INTRUSION DETECTION SYSTEM DESIGN & ANALYSIS

32130 Fundamental of Data Analytics

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1. Introduction

In the following report we will be working on building a predictive model to classify network intrusion events based on the labelled dataset of network traffic features such as Header Length, flow duration, Packet's length etc. The primary objective of the predictive model is to accurately identify the intrusion based on the network traffic data which will be used for future work in intrusion detection. The classifier should accurately classify the intrusion into one of the following categories:

- Mirai-greip_flood
- Recon-OSScan
- DictionaryBruteForce

2. Dataset

Two datasets are available: train_IoT_Intrusion_Detection.csv (referred to as the Training Dataset) and unknowndataset.csv (referred to as the Unknown Dataset). The training dataset is utilized to train the Machine Learning (ML) model, while the Unknown Dataset is used to evaluate the model's performance and predict intrusions based on the trained model. Both datasets consist of network traffic records, each containing multiple features that capture various aspects of network activity. Each record in the training dataset is labelled with one of the intrusion types. The datasets include both numerical and categorical features that require pre-processing before model training. Specific fields such as fin_flag_number, rst_flag_number, HTTP, HTTPS, and DNS are binary indicators, signifying whether the respective flag or protocol is in use (0 or 1). Additionally, the description for the "Unnamed" column is not provided. The primary distinction between these datasets is the presence of the "label" column in the training dataset, which is absent in the Unknown Dataset.

3. Technologies used.

To develop a machine learning (ML) model capable of predicting intrusion types based on network traffic data, we utilize Python for various tasks, including pre-processing, dataset transformation, model training, prediction, and analysis. The following libraries are integral to this process:

- **Pandas**: Provides data manipulation and analysis tools essential for handling datasets.
- **Scikit-learn (sklearn)**: Offers a robust framework for model development and evaluation.
- **Matplotlib**: Facilitates data visualization to aid in understanding model performance and data distribution.
- **NumPy**: Enables efficient numerical computations necessary for pre-processing and model training.

These technologies collectively enable a comprehensive approach to developing and evaluating our intrusion detection model, ensuring a robust and accurate classification of network intrusions.

```
[13] import pandas as pd
     from sklearn.preprocessing import StandardScaler, LabelEncoder
     from sklearn.linear_model import LogisticRegression
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.preprocessing import normalize
     from sklearn.svm import SVC
     from sklearn.neural_network import MLPClassifier
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import accuracy_score, classification_report, roc_curve, auc
     from sklearn.preprocessing import label_binarize
     import matplotlib.pyplot as plt
     import numpy as np
     import seaborn as sns
     from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

Figure 1 Libraries used.

4. Design of model

In this section we will be discussing steps and analysis techniques that we have performed to design our ML model.

4.1. Dataset analysis

The dataset comprises 15,600 rows and 48 columns, with each column representing a specific attribute. Upon conducting a thorough analysis, we gained several insights:

- **Unnamed Column**: The Training Dataset contains an unnamed column without any provided description. However, when sorted in ascending order and compared with the similarly sorted Unnamed column in the Unknown Dataset, it is evident that the Unknown Dataset's unnamed column includes the missing rows from the Training Dataset. This suggests that the unnamed column could potentially serve as a Serial No.
- **Drate Column**: The 'Drate' column contains only the value zero, indicating that it does not require any pre-processing. This also signifies that it has no impact on the classifier model.
- **Label Column**: The 'Label' column is crucial as it denotes the type of intrusion and is the only column in string format. This column must be transformed for model training purposes.
- **Duration Column**: The 'Duration' column has the highest number of outliers compared to other columns, highlighting the need for outlier analysis and removal.
- **Binary Columns (e.g., HTTP, DNS, syn_flag_number)**: These columns contain binary values, indicating whether a specific flag or protocol was used during the intrusion. While they play a significant role in training the model to detect intrusions, they do not require any transformations or pre-processing.

4.2. Dataset pre-processing/transformations

In this section, we will discuss the pre-processing and transformation techniques to be implemented based on the insights gained from the dataset analysis. Initially, we will plot box plots for outlier analysis for all columns, excluding those with only binary values (e.g., HTTP, DNS, TCP, etc.), the Unnamed column, and the Label column, as previously mentioned.

