Abstract

Industrial Internet of Things (IIoT) networks have become an increasingly attractive target of cyberattacks. Powerful Machine Learning (ML) models have recently been adopted to implement Network Intrusion Detection Systems (NIDSs), which can protect IIoT networks. For the successful training of such ML models, it is important to select the right set of data features, which maximise the detection accuracy as well as computational efficiency. This paper provides an extensive analysis of the optimal feature sets in terms of the importance and predictive power of network attacks. Three feature selection algorithms; chi-square, information gain and correlation have been utilised to identify and rank data features. The features are fed into two ML classifiers; deep feed-forward and random forest, to measure their attack detection accuracy. The experimental evaluation considered three NIDS datasets: UNSW-NB15, CSE-CIC-IDS2018, and ToN-IoT in their proprietary flow format. In addition, the respective variants in NetFlow format were also considered, i.e., NF-UNSW-NB15, NF-CSE-CIC-IDS2018, and NF-ToN-IoT. The experimental evaluation explored the marginal benefit of adding features one-by-one. Our results show that the accuracy initially increases rapidly with the addition of features, but converges quickly to the maximum achievable detection accuracy. Our results demonstrate a significant potential of reducing the computational and storage cost of NIDS while maintaining near-optimal detection accuracy. This has particular relevance in IIoT systems, with typically limited computational and storage resource.

Keywords: Feature Selection, IIoT, Machine Learning, Network Intrusion Detection Systems

1. Introduction

Industrial Internet of Things (IIoT) is the application of digital objects such as sensors in the industrial sector [1]. It enables industries to operate efficiently and reliably using advanced digital technologies such as machine-to-machine communication and Artificial Intelligence (AI). IIoT integrates information technology with operational technology to provide industries with automation and optimisation capabilities. It aims to improve the communication, quality, productivity, and efficiency of industrial systems. Deployed sensors collect real-time information to help organisations
in their decision making processes. Machines are equipped with AI tools to efficiently deliver and automate industrial tasks. While the adoption of IIoT can empower the industrial sector, having defensive security strategies in place is an ongoing research issue [2]. IIoT attracts new kinds of challenges due to the integration of the physical and digital worlds, where the cost of error can be devastating, such as operational disruption and financial loss. The existence of a large number of deployed endpoints provides an increased attack surface for malicious actors to gain entry into industrial systems. A notorious attack example is the Ukrainian power grid in December 2015 [3], where attackers gained remote access to the grid’s control unit and disrupted power to over 230,000 users. Another example is the deployment of the WannaCry ransomware into the IIoT network of a Taiwanese chip manufacturer in 2018 [4] that resulted in damages of approximately $170 million. Therefore, with increased dependence on digitalisation and automation, industrial organisations are looking for enhanced methods for securing their IIoT networks.

Network Intrusion Detection Systems (NIDSs) are implemented in IIoT networks to preserve the three security principles of information systems; confidentiality, integrity, and availability [5]. They scan and analyse network traffic to detect signs and patterns that indicate a potential attack. Traditional types of NIDSs aim to match incoming traffic signatures to a predetermined list of known malicious signatures. This usually leads to a high Detection Rate (DR) against known attacks. However, these systems have been proven unreliable against new and previously unseen attacks (zero-day attacks), or variants of existing attacks [6]. AI and in particular Machine Learning (ML), has gained increasing attention over the past few years, mainly due to the increased power of ML models and algorithms, combined with the increased availability of data and computation power. ML-based NIDSs represent an emerging technology for detecting network traffic that represents malicious activity on a target network. ML has been successfully adopted by researchers for the development of more advanced NIDS technology, achieving a promising attack detection performance [7]. Supervised ML aims to extract and learn complex security events from labelled data samples. However, obtaining labelled datasets from real-world production networks is extremely challenging due to a number of practical and privacy issues. Therefore, researchers have created synthetic NIDS datasets that are typically generated in controlled test-bed environments, where data labels for both benign and attack traffic can reliably and easily be added.

Feature selection is a critical step in building an efficient ML-based network attack detection model. A smaller set of features can be expected to result in a more efficient collection and storage which is necessary for a high-speed IIoT network environment [8]. In other words, the performance of ML-based NIDSs depends on the quality and integrity of the data used to train and evaluate the ML models. This paper aims to evaluate the feature importance of six publicly available NIDS datasets; UNSW-NB15, NF-UNSW-NB15, ToN-IoT, NF-ToN-IoT, CSE-CIC-IDS2018, and NF-CSE-CIC-IDS2018. Three feature selection algorithms, namely Chi-square (CHI), Information
Gain (IG), and Correlation (COR), have been utilised to identify the top features in each dataset. The features have been fed into two ML classifiers; Deep Feed Forward (DFF) and Random Forest (RF) to evaluate their attack detection performance. The rest of the paper is organised as follows. The related works are discussed in the following section, and the analysis of feature importance in NIDS datasets is explained in Sections. In Section 4, the comprehensive methodological approach adopted in our paper is explained. Finally, the results achieved are represented and discussed in Section 5. The paper’s key contribution is the comprehensive analysis of feature importance across six NIDS datasets and 2 ML-based classifiers. The main findings are: First, a small feature subset can be sufficient to achieve the same detection performance as the full set of features. Secondly, there is a high variability of feature ranking across feature selection algorithms and NIDS datasets. Finally, we demonstrated that certain features, such as the TTL-based features in the UNSW-NB15 dataset, have an unrealistically high predictive power, and they should be removed in order to achieve reliable experimental results.

