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Using CVSS scores can make more informed and more adapted Intrusion Detection Systems


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Abstract: Intrusion Detection Systems (IDSs) are essential cybersecurity components. Previous cyberattack detection methods relied more on signatures and rules to detect cyberattacks, although there has been a change in paradigm in the last decade, with Machine Learning (ML) enabling more efficient and flexible statistical methods. However, ML often suffers from the lack of, and proper use of, cybersecurity information, be they for proper evaluation or even improving performance. This paper shows that using a *de facto* standard in cybersecurity: the Common Vulnerability Scoring System (CVSS), can improve IDSs at different levels, from helping in training an IDS, to more properly evaluating its performance, even taking into account systems with different protection requirements. This paper introduces Cyber Informedness, a new metric considering cybersecurity information to give a more informed representation of performance, influenced by the severity of the attacks encountered. Consequently, this metric is also able to differentiate performance of IDSs when security requirements, Confidentiality, Integrity and Availability, are defined using CVSS' environmental parameters. Finally, sub-parts of this metric can be integrated into the training phase's loss of Neural Networks (NNs)-based IDSs to build IDSs that better detect more severe attacks.

Keywords: Cybersecurity, Metrics, Machine Learning, Intrusion Detection Systems, CVSS

Categories: I.2.1, I.2.6

1 Introduction

The world is increasingly digitalized, which brings a plethora of cybersecurity threats. While it is essential to make systems more secure by design [Ashibani and Mahmoud 2017], nothing is ever perfectly secure, so alternative solutions are needed. IDSs are used to monitor and analyze traffic and system logs to detect anomalies and potential attacks. Traditional IDSs are signature-based and rather successful in detecting known attacks,

with a very low probability of giving false alarms with sufficiently well-crafted rules, but they can easily miss zero-day or polymorphic threats [Hindy et al. 2020].

In the last decade, however, one of the most extensive research directions concerns ML algorithms. Many works [Sarker et al. 2020, Ferrag et al. 2020, Xin et al. 2018, Khraisat et al. 2019, Lakshminarayana et al. 2019] have expanded upon ML and Deep Learning (DL) performance relative to intrusion detection on popular datasets, and show that those approaches perform well. Finally, other approaches such as Artificial Immune Systems [Aickelin et al. 2013], Genetic Programming [Abadeh et al. 2011] or approaches based on Fuzzy Logic [Masdari and Khezri 2020, Yang et al. 2017, Wang et al. 2010] can either replace or complete classical ML approaches. While there has been much progress in devising different methods to perform intrusion detection using cybersecurity data, cybersecurity knowledge has rarely been used to improve upon these methods.

As far as metrics are concerned, Intrusion Detection is addressed from the ML viewpoint with generic metrics such as Accuracy, Precision, Recall or F1-Score. While these metrics are extensively used and tested, they suffer from significant flaws, particularly when performing multi-class classification. Indeed, imbalance in the data heavily influences results, and poor results on underrepresented classes are generally hidden. Furthermore, those metrics treat all data equally and are unable to cater for differences in the cost of mistakes (attacks missed or false alarms). Failing to detect port scans will obviously be less penalizing than failing to detect the exfiltration of confidential data.

While integrating cybersecurity knowledge into ML-based IDSs might prove fruitful, it does pose a number of challenges. The typical way to provide information to ML methods is by using training data. Therefore, integrating cybersecurity knowledge will require to transform the knowledge to supplement this data. In cybersecurity, attacks are generally defined by their Techniques, Tactics and Procedures (TTPs), the impact they have on the attacked systems and therefore often have a score related to their criticality. While integrating the MITRE ATT&CK framework¹ to improve ML-based IDSs might be the most beneficial because of its completeness, it would require a significant adaptation of their training mechanisms. On the contrary, adding a numerical value representing the severity of attacks is a much easier task. This score is generally computed using the CVSS², which takes into account parameters relative to the difficulty of performing an attack, as well as its impact, to compute a score representative of the attack's severity.

In a previous work [Duraz et al. 2023], authors introduced three new metrics based on CVSS, Miss Cost (MC), False Alarm Cost (FAC) and Cyber Informedness (CI) to provide a more informed evaluation of the actual performance of ML-based IDSs. These metrics can benefit both the cybersecurity expert that will use and integrate this IDS and the ML expert that builds and validates an IDS based on ML algorithms by showing results that both sides have more confidence in.

This work supplements previous research by extending the use of CVSS scores with respect to ML-based IDSs. As such, the contribution of this research is twofold:

- Show that CVSS scores' environmental parameters can be used to help selecting IDSs that are more adapted to specific system configurations with their own security requirements.
- Introduce a new loss formulation for NN-based IDSs that builds upon the Cross-Entropy Loss and two of the newly defined metrics, Miss Cost (MC) and False Alarm Cost (FAC) to train NN-based IDSs. Furthermore, the newly formulated loss

¹ <https://attack.mitre.org/>

² <https://www.first.org/cvss/v3.1/specification-document>

is shown to help NN-based IDSs in detecting more severe attacks, while at the same time helping in reducing the amount of missed attacks.

Consequently, this work closes the loop started in [Duraz et al. 2023] by integrating cybersecurity knowledge into both phases (training and evaluation) of an IDS's design. From simply evaluating performance in a more informed way, the new methodology proposed also enables a better adaptation to protecting systems with specific requirements, as well as the possibility to influence training to obtain IDSs that better detect more severe attacks.

The rest of the paper is organized as follows: Section 2 presents related works. Section 3 describes the proposed approach, while Section 4 presents the experimental setup. Section 5 presents and analyzes the results. Finally, Section 6 concludes the paper and discusses future avenues of research.