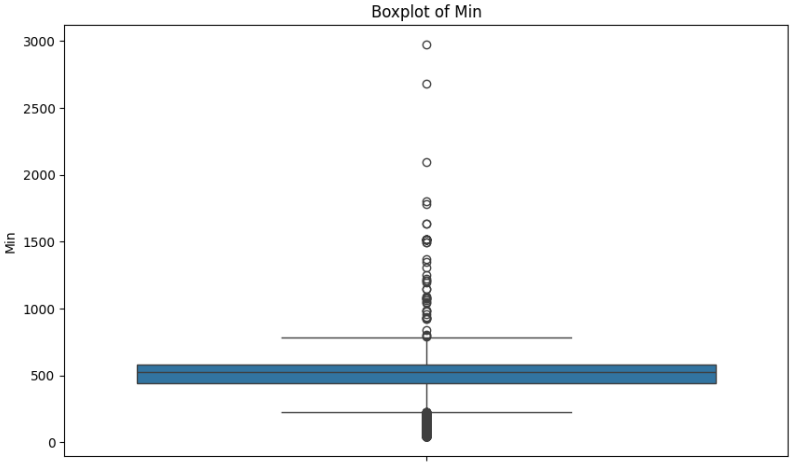

Figure 2 outlier analysis of Min column.

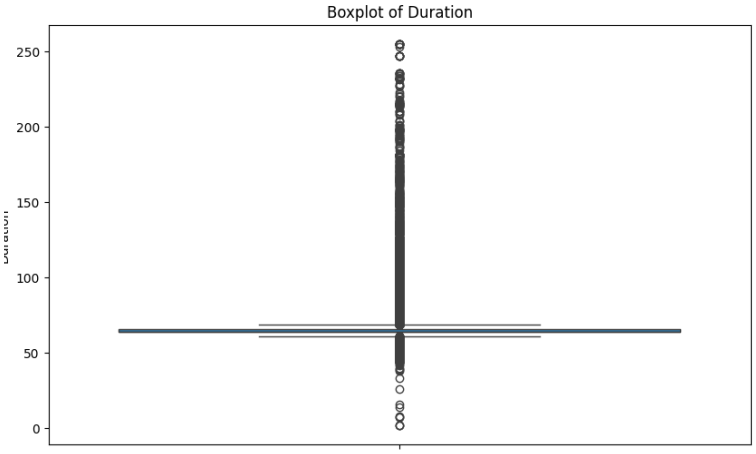

Figure 3 Outlier analysis of Duration column.

4.2.1. Outlier analysis

Upon comparing columns such as Min, which has a higher feature importance, to the Duration column, we observe that the Duration column exhibits a significantly higher number of outliers. Consequently, we will perform outlier removal using the Interquartile Range (IQR) method. The rationale for choosing this method over others lies in its robustness and lack of assumptions regarding the underlying data distribution. This is particularly advantageous for network traffic data, which often does not follow a normal distribution. By employing the IQR method, we aim to enhance the data quality and improve the performance of our machine

learning model by reducing the noise and ensuring the integrity of the dataset (Australian Bureau of Statistics, 2023) (Bhandari, 2023).

4.2.2. Standardization of data

Standardizing the data is crucial in many machine learning applications as it ensures that each feature contributes equally to the model's predictions. Standardization transforms the features to have a mean of zero and a standard deviation of one, aligning them on a common scale (Scientist, 2023).

While other methods, such as normalization, also aim to align the data on a common scale, I chose standardization due to the highly varied nature of network traffic data and the presence of numerous outliers. These outliers can significantly skew the results when using min-max normalization. Standardization, on the other hand, is robust against outliers, providing a more reliable and consistent approach for preparing the data for model training.

Similar to the case of outlier analysis, in this process, we will also exclude certain columns that do not contribute meaningfully to the model training. Specifically, we will drop the Drate column, as it contains only the value of 0; the Label column, as it consists solely of string values; and the Unnamed column, due to its lack of significant impact on the training of the model.

4.2.3. Data transformation

The Label column signifies the type of intrusion detected, playing a key role in training the model to identify intrusions in the future. However, since the column values are in string format, they must be transformed into an integer format. The code provided below accomplishes this by encoding the intrusion types as follows: Mirai-greip_flood as 1, Recon-OSScan as 2, and DictionaryBruteForce as 3. This transformation facilitates efficient model training and accurate intrusion detection.

```
label_encoder = LabelEncoder()
training_data['label_encoded'] = label_encoder.fit_transform(training_data['label'])
```

Figure 4 label encoding code.

4.2.4. Balancing Pre-Processing and Real-World Applicability

In conclusion, the pre-processing and transformation techniques have been meticulously applied to achieve optimal accuracy with the dataset. It is crucial, however, to balance the extent of pre-processing to ensure that the real-world applicability of the intrusion detection system is not compromised. Each datapoint in the dataset represents a detected intrusion, and excessive pre-processing could result in the elimination of significant data points during noise reduction or data smoothing. While this might improve the model's performance during testing, it could lead to a failure in detecting numerous intrusions in real-life applications. Therefore, careful consideration has been given to maintain the integrity of the dataset, ensuring the model remains robust and effective in practical scenarios.

