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Effective Intrusion Detection System Using XGBoost

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Abstract: As the world is on the verge of venturing into fifth-generation communication technology and embracing concepts such as virtualization and cloudification, the most crucial aspect remains "security", as more and more data get attached to the internet. This paper reflects a model designed to measure the various parameters of data in a network such as accuracy, precision, confusion matrix, and others. XGBoost is employed on the NSL-KDD (network socket layer-knowledge discovery in databases) dataset to get the desired results. The whole motive is to learn about the integrity of data and have a higher accuracy in the prediction of data. By doing so, the amount of mischievous data floating in a network can be minimized, making the network a secure place to share information. The more secure a network is, the fewer situations where data is hacked or modified. By changing various parameters of the model, future research can be done to get the most out of the data entering and leaving a network. The most important player in the network is data, and getting to know it more closely and precisely is half the work done. Studying data in a network and analyzing the pattern and volume of data leads to the emergence of a solid Intrusion Detection System (IDS), that keeps the network healthy and a safe place to share confidential information.

Keywords: classifiers; eXtreme Gradient Boosting (XGBoost); intrusion detection system (IDS); network socket layer-knowledge discovery in databases (NSL-KDD)

1. Introduction

One of the most important needs in life is security, whether in normal day-to-day life or in the cloud world. The year 2017 witnessed a series of ransomware attacks (a simple form of malware that locks down computer files using strong encryption, and then hackers ask for money in exchange for release of the compromised files), targets including San Francisco's light-rail network, Britain's National Health Service, and even companies such as FedEx. One example is the WannaCry Ransomware Attack which compromised thousands of computers, and lately companies such as Amazon, Google, and IBM have started hiring the best minds in digital security so that their establishments across the world do not get easily compromised. Moreover, one can ask Amazon, Twitter, Netflix, and others about the Denial of Service attacks their servers faced back in 2016 [1], in which the attackers flooded the system with useless packets, making the system unavailable. There were virtual machine escape attacks reported back in 2008 by Core Security Technologies, in which a vulnerability (CVE-20080923) was found in VMware's (software developing firm named VMware Inc., Palo Alto, CA, USA) mechanism of shared folders, which made escape possible on VMWare's Workstation 6.0.2 and 5.5.4 [2]. The virtual-machine escape is a process of escaping the gravity of a virtual machine (isolated guest operating system) and then communicating with the host operating system. This can lead to a lot of security hazards. Attackers find new ways to exploit the network, and the security handlers need to be one step ahead by plugging all leakages beforehand. Many organizations are specially dedicated to come up with a security architecture that is robust enough to be employed in a clouding environment.

Cato Networks (Israel), Cipher Cloud (San Jose, California), Cisco Security (San Jose, California), Dell Security (Texas) [3], and Hytrust (California) are some of the organisations that are built with the sole purpose of making the cloud environment a safe place. Various researchers have put a lot of work into the field of cloud security and have proposed Intrusion Detection Systems (IDS) as a solid approach to tackle the issue of security. What an IDS does is that it captures and monitors the traffic and system logs across the network, and also scans the whole network to detect suspicious activities. Anywhere the IDS sees a vulnerability, it alerts the system or the cloud administrator about the possible attack. IDSs are placed at different locations in a network; if placed at the host, they are termed host-based IDSs (HIDS), while those placed at network points such as gateways and routers are referred to as Network based IDSs (NIDS). One employed at the Hyper-Visor (or VMM, Virtual Machine Monitor) is called the Hyper-Visor-based IDS (HVIDS). The HIDSs keep an eye on the VMs running and scan them for suspicious system files, system calls, unwanted configurations, and other irregular activities. The NIDS is basically employed to check for anomalies in the network traffic. The HVIDS is capable enough to filter out any threats looming over the VMs (Virtual Machines) that are running over the hypervisor. Some widespread techniques are Misuse detection techniques, in which already-known attack signatures and machine-learning algorithms are used to find out any mismatch with the captured data and any irregularities are reported. Similarly, in an anomaly detection, the system matches the behavioral pattern of data coming into the network with a desired behavioral pattern, and a decision is taken on letting the data flow further into the network or filtering it there and then. Thus, anomalies are detected. VMI is Virtual Machine Introspection in which programs running on VMs are scanned and dealt with. The VM introspection can be done in various ways such as kernel debugging, interrupt based, hyper-call authentication based, guest-OS hook based, and VM state access based. These all ways help to determine whether any suspicious programs are running at the low-level or high-level semantic end of the VM. There are many tools available such as Ether [4] (a framework designed to do malware analysis, leveraging hardware virtualization extensions to remain hidden from malicious software), that help in performing this task from outside the VM. The traditional IDS techniques were vulnerable as they were basically employed from within the VM, but with VMI the chances of the VM being attacked are less as the introspection is being done from outside using VMM technology. The VMM software helps to create and run all VMs attached to it. It represents itself to attackers as being the targeted VM and prevents direct access to the physical hardware at the real VM. The VMI technique is employed at the VMM (privileged domain) that helps to keep an eye on other domains. The catch here is that the hypervisor or VMM itself may be attacked. For that scenario, HVI (Hyper-Visor Introspection) is developed; this depends mainly on hardware involvement to check the kernel states of the host and hypervisor operating system. Here, attacks such as rootkit, side-channel attacks, and hardware attacks can take place.

This paper will present a model through which various parameters related to the data are calculated, based on which an IDS could be developed to help secure the network. Section 1 offers a brief introduction to the IDS and data integrity importance; Section 2 discusses the motivation and reasons to pick up this subject as an area of research; Section 3 covers a literature review related to the topic which will describe the various methods used to classify data; Section 4 represents the classification model used to carry out the results; Section 5 offers more theory and background on the immediate techniques used in this paper, including decision trees, boosting, and XGBoost; Section 6 explains the mathematical aspects of XGBoost and how the algorithm works in general; Section 7 presents the main results achieved through the XGBoost algorithm on the NSL-KDD (network socket layer-knowledge discovery in databases) dataset; and finally Section 8 concludes the paper.

2. Motivation

The main idea that sits behind deploying IDS in a network is to stop attacks happening from outside and within the network. The findings in this paper can help in building a strong IDS, which can keep an eye on the data entering a network and simultaneously filter out suspicious entries. It is recommended that the IDS be deployed at two points. As there is a firewall protecting the host network or the private network, it is better to place the IDS behind the firewall, as seen in Figure 1. Thereby the work of the IDS is reduced and there will be a saving of resources, as the IDS can only tackle suspicious entries that were unable to be detected by the firewall.

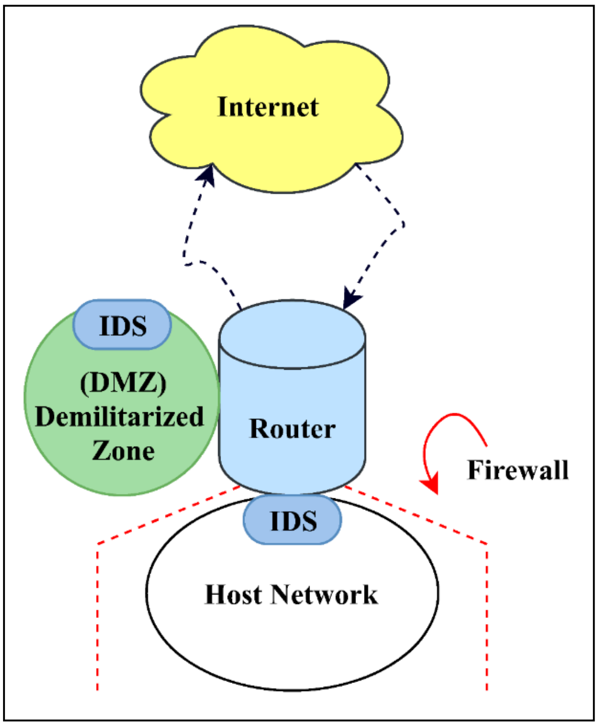


Figure 1. Recommended placement of Intrusion Detection System (IDS) in a network.

The IDS deployed can work efficiently and look for suspicious activities within the network. The main attacks come from outside the host network, from the internet that is trying to send data to the host network. The main area where this issue can be tackled is the DMZ, which is a demilitarized zone (the servers that are responsible to connect the host network with the outside world). So, there can be an IDS that can be deployed endemic to the DMZ and this can help in eliminating the majority of the mischievous data trying to penetrate the firewall. For more security, a no-access policy should be assigned to the DMZ servers [5] because, if the DMZ gets compromised, the host network remains safe. This arrangement of IDS can lead to a more secure network and the machine-learning algorithms employed within the IDS can help to make the network more secure and intelligent. These IDSs can be interrogated, and a huge amount of data related to machines can be extracted which can lead to further studies regarding IoT (Internet of Things—network of items embedded with electronics, sensors, actuators, software and connectivity (cloud) to connect and exchange data in order to provide services such as smart homes, smart transport and others), Artificial Intelligence, data mining, machine learning, and others.

