

Machine Learning pour la cybersécurité

Leclerc_SXXI

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Présentation du jeu de données

- Hardware in the loop (HIL)
 - Network Dataset
 - Physical Dataset

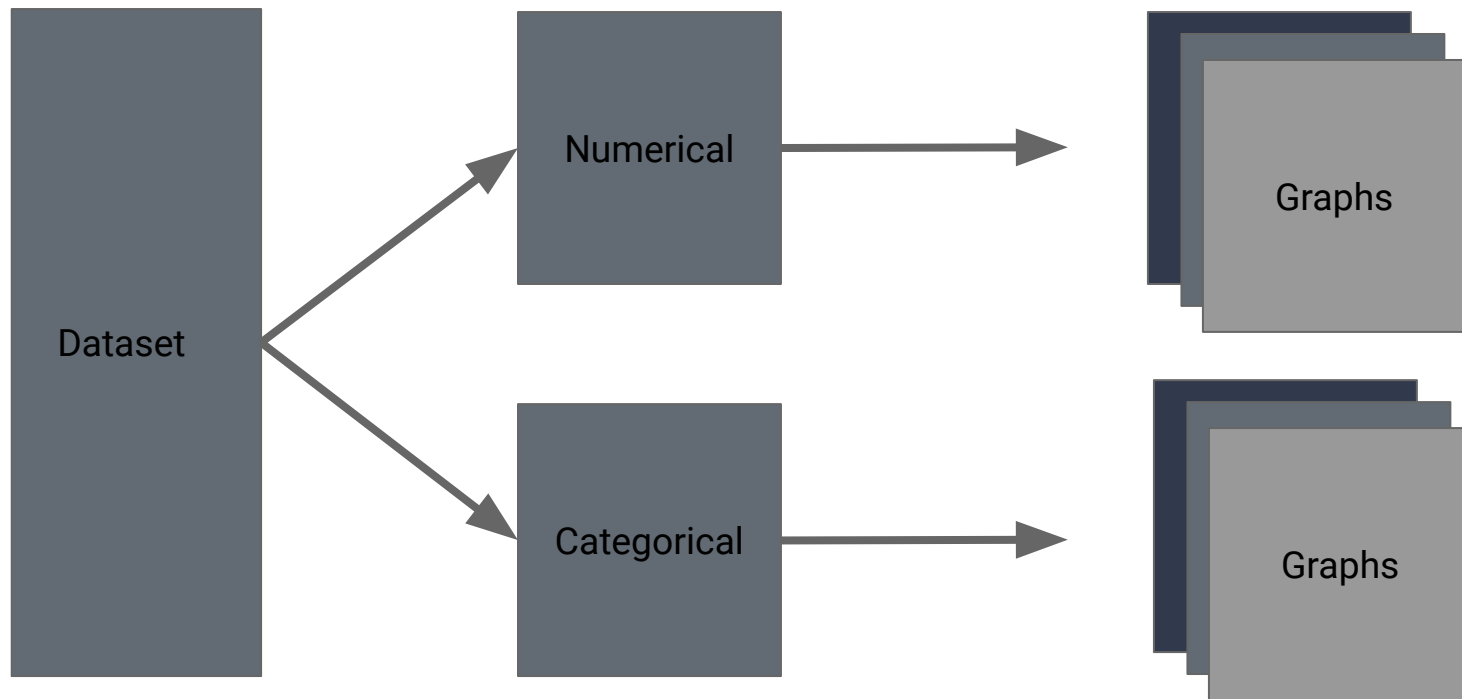
| N° | Features | Description |
|----|-----------------|-------------------------------------------------------------------------|
| 1 | Time | Date of acquisition |
| 2 | Src IP address | Source IP address |
| 3 | Dst IP address | Destination IP address |
| 4 | Src MAC address | Source MAC address |
| 5 | Dst MAC address | Destination MAC address |
| 6 | Src Port | Source port |
| 7 | Dst port | Destination port |
| 8 | Proto | Protocol |
| 9 | TCP flags | CWR ECN URG ACK PSH RST SYN FIN flags |
| 10 | Payload size | Size of packet payload |
| 11 | MODBUS code | MODBUS function code |
| 12 | MODBUS value | MODBUS response value |
| 13 | num_pkts_src | Number of packets of the same source address in the last 2 seconds |
| 14 | num_pkts_dst | Number of packets of the same destination address in the last 2 seconds |

