UNR-IDD: Intrusion Detection Dataset using Network Port Statistics

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***Abstract*—With the expanded applications of modern-day networking, network infrastructures are at risk from cyber attacks and intrusions. Multiple datasets have been proposed in the literature that can be used to create Machine Learning (ML) based Network Intrusion Detection Systems (NIDS). However, many of these datasets suffer from sub-optimal performance and do not adequately represent tail classes. To address these issues, in this paper, we propose the University of Nevada - Reno Intrusion Detection Dataset (UNR-IDD) that provides researchers with a wider range of samples and scenarios. The proposed dataset utilizes network port statistics for more fine-grained control and analysis of intrusions. Using different ML algorithms, we provide a benchmark to show efficient performance for both binary and multi-class classification tasks. The paper further explains the intrusion detection activities rather than providing a generic black-box output of the ML algorithms. In comparison with the other established NIDS datasets, we obtain better performance with an F_μ score of 94% and a minimum *F* score of 86%. This performance can be credited to prioritizing high scoring average and minimum F-Measure scores for modeled intrusions.**

***Index Terms*—Computer networks, network intrusion detection, machine learning, dataset**

I. Introduction

Modern computer networks and their connected applications have reached unprecedented growth with implementations like the internet of things, smart homes, and software-defined networks. However, this has also increased the potential for network intrusions that attempt to compromise the major principles of these computing systems: availability, authority, confidentiality, and integrity [1]. These threats are difficult to detect unaided, as they display indistinguishable network traffic patterns as normal functionality [2]. Approaches like traditional firewalls cannot detect these intrusions as they do not possess the ability to inspect and conduct deep packet inspection. This has led to the rise in Network Intrusion Detection Systems (NIDS) which aim to provide higher protection [3]. NIDS constantly monitor the network traffic patterns for any kind of malicious behavior. Modern networking applications have become more diverse, dynamic, interconnected, and geographically distributed, with a larger number of users, applications, and nodes, generating substantial amounts of shared data. Protecting these large-scale networks has become a challenge as existing NIDS show inefficient intrusion detection performance, including high false alarm rates and zero-day attacks [4].

The usage of machine learning (ML) for NIDS has gained traction in the last decade as various open-sourced datasets have been proposed and established. Customary NIDS datasets include NSL-KDD [5], UNSW-NB15 [3], and CIC-IDS-2018 [6]. However, a common problem that has been identified with many of these datasets is inadequate modeling of tail classes [7]. Tail classes refer to certain labels with limited samples compared to other labels, leading to poor performance when fitting the ML model. Researchers have been looking at methods to address this issue of tail classes. Commonly investigated methods include undersampling and oversampling. However, oversampling increases the size of the dataset, increasing training time, memory, and complexity. Correspondingly, undersampling can reduce data samples from the majority classes, affecting the overall performance of prediction models [8]. It can also be argued that because these techniques manipulate existing data samples, they do not add any new insights.

Other proposed methods to address tail class representation include transfer learning, data augmentation, representation learning, and ensemble methods [7]. These techniques, however, have limitations in their own regard. For example, transfer learning and data augmentation could further increase class variability as head classes have more samples and would be augmented more. In representation learning, the accumulated training stages make decoupled training less practical to be integrated with existing well-formulated methods. Ensemble methods can lead to higher computational costs due to the presence of multiple classifiers. A valid method to ensure that tail classes have adequate representation is to prioritize them during data generation to ensure adequate modeling and uniform high performance. This necessitates the need for a new NIDS dataset in which all labels are adequately represented.

Another limitation of the current datasets is that they mostly depend on flow level statistics. This can limit the transferability of the NIDS solutions to other network configurations since the flow statistics depend on the network topology and traffic characteristics. In addition, many of these datasets contain redundant features that play no impact in being able to detect potential network intrusion types. Depending on the ML approach being utilized, these features can also increase the cardinality of the dataset, leading to increased training and inference times. Finally, some existing datasets suffer from incomplete or missing records. These records or samples must be ignored or dropped from the overall dataset, which leads to sub-optimal performance. Addressing the above-mentioned

limitations is vital to ensuring that proper NIDS are being developed to adequately protect networking infrastructures from intrusions.