An IDS acts as a sensor, monitoring the network it is employed in. It senses the network for irregularities and reports them to the network administrator. The best thing that can be done to the IDS is that the IDS can be used to interact with a mobile phone. The IDS can give regular updates to the administrator about the network status. It can interact with applications that would want to get attached to the IDS. The IDS plays a very important role in a network as it monitors the network, triggers a response to the concerned party when any violation is sensed, and, through machine learning, adapts itself to new network changes, thus eliminating the need for constant updates. It can be in no sense underestimated what an IDS can achieve in bringing security to a network. The more developed and interactive the IDS is, the faster the response to any illegal activity.

Moreover, there can be applications specifically developed in the future which sit on your mobile screen, and one touch could give the IDS status of your network, or even the network your phone is attached to. This can serve as a signal to the user of a network regarding how secure the networking environment is.

The main motivation is to build up a strong classification model that sits within an IDS and can classify the data entering the network with as much accuracy as possible. This paper provides results which tell us that XGBoost is very well suited to build up a strong classification model. This can lead to a strong IDS, and a strong IDS enables the network to be a secure place to share information.

3. Literature Review

Ektefa [6] compared the C4.5 and SVM (Support Vector Machine) algorithms and, in the findings represented by him, C4.5 worked better for data classification. Most classifiers are based on the error rate, so they cannot be extended to multiclass complex real problems. Holden came up with a hybrid PSO (Particle Swarm Optimization) algorithm to deal with normal attribute values but it lacked many features [7]. Ardjani used SVM and PSO together to optimize the performance of the SVM [8]. As the data set used for an IDS is mostly multidimensional in nature, it is important to get rid of inconsistent and redundant features before extracting the features for classification of data. The selection of features through genetic algorithms gives a better result than when individually applied. Panda uses two major classification methods, namely, normal or attack [9]. The combination of RBF (Gaussian Radial Basis Function) and the J48 algorithm (a type of greedy algorithm based on decision trees) has a higher RMSE (Root Mean Square Error) rate and is more prone to errors. Compared to this, Random Forest and Nested Dichotomies show a 99% detection rate and an error rate of a mere 0.06%.

Petrussenko Denis used LERAD (Learning Rules for Anomaly Detection) to detect attacks at the network level by using the network packets and TCP flow to learn about new attack patterns and the general trend of packet flow [10]. He found that LERAD worked well using the DARPA (Defence Advanced Research Projects Agency) data set, giving a high detection rate. Mahoney used the various available anomaly methods like ALAD (Application Layer Anomaly Detector), PHAD (Packet Header Anomaly Detector), and LERAD (performed the best) to model the application, data-link, and other layers of the model [11]. SNORT (developed by CISCO Systems), which is an open source IDS (used in collaboration with PHAD and NETAD) [12], tested on the IDEVAL (Intrusion Detection Evaluation) data set detects up to 146 attacks out of a possible 201 attacks, when monitored for a week.

The Unsupervised method uses a huge volume of data and has less accuracy. To overcome this a semi-supervised algorithm is used [13]. Fuzzy Connectedness-based Clustering is used using the properties of clusters such as Euclidean distance and statistics [14]. This helps to detect known and unknown shapes. Ching Hao used unlabelled data in a co-training framework to better intrusion detection [15]. Here a low error rate was achieved, which helped in setting up an active learning method to enhance the performance. The semi-supervised technique is used to filter false alarms and provides a high detection rate [16].

To improve the accuracy, a Tri Training SVM algorithm is used [17]. Adding further, Monowar H. Bhuyan used the tree-based algorithm to come up with clusters in the dataset without the use of labelled data [18]. However, labelling can be done on the data set by using a cluster labelling technique which is based on the Tree CLUS (clusters) algorithm (works faster for numeric and other mixed datasets).

The Partially Observable Markov Decision Process was used to determine the cost function using both the anomaly and misuse-detection methods [19]. The Semi-Supervised technique is then applied to a set of three different SVM classifiers and to the same PSVM (Principal SVM) classifiers.

DDoS, that is Distributed Denial of Service Attacks, are the most difficult to counter, as they are difficult to detect, but two ways are suggested to tackle them. The first way is to filter the traffic there and then by eliminating the mischievous traffic beforehand, and the second method is to gradually degrade the performance of the legitimate traffic. The major reason for the widespread DDoS attacks is the presence of Denial of Capability attacks. The Sink Tree model helps to eliminate these attacks [20].

The DDoS attacks are not endemic to a network, but they harm the whole network. Zhang [21] proposed a proactive algorithm to tackle this problem. Here, the network was divided into clusters, with packets needing permission to enter, exit, or pass through other clusters. The IP prefix-based method is used to control the high-speed traffic and detect the DDoS attacks, which come in a streaming fashion. There is some suggestion to use acknowledgment-based ways to supress intrusion. Here, the clock rates are synchronized with each other (client and server) and any lack or delay in the clock rates or acknowledgment loss allows the adversary to cause a direct attack on the client [22].

Pre-processing the network data consumes time, but classification and labelling of data are the main challenges encountered in an IDS [23]. Issues such as classification of data, high-level pre-processing, suppression, and mitigation of DDoS attacks, False Alarm Rates, and the Semi-Supervised Approach need to be dealt with to come up with a strong IDS model, and this paper is a step towards achieving it. Most of the classification methods discussed above had their own advantages and limitations, XGBoost was chosen because it helped in tackling majority of the flaws that emerged from the existing models. The reasons XGBoost is handpicked to be the preferred classification model when dealing with issues encountered in real word classification problems are the following:

- XGBoost is approximately 10 times faster than existing methods on a single platform, therefore eliminating the issue of time consumption especially when pre-processing of the network data is done.
- XGBoost has the advantage of parallel processing, that is uses all the cores of the machine it is running on. It is highly scalable, generates billions of examples using distributed or parallel computation and algorithmic optimization operations, all using minimal resources. Therefore, it is highly effective in dealing with issues such as classification of data and high-level pre-processing of data.
- The portability of XGBoost makes it available and easier to blend on many platforms. Recently, the distributed versions are being integrated to cloud platforms such as Tianchi of Alibaba, AWS, GCE, Azure, and others. Therefore, flexibility offered by XGBoost is immense and is not tied to a specific platform, hence the IDS using XGBoost can be platform-independent, which is a major advantage. XGBoost is also interfaced with cloud data flow systems such as Spark and Flink.
- XGBoost can be handled by multiple programming languages such as Java, Python, R, C++.
- XGBoost allows the use of wide variety of computing environments such as parallelization (tree construction across multiple CPU Cores), Out of core computing, distributed computing for handling large models, and Cache Optimization for the efficient use of hardware.
- The ability of XGBoost to make a weak learner into a strong learner (boosting) through its optimization step for every new tree that attaches, allow the classification model to generate less False Alarms, easy labelling of data, and accurate classification of data.
- Regularization is an important aspect of XGBoost algorithm, as it helps in avoiding data overfitting problems whether it be tree based or linear models. XGBoost deals effectively with data-overfitting problems, which can help to deal when a system is under DDoS attack, that is flooding of data entries, so the classifier is needed to be fast (which XGBoost is) and the classifier should be able to accommodate data entries.
- There is enabled cross-validation as an internal function. Therefore, there is no need of external packages to get cross validation results.
- XGBoost is well equipped to detect and deal with missing values.
- XGBoost is a flexible classifier as it gives the user the option to set the objective function as desired by setting the parameters of the model. It also supports user defined evaluation metrics in addition to dealing with regression, classification, and ranking problems.
- Availability of XGBoost at different platforms makes it easy to access and use.
- Save and Reload functions are available, as XGBoost gives the option of saving the data matrix and relaunching it when required. This eliminates the need of extra memory space.

- Extended Tree Pruning, that is, in normal models the tree pruning stops as soon as a negative loss is encountered, but in XGBoost the Tree Pruning is done up to a maximum depth of tree as defined by the user and then backward pruning is performed on the same tree until the improvement in the loss function is below a set threshold value.

All these important functionalities add up and enable the XGBoost to outperform many existing models. Moreover, XGBoost has been used in many winning solutions in machine learning competitions such as Kaggle (17 out of 29 winning solutions in 2015) and KDDCup (top 10 winning solutions all used XGBoost in 2015) [24]. Therefore, it can be said that XGBoost is very well equipped to deal with majority of the problems that face a real-world network.

4. Classification Model

The classification model in Figure 2 and the flow of work chart in Figure 3 represent the way the dataset was interrogated in the model. The dataset included test and train type data. Both sets were first concatenated to make the data into one file. Python was used as the environment on which this combined data had to run. Moving further, the XGBoost package was downloaded as well as Anaconda software, which basically comes with in-built packages. Using Python, the required packages were called. The dataset was opened on the Python platform and, by setting various parameters related to XGBoost (discussed in detail in Section 6), the code was run for XGBoost on the NSL-KDD dataset. The results included confusion matrix, precision, Receiver Operating Characteristics (ROC), and accuracy.