Network Dataset

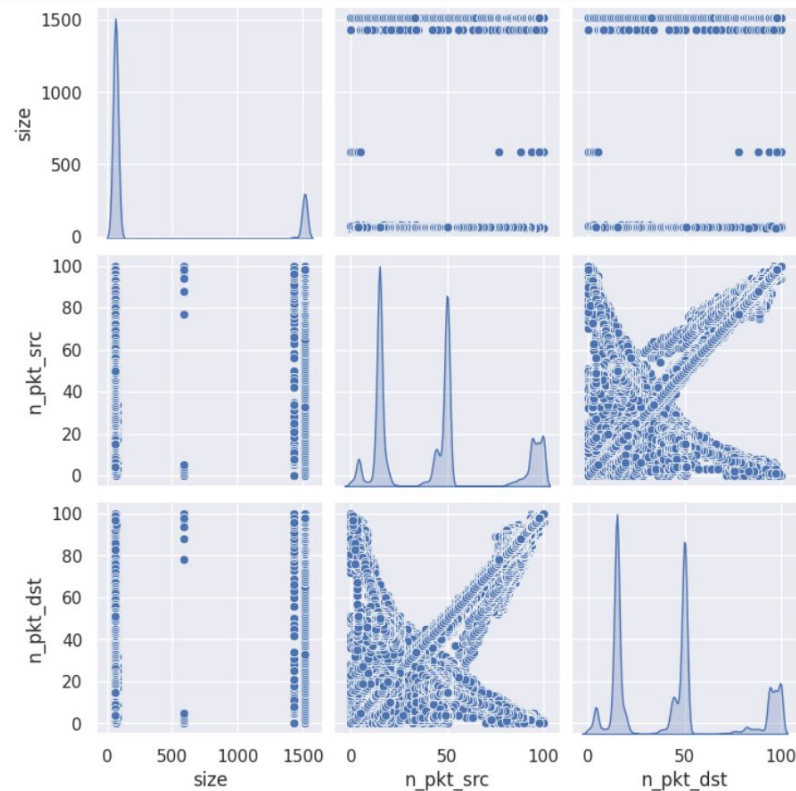
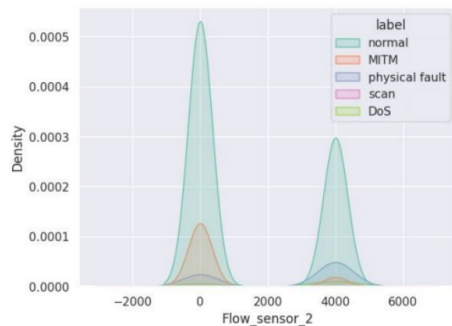
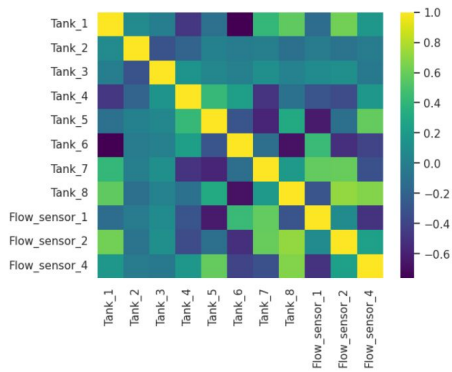
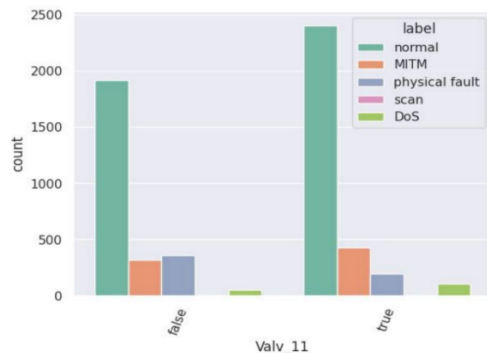
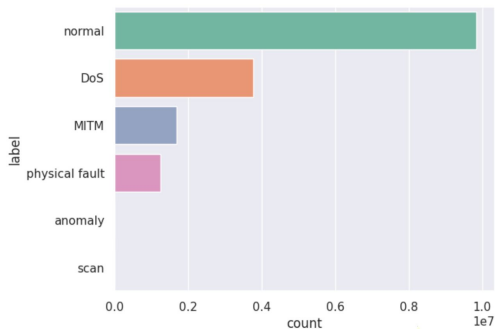
| N° | Features | Description | N° | Features | Description |
|----|---------------|---------------------------------|----|----------|----------------------------|
| 1 | Time | Datetime of acquisition | 22 | Valv_3 | State of solenoid valve 3 |
| 2 | Tank_1 | Pressure sensor value of tank 1 | 23 | Valv_4 | State of solenoid valve 4 |
| 3 | Tank_2 | Pressure sensor value of tank 2 | 24 | Valv_5 | State of solenoid valve 5 |
| 4 | Tank_3 | Pressure sensor value of tank 3 | 25 | Valv_6 | State of solenoid valve 6 |
| 5 | Tank_4 | Pressure sensor value of tank 4 | 26 | Valv_7 | State of solenoid valve 7 |
| 6 | Tank_5 | Pressure sensor value of tank 5 | 27 | Valv_8 | State of solenoid valve 8 |
| 7 | Tank_6 | Pressure sensor value of tank 6 | 28 | Valv_9 | State of solenoid valve 9 |
| 8 | Tank_7 | Pressure sensor value of tank 7 | 29 | Valv_10 | State of solenoid valve 10 |
| 9 | Tank_8 | Pressure sensor value of tank 8 | 30 | Valv_11 | State of solenoid valve 11 |
| 10 | Pump_1 | State of pump 1 | 31 | Valv_12 | State of solenoid valve 12 |
| 11 | Pump_2 | State of pump 2 | 32 | Valv_13 | State of solenoid valve 13 |
| 12 | Pump_3 | State of pump 3 | 33 | Valv_14 | State of solenoid valve 14 |
| 13 | Pump_4 | State of pump 4 | 34 | Valv_15 | State of solenoid valve 15 |
| 14 | Pump_5 | State of pump 5 | 35 | Valv_16 | State of solenoid valve 16 |
| 15 | Pump_6 | State of pump 6 | 36 | Valv_17 | State of solenoid valve 17 |
| 16 | Flow_sensor_1 | Flow sensor value 1 | 37 | Valv_18 | State of solenoid valve 18 |
| 17 | Flow_sensor_2 | Flow sensor value 2 | 38 | Valv_19 | State of solenoid valve 19 |
| 18 | Flow_sensor_3 | Flow sensor value 3 | 39 | Valv_20 | State of solenoid valve 20 |
| 19 | Flow_sensor_4 | Flow sensor value 4 | 40 | Valv_21 | State of solenoid valve 21 |
| 20 | Valv_1 | State of solenoid valve 1 | 41 | Valv_22 | State of solenoid valve 22 |
| 21 | Valv_2 | State of solenoid valve 2 | | | |