2. Related Work

In this section, key related works that have aimed to identify the optimal network traffic feature sets in NIDS datasets are discussed. Zhang et al. [9] applied a Deep Feed Forward (DFF) neural network on the UNSW-NB15 dataset, after utilising a denoising AutoEncoder (AE) to identify the ten most representative features. The overall classification accuracy achieved is 98.80%, with a False Alarm Rate (FAR) of 0.57%. However, a relatively low DR of 94.43% and the lack of evaluation using other ML classifiers limits the effectiveness of the proposed optimal feature set.

In [10], the authors explored the effect of performing k-means clustering and adding correlation-based feature selection methods to Naive Bayes (NB) and Decision Tree (DT) classifiers. The aim was to find the optimal subset of features to be utilised for the experiment. The study also found which features contribute the most to the detection of each attack type present in the UNSW-NB15 dataset. The results showed that the correlation-based feature selection method improved the NB model results but had no effect on the DT classifier.

In [11], the authors measured the IG of each feature in the NSL-KDD dataset. The authors select 8 features based on an IG threshold value of 0.40 to potentially increase the accuracy of their ML model. Their proposed hybrid model is designed using J48, Meta Pagging, RF, REPTree, AdaBoostM1, DecisionStump and NB classifiers. The accuracy achieved by the binary classification is 99.81%. The authors also applied the wrapper method [12] to select the best feature subset and the classification accuracy obtained is 98.56% in the multi-class classification case.

In [13], the authors utilised Association Rule Mining (ARM) as a feature selection algorithm to generate the most relevant list of features in the UNSW-NB15 and KDD9 datasets. The ARM method is implemented using the apriori algorithm defined by a set of 100 rules to select 11 features.
for each attack class. The classification is performed by the NB and Expectation-Maximization (EM) models to evaluate the selected features. The study shows that ARM performed well on the KDD99 dataset, however, the classifiers are not able to detect some attack types of the UNSW-NB15 dataset.

In [14], an ensemble feature selection approach has been designed that applies four techniques, i.e., correlation, consistency, IG, and Tanimoto distance [15]. The generated features of four datasets are then combined using a subset combination method depending on how many times the feature is identified by the feature selection methods. The combination of features identified three or more times achieved the best metrics across the datasets. The authors confirmed the reliability of the selected features by conducting an analysis of variance (ANOVA) method.

A-Zewairi et al. [16] applied a DFF on the UNSW-NB15 dataset to measure the effectiveness of the Gedeon method [17] in selecting the important features, which are used in the experiment and listed in the paper, and grouped according to their level of importance. The authors also compared three activation functions (ReLU, tanh, and maxout), each with and without a dropout mode, which showed that the ReLU function without a dropout mode achieved the best results. The best accuracy of 98.99% and FAR of 0.56% is obtained by training the model using the top 20% of the important features.

Mogal et al. [18] applied NB and Logistic Regression (LR) classifiers on the UNSW-NB15 and KDDcup99 datasets, choosing accuracy and prediction time as the defining metrics. They applied two feature selection techniques; Central Point and ARM apriori algorithms to select the most highly ranked features. However, the paper does not mention the number or types of features chosen to train or test the models. Although these feature selection and reduction techniques did not increase the level of accuracy of the classifiers, they notably decreased their prediction times. The best levels of accuracy of 99.94% and 99.96% were obtained using LR on the reduced KDDcup99 dataset and NB on the full feature set of the UNSW-NB15 dataset respectively.

In [19], the authors designed a bidirectional long and short-term memory with a multi-feature layer (B-MLSTM) model to secure IIoT networks from low frequency and multistage attacks. The proposed system learns the attack interval pattern through historical data, using the sequence and stage feature layers to effectively detect attacks at different intervals. A double-layer reverse unit is introduced to update the detection model’s parameters. The proposed scheme has a lower false alarm rate compared with related works on three IIoT datasets.

Overall, extensive research has been done with the aim of identifying the optimal feature sets in different NIDS datasets. However, the experimental methodology of the aforementioned papers requires a presumption of several selection criteria or thresholds, such as a certain feature selection or an ML algorithm, rules of selection and the number of considered feature subsets. The necessity of deciding a predetermined selection method assuming that it would generalise across datasets limits
its reliability due to the differences in datasets [20].

In contrast to prior works, this paper presents a more systematic and more extensive evaluation of NIDS feature sets, considering a significantly larger number of feature subsets and NIDS datasets. Table 1 highlights this by showing the number of ML classifiers, the number of feature selection algorithms, the number of feature sets, and the number of NIDS datasets considered in this paper, compared to the key related works. A key novel aspect and contribution of this paper is the consideration of recently released NIDS datasets (ToN-IoT, NF-UNSW-NB15, NF-ToN-IoT and NF-CSE-CIC-IDS2018), for which no feature set analysis has been published yet.

