A Technical Evaluation of the Performance of Classical Artificial Intelligence (AI) And Methods Based on Computational Intelligence (CI) i.e Supervised Learning, Unsupervised Learning And Ensemble Algorithms In Intrusion Detection Systems

Kudakwashe ZVARESHE[1] Innocent MAPANGA[2] Prudence KADEBU[3]

Information Technology Department[1], Computer Science Department[2], Software Engineering Department[3] Harare Institute of Technology Zimbabwe

kzvarevashe@hit.ac.zw[1], imapanga@hit.ac.zw[2], pkadebu@hit.ac.zw[3]

Abstract

The emergence of new technologies in this dynamic information era has caused a tremendous increase in the rate at which data is being generated through interactive applications thereby increasing the movement of information and data on communication networks as individuals, organizations and business interact on a daily basis. Big Data is flooding our networks and storage devices stimulating a cause for concern in terms of processing, storage**,** access and security of large blocks of data in most networks. The facilitation of online research services is always under the risk of intruders and malicious activity. Most techniques used in today's Intrusion Detection Systems are not able to deal with the dynamic and complex nature of cyber-attacks on computer networks. Over the years, Intrusion Detection Systems .Various methods have been developed by many researchers to detect intrusions aimed at networks as well as standalone devices which are based on machine learning algorithms, neural networks, statistical methods etc. In this paper, we study several such schemes and compare their performance. The experiments are done using WEKA (Waikato Environment for Knowledge Analysis) and one of the most popular Intrusion Detection Systems datasets which is NSL-KDD99 so as to analyse the consistency of each algorithm. We divide the schemes into methods based on classical artificial intelligence (AI) and methods based on computational intelligence (CI) i.e supervised learning, unsupervised learning, ensemble and immune algorithms. We explain how various characteristics of CI techniques can be used to build efficient IDS. This paper will further evaluate the performance of the algorithms using the following parameters: accuracy, detection rate and false alarm.

Keywords: Big Data, Intrusion Detection, NSL - KDD99, Machine Learning, Neural Networks, WEKA

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1. Introduction

The current advances in Information and Communication Technologies the world over have brought significant benefits to individuals and businesses. Conversely, this has substantially increased the threat landscape in as far as security of systems is concerned. No matter how much security controls are present in a particular system, intrusions are imminent (Ibrahim et al, 2013) thus creating need for intrusion detection. This is largely because security is based on rules and configurations that are set by the owners or users of a product. Mistakes can happen and loopholes always create opportunities which intruders exploit. It is imperative to seek out ways to detect intrusions in a system in order to avert or reduce the impact of an attack. An Intrusion Detection Systems (IDS) is a software that monitors a single or a network of computers for malicious activities (attacks) that are aimed at stealing or censoring information or corrupting network protocols (Kemmerer & Vigna, 2002). IDSs are also defined as special-purpose devices to detect anomalies and attacks in the network. Anomaly detection and misuse detection are two approaches to IDSs (Tavallaee et al 2009). The former is popularly applied for research purposes while the latter is targeted for commercial products. In either case, the IDS can identify an attack. Intrusion Detection is regarded as the second line of defence. Various techniques and methods are applied in IDSs. In this work we look at two broad categories i.e. Classical Artificial Intelligence methods and Computational Intelligence methods with respect to IDSs. We carry out several experiments on various algorithms in each category. Classical Artificial Intelligence methods include techniques such as Multilayer Perceptron, Voted-Perceptron and CHIRP. Computational Intelligence methods include Naive Bayes, Adaboost, Random Forest etc. These techniques perform best under different scenarios. Thus, they differ in their accuracy in detection, false positive rates and efficiency.

The rest of the paper is organized as follows: section II presents some related work on Intrusion Detection Systems (IDSs) and relevant techniques from literature. Section III explores the different types of IDSs. Section IV provides an analysis of the schemes for intrusion detection systems. Section V. discusses experimental results and lastly the conclusion and future are given in section VI.

2. Related Work

The success of a technique in detecting an intrusion hinges largely on the quality of the data on which it is trained. There are a few datasets that are commonly used for evaluating performance of techniques applied in IDSs. KDD99 is a dataset prepared in (Stolfo et al, 2000) from data generated in the DARPA'98 IDS evaluation (Lippmann, et al 2000) It has shortcomings of redundant records and high level of difficulty (Tavallaee et al 2009). Learning algorithms trained on the dataset give results that are inclined towards frequent records over less frequent records which usually show anomalies. This makes the results obtained from experiments done on this dataset very much unreliable. NSL-KDD datasets is an improvement of the KDD99 dataset (Tavallaee et al 2009) as a way to overcome the challenges imposed by the KDD99 dataset. All redundant records are removed in both the test and training sets. The difficulty in the dataset is also reduced as the number of selected records from each difficulty level group is inversely proportional to the percentage of records in the original KDD data set. The number of records in both the training and test set are reasonable thus allowing running of all records rather than a sample of records to yield consistent and comparable results.