In this paper, we propose the University of Nevada - Reno Intrusion Detection Dataset (UNR-IDD). The main difference between UNR-IDD and existing NIDS datasets is that UNR-IDD consists primarily of network port statistics. These refer to the observed port metrics recorded in switch/router ports within a networking environment. The dataset also includes delta port statistics which indicates the change in magnitude of observed port statistics within a time interval. Compared to datasets that primarily use flow statistics, UNR-IDD can provide a more fine-grained analysis of network flows as decisions are made at the port level versus the flow level. This can lead to rapid identification of potential intrusions. We also address the limitation of tail classes. Our dataset ensures that there are enough samples for ML classifiers to achieve high F-Measure scores, uniquely. Our dataset also ensures that there are no missing network metrics. The proposed observable dataset metrics can be obtained through most networking architectures. However, for our testbed, we have used a software-defined network (SDN) environment, due to the wide relevance of and usage of SDN architectures across industries, organizations, and critical infrastructures. In summary, the main contributions of our dataset include:

- The primary usage of port and delta port statistics to model the various intrusions in the dataset.
- Confirms enough samples to ensure high-performance metrics across all tail classes.
- Ensuring all data samples are filled and there is no missing data in the dataset.
- Provides performance comparison of intrusion detection models when using UNR-IDD and other NIDS datasets.

The rest of the paper is structured as follows: Section II provides the literature study. Our dataset collection, configuration, and generation methods are detailed in Section III. Section IV presents experimental results and discussions. Finally, conclusions are drawn in Section V.

II. Related Work

Some of the very first datasets that emerged for creating NIDS include the DARPA [9] and KDDCup99 [10]. The main issue with these datasets is that they are outdated. KDDCup99 suffers from redundant and duplicate data samples. DARPA does not represent modern networks as it was simulated in a military network environment. Thus, it contains artificially high feature magnitudes compared to real traffic data. Other proposed datasets for NIDS include CAIDA [11], CDX [12], Kyoto [13], Twente [14], and ISCX2012 [15]. CAIDA dataset suffers from having very limited features and was only constrained to being able to detect Distributed Denial of Service (DDoS) attacks. Similarly, the CDX dataset only contains five features and could only detect buffer overflow attacks. The Kyoto dataset is restricted to two classes and contains limited features, which restraints its functionality. The Twente and ISCX2012 datasets solely focused on IP flows within the network level, which restricts their capability as they are flow-oriented and do not provide network-level information that can be used to detect network-wide issues. The size of the Twente dataset is also small to perform adequate modeling of the intrusions [16].

Three customary NIDS datasets are NSL-KDD [5], CIC-IDS-2018 [6], and UNSW-NB15 [3]. These datasets also have several limitations. For instance, the UNSW-NB15 suffers from inconsistent performance for machine learning classifiers. It requires more rigorous and expanded machine learning mechanisms which increases training and inference times. The NSL-KDD and CIC-IDS-2018 datasets suffer from missing data samples within their datasets. Many of these datasets also suffer from the issue of containing inadequately modeled tail classes which lead to inconsistent performance.

For more effective intrusion detection, we need to ensure that a dataset contains a wide variety of intrusion categories. We also need to make sure that it is complete as missing data can negatively impact the performance of prediction models. The primary usage of port level statistics, in conjunction with some flow statistics, for NIDS is another attractive research direction that can be employed to check their efficacy at detecting network intrusions. Lastly, it is critical to ensure that tail classes have adequate representation so that prediction models can accurately capture their unique behavior and attain high performance.