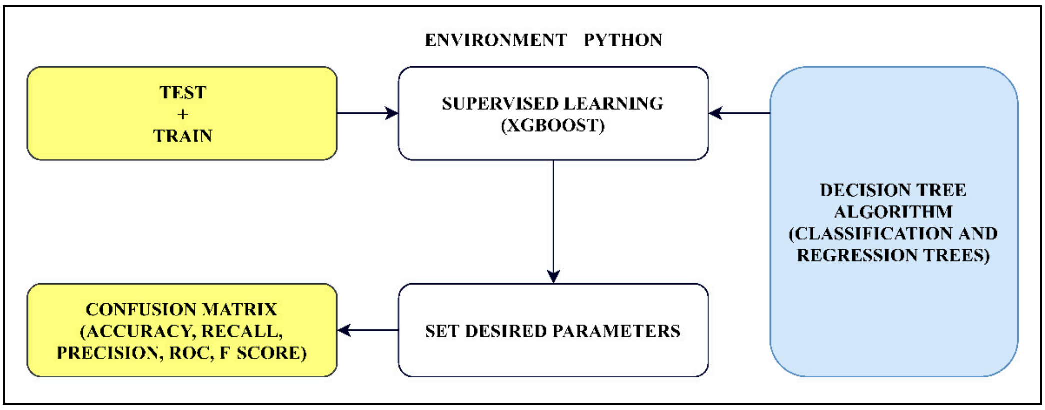

ENVIRONMENT PYTHON
TEST + TRAIN
SUPERVISED LEARNING (XGBOOST)
DECISION TREE ALGORITHM (CLASSIFICATION AND REGRESSION TREES)
CONFUSION MATRIX (ACCURACY, RECALL, PRECISION, ROC, F SCORE)
SET DESIRED PARAMETERS

Figure 2. Classification model. ROC, receiver operating characteristics.

The flow of work chart in Figure 3 gives a more detailed idea how the steps in the implementation of the model worked. Initially, the train and test data were made into one combined data set containing the 41 features of NSL-KDD dataset and the 42nd feature represented the labelling of the entry as being "normal" or an "anomaly". This represented the first step of the flow chart. In the second step, the concatenated data was made into all numeric type, that is any entries that were other than integer type of data were converted to an integer, so that the XGBoost algorithm could be deployed on the dataset. The third step was calling the required packages from Anaconda library as well as calling the XGBoost classifier from the XGBoost library. The desired parameters were set (mentioned under "Results and Discussions") and the XGBoost algorithm was run over the dataset. The result gave a confusion matrix, that helped to define the various results, such as the number of instances that were predicted as "normal" or "anomaly", the True Positives, True Negatives, False Positives, False Negatives. Finally, the parameters of Accuracy, Recall, Precision, Sensitivity, Selectivity, and F-score were also calculated. This represented the last step of the flow chart.

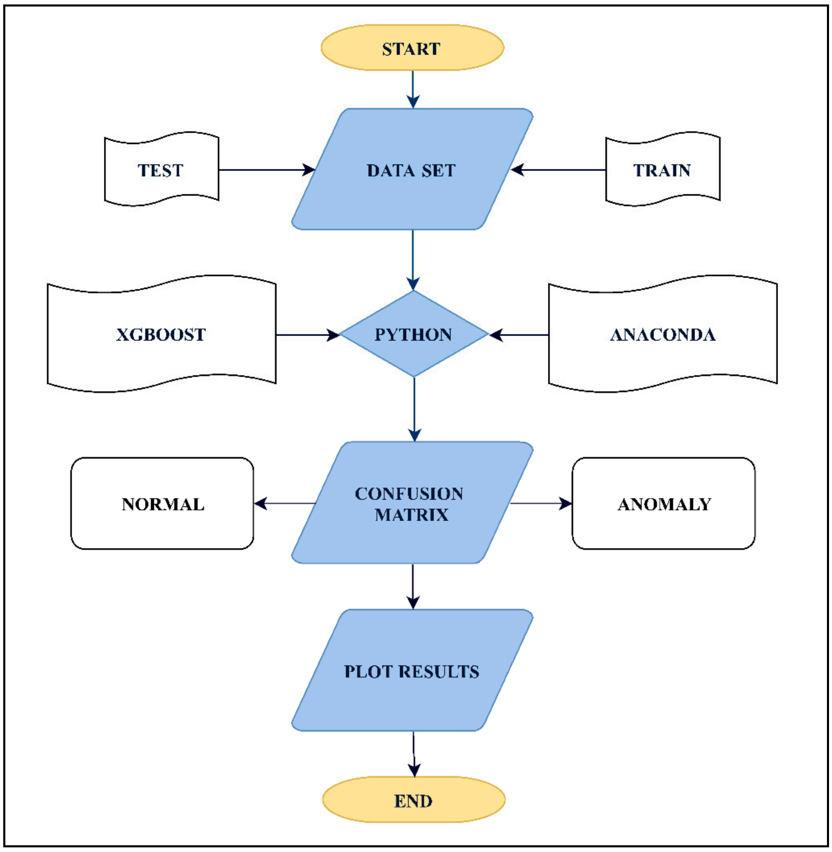


Figure 3. Flow of work chart.

5. Theory and Background

The classification model used in this paper is a part of machine learning. These types of models learn from the data they get exposed to and can even make predictions related to it. This helps in applications dealing with intrusion detection, email filtering, and others. Moreover, the classification model in this case is based on supervised learning. This machine-learning technique uses input variables and output variables, and, through an algorithm the mapping function, is used to map the input variables to the output variable. This data-learning technique is useful as, when new data is received, the already-learnt mapped function helps to classify data easily and so data can be separated or filtered. Hence, data are used to learn and build an algorithm and, based on the learned algorithm, data is predicted; this very concept makes the core of any machine-learning classification model. There are three main concepts around which the whole results revolve. They are Decision Trees, Boosting, and XGBoost. Each will be looked at to give a general view of the main ideas they include.

5.1. Boosting

Boosting, a machine-learning algorithm, can be used to reduce bias and variance from the dataset. Boosting helps to convert weak learners to strong ones. A weak-learner classifier is weakly correlated with the true classification, whereas strong learners are strongly correlated. Algorithms that can do the above simply became known as "boosting". Most algorithms iteratively learn weak classifiers and add them to a strong one. The data added are weighted, so that data that are correctly classified shed weight and those misclassified gain weight. All in all, the data gets reweighted when building up a strong learner from a set of weak learners. Algorithms such as AdaBoost, an adaptive boosting algorithm developed by Schapire and Freund (they won the Godel Prize for it) [25] are recommended. The main variation between various boosting algorithms is the method of weighting the training data and its hypothesis. In Python, XGBoost can be used. It is in an open-source library which provides a boosting algorithm in Python and other languages such as C++ and Java.

5.2. Decision Trees

Decision trees are algorithms that classify instances based on feature values. Each node of a decision tree is a feature in an instance that is waiting to be classified. A feature is picked up to split the training data and it becomes the root node. A similar procedure is followed, and the tree starts digging deep, making sub-trees until the same class subsets are formed. One of the limitations of decision trees is diagonal portioning. However, Zhang [21] suggested ways to construct multivariate trees by using new features with operators such as conjunction, negation and disjunction.

C4.5—The most well-known algorithm to design decision trees is C4.5 (Quinlan, 1993). It uses the Information Gain as the criterion to choose which feature can be made the splitting feature. It accepts both numeric and symbolic values and generates a classification tree. It recursively splits to form subsets of the same class. Its only limitation is that it is allergic to diagonal partitioning and works poorly when the density of points in some regions is low. However, multivariate trees have been developed lately to solve the above problem (Brodley and Utgoff [26]).

RF—A random-forest classifier (Breiman, 2001) is made up of many classification trees. The *k*th classification tree is a classifier denoted by an unlabelled input vector and a randomly generated vector by selection of random features of the training data for each node. The randomly generated vector of different classification trees in the forest are not related to each other but are generated by the same distribution algorithm. For unlabelled data, each tree will provide a prediction or vote and so labelling is done. There are many more algorithms that can be used such as the J48 technique and others.

5.3. XGBoost

XGBoost was mainly designed for speed and performance using gradient-boosted decision trees. It represents a way for machine boosting, or in other words applying boosting to machines, initially done by Tianqi Chen [27] and further taken up by many developers. It is a tool that belongs to the Distributed Machine Learning Community (DMLC). XGBoost or eXtreme Gradient Boosting helps in exploiting every bit of memory and hardware resources for tree boosting algorithms. It gives the benefit of algorithm enhancement, tuning the model, and can also be deployed in computing environments. XGBoost can perform the three major gradient boosting techniques, that is Gradient Boosting, Regularized Boosting, and Stochastic Boosting. It also allows for the addition and tuning of regularization parameters, making it stand out from other libraries. The algorithm is highly effective in reducing the computing time and provides optimal use of memory resources. It is Sparse Aware, or can take care of missing values, supports parallel structure in tree construction, and has the unique quality to perform boosting on added data already on the trained model (Continued Training) [28].