4.3. Machine-Learning model analysis

Choosing the right machine learning (ML) model is critical due to its direct impact on the accuracy and reliability of intrusion detection. An appropriately selected model ensures that the nuanced patterns within the network traffic data are effectively captured and interpreted, leading to accurate classification of intrusion types. Given the diversity and complexity of the dataset, which includes both numerical and categorical features, the model must be capable of handling varied data types and addressing potential noise and anomalies. Additionally, a well-suited model contributes to efficient training and prediction processes, optimizing computational resources and time. Ultimately, the right ML model not only enhances the predictive performance but also ensures the robustness and generalizability of the intrusion detection system in real-world applications. Here, we have chosen models such as Random Forest, K-Nearest Neighbors (KNN), Logistic Regression, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP) to evaluate their performance in this context.

4.3.1. Random Forest

- **Ensemble Learning Technique:** Combines multiple decision trees to improve predictive accuracy and control over-fitting.
- **Robustness:** Effective in handling large datasets with high dimensionality and robustness against noise and overfitting.
- **Mechanism:** Each decision tree is trained on a random subset of the data and features, introducing diversity, and reducing variance.
- **Prediction Phase:** Outputs the majority vote among all the trees, ensuring robust and accurate classifications.
- **Suitability:** Ideal for this dataset due to its ability to manage diverse and complex features efficiently (Shafi, 2023).
- **Configuration parameters:** n_estimators=1000 where it is the number of trees and random_state =42 where it controls both the randomness of the bootstrapping of the samples used when building trees.

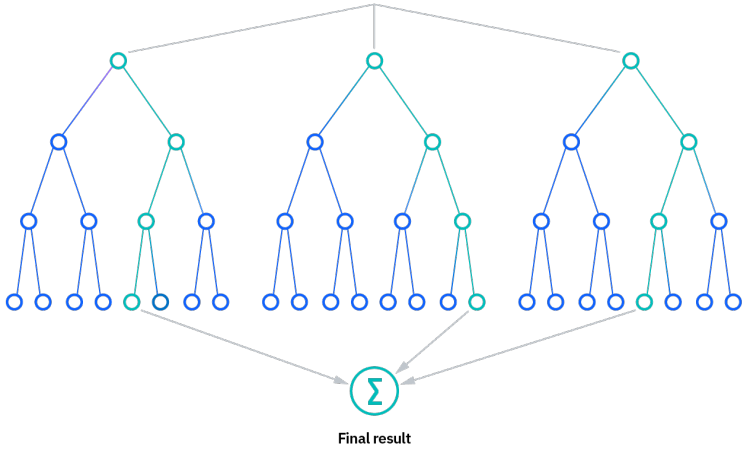

Figure 5 Random Forest representation (IBM,2023)

4.3.2. K Nearest Neighbours

- **Simplicity and Versatility:** Classifies data points based on proximity to other data points, making it intuitive and easy to implement.
- **Distance Calculation:** Uses the Euclidean distance method to identify 'k' closest training examples for classification.
- **Flexibility:** Can be adapted for both classification and regression tasks.
- **Strength:** Effective for datasets where the relationships between data points are critical for accurate predictions.
- **Suitability:** Suitable for this case due to its ability to handle varied data types and its straightforward implementation (*RPubs - 4.3 - KNN Classification*, 2019).
- **Configuration parameters:** n_neighbours=3 it says the numbers we want to use and since we 3 different intrusions. I've left the algorithm= "auto" as I am letting the module choose the best preferred module.

4.3.3. Logistic Regression

- **Binary Classification:** Estimates the probability of class membership by fitting data to a logistic function.
- **Interpretability:** Provides clear insights into the significance and strength of relationships between variables through its coefficients.
- **Efficiency:** Simple and effective in situations with linear relationships between features and outcomes.
- **Output:** Produces probabilities between 0 and 1, allowing for straightforward interpretation of results.
- **Suitability:** Ideal for this dataset due to its efficiency and interpretability, particularly useful for initial stages of model evaluation (GeeksforGeeks, 2024).
- **Configuration parameters:** I've set the max_iter =1000 where defines the no of maximum iterations it can perform.

$$\text{Logit}(pi) = 1/(1+ \exp(-pi))$$

$$\ln(pi/(1-pi)) = \text{Beta}_0 + \text{Beta}_1*X_1 + \ldots + B_k*K_k$$

Figure 6 Logistic regression formula. (IBM, 2024)

4.3.4. Support Vector Machine

- **Powerful Algorithm:** Used for both classification and regression, finds the hyperplane that best separates data points of different classes.
- **Kernel Functions:** Employs functions like linear, polynomial, and RBF to handle non-linear relationships.
- **Robustness:** Particularly effective in high-dimensional spaces and robust against overfitting.