III. UNR-IDD Dataset

We setup up our testbed using an SDN simulation environment due to the ease of usability and implementation. It also ensures that the dataset is not dependent on any static topology and can be configured to reproduce the network activity of various topologies. Following the testbed configuration, we perform flow simulations within the SDN topology to replicate appropriate functionality. During these flow simulations, desired network statistics are collected, under normal and attack conditions.

A. Testbed Configuration

To set up the testbed, we use Open Network Operating System (ONOS) SDN controller (API version 2.5.0) alongside Mininet for the network topology generation. ONOS uses the Open Service Gateway Initiative (OSGi) service component at runtime for the creation and activation of components and auto-wiring components together, making it easy to create and deploy new user-defined components without altering the core constituents. Mininet creates the desired virtual network, and runs a real kernel, switch, and application code, on a single machine, thereby generating a realistic testbed environment. We also implemented our ONOS application to collect network statistics. Specifically, we gathered delta and cumulative port, flow entry, and flow table statistics for each connected Open vSwitch in the Mininet topology. We created a custom Mininet topology using Mininet API (version 2.3.0) with Open Flow (OF) 14 protocol deployed to the switches. The generated SDN

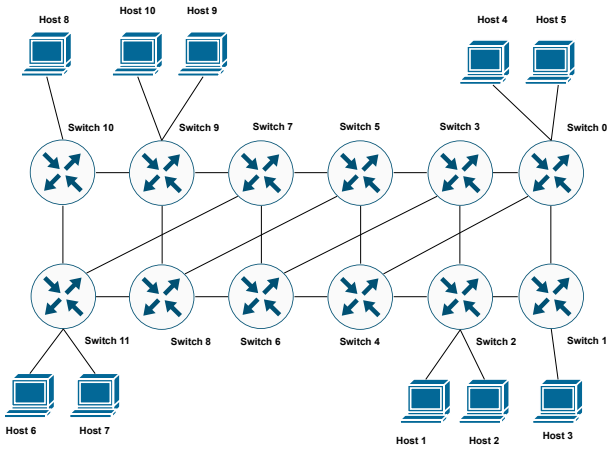


Fig. 1: Simulated SDN topology

topology for our experiments is illustrated in Figure 1, which consists of 10 hosts and 12 switches.

B. Flow Simulation

IPerf is used to create TCP and UDP data streams simulating network flows in virtual and real networks using dummy payloads. By using the Mininet API and IPerf, we created a Python script to simulate realistic network flows. Once every 5 seconds, we initiated Iperf traffic between a randomly chosen source-destination host pair with a bandwidth of 10 Mbps and duration of 5 seconds. These values must be carefully chosen as they are dependent on the number of nodes, hosts, switches, and geographical spread of the simulated network. We then simulate flows under normal and intrusion conditions to gather data in every scenario. To ensure that each normal and intrusion category is minimally variable and adequately represented, we execute the same number of flows while simulating each scenario.

C. Data Collection

We create a custom application to collect and log the available statistics that are captured periodically (once in every 5 seconds) from OpenFlow (OF) switches. The statistics are collected through by means of *OFPPortStatsRequest* and *OFPPortStatsReply* messages between controller and switches. The delta port statistics are computed on the controller side by taking the difference between the last two collected data instances. We create a key-value map of this data by gathering it from the data storage service, using the "Device Service" API provided by ONOS. After this, we logged the map of the collected statistics to a Javascript Object Notation (.json) file with a name $N_i.json$. Table I shows the collected port statistics and their descriptions per port on every switch in the simulated SDN. These statistics relay the collected metrics and magnitudes from every single port within the SDN when a flow is simulated between two hosts. Table II illustrates the collected delta port statistics and their descriptions per port on every switch. These delta statistics are used to capture the change in collected metrics from every single port within the SDN when a flow is simulated between two hosts, at a time

TABLE I: Port statistics collected for every port on every switch

Port Statistic	Description
Received Packets	Number of packets received by the port
Received Bytes	Number of bytes received by the port
Sent Packets	Number of packets sent by the port
Sent Bytes	Number of bytes sent
Port alive Duration	The time port has been alive in seconds
Packets Rx Dropped	Number of packets dropped by the receiver
Packets Tx Dropped	Number of packets dropped by the sender
Packets Rx Errors	Number of transmit errors
Packets Tx Errors	Number of receive errors