Physical Dataset Features

Analyse exploratoire des données

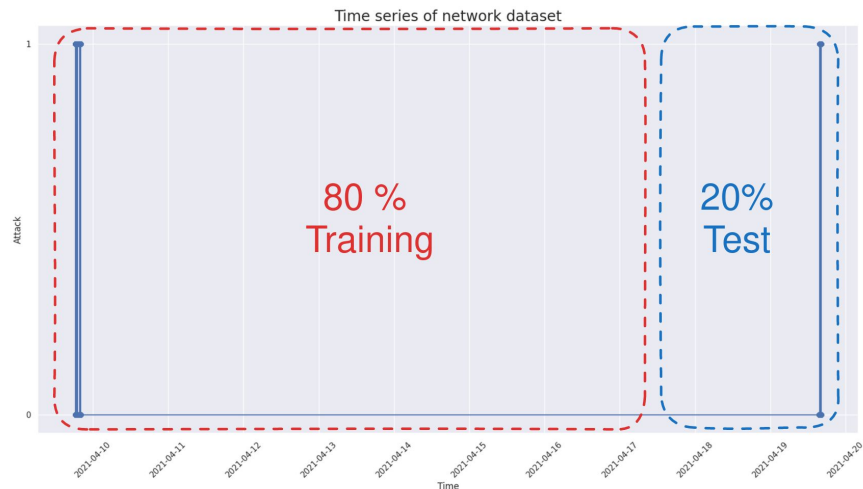


Analyse exploratoire des données



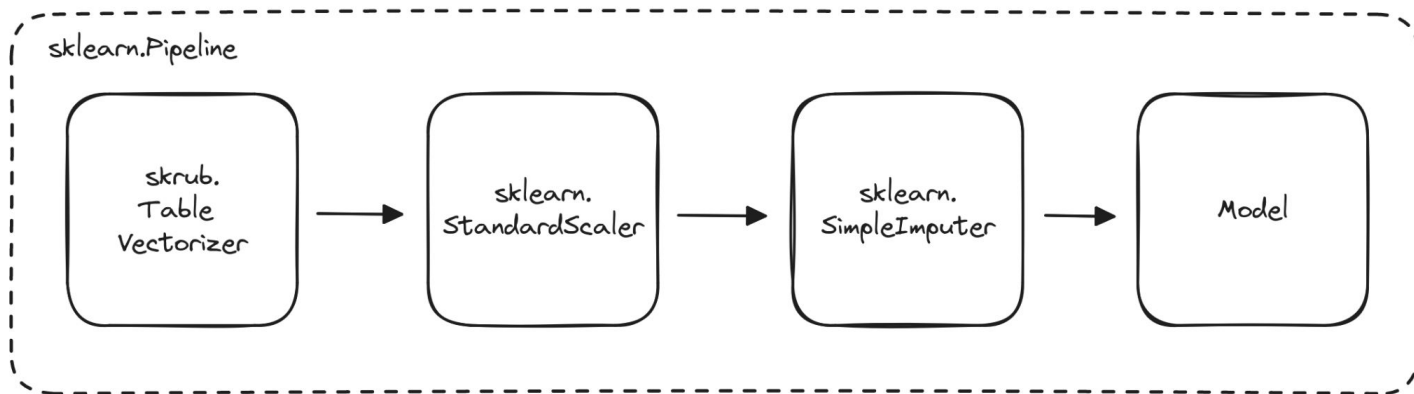
Traitement des données

- Apprentissage déséquilibré
 - Undersampling
 - Balanced RandomForestClassifier
 - Oversampling (SMOTE)
- Séparation temporelle
 - Éviter les biais sur les prédictions temporelles

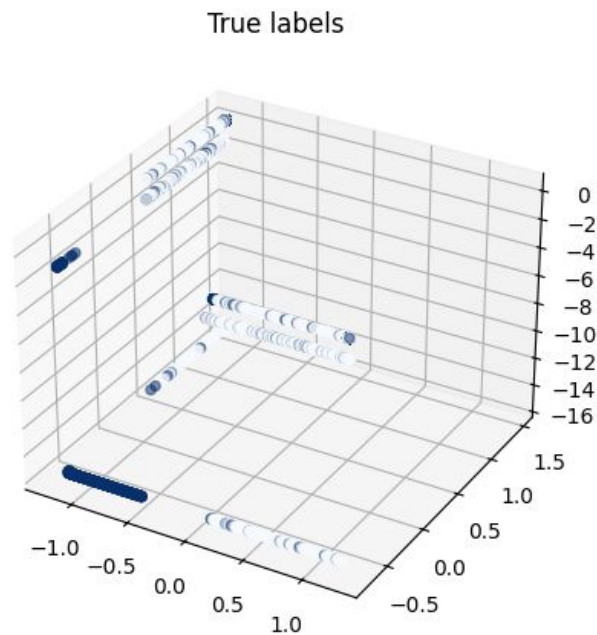
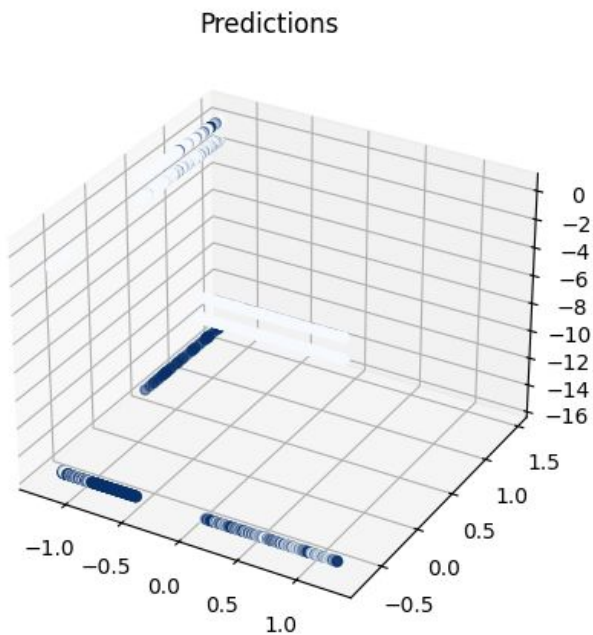