6. Mathematical Explanation

XGBoost functions around tree algorithms. The tree algorithms take into account the attributes of the dataset; they can be called features or columns and then these very features act as the conditional node or the internal node. Now, corresponding to the condition at the root node, the tree splits up into branches or edges. The end of the branch that does not produce any further edges is referred to as the leaf node, and generally splitting is done to reach a decision. The diagram in Figure 4 is a representation of how a decision tree or classification tree works, based on an example dataset, predicting whether a passenger survives or not.

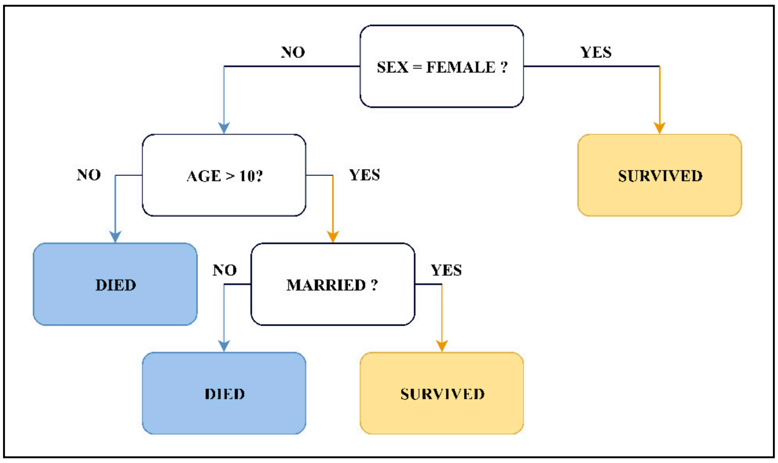


Figure 4. The working of Decision Trees.

XGBoost also applies decision-tree algorithms to a known dataset and then classifies the data accordingly. The concept of XGBoost revolves around gradient-boosted trees using supervised learning as the principal technique. Supervised learning basically refers to a technique in which the input data, generally the training data p_i having multiple features (as in this case), is used to predict target values s_i.

The mathematical algorithm (referred to as the model) makes predictions s_i based on trained data p_i. For example, in a linear model, the prediction is based on a combination of weighted input features such as $\hat{s}_i = \sum_j \theta_j p_{ij}$ [29]. The parameters need to be learnt from the data. Usually, θ is used to represent the parameters and, depending on the dataset, there can be numerous parameters. The predict value s_i helps to classify the problem at hand, whether it be regression, classification, ranking, or others. The main motive is to find the appropriate parameters from the dataset used for training purposes. An objective function is set up initially which describes the model performance. It must be mentioned that each model can differ depending on which parameter is used. Suppose that there is a dataset in which "length" and "height" are features of the dataset. Therefore, on the same dataset numerous models can be set up, depending on which parameters are used.

The objective function [29] comprises two parts: the first part is termed a training loss and the second part is termed a regularization.

$$obj(\theta) = TL(\theta) + R(\theta) \tag{1}$$

The regularization term is represented by R and TL is for Training Loss. The TL is just a measure of how predictive the model is. Regularization helps to keep the model's complexity within desired limits, eliminating problems such as over-stacking or overfitting of data which can lead to a less accurate model. XGBoost simply adds the prediction of all trees formed from the dataset and then optimizes the result.

Random Forest also follow the model of tree ensembles. Therefore, it can be said that the boosted trees, in comparison to random forest, are not too much different in terms of their algorithmic make-up, but they differ in the way we train them. A predictive service of tree ensembles should work both for random and boosted trees. This is a major advantage of supervised learning. The main motive is to learn about the trees, and the simple way to do it is to optimize the objective function [29].

The question that arises here is how the trees are set up in terms of the parameters used. To determine these parameters the structure of the trees and their respective leaf scores are to be calculated (generally represented by a function f_t). It is not a straightforward task to train all the trees in parallel. XGBoost tries to optimize the learned tree (training) and adds a tree at every step. One question that arises is which tree to add at each step, the answer being to add the tree that fulfills the objective of optimizing our objective function [29].

The new objective function (say at step t) takes the form of an expansion represented by Taylor's theorem, generally including up to the second order.

$$obj^{(t)} = \sum_{i=1}^{n}\left[m_i f_t(p_i) + \frac{1}{2}c_i f_t^2(p_i)\right] + R(f_t), \tag{2}$$

where m_i and c_i are taken as inputs.

The result reflects the desired optimization for the new tree that wants to add itself to the model. This is the way that XGBoost deals with loss functions such as logistic regression.

Moving further, regularization plays an important part in defining the complexity of the tree *R(f)*. The definition of tree *f(p)* can be refined as [29]

$$f_t(p) = w_{q(p)},\ w\epsilon R^L,\ q : R^d \rightarrow \{1,2,3,4\ldots,\ L\}. \tag{3}$$

In the above equation, w represents a vector for leaf scores (same score for data points using the same leaf) and function q assigns leaves to the corresponding data points. L is the number of leaves. In XGBoost, the complexity is [29]

$$R(f) = \alpha L + \frac{1}{2}\beta\sum_{j=1}^{L} w_j^2. \tag{4}$$

Therefore, the equation of regularization can be put in Theorem (1), to get the new optimized objective function at step t, or the tth tree. The resultant model represents the new reformed tree model and is a measure of how good the tree structure $q(p)$ is.

The tree structure is established by calculating the regularization, leaf scores, and objective function at each level, as it is not possible to simultaneously calculate all combinations of trees. The gain is calculated at each level as a leaf is split into a left leaf and a right leaf, and the gain is calculated at the current leaf with the regularization achieved at the possible additional leaves. If the gain falls short of the additional regularization value, then that branch is abandoned (concept also called pruning). This is how XGBoost runs deep into trees and classifies data, and hence accuracy and other parameters are calculated.

7. Results and Discussion

7.1. Dataset Used

Firstly, the dataset was set up, the train and test dataset were checked for missing values and then concatenated to form a combined dataset. The NSL-KDD dataset was used, an improved version of the KDD dataset, as the initial KDD dataset had redundancy and classifiers tended to be biased because of that [30]. The 42nd column in both train and test had the binary labelling of each row as "anomaly", or "normal". This feature was used as a target value to classify the data and plot the confusion matrix. The combined dataset was converted into the all-numeric data type, for the calculations to be done easily without any errors. Tables 1 and 2 represent the number of entries and datatypes in the train, test, and combined datasets. The code was run on the combined (converted) dataset to yield the results.

Table 1. Number of entries in dataset used.

Dataset	No. of Rows	No. of Columns	Memory Space
Train	125973	42	40.4 MB
Test	22544	42	7.2 MB
Combined (not converted)	148517	42	48.7 MB
Combined (converted)	148517	42	44.8 MB

Table 2. Datatypes of the dataset (values represent numbers of columns).

Dataset	Float64	Int64	Object	Int8
Train	15	23	4	-
Test	15	23	4	-
Combined (not converted)	15	23	4	-
Combined (converted)	15	23	-	4

It must be noted that the 42nd column used in both the training and testing datasets showed whether the data entry was anomaly or normal.

As seen above, there were still four columns in the combined (not converted) dataset which contained data other than numerical or float type values. So, to run the boosting algorithm, it was important to convert the combined dataset into numeric datatype; that meant we needed to convert the object datatype into float or integer datatype. The conversion led to a drop in the memory space occupied by the combined dataset. The combined (converted) dataset now accounted for about 44.8 MB of memory space. This meant that there was a drop of 3.9 MB of memory space when the data were converted into numerical values.

There is a constant debate about the dataset used to base the classification model on, as the dataset used may not represent existing real networks. However, NSL-KDD dataset can be used as an effective benchmark dataset to compare numerous classification methods. Adding further, the number of entries in the train and test dataset of NSL-KDD are reasonable. This advantage of NSL-KDD dataset enables the user to use the complete set at once rather than selecting sample size at random. As mentioned earlier that NSL-KDD is an upgradation of KDD dataset and it removes the drawbacks of the KDD dataset. Some of the important aspects of NSL-KDD dataset are as follows:

- In KDD dataset, the classifiers showed biasing towards the more frequent records, hence, in NSL-KDD dataset the redundant records in the train set were not included.
- There is no repetition of records even in the test set of NSL-KDD dataset. Therefore, this eliminated the classifiers ability to show deceiving high detection rates courtesy reoccurring records.
- As the number of records for each difficulty level group in NSL-KDD dataset is inversely proportional to the percentage of records in the original KDD dataset; as a result, the NSL-KDD provided a wider range for the classification methods to do detection on. This made NSL-KDD dataset more efficient in classification rates based on different classification methods.
- One major reason to set the classification method on NSL-KDD dataset was to compare it with the previously known results of different classification methods based on NSL-KDD dataset (further elaborated in Table 6 under Section 7.6). This will make the evaluation results more consistent and comparable.

