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A Detailed Analysis of Benchmark Datasets for Network Intrusion Detection System

Mossa Ghurab[1], Ghaleb Gaphari[1], Faisal Alshami[2], Reem Alshamy[1*] and Suad Othman[1]

[1]Department of Computer Science, Faculty of Computer & IT (FCIT), Sana'a University, Yemen.
[2]Software College Northeastern University, Shenyang 110819, China.

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This work was carried out in collaboration among all authors. Authors MG, GG and FA designed the study and managed literature searches. Authors RA and SO managed the analyses of the study and review the final draft of the manuscript literature searches. All authors read and approved the final manuscript.

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ABSTRACT

The enormous increase in the use of the Internet in daily life has provided an opportunity for the intruder attempt to compromise the security principles of availability, confidentiality, and integrity. As a result, organizations are working to increase the level of security by using attack detection techniques such as Network Intrusion Detection System (NIDS), which monitors and analyzes network flow and attacks detection. There are a lot of researches proposed to develop the NIDS and depend on the dataset for the evaluation. Datasets allow evaluating the ability in detecting intrusion behavior. This paper introduces a detailed analysis of benchmark and recent datasets for NIDS. Specifically, we describe eight well-known datasets that include: KDD99, NSL-KDD, KYOTO 2006+, ISCX2012, UNSW-NB 15, CIDDS-001, CICIDS2017, and CSE-CIC-IDS2018. For each dataset, we provide a detailed analysis of its instances, features, classes, and the nature of the features. The main objective of this paper is to offer overviews of the datasets are available for the NIDS and what each dataset is comprised of. Furthermore, some recommendations were made to use network-based datasets.

**Corresponding author: E-mail: reemalshamy2020@gmail.com;*

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1. INTRODUCTION

Network security has become increasingly important with the rising growth of computer networks and the increasing use of computer applications on these networks. The big challenge facing network engineers and researchers today is to identify malicious activities in a host or over a network [1]. The cybersecurity research area focuses on ability to act proactively to prevent or mitigate attacks.

NIDS is placed at a strategic point in the network where it monitors all the traffic, it analysis the traffic to detect possible attacks. Mostly, NIDS follows one of the two major detection methods: Anomaly-based Intrusion Detection System (AIDS) and Signature-based Intrusion Detection System (SIDS). In addition, a lot of researchers have proposed hybrid method. SIDS is quite popular in commercial applications for designing effective commercial NIDS, it is designed to detect known attacks that are preloaded in the NIDS datasets. AIDS is limited to academics for research and development, it compares current user activities against predefined profiles is used to detect abnormal behaviors that might be intrusions. AIDSs are prime in detecting network-level attacks, it is an effective way to detect unknown attacks [2-5]. AIDSs are better than SIDSs in the detection of new attacks [6,7]. A hybrid detection is combined two methods to overcome disadvantages in SIDS and obtain advantages for AIDS [8]. But in general, NIDS needs existing information to detect future attacks.

Datasets need to train and evaluate AIDS [9]. Moreover, benchmark datasets are a good basis for evaluating and comparing the quality of different NIDS, which researchers in the field can use to train and test their models [10,11]. Various Machine Learning (ML) algorithms are applied in NIDS to distinguish between normal traffic and anomalies or attacks in network traffic [12]. These approaches include Support Vector Machine (SVM) [13], Random Forest (RF) [14], and SVMwithSGD [15].

Various datasets have appeared since 1998 until now, some of these datasets suffer from providing volume and variety of network traffic, and others do not have different or new attack patterns, while others lack metadata information. Many researchers have used various machine and deep learning techniques depending on the presence or absence of labelled datasets. This paper concentrates on ML techniques, both supervised and unsupervised learning methods that are used by researchers in this field to detect attacks in the network traffic. The main objective of this paper is to provide researchers idea about what the benchmark datasets are publicly available for evaluate NIDS and what each dataset is comprised of in terms of instances, features, classes, and the nature of the features.

The rest of this review is organized as follows: Section 2 offers the related work. Section 3 provides a detailed analysis of various benchmark datasets. Section 4 offers discussions and recommendations for the use of network datasets. Finally, this paper concludes with future work.

2. RELATED WORK

A lot of researches focus on analyzing benchmark datasets. Almost NIDS researches often focus on analyzing a single dataset of NIDS evaluation or introduce a general review of datasets, a little of researches that presented a detailed analysis of benchmark and recent datasets for NIDS. This section summarizes some studies that analyzed NIDS datasets.

Panigrahi et al. [3] introduced a detailed analysis of the most recent dataset namely the CICIDS2017 dataset, it consisting of the latest attacks and features. This dataset draws the interest of many researchers because it represents attacks that old datasets did not address. Various lack of the dataset have been studied and outlined. The presented a detailed characteristics of the CICIDS2017 dataset only.

Khraisat et al. [4] demonstrated a survey of NIDS approaches, types, and technologies with their advantages and limitations. The various ML techniques that are suggested to detect zero-day attacks are displayed. However, such approaches may have the problem of generating and updating the information about new attacks and poor accuracy or generate high false alarms. Summarized recent studies and explored contemporary models for improving performance NIDS as a solution to overcome on NIDS problems. Additionally, the most common public datasets used in NIDS were showed.

Ring et al.[9] presented a survey about the datasets used for NIDS and describe the flow-based network data and underlying packet in detail. The paper identified fifteen different properties to evaluate the suitability of individual datasets for specific evaluation scenarios, it also highlighted the peculiarities of each dataset. Furthermore, they provided a discussion and observations and also provided some recommendations for the use and the creation of NIDS datasets.

Hamid et al. [11] provided a review for six benchmark (DARPA98, KDD99, NSL-KDD, UNM, Caida DDoS, and UNSW-NB15) datasets. Moreover, they introduced a detailed discussion for three datasets (KDD99, NSL-KDD, and UNSW-NB 15) based on the number of instances, features, classes, and nature of features. In experimental, they used the K-NN classifier on these six datasets and demonstrated the K-NN classifier algorithm performed better on the NSL-KDD dataset and achieved high performance.