2 Related work

For ML-based IDSs, cybersecurity datasets are required. Unfortunately, it is difficult to obtain realistic data, i.e., with at least a diversity of up-to-date attacks, a complete environment, as well as traffic representative of the real world (imbalanced, with errors, etc.). Using real world data is an obvious choice, but is often impossible to obtain because of confidentiality and/or security reasons. Another solution is to create a synthetic dataset. While it eliminates the previous problems, it is much more difficult to make it realistic. It is important to follow a thorough methodology, such as highlighted by [Bhuyan et al. 2015, Sharafaldin et al. 2017], to ensure quality of the data created.

2.1 Datasets

KDD'99 [KDD Cup 99 Data 1999] and NSL-KDD [Tavallae et al. 2009] are the two most used datasets [Hindy et al. 2020]. However, these datasets, and particularly the former, are heavily criticized because of their age and various other problems such as redundancy [Creech and Hu 2013, Siddique et al. 2019, Tobi and Duncan 2018].

The UNSW-NB15 [Moustafa and Slay 2015] and CIC-IDS2017 [Sharafaldin et al. 2018] datasets are more recent and based on quite complete environments. CIC-IDS2017 follows the methodology defined in [Sharafaldin et al. 2017] and criteria defined in [Gharib et al. 2016] to ensure quality of the created dataset. Both being more recent datasets, it also ensures that the environment and simulated traffic are more representative of nowadays' real-world traffic. Furthermore, the UNSW-NB15 dataset has CVE (Common Vulnerability Exposure) information recorded for six attack categories that can be helpful in obtaining CVSS scores. While the CIC-IDS2017 dataset does not have CVE information, it is possible, given the information provided in [Sharafaldin et al. 2018], to assign CVSS scores to the respective attack classes. Although the more recent DAPT dataset [Myneni et al. 2020] appears to better represent current attack methodologies, it is hard to obtain CVSS scores for this dataset and has thus not been retained in this study. Consequently, the UNSW-NB15 and CIC-IDS2017 datasets are retained for this research.

2.1.1 UNSW-NB15

It was created using the IXIA, Argus and Bro-IDS tools to generate traffic and attacks, as well as extract features. The resulting dataset is composed of 47 features, plus attack categories and binary labels. An advantage of this dataset is that IP addresses and timestamps

are retained which enables better quality verification of the dataset. It can ensure that, for example, samples are not redundant, as for the KDD'99 dataset. Attack categories also provide detailed information about the attack performed that is rarely available in other intrusion detection datasets. Details on class distribution are presented in Table 1.

2.1.2 CIC-IDS2017

The dataset was created on a test bed with agents simulating normal traffic using different basic protocols, and six different attack profiles. Data was collected over several days, and packet capture files were aggregated using CICFlowMeter³ to extract 78 numerical features representing various statistical properties of the aggregated flows. Details on class distribution are presented in Table 1.

Table 1: Datasets details

Dataset	Number of instances per class	Total
UNSW-NB15	Normal: 2218761, Generic: 215481, Exploits: 44525, Fuzzers: 24246, DoS: 16353, Reconnaissance: 13987, Analysis: 2677, Backdoor: 2329, Shellcode: 1511, Worms: 174	2540047
CIC-IDS2017	Benign: 2273097, DoS Hulk: 231073, Portscan: 158930, DDoS: 128027, DoS GoldenEye: 10293, FTP-Patator: 7938, SSH-Patator: 5897, DoS Slowloris: 5796, DoS Slowhttptest: 5499, Botnet: 1966, Web Attack Brute Force: 1507, Web Attack XSS: 652, Infiltration: 36, Web Attack SQL Injection: 21, Heartbleed: 11	2830743

2.2 Metrics

In order to evaluate performance of different ML-based IDSs, various metrics are generally used. The most complete representation of an IDS's performance and basis for most metrics, e.g., Accuracy, Precision, Recall, F1-Score, is the full confusion matrix. While the full confusion matrix remains one the best representation of performance, it can quickly become difficult to use as the number of classes increases. For research on intrusion detection, the metrics mentioned above that are generally used share two major drawbacks. Firstly, they are unable to treat differently different attack classes, and this is problematic because attacks are not equally dangerous, and remediation mechanisms are different. Secondly, they are mostly not resistant to imbalance.

Imbalance in the data is a problem already highlighted in the literature. It has been described in details in [Jeni et al. 2013, Gu et al. 2009, Sokolova et al. 2006], showing that many metrics might be ill-defined in case of heavily imbalanced datasets. In intrusion detection, normal traffic generally represents a part of the data significant enough for IDSs to show a high performance while potentially missing all attacks, e.g., classifying all traffic as normal (thus missing all attacks) in UNSW-NB15 still achieves more than

³ CICFlowMeter is an Ethernet traffic bi-flow generator and analyzer for anomaly detection that has been used in many cybersecurity datasets: <https://github.com/ahlashkari/CICFlowMeter>

87% Accuracy. It thus highlights the need to find better metrics, or simply account for the skewness of class distributions.

To solve the imbalance problem, [Chicco 2017] has suggested the use of the Matthews Correlation Coefficient (MCC) that is probably the most complete metric with regard to summarizing the confusion matrix since it captures all the information contained therein, i.e., both True and False Positives and Negatives. While it is originally defined for binary classification, it can also be extended to the multi-class setting.

However, authors in [Zhu 2020] offer a strong rebuttal to the use of MCC in case of imbalanced datasets and suggest using metrics that are more stable with regard to imbalance, such as the geometric mean of TPR (True Positive Rate) and TNR (True Negative Rate) and Bookmaker Informedness (BI) equal to $TPR + TNR - 1$.