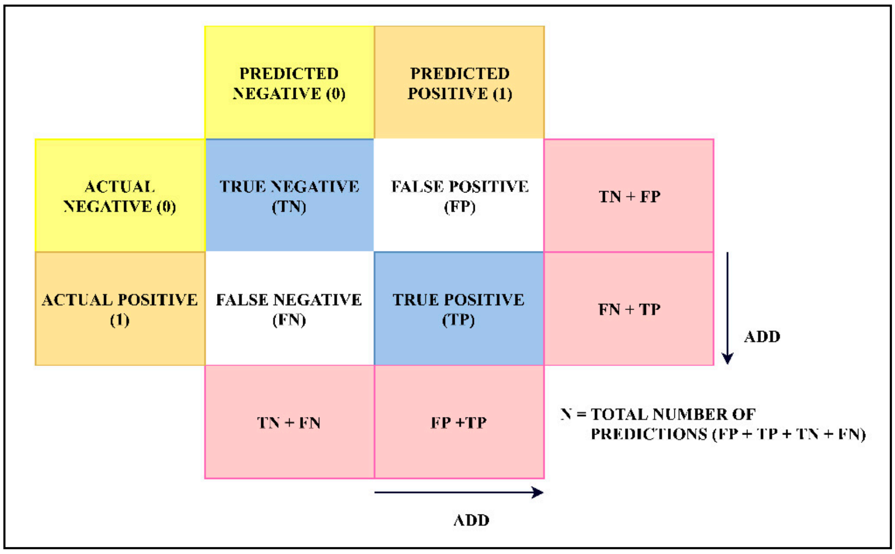
7.2. Confusion Matrix

XGBoost has many parameters, and one can use these parameters to perform specific tasks. The following are some of the parameters that were used to get the results (the purpose of the parameters is also explained briefly) [31]:

- The “learning_rate” (also referred to as “eta”) parameter is basically set to get rid of overfitting problems. It performs the step size shrinkage, and weights relating to the new features can be easily extracted (was set as 0.1).
- The “max_depth” parameter is used to define how deep a tree runs: the bigger the value, the more complex the model becomes (was set as 3).
- The “n_estimators” parameter refers to the number of rounds or trees used in the model (was set as 100).
- The “random_state” parameter is also a learning parameter. It is also sometimes referred to as “seed” (was set as 7).
- The “n_splits” parameter is used to split up the dataset into *k* parts (was set as 10).

The above-mentioned parameters are tree booster parameters and based on the above the following results were calculated. There are many parameters that can be set up, but this mainly depends on the user and the model. If parameters are not set, XGBoost picks up the default values, though one can define the parameters as per the desired model.

The matrix in Figure 5 represents what a confusion matrix is made up of.



	PREDICTED NEGATIVE (0)	PREDICTED POSITIVE (1)	
ACTUAL NEGATIVE (0)	TRUE NEGATIVE (TN)	FALSE POSITIVE (FP)	TN + FP
ACTUAL POSITIVE (1)	FALSE NEGATIVE (FN)	TRUE POSITIVE (TP)	FN + TP
	TN + FN	FP +TP	

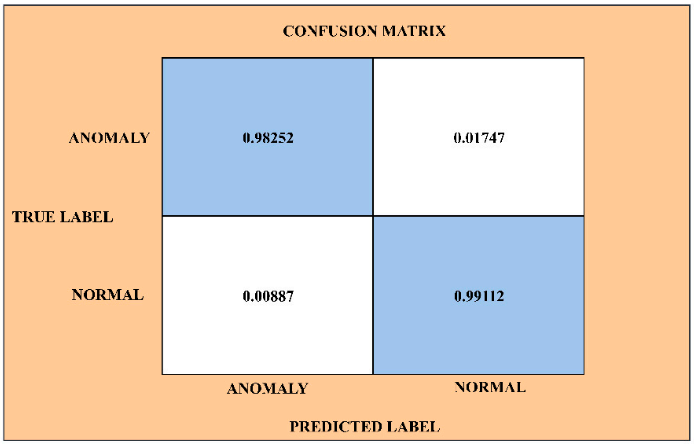
Figure 5. Confusion Matrix Representation.

The quantities defined in Figure 5 will be used to calculate all the results achieved. There are four main values, which are calculated by running the confusion matrix. These values are further used to calculate the accuracy, precision, recall, F1 score, and ROC curve, and finally plot the confusion matrix itself.

To elaborate, there are four main values: True Negative (TN) (negative in our dataset was the target name "anomaly" labelled as 0), True Positive (positive in our dataset was the target name "normal" labelled as 1), False Negative, and False Positive.

True Positive is a value assigned to an entry of the dataset when a known positive value is predicted as positive, in other words if the color is red, and is predicted as red. True Negative is when a known negative value is predicted as negative, that is the color is not red and is predicted as being not red. On the other side, there are False Negative and False Positive. False Positive is when a known positive value is predicted as negative, that is a known red color is predicted as not being red. False Negative is the other way around, a known negative value is predicted as positive, that is the red color is predicted when the known color was not red.

The Confusion Matrix represents the quality of the output of a classifier on any dataset. The diagonal elements (blue box in Figures 5 and 6) represent correct or true labels, whereas the off-diagonal (white box in Figures 5 and 6) elements represent the elements misclassified by the classification model. Therefore, the higher the values of the diagonal elements of the confusion matrix, the better and more accurate the classification model becomes.



CONFUSION MATRIX

TRUE LABEL	ANOMALY	NORMAL
ANOMALY	0.98252	0.01747
NORMAL	0.00887	0.99112

PREDICTED LABEL

Figure 6. Confusion Matrix with Normalization.

Figure 6 represents the confusion matrix in normalized form, that is in numbers between 0 and 1. It provides better and easier understanding of the data.

The different parameters of the Confusion Matrix represent the results giving TP, TN, FP, and FN. Using these, the specificity and sensitivity of the dataset can be calculated, which is just a measure of how good the classification model is. The following were the results from the confusion matrix:

- TP = 99.11% (0.991123108469).
- FP = 1.75% (0.0174775758085).
- FN = 0.89% (0.00887689153061).
- TN = 98.25% (0.982522424192).

FP and FN should be as low as possible, whereas TP and TN should be as high as possible. The model is a good classification model as there is a high fraction of correct predictions as compared to the misclassifications. Moreover, the sensitivity and specificity can be calculated.

- $Sensitivity = TP/(FN + TP)$ (also called TPR)

  $$= 99.11\%.$$

- $Specificity = TN/(TN + FP)$

  $$= 98.25\%$$

- Therefore, FPR can be calculated:

  $$\begin{aligned} FPR &= (1 - specificity) \\ &= (1 - 0.9825) \\ &= 0.0175 \end{aligned}$$

As a cross-check, looking at Figure 5, $TN + FN + FP + TP = N$ is the total number of predictions. If we apply this formula, taking values from Figure 6, then the result comes out to be $N = (TN + FN + FP + TP)$ = (70,214 + 684 + 1249 + 76,370), the representation of values in non-normalized form = 148,517, that is the total number of entries (rows) in the combined dataset. Therefore, the result obtained from the Confusion Matrix validates the dataset entries.

The confusion matrix is the heartbeat of the classification model. Looking at the results above, the classification model achieves very good results, but more parameters can be set up and the best possible accuracy should be aimed at. The higher the values of TN and TP and the lower the values of FN and FP, the stronger the model emerges. It must be mentioned here that this classification model can form an integral part of an IDS in helping it to classify data as anomaly or normal. The confusion matrix can be a source of data from which optimization of the model can be initiated. By setting up more-specific parameters, accuracy, precision, recall, and other results can be optimized to achieve perfect results.

7.3. Accuracy/Recall/Precision

Figure 7 represents the plot of accuracy, precision, and recall as fractions of K, K being the value relating to the number of splits in tree formations.

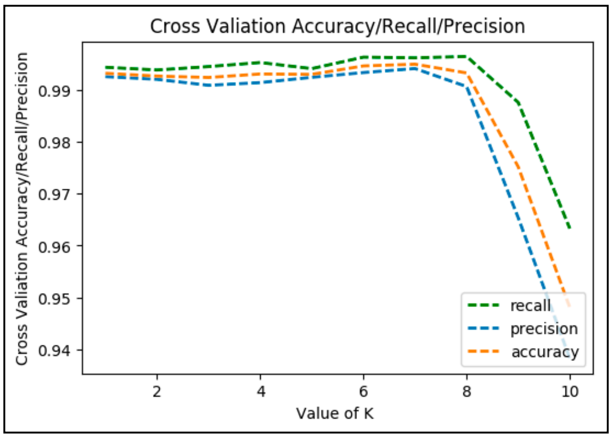


Figure 7. Results for Accuracy, Precision, and Recall.