Prétraitement et transformation

- Échantillonnage du jeu de données network
- TableVectorizer → OneHotEncoder
- Imputation des valeurs manquantes
- Scaling des features numériques



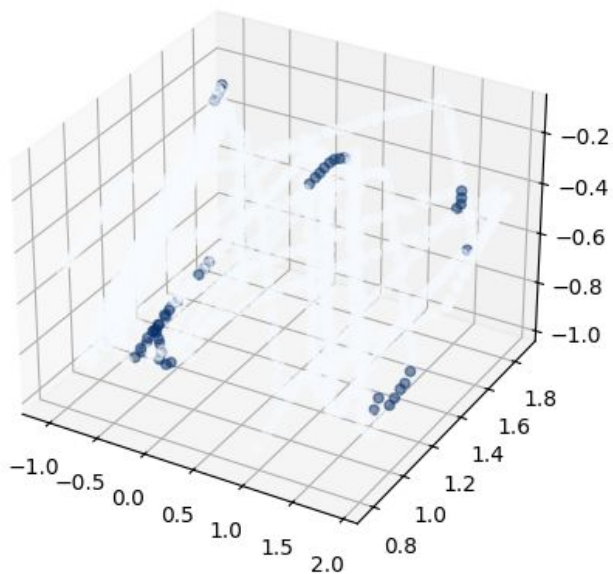
LocaloutlierFactor et IsolationForest



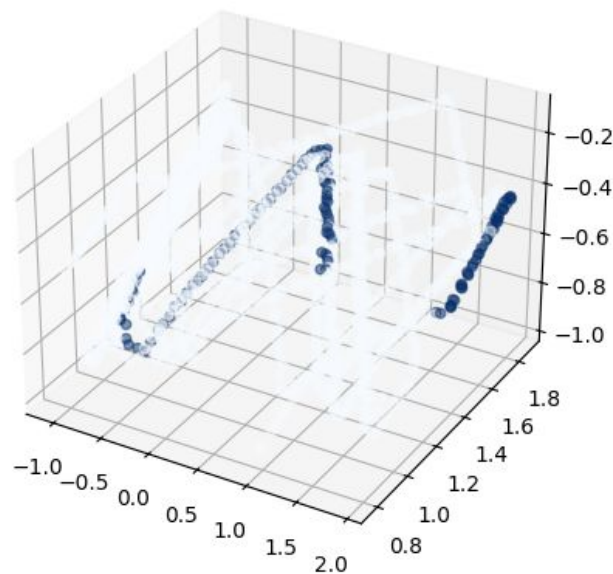
LocalOutlierFactor - network Dataset - contamination 0.01

