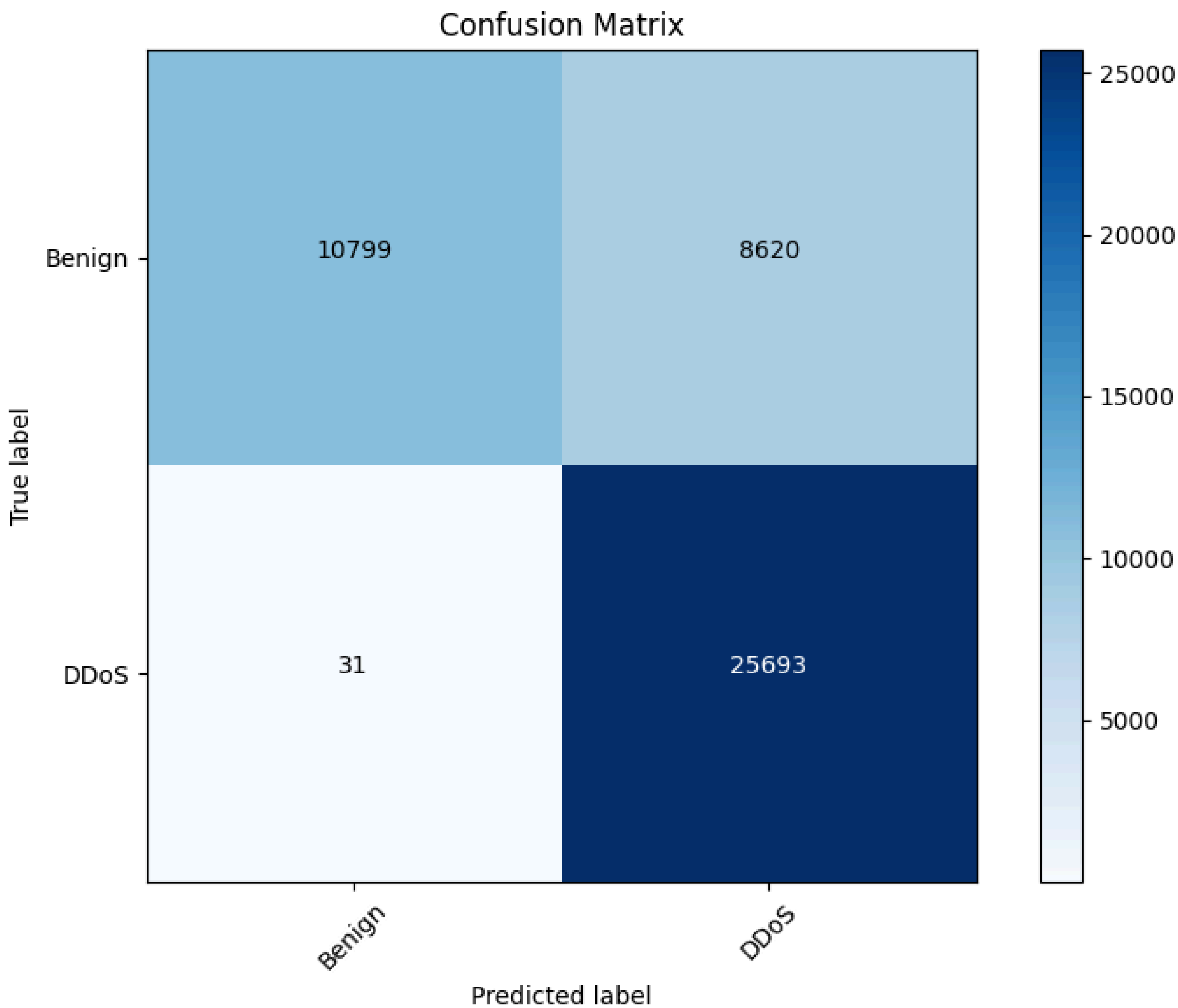
Classification Report

```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.997138	0.556105	0.714007	19419.000000
DDoS	0.748783	0.998795	0.855906	25724.000000
Accuracy	0.808365	0.808365	0.808365	0.808365
Macro avg	0.872960	0.777450	0.784956	45143.000000
Weighted avg	0.855617	0.808365	0.794866	45143.000000

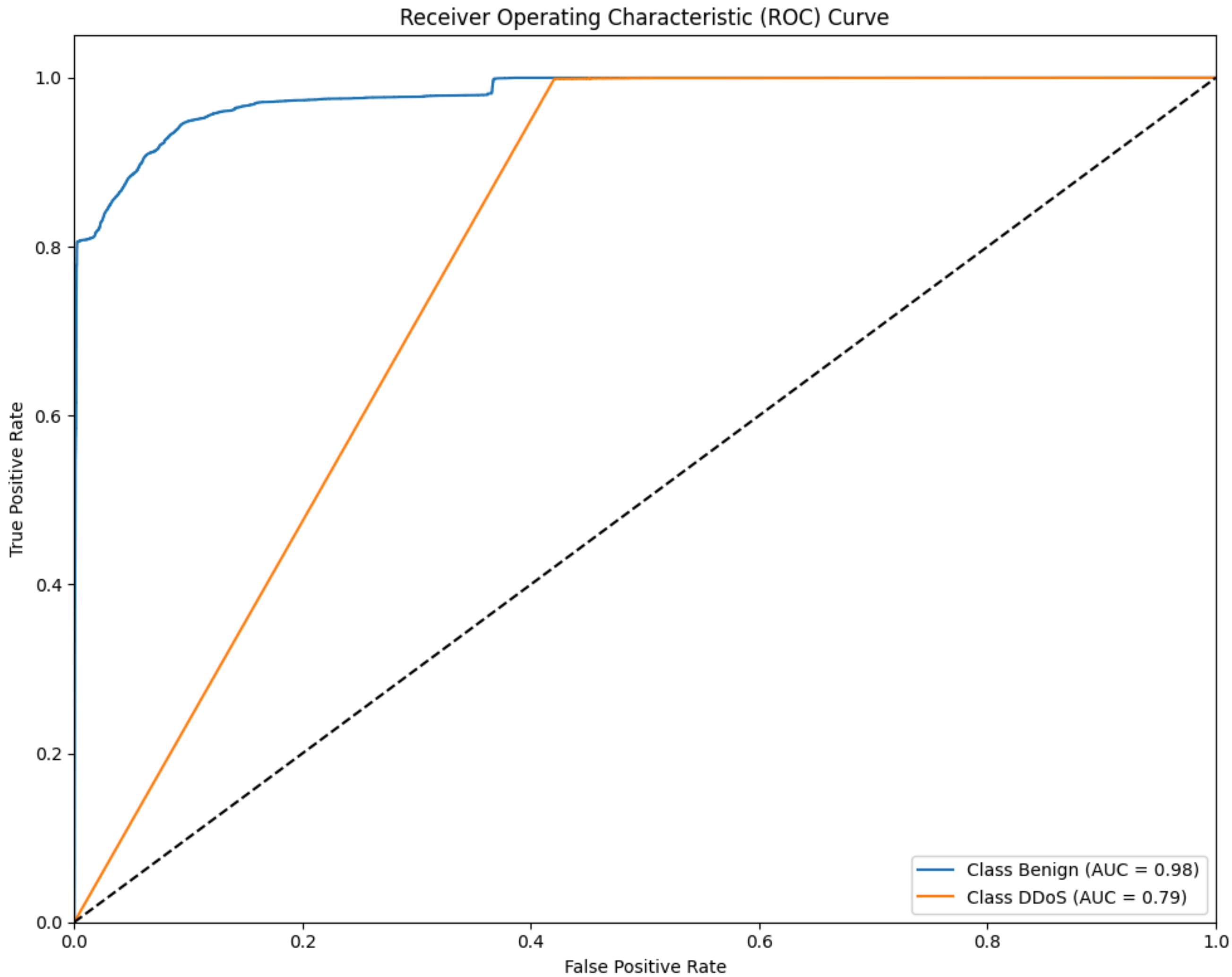
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

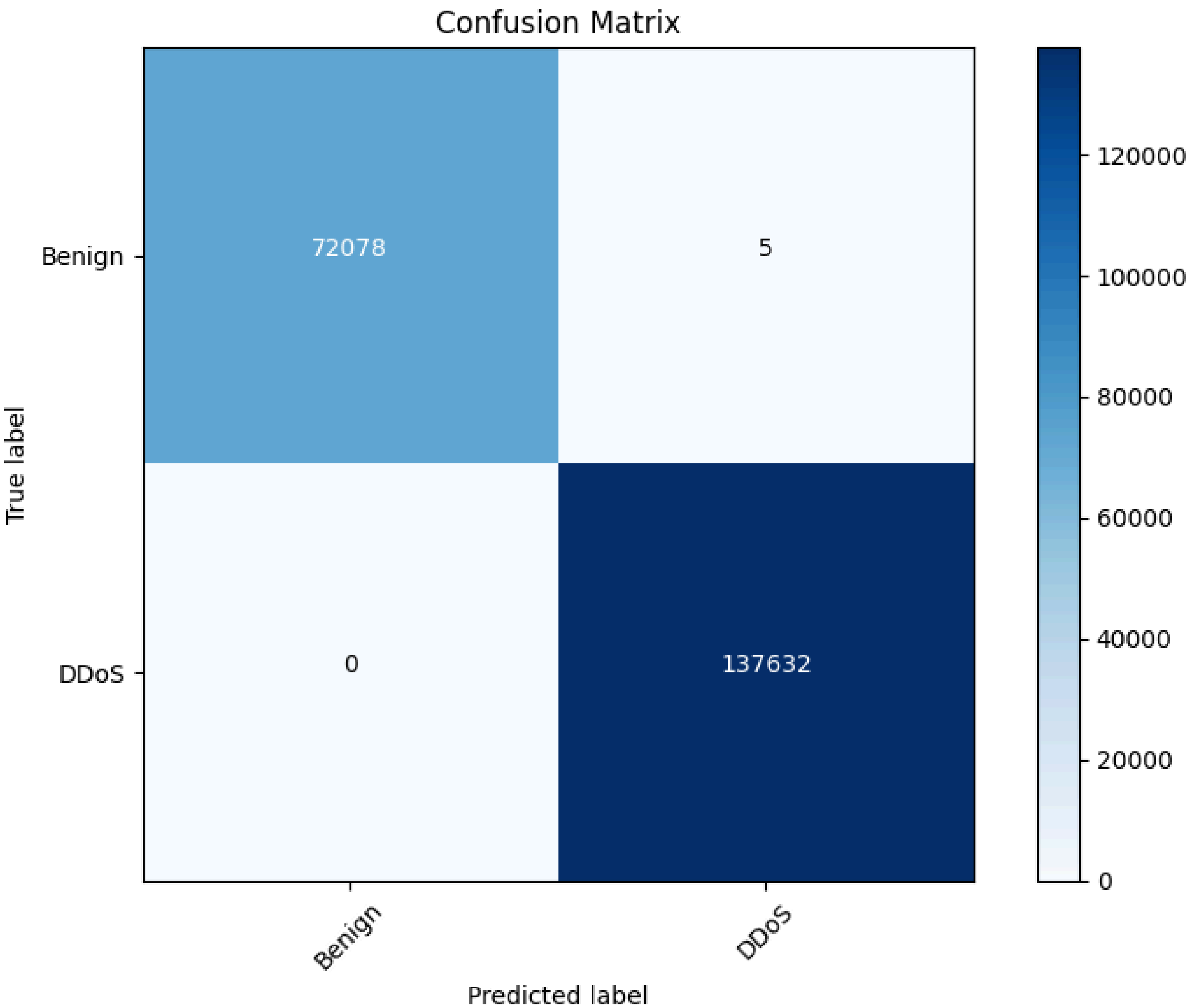
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	1.000000	0.999931	0.999965	72083.000000
DDoS	0.999964	1.000000	0.999982	137632.000000