- **Support Vectors:** Utilizes support vectors to maximize the margin between classes, ensuring accurate classifications.
- **Suitability:** Chosen for its adaptability and robustness, making it a strong candidate for complex classification problems in this dataset (*1.4. Support Vector Machines*, 2024).

4.3.5. Multi-Layer Perceptron

- **Artificial Neural Network:** Consists of multiple layers of nodes, fully connected, with each layer learning to approximate complex functions.
- **Backpropagation:** Uses iterative optimization through backpropagation to improve model performance.
- **Activation Functions:** Applies non-linear activation functions to capture intricate patterns in the data.
- **Versatility:** Widely used for classification, regression, and complex applications like image and speech recognition.
- **Suitability:** Selected for its ability to iteratively learn and improve from the data, making it powerful for handling the complexity of the intrusion detection dataset (Jaiswal, 2024).
- **Configuration parameters:** hidden_layer_sizes=(5,2) this indicates the first hidden layer has 5 neurons and the second hidden layer has 2 neurons. Max_iter=1000 so the algorithm iterates under convergence, or 1000 iterations have reached. Random_state=42 which is basically same as the other model where determines random number generation for weights and bias initialization.

4.4. Program follows.

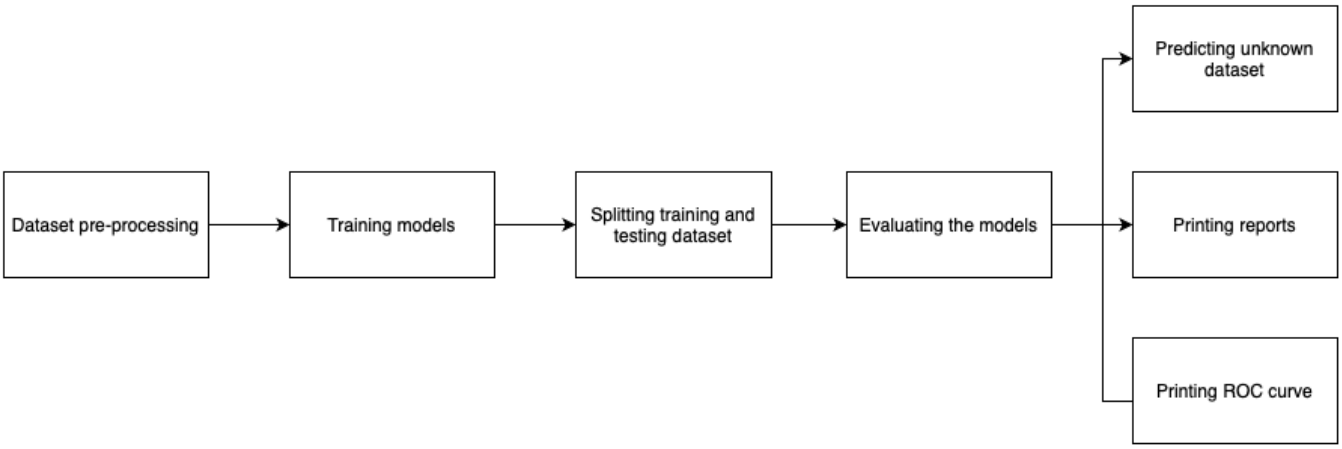

Figure 7 Code flowchart.

Initially, the dataset undergoes pre-processing, after which it is used to train the selected models. The dataset is subsequently divided into training and testing subsets for evaluation purposes. These models are then assessed based on accuracy and other pertinent metrics. Following the evaluation, classification reports and ROC curves are generated to visualize performance. Finally, the trained models are employed to make predictions on an unknown dataset, demonstrating their practical applicability.

5. Output Analysis

To analyse our model's efficiency, we will evaluate several key metrics: accuracy, precision, recall, and F1-score.

- **Accuracy** measures the overall correctness of the model by calculating the ratio of correctly predicted instances to the total instances. It provides a general idea of how well the model performs across all classes.
- **Precision** assesses the model's ability to correctly identify positive instances out of the total predicted positives. High precision indicates a low false positive rate, which is particularly important in scenarios where false alarms are costly.
- **Recall**, also known as sensitivity or true positive rate, evaluates the model's capability to detect all actual positive instances within the dataset. High recall is crucial in contexts where missing a positive instance is highly detrimental.
- **F1-score** is the harmonic mean of precision and recall, offering a balanced measure that accounts for both false positives and false negatives. This metric is particularly useful when dealing with imbalanced datasets, as it provides a single number to evaluate the model's performance.

These metrics collectively provide a comprehensive understanding of the model's performance, enabling us to identify strengths and potential areas for improvement. By scrutinizing these variables, we ensure that our model is not only accurate but also reliable and effective in real-world applications.