Initially, the combined dataset was run to generate the classification accuracy using only two parameters, "test size" = 0.33 and "seed" = 7, then the model generated an accuracy of 98.98%. This reflected that the model was generating high accuracy with an error rate of a mere 1.02%. However, when more parameters were set up as discussed earlier, the number of splits increased and as the number of splits reached 8, the accuracy, precision, and recall had a dip, as seen above in Figure 7. It could be seen that all these parameters were in direct relation to the number of splits. Explaining the involved parameters, it can be said that the classification accuracy was basically dividing the number of correct predictions by the total number of predictions made and multiplying the result by 100. The accuracy calculated through XGBoost was:

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) = 98.70\%.$$

The Precision was calculated by dividing the number of True Positives (TP) by the total number of True Positives and False Positives (FP) [32]. TP refers to the correct prediction of data being normal (or positive), FP (also referred to as Type I error) refers to the incorrect prediction of data being normal (or positive).

$$Precision = TP/(TP + FP) = 98.41\%.$$

Moving further, the Recall parameter was calculated by dividing the number of TPs by the total number of TPs and False Negatives (FNs). FN (Type II error) refers to the incorrect prediction of data being an anomaly (or negative). There is something also called True Negatives (TN), which refers to correct prediction of data being an anomaly (or negative).

$$Recall = TP/(TP + FN) = 99.11\%.$$

The F1 score was also calculated; it is the average (weighted) of Precision and Recall. Even though accuracy takes more limelight, it can be useful for an even class distribution (where FP and FN are quite similar), but for an uneven class distribution where the cost of FP and FN are quite different then it is more useful to look at the F1 score [33].

$$F1\_Score = 2{*}(Recall{*}Precision)/(Recall + Precision) = 98.76\%.$$

This is how XGBoost comes out with the results and, out of the three results, the best results were for recall, followed by accuracy and precision. As the number of splits increases, there is seen to be a decrease in the values because more splits allow the model to learn relations very specific to a dataset.

7.4. ROC Curve

Figure 8 reflects how accurate the prediction is: the area under the curve is what reflects the accuracy in prediction. A higher area under the curve is desired.

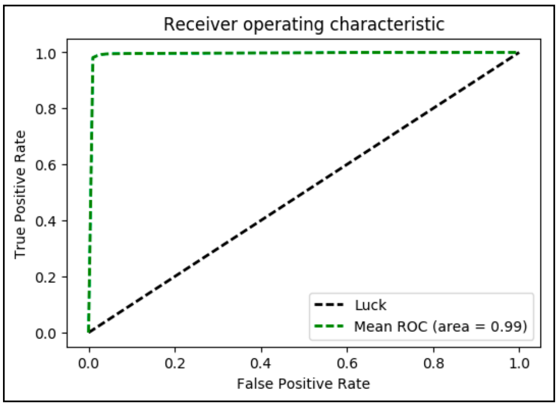


Figure 8. Receiver Operating Characteristic curve.

The graph in Figure 8 is known as a ROC curve, and it represents the plotting of the True Positive Rate (TPR) against the False Positive Rate (FPR). The TPR is also referred to as the *"sensitivity"*, calculated the same way that Precision was calculated, that is *(TP/(FN+TP))*. The FPR on the other hand is calculated as *(1-specificity)*, where *"specificity"* is calculated as *(TN/(TN+FP))*. So, to sum it up, the TPR is a measure of how often the prediction is correct, when there is a positive value, and the FPR is how often the prediction is incorrect when the value is in fact negative. Looking at Figure 8, it can be said that the closer is the curve to the left-hand and the top-hand borders of the ROC plotting area, the more accurate the dataset. The area under the curve is a measure of accuracy of the predictions; as seen above it is 0.99, which is excellent in terms of accuracy of the predictions. ROC helps to achieve a trade-off between specificity and sensitivity [34].

7.5. Feature Score (F-Score)

Moving further, using an in-built function, the feature importance was also plotted. Figure 9 represents the result achieved.

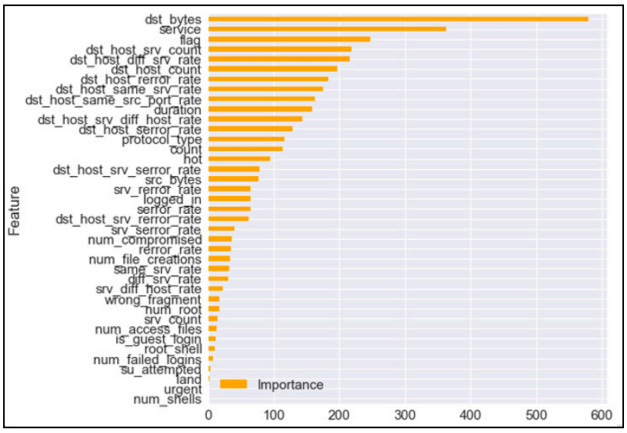


Figure 9. Representation of F-Score.

Table 3 represents the meaning of the features used in the dataset [35].

Table 3. Meaning of Features used in the dataset.

Name of Feature	Meaning of Feature
duration	It represents the connection time.
protocol_type	It represents the protocol used in the connection.
service	It represents the service used by the destination network.
flag	It represents the connection status (error or no error).
dst_bytes	The number of data bytes transferred from destination to source in a single connection.
src_bytes	The number of data bytes transferred from source to destination in a single connection.
land	It is 1 if source and destination IP addresses and port numbers match, 0 if not.
wrong_fragment	It represents the number of wrong fragments in a single connection.
urgent	It represents the number of urgent packets (urgent bit is present) in a single connection.
hot	It represents the number of root or administrator indicators in the data sent, that is whether the packet is entering the system directory, and is it creating and executing programs.
num_failed_logins	It represents the number of times a login attempt has failed.
logged_in	It is 1 if successfully logged in, otherwise 0.
num_compromised	It represents the number of compromised positions in the data in a single connection.
root_shell	It toggles to 1 if the root shell is obtained, otherwise remains 0.
su_attempted	It toggles to 1 if "su root" command used, otherwise remains 0.
num_root	It represents the number of times operations were performed as the root in the connection.
num_file_creations	It represents the number of times the file creation command was used in the connection.
num_shells	It represents the number of shell prompts encountered in the connection.
num_access_files	It represents the number of times operations were performed using access control files.
num_outbound_commands	It represents the number of times an outbound command was issued in a connection.
is_hot_login	It represents whether the login belongs to the root or administrator. If so 1, else 0.
is_guest_login	It toggles to 1 if the login belongs to a guest, otherwise remains 0.
count	It counts the number of times the same destination host is used as the current connection in the past 2 s.
srv_count	It represents the number of times a connection in the past 2 s used the same destination port number as that of the current connection.
serror_rate	The connections (in percentage) that used "flag" s3, s2, s1 or s0 among the connections aggregated in "count".
srv_serror_rate	The connections (in percentage) that used "flag" s3, s2, s1 or s0 among the connections aggregated in "srv_count".
rerror_rate	The connections (in percentage) aggregated in "count", that used the "REJ" flag.
srv_rerror_rate	The connections (in percentage) aggregated in "srv_count", that used the "REJ" flag.
same_srv_rate	The connections (in percentage) aggregated in "count", that used the same service.
diff_srv_rate	The connections (in percentage) aggregated in "count", that used a different service.
srv_diff_host_rate	The connections (in percentage) aggregated in "srv_count", that had a different destination addresses.
dst_host_count	The feature counts when connections have the same destination host IP address.
dst_host_srv_count	The connections that used the same port number.
dst_host_same_srv_rate	The percentage of connections aggregated in "dst_host_count", that used the same service.
dst_host_diff_srv_rate	The percentage of connections aggregated in "dst_host_count", that used a different service.
dst_host_same_src_port_rate	The percentage of connections aggregated in "dst_host_srv_count", that used the same port number.
dst_host_srv_diff_host_rate	The percentage of connections aggregated in "dst_host_srv_count", that had a different destination address.
dst_host_serror_rate	The percentage of connections aggregated in "dst_host_count", that used "flag" s3, s2, s1 or s0.
dst_host_srv_serror_rate	The percentage of connections aggregated in "dst_host_srv_count", that used "flag" s3, s2, s1 or s0.
dst_host_rerror_rate	The percentage of connections aggregated in "dst_host_count", that used the "REJ" flag.
dst_host_srv_rerror_rate	The percentage of connections aggregated in "dst_host_srv_count", that used the "REJ" flag.

Figure 9 showed that the feature representing "dst_bytes" was the most important attribute as it had the highest F-score, and on the other hand, "num_shells" was the least important attribute as it had the lowest F-score. It must be noted that the F-score was calculated by setting up a model having parameters defined as:

- "learning_rate"—0.1, "max_depth"—5, "sub-sample"—0.9, "colsample_bytree"—0.8, "min_child_weight"—1, "seed"—0, and "objective": "binary: logistic" (Why are these specific values chosen? Look at Tables 4 and 5).