The study by Ferrag et al. [16] showed a survey of deep learning approaches for intrusion detection. They showed thirty-five popular cyber datasets and presented a classification of these datasets into seven categories. Furthermore, seven deep learning models were also analyzed. They used deep learning approaches on two recent (CSE-CIC- IDS2018 and Bot-IoT) datasets and compared performance based on false alarm rate, accuracy, and detection rate. This study introduced a general review on datasets that used for NIDS.

Hindy et al. [17] indicated to specify research gaps, and lack of existing datasets and their effect on the building NIDS, and the growing number of complex attacks. It also provided researchers with two basic pieces of information; a review of well-known datasets, and analyze their use and their effect on the evolution of NIDS. Furthermore, the paper showed that only 33.3% of the attacks were covered by current NIDS research. Additionally, current datasets demonstrated a clear shortage of real network attacks, attack representation, which together border the detection accuracy of attacks for NIDS.

3. NIDS DATASETS

Datasets play an important role in evaluating NIDS, which can be used for experiments and validating new techniques [18]. Researchers relied on benchmark datasets to evaluate their results. However, currently available datasets lack realistic characteristics of recent network traffic [19]. Moreover, NIDS is unable to adapt to constant changes in networks. Networks are constantly changing, for this reason depending solely on old datasets does not help the progress of NIDS. The process of generating new datasets should consider this constant change fact in the network [17]. The detailed analysis of the datasets illustrate in the following subsections.

3.1 KDD99 Dataset

The KDD99 was created by MIT and utilized in the International Knowledge Discovery and Data Mining Tool Competition [20]. The benchmark dataset for Intrusion Detection System (IDS) was KDD99 released by DARPA [18]. The dataset was prepared in 1999 and has become the most widely used dataset for the evaluation of anomaly detection although KDD99 dataset is more than 20 years old [21]. KDD99 dataset consists of 4,898,431 instances each of which consists of 42 features. Table 1 shows KDD99 dataset features.

KDD99 contents a total of 22 training attacks types and one normal, with 17 additional types in the testing data only [22]. The 41 features labelled as either special attack type (DOS, U2R, R2L, and Probe) or normal. It is believed that attacks can be detected with the knowledge learned from the registered attacks [23]. Although widely used, this dataset has inherent flaws [2]. Attack types invKDD99 dataset can be fall into one of the main four categories:

1. Denial of Service Attack (DOS): The attacker makes some computing or memory resources very busy or too full by doing some calculations to handle the legitimate logical request, denies legitimate users from accessing the machine.
2. Probing Attack: The attacker attempts to collect information about the computer network for a specific purpose by circumventing security controls.
3. Remote to Local Attack (R2L): This type of attack occurs when an attacker exploits vulnerabilities to provide local access to a network, and the attacker begins to send packets to the device over the network.
4. User to Root Attack (U2R): An attacker exploits root access, and an attacker could exploit some vulnerabilities to access a system's regular user account. Table 2

shows the attack types in the KDD99 dataset with the main attack category.

Most researchers used KDD99 dataset to evaluate results and because of the computational requirements for the full KDD99 dataset and the inherent drawbacks of the dataset, mostly the researchers relied on part of the dataset and were trained and tested the model proposed. Here are some studies that used KDD99 dataset:

Othman et al. [15] proposed Spark-Chi-SVM approach for intrusion detection using KDD99 dataset. The ChiSqSelector is applied for feature Selection and the SVMwithSGD classifier is applied to build an intrusion detection model using Apache Spark. The results showed that the proposed model achieved high performance compared with the Chi-Logistic Regression classifier. The Spark-Chi-SVM experimental model showed high performance and less training time.

Lv et al. [24] proposed the KPCA-DEGSA-HKELM approach using a 10% subset of the KDD99 dataset and the UNSW-NB 15 dataset, which has been divided into the training and testing set. To reduce the dimensions and feature extraction, the Kernel Principal Component Analysis (KPCA) was used. A combination of the differential evolution (DE) and gravitational search algorithm (GSA) is applied to optimize the parameters of HKELM (Extreme Learning Machine with a Hybrid Kernel Function), which develops its global and local optimization abilities during prediction attacks. Then, KPCA-DEGSA-HKELM approach is obtained with achieved high accuracy and the time-saving.

Farooq et al. [25] used the NS-3 simulator and SVM classifier to determine whether the network traffic is normal or specific attack (Dos, Probe, R2L, and U2R) using KDD99 Dataset for training and testing. In the experiment, the authors used feature selection techniques. Results obtained showed the accuracy of 99.

Table 1. KDD99 dataset features

No	Features	No	Features
1	duration lenght	22	is_guest_login
2	protocol_type	23	count
3	service	24	srv_count
4	flag	25	serror_rate
5	src_bytes	26	srv_serror_rate
6	dst_bytes	27	rerror_rate
7	land	28	srv_rerror_rate
8	wrong_fragment	29	same_srv_rate
9	urgent	30	diff_srv_rate
10	hot	31	srv_diff_host_rate
11	num_failed_logins	32	dst_host_count
12	logged_in	33	dst_host_srv_count
13	lnum_compromised	34	dst_host_same_srv_rate
14	lroot_shell	35	dst_host_diffsrv_rate
15	lsu_attempted	36	dst_host_same_src_port_rate
16	lnum_root	37	dst_host_srv_diff_host_rate
17	lnum_file_creations	38	dst_host_serror_rate
18	lnum_shells	39	dst_host_srv_serror_rate
19	lnum_access_files	40	dst_host_rerror_rate
20	lnum_outbound_cmds	41	dst_host_srv_rerror_rate
21	is_hot_login	42	Class

Table 2. KDD99 attack types

Main attack	Attack type
Normal	normal
DOS	smurf, teardrop, neptune, back, pod, land
Probe	ipsweep, portsweep, nmap, satan
R2L	phf, guess_passwd, spy, warezmaster, ftp_write, warezclient, imap, multihop
U2R	buffe_overflow, loadmodule, perl, rootkit

Singh et al. [26] proposed a hybrid intrusion system (H-IDS) using the KDD99 dataset. H-IDS introduced a hybrid strategy with intelligent water drops to execute the feature selection (IWD) and support vector machine (SVM) for classification network traffic. Experimentations showed H-IDS helps to achieve the goal by attaining high classification, detection, and precision.