5.1. Unprocessed dataset

Here is the output that is obtained from using dataset that does not have any pre-processing techniques applied to it.

5.1.1. Accuracy

Model Accuracy	**Model Accuracy**
Logistic Regression	0.979
Random Forest	0.994
SVC	0.985
K-Nearest Neighbours	0.981
MLP Classifier	0.980

5.1.2. Precision

Model	**DictionaryBruteForce**	**Mirai-greip_flood**	**Recon-OSScan**
Logistic Regression	1.00	1.00	0.86
Random Forest	1.00	1.00	0.95
SVC	0.73	1.00	0.90
K-Nearest Neighbours	0.38	1.00	0.92
MLP Classifier	1.00	1.00	0.88

5.1.3. Recall

Model	**DictionaryBruteForce**	**Mirai-greip_flood**	**Recon-OSScan**
Logistic Regression	0.20	0.99	0.99
Random Forest	0.59	1.00	1.00
SVC	0.18	1.00	0.99
K-Nearest Neighbours	0.36	1.00	0.93
MLP Classifier	0.18	0.99	0.98

5.1.4. F1-score

Model	**DictionaryBruteForce**	**Mirai-greip_flood**	**Recon-OSScan**
Logistic Regression	0.34	0.99	0.92
Random Forest	0.74	1.00	0.98
SVC	0.29	1.00	0.94
K-Nearest Neighbours	0.37	1.00	0.92
MLP Classifier	0.31	0.99	0.92

5.1.5. ROC Curve

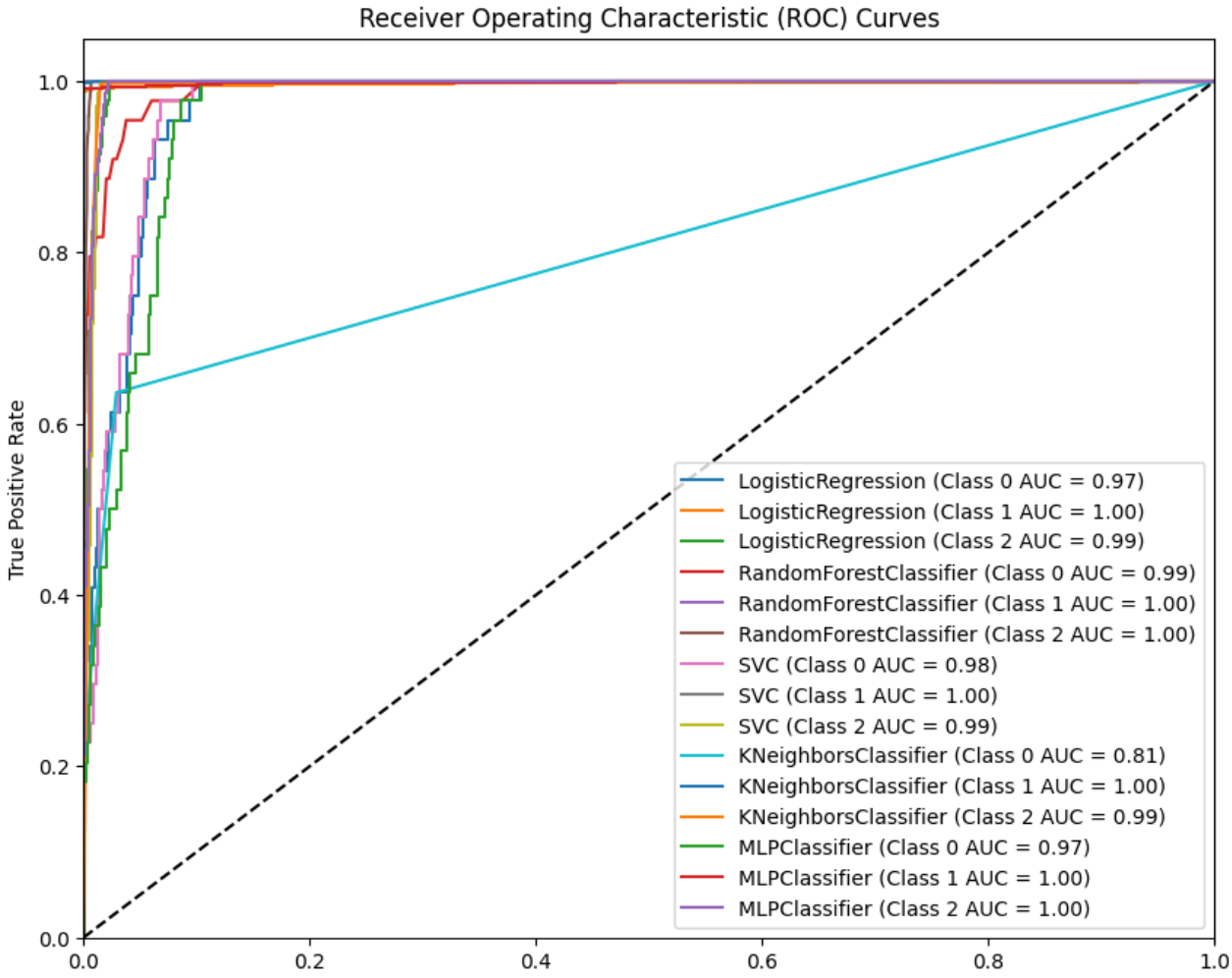

Figure 8 Receiver operating curve using unprocessed dataset.