TABLE II: Delta port statistics collected for every port on every switch

Delta Port Statistic	Description
Delta Received Packets	Change in number of packets received by the port
Delta Received Bytes	Change in number of bytes received by the port
Delta Sent Packets	Change in number of packets sent by the port
Delta Sent Bytes	Change in number of bytes sent
Delta Port alive Duration	Change in the time port has been alive in seconds
Delta Packets Rx Dropped	Change in number of packets dropped by the receiver
Delta Packets Tx Dropped	Change in number of packets dropped by the sender
Delta Packets Rx Errors	Change in number of transmit errors
Delta Packets Tx Errors	Change in number of receive errors

interval of 5 seconds. Additionally, we also collect some flow entry and flow table statistics to work in conjunction with the collected port statistics as seen in Table III. These metrics provide information about the conditions of switches in the network and can be collected in any network setting.

D. Intrusions

The following intrusions are simulated in the data collection phase:

- **TCP-SYN Flood**: A Distributed Denial of Service (DDoS) attack where attackers target hosts by initiating many Transmission Control Protocol (TCP) handshake processes without waiting for the response from the target node. By doing so, the target device's resources are consumed as it must keep allocating some memory space for every new TCP request.
- **Port scan**: An attack in which attackers scan available ports on a host device to learn information about the services, versions, and even security mechanisms that are running on that host.
- **Flow Table Overflow**: An attack that targets network switches/routers where attacks compromise the functionality of a switch/router by consuming the flow tables that forward packets with illegitimate flow entries and rules so that legitimate flow entries and rules cannot be installed.
- **Blackhole**: An attack that targets network switches/routers to discard the packets that pass through, instead of relaying them on to the next hop.
- **Traffic Diversion**: A attack that targets network switches/routers to reroute the direction of packets away from their destination, to increase travel time, and/or to spy on network traffic through a man-in-the-middle scenario.

TABLE III: Flow statistics collected

Statistic	Description
Connection Point	Network connection point expressed as a pair of the network element identifier and port number
Total Load/Rate	Obtain the current observed total load/rate (in bytes/s) on a link
Total Load/Latest	Obtain the latest total load bytes counter viewed on that link
Unknown Load/Rate	Obtain the current observed unknown-sized load/rate (in bytes/s) on a link
Unknown Load/Latest	Obtain the latest unknown-sized load bytes counter viewed on that link
Time seen	When the above-mentioned values were last seen
is_valid	Indicates whether this load was built on valid values
TableID	Returns the Table ID values
ActiveFlowEntries	Returns the number of active flow entries in this table.
PacketsLookedUp	Returns the number of packets looked up in the table.
PacketsMatched	Returns the number of packets that successfully matched in the table
MaxSize	Returns the maximum size of this table.

TABLE IV: Multi-class Classification Labels

Label	Description
Normal	Normal Network Functionality
Attack	Network Intrusion

These intrusion types were selected for this dataset as they are common cyber attacks that can occur in any networking environment. Also, these intrusion types cover attacks that can be launched on both network devices and end hosts.

E. Labels

This dataset can be broken down into two different machine learning classification problems: binary and multi-class classification. The goal of binary classification is to differentiate intrusions from normal working conditions. Binary classification can estimate if a network is under attack but does not provide any information about the type of attack. The labels for binary classification in UNR-IDD are illustrated in Table IV.

The goal for multi-class classification, however, is to differentiate the intrusions not only from normal working conditions but also from each other. Multi-class classification helps us to learn about the root causes of network intrusions. The labels for multi-class classification in UNR-IDD are illustrated in Table V.