According to [Zhu 2020], BI accounts for imbalance and can reflect a less biased view of performance. Its formula is simple, yet appears to offer what most other metrics cannot, i.e., it allows to capture performance on both positive and negative instances with equal importance, irrespective of the imbalance. It is something that Accuracy or MCC are not capable of doing. However, resistance to imbalance of the MCC and BI metrics is still relatively unclear in the multi-class setting, since both [Chicco 2017] and [Zhu 2020] limited their analysis to the binary setting. Furthermore, although some metrics might appear more suitable than others, it is advised in [Sokolova et al. 2006] to rely on multiple metrics to correctly compare two algorithms.

Finally, MCC and BI appear to offer a solution to the imbalance problem. However, there is currently no metric that offers to solve the problem of attack classes that are inherently not equally important for the monitored system. For example, breaches in servers holding classified data need to be prioritized much more than simple brute-forcing attempts. Therefore, new metrics based on CVSS presented in this paper can fill in this gap. Following the advice in [Sokolova et al. 2006], multiple metrics will thus be retained to evaluate performance of ML-based IDSs: Accuracy, Precision (PPV), Recall (TPR), F1-Score, MCC, BI, and the new metrics based on CVSS. Furthermore, new metrics based on CVSS will be generalisations of other metrics, for more credibility and better comparison between results.

2.3 CVSS for IDSs

CVSS is one of the most extensively used frameworks in cybersecurity, and allows attribution of numerical scores to vulnerabilities. Since vulnerabilities are exploited by attacks, these attacks can also, by association, be attributed CVSS scores. Therefore, CVSS scores can be used to get a numerical representation of a system's security by accounting for attacks it is susceptible to. Research on the usage of CVSS scores in the context of cybersecurity has mainly focused on evaluating the security and few has been done to evaluate IDSs. While the idea of leveraging CVSS in Intrusion Detection is not recent, as in [Aussibal and Gallon 2008] where it has been used to evaluate severity of alerts raised by probes, its actual use has not progressed much since then.

In [Gao et al. 2018, Frigault et al. 2017], CVSS scores have been used in coordination with attack graphs and Bayesian networks to evaluate or estimate the security of networks, thus extending the use of CVSS scores to also consider attack paths instead of a single vulnerability. In [Boudermine 2023], CVSS scores are used with dynamic attack graphs to evaluate the overall security of a system.

Although CVSS scores are originally defined for regular IT networks, [Ur-Rehman et al. 2020] have focused on extending the framework to also encompass Industrial Control Systems, showing the interest in such framework to evaluate security of a system. Finally,

recent work [Bolivar et al. 2019] suggests that CVSS can be used to prioritize what is more severe. While research to extend CVSS scores to more use-cases exists, it focuses on evaluating the security of a system and can be researched further to improve IDSs. This work focuses on improving design and evaluation of IDSs by using CVSS to both train and evaluate IDSs for a more informed representation of the security it provides.

3 Integrating CVSS scores into IDSs

CVSS scores can be integrated into all phases pertaining to building an IDS, as shown in Figure 1. First, CVSS scores and their usage can be influenced by the definition of the system to be protected. Taking into account Confidentiality, Integrity and Availability (CIA) requirements of the system can change CVSS scores via their environmental parameters. In this way, CVSS scores will be adapted to the given system, opening the way for building IDSs that are more adapted to a given system when evaluated with metrics using CVSS scores. Secondly, CVSS scores can be integrated into the training phase of ML-based IDSs. While this might require substantial work for most ML-based IDSs, CVSS scores can relatively easily be integrated in the loss formulation of NNs-based IDSs. Last but not least, CVSS scores can be integrated into evaluation metrics that can take into account the severity of attacks, thus making more informed IDSs. Because the evaluation metrics integrating CVSS are the basis for all three, this is developed first.

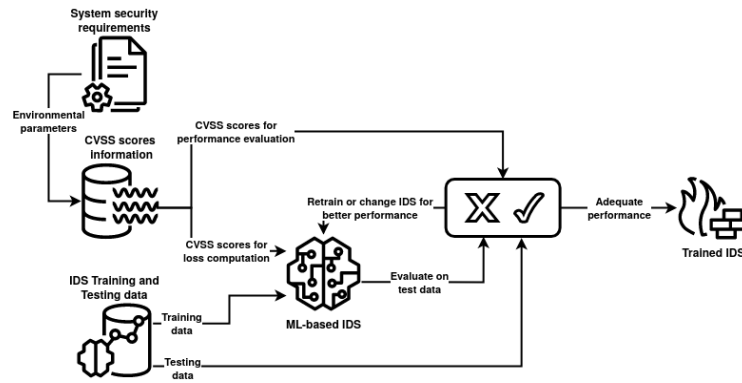


Figure 1: CVSS integration into IDSs

3.1 CVSS in Evaluation metrics

Besides being an evaluation of performance, a given metric (or set of metrics) in cybersecurity should be able to provide objective information about the actual cost of being mistaken, particularly in critical situations. In this paper, three new metrics using CVSS scores and accounting for missed attacks and false alarms are thus created.

3.1.1 False Alarm Cost and Miss Cost

Let c be a class, with $c \in \{0, 1, \dots, C\}$ and 0 being the normal class. For every instance i , let G_i be the ground truth value and D_i be the decision for this instance. $CVSS_i$ is the CVSS score corresponding to instance i .

$\mathbf{1}$ stands for the indicator function and $\bar{\bullet}$ is the averaging operator. $\overline{CVSS_c}$ thus corresponds to the mean of CVSS scores for instances belonging to class c , which is necessary when instances of the same class do not have the same CVSS score (as is the case in the UNSW-NB15 dataset).