LocaloutlierFactor et IsolationForest

Predictions

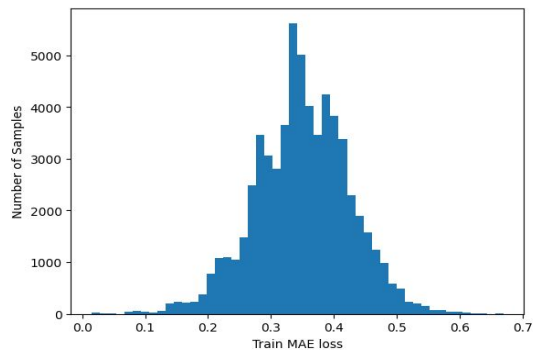


True labels

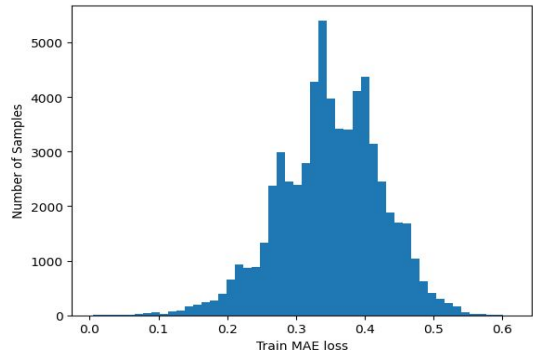


IsolationForest - physical Dataset - contamination 0.05

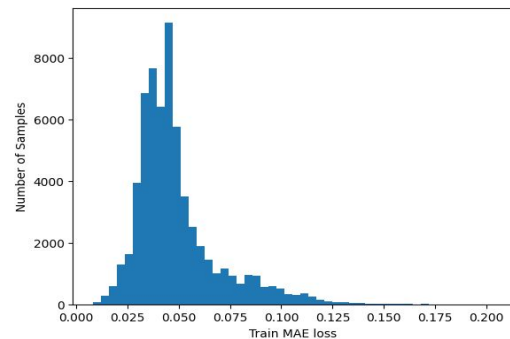
LSTM



(a) Histogram of train MAE loss for n pkt dst