Ghasemi et al. [27] suggested a GA-KELM approach for built models on KDD99 and NSL-KDD datasets based on five different labels, have been gathered as a new dataset. GA used for feature selection task. Kernel Extreme Learning Machine (KELM) used as a classification algorithms. The proposed approach can easily outperform general classification algorithms which use all the features of the employed dataset with the highest accuracy.

3.2 NSL-KDD Dataset

The NSL-KDD is a public dataset, which has been developed from the previous KDD99 dataset [22]. A statistical analysis performed on KDD99 dataset raised important issues that significantly affect the accuracy of intrusion detection and lead to a misleading evaluation of AIDS [28]. The main problem with KDD99 dataset is the huge amount of duplicate packets, analysis of training and testing KDD99 dataset revealed that approximately 78% and 75% of network packets are repeated in both training and test set [29]. Table 3 shows statistics of redundant instances in KDD99 train and test set.

This huge amount of duplicate instances will affect the training set on ML methods to be biased towards normal instances and thus prevent them from attacks detection which is usually more harmful to the computer system [29,30]. Although this new version of KDD99 dataset but it still has some problems and may not typically represent current real networks, due to lack of public datasets for network-based IDS, It can still be applied as an effective dataset to help researchers evaluate different intrusion detection approaches [31]. The advantage for NSL-KDD dataset are:

1. No redundant instances in the training dataset, so the classifier will not produce any biased result.
2. No duplicate instances in the testing dataset which have better reduction rates.

NSL-KDD testing dataset consists of 22,544 instances and the training dataset consists of 125,973 instances. The size of NSL-KDD dataset is sufficient to make it practical to use the whole NSL-KDD dataset without the need for random sampling. NSL-KDD training and testing dataset instances are shown in Table 4 with its class [32].

The 42 features include data about the various five classes of network connection, and each instance classifies as a normal class or into one of four attacks. The four classes are grouped as Dos, Probe, R2L, and U2R. The training dataset consists of 23 classes and the testing dataset

Table 3. Statistics of redundant instances in KDD99 train set

	Original instances	Distinct instances	Reduction Rate
Attacks	3,925,650	262,178	93.32%
Normal	972,781	812,814	16.44%
Total	4,898,431	1,074,992	78.05%
Statistics of redundant instances in KDD99 test set			
	Original instances	**Distinct instances**	**Reduction Rate**
Attacks	250,436	29,378	88.26%
Normal	60,591	47,911	20.92%
Total	311,027	77,289	75.15%

Table 4. NSL-KDD dataset instances

Training dataset		Testing dataset	
Class	**Instances**	**Class**	**Instances**
Normal	67343	Normal	9711
DOS	45927	DOS	7458
Probe	11656	Probe	2421
R2L	995	R2L	2754
U2R	52	U2R	200
Total	125973	Total	22544

consists of 38 classes that include 21 attacks from training dataset, 16 novel attacks and 1 normal class, class label of instances in the dataset are categorized into 5 main categories (Normal, Dos, Probe, U2R, and R2L). This dataset includes a large number of features to classify different attack types. The nature of features in NSL-KDD dataset is divided into four groups (Basic, Traffic, Host, and Content features). The types information of all the 41 features available in NSL-KDD dataset: four are binary, three are nominal, and 34 features are continuous [33]. Table 5 displays types of features in NSL-KDD dataset.

Most researchers used NSL-KDD dataset to evaluate, mostly the researchers relied on part of the dataset and were trained and tested the model proposed. Here are some studies that used NSL-KDD dataset:

Bhati et al. [34] anal analyzed Linear SVM, Quadratic SVM, Fine Gaussian SVM, and Medium Gaussian SVM techniques on NSL-KDD dataset, which separated into two sets: one is a training set and another is testing. This analysis concluded that Fine GaussianSVM provides the best accuracy and least error for intrusion detection.

Biswas et al. [35] proposed an IDS model using five-fold cross-validation on NSL-KDD dataset. The authors used a different mix of feature selection algorithms and classifiers. IGR, PCA, CFS, and minimum redundancy maximum-relevance feature selection techniques are applied for feature selection. K-NN, DT, NN, SVM and NB classifiers are used for classifiers. K-NN classifier produced better performance than others and, among the feature selection methods, the IGR feature selection method is better than others.

Belavagi et al. [36] discussed the prediction analysis of different supervised ML algorithms namely Support Vector Machine, Logistic Regression, Gaussian Naive Bayes, and Random Forest using NSL-KDD dataset. Experimental results showed that the Random Forest achieved very good performance in identifying Dos, Probe, and U2R attacks, but it was poor in the identification of R2L attacks.

Thaseen et al. [37] suggested model for the intrusion detection using NSL-KDD dataset. Chi-square is applied for feature selection and multi class SVM is used as a classifier. Experimental results showed that the proposed model better in detection rate and reduced false alarm rate.

3.3 Kyoto 2006+ Dataset

This dataset has been built on 3 years through honeypots data of Kyoto University [38,39]. Therefore there is no manual labeling and anonymity process, but it has a bounded view of network traffic because only directed attacks on honeypots can be observed [40]. This dataset covers over three years of real traffic data collected from honeypots which were captured from Nov. 2006 to Aug. 2009 and regular servers that are deployed at Kyoto University [41]. During the observation period, there were 43,043,255 attack sessions, 425,719 unknown attacks sessions, and 50,033,015 normal sessions. Table 6 displays the overall characteristics of honeypot data in the Kyoto 2006+ dataset.

Since normal traffic is frequently simulated during attacks and only produces DNS and mail traffic data, which does not reflect normal traffic in the real world, there are no false positives alerts,

Table 5. Types of features in NSL-KDD dataset

Type	Features
Nominal	protocol_type, Service, Flag.
Binary	land, logged_in, is_host_login, is_guest_login.
Numeric	duration, src_bytes, dst_bytes, wrong_fragment, urgent, hot, num_failed_logins, num_compromised, root_shell, su_attempted, num_root, num_file_creations,num_shells, num_access_files, num_outbound_cmds, count, srv_count, serror_rate, srv_serror_rate, rerror_rate, srv_rerror_rate, same_srv_rate diff_srv_rate, srv_diff_host_rate, dst_host_count, dst_host_srv_count, dst_host_same_srv_rate, dst_host_diff_srv_rate, dst_host_same_src_port_rate, dst_host_srv_diff_host_rate, dst_host_serror_rate, dst_host_srv_serror_rate, dst_host_rerror_rate, dst_host_srv_rerror_rate.