Accuracy	0.999976	0.999976	0.999976	0.999976
Macro avg	0.999982	0.999965	0.999974	209715.000000
Weighted avg	0.999976	0.999976	0.999976	209715.000000

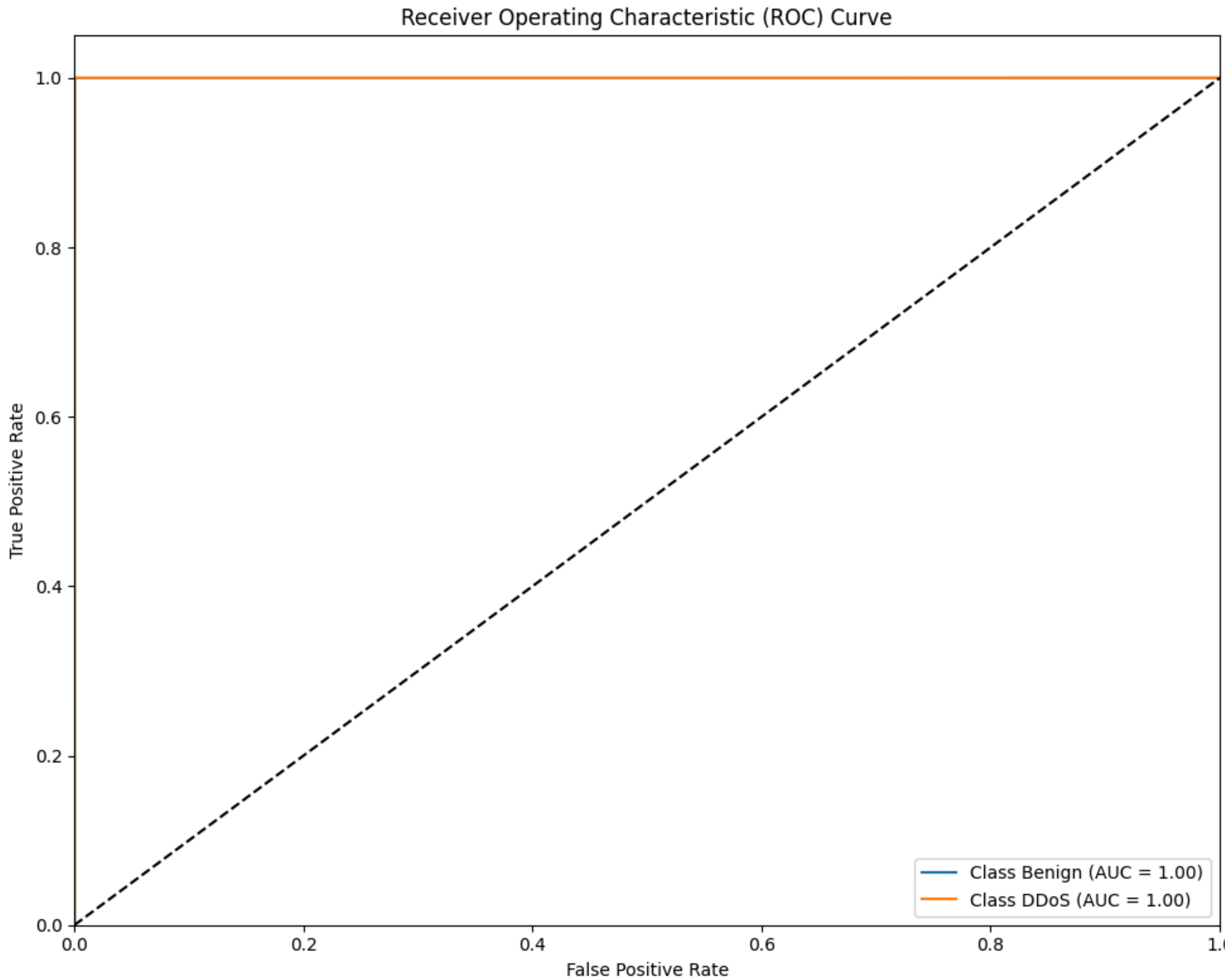
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



DoS

2017 Data + Predictions

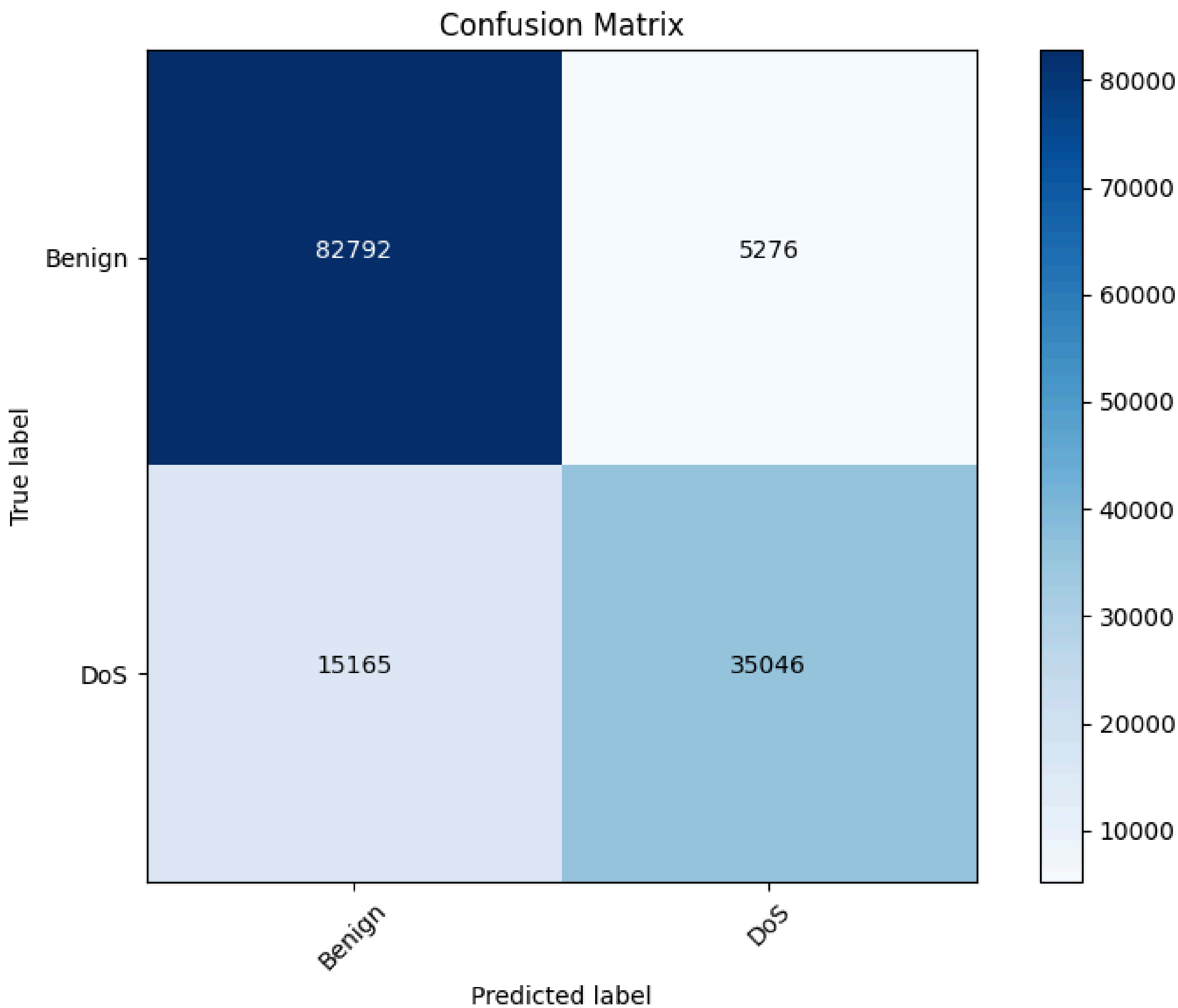
Classification Report

```
workflow_2017.report_df
```

	precision	recall	f1-score	support
Benign	0.845187	0.940092	0.890117	88068.000000
DoS	0.869153	0.697975	0.774215	50211.000000
Accuracy	0.852176	0.852176	0.852176	0.852176
Macro avg	0.857170	0.819033	0.832166	138279.000000
Weighted avg	0.853890	0.852176	0.848031	138279.000000