IV. Experimentation, Results, and Analysis

To showcase the functionality of our proposed dataset, UNR-IDD, we run evaluations using the dataset and demonstrate the performance achieved. We illustrate results across multiple scenarios by varying the classification type, the ML algorithms, and other prominent NIDS in the literature. For performance evaluation, we are using accuracy (*A*), precision (*P*), Recall (*R*), and F-Measure (F) scores as the metrics. In addition, we are also using the mean scores for precision (P_μ), recall (R_μ), and f-measure (F_μ) across all label types in the

TABLE V: Multi-class Classification Labels

Label	Description
Normal	Normal Network Functionality
TCP-SYN	TCP-SYN Flood
PortScan	Port Scanning
Overflow	Flow Table Overflow
Blackhole	Blackhole Attack
Diversion	Traffic Diversion Attack

TABLE VI: Binary Classification Performance

Label	*P*	*R*	*F*
Attack	1.0	1.0	1.0
Normal	1.0	1.0	1.0

datasets during multi-class classification. This will provide us with the mean performance achieved on the dataset for all label types.

First, we observe the performance that is being achieved from the proposed dataset on both binary classification and multi-class classification scenarios. For this, we are utilizing a Random Forest (RF) as our ML algorithm. We chose to use an RF due to its relevance and wide usage when studying NIDS in literature. The binary classification performance and multi-class classification performance achieved from the dataset can be observed in Table VI and Table VII, respectively. We can see that in Table VI, both label types are providing a performance of 1.0 for *P*, *R*, and *F* scores. This means that the dataset is linearly separable, and the RF has no trouble detecting if a given network flow is normally functioning or under any potential intrusion. Similarly, in Table VII, we see the RF achieving excellent performance as well. All the label types achieve high scores for *P*, *R*, and *F* scores. These can be attributed to the fact that each label type has adequate representation and enough data samples thereby, makes them linearly separable from each other. This makes it easier for machine learning classifiers to recognize them individually, which does not deteriorate performance. These results demonstrate one of the main contributions of this proposed dataset, which is ensuring that all labels have enough data samples to achieve high performances, individually and as a collective.

Next, we observe the performance that is being achieved from the proposed dataset using multiple ML algorithms: RF, Multi-layer Perceptron (MLP), Support Vector Machine (SVM), Bagging Classifier (BC), KNeighborsClassifier (KNC), and AdaBoost Classifier (ABC). We chose to use these algorithms due to their relevance and wide usage when studying NIDS in literature, along with their ease of accessibility through the sklearn libraries. The performance achieved by the algorithms on UNR-IDD is provided in Table VIII. We can see that the best performance is achieved by the RF and BC classifiers as they achieve the near-optimal P_μ, R_μ, and F_μ scores. This is followed by the SVM, KNC, and ABC classifiers which achieves above-average scores, succeeded by the MLP which achieves substandard performance. These results can be associated with the fact that an RF classifier is an ensemble classifier consisting of multiple decision trees and can overcome the problem of overfitting. Similar functionality occurs in BC as it also is an ensemble classifier whose default classifier is a decision tree. Accuracy and variable importance

TABLE VII: Multi-class Classification Performance

Label	*P*	*R*	*F*
Blackhole	0.98	0.98	0.98
Diversion	0.99	0.97	0.98
Normal	1.0	1.0	1.0
Overflow	0.98	0.76	0.86
PortScan	0.91	0.94	0.92
TCP-SYN	0.91	0.92	0.92

TABLE VIII: Multi-class Classification Performance using Machine Learning Algorithms