For each attack class c ($c \neq 0$), and with N the total number of instances, we define the False Alarm Cost (FAC, Equation 1) and the Miss Cost (MC, Equation 2) as follows:

$$FAC_c \stackrel{def}{=} \frac{\sum_{i=1}^N \mathbf{1}_{D_i=c} \cdot \mathbf{1}_{G_i \neq D_i}}{10 \sum_{i=1}^N \mathbf{1}_{D_i=c}} \cdot \overline{CVSS_c} \quad (1)$$

$$MC_c \stackrel{def}{=} \frac{\sum_{i=1}^N \mathbf{1}_{D_i \neq c} \cdot \mathbf{1}_{G_i=c} \cdot CVSS_i}{10 \sum_{i=1}^N \mathbf{1}_{G_i=c}} \quad (2)$$

In both formulae, the number 10 in the denominator represents the maximum possible value of a CVSS score, thus acting as a normalizing constant (bounding results between 0 and 1) while also highlighting the importance of attacks having a higher score.

As such, both formulae are generalizations of ML metrics. FAC is the generalization of the False Discovery Rate, the proportion of mistakes by predicting a specific class. Intuitively, it represents the frequency of false alarms, weighted by the CVSS score of these alarms. MC is the generalization of the False Negative Rate, the proportion of class instances that are incorrectly classified. Intuitively, it represents the frequency of missed attacks, weighted by their individual CVSS scores. These newly defined metrics are equal to their ML metrics counterparts when all CVSS scores are equal to 10 for classes different from normal traffic.

3.1.2 Cyber Informedness

Both metrics mentioned above can be combined into a single metric taking into account both False Positives and False Negatives that is defined analogously to BI. Therefore, it is assumed it would similarly exhibit nice properties regarding class imbalance.

For each class c ($c \neq 0$), the Cyber Informedness (CI) metric that contains both FAC and MC is given by (3).

$$CI_c \stackrel{def}{=} 1 - FAC_c - MC_c \quad (3)$$

This metric aims to give a cybersecurity-informed idea about the performance of an IDS, aggregating both FAC and MC, with 1 being the best possible score. It also represents the success of an IDS to correctly identify a specific attack, with less penalties for failing to recognize less critical attacks.

3.1.3 Practical implications of the metrics

In order to use these newly defined metrics, the best case scenario would be to have, in the data, CVE IDs or CVSS scores related to the vulnerabilities exploited by attacks. It is, however, rarely the case. Therefore, another alternative is to directly get the CVSS scores used in this customizable metric through a publicly available calculator⁴, which is doable when given enough details about the attacks.

Besides being based on a *de facto* standard in cybersecurity, the three cyber-related metrics can also provide additional benefits in practice when protecting a system. First and foremost, it inherently takes into account the severity of attacks encountered and puts more focus on attacks that are dangerous for the system. For example, failing to detect Heartbleed attacks [Durumeric et al. 2014] will have a more direct impact than failing to detect brute forcing attempts.

Secondly, it is possible to adapt the score depending on the system that needs to be protected. The CVSS score already includes this possibility with the Environmental score, where it is possible to specify Confidentiality, Integrity and Availability requirements of the system, influencing the resulting attack score.

This allows to pick different IDSs for different systems, depending on how adapted they are to a specific system, because the risk posed by an attack on a particular system is appropriately reflected on the new metrics.

3.2 CVSS in the loss computation

In much the same way as in the previously defined metrics, CVSS scores can be integrated into a loss used by a NN to train. Since in most multi-class classification problems, the loss used is a Cross-Entropy Loss (CEL), CVSS scores have been integrated into a custom loss based on the CEL.

Let c be a class, with $c \in \{0, 1, \dots, C\}$ and 0 being the normal class. For every instance i , let x_i represents the output logits of the Neural Network, G_i be the ground truth value and D_i be the decision for this instance. $CVSS_i$ is the CVSS score corresponding to instance i . Finally, let V be the set of indices for which $CVSS_i$ exists.

As a reminder, the basic CEL is defined in Equation 4.

$$CEL \stackrel{def}{=} \sum_{i=1}^N -\log \frac{\exp(x_{i,G_i})}{\sum_{c=1}^C \exp(x_{i,c})} \quad (4)$$

To properly integrate CVSS scores into a custom loss, this custom loss has been divided in three different parts:

- Miss Cross-Entropy Loss (MCEL), a part accounting for missed attacks, defined analogously to MC. It is defined in Equation 5.
- Remaining Cross-Entropy Loss (RCEL), a part accounting for missed attacks when CVSS score does not exist, which is required for the UNSW-NB15 dataset. It is defined in Equation 6.
- False Alarm Cross-Entropy Loss (FACEL), a part accounting for false alarms, defined analogously to FAC. It is defined in Equation 7.

⁴ <https://www.first.org/cvss/calculator/3.1>

$$\text{MCEL} = \sum_{i=1}^N -\log \frac{\exp(x_{i,G_i})}{\sum_{c=1}^C \exp(x_{i,c})} \cdot \mathbf{1}_{G_i \neq 0, G_i \neq D_i, i \in \mathcal{V}} \cdot \text{CVSS}_i \quad (5)$$

$$\text{RCEL} = \sum_{i=1}^N -\log \frac{\exp(x_{i,G_i})}{\sum_{c=1}^C \exp(x_{i,c})} \cdot \mathbf{1}_{G_i \neq 0, G_i \neq D_i, i \notin \mathcal{V}} \quad (6)$$

$$\text{FACEL} = \sum_{i=1}^N -\log \frac{\exp(x_{i,G_i})}{\sum_{c=1}^C \exp(x_{i,c})} \cdot \mathbf{1}_{G_i=0, D_i \neq 0} \cdot \overline{\text{CVSS}_{D_i}} \quad (7)$$

Finally, the complete loss CVSSCEL is defined in Equation 8, simply being a sum of its three parts.

$$\text{CVSSCEL} \stackrel{\text{def}}{=} \text{MCEL} + \text{FACEL} + \text{RCEL} \quad (8)$$

Because it is composed of three different losses that are simply summed, it is relatively trivial to give more importance to one loss, e.g., give more importance to MCEL by adding a weight to it if missing attacks is more critical than raising false alarms.