Table 6. Overall characteristics of honeypot data

	Number of sessions	Average number of sessions per day
Total	93,076,270	93,638
Normal	50,033,015	50,335
Known attack	42,617,536	42,874
Unknown attack	425,719	428

which is important to reduce the number of alerts. This dataset consists of 24 statistical features: 14 conventional features and 10 additional features. Among them, the first 14 features were extracted based on KDD99 dataset, which is a very popular and widely used performance evaluation data for intrusion detection research. In addition to these 14 features, they have extracted 10 additional features that may enable them to more effectively investigate what is happening on their network. Of course, it can also be used for training and testing with 14 convention features [42]. This dataset is also available for Big Data analysis, of which size is 19.683 gigabytes. This dataset contains three class types: -1 attack, -2 shellcode, and 1 normal [43]. Kyoto 2006+ dataset features are shown in Table 7.

There are researchers used Kyoto 2006+ dataset to evaluate. Here are some studies that used Kyoto 2006+ dataset:

Kumar et al. [44] proposed Network Anomaly Detection Algorithm (NADA) based on distance measure and Relief-F. The proposed algorithm used KDD99 and Kyoto 2006+ datasets on Matlab. Common classification algorithms such as Naïve Bayes, SVM, and Decision Trees were also implemented. NADA outperforms all the other classifiers with regard to the time taken for execution. Experimental results observed that the detection rate, accuracy, F-Score, and MCC are higher in NADA and false alarm rate is lower.

Salo et al. [45] suggested the IG-PCA-Ensemble approach on three datasets, namely NSL-KDD, Kyoto 2006+, and ISCX 2012. The proposed model with the ensemble exhibited achieved better performance regarding false alarm rate, detection rate, and classification accuracy.

Sahu et al. [46] used the Decision Tree (J48) algorithm to classify the network packet. They used a labelled network dataset called Kyoto 2006+ dataset. For training and testing, they used 134665 network instances. Experimental he experimental results showed, the proposed model is able to detect unknown attacks.

3.4 ISCX 2012 Dataset

Information Security Centre of Excellence (ISCX) was generated ISCX 2012 dataset by the Canadian Institute for cybersecurity [47]. ISCX 2012 was generated by a dynamic approach and present good guidelines for generating realistic and useful IDS evaluation datasets during one week [48]. Their approach consists of: 1) the Alpha Profile has implemented various scenarios of multistage attacks to flow the abnormal segment of the dataset. 2) the beta profile is the benign traffic generator, produced realistic network traffic with background noise [49].

ISCX 2012 benchmark dataset contains statistical features (time_stamp, source_bytes, dst_bytes, source_packets, dst_packets, protocol, direction, Tag, source_ip, dst_ip) taken with a single interface on the switch to which all traffic is directed to it. In this dataset, the effect of real network traffic traces were analyzed to determine the normal behavior of computers from the real traffic of HTTP, IMAP, SMTP, POP3, SSH, and FTP protocols. It depends on realistic network traffic, which is labelled and contains various attack scenarios.

Table 7. Features of Kyoto 2006+ dataset

Feature Type	Feature
Conventional features	Duration, Service, Source_bytes, Destination_bytes, Count, Same_srv_rate, Serror_rate, Srv_serror_rate, Dst_host_count, Dst_host_srv_count, Dst_host_same_src_port_rate, Dst_host_serror_rate, Dst_host_srv_serror_rate, Flag (14).
Additional features	IDS_detection, Malware_detection, Ashula_detection, Label, Source_IP_Address , Source_Port_Number, Destination_IP_Address, Destination_Port_Number, Start_Time, Duration (10)

It is a labelled dataset, comprises over two million traffic packets that attack data representing 2% of the whole traffic [50]. This dataset has four types of attack scenario consisting of Infiltrating the network from inside, HTTP denial of service (DoS), Brute force SSH, and Distributed Denial of service using an IRC botnet (DDoS) [51,52]. Different attack scenarios are executed at different times and each attack consists of 5 steps: (1) information gathering and reconnaissance (passive or active), (2) vulnerability identification and scanning, (3) gaining access and compromising a system, (4) maintaining access and creating backdoors (5) and covering tracks.

The total size of ISCX 2012 dataset is 90.9 GigaBytes (GB). The traces were obtained in seven days of recent and realistic malicious and normal network activities under practical and systematic conditions [53]. Table 8 summarizes the complete ISCX 2012 dataset. As can be seen in Table 8, every attack scenario was applied for only a single day and two days contained only regular traffic and explain the diversity of the regular network behavior and the complexity of the attack scenarios [50,54].

Although ISCX 2012 dataset includes real-life network attacks, it also has some shortcomings: A considerable amount of network flows was unlabelled, attack scenarios are not described in detail in terms of when the attack is started and ended and some flow records are given in uniflow format whereas others are in biflow format and some flow records include null values [52]. When compared with the recent datasets this dataset can be characterized as follows: realistic network configuration because of the real testbed, realistic traffic because of the real and recent attacks [47]. This dataset is provided in PCAP as well as a custom XML file for network flows created with the IBM QRadar device. The XML flow file contains round truth labels, remember that network flow is collected from a number of IP packets and consists of source and destination IP addresses, source, destination port numbers, and protocol [54]. The 14 features that can be extracted from the labelled XML file of network flows are summarized in Table 9.

The some studies that used ISCX 2012 + dataset summarized as:

Mighan et al. [55] suggested a hybrid scheme that combines the advantages of a deep network and ML algorithms on Apache Spark. The autoencoder network used for feature extraction, which is followed by several classification such as support vector machine, random forest, decision trees, and Naive Bayes. The ISCX 2012 dataset is used in an experiment to validate the proposed model and evaluated the performance in terms of accuracy, f-measure, sensitivity, precision, and time.