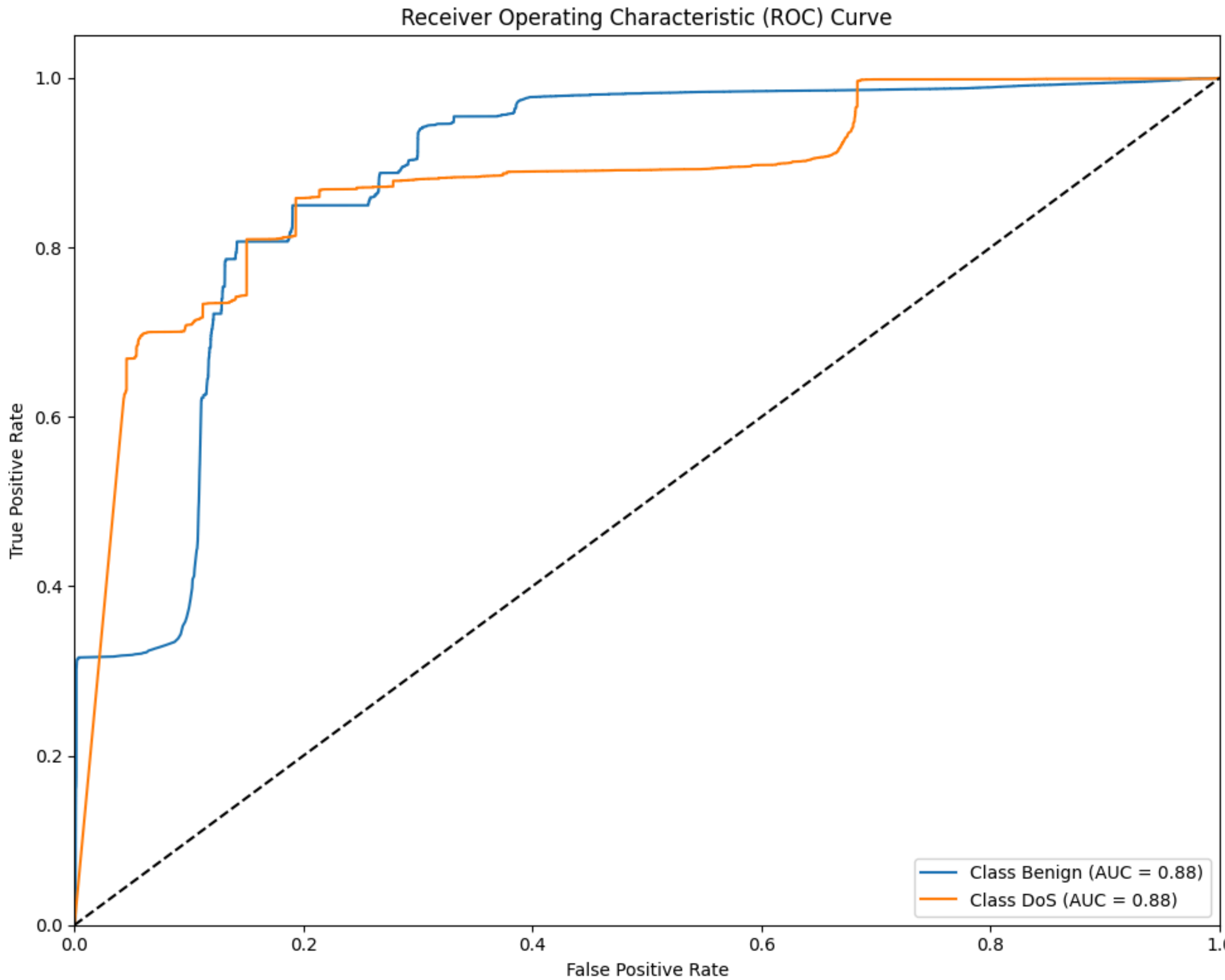
Confusion Matrix

```
workflow_2017.plot_confusion_matrix()
```



ROC Curve

```
workflow_2017.plot_roc_curve()
```



2018 Data + Predictions

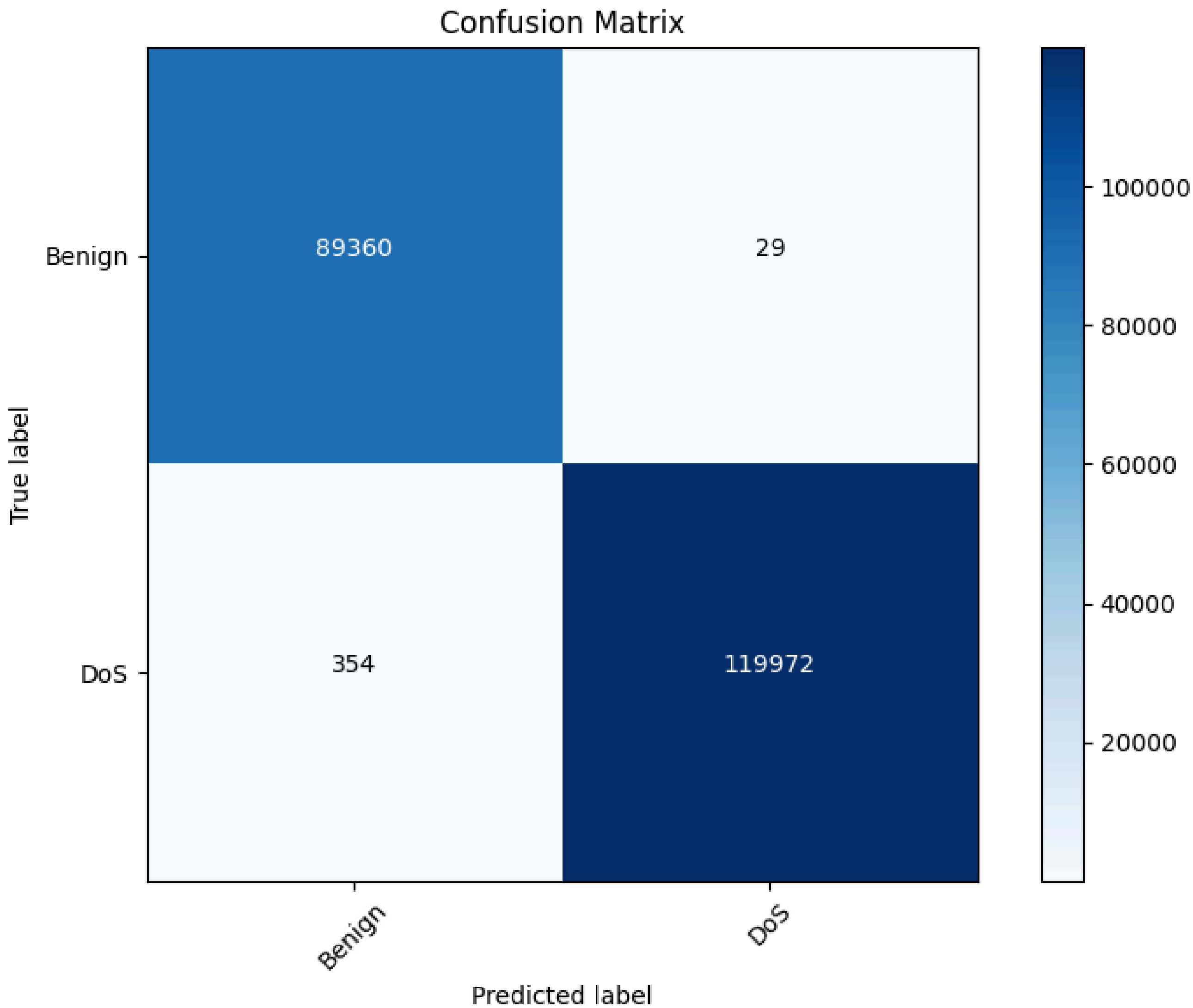
Classification Report

```
workflow_2018.report_df
```

	precision	recall	f1-score	support
Benign	0.996054	0.999676	0.997862	89389.000000
DoS	0.999758	0.997058	0.998406	120326.000000
Accuracy	0.998174	0.998174	0.998174	0.998174
Macro avg	0.997906	0.998367	0.998134	209715.000000
Weighted avg	0.998179	0.998174	0.998174	209715.000000

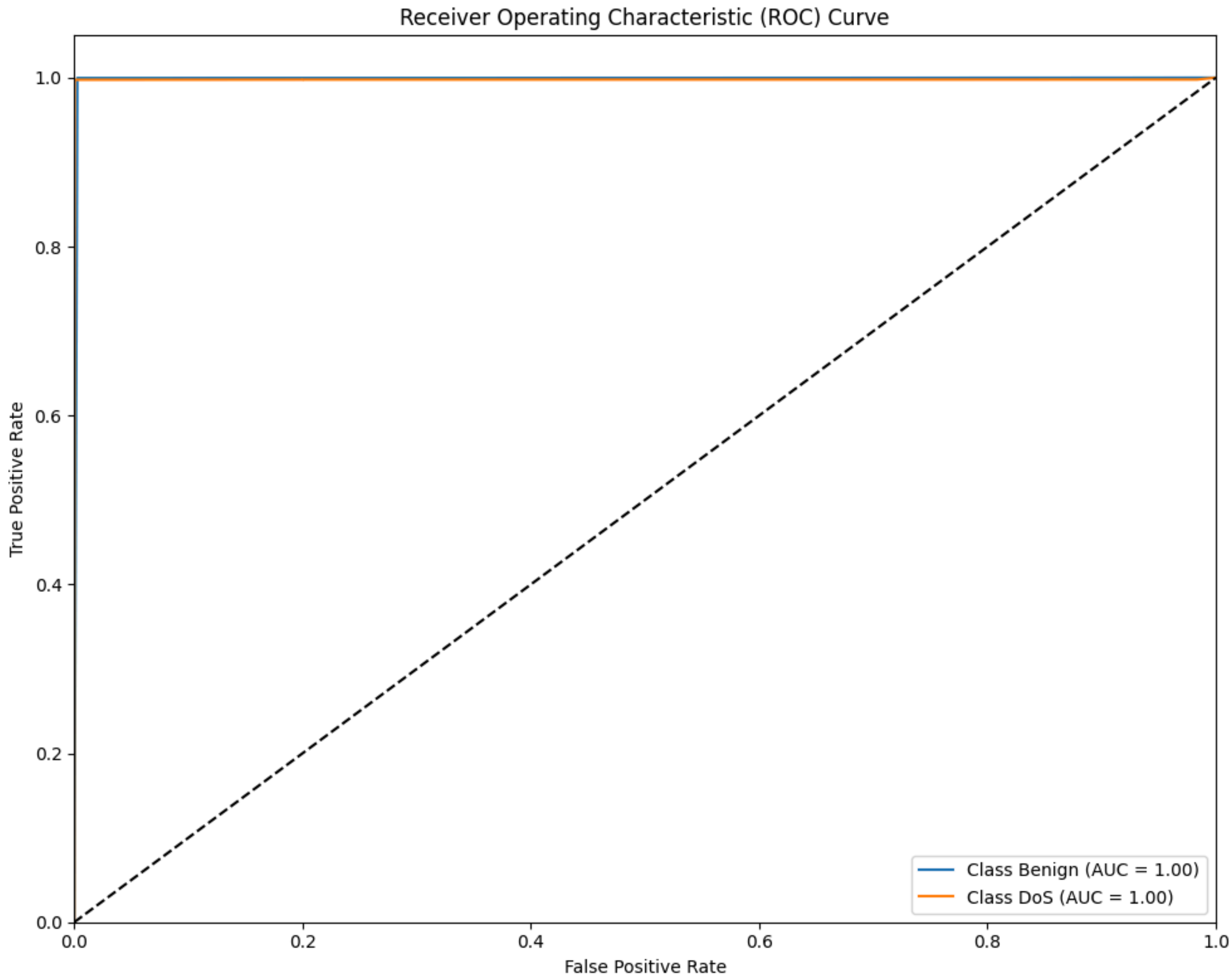