4 Experimental Setup

4.1 Choice of metrics

The finalized set of metrics chosen, both for comparison purposes and validation of the newly introduced metrics, is:

- Common ML metrics: Accuracy, F1-score, TPR (Recall), PPV (Precision).
- Metrics potentially resistant to imbalance: MCC and BI. Both range between -1 and 1 .
- Cyber-informed metrics: MC, FAC and CI. The former two range between 0 and 1 while the latter ranges between -1 and 1 .

All metrics, except Accuracy and MCC, were computed on a per-class basis. The averaging method retained is macro-averaging, which averages irrespective of the class imbalance to reduce its influence.

4.2 ML algorithms

In order to evaluate the proposed set of metrics and understand the differences brought by the introduction of cybersecurity-based metrics, experiments were run with a wide range of algorithms, trying various hyper-parameter combinations to find the best performing IDS on the two datasets considered. The retained algorithms are:

- A dummy classifier, classifying every instance as of the most frequent class (normal traffic in both datasets) to serve as a baseline.
- Relatively simple algorithms that should give an idea about the complexity of the classification task: Gaussian Naïve Bayes (GNB), Logistic Regression (LR), Linear Support Vector Classification (LSVC), K-means, Decision Trees (DTs).
- More complex algorithms that should reflect the expected performance of IDSs relying on ML: Random Forests (RFs), Multi-Layer Perceptron (MLP), Deep Neural Networks (DNNs).

All algorithms are from the *scikit-learn*⁵ library except DNNs that were programmed using the *PyTorch*⁶ and *PyTorch Lightning*⁷ libraries. In order to evaluate K-means, which is an unsupervised algorithm and does not predict a label, labels were attributed to individual clusters by a majority vote, i.e., the class that is the most represented inside a cluster is the class assigned to it.

4.3 Dataset Pre-processing

Both the UNSW-NB15 and CIC-IDS2017 datasets were split using a stratified scheme into 70% train (60% and 10% validation for DNNs) and 30% test sets.

For the UNSW-NB15 dataset, features such as IP addresses, timestamps, *attack_cat* were removed, while categorical features or features having a small number of unique values, were one-hot encoded. The resulting dataset has 229 features.

For the CIC-IDS2017 dataset, two features and 5792 instances were removed because of problematic or missing values. A further eight features were removed because they only had one value. The resulting dataset has 70 features.

4.4 CVSS Scores for Cyber-related Metrics

Since it is possible to obtain CVSS scores for the UNSW-NB15 dataset with ground truth information, these scores were collected and assigned to the corresponding instances for the computation of the new metrics. However, the CVSS scores assigned to attacks of this dataset used the CVSS 2.1 standard and thus can be a bit different from the more recent CVSS 3.1 standard used for the other dataset. CVE IDs were thus used to get CVSS scores following the 3.1 standard when possible.

For the CIC-IDS2017 dataset, however, there is no such information. Although this information is missing, the attacks performed were described in sufficient details in the original paper [Sharafaldin et al. 2018], allowing to manually craft CVSS scores since the described attacks seem to exploit the same vulnerabilities for a given attack category. It is possible because the given classes individually contain very similar attacks and thus do not suffer much from heterogeneity in a given class. For this dataset, the scores obtained through the CVSS calculator⁸, as well as the vector used for computation, are visible in Table 2. While Denial of Service (DoS) and Distributed Denial of Service (DDoS) attacks can have a relatively similar impact, DoS attacks tend to reduce performance of the target until an eventual shutdown, whereas DDoS can quickly make the targeted resource unavailable, thus the difference in impact.

⁵ <https://scikit-learn.org/stable/index.html>

⁶ <https://pytorch.org/>

⁷ <https://www.pytorchlightning.ai/>

⁸ <https://www.first.org/cvss/calculator/3.1>

Table 2: CVSS scores for CIC-IDS2017

Attacks	AV	AC	PR	UI	S	C	I	A	CVSS Scores		
									Basic	Env. 2	Env. 3
DoS Slowloris DoS Slowhttptest DoS GoldenEye DoS Hulk	Network	Low	None	None	Unchanged	None	None	Low	5.3	4.6	6.1
Portscan FTP-Patator Web Attack Brute Force SSH-Patator	Network	Low	None	None	Unchanged	Low	None	None	5.3	6.1	4.6
Web Attack XSS	Network	Low	None	None	Unchanged	None	Low	None	5.3	5.3	5.3
Infiltration	Local	High	None	Required	Changed	High	None	None	5.5	6.5	2.9
Web Attack SQL Injection	Network	Low	None	None	Unchanged	Low	Low	Low	7.3	7.4	7.4
DDoS	Network	Low	None	None	Unchanged	None	None	High	7.5	5.7	9.3
Heartbleed	Network	Low	None	None	Unchanged	High	None	None	7.5	9.3	5.7
Botnet	Network	Low	None	None	Unchanged	High	High	High	9.8	9.8	9.8

AV: Attack Vector, AC: Attack Complexity, PR: Privileges Required, UI: User Interaction, S: Scope, C: Confidentiality, I: Integrity, A: Availability.
 Env. 1 corresponds to High Confidentiality, Medium Integrity, Low Availability requirements.
 Env. 2 corresponds to Low Confidentiality, Medium Integrity, High Availability requirements.
 Details about possible values for each category, as well as their signification, can be found at <https://www.first.org/cvss/v3.1/specification-document>.