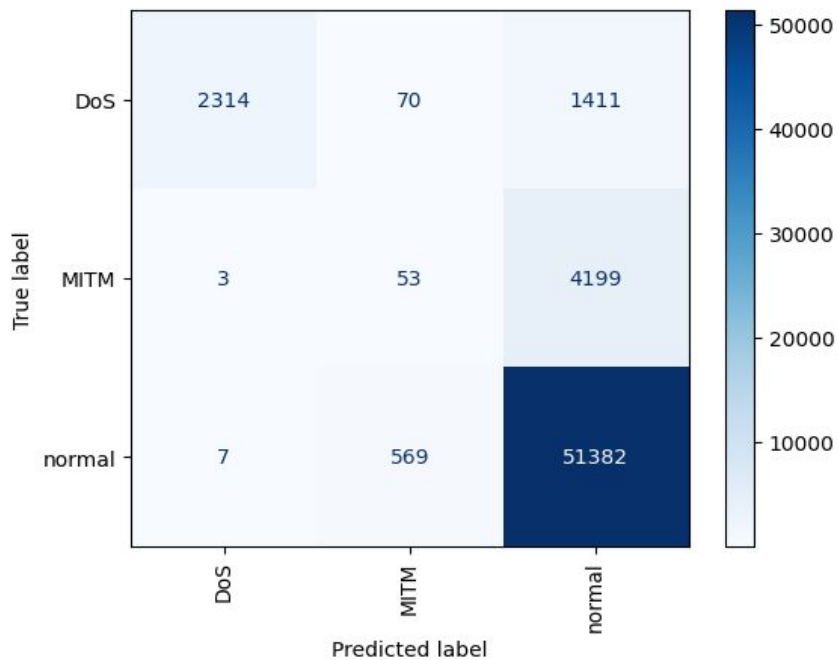


(b) Histogram of train MAE loss for n pkt src

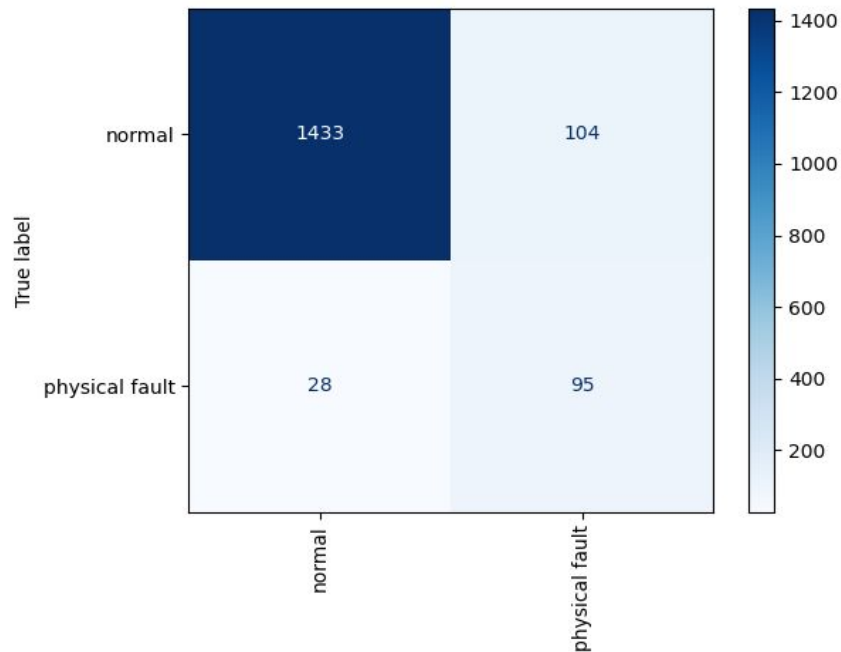


(c) Histogram of train MAE loss for size

DecisionTree

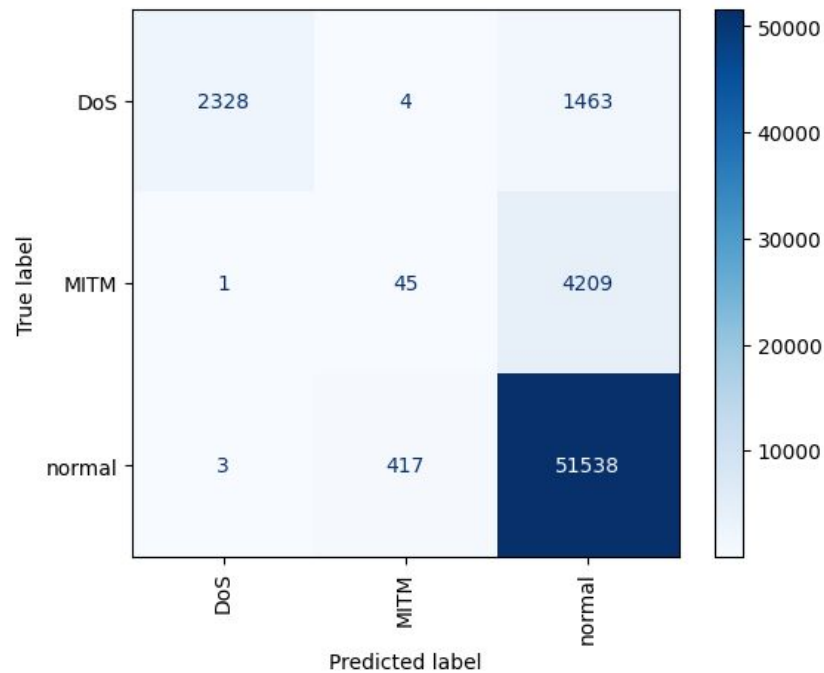


network dataset