| Paper                  | No. of ML Models | No. of Feature Selection Algorithms | No. of Considered Feature Subsets | No. of NIDS Datasets |
|------------------------|------------------|-------------------------------------|-----------------------------------|----------------------|
| Zhang et al. [9]       | 1                | 1                                   | 1                                 | 1                    |
| Bagui et al. [10]      | 2                | 1                                   | 1                                 | 1                    |
| Aljawarneg et al. [11] | 7                | 2                                   | 1                                 | 1                    |
| Moustafa et al. [13]   | 2                | 1                                   | 1                                 | 2                    |
| Binbusayyis et al. [13]| 1                | 4                                   | 1                                 | 4                    |
| Mogal et al. [18]      | 2                | 2                                   | 1                                 | 2                    |
| Xinghua et al. [19]    | 1                | N/A                                 | N/A                               | 3                    |
| This paper             | 2                | 3                                   | 8 or 15 depending on dataset      | 6                    |

3. Datasets

An ML-based NIDS learns and extracts the patterns of benign and attack flows present in network traffic. These patterns are learned in terms of data features extracted from network traffic. The performance of an ML-based NIDS is determined by the choice of network traffic features in the design process. Choosing a better feature set leads to a higher-performing ML model and better traffic classification performance. In IIoT networks, devices deployed at the edge might not be equipped with sufficient computational power and storage capacity to extract a large number of network traffic features. Hence, removing redundant and irrelevant features can reduce the computational and storage demand of NIDSs in scenarios with resource-constrained edge devices, such as in the case of IIoT. A careful choice of feature subset can minimise the classification performance loss compared to the case where the full set is used. As is demonstrated in this paper, in some cases, an optimally chosen feature subset can provide even better classification performance than the use of the complete feature set.

Due to privacy and practical concerns in obtaining real-world labelled NIDS datasets, researchers have generated a number of synthetic benchmark NIDS datasets, which have typically been generated
on test-bed networks. These datasets have been widely used for the evaluation of ML-based network traffic classifiers and intrusion detection systems. Current NIDS datasets contain features that have been chosen with the aim of providing relevant predictive power in order to classify the traffic. The feature sets provided to the most relevant NIDS datasets are quite different, due to the different choice of feature extraction tools and design decisions made by the creators of these datasets. In this paper, a comprehensive approach to identifying the feature importance is adopted for the considered NIDS datasets. Unlike other research papers, our approach is not limited to any presumptions made regarding the optimal feature set, as multiple feature selection algorithms, ML classifiers, and a large number of feature subsets are explored. In this paper, six publicly available and recently published NIDS datasets are considered for our experiments. Three of these datasets use a common NetFlow-based [20] feature set. Having a common feature set across different NIDS datasets allows us to gain more direct and generalisable insights into the choice of feature subsets.

- **ToN-IoT** [21] - This is a heterogeneous dataset released by the Cyber Range Lab of the Australian Centre for Cyber Security (ACCS) in 2019. It is a comprehensive dataset that includes the telemetry data of an IIoT network. Several portions of the dataset contain different traces of IIoT services, network traffic, and Operating System (OS) logs. The data was generated using a realistic industrial network testbed. The dataset contains several attack scenarios such as backdoor, DoS, Distributed DoS (DDoS), injection, Man In The Middle (MITM), password, ransomware, scanning and Cross-Site Scripting (XSS). Bro-IDS tool, now called Zeek [22], was utilised to extract 44 network traffic features.

- **NF-ToN-IoT** [20] - This dataset is a variant of the ToN-IoT dataset, but with a different feature set. The goal was to use a common, standard-based feature set for different NIDS datasets. NetFlow was chosen as a basis for this, due to its wide availability in production networks, and eight basic NetFlow fields were selected as NIDS features. In order to create the NF-ToN-IoT dataset, the packet capture (pcap) file of the network part of the original ToN-IoT dataset was converted into NetFlow format using the nprobe [23] tool. This dataset contains the same attack types as the original file, but with a NetFlow based feature set with eight features.

- **UNSW-NB15** [24] - This is a very widely used dataset in the NIDS research community, released in 2015 by the Cyber Range Lab of the ACCS. The authors utilised the IXIA PerfectStorm tool to generate benign traffic. Nine attack scenarios are implemented in a test-bed, i.e., fuzzers, analysis, backdoor, Denial of Service (DoS), exploits, generic, reconnaissance, shellcode and worms. The Argus and Bro-IDS tools were utilised to extract 49 network traffic features.

- **NF-UNSW-NB15** [20] - As in the case of NF-ToN-IoT, the original packet captures (pcaps)
of the UNSW-NB15 dataset were converted into NetFlow format using the nProbe tool to generate a NetFlow-based dataset named NF-UNSW-NB15. The dataset includes eight Netflow features and includes the same nine different attack scenarios as in the original UNSW-NB15 dataset.

- **CSE-CIC-IDS2018** [25] - This is an NIDS dataset released by a project involving the Communications Security Establishment (CSE) & Canadian Institute for Cybersecurity (CIC) in 2018. The testbed is configured with the aim to replicate a realistic organisational network, made up of five departments and a server room consisting of various application servers. Different attack types, such as brute-force, bot, DoS, DDoS, infiltration, and web attacks are conducted on an external network to simulate realistic external attack scenarios. The CICFlowMeter-v3 tool was implemented to extract a total of 77 features to create the dataset.

- **NF-CSE-CIC-IDS2018** [20] - As in the above two NetFlow-based datasets, the pcaps of the CSE-CIC-IDS2018 dataset were converted to the NF-CSE-CIC-IDS2018 dataset with eight NetFlow-based features. The dataset includes the same 14 attack types as the original CSE-CIC-IDS2018 dataset.