Confusion Matrix

```
workflow_2018.plot_confusion_matrix()
```



ROC Curve

```
workflow_2018.plot_roc_curve()
```



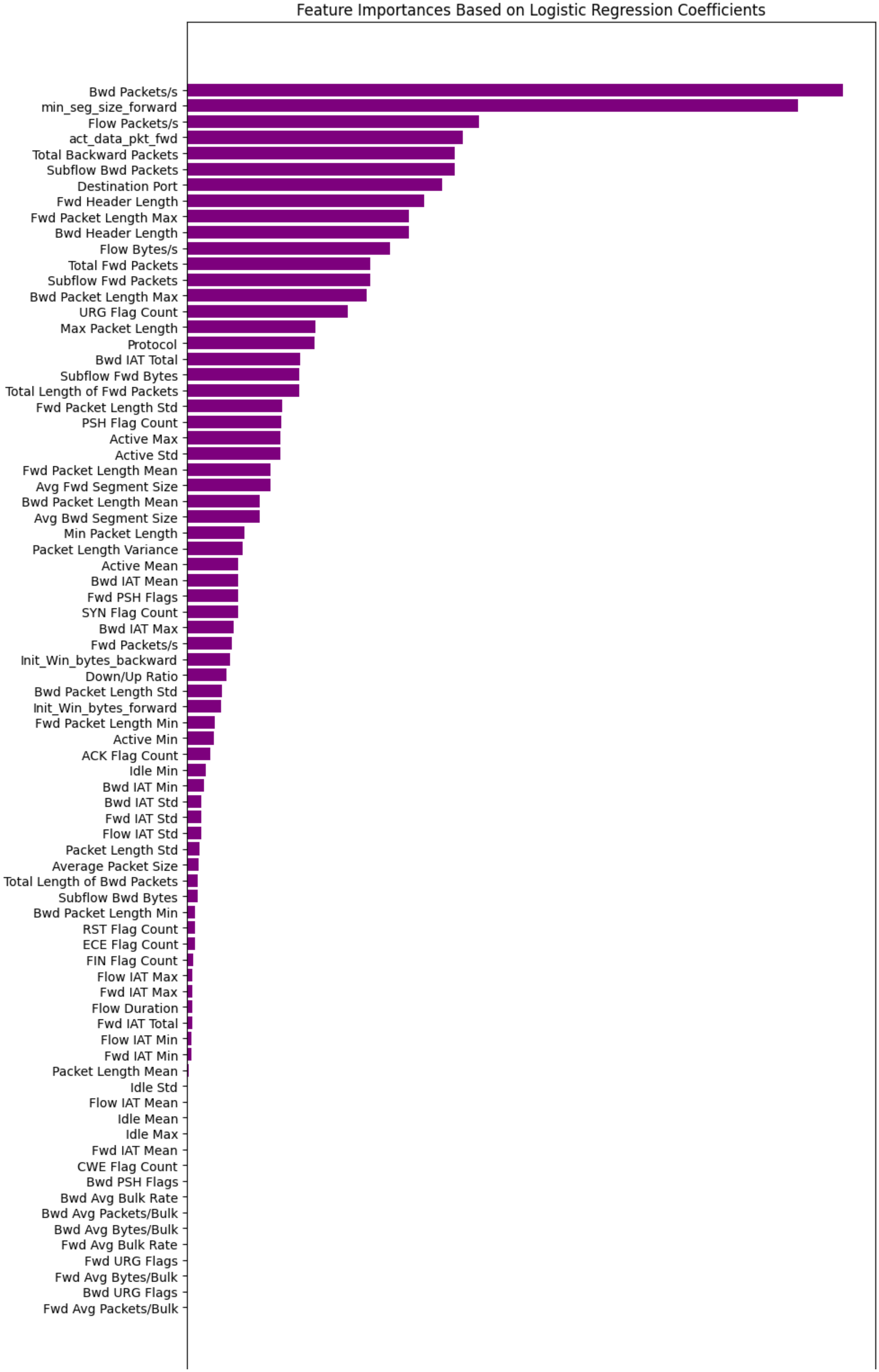
Comparisons

Feature Importance

For each model, we generated a graph of feature importances to better indicate which aspects of the traffic data were most important to the model for detection. This also helped us detect any potential spurious correlations, where features that are actually irrelevant to attack detection are being prioritized by the model. It also helped us better learn about the structure of network attacks and how they are represented in traffic data.