The input features used in IDS is also another factor that is of importance. According to Chae et al. (2013), if the correct features are used, the IDS becomes more computationally efficient and effective They evaluate the performance of standard feature selection methods and go on

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to propose a new feature selection method using the Attribute Ratio (AR) which is calculated by mean and frequency of features.

The area of Intrusion Detection research has greatly matured as evidenced by the expanse of techniques that have been applied on relevant datasets in various experiments in a bid to enhance intrusion detection capability. Ibrahim et. al analysed the performance of Self Organization Map (SOM) an Artificial Neural Network, in an Intrusion Detection System (Ibrahim et al, 2013). The IDS consists of three modules, for database creation, preprocessing and detection of attack. This is applied to KDD99 and NSL-KDD datasets. In this work SOM is found to perform better than other techniques applied on KDD99 over on the NSL-KDD datasets with a detection rate of 92.37% and 75.49%respectively.

Revathi.&. Malathi (2013) make an analysis of algorithms for Intrusion Detection applied on the NSL-KDD dataset. Experiments are performed using Machine Learning algorithms which are SVM, J48, Random forest, CART and Naive Bayes algorithms. This is done using a dataset with 41 features and also a dataset of 15 features reduced using the CFS subset technique for dimensionality reduction. In both cases, Random Forest algorithm shows the highest accuracy rate of 99.1% and 99.8% respectively for a normal attack. AdaBoost-based algorithm with decision stumps used as weak classifier is used for intrusion detection in Weiming Hu et al (2008). The algorithm is tested on Knowledge Discovery and Data Mining CUP 1999 data set. The algorithm is found to have a high running speed, low false- alarm and high detection rates of about 0.307% and 90.04% respectively on the test set. Pachghare, & Kulkarni (2011) et al. makes a comparative analysis of various decision tree based algorithms such as J48, Random Forest, Random Tree, NB Tree, LAD Tree etc . In this analysis J48 Graft gives the best results compared to the other types of decision trees.

Hybrid Intrusion Detection Systems have been proposed in a number of researches. These combine strengths of different algorithms so as to improve existing techniques. In Zhang and Zulkernine, (2006) an approach is proposed that combines the benefits of misuse and anomaly detection. Most Intrusion detection techniques are usually based on either misuse detection or anomaly detection, not both. Random Forests algorithm is used in the misuse detection to detect known intrusions while outlier detection also provisioned by the random forests algorithm is used in detection of unknown intrusions. The misuse detection performs well for known intrusions. However, outlier detection in Random Forest algorithm is found not to perform very accurately as it results in many false positives.

A model based on a combination of Hidden Markov Model (HMM) and Rough Set Reduction is proposed and applied in Anomaly Detection (Zihui Che & Xueyun Ji, 2010). The HMM and rough set based approach can identify misuse and malicious intrusion by means of attributes reduction.

3. Types of Intrusion Detection Systems

The major classifications of intrusion detection systems are active and passive IDSs. An active Intrusion Detection Systems (IDS) is sometimes referred to as an Intrusion Detection and Prevention System (IDPS). It is designed in such a way that malicious traffic will be dropped without external intervention. The IDPS has the advantage of providing real-time remedial solution in response to an intrusion. A passive IDS on the other hand does not provide any solution in the wake of an attack. Rather, it only monitors and analyzes network traffic activity and alert an operator to the possible attack. Table 1 shows some types of IDSs

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Table 1: Types of Intrusion Detection Systems

Type	Description
Network Intrusion Detection System (NIDS)	Network Based-Network IDSs (NIDS) are placed in key areas of network infrastructure and monitors the traffic as it flows to other host.
The Host Intrusion Detection System	Host Based-Intrusion Detection System is installed on a host in the network.
Stack Based IDS	Stack based IDS is latest technology, which works by integrating closely with the TCP/IP stack, allowing packets to be observed as they make their way way up the OSI layers.
Signature Based IDS	Signature-Based IDS use a rule set to identify intrusions by looking out for patterns specific to known and documented attacks.
Anomaly Based IDS	Anomaly-Based IDS analyses ongoing traffic, activity, transactions and behavior in order to identify intrusions by detecting anomalies.
Network behavior anomaly detection (NBAD)	Network behavior anomaly detection (NBAD) is the monitoring of the network for any anomalous behaviour in traffic flow.

4. Schemes for Intrusion Detection Systems

4.1 Classical Artificial Intelligence Methods

Multi-Layer perceptron (MLP) is a feedforward neural network which maps a set of inputs to a set of outputs with multiple layers between them. The flow of data happens in forward direction from input to output layer. Training of MLP is done with the backpropagation learning algorithm. MLP goes beyond merely classifying an event as an attack or normal traffic but also it can be used to classify many different types of attacks. (Frank,1994). It is widely used for classification, pattern recognition and prediction. Multi-Layer Perceptron can solve problems which are not linearly separable.

4.2 Voted Perceptron

The Voted perceptron is an improvement of the classical perceptron algorithm which uses kernel functions which gives an improvement in performance, both in test accuracy and in computation time. A list of all prediction vectors that are generated after each and every mistake in prediction is maintained during training. For each such vector, the number of iterations it "survives" until the next mistake is made is counted which is referred to as the "weight" of the prediction vector. A prediction is then calculated by a weighted majority vote derived from binary prediction of each one of the prediction vectors (Freund & Schapire, 1998) .