Dwivedi et al. [56] proposed the EFSAGOA approach by using ISCX 2012 dataset. The EFS is used to rank the features for selecting the high ranked subset of features, and the AGOA is used to determine significant features. AGOA used SVM as a fitness function to choose the extremely efficient features and to maximize the classification performance. The proposed approach obtained high accuracy, detection rate, and low false alarm rate.

Table 8. Overview of ISCX2012 dataset

Date	Number of Flows	Number of Attacks	Description
11/6/2010 Friday	474,278	0	Normal Activity No malicious activity
12/6/2010 Saturday	133,193	2,086	Normal Activity Non-classified attacks
13/6/2010 Sunday	275,528	20,358	Infiltering the network from Inside Normal Activity.
14/6/2010 Monday	171,380	3,776	HTTP Denial of Service Normal Activity.
15/6/2010 Tuesday	571,698	37,460	Distributed Denial of Service using an IRC Botnet.
16/6/2010 Wednesday	522,263	11	Normal Activity No malicious activity.
17/6/2010 Thursday	397,595	5,219	Brute Force SSH Normal Activity.
Total	2,545,935	68,910	2.71% malicious

Note: "Number of attacks" is the subset of flows that contain an attack

Table 9. ISCX 2012 dataset features

No.	Feature	Description	Unique
1	SrcIP	Source IP address	2,478
2	DstIP	Dest. IP address	34,552
3	SrcPort	Source port	64,482
4	DstPort	Dest. port	24,238
5	AppName	Application name	107
6	Direction	Direction of flow	4
7	Protocol	IP protocol	6
8	Duration	Flow duration	N/A
9	TotalSrcBytes	Total source bytes	N/A
10	TotalDstBytes	Total dest. bytes	N/A
11	TotalBytes	Total bytes	N/A
12	TotalSrcPkts	Total source packets	N/A
13	TotalDstPkts	Total dest. packets	N/A
14	TotalPkts	Total packets	N/A

Note: "uniques" means the number of possible values of a categorical feature

Aldwairi et al. [57] Restricted Boltzmann Machine technique (RBM) was applied to distinguish between normal and anomalous NetFlow traffic. RBM can be classified as normal and anomalous NetFlow traffic using ISCX 2012 dataset.

3.5 UNSW-NB 15 dataset

The UNSW-NB 15 dataset was generated in the Cyber Range Lab of the Australian Centre for Cyber Security (ACCS) by the IXIA Storm tool to extract a hybrid of modern normal and modern attack behaviors [58]. It is one of the recent datasets to evaluate NIDS, it has become available to researchers since late 2015 [59].

A tcpdump tool was used to capture 100 GigaBytes (GB) of the raw network traffic (pcap files), each pcap file contains 1000 MB in order to make analysis of packets easier [60]. The simulation period was 16 hours on Jan 22, 2015, and 15 hours on Feb 17, 2015, for capturing 100 GB [61]. Twelve algorithms and tools such as Argus and Bro-IDS were executed in a parallel implementation to UNSW-NB15 dataset. It consists of 49 features and 2, 540,044 instances which are stored in four CSV files [62]. The features of the UNSW-NB 15 dataset are categorized into six broad groups, the descriptions of which are given in Table 10.

The features are categorized into six groups that include (13) basic features, (8) content features, (9) time features, (7) connection features, (12) additional features and two features for class label. A total of 49 features determining the features of connections are present for each data instance. The features are mixed in nature with some being nominal, some being numeric (Integer, Binary and Float) and some taking on timestamp values as given in Table 11 [11].

The dataset has a total number of 2540044 labelled instances, each being labelled either normal or attack, the total number of attacks in the dataset is 321283 instances and the total number of normal instances is 2218761. The size of the normal information packets represents 88% of the dataset size, while the attack information packets represent 12%. The distribution of instances across the two groups is presented in Table 12.

UNSWNB15 is a complex dataset, it represents modern network and attack traffic and can be used for reliable evaluation of NIDS [60]. The main categories of instances are nine types of attacks and one group representing the normal instances in the dataset. The attacks are categorized as Fuzzers, Reconnaissance, Shellcode, Analysis, Backdoors, DoS, Exploits, Generic, and Worms [61,62]. The attacks, subcategory of attacks, and the distribution of all UNSW-NB 15 dataset instances are given in Table 13.

There are several recent studies that used UNSW-NB 15 dataset such as:

Thaseen et al. [63] proposed a correlation-based feature selection integrated with neural network for identifying anomalies attacks using NSL-KDD and UNSW-NB 15 dataset. The results showed that the proposed model is superior in terms of accuracy, sensitivity, and specificity in comparison with other studies.

Nawir et al. [64] suggested a distributed online implementation of averaged one dependence

estimator (DOAODE) method for a NIDS. They extended the prior work to predict the multi-class labels based on the UNSW-NB15 dataset [65]. The experimental results showed that the DOAODE classifier for is high in accuracy and fast to train the network traffic.

Raman et al.[66] Designed an intelligent IDS consists of an efficient feature selection technique and a robust classification model. The experimental validation used NSL-KDD and UNSW-NB 15 datasets under two scenarios: SVM trained with all features and SVM trained with optimal model features obtained from HC-IBGSA proved the significance of HC-IBGSA in terms of various performance metrics (classification accuracy, detection rate, and false alarm rate). The proposed HC-IBGSA SVM was implemented using python. The Weka and Matlab were used for validation purposes. The experimental displayed HC-IBGSA improved the performance of SVM in terms of detection rate and false alarm rate.

Belouch et al. [67] evaluated the performance using four ML algorithms (SVM, Naïve Bayes, Decision Tree, and RF) on Big Data processing tool. The general performance comparison evaluated in terms of training and prediction time, and detection accuracy. The RF classifier gave the best performance in terms of accuracy, specificity, sensitivity, and execution time.