To evaluate changes in performance with CVSS-related metrics with CVSS environmental scores, three different "environments" were used:

- The basic environment, without any modification.
- A high Confidentiality, medium Integrity and low Availability (Environment 2), e.g., a marketing company's client database with other backups for data redundancy.
- Low Confidentiality, medium Integrity and high Availability (Environment 3), e.g., a video streaming service.

Environment 2 (Env. 2) and Environment 3 (Env. 3) in Table 2 are representative of two different systems with different CIA requirements. Therefore, CVSS scores changes are reported. These changes in CVSS scores will in turn impact the relative performance reflected by CVSS-related metrics to help in selecting the IDSs that are most adapted to a particular environment.

4.5 UNSW-NB15 data subset for CVSSCEL

To more effectively evaluate the impact and effectiveness of integrating CVSS scores into the loss formulation, only a subset of the UNSW-NB15 dataset has been retained. This particular choice has been made to focus on the influence of the loss integrating CVSS scores while reducing the impact of other variables. This version of the dataset will thus be used in subsection 5.3. As shown in Table 3, only browser exploits with different CVSS scores and normal traffic were retained. Browser exploits were separated into a class corresponding to their CVSS score, e.g., browser exploits with a CVSS score of 10 belong to class exploits-Browser-10, because they are exploits targeting different vulnerabilities and with potentially different attack mechanisms. By selecting a single attack class separated in multiple sub-classes, traffic should overall be much more homogeneous between attack classes, and as stated previously, should reduce the influence of variables other than the loss using CVSS scores.

Table 3: Datasets details

Dataset	Number of instances per class	Total
UNSW-NB15	Normal: 2218761, exploits-Browser-10.0: 537, exploits-Browser-9.3: 13988, exploits-Browser-8.5: 232, exploits-Browser-7.6: 233, exploits-Browser-7.5: 1149, exploits-Browser-7.1: 94, exploits-Browser-6.8: 511, exploits-Browser-5.1: 1589, exploits-Browser-5.0: 274, exploits-Browser-4.3: 443	2237811

This task is highly difficult for two reasons: classes are even more imbalanced than in the original UNSW-NB15 dataset as normal traffic represents more than 99% of the data, and the different attack classes are very similar, making it much harder to differentiate them. Moreover, one attack class is also much more present than the eight other classes.

5 Results

In order to evaluate the usefulness of the newly defined metrics, IDSs based on algorithms presented in subsection 4.2 were trained and tested on the datasets shown in Table 1. Results according to the relevant metrics are presented in Table 4. For each category of ML algorithm, a coarse grid-search scheme was used to pick hyper-parameter values and the IDS obtaining the best results was kept. For those IDSs, results are shown for the retained metrics. Considering only some of the metrics, particularly Accuracy and MCC, it is difficult to see which IDS performs better than others. The most significant differences on both datasets can be seen with PPV and the newly defined metrics.

Table 4: Performances on the UNSW-NB15 and CIC-IDS2017 datasets

Dataset	Algorithm	Acc.	F1	TPR	PPV	MCC	BI	MC	FAC	CI
UNSW-NB15	Dummy	0.873	0.093	0.1	0.087	0	-0.102	0.395	0.623	-0.019
	GNB	0.490	0.130	0.296	0.264	-0.039	-0.253	0.329	0.494	0.175
	LR	0.974	0.447	0.444	0.586	0.888	0.405	0.221	0.286	0.492
	LSVC	0.972	0.445	0.436	0.480	0.879	0.394	0.264	0.344	0.391
	K-means	0.874	0.159	0.187	0.188	0.521	0.043	0.333	0.558	0.108
	DT	0.979	0.586	0.565	0.666	0.910	0.535	0.186	0.228	0.584
	RF	0.981	0.571	0.549	0.738	0.919	0.521	0.205	0.180	0.614
	MLP	0.980	0.520	0.518	0.772	0.912	0.488	0.220	0.153	0.625
	DNN	0.978	0.505	0.511	0.627	0.908	0.480	0.206	0.257	0.535
CIC-IDS2017	Dummy	0.803	0.059	0.066	0.053	0	-0.172	0.563	0.563	-0.126
	GNB	0.723	0.499	0.848	0.469	0.572	0.579	0.069	0.321	0.609
	LR	0.990	0.639	0.633	0.788	0.973	0.623	0.233	0.147	0.618
	LSVC	0.986	0.546	0.589	0.602	0.960	0.574	0.256	0.253	0.490
	K-means	0.868	0.146	0.138	0.158	0.549	-0.019	0.518	0.500	-0.018
	DT	0.998	0.839	0.843	0.836	0.995	0.842	0.101	0.104	0.794
	RF	0.998	0.850	0.836	0.870	0.995	0.834	0.106	0.085	0.808
	MLP	0.996	0.725	0.721	0.835	0.989	0.718	0.177	0.103	0.719
	DNN	0.997	0.757	0.739	0.896	0.991	0.736	0.168	0.067	0.764

Values were truncated to the third decimal. Best results for a given metric and dataset are in **bold**.

5.1 Zoom comparison of two IDS' performances

A more significant difference can often be seen with the newly defined metrics. The following example compares results presented in Table 4 for the LSVC (Linear Support Vector Classification) and MLP (Multi-Layer Perceptron) on the UNSW-NB15 dataset.

When looking at the results, the Accuracy of both IDSs is very close, whereas results are very different according to FAC and CI. For the Accuracy, this is understandable because results on most classes are very close. Both IDSs have relatively similar performance (under a 5% difference) on all classes, except Exploits and DoS.