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4.2 CHIRP

CHIRP classifier, is an iterative sequence of three stages (projecting, binning, and covering) that are designed to deal with the curse of dimensionality, computational complexity, and nonlinearly separable (Wilkinson, 2011) CHIRP is a nonparametric, ensemble classifier works on any data set, thus it is suitable for diverse data sets regardless of unavailability of prior knowledge of the structure of the data set.

5. Computational Intelligence

5.1 Random Forest

Random Forest is an ensemble learning method used for solving both regression and classification problems. It can be applied for dimensionality reduction, resolving missing values, outliers and other tasks in data exploration. It is a result of combination of weak models to form a more efficient model. Random Forest generates several classification trees to form a forest. Each tree places a vote for classifying an object (Zhang & Zulkernine,2008)

5.2 Real Adaboost

Adaboost is an ensemble technique which assists in combining a number of "weak classifiers" into a solitary "strong classifier". A weak classifier is one that performs poorly, but performs much better than random guessing. A perfect example can be seen in the classification of sexes using height. One could say anyone over 5' 9" is a male while anyone below that height maybe classified as a female. This method can lead to a lot of misclassifications but the accuracy will still be greater than 50%.

5.3 S VM

It is a machine learning algorithm that is used for classification and regression. It is based on the idea of a decision plane that separates members belonging to different classes. Each data item is plotted as a point in n-dimensional space with the value of each of the n features being the value of a particular coordinate. SVM aims to produce a model which predicts target value of data instances in the testing set with only the attributes given (Vidhya, 2013) **Naïve Bayes**

It is a classification technique that is based on Bayes' Theorem with an assumption of independence between predictors/features. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. For example, a fruit may be considered to be an apple if it is red, round, and about 3 inches in diameter. Even if these features depend on each other or upon the existence of the other features, a Naive Bayes classifier would consider all of these properties to independently contribute to the probability that this fruit is an apple. This indeed is a strong assumption but it results in a fast and effective method. Naive Bayes algorithm has been successfully applied to spam filtering and document classification.

6. EXPERIMENTS AND RESULTS

All experiments were done using WEKA (Waikato Environment for Knowledge Analysis). "WEKA is a collection of machine learning algorithms for data mining tasks" (Weka3, n.d.) It is an Open Source software providing an extensive set of tools for data preprocessing, association rules, classification, regression, clustering and visualisation. The training dataset used is NSL-KDD dataset which contains 42829 instances with several types of attacks. The testing dataset consisted of 22544 instances. Figure 1 shows the steps that are followed in the classification process. Table 2 shows the results from the experiments that were performed by

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applying the various algorithms on the datasets. Analysis is done based on build time, test time and true positives

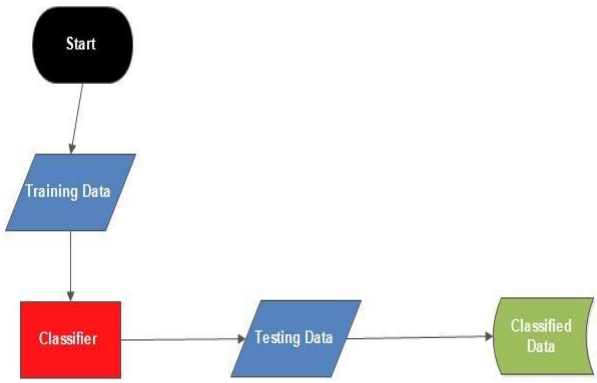

Figure 1: Classification Process

Table 2: Experiment Results

Algorithm	Build Time	Test Time	True Positives
MLP	7695.91s app 2.1 hrs	1.31	77.71
Chirp	429.72s app 7.15mins	0.49s	76.8808
Voted Perceptron	19.43s	54.11s	41.1595
Random Forest	80.39s	0.83s	80.4516
Real Adaboost	8.71s	0.14s	80.4205
Bagging	41.69s	0.15s	82.6295
SVM	21873.47s app 6hrs	396.58s app 6mins	72.3518
Naïve Bayes	0.79s	0.96s	76.1178
Ensemble Selection	106.33s app 1.7mins	4.02	84.3018

which denote the accuracy of the algorithm in detecting intrusions. The results displayed by the table indicate that ensemble selection offers the highest detection rate with an accuracy of 84% albeit with a higher build time and test time. Bagging performed very well with a lower build time and test time. All the methods falling under Computational Intelligence performed very well. on the other hand Classic Artificial Intelligence methods ie. MLP, CHIRP and Voted-Perceptron were outperformed by CI methods.

7. CONCLUSION

The results of the experiments show us that Ensemble Selection is a much better technique compared to the other algorithms as it yielded more true positives and a higher precision and recall value. The Voted Perceptron yielded the worst results meaning that it may not be the best algorithm to use for intrusion detection. Computational Intelligence methods outperformed Classic Artificial Intelligence methods. We will analyse the performance of Immune algorithms. In our future work, we will use the winning Algorithm to design a prototype.

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