3.6 CIDDS-001 Dataset

The CIDDS-001 (Coburg Intrusion Detection DataSet) is a labelled flow-based dataset. This dataset developed for the evaluation purpose of Anomaly-based Network Intrusion Detection System (NIDS) [68]. CIDDS-001 dataset consists of unidirectional NetFlow data, it consists of traffic data from OpenStack environment having internal servers (backup, mail, file, and web) and External Servers External Server (file synchronization and web server), which is deployed on the internet to capture real-time and up-to-date traffic from the internet [69]. CIDDS-001 dataset consists of realistic normal and

Table 10. UNSW-NB 15 dataset features categorization

No	Name of the category	Description
1	Flow features	It contains identifier attributes between hosts such as client-to-serve or server to-client.
2	Basic features	It includes features that distinguish the protocol connections.
3	Content features	It contains the TCP / IP features and also contains some features of the http services.
4	Time features	It contains of time features such as round trip time of TCP protocol start/end packet time arrival time between packets etc.
5	Additional generated features	Special purpose features that take care of service protocols.
	General purpose features(from number 36 - 40)	
	Connection features (from number 41-47)	Built based on a chronological order of the last time feature.
6	Labelled Features	It represents the label of the instances.

Table 11. Features type of UNSW-NB15 dataset

No.	Feature Type	Count
1	Nominal	6
2	Integer	28
3	Binary	3
4	Float	10
5	Timestamp	2

Table 12. Details of instances in UNSW-NB15 dataset

Name	Count
Total Number of events	2540044
Normal	2218761
Attacks	321283

Table 13. Categorizations of attacks in UNSW-NB 15 dataset

Attack type	Attack Subcategory	Number of Events
Normal	-	2,218,761
Fuzzers	FTP,HTTP,RIP,SMB,Syslog,PPTP,FTP,DCERPC, OSPF,TFTP,DCERPC,OSPF,BGP	24246
Reconnaissance	Telnet, SNMP, SunRPC Portmapper (TCP) UDP Service , SunRPC Portmapper (TCP) UDP Service, SunRPC Portmapper (TCP) TCP Service, SunRPC Portmapper (UDP) UDP Service, NetBIOS, DNS, HTTP, SunRPC Portmapper (UDP), ICMP, SCTP, MSSQL,SMTP,NETBIOS, DNS	13987
Shellcode	FreeBSD, HP-UX, NetBSD, AIX, SCO Unix, Linux, Decoders, IRIX, OpenBSD, Mac OS X, BSD, Windows, BSDi, Multiple OS, Solaris	1511
Analysis	HTML,Portscanner,Spam	2677
Backdoors	-	2329
DoS	Ethernet, Microsoft O_ce, VNC, IRC, RDP, TCP, VNC, FTP, LDAP, Oracle, TCP, TFTP, DCERPC, XINETD, IRC, SNMP, ISAKMP, NTP, Telnet, CUPS, Hypervisor, ICMP, SunRPC, IMAP, Asterisk, Browser	16353
Exploits	Evasions, SCCP, SSL, VNC, Backup Appliance, Browser, Clientside Microsoft O_ce, Interbase, Miscellaneous Batch, SOCKS, TCP, Apache,IMAP, Microsoft IIS, Clientside, Clientside Microsoft Paint, IDS, SSH, ICMP, IDS, DCERPC, FTP, RADIUS, SSL, WINS, POP3, Unix r Service, Cisco IOS, lientside Microsoft Media Player, Dameware,LPD,MSSQL ,O_ce Document, RTSP,SCADA,VNC, ebserver, All,LDAP, NNTP, IGMP, Oracle, RDesktop, Telnet, Apache, PHP, SMB, SunRPC, Web Application, DNS, Evasions, ADIUS, BrowserFTP, PPTP, SCCP,SIP,TFTP	44525
Generic	All,SIP, HTTP, SMTP, IXIA, TFTP, SuperFlow, HTTP, TFTP	215481
Worms	-	174

attacks traffic that allow for an important measurement of NIDS on Cloud environment. It is divided into four parts each is created during a week. It contains 14 features, the first 10 features are the default NetFlow features and the last four features are additional features [70]. The CIDDS-001 dataset contains 16 million flows. It was captured over a period of two weeks [71]. Attack flows are captured in the dataset within four attacks types (suspicious, attacker, unknown, and victim) [72,73] . Table 14 provides a description for CIDDS-001 dataset features.

A lot of studies are being done on the development of effective NIDS using CIDDS-001 dataset. Here are some studies that used CIDDS-001 dataset:

Rashid et al. [74] introduced a comparative analysis on benchmark datasets NSL-KDD and CIDDS-001 using machine and deep learning algorithms. For getting optimal results, they used the hybrid feature selection and ranking methods. Six classification algorithms used such as SVM, Naïve Bayes, k-NN, Neural Networks, DNN, and DAE. The experimental results showed that k-NN, SVM, NN, and DNN classifiers achieved high performance on the NSLKDD dataset whereas k-NN and Naïve Bayes classifiers achieved high performance on the CIDDS-001 dataset.

He et al. [75] suggested ensemble approach for feature selection on KDD99, UNSW-NB15, and CIDDS-001 datasets. They used Mean Decrease Impurity (MDI), Random Forest Classifier (RFC), Stability Selection (SS), Recursive Feature Elimination (RFE), and Chi-square to get the score of each feature. Then, a simple voting method used to integrate feature selection methods. Decision Tree (DT), k-NN (k-nearest neighbor), SVM, and Multi-Layer Perception (MLP) are used for classification. They compared the feature subsets with classification accuracy before and after the ensemble. The experiment showed that the EFS achieved high accuracy in classification.

Verma et al. [76] discussed the statistical analysis and evaluation using the CIDDS-001 dataset. Two techniques, K-NN and k-means clustering were used. On the basis of evaluation

results, it concluded that both K-NN and k-means clustering perform well over CIDDS-001 dataset.

3.7 CICIDS2017 Dataset

CICIDS2017 generated by Canadian Institute for cybersecurity IDS, it is a very recent dataset [77]. CICIDS2017 contains up-to-date network attacks but also it meets all criteria of real-world attacks, it is a refinement of ISCX2012 dataset [47]. Since the start of CICIDS2017 dataset, the dataset has begun to attract researchers to analyze and develop new models and algorithms [78].