Brute Force

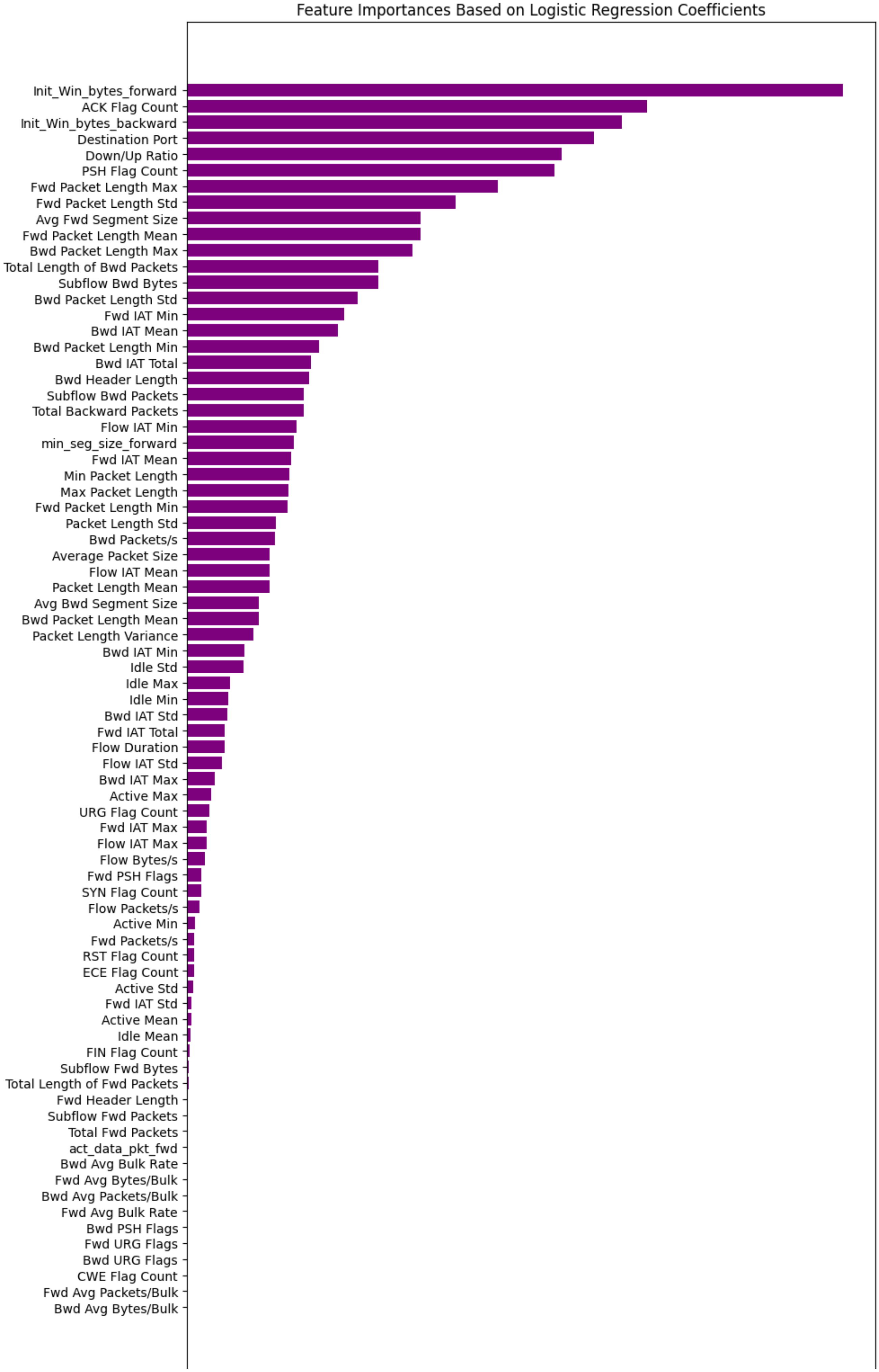
```
brute_workflow.plot_feature_importance()
```

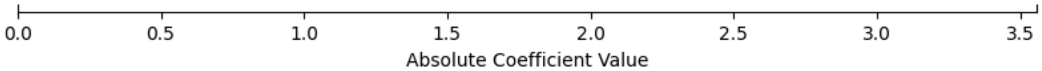

Feature Importances Based on Logistic Regression Coefficients
Bwd Packets/s
min_seg_size_forward
Flow Packets/s
act_data_pkt_fwd
Total Backward Packets
Subflow Bwd Packets
Destination Port
Fwd Header Length
Fwd Packet Length Max
Bwd Header Length
Flow Bytes/s
Total Fwd Packets
Subflow Fwd Packets
Bwd Packet Length Max
URG Flag Count
Max Packet Length
Protocol
Bwd IAT Total
Subflow Fwd Bytes
Total Length of Fwd Packets
Fwd Packet Length Std
PSH Flag Count
Active Max
Active Std
Fwd Packet Length Mean
Avg Fwd Segment Size
Bwd Packet Length Mean
Avg Bwd Segment Size
Min Packet Length
Packet Length Variance
Active Mean
Bwd IAT Mean
Fwd PSH Flags
SYN Flag Count
Bwd IAT Max
Fwd Packets/s
Init_Win_bytes_backward
Down/Up Ratio
Bwd Packet Length Std
Init_Win_bytes_forward
Fwd Packet Length Min
Active Min
ACK Flag Count
Idle Min
Bwd IAT Min
Bwd IAT Std
Fwd IAT Std
Flow IAT Std
Packet Length Std
Average Packet Size
Total Length of Bwd Packets
Subflow Bwd Bytes
Bwd Packet Length Min
RST Flag Count
ECE Flag Count
FIN Flag Count
Flow IAT Max
Fwd IAT Max
Flow Duration
Fwd IAT Total
Flow IAT Min
Fwd IAT Min
Packet Length Mean
Idle Std
Flow IAT Mean
Idle Mean
Idle Max
Fwd IAT Mean
CWE Flag Count
Bwd PSH Flags
Bwd Avg Bulk Rate
Bwd Avg Packets/Bulk
Bwd Avg Bytes/Bulk
Fwd Avg Bulk Rate
Fwd URG Flags
Fwd Avg Bytes/Bulk
Bwd URG Flags
Fwd Avg Packets/Bulk

Backward packets were the top feature for detecting brute force attacks. A backward packet refers to the traffic sent from the target server back to the client. During a brute force attack, the attacker repeatedly attempts to log in with different credentials, triggering numerous responses from the server, such as error messages or login status updates. This increased volume of backward packets is a strong indicator of brute force activity, so it being a key feature is consistent with the nature of the attack.