5.2. Pre-Processed dataset

Here is the output that is obtained from using dataset that does have pre-processing techniques applied to it.

5.2.1. Accuracy

Model	Accuracy
Logistic Regression	0.9937
Random Forest	0.9973
SVC	0.9937
K-Nearest Neighbours	0.9945
MLP Classifier	0.9937

5.2.2. Precision

Model	Dictionary Brute Force	Mirai-greip_flood	Recon-OSScan
Logistic Regression	1.00	1.00	0.86
Random Forest	1.00	1.00	0.93
SVC	1.00	1.00	0.82
K-Nearest Neighbours	0.83	1.00	0.85
MLP Classifier	1.00	1.00	0.86

5.2.3. Recall

Model	Dictionary Brute Force	Mirai-greip_flood	Recon-OSScan
Logistic Regression	0.24	1.00	0.97
Random Forest	0.71	1.00	0.99
SVC	0.18	1.00	1.00
K-Nearest Neighbours	0.29	1.00	0.99
MLP Classifier	0.29	1.00	0.96

5.2.4. F1-score

Model	Dictionary Brute Force	Mirai-greip_flood	Recon-OSScan
Logistic Regression	0.38	1.00	0.91
Random Forest	0.83	1.00	0.95
SVC	0.30	1.00	0.90
K-Nearest Neighbours	0.43	1.00	0.91
MLP Classifier	0.45	1.00	0.91

5.2.5. ROC Curve

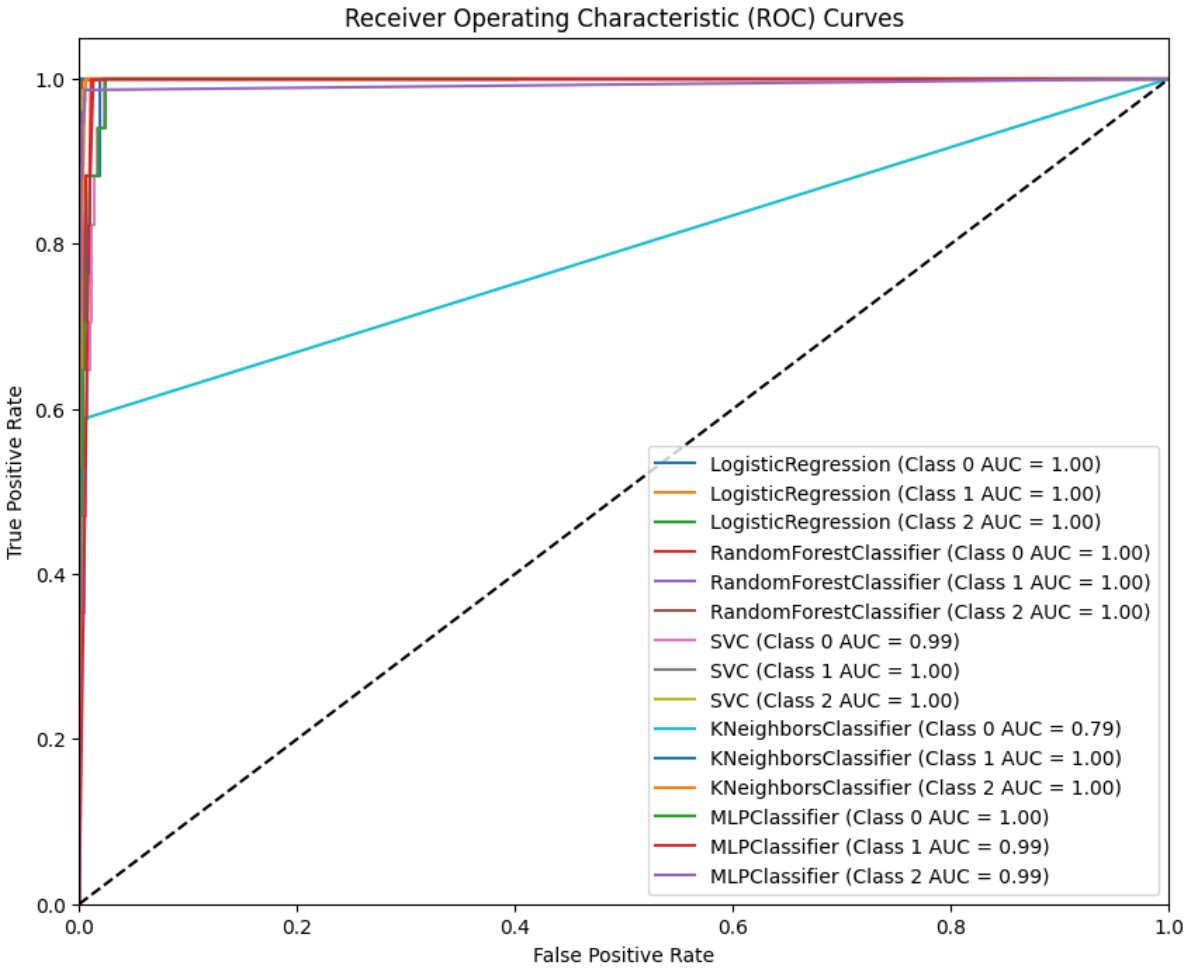

Figure 9 Receiver operating curve using pre-processed dataset.