This dataset consists of labelled network flows, and including CSV files for machine and deep learning (MachineLearningCSV.zip) are publicly available for researchers and the corresponding profiles, full packet payloads in PCAP format, and the labelled flows (GeneratedLabelledFlows.zip) [79]. ML file of the CICIDS2017 dataset (MachineLearningCSV.zip contains eight CSV files that represent the profile of the network traffic for five days, which includes normal and attack traffic for each day. This dataset contains attack information as five days traffic data, Thursday and Friday working hour afternoon data are well suited for binary classification, Likewise, Tuesday, Wednesday, and Thursday morning data for designing a multiclass detection model [3]. The files containing of CICIDS-2017 dataset are displayed in Table 15.

However, it should be noted that the best detection model should be able to detect attacks of any type. Therefore, to design such as typical IDS, the traffic data of all day should be combined to form a single dataset to be used by IDS. The dataset shape in terms of the number of instances 2830743 and 79 features. The overall characteristics of CICIDS2017 dataset are shown in table 16 [80].

Table 14. CIDDS-001 dataset features

No	Feature Name	Feature Description
1	Src IP	IP Address of the source node.
2	Src_Port	Port of the source node.
3	Dest_IP	IP Address of the destination node.
4	Dest_Port	Port of the destination node.
5	Proto	Transport Protocol (e.g. ICMP, TCP, or UDP).
6	Date_first_seen	Start time flow first seen.
7	Duration	Flow duration.
8	Bytes	Number of transmitted bytes.
9	Packets	Number of transmitted packets.
10	Flags	OR concatenation of all TCP Flags.
11	AttackDescription	Provides additional information about the set attack parameters (e.g. the number of attempted password guesses for SSH-Brute-Force attacks).
12	AttackType	Types of attack (portScan, dos, bruteForce, PingScan).
13	AttackID	Unique Attack id. Allows attacks which belong to the same class carry the same attack id.
14	Class	Class label (Normal, Attacker, Victim, Suspicious, and Unknown).

Table 15. Descriptions of files containing CICIDS-2017 dataset

Name of Files	Attacks found	Flow count
Monday-WorkingHours.pcap_ISCX.csv	No Attack	529918
Tuesday-WorkingHours.pcap_ISCX.csv	Benign, FTP-Patator, SSH-Patator	445909
Wednesday-workingHours.pcap_ISCX.csv	Benign, DoS GoldenEye, DoS Hulk, DoS Slowhttptest, DoS slowloris, Heartbleed	692703
Thursday-WorkingHours-Morning-WebAttacks.pcap_ ISCX.csv	Benign, Web Attack – Brute Force, Web Attack – Sql Injection, Web Attack – XSS	170366
Thursday-WorkingHours-Afternoon-Infilteration.pcap_ ISCX.csv	Benign, Infiltration	288602
Friday-WorkingHours-Morning.pcap_ISCX.csv	Benign, Bot	191033
Friday-WorkingHours-Afternoon-PortScan.pcap_ISCX.csv	Benign, PortScan	225745
Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv	Benign, DDoS	286467

Table 16. Overall characteristics of CICIDS2017 dataset

Dataset Name	CICIDS2018
Dataset Type	Multi class
Year of release	2017
Total number of distinct instances	2830743
Number of features	79
Number of distinct classes	15

According to the author of CICIDS2017 dataset, it stored in eight different files containing five days normal and attacks traffic data of the Canadian Institute of Cybersecurity [78,80]. The dataset shape in terms of the number of 79.

CICIDS2017 dataset contains a wide range of attack types based on the 2016 McAfee report (DOS, DDOS, Web-based, Brute force, Infiltration, Scan, Bot, and Heart-bleed), it is publicly available. The whole shape of a dataset that contains 2830743 instances and 79 features (78 features plus one for attacks type labels) containing 15 class labels (1 normal and 14 attacks). Surprisingly, no redundant instances found. The characteristics of the CICIDS2017dataset and the detailed class occurrence are displayed in Table 17.

The some studies that used CICIDS2017 dataset are:

Krishna et al. [81] introduced Fast k-Nearest Neighbor Classifier (FkNN) as a better ML algorithm for NIDS on Cloud Environment. From the experimental results, they concluded that the FkNN classifier achieved high accuracy with less detection time.

Alrowaily et al. [82] applied seven ML algorithms using CICIDS2017 dataset. They used several performance metrics to examine the algorithms. The experimental results displayed that the K-NN classifier outperformed in terms of accuracy, recall, precision, and F1-score as compared to other classifiers.

Zhang1 et al. [83] proposed a real-time detection system for high-speed network environments, which is implemented by a distributed Random Forest classification algorithm based on Apache Spark. They implemented using CICIDS2017 dataset. The experimental results and comparisons showed that the proposed detection model has a shorter detection time, achieved higher accuracy, and can realize a real-time intrusion detection in a high-speed network environment.

3.8 CSE-CIC-IDS2018 Dataset

The CSE-CIC-IDS2018 created by Communications Security Establishment (CSE) and Canadian Institute for Cybersecurity (CIC) in 2018 for intrusion detection and malware anticipation, datasets by CIC and ISCX have been utilized worldwide [84]. Furthermore, the dataset was enhanced by considering the criteria used to create the CIC-IDS201 [85]. It contains different attack scenarios: DoS, DDoS, Heartbleed, Brute-force, Botnet, Web attacks, and inside network infiltration. The attacking infrastructure includes 50 machines and the victim organization has 5 divisions and includes 420 machines and 30 servers [86].

This dataset has been published online for researchers with nearly 5 million data in CSV and PCAP format. The unprocessed PCAP data should be used if new features need to be extracted. The CSV format dataset can be used in artificial intelligence technologies.

The dataset was edited daily, and raw data were recorded. When creating data, 80 statistical properties such as time, number of packets, number of bytes, packet length, etc. The numbers of attacks and number of instances are shown in Table 18 [87].