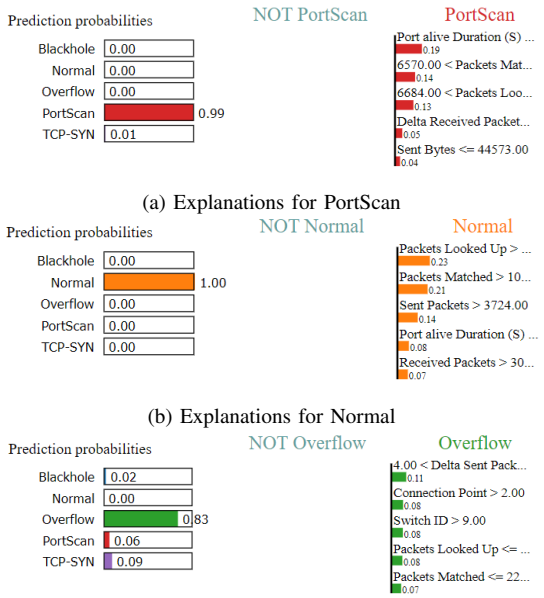
Algorithm	P_μ	R_μ	F_μ
SVM	0.89	0.79	0.81
MLP	0.59	0.54	0.54
RF	0.96	0.92	0.94
BC	0.95	0.93	0.94
KNC	0.79	0.75	0.77
ABC	0.69	0.59	0.55

are also automatically generated in RF and BC [17], compared to the other classifiers observed.

We also analyze the explainability of the RF model across various labels for a more comprehensive analysis. This is conducted by analyzing the predictions of the model, on testing samples with varying predicted labels, using the Local Interpretable Model-agnostic Explanations (LIME) framework [**?**]. These results are provided in Figure 2. We evaluationsan-other proposed contribution to the UNR-IDD dataset, which incorporates the primary usage of port and delta port statistics to model the various intrusions in the dataset.

Lastly, we compare the performance that is being achieved from the proposed UNR-IDD dataset to two open-sourced NIDS datasets: NSL-KDD and CIC-IDS-2018. These two are established NIDS datasets that are frequently used for researching network intrusion and anomaly detection. We use the same RF classifier for all three datasets and their performance is evaluated using A, P_μ, R_μ, and F_μ. We also introduce a new metric, min *F*, which represents the minimum F-Measure score that is achieved for any label in that dataset. This metric can highlight the variability between F_μ and the min *F* value in each dataset.

We observe the impact of the dataset sizes on the training times. We provide this comparison in Table IX where we provide the dataset dimensions (samples and features) for all the datasets. As observed, CIC-IDS-2018 contains 6,291,450 samples and 80 features, NSL-KDD contains 125,974 samples and 43 features, and UNR-IDD contains 37,412 samples and 34 features. This emphasizes that the proposed UNR-IDD dataset has the lowest operational footprint out of the observed NIDS datasets. For evaluation, we note both the Overall Training Time (OTT) in seconds (s) and Normalized Training Time (NTT) in milliseconds (s). We observe that UNR-IDD, due to its smaller dimensions, takes less time to train at 4.03s than NSL-KDD at 9.84s and much less time to train than CIC-IDS-2018 at 9056.23s. NTT can be defined as the time taken to train one sample and can be computed by dividing the OTT by the number of samples. We notice that the NTT is least for the NSL-KDD with 0.078 ms/sample, with UNR-IDD achieving comparable performance to it with 0.107 ms/sample. This can be attributed to NSL-KDD having only 3 categorical



(a) Explanations for PortScan

(b) Explanations for Normal

(c) Explanations for Overflow

Fig. 2: LIME Explanations for UNR-IDD

features per sample, whereas UNR-IDD contains 5 categorical features per sample. CIC-IDS takes the most NTT out of the three datasets with 1.439 ms/sample. From the perceived OTT and NTT, we observe that the UNR-IDD provides the quickest OTT and very comparable NTT. This signifies that using UNR-IDD, a competent ML model for intrusion detection can be generated much quicker as it can train the overall dataset the fastest while training each sample with comparable speed to that of the other observed NIDS datasets.