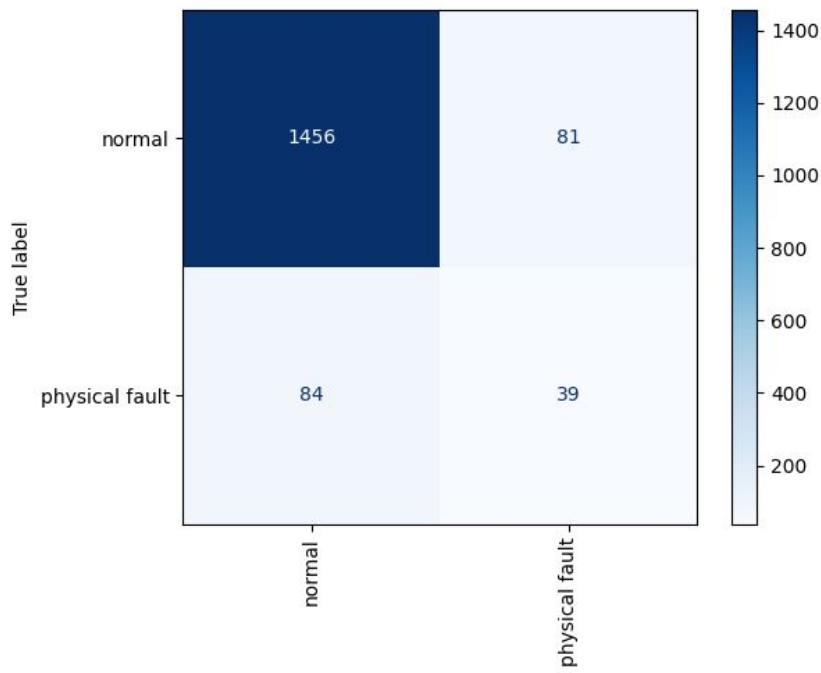


physical dataset

RandomForest

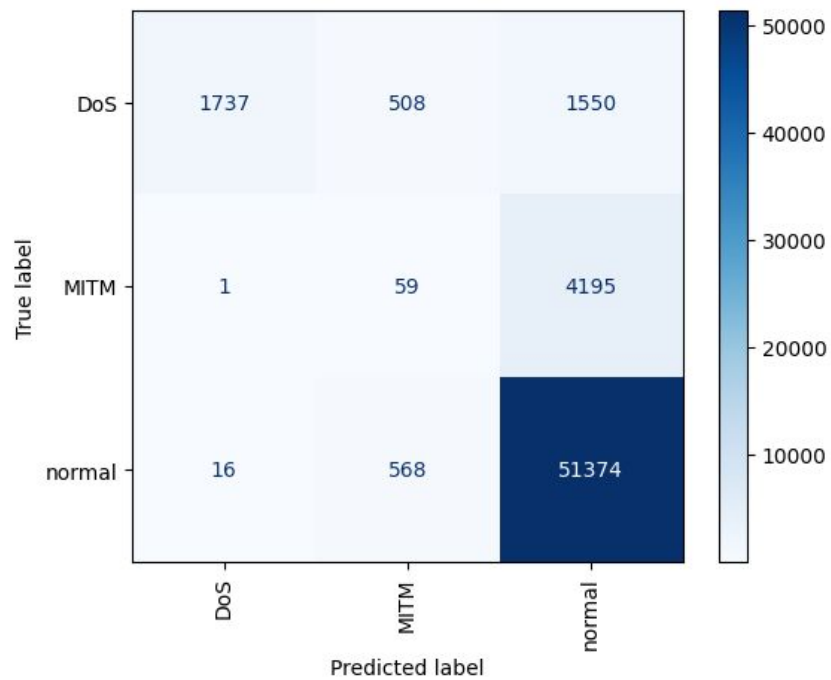


network dataset

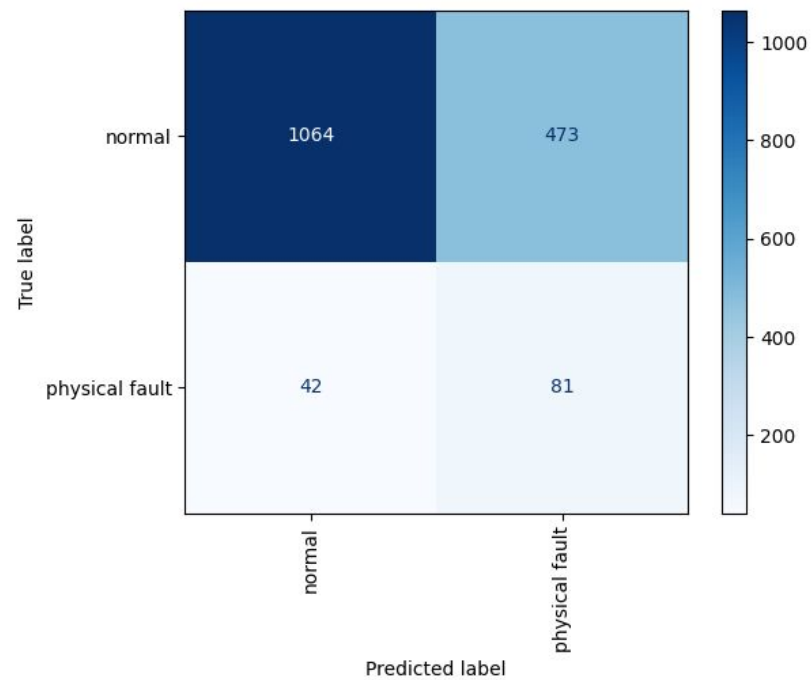


physical dataset

LinearSVM

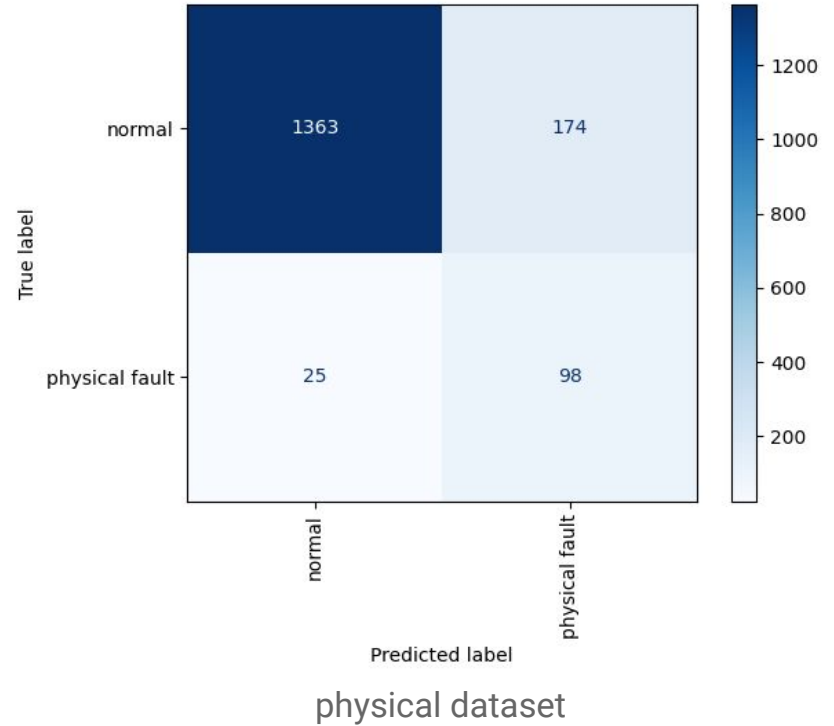
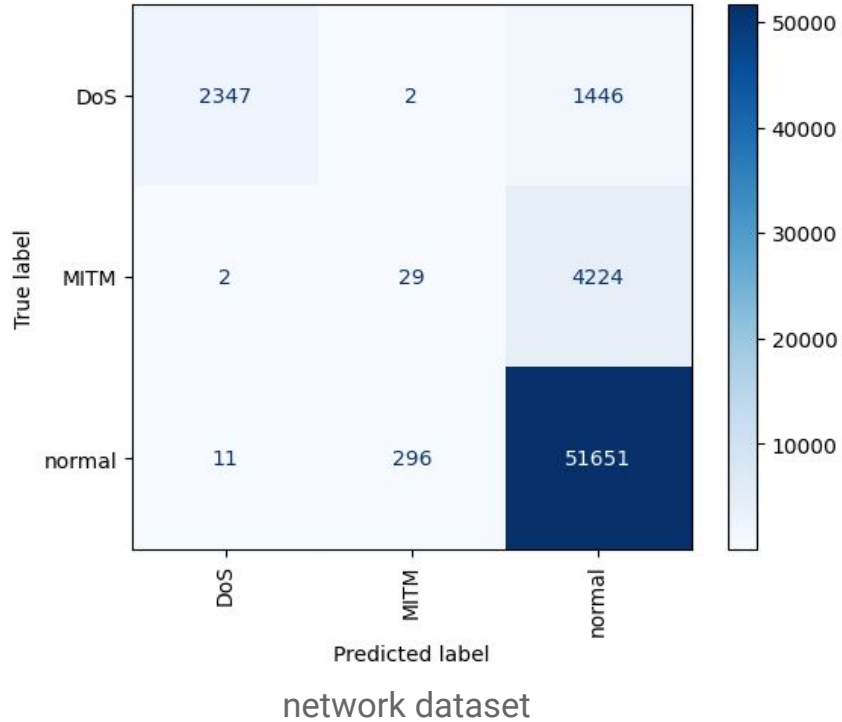