### 4. Experimental Methodology

In this paper, six publicly available synthetic datasets, each reflecting modern attack types and benign network traffic, are considered. Three feature selection algorithms; chi-square, IG, and correlation are applied to the full set of features. The features are then ranked based on their importance identified by each feature selection method. Finally, two well-known ML classifiers; Deep Feed Forward (DFF) neural network and Random Forest (RF) are used to measure the attack detection performance of the different feature subsets. The experiment starts with considering the single most highly ranked feature, the sub-set of the top two most highly ranked features, and so forth, up to the set with the 15 top-ranked features. The Python programming language, in combination with the Scikit-learn library [26] was used to implement the feature selection methods and the RF classifier. The DFF classifier was implemented using Tensorflow library [27].

To prepare the datasets for the experiments, duplicate samples were removed. The flow identifier features such as Flow IDs, timestamps, source/destination IP addresses, and port numbers were dropped to avoid bias towards attacking/victim nodes and applications. Moreover, any non-numerical features were converted to numerical values using label encoding. Min-max normalisation was applied to scale the feature values to a range of 0 to 1. The datasets have been split into 70%-30% for training and testing purposes. Finally, Stratified 5-fold Cross-Validation is used to address the imbalance issue and to achieve reliable results.
4.1. Feature Selection

Feature selection is the process of reducing the number of features in a dataset without losing important or relevant information. Supervised feature selection algorithms aim to rank the features by measuring their statistical relationship to the class label [28]. The highest-ranked features hold most of the valuable information to predict the traffic class type. The following three supervised feature selection algorithms have been used in this paper to rank the features in the considered NIDS datasets.

- **Chi-square** [29] - The chi-square $\chi^2_c$ test is used to measure the independence of a feature and its respective class label. Chi-square measures how the expected label $E$, and feature $O$ deviates from each other. The degree of freedom $c$ is used to determine if the null hypothesis can be rejected. A high chi-square value indicates that the hypothesis of independence should be rejected as the occurrence of the feature and class are dependent, and the feature should be used in the classification experiments. Equation (1) shows the relevant definition.

$$\chi^2_c = \sum \frac{(O_i - E_i)^2}{E_i}$$

- **Information Gain** [30] - A parametric formula is used to measure the mutual dependence between the features and the label, higher values indicate higher contribution in making the correct classification and hence a valuable feature. Equation (2) defines the IG, or mutual information $I(X;Y)$, for labels $X$ and features $Y$, where $H(X)$ is the entropy for $X$ (i.e., uncertainty about $X$), and $H(X | Y)$ is the conditional entropy for $X$ given $Y$. IG is a symmetric measure of mutual dependence between two feature sets, and it measures the reduction in the uncertainty (entropy) about the traffic labels if we are given a set of features. This reduction in uncertainty (entropy) corresponds to a gain in information, as shown in Equation (2).

$$I(X;Y) = H(X) - H(X | Y)$$

- **Correlation** [31] - In this feature selection or ranking method, Pearson’s correlation coefficient algorithm is used to compute the linear correlation score between the labels and features. It is defined as the covariance of the labels ($X$) and features ($Y$), divided by the product of their standard deviations, as shown in Equation (3).

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

4.2. Machine Learning

Machine Learning (ML) is a subset of AI that can learn and extract complex patterns from data. In the context of IIoT-NIDS, ML can learn to detect security events from IIoT network traffic, which
can be utilised in detecting network intrusions and attacks. The building of ML models following a supervised classification method includes 2 processes; training and testing. During the training phase, the model is trained with labelled network features to extract and learn patterns. The testing phase involves evaluating the detection reliability of the model by measuring its performance in classifying unseen traffic into an attack or benign class. The predictions are compared with the actual labels to evaluate the ML model using the standard evaluation metrics listed and defined in Table 2, in which TP, FP, TN, and FN represent the number of True Positives, False Positives, True Negatives and False Negatives respectively. For our experiments, we considered the following two classifiers:

- **Deep Feed Forward (DFF)** - A DFF neural network model consisting of 3 hidden layers is used as a network traffic classifier in our experiments. The input layer is set to match the input’s number of dimensions and each hidden layer contains 10 nodes, using the ReLU activation function. The output layer is a single node sigmoid classifier. Between each layer, the model implements a dropout rate of 20% to avoid overfitting. Finally, the binary cross-entropy loss function was used in conjunction with the Adam optimiser.

- **Random Forest (RF)** - An RF classifier is used, consisting of 50 randomised Decision Tree classifiers on various subsamples of the dataset. The Gini impurity function is utilised to measure the quality of a split and hence to configure the Decision Trees.