5.3. Result analysis

The comparative analysis of model performance between the unprocessed and processed datasets reveals substantial improvements in the effectiveness of our intrusion detection models, highlighting the benefits of data pre-processing. For instance, the Logistic Regression model's accuracy surged from approximately 97.92% with the unprocessed dataset to 99.37% following data pre-processing. This substantial increase indicates a marked enhancement in the model's ability to correctly classify instances, thereby enhancing its reliability.

A closer examination of the classification metrics reveals that precision and recall have also improved significantly across multiple models. The Random Forest Classifier, for example, demonstrated an accuracy of 99.73% with the processed dataset, compared to 99.42% with the unprocessed one. This indicates not only a higher correct classification rate but also a more nuanced understanding of the data, allowing the model to distinguish between various types of attacks more effectively.

Moreover, precision and recall rates for critical attack classes, such as the Mirai-greip flood, reached 100% in the processed dataset. This indicates that the model is effectively identifying all relevant instances of this attack type while minimizing false positives. Such precision is essential in the context of intrusion detection systems (IDS), as it helps prevent alert fatigue among security analysts who must sift through numerous alerts.

The F1 score, which combines precision and recall into a single metric, further underscores these enhancements. For instance, the F1 scores for models using the processed dataset consistently outperformed those using the unprocessed dataset, reflecting a more balanced performance in correctly identifying both positive and negative instances. This balance is crucial for ensuring that the IDS not only detects intrusions but does so with a high degree of accuracy and reliability.

Overall, the enhancements observed from the processed dataset underscore the critical role of data pre-processing in the effectiveness of intrusion detection models. By improving classification accuracy, precision, recall, and F1 scores, the processed dataset allows for a more robust threat detection capability. This ultimately leads to more reliable cybersecurity measures, reducing the risk of undetected intrusions and enhancing overall system security. These improvements position the **RANDOM FOREST CLASSIFIER AS THE MOST EFFECTIVE MODEL**, better equipped to protect networks against evolving cybersecurity threats and ensure a more proactive defence strategy.

5.4. ROC Curve analysis

For plotting ROC curves, we have transformed the label from Mirai-greip_flood, Recon-OSScan and DictionaryBruteForce to Class 0, Class 1 and Class 2 respectively. The analysis of the ROC curves for various models trained on both unprocessed and pre-processed datasets reveals significant insights into the impact of data preparation on model performance. For the unprocessed dataset, models like Logistic Regression, Random Forest, SVM, and MLP exhibited strong performance with high AUC scores, though Logistic Regression and SVM showed slight vulnerabilities in distinguishing Class 0. KNN, however, struggled more noticeably, particularly with Class 0, indicating difficulties in handling unprocessed data.

In contrast, the pre-processed dataset led to a remarkable improvement in performance for most models. Logistic Regression and Random Forest achieved perfect AUC scores across all classes, highlighting the effectiveness of pre-processing in enhancing class separability. SVM also showed improved performance, particularly for Class 0, demonstrating better discrimination capabilities. KNN, however, did not benefit as much from pre-processing, with its performance for Class 0 slightly declining. MLP maintained its strong performance, with minor improvements, underscoring its robustness. Overall, the pre-processed dataset provided better results, emphasizing the critical role of data pre-processing in optimizing model accuracy and reliability.