network dataset

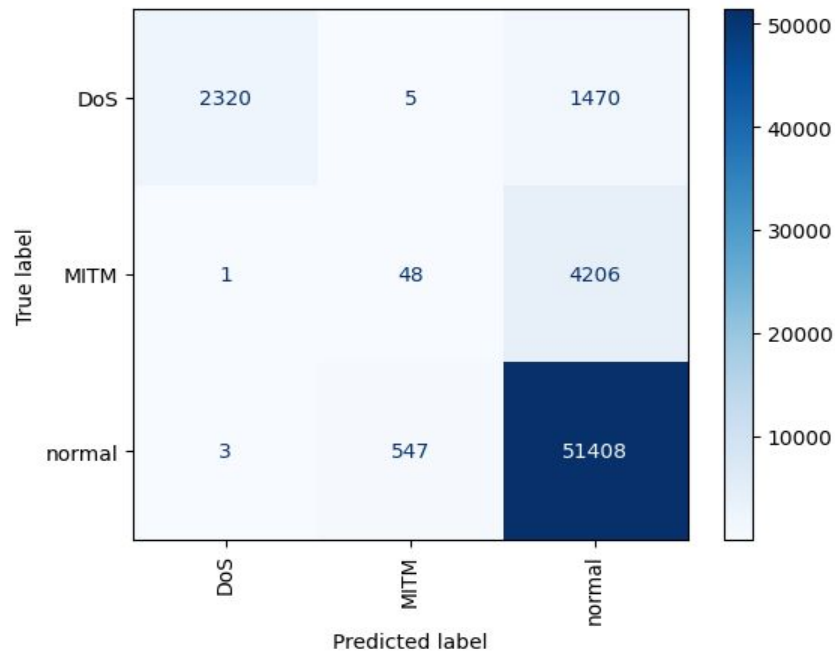


physical dataset

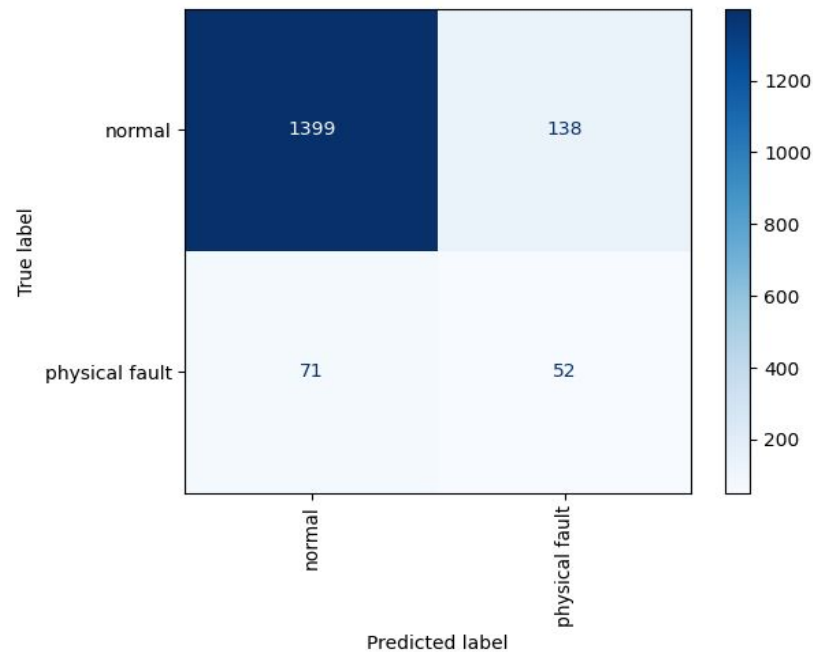
XGBoost



BalancedRandomForest



network dataset



physical dataset

Résultat des modèles – Network Dataset

| | Accuracy | Balanced Accuracy | Precision (weighted) | Recall (weighted) | F1 Score (weighted) | MCC |
|------------------------|-------------|-------------------|----------------------|-------------------|---------------------|-------------|
| Decision Tree | <u>0.90</u> | 0.55 | <u>0.85</u> | <u>0.90</u> | <u>0.87</u> | <u>0.49</u> |
| Random Forest | <u>0.90</u> | 0.54 | <u>0.85</u> | <u>0.90</u> | <u>0.87</u> | 0.47 |
| Balanced Random Forest | <u>0.90</u> | 0.54 | <u>0.85</u> | <u>0.90</u> | <u>0.87</u> | 0.46 |
| LinearSVC | 0.89 | 0.49 | 0.84 | 0.89 | 0.86 | 0.39 |
| XGBoost | <u>0.90</u> | 0.54 | <u>0.85</u> | <u>0.90</u> | <u>0.87</u> | 0.48 |
| Local Outlier Factor | 0.86 | 0.56 | 0.82 | 0.86 | 0.82 | 0.19 |
| Isolation Forest | 0.86 | <u>0.65</u> | <u>0.85</u> | 0.87 | 0.86 | 0.35 |

Résultat des modèles – Physical Dataset

| | Accuracy | Balanced Accuracy | Precision (weighted) | Recall (weighted) | F1 Score (weighted) | MCC |
|------------------------|-------------|-------------------|----------------------|-------------------|---------------------|-------------|
| Decision Tree | <u>0.92</u> | <u>0.85</u> | <u>0.94</u> | 0.92 | <u>0.93</u> | <u>0.56</u> |
| Random Forest | 0.90 | 0.63 | 0.90 | 0.90 | 0.90 | 0.26 |
| Balanced Random Forest | 0.87 | 0.66 | 0.90 | 0.87 | 0.89 | 0.27 |
| LinearSVC | 0.69 | 0.67 | 0.90 | 0.69 | 0.76 | 0.19 |
| XGBoost | 0.88 | 0.84 | <u>0.94</u> | 0.88 | 0.90 | 0.48 |
| Local Outlier Factor | <u>0.92</u> | 0.52 | 0.89 | <u>0.93</u> | 0.89 | 0.15 |
| Isolation Forest | <u>0.92</u> | 0.50 | 0.87 | 0.89 | 0.86 | 0.03 |

Conclusion

- Taux de détection élevé pour les attaques DoS avec un taux minimal de **faux positifs**.
- **Détection des attaques MITM** peut nécessiter des caractéristiques supplémentaires.
- Le **prétraitement** à l'impact le plus important sur le modèle.
- Le traitement des **déséquilibres** des classes a un impact considérable sur les résultats du modèle
- Un modèle simple, comme le classificateur d'arbre de décision, présente de bonnes performances. **Recommandation XGBoost pour l'overfitting**.

Demo