### Table 2: Evaluation metrics

| Metric             | Equation           | Explanation                                      |
|--------------------|--------------------|--------------------------------------------------|
| Recall             | \( \frac{TP}{TP+FN} \) | Fraction of attacks detected = DR               |
| Precision          | \( \frac{TP}{TP+FP} \) | The fraction of detected attacks to total alarms |
| F1-score           | \( 2 \times \frac{Recall \times Precision}{Recall + Precision} \) | The weighted average of the precision and recall |
| Accuracy           | \( \frac{TP+TN}{TP+FP+TN+FN} \) | Fraction of the correctly classified samples     |
| False Alarm Rate   | \( \frac{FP}{FP+TN} \) | Fraction of benign samples classified as attack |
| Area Under the Curve (AUC) | Area under the Receiver Operating Characteristics (ROC) curve \([32]\) |

5. Results

In our experiments, all the features of each NIDS dataset are ranked based on their importance using the three feature selection algorithms, i.e., chi-square, IG, and correlation. We initially consider
the classification performance by using only the most highly ranked feature. We then keep adding individual features to the feature subset in order of their rank. We consider all feature subsets from size 1 to 15, and we evaluate the corresponding classification performance for both our DFF and RF classifiers. We consider the three original NIDS datasets, as well as their variants with a NetFlow feature set.

5.1. UNSW-NB15 and NF-UNSW-NB15

5.1.1. Full Feature Set

In the initial experiment, the features of the UNSW-NB15 dataset have been ranked, and the ranking of the top 15 features for the three respective feature selection algorithms are shown in Table 3. While a direct comparison is difficult, due to the unique choice of features and feature naming in each dataset, we can observe that there is no clear consistent ranking. Figure 1 shows the attack detection performance (y-axis) using the AUC score. The AUC score is used as it is not sensitive to the class imbalance in the considered NIDS datasets. The AUC score is shown for different feature sub-set sizes (x-axis), ranging from 1 to 15. For comparison, the bar on the left represents the AUC results achieved with the full feature set. The three graphs in each figure represent the results based on the feature ranking of the three different feature selection algorithms. The sub-figure on the left (a) shows the results for the DFF classifier, and the subfigure on the right (b) shows the corresponding result for the RF classifier.

What immediately stands out in the figure is that the maximum AUC is achieved with only a single feature, and the addition of any of the next highest-ranked features does not provide any significant additional benefit in terms of classification accuracy. This is consistent for both the DFF as well as the RF classifier. Further investigation, prompted by this unexpected result, showed

| Rank | Chi-square   | Information Gain | Correlation |
|------|--------------|------------------|-------------|
| 1    | ct_state_ttl | sttl             | sttl        |
| 2    | sttl         | proto            | ct_state_ttl|
| 3    | dttl         | dttl             | dttl        |
| 4    | ct_dst_sport_ltm | swin     | tcprtt      |
| 5    | ct_dst_sport_ltm | dwin     | ackdat      |
| 6    | ct_dst_sport_ltm | ct_state_ttl | synack     |
| 7    | Sload        | sbytes           | ct_dst_sport_ltm |
| 8    | dmeansz      | state            | ct_dst_sport_ltm |
| 9    | ackdat       | dbytes           | Sload       |
| 10   | tcprtt       | dmeansz          | ct_arc_dport_ltm |
| 11   | synack       | Sload            | state       |
| 12   | swin         | Dload            | ct_srv_src  |
| 13   | dwin         | Distpkt          | ct_srv_dst  |
| 14   | Dload        | smeansz          | ct_arc_ltm  |
| 15   | state        | tcprtt           | Sjit        |
that the top ranked features for the three feature selection algorithms are all Time-to-Live (TTL) based features in the UNSW-NB15 dataset, i.e., $sttl$, $dttl$, and $ct\_state\_ttl$. A more detailed analysis considered the AUC score achieved by each of these three TTL-based features individually, for both classifiers. Figure 2 shows these results. As a baseline, the AUC score achieved with the full feature set consisting of 38 features is shown on the left. For the RF classifier, the performance achieved using any of the TTL-based features individually is even higher than for the full feature set. The fact that the addition of irrelevant or ‘noisy’ features can decrease classification performance in RF classifiers is not surprising [12]. However, what is indeed surprising that a single TTL-based feature achieves close to the maximum classification performance achieved by the full feature set of 38 features. We cannot think of any plausible explanation why a single TTL-based feature should have such predictive power for the detection of attack traffic in a practical network scenario. What is a more likely explanation of the observed phenomenon is that it is due to the specific of the test-bed where the synthetic dataset was generated, e.g., the respective placement of attack and victim nodes.

Figure 1: UNSW-NB15 detection performance

![Figure 1](image1.png)

(a) DFF

(b) RF

Figure 2: AUC of TTL-based features in UNSW-NB15

![Figure 2](image2.png)

We, therefore, believe that for any reliable and valid evaluation of ML-based classifiers, these 3 features should be removed from the UNSW-NB15 dataset, since they provide an unrealistically high predictive power, akin to what could be called a 'hidden label'. While some papers such as [33], [9] and [16], with a focus on feature selection, have reported the $sttl$ feature as the most relevant for attack detection, no paper has so far has investigated and reported the problem of the improbably

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high predictive power of a single TTL-based feature, to the best of our knowledge. Since the UNSW-NB15 dataset is highly relevant and widely used in the research community for the evaluation of ML-based network intrusion detection systems, we believe this is a significant finding. Based on our analysis, the use of the full UNSW-NB15 feature set including the TTL-based features, such as done in a large number of recent research papers, might produce compromised results that are unlikely to generalise to other, realistic network scenarios. Consequently, for our further analysis in this paper, we remove the \textit{sttl}, \textit{dttl}, and \textit{ct\_state\_ttl} features from the UNSW-NB15 dataset.