LSVC outperforms MLP by correctly classifying 69% of DoS instances versus 37%. On the other hand, MLP significantly outperforms LSVC by correctly classifying 74% of Exploits instances versus 46%.

In the UNSW-NB15 dataset, for attacks that do have CVE IDs and thus an assigned CVSS score, Exploits is the class with the highest average CVSS score because most instances have a high CVSS score (9.3 or 10). DoS attacks, on the contrary, generally have CVSS scores between 5 and 8. Exploits attacks are generally more dangerous, i.e., have a higher CVSS score, which is directly translated into those two metrics. Indeed, the MLP that performs better on Exploits has results that are more than two times better for FAC and close to 60% better on the CI metric. Furthermore, the relative difference in results of both models is higher for metrics using CVSS than their counterparts (CI vs BI, FAC vs PPV, MC vs TPR), which shows that the MLP-based IDS is globally better at detecting attacks with a higher CVSS.

Operationally, it means the MLP-based IDS will more often detect attacks that are critical and might endanger the system. When using such an IDS, automated mitigation strategies can be used with more confidence, and human operators will be able to divert their energy in investigating other more relevant alarms that might represent previously undetected attacks.

5.2 CVSS' Environmental score

The CVSS Environmental Score allows to define requirements in Confidentiality, Integrity and Availability, and to modify base vector values. In doing so, scores returned by the CVSS scoring system differ from what would be returned without any requirements.

The main advantage of using the Environmental Score is being able to find and differentiate IDSs that might be more adapted to protect a system given its security requirements, when their performance according to common metrics are relatively similar. In Table 5, two very similar DTs were compared using three environments as defined in subsection 4.4. Both are `DecisionTreeClassifier` from the scikit-learn library, and the only difference between both is the criterion used. The first, DT 1, was trained with a Gini criterion while the second, DT 2, was trained with an entropy criterion with otherwise equal parameters. Both IDSs being very similar, performance is also expected to be very similar.

Both models results are almost equal on all classes, except for Infiltration (High impact on Confidentiality) and Web Attack SQL Injection (Low impact on Confidentiality, Integrity and Availability). DT 1 has a 60% Accuracy while DT 2 has a 20% Accuracy for Infiltration. For Web Attack SQL Injection, DT 1 has a 33% Accuracy, while DT 2 has a 67% Accuracy. Using common ML metrics, it is uncertain which IDS is the best.

The difference in CVSS scores for both Infiltration (Basic Env.: 5.5, Env. 2: 6.5, Env. 3: 2.9) and Web Attack SQL Injection (Basic Env.: 7.3, Env. 2: 7.4, Env. 3: 7.4) can be read in Table 2. Because Web Attack SQL Injection's CVSS score is higher, it is not surprising that DT 2's performance with regard to the basic environment is better with CVSS related metrics. However, when the Confidentiality requirement is higher as in Env. 2, it increases the CVSS score of Infiltration instances to 6.5, thus closing the gap in performance in both models and both models can be considered more or less equal. Finally, with a lower requirement on Confidentiality, Infiltration attacks are less severe and thus DT 2's performance according to CVSS related metrics appears clearly higher than DT 1's. Therefore, as long as requirements in Integrity and Availability are not too far from requirements in Confidentiality, DT 2 would be more adequate. On the contrary, without requirements in Integrity and Availability and with at least medium

Table 5: Model performances of two DTs on the CIC-IDS2017 dataset for different environments

Environment	Model	TPR	PPV	BI	MC	FAC	CI
Basic Environment	DT 1	0.830	0.880	0.828	0.117	0.080	0.802
	DT 2	0.824	0.882	0.822	0.114	0.069	0.815
Env. 2 (High C, Medium I, Low A)	DT 1	0.830*	0.880*	0.828*	0.130	0.085	0.783
	DT 2	0.824*	0.882*	0.822*	0.132	0.080	0.786
Env. 3 (Low C, Medium I, High A)	DT 1	0.830*	0.880*	0.828*	0.104	0.076	0.818
	DT 2	0.824*	0.882*	0.822*	0.096	0.059	0.843

Values were truncated to the third decimal. C: Confidentiality, I: Integrity, A: Availability.
 * TPR, PPV and BI values are equal for all environments.

requirements in Confidentiality, it is highly probable the DT 1 model would be more adequate.

5.3 Using CVSS to train Neural Networks

While integrating CVSS scores into evaluation metrics might help in choosing a more adequate IDS, it does not make them better. This is where integrating CVSS score into the training phase of IDSs counts, to build IDSs that will inherently detect more often severe attacks. In order to test the advantages of using a loss integrating CVSS scores, two NNs (Neural Networks) were trained and test on the dataset reported in Table 3, one with a classic CEL (Cross-Entropy Loss) as in Equation 4, and the other with the loss using CVSS scores as formulated in Equation 8.

Results of IDSs trained with either loss are reported in Table 6. Interestingly, only taking classic ML metrics into account, the IDS trained using the loss with CVSS already exhibits a close to 50% higher PPV (Precision), which means the IDS is much more often right when predicting different attacks.

Table 6: Performance of NNs trained with a basic CEL or with CVSSCEL

Training Loss	TPR	PPV	BI	MC	FAC	CI
Basic CEL	0.258	0.246	0.233	0.579	0.589	-0.169
CVSSCEL	0.288	0.360	0.263	0.547	0.488	-0.035

Values were truncated to the third decimal.

Taking into account CVSS-related metrics, the IDS trained using the loss with CVSS

is also clearly more effective in detecting attacks, and possibly more severe attacks. In order to properly investigate whether training with a loss using CVSS scores do help in detecting more severe attacks, it is required to go over performance of the IDSs on different classes. In Figure 2, results of the two IDSs are shown with regard to Accuracy (a), percentage of completely missed attacks (instances classified as normal for each class) (b) and CI scores (c). For convenience, the IDS trained without CVSS scores will be called CEL-IDS, and the one trained with will be called CVSSCEL-IDS.