The following are some of the additional parameters used and their meaning:

- The "min_child_weight" parameter defines the required sum of instance weight in a child. If the sum of instance weights in a leaf node falls short of this parameter, further steps are abandoned.
- The "subsample" parameter allows XGBoost to run on a limited set of data and prevents overfitting.
- The "colsample_bytree" parameter corresponds to the ratio of columns in the subsample when building trees.

- The "objective": "binary: logistic" parameter is a learning parameter and is used to specify the task undertaken: in this case uses logistic regression for binary classification.

It must be mentioned that various combinations of parameters having different values were run, and every time the attribute importance did not change for the most important attribute, as "dst_bytes" received the highest F-score each time the parameter values were changed. However, the least important end changed with a change in parameter values. So, it can be said that the parameters did have a direct effect on the F-scores of the attributes, as any change in parameters reflected a change in the F-score of the attributes in the NSL-KDD dataset. We set up the model parameters as above, as running the code with these values had given the best results in terms of mean and standard deviation. This will be elaborated further.

The following were some of the F-scores using the above-mentioned parameters:

- "dst_bytes"—this attribute of the dataset accounted for the highest F-score of about 579.
- "num_shells" and "urgent"—this attribute of the combined test and train dataset accounted for the least F-score of 1.

Further, more features were extracted out of the dataset importing GridSearchCV from the sklearn package. This functionality of sklearn enabled us to evaluate the grid score, which showed the mean and the corresponding standard deviation of the dataset using parameters such as "subsample", "min_child_weight", "learning_rate", "max_depth", and others. The following were some of the results:

- Two models were run. In the first model, the following were fixed parameters: "objective": "binary: logistic", "colsample_bytree"—0.8, "subsample"—0.8, "n_estimators"—1000, "seed"—0, "learning_rate"—0.1. The model was run to calculate the best values of the mean and the corresponding standard deviation for different combinations of the parameters "min_child_weight" and "max_depth". Table 4 represents the result achieved.

Table 4. Model 1.

Parameters			
"max_depth"	**"min_child_weight"**	**Mean**	**Standard Deviation**
3	1	0.99913	0.00013
3	3	0.99907	0.00010
3	5	0.99894	0.00014
5	1	0.99921	0.00015
5	3	0.99914	0.00013
5	5	0.99907	0.00010
7	1	0.99919	0.00018
7	3	0.99913	0.00014
7	5	0.99905	0.00015

From the above, it can be seen that the highest mean was 0.99921 achieved when the "min_child_weight" and "max_depth" parameters were set as 1 and 5, respectively; therefore, these parameter values were used while plotting the feature score (Figure 9).

- In the second model, the following parameters were fixed: "min_child_weight"—1, "seed"—0, "max_depth"—3, "n_estimators"—1000, "objective": "binary: logistic", "colsample_bytree"—0.8. The model was run to calculate the best values of mean and standard deviation for different combinations of the parameters of "learning_rate" and "subsample". Table 5 represents the result achieved.

Table 5. Model 2.

Parameters			
"learning_rate"	**"subsample"**	**Mean**	**Standard Deviation**
0.1	0.7	0.99912	0.00016
0.1	0.8	0.99913	0.00013
0.1	0.9	0.99917	0.00013
0.01	0.7	0.99601	0.00028
0.01	0.8	0.99589	0.00022
0.01	0.9	0.99583	0.00023

From the above, it can be seen that the highest mean was 0.99917, achieved when the "learning_rate" and "subsample" parameters were set as 0.1 and 0.9, respectively.

The higher the value of the mean the better the accuracy of the model is, and hence the better the readings will be reflected at the confusion matrix, ROC, precision, and recall results. Looking at models 1 and 2, the parameters were set up and the F-score was calculated as seen in Figure 9. Therefore, now it can be understood why the parameters as discussed in the feature score (Figure 9) were set up, as they accounted for higher mean values as seen in models 1 and 2, though one can choose a new model by assigning parameter values as desired and based on those very values the F-score can be calculated.

There can be many combinations to find the best parameter values used to set up a final model. The whole motive is to find a model which gives the best results. The higher the mean values, the better the model is to predict accuracy and other targets. The above two models were run to just know the effect of parameters on a model. The best-fit values can be extracted and used in future models so that accuracy reaches close to 100%. Every model has a different feature score; all it depends on is the value of parameters set. Models 1 and 2 were run and, extracting from these two models the best-fit parameters, a final model was set up. The feature score was plotted in relation to the final model as seen in Figure 9.

7.6. Comparison with other Classification Methods

The NSL-KDD dataset has been used as a dataset to test different classification methods by many researchers. The Table 6 displays the various results achieved by various classification models. The Accuracy of these methods has been displayed in Table 6 to establish why XGBoost needs to be looked at as a strong classification model. Looking at the work of many researches as referenced in Table 6, XGBoost brings about the best results out of the NSL-KDD dataset. The accuracy achieved by XGBoost model of 98.70% is the best as compared to the other models employed on the same dataset. It must be mentioned that the same dataset was used to measure the results and XGBoost sits at the top in terms of giving an accuracy in the classification of data. The Random Forest technique which is widely used gave an accuracy of 96.12% [36]. It must be mentioned that these classification techniques in Table 6 are some of the major classification techniques tested and based on them researchers even carry out hybrid models, in which two or more techniques in one model are used. The results are promising in those, but it must be noted that XGBoost implemented independently gave such promising results. Therefore, there is such a large room of optimizing the results achieved by XGBoost by carrying out more researches, using hybrid models as well which can be based on XGBoost. It can be easily said that XGBoost is a solid approach and the results it generated cannot be overlooked as they present a huge room of improvement by playing with the parameters of the desired model.

A brief description of the various classification methods used in Table 6 are as follows:

- Decision Table—In this classification model, an entry follows a hierarchical structure and the entry at a higher level in the table gets split into a further table based on a pair of additional attributes.

- Logistic—is a classification model which is a typical regression model in which the relationship between various variables is analysed. The relationship between dependent and independent variables is looked at.
- SGD—a classifier based on linear models with stochastic gradient descent learning. The gradient related to the loss is estimated at each sample at a time.
- Random Forests and Random Trees—this classification method basically employs decision trees to classify data.
- Stochastic Gradient Descent—a classification method also known as incremental gradient descent. It is an iterative method deployed with the sole purpose of minimizing the objective function.
- SVM—It is a supervised learning method of classification. The training samples are categorized in two categories and new samples are split into these two categories depending on their respective closeness to the respective two categories.
- Bayesian Network—In this classification method a directed acyclic graph or DAG is used. The various nodes in the DAG represents the features and the arcs between the adjacent nodes represent the dependencies. It is a method based on conditional probability.
- Neural Networks—A backpropagation algorithm is used implementing feedforward network.
- Naïve Bayes—This classification method is based on probabilistic classifiers using Bayes theorem.
- CART—decision trees employing Classification and Regression Trees.
- J48—a decision tree classification method based on greedy algorithm.
- Spegasos—Implements the stochastic variant of the Pegasos (Primal Estimated sub-Gradient solver for SVM).

The most important thing in an IDS is the environment it is set in. The type of data-entries in the IDS are directly related to the type of environment the IDS is deployed in. This is where XGBoost gets an advantage as it is flexible in its implementation. XGBoost can take many data-types as the input entries and gives the choice of simultaneously running on different Operating Systems such as Linux and Windows. Moreover, data overfitting problems are handled well in XGBoost and the XGBoost offers the flexibility of applying the Decision Tree Algorithms as well as Linear Model Solvers. The results in Table 6 are the appropriate comparisons between the different classification methods.

Table 6. Comparison among different classification methods.

Classifier	**Accuracy on NSL-KDD Dataset (%)**
Proposed XGBoost	98.7
Decision Table [37]	97.5
Logistic [38]	97.269
SGD [38]	97.443
RBF Classifier [37]	96.7
Rotation Forest (using 5 classes for labelling data as Normal and (Probe, DoS, R2L, and U2R) as Anomaly) [36]	96.4
SMO (Sequential Minimal Optimization) [37]	96.2
Random Tree (using 5 classes for labelling data as Normal and (Probe, DoS, R2L, and U2R) as Anomaly) [36]	96.14
Random Forest (using 5 classes for labelling data as Normal and (Probe, DoS, R2L, and U2R) as Anomaly) [36]	96.12
Spegasos [37]	95.8
Stochastic Gradient Descent [37]	95.8
SVM [37]	92.9
Bayesian Network [37]	90.0
RBF Network [37]	87.9
Naïve Bayes [37]	86.2
CART (using 5 classes for labelling data as Normal and (Probe, DoS, R2L, and U2R) as Anomaly) [39]	81.5
ANN (Artificial Neural Network) (binary class) [40]	81.2
J48 (using 5 classes for labelling data as Normal and (Probe, DoS, R2L, and U2R) as Anomaly) [39]	80.6
Voted Perception [37]	76.0
Self-Organizing Map (SOM) (Neural Network) [37]	67.8

There is always a constant comparison between different classification methods, and researchers have always struggled to find the optimum classification method. Lately, researches have contested the implementation of XGBoost and the RF classification method on datasets to find the better classification model. The results do give XGBoost an advantage over the RF classification method [41]. Moreover, XGBoost can in parallel do classification on multiple operating systems [42] and by setting the parameters the desired decision tree algorithm can be run on XGBoost, that is XGBoost can be the desired algorithm plus the boosting applied to it. Therefore, it stands out and should be considered an important player in the field of classification.