5.1.2. Revised Feature Set

As discussed above, from here onward we consider a revised UNSW-NB15 dataset, where the three TTL-based features have been removed. Table 4 shows the ranked features for this dataset, based on the three feature selection algorithms. The table also shows the feature ranking of the NF-UNSW-NB15 dataset, with a feature set consisting of the following eight NetFlow-based fields: \textit{IN\_BYTES}, \textit{OUT\_BYTES}, \textit{IN\_PKTS}, \textit{OUT\_PKTS}, \textit{PROTOCOL}, \textit{TCP\_FLAGS}, \textit{FLOW\_DURATION}, and \textit{L7\_PROTO}. It is interesting to note that there does not seem to be a consistent feature ranking among the three feature selection algorithm. For example, the top-ranked feature according to IG (\textit{proto}) does not appear in the list of the top 15 features of the other two feature rankings. Figure 3 shows the attack detection performance (AUC score) on the revised datasets, for a feature

| Rank | UNSW-NB15 | NF-UNSW-NB15 |
|------|------------|--------------|
| 1    | \textit{ct\_dst\_sport\_ltm} | \textit{PROTO} |
| 2    | \textit{ct\_dst\_src\_ltm} | \textit{TCP\_FLAGS} |
| 3    | \textit{ct\_src\_dport\_ltm} | \textit{PROTOCOL} |
| 4    | \textit{Sload} | \textit{TCP\_FLAGS} |
| 5    | \textit{dmeansz} | \textit{FLOW\_DURATION} |
| 6    | \textit{ackdat} | \textit{OUT\_BYTES} |
| 7    | \textit{tcprtt} | \textit{L7\_PROTO} |
| 8    | \textit{synack} | \textit{IN\_BYTES} |
| 9    | \textit{swin} | \textit{IN\_BYTES} |
| 10   | \textit{dwin} | \textit{OUT\_PKTS} |
| 11   | \textit{Dload} | \textit{OUT\_BYTES} |
| 12   | \textit{state} | \textit{L7\_PROTO} |
| 13   | \textit{ct\_srv\_src} | \textit{TCP\_FLAGS} |
| 14   | \textit{ct\_srv\_dst} | \textit{TCP\_FLAGS} |
| 15   | \textit{dtcpb} | \textit{TCP\_FLAGS} |
set size (x-axis) that is increased by increments of 1, with features added in order of their rank according to the feature selection algorithm, i.e., chi-square, IG, and correlation respectively. The top two sub-figures show the results for the UNSW-NB15 dataset and for the DFF (a) and RF (b) classifiers respectively.

![Figure 3: UNSW-NB15 and NF-UNSW-NB15 detection performance](image)

As in Figure 3, the bar on the left shows the AUC score achieved with the complete feature set, i.e., 35 features in this case. For the DFF classifier, we notice a gradual increase in the AUC score with the addition of features up to 6 features, where the AUC score converges to its maximum value for the chi-square and Correlation-based feature ranks. For the features ranked according to IG, this convergence to the maximum only happens for 12 features or more. This illustrates the importance of choosing the right feature selection algorithm. In the case of the RF classifier (Figure 1(b)), we observe a similar pattern, where the maximum AUC score is achieved for a small sub-set of features of size 4-6. In this case, the IG algorithm performs better and achieve the (close to) maximum AUC score for only 4 features. Figures 1(c) and (d) show the corresponding results for the NF-UNSW-NB15 dataset, where we can observe a similar pattern. However, the difference here is that the range of the x-axis is limited to 1–8 since the dataset contains only 8 features.

Table 5 shows the key classification evaluation metrics for both the full feature set and the feature sub-set size (with the corresponding feature selection algorithm) that achieves the maximum classification performance in terms of AUC score. The results are shown for both the original UNSW-NB15 dataset as well as NF-UNSW-NB15. What is consistent across all different cases and metrics is that the chosen feature sub-set, with a fraction of the full size (in the case of UNSW-NB15), achieves either better or close-to-equal classification performance compared to the case where the complete
Table 5: UNSW-NB15 and NF-UNSW-NB15 full metrics

| Dataset          | Classifier | Features (Count) | Accuracy  | AUC     | F1 Score | DR       | FAR      |
|------------------|------------|------------------|-----------|---------|----------|----------|----------|
| UNSW-NB15        | DFF        | Full (35)        | 96.93%    | 0.9890  | 0.76     | 99.64%   | 3.21%    |
|                  |            | CHI (7)          | 96.63%    | 0.9843  | 0.74     | 99.14%   | 3.50%    |
|                  | RF         | Full (35)        | 99.27%    | 0.9580  | 0.92     | 91.95%   | 0.36%    |
|                  |            | IG (7)           | 98.62%    | 0.9800  | 0.87     | 97.31%   | 1.31%    |
| NF-UNSW-NB15     | DFF        | Full (8)         | 90.92%    | 0.9574  | 0.57     | 82.38%   | 8.68%    |
|                  |            | CHI (7)          | 94.99%    | 0.9500  | 0.65     | 79.44%   | 4.28%    |
|                  | RF         | Full (8)         | 98.50%    | 0.9622  | 0.85     | 93.71%   | 1.27%    |
|                  |            | IG (3)           | 98.00%    | 0.9814  | 0.81     | 98.28%   | 2.01%    |