DDoS

```
ddos_workflow.plot_feature_importance()
```

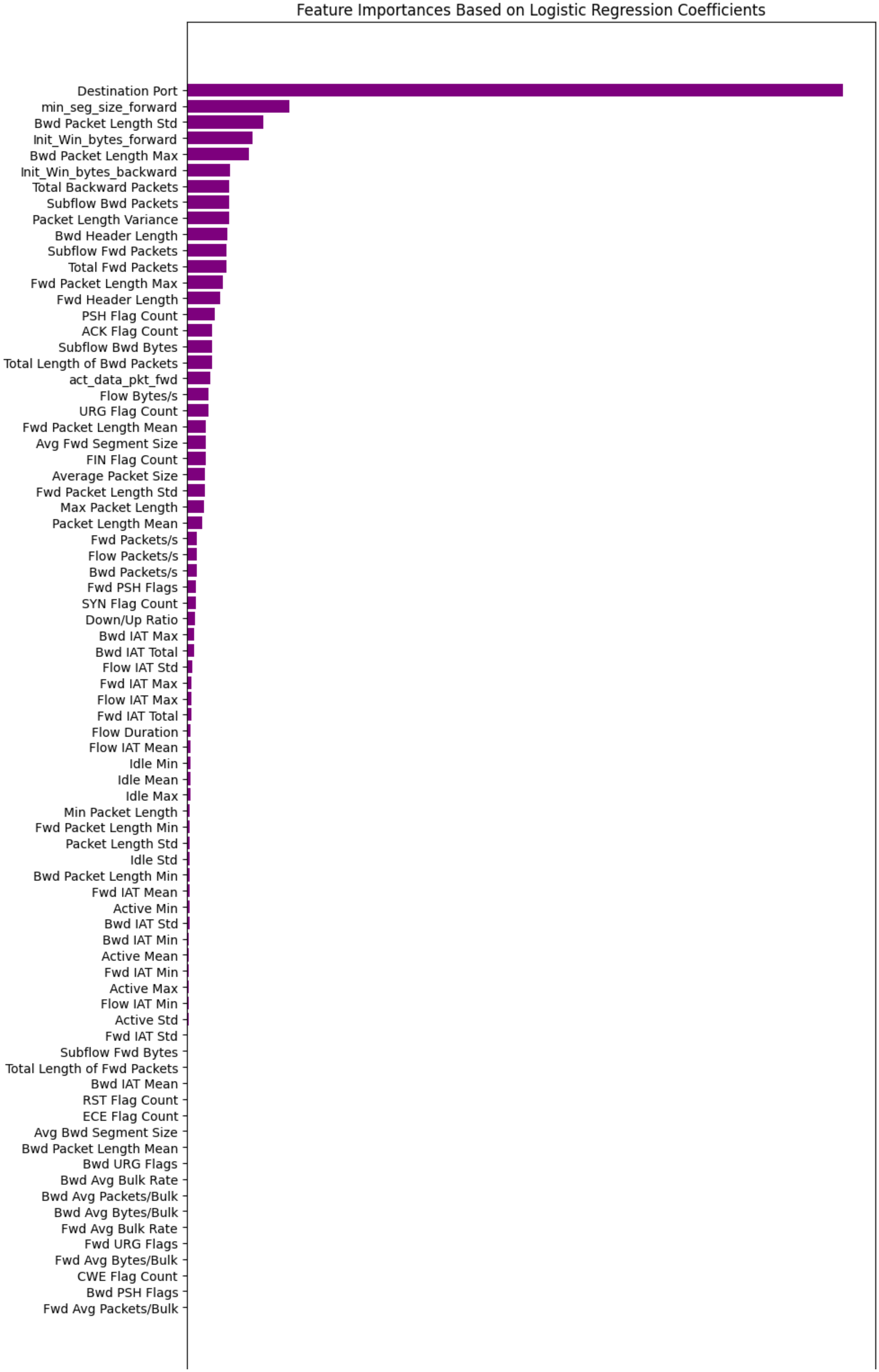

Feature Importances Based on Logistic Regression Coefficients
Init_Win_bytes_forward
ACK Flag Count
Init_Win_bytes_backward
Destination Port
Down/Up Ratio
PSH Flag Count
Fwd Packet Length Max
Fwd Packet Length Std
Avg Fwd Segment Size
Fwd Packet Length Mean
Bwd Packet Length Max
Total Length of Bwd Packets
Subflow Bwd Bytes
Bwd Packet Length Std
Fwd IAT Min
Bwd IAT Mean
Bwd Packet Length Min
Bwd IAT Total
Bwd Header Length
Subflow Bwd Packets
Total Backward Packets
Flow IAT Min
min_seg_size_forward
Fwd IAT Mean
Min Packet Length
Max Packet Length
Fwd Packet Length Min
Packet Length Std
Bwd Packets/s
Average Packet Size
Flow IAT Mean
Packet Length Mean
Avg Bwd Segment Size
Bwd Packet Length Mean
Packet Length Variance
Bwd IAT Min
Idle Std
Idle Max
Idle Min
Bwd IAT Std
Fwd IAT Total
Flow Duration
Flow IAT Std
Bwd IAT Max
Active Max
URG Flag Count
Fwd IAT Max
Flow IAT Max
Flow Bytes/s
Fwd PSH Flags
SYN Flag Count
Flow Packets/s
Active Min
Fwd Packets/s
RST Flag Count
ECE Flag Count
Active Std
Fwd IAT Std
Active Mean
Idle Mean
FIN Flag Count
Subflow Fwd Bytes
Total Length of Fwd Packets
Fwd Header Length
Subflow Fwd Packets
Total Fwd Packets
act_data_pkt_fwd
Bwd Avg Bulk Rate
Fwd Avg Bytes/Bulk
Bwd Avg Packets/Bulk
Fwd Avg Bulk Rate
Bwd PSH Flags
Fwd URG Flags
Bwd URG Flags
CWE Flag Count
Fwd Avg Packets/Bulk
Bwd Avg Bytes/Bulk



Init_win_bytes_forward was the top feature for detecting DDoS attacks. This feature refers to the initial window size (the amount of data that can be sent over a connection before receiving an acknowledgment from the receiver) from the client to the server. During a DDoS attack, a large number of malicious requests are sent to overwhelm the target system, often involving high-volume traffic that can lead to abnormal window size patterns in the network flows.

DoS

```
dos_workflow.plot_feature_importance()