In Figure 3, we observe that both the NSL-KDD and CIC-IDS-2018 datasets achieve 99% *A* scores. Relatively, the UNR-IDD dataset achieves comparable performance with an *A* score of 95%. This can be attributed to the UNR-IDD dataset being smaller, overall, than NSL-KDD and significantly smaller, overall, than CIC-IDS-2018 in terms of both the number of samples and features. We also note that the P_μ score for the UNR-IDD dataset is equivalent to that of CIC-IDS-2018 at 96%. Compared to this, NSL-KDD achieves a P_μ score of 79%. Similarly, the R_μ score for UNR-IDD is higher than CIC-IDS-2018 and NSL-KDD at 93% versus 91% and 74%, respectively. The most important contribution of the proposed UNR-IDD dataset is its effect on F-Measure scores. Since each tail class is adequately represented in the dataset, it achieves the highest F_μ out of all three datasets with 94% compared to 93% and 76% for CIC-IDS-2018 and NSL-KDD, respectively. Similarly, the minimum *F* score that is achieved across all three datasets is highest in the UNR-IDD dataset with 86%, while the CIC-IDS-2018 and NSL-KDD datasets achieve a minimum *F* score of 58% and 0% respectively. This highlights the UNR-IDD's prioritization of the F-Measure score as it achieves the least variability between the F_μ and the min *F* value observed among all the datasets.

The proposed UNR-IDD dataset can perform network intrusion detection with competent performance. The dataset

TABLE IX: Training Analysis of the NIDS Datasets

Dataset	Samples	Features	OTT (s)	NTT (ms)
UNR-IDD	37,412	34	4.03	0.107
NSL-KDD	148,517	43	9.84	0.078
CIC-IDS-2018	6,291,480	80	9056.23	1.439

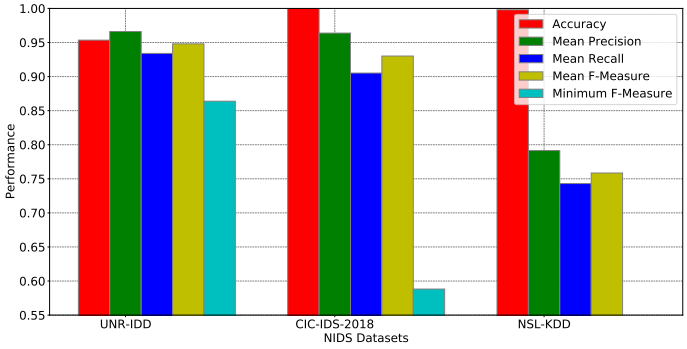


Fig. 3: Performance Analysis of UNR-IDD, NSL-KDD, and CIC-IDS-2018 datasets

prioritizes representation for all tail classes and ensures that each label achieves high performance and F scores. Compared to customary datasets, UNR-IDD is a smaller overall dataset. However, the dataset still provides efficient performance across all the labels. Due to this, anomaly/intrusion detection could be trained more easily in resource-constrained network devices or low-end servers. Presently, this dataset can be publicly accessed on Kaggle [18].

V. Conclusion and Future Work

In this paper, we propose the University of Nevada - Reno Intrusion Detection Dataset (UNR-IDD) for network intrusion detection. The dataset addresses several limitations of existing datasets by primarily using network port statistics and delta port statistics, to achieve a more fine-grained analysis of the network and rapid identification of potential intrusions within a network. Emphasis is also placed on improving representation for all tail classes, so that each class has adequate representation and achieves high performance individually, in conjunction with the whole dataset. Also, to ensure optimal performance, there are no incomplete or missing data samples within the dataset. The dataset is generated using an SDN simulation environment and desired network statistics are collected through OpenFlow metrics. Simulation and results show that the dataset can achieve efficient performance for both binary and multi-class classification scenarios and achieves the best performance when using an RF classifier. Results also show that the dataset achieves better performance than other established datasets, with a priority for improved and high scoring F_μ and min F scores. This highlights the dataset's prioritization of adequate label representation, compared to other datasets. Future work in this research can include augmenting the dataset with more intrusion categories. Potential categories include data plane threats like ARP spoofing, side-channel attacks, control plane threats like network manipulation, and application plane threats like API exploitation, application manipulation, and brute-force/password guessing attacks.

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