Table 5 shows the ranked features for the ToN-IoT dataset, as well as its NetFlow-based variant NF-ToN-IoT. As in the case of the UNSW-NB15 dataset, we see big differences in the feature ranks across the three feature selection algorithms. Figure 4 shows the attack detection performance
(AUC score) for these datasets using the ranked feature sub-sets or increasing size, corresponding to Figure 2 for the UNSW-NB15 datasets. For both classifiers and the ToN-IoT dataset, we see a more gradual conversion to the maximum AUC score, and a greater number of features (>10) is required to converge to the maximum, compared to the UNSW-NB15 datasets where 4-6 features were sufficient. In contrast, for the NF-ToN-IoT dataset, a relatively small fraction of 2-3 features (of the total of 8) can achieve a close to maximum performance. As before, we again notice a significant difference between the three feature selection algorithms.

Table 7 shows the full evaluation metrics of the ToN-IoT and NF-ToN-IoT datasets. As already observed in Figure 3, in the case of ToN-IoT a much larger feature sub-set is required to achieve the maximum classification performance, i.e., 15 features in the case of DFF and 20 features in the case of RF. However, in both cases, the feature sub-sets achieve slightly better performance than the full
set with 38 features. A similar result is observed for the RF classifier and the NF-ToN-IoT dataset, where 6 out of the total of 8 features are required to achieve the maximum AUC score. In contrast, the DNN classifier only requires to top 3 features, according to the chi-square ranking, in order to achieve the best performance, which happens to better than the performance of the full feature set. In summary, there seems to be no one-size-fits-all solution, and the behaviour is quite different for different datasets, feature selection algorithms, and classifiers.

5.3. CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018

Table 8: CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018 ranked features

| Rank | Chi-square | Information Gain | Correlation |
|------|------------|------------------|-------------|
| CSE-CIC-IDS2018 | | | |
| 1 | ACK Flag Cnt | Init Fwd Win Byts | Fed Seg Size Min |
| 2 | Init Bwd Win Byts | Fwd Seg Size Min | ACK Flag Cnt |
| 3 | Init Fwd Win Byts | Fwd IAT Max | Init Fwd Win Byts |
| 4 | Bwd IAT Tot | Fwd IAT Tot | RST Flag Cnt |
| 5 | Protocol | Fwd IAT Mean | ECE Flag Cnt |
| 6 | Fwd Seg Size Min | Protocol | Bwd Pkts/s |
| 7 | Fwd PSN Flags | Flow IAT Max | Fed Act Data Pkts |
| 8 | SYN Flag Cnt | Fwd Seg Size Avg | Tot Fwd Pkts |
| 9 | RST Flag Cnt | Fwd Pkt Len Mean | Subflow Fwd Pkts |
| 10 | ECE Flag Cnt | Flow IAT Mean | Fed Header Len |
| 11 | Bwd Pkt Len Min | Tot Len Fwd Pkts | Subflow Fwd Byts |
| 12 | Bwd IAT Max | Subflow Fwd Byts | Tot Len Fwd Pkts |
| 13 | URG Flag Cnt | Flow Duration | Fed URG Flags |
| 14 | Fwd Pkt Len Min | Fwd Header Len | CWE Flag Count |
| 15 | Pkt Len Min | Fwd Pkt Len Max | Fed IAT Min |

| Rank | Chi-square | Information Gain | Correlation |
|------|------------|------------------|-------------|
| NF-CSE-CIC-IDS2018 | | | |
| 1 | FLOW_DURATION | IN_BYTES | TCP_FLAGS |
| 2 | L7_PROTO | PROTOCOL | IN_PKT |
| 3 | TCP_FLAGS | FLOW_DURATION | IN_BYTES |
| 4 | PROTOCOL | OUT_BYTES | OUTBYTES |
| 5 | IN_PKT | TCP_FLAGS | OUT_PKT |
| 6 | IN_BYTES | OUT_PKT | L7_PROTO |
| 7 | OUT_PKT | IN_PKT | PROTOCOL |
| 8 | OUT_BYTES | L7_PROTO | FLOW_DURATION |

Table 8 lists the selected features ranked by their respective scores by each feature selection algorithm for the CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018 datasets. The top features identified were unique to each feature selection algorithm applied. Figure 5 visually represents the attack detection performance of the datasets with an increasing feature set size. CSE-CIC-IDS2018 is a large dataset consisting of 77 features. However, a very small number is sufficient for the DFF and RF classifiers to achieve an attack detection performance that is close to the one achieved by the full feature set. In that regard, the results are therefore similar to the case of the UNSW-NB15 dataset.

The full evaluation metrics of the CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018 datasets are listed in Table 9. The table illustrates that most of the CSE-CIC-IDS2018 dataset’s original features can be considered irrelevant, as only around 7% of them are needed to achieve the maximum attack
Figure 5: CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018 detection performance

detection performance. The features selected by the chi-square technique are the best in detecting the attacks present in these datasets. The top 6 and 3 features are required for the DFF and RF classifiers respectively to achieve the maximum performance in the CSE-CIC-IDS2018 dataset. The respective top 3 and 6 NetFlow features identified by the chi-square technique are sufficient for both the DFF and RF classifiers to reach maximum performance.