5.5. Kaggle Result analysis

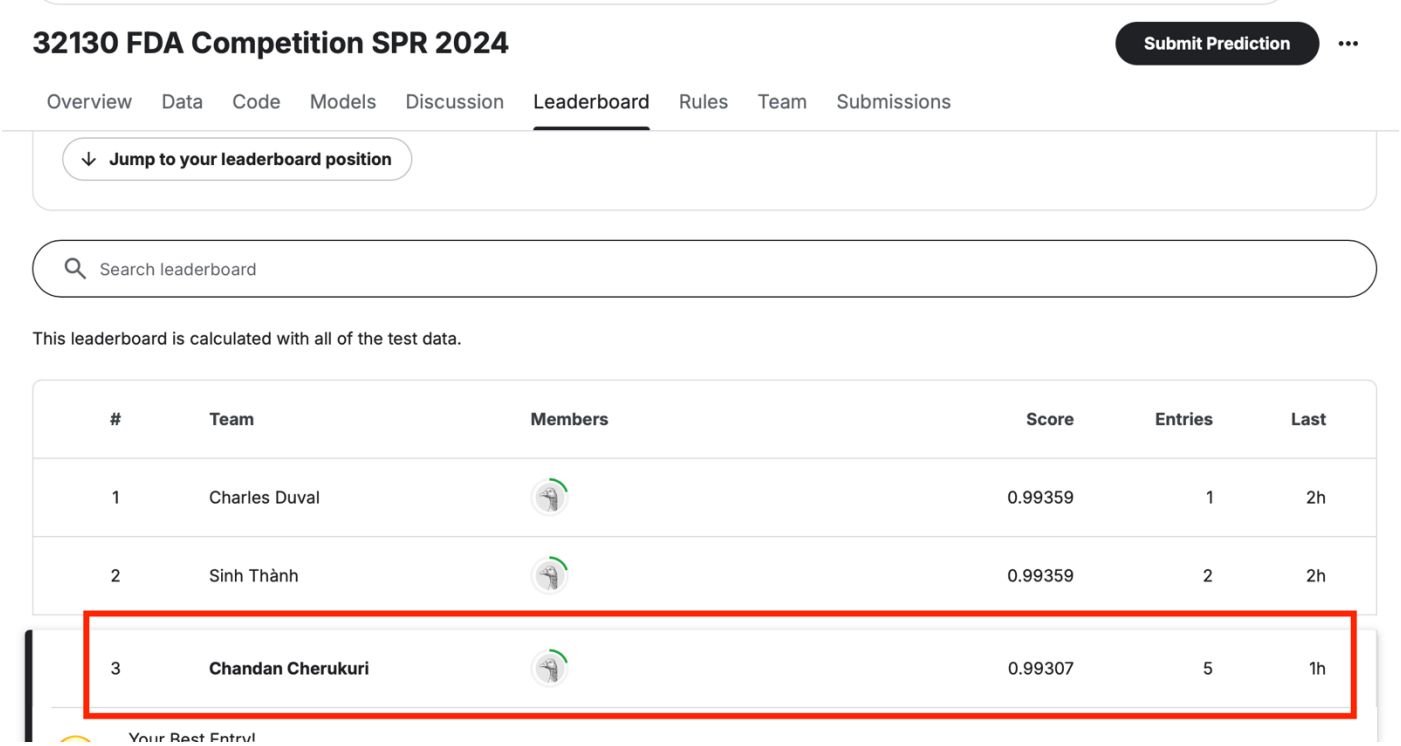

Figure 10 Kaggle leader board.

Upon examining the prediction outputs from both the unprocessed and processed datasets, it is evident that THE **UNPROCESSED DATASET PROVIDED SUPERIOR PREDICTIONS ON THE UNKNOWN DATASET COLUMNS.** This observation suggests that, despite the processed dataset demonstrating higher accuracy within the controlled testing environment, it did not surpass the performance of the unprocessed dataset in practical application. A plausible explanation for this discrepancy is that the unprocessed dataset retained outliers, which, in this context, were likely indicative of intrusions. Consequently, the unprocessed dataset achieved a more effective detection rate, thereby yielding a higher efficiency score.

6. Conclusion

In conclusion, this assignment has successfully demonstrated the critical importance of data pre-processing and model selection in the design of an effective intrusion detection system (IDS). Through detailed analysis and application of various machine learning techniques, it was observed that the accuracy, precision, recall, and F1 scores improved significantly when pre-processing techniques such as outlier removal and standardization were applied to the dataset. These steps ensured a more reliable and robust classification of network intrusions.

The Random Forest Classifier emerged as the most effective model, achieving the highest accuracy, and demonstrating a nuanced understanding of the dataset, which is crucial for correctly identifying different types of intrusions. Additionally, the improvements in ROC curves further emphasized the importance of pre-processing in enhancing class separability, thereby improving the model's overall performance.

Ultimately, the results underscore the necessity of careful data preparation and the strategic selection of machine learning algorithms in the development of reliable IDS solutions. These findings not only enhance the effectiveness of the current models but also provide a solid foundation for future improvements in network security measures.

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