```

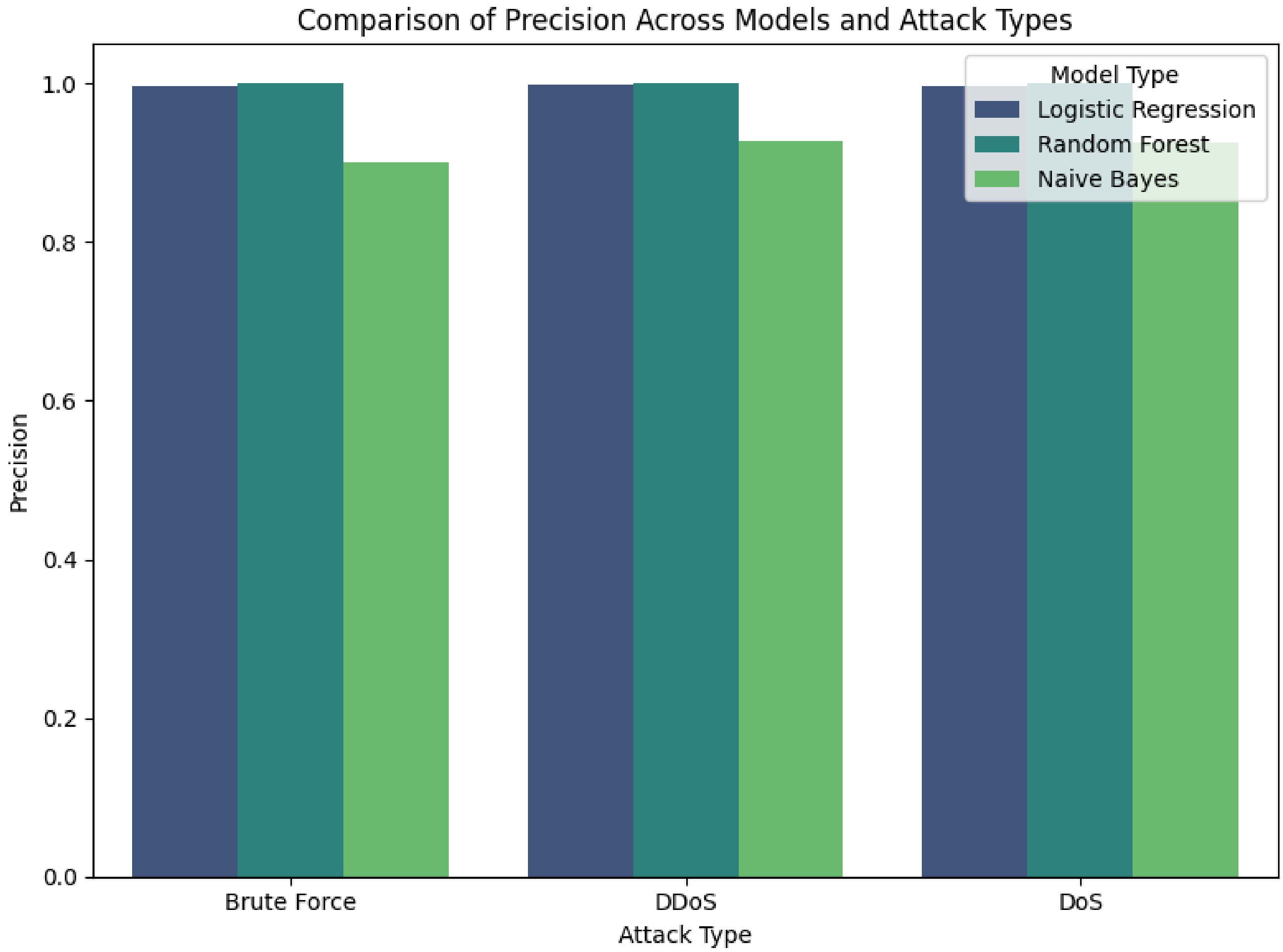

Feature Importances Based on Logistic Regression Coefficients
Destination Port
min_seg_size_forward
Bwd Packet Length Std
Init_Win_bytes_forward
Bwd Packet Length Max
Init_Win_bytes_backward
Total Backward Packets
Subflow Bwd Packets
Packet Length Variance
Bwd Header Length
Subflow Fwd Packets
Total Fwd Packets
Fwd Packet Length Max
Fwd Header Length
PSH Flag Count
ACK Flag Count
Subflow Bwd Bytes
Total Length of Bwd Packets
act_data_pkt_fwd
Flow Bytes/s
URG Flag Count
Fwd Packet Length Mean
Avg Fwd Segment Size
FIN Flag Count
Average Packet Size
Fwd Packet Length Std
Max Packet Length
Packet Length Mean
Fwd Packets/s
Flow Packets/s
Bwd Packets/s
Fwd PSH Flags
SYN Flag Count
Down/Up Ratio
Bwd IAT Max
Bwd IAT Total
Flow IAT Std
Fwd IAT Max
Flow IAT Max
Fwd IAT Total
Flow Duration
Flow IAT Mean
Idle Min
Idle Mean
Idle Max
Min Packet Length
Fwd Packet Length Min
Packet Length Std
Idle Std
Bwd Packet Length Min
Fwd IAT Mean
Active Min
Bwd IAT Std
Bwd IAT Min
Active Mean
Fwd IAT Min
Active Max
Flow IAT Min
Active Std
Fwd IAT Std
Subflow Fwd Bytes
Total Length of Fwd Packets
Bwd IAT Mean
RST Flag Count
ECE Flag Count
Avg Bwd Segment Size
Bwd Packet Length Mean
Bwd URG Flags
Bwd Avg Bulk Rate
Bwd Avg Packets/Bulk
Bwd Avg Bytes/Bulk
Fwd Avg Bulk Rate
Fwd URG Flags
Fwd Avg Bytes/Bulk
CWE Flag Count
Bwd PSH Flags
Fwd Avg Packets/Bulk

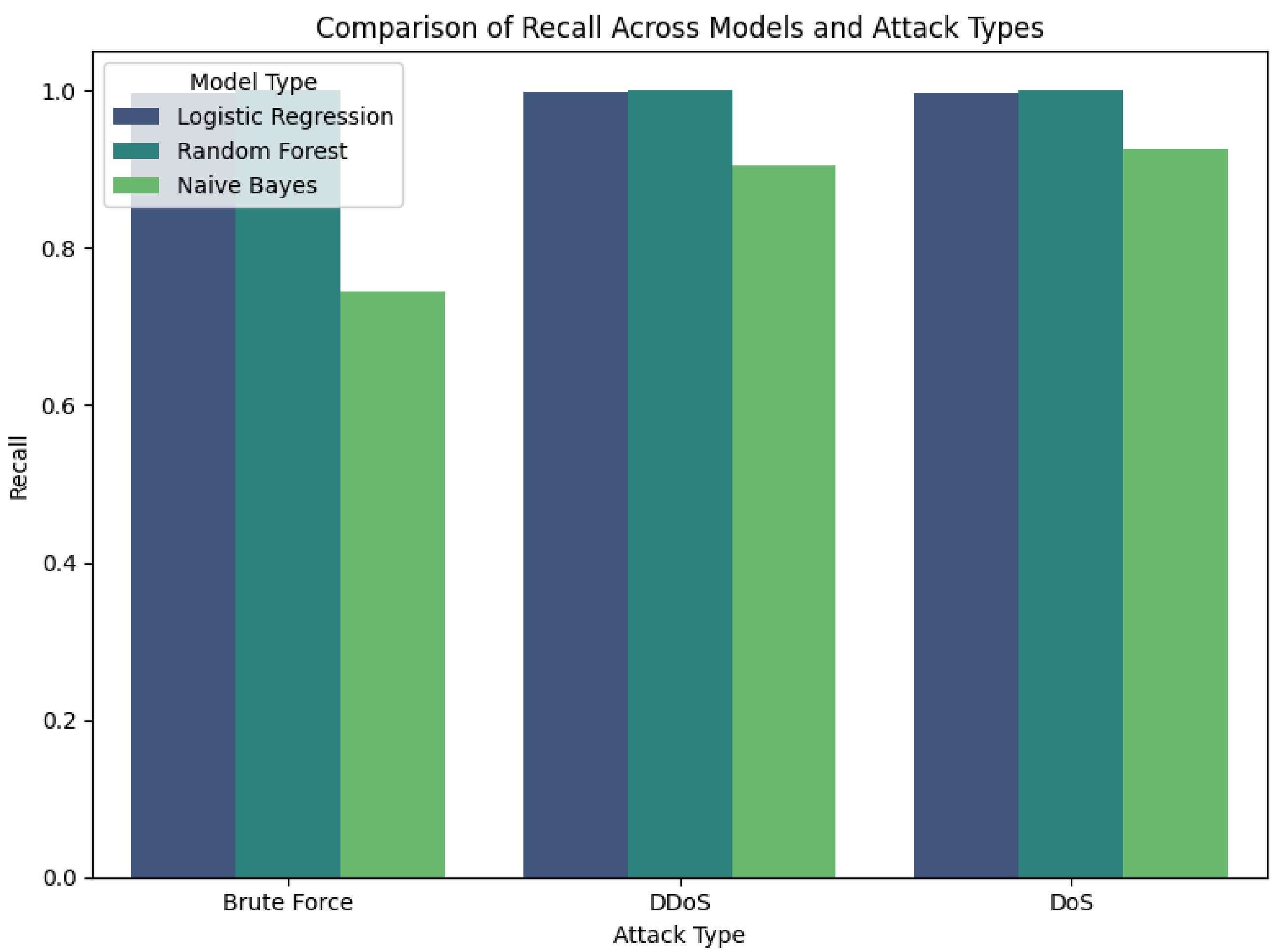
Destination port was the top feature for detecting DoS attacks. During a DoS attack, the attacker typically floods the target with a high volume of requests aimed at a specific service, causing the destination port to experience an unusual spike in traffic. This concentrated targeting of a particular port makes the destination port a strong feature for detecting DoS attacks, as it can easily distinguish attack traffic from normal network activity that is distributed across multiple services.