There are several recent studies that used CSE-CIC-IDS 2018 dataset such as:

Karatas et al. [85] applied six ML IDS (DT, K-NN, Gradient Boosting, RF, Adaboost, and Linear Discriminant Analysis algorithms) by using CSE-CIC-IDS2018 dataset, it is an imbalanced dataset. To reduce the imbalance problem, Synthetic Minority Oversampling TEchnique (SMOTE) was applied. The use of the dataset from which samples were taken increased the average resolution of the samples. The experimental results demonstrated that the implemented models have very good accuracy.

Kanimozhi et al. [88] proposed Artificial Neural Networks by using an up-to-date cybersecurity dataset (CSE-CIC-IDS2018). The proposed approach provided an outstanding performance of Accuracy and average area under the ROC (Receiver Operator Characteristic) curve, and the average False Positive rate.

Kim et al. [87] suggested Convolutional Neural Network (CNN) model and Recurrent Neural

Table 17. Class instance occurrence of CICIDS2017 dataset

Class Labels	Flow count
BENIGN	2273097
DoS Hulk	231073
PortScan	158930
DDoS	128027
DoS GoldenEye	10293
FTP-Patator	7938
SSH-Patator	5897
DoS slowloris	5796
DoS Slowhttptest	5499
Bot	1966
Web Attack – Brute Force	1507
Web Attack – XSS	652
Infiltration	36
Web Attack – Sql Injection	21
Heartbleed	11
Total	2830743

Table 18. Class instance occurrence of CSE-CIC-IDS2018 dataset

Class	Number of Instances
Benign	2,856,035
Bot	286,191
Brute Force	513
DoS	1,289,544
Infiltration	93,063
SQL injection	53
Total	4,525,399

Table 19. Public datasets for NIDS

Dataset	Number of features	Number of instances	Name of attacks	Separate train-test set
CSE-CIC-IDS2018 [84]	80	4,525,399	Bot, Brute Force, Dos, Infiltration, SQL injection.	No
CICIDS2017 [79]	79	2830743	DoS Hulk, PortScan, DDoS, DoS GoldenEye, FTP-Patator, SSH-Patator, DoS slowloris, DoS Slowhttptest, Bot, Web Attack – Brute Force, Web Attack – XSS, Infiltration, Web Attack – Sql Injection, Heartbleed.	No
CIDDS-001 [71]	14	16 million	suspicious, unknown, attacker, and victim	No
UNSW-NB15 [89]	49	2540044	Fuzzers, Reconnaissance, Shellcode, Analysis, Backdoors, DoS, Exploits, Generic, and Worms	Yes
ISCX2012 [90]	14	2,545,935	Infiltrating, Brute force SSH, HTTP denial of service (DoS), and Distributed Denial of service (DDoS).	No
Kyoto 2006+ [91]	24	93,076,270	Attack, Shellcode.	No
NSL-KDD [28]	42	148,517	Dos, Probe, R2L, and U2R.	Yes
KDD99 [92]	42	4,898,431	Dos, Probe, R2L, and U2R.	Yes

Network (RNN) model using KDD99 and CSE-CIC-IDS2018 datasets. The experimental results displayed the CNN model was able to identify DoS attacks compared to the RNN model.

Lin et al. [86] proposed a dynamic network anomaly detection system using CSE-CIC-IDS2018 dataset. They used LSTM to build the neural network model and incorporate the attention mechanisms to deal with time-correlated network traffic classification issues. In order to solve the class-imbalance problem, they used the SMOTE algorithm as well as the improved loss function to optimize the training process. The experimental results achieved a very good result in traffic classification.

Table 19 summarizes general comparisons between the above benchmark datasets. In Table 19, we order the datasets from the recent to oldest. It displays the number of instances and features, names of attacks in each dataset, and if the available dataset is divided into two files; one for training and the other for testing.

4. DISCUSSION AND RECOMMENDATION

Network-based datasets are essential for NIDS training and evaluation. It can be used to compare the quality of different NIDS with each other. In any case, the datasets must be represented to be suitable for those tasks. The community is aware of the importance of realistic network data. Therefore, this paper analyzed public available datasets in NIDS to support researchers to find the appropriate dataset for their specific evaluation scenario. Furthermore, this work focuses on a collection of dataset properties as a basis for comparing available datasets and for identifying suitable datasets. The recommendations in this paper have been coming from our analysis of eight datasets. The authors make the following recommendations about the use of available datasets:

- Use recent datasets: As mentioned above, no perfect dataset exists for NIDS. However, this paper demonstrates that there are many datasets available for packet and flow-based network traffic. So, we recommend users to evaluate their intrusion detection methods with more than one dataset to avoid overfitting to a particular dataset and evaluate their methods in a more general context. Moreover, this paper recommends users to use recent datasets such as UNSW NB15, CIDDS-001, CICIDS2017, and CSE-CIC-IDS2018 in evaluating NIDS; it reflects modern scenarios of attacks.
- The general recommendation to use CICIDS2017, CIDDS-001, CSE-CIC-IDS2018, and UNSW-NB 15 datasets. These datasets may be suitable for general evaluation settings. CICIDS2017, UNSW-NB 15, and CSE-CIC-IDS2018 datasets contain a wide range of attack scenarios.
- The recommendation does not sight that other datasets are inappropriate. For instance, KDD99, Kyoto 2006+, NSL-KDD, and ISCX2012 datasets do not include in our recommendation due to their increasing age.

5. CONCLUSION

Network-based datasets are essential for training and evaluating intrusion detection methods. This paper introduced a detailed analysis of benchmark and recent datasets for network intrusion detection systems. The authors described eight well-known datasets that include: KDD99, NSL-KDD, KYOTO 2006+, ISCX2012, UNSW-NB 15, CIDDS-001, CICIDS2017, and CSE-CIC-IDS2018. For each dataset, we provided a detailed analysis of it is instances, features, classes, and the nature of the features. The authors recommend to use recent datasets such as CIDDS-001, CICIDS2017, and CSE-CIC-IDS2018 in evaluating NIDS; it reflects modern scenarios of attacks. The main objective of this paper was to offer an overview of the available datasets for NIDS and what each dataset was consists of. Furthermore, it presented some recommendations for using benchmark network-based datasets. As future work, it is possible to work in enhancing the current work by implementing various ML algorithms using recent datasets.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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