XGBoost compared to traditional Boosted models increases the speed up to 10 times and hence, the classification model becomes better as in a network model speed plays an important role [42]. XGBoost is quite flexible as it does not depend on the type of data entering a network, it can easily convert the entering data into numeric type and from there can classify data at good speed and accuracy. The overfitting and other problems related to other classification methods are easily dealt by XGBoost. The catch in the model is that the parameters set in the XGBoost model play an important role in defining the way the classification model brings about the result. There can be numerous models based on XGBoost, the depth and splits related parameters of Decision Trees or the Algorithm intended to run on XGBoost can be set, each such setting will generate a new model and new results. Therefore, the flexibility XGBoost offers is of a very high standard. There may be questions related to the type of environment XGBoost can be used in, but when companies such as Google have tested and adopted this model on ground, it clearly tells that XGBoost is a go-to classification model [43].

8. Conclusions

The prediction of data is excellent in this classification model (Accuracy = 98.70%) and based on this, future research could be set up which can help in initiating models designed to detect intrusions. This research can help to design an IDS of the future, especially when security remains such an issue. The findings are a reflection as to how effective and accurate XGBoost is when it comes to predicting a dataset. The findings are very accurate, and the error rate is very low. These findings can be further elaborated to design Intrusion Detection Systems which are robust and can be employed in architectures of the future such as IoT, 5G, and others.

A lot of work has been done in the field of classification models and their importance when it comes to the classification of data. As discussed earlier, classification methods such as SVMs, RBF, Neural Networks, Decision Trees, and others have been tested to classify data. Even the hybrid models have come up which employ more than one methods. Many researches have been carried out and as compared to most of the classification methods XGBoost gives relatively higher results. XGBoost is a relatively new concept as compared to others and its results are making it a model to investigate. Random Forests and hybrid models do come close to the accuracy achieved by XGBoost classification method when employed on NSL-KDD dataset, but in a real environment the type of data in a network will be different and that brings to the main question as to which classification method to adopt. Countering this question many investigators have majorly tried to compare the RF techniques and the XGBoost technique on various datasets, and the results give XGBoost an edge over the RF counterpart. The other important thing is that the RF are very prone to overfitting, and to achieve a higher accuracy, RF needs to create high number of decision trees, and moreover the data needs to be resampled again and again, with each sample requiring to train the new classifier. The different classifiers generated try to overfit the data in a different way, and voting is needed to average out those differences. The re-training aspect of RF is eliminated in XGBoost techniques, which basically add a new classifier to the already trained ensemble. This may seem a small difference between the two techniques but when they will be applied to an IDS, then they can affect the performance and complexity of the IDS in a big way. The only difference is that the XGBoost requires more care in setting up.

Moving further, there are a few more things that add weight to XGBoost as being a perfect classification method as this algorithm provides accuracy, feasibility, and efficiency. It automatically can operate in parallel on Windows and Linux (has both linear model solver as well as tree learning algorithms) and is up to 10 times faster than the traditional GBM (Generalized Boosted Models). Xgboost offers flexibility as to what type of input it can take, also accepts sparse input for both tree and linear booster. XGBoost also supports customized objective and evaluation functions. As a real-life application example, XGBoost has been widely adopted in industries such as Google, Tencent, Alibaba, and more, solving machine learning problems involving Terabytes of real life data.

The success and impact of the XGBoost algorithm is very well documented in numerous machine learning and data mining competitions. As an example, the records from machine learning competition site "Kaggle", show that majority of winning solutions use XGBoost (17 winning solutions out of 29 used XGBoost in 2015). In the KDDCup competition in 2015, XGBoost was used by every winning team in the top 10. The winning solutions were solutions to problems such as malware classification; store sales prediction; motion detection; web text classification; customer behaviour prediction; high energy physics event classification; product categorization; ad click through rate prediction; hazard risk prediction, and many others. So, it can be well established that the datasets used in these solutions differed and many problems such as False Alarms, classification of data, and high-level pre-processing were dealt with, but the only thing that remained constant was the use of "XGBoost" as the preferred classification technique (especially when it came to the choice of learner).

Many E-Commerce companies have also adopted XGBoost as the classification method for various purposes, as seen by a leading German fashion firm (ABOUT YOU) employing XGBoost to do return prediction in a faster and robust way. The company was able to process up to 12 million rows in a matter of minutes achieving a high accuracy in predicting whether a product will be returned or not.

These are a few examples and XGBoost's capability to use cloud as a platform makes it a hit in emerging markets. The new technologies are all based around the concept of cloudification and virtualization, and this is where XGBoost has an advantage. As its flexibility, no specific platform need, multiple accessible languages, availability, high quality results in less time, handling of sparse entries, out of core capability and distributed structure make it a well-suited classification method (consumes less resources on top of that).

The most important factor that emerges in classification problems is the scalability and this is where XGBoost is best at. It is highly scalable algorithm. It runs approximately ten times faster than existing methods on a single platform, and scales to millions and billions of examples as per the memory settings. The scalability is achieved through the algorithmic optimizations and smart innovations such as: a unique tree learning algorithm for handling sparse data; a weighted quantile procedure to handle the instance weights in approximate tree learning; the use of parallel and distributed computation leading to quick learning which makes the model exploration faster; and one of the most important strengths of XGBoost is the ability to provide out of core computation which allows the data scientists to process data including billions of examples on a cheap platform such as desktop.

These advantages have made XGBoost a go-to algorithm for Data Scientists, as it has already shown tremendous results in tackling large scale problems. Its properties such as user-defined objective function make it highly flexible and versatile tool that can easily solve problems related to classification, regression, and ranking. Moreover, as an open source software, it is easily available and accessible from different platforms and interfaces. This amazing portability of XGBoost allows compatibility with major Operating Systems therefore breaking static properties of previously known classification models. The new functionality that XGBoost offers is that it supports training on distributed cloud platforms, such as AWS, GCE, Azure, and others. This is a major advantage as the new technologies related to IoT and 5G is all built around cloud, and XGBoost is also easily interfaced with cloud dataflow systems such as Spark and Flink. XGBoost can be used through multiple programming languages such as Python, R, C++, Julia, Java, and Scala. XGBoost has already proven to push the boundaries of computing power for boosted tree algorithm as it lays special attention to model performance and computational speed. On a financial front, XGBoost systems consume less resources as compared to other classification models, they also help in saving and reloading of data whenever required.

The implementation of XGBoost offers advanced features for algorithm enhancement, model tuning, and computing environments. The assessment of all classification methods leads to the choice of XGBoost being used as the classification method as it can solve real world scale problems using less resources. The impact of XGBoost cannot be neglected and it can be said that XGBoost employed as an integral part of IDS performing functions as described above can emerge as a stronger classification model than many others.

The focus is to build a strong classification model for use in IDS. A strong classification model means one which can give near-perfect results. This will lead to a stronger IDS, which, when deployed in a certain network, will make it more secure and there will be much fewer chances of intrusion as the classification model running is of very high standard. The next bit is using the IDS as a sensor to alert the administrator about any irregularities. The IDS can be used as a one- stop device to extract information about the network. So, IDS can also act as a data source and its machine learning capabilities make it a flexible technology, avoiding regular updating. The IDS in future can also be made interactive with IoT devices. It can also form an integral part of Artificial Intelligence, as security is also a problem in the robotic world (even robots can be hacked). Airplanes, cars, mobile networks, the world of IoT, Artificial Intelligence, and smart devices all need IDS sensors employed in their architecture. Basically, anything that has internet and machines involved can use IDS as a security feature.

The future world needs its privacy intact, so the developing robotic technology that will do a lot of work in future needs IDS. There is nothing perfectly safe in a network and there must be an IDS in a network to monitor everything, as people travelling in planes, cars, etc. should be able to trust the machines that are responsible for dropping them home. For example, any hacking resulting in a plane getting hijacked due to intrusions in the network can lead to devastating results.

To summarize, XGBoost needs to be a go-to classification method because it offers flexibility and can simultaneously work on different operating systems, gives a higher accuracy, can accept diverse data as inputs, offers both linear model solver and tree algorithms, and finally has been deployed in industries to tackle Terabytes of data. Therefore, it is already accepted in society and is giving tremendous results.

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