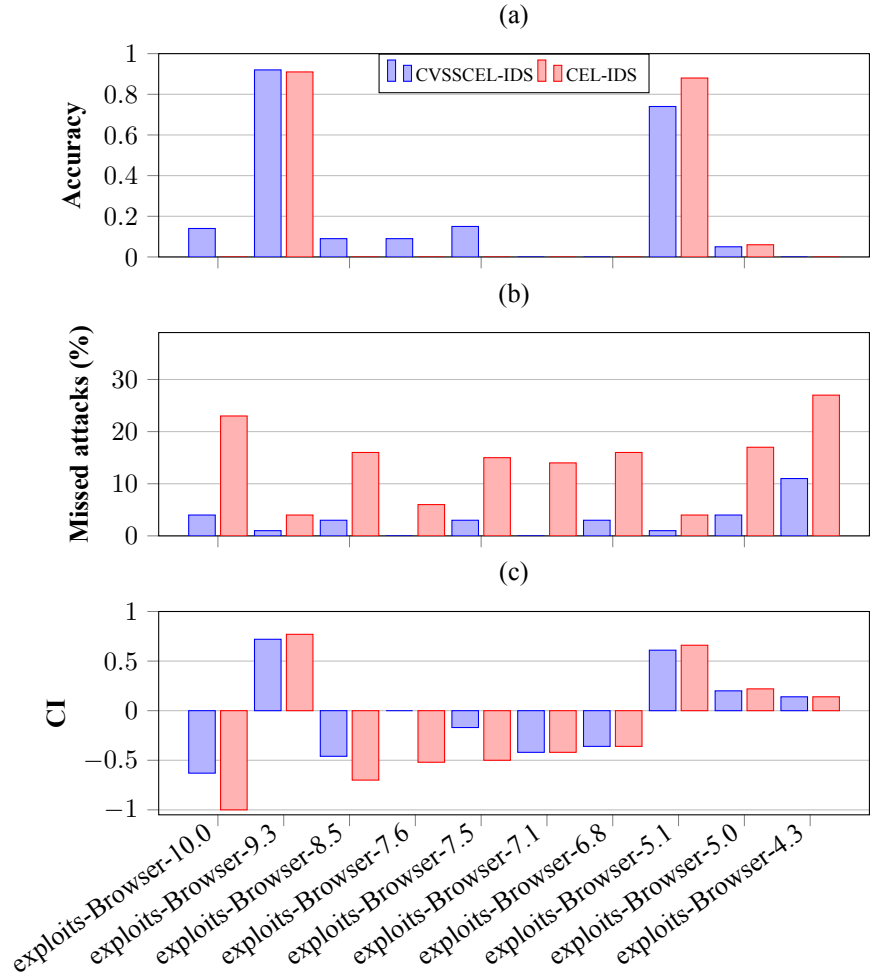


Figure 2: Comparison of two IDSs trained with a CVSSCEL (CVSSCEL-IDS) and with a basic CEL (CEL-IDS).

Because exploits-Browser-9.3 and exploits-Browser-5.1 are more frequent than other attack classes, their Accuracy is expectedly higher for both IDSs. However, CVSSCEL-

IDS has an Accuracy around 10% higher for the four other most severe attacks, which is quite significant considering these attacks are completely undetected by CEL-IDS.

Furthermore, almost all attacks were completely missed 10 to 20% less by CVSSCEL-IDS, and were often misclassified as exploits-Browser-9.3 if not correctly classified. A possible explanation is that using CVSS scores in the loss formulation ends up penalizing missed attacks (particularly severe attacks) much more, thus forcing the IDS to refine its representation of attack classes more than without using CVSS scores.

Finally, results using the CI metric for each class also tend to validate the higher performance of the IDS trained using CVSS scores.

6 Conclusion and Future Work

Using CVSS scores with IDSs seem to be able to fulfil multiple purposes, be it for training to help IDSs detect more severe attacks, or to be integrated in evaluation metrics to find IDSs that are better at detecting severe attacks or more adapted to a particular system. When models show very similar performance on the newly defined metrics, it generally means that their performance is similar on all attacks or that they differ for attacks having similar CVSS scores. The high performance on critical attacks is thus adequately highlighted. Interestingly, some IDSs, although exhibiting relatively poor performance in general, can have an unexpectedly good performance in some aspects, e.g., the GNB-based IDS for CIC-IDS2017 which is the best attack detector at the cost of more false alarms. Thus, using those IDSs could be interesting when implementing ensemble methods for intrusion detection.

Using CVSS scores with environmental parameters also seem to enable building IDSs being targeted at protecting specific systems with different requirements. However, CVSS base vectors of the encountered attacks need to be available to be able to compute modified CVSS scores, thus requiring more information on the attacks.

Finally, integrating CVSS scores into a loss formulation to train NN-based IDSs seem highly effective and does not seem to really suffer from evident drawbacks. A possible shortcoming of using such methods is that integrating CVSS scores into the training of an IDS does not seem as simple with ML methods other than NNs.

Although these new metrics are based on a *de facto* cybersecurity standard score, using such standard requires a more consistent effort in data collection to take advantage of CVSS scores to train and find better and more adapted IDSs.

In future work, the integration of CVSS score could be adapted to use the version 4.0 (still under review) of the framework. The usage could also be extended to ICS datasets, which would require a new computation of CVSS scores. It could also be interesting to see if using CVSS scores greatly impacts ensemble methods. Finally, the methodology presented in this paper could be extended to take into account attack graphs, to use CVSS scores in a more comprehensive way.

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