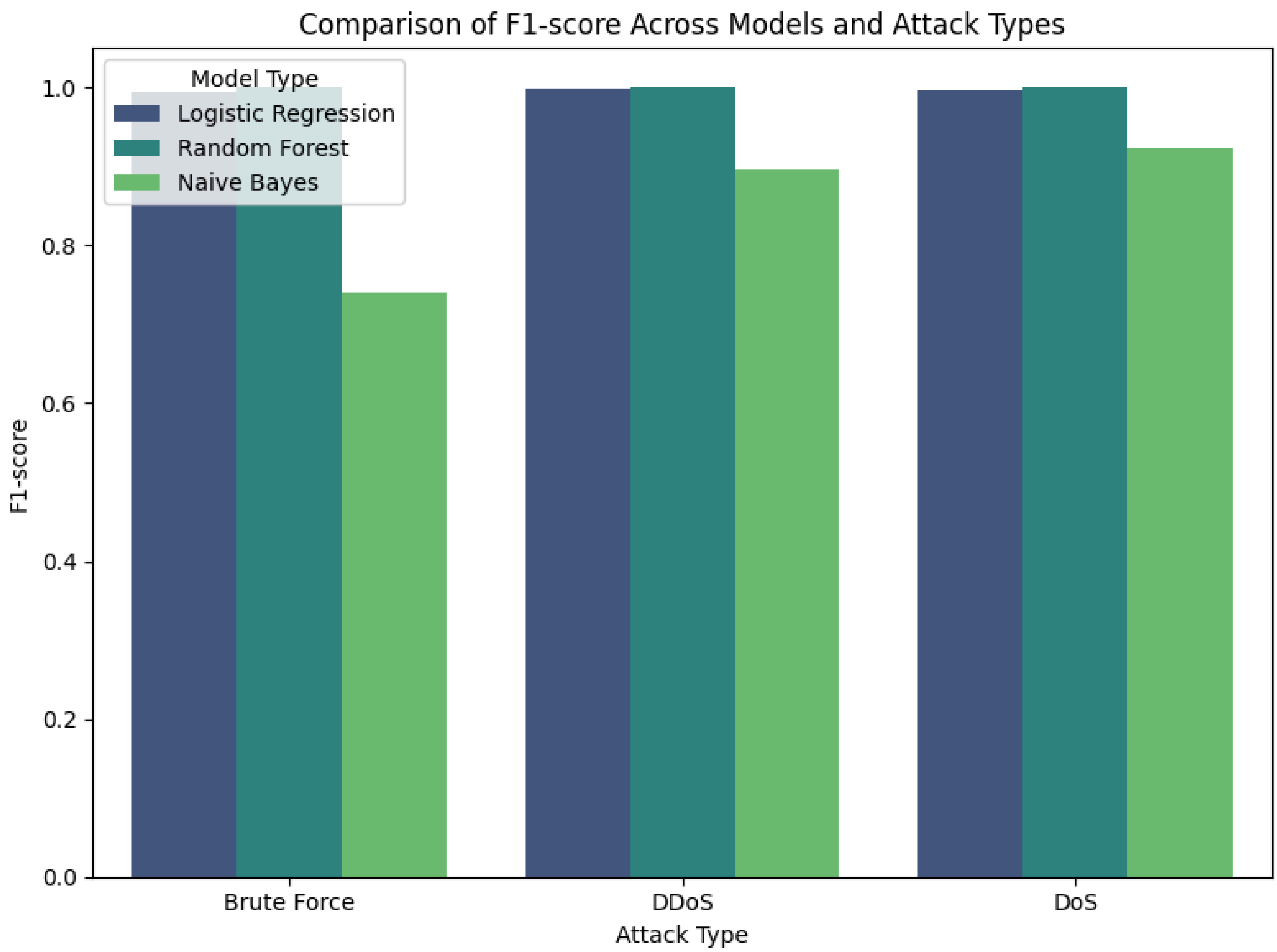
Overall Model Performance

```python
for metric in metrics_melted['Metric'].unique():
    plt.figure(figsize=(8, 6))
    sns.barplot(
        data=metrics_melted[metrics_melted['Metric'] == metric],
        x='attack_type',
        y='Value',
        hue='model_type',
        ci=None,
        palette='viridis'
    )
    plt.title(f'Comparison of {metric.capitalize()} Across Models and Attack Types')
    plt.xlabel('Attack Type')
    plt.ylabel(metric.capitalize())
    plt.legend(title='Model Type')
    plt.tight_layout()
    plt.show()
```

```
/var/folders/zz/1dtb5n794qbf5bn8fxwmn2zw0000gn/T/ipykernel_50983/1070574859.py:3:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zz/1dtb5n794qbf5bn8fxwmn2zw0000gn/T/ipykernel_50983/1070574859.py:3:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
/var/folders/zz/1dtb5n794qbf5bn8fxwmn2zw0000gn/T/ipykernel_50983/1070574859.py:3:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(
```


Comparison of Precision Across Models and Attack Types
Model Type
Logistic Regression
Random Forest
Naive Bayes
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Brute Force
DDoS
DoS
Attack Type


Comparison of Recall Across Models and Attack Types
Model Type
Logistic Regression
Random Forest
Naive Bayes
Recall
0.0
0.2
0.4
0.6
0.8
1.0
Brute Force
DDoS
DoS
Attack Type




```
print(f"The overall best model is: {best_model}")
print(f"The average F1-score of this model is: {best_f1_score:.4f}")
print("\nAverage F1-scores of all models:")
print(avg_f1_scores)
metrics_df
```

```
The overall best model is: Random Forest
The average F1-score of this model is: 0.9999

Average F1-scores of all models:
model_type
Logistic Regression    0.996879
Naive Bayes            0.853477
Random Forest          0.999890
Name: f1-score, dtype: float64
```

	precision	recall	f1-score	attack_type	model_type
Weighted avg	0.991651	0.991888	0.990658	Brute Force	Logistic Regression
Weighted avg	0.999857	0.999856	0.999856	Brute Force	Logistic Regression
Weighted avg	0.998871	0.998870	0.998870	DDoS	Logistic Regression
Weighted avg	0.999995	0.999995	0.999995	DDoS	Logistic Regression

	precision	recall	f1-score	attack_type	model_type
Weighted avg	0.991898	0.991900	0.991898	DoS	Logistic Regression
Weighted avg	0.999995	0.999995	0.999995	DoS	Logistic Regression
Weighted avg	0.999944	0.999944	0.999944	Brute Force	Random Forest
Weighted avg	0.999952	0.999952	0.999952	Brute Force	Random Forest
Weighted avg	0.999911	0.999911	0.999911	DDoS	Random Forest
Weighted avg	1.000000	1.000000	1.000000	DDoS	Random Forest
Weighted avg	0.999530	0.999530	0.999530	DoS	Random Forest
Weighted avg	1.000000	1.000000	1.000000	DoS	Random Forest
Weighted avg	0.937744	0.968372	0.952812	Brute Force	Naive Bayes
Weighted avg	0.862218	0.518906	0.527000	Brute Force	Naive Bayes
Weighted avg	0.855617	0.808365	0.794866	DDoS	Naive Bayes
Weighted avg	0.999976	0.999976	0.999976	DDoS	Naive Bayes
Weighted avg	0.853890	0.852176	0.848031	DoS	Naive Bayes
Weighted avg	0.998179	0.998174	0.998174	DoS	Naive Bayes

Conclusion

The overall results of this project highlight key findings regarding the performance of different machine learning models in detecting network attacks. We evaluated model performance using F1 scores, a commonly used metric for assessing the balance between precision and recall in classification tasks. Our analysis revealed that, while all models exhibited similar success in detecting brute force attacks, the performance for DDoS and DoS attacks varied significantly across model types. This discrepancy is likely due to the uneven distribution of data for each attack type in the datasets, which were not consistently balanced. Specifically, brute force attack flows had substantially higher traffic volume compared to DDoS and DoS attacks, which likely contributed to the more stable performance of the models on this particular attack type. In contrast, for attack types with less abundant training data, model performance was more variable.

Through averaging the F1 scores, we identified logistic regression as the most effective model for detecting all three attack types, achieving an average F1 score of 0.62. The relatively superior performance of logistic regression may be attributed to its suitability for smaller datasets and its strength in binary classification tasks, such as distinguishing between benign and malicious traffic. However, it is important to consider several limitations within our project design and dataset that may influence the interpretation of these results.

First, there were notable inconsistencies in the availability of training data from 2017 and test data from 2018. The DoS attack class, for example, exhibited an imbalance between benign and attack packets, which could have led to biased predictions, with the model potentially favoring benign traffic. When datasets are imbalanced, models tend to perform better on the majority class, which may have contributed to the underperformance in detecting DoS attacks.

Another limitation lies in the generation of the packet capture data. Due to privacy constraints, the researchers could not use real network traffic and instead simulated both benign and attack traffic over a one-week period. This simulated traffic may not accurately reflect real-world network behavior, which could affect the generalizability of our results.

Finally, our own project design may have been overly complex, as we attempted to study multiple attack types simultaneously. To better understand how machine learning models respond to attacks that evolve over time, a larger and more diverse dataset spanning several years would be necessary. In the original design for this study, the goal was to incorporate the **CCIDOS2019** dataset as well, to evaluate the performance of these models over three years; however, there was not sufficient data for all three attack types present in all three datasets. This points to a larger issue with our source of data: the attack types and the volume of data available for each attack have not been consistently maintained across years, making it difficult to normalize and compare multiple datasets from the same source. In hindsight, focusing on a single attack type, such as DDoS, could have simplified the analysis and yielded more precise insights into model performance over time.

If we were to expand the study's evaluation metrics, we would also have included an analysis of processing time and cost for the different machine learning models, including CPU, GPU, and memory usage. This would have been highly relevant to network administrators and cybersecurity companies, who often face the challenge that the best-performing model is not necessarily the one with the highest accuracy, but the one that is also cost-effective and efficient to deploy in a real-world setting.