Table 9: CSE-CIC-IDS2018 and NF-CSE-CIC-IDS2018 full metrics

| Dataset           | Classifier | Features (Count) | Accuracy | AUC  | F1 Score | DR    | FAR  |
|-------------------|------------|------------------|----------|------|----------|-------|------|
| CSE-CIC-IDS2018   | DFF        | Full (77)        | 96.45%   | 0.9501 | 0.87     | 81.31%| 0.91%|
|                   |            | CHI (6)          | 92.45%   | 0.9461 | 0.79     | 86.31%| 6.48%|
|                   | RF         | Full (77)        | 98.01%   | 0.9668 | 0.93     | 94.79%| 1.43%|
|                   |            | CHI (3)          | 98.36%   | 0.9654 | 0.94     | 93.95%| 0.86%|
| NF-CSE-CIC-IDS2018| DFF        | Full (8)         | 85.74%   | 0.9256 | 0.61     | 92.74%| 15.23%|
|                   |            | CHI (3)          | 85.61%   | 0.9155 | 0.61     | 93.25%| 15.45%|
|                   | RF         | Full (8)         | 95.51%   | 0.9512 | 0.84     | 94.61%| 4.36%|
|                   |            | CHI (6)          | 95.51%   | 0.9512 | 0.84     | 94.60%| 4.36%|

5.4. Discussion

Figure 6 provides a summary view of our feature analysis results. Figure (a) shows the AUC score achieved by using the DFF classifier on the top 3 features, based on the three considered feature selection algorithms. For comparison, the data point on the very left shows the AUC score achieved with the full feature set. The results are shown for all 6 considered NIDS datasets. We observe significantly varying results for the different feature selection algorithms. For example, for
the CSE-CIC-IDS2018 dataset, the top 3 feature set chosen by the chi-square algorithm achieves an AUC score of 0.9654 using the RF classifier that is close to the one achieved with the full feature set. In contrast, the top 3 feature set selected by the chi-square algorithm for the UNSW-NB15 and ToN-IoT datasets suffer a big drop in performance compared to the full feature set.

Figure 6 (c) shows the corresponding results for the RF classifier. Again, we observer that for some combinations of datasets and feature selection algorithm, e.g., (CSE-CIC-IDS2018, chi-square) and (NF-UNSW-NB15, IG), the top 3 feature subset can achieve the same AUC score as the full feature set, or even higher in some cases. In contrast, for some combinations such as (ToN-IoT, IG) and (UNSW-NB15, IG), the top 3 feature set achieves a significantly reduced performance. Figures 6 (b), and (d) show the same results for the feature subsets consisting of the top 6 ranked features for the DFF and RF classifiers respectively. We can observe that for most datasets, the top 6 feature set can match the AUC score of the full feature set if the best respective feature selection ranking is chosen. The only noticeable exception in this regard is the ToN-IoT dataset, where the top 6 feature suffers a significant drop in AUC score compared to the full feature set, in particular for the RF classifier.

In summary, our results show a large degree of variability of the results across the different considered datasets and feature selection algorithms, in regards to the network attack detection performance of varying size feature subsets. The results demonstrate that there is no simple one-size-fits-all approach for feature selection, and a careful analysis needs to be undertaken. If the
feature selection algorithm is carefully chosen and matched to the NIDS dataset at hand, a relatively small feature subset can achieve the detection performance of the full feature set. A good example of this is the case of the RF classifier and CSE-CIS-IDS2018 dataset, where the top 3 features (based on chi-square) achieve the same (or even slightly higher) AUC score than the full set of 77 features. Such a significantly reduced feature set has the benefit of reduced resource consumption for feature extraction and storage, as well as attack detection, due to the reduced classifier model complexity. This is likely to be particularly relevant in IIoT and IoT scenarios, more broadly, with resource-limited devices.

6. Conclusion

In this paper, a comprehensive evaluation of feature importance across multiple NIDS has been conducted. Three feature selection techniques, i.e., chi-square, IG and correlation, have been utilised to rank the features of the considered datasets. In an extensive experimental study, the classification performance of different feature subsets, ranging from size 1 to 15 for the 3 original datasets, and 1 to 8 for the variants with the NetFlow based feature sets, have been evaluated. For each feature set size, three feature sets were considered, one for each feature selection algorithm and the corresponding ranking. These feature sets have been created for each of the 6 NIDS datasets, and have been evaluated for both the DFF and RF classifier, resulting in a total of 414 experiments and data points. A key finding of these experiments is that a small subset of features can achieve the same or even higher detection performance as the full feature set. This has the potential for a significant reduction in model complexity, as well as computational and storage costs for feature extraction, which is critical in resource-constrained IIoT environments.

Another important result of this paper is that there and there is no simple or general rule to choose the optimal feature set and size since there is a large amount of variability across the different datasets and classifiers in that regard. In order to find the smallest feature set that can achieve the best classification performance, a careful analysis has to be performed for the considered scenario. A final finding of our research is that a high degree of care needs to be taken when ML-based network intrusion detection algorithms and models are evaluated on synthetic NIDS datasets. As we have demonstrated, some of the features have an unrealistically high predictive power, such as the TTL-based features in the UNSW-NB15 dataset, and should be removed prior to the classification experiments. This is critical in order to get reliable evaluation results that can generalise to realistic network scenarios. This further supports our case for advocating a careful and extensive feature analysis when developing and evaluating ML-based network intrusion detection systems.
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