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An Ensemble-Based Classifier Network Intrusion Detection

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Abstract: An Intrusion Detection System monitors the flow of data on a network through the computer for the search of malicious activities which are majorly known as threats and viruses. There are two types of intrusion detection, one, Signature-based detection where the intrusion detection collects the information, analyses it, and then compares them to the attack signatures stored in the database. The second one is an Anomaly-based intrusion detection system that learns normal and anomalous behaviour by analysis in various benchmark datasets. Common challenges for Intrusion Detection Systems are large amounts of data to process, low detection rates, and high rates of false alarms. Considering anomaly pattern as detecting a point in time where the behaviour of the system is unusual and significantly different from past behaviour. In such context anomaly detection mean detecting the behaviours that deviate from normal behaviours. An ensemble based classifier method is considered using Naïve Bayes and Multivariate Linear Regression algorithms. To get a better accuracy rate of the intrusion for real time data packets are received in the system. On the experimental results achieved, we are proposing the Naïve Bayes and Multivariate techniques as an efficient method for network intrusion detection.

Keywords: Network Intrusion Detection, NSL KDD Dataset, Classifiers, Ensemble, Naïve Bayes, Multivariate Linear Regression, Feature Selection.

1. Introduction

As with the increasing applications of the computer and network nowadays, the security problems in information system are becoming complicated. Though we have a lot of methods in machine learning, there are issues in handling huge and imbalanced dataset machine learning based intrusion detection systems for real-time data packets, it faces a lot of challenges to process the entire data. Hence, it is necessary to identify types of intrusions through network traffic behavior. The Intrusion detection system is divided into two categories: Host Based Intrusion Detection System and Network Based Intrusion Detection System.

Host Based Intrusion Detection System can detect the internal changes, where, an attack can occur inside the computer due to certain applications and would spread inside the system. But, Network Intrusion Detection System detects malicious activities in the packets of the network as they enter the network or by unusual behavior on the network by their attacks. The advantage of a network intrusion detection system is monitoring a large network.

The intrusion detection system has many methods and classifiers based on the datasets and attacks. The machine learning techniques have been adapted for the detection rate. It reduces false positives and increases the true positives trying to give an accuracy rate for the real time packets for large amount of data.

We have considered the data set of the NSLKDD dataset as there are many challenges in evaluating the performance of Network intrusion detection is the unavailability of network based dataset. In this paper, we are using the machine learning models such as Naïve Bayes and Multivariate linear regression models with the ensemble method technique using the NSLKDD dataset.

1.1 Dataset

In the past few decades, data mining and machine learning techniques have been extensively researched in developing intrusion detection systems using different intrusion detection datasets. In 1998 DARPA Intrusion Detection Evaluation Program was prepared which contains different attacks between internet protocols. It had been managed by MIT Lincoln Labs. The main objective of the work was to survey and evaluate research in intrusion detection.

NSL-KDD Data: Are utilized in many of the machine learning methods. NSL-KDD dataset does not include redundant records within the train set; hence the classifiers will not be biased towards frequent records. The amount of records within the NSLKDD dataset train and test sets is reasonable, which makes this dataset affordable to run the experiments on an entire set. Data files in NSL-KDD are KDDTrain+.ARFF, KDDTrain+.TXT, KDDTrain+_20Percent.ARFF, and KDDTrain+_20Percent.TXT, even KDDTrain+.ARFF, KDDTrain+.TXT, KDD-Train+_21Percent.ARFF, and KDDTrain+_21Percent.TXT. There are 41 features of NSL-KDD

Table 1: Features of NSL-KDD Dataset

Number	**Feature**	**Type of feature**	**Number**	**Feature**	**Type of feature**
1	Duration	Numeric	22	Is_guest_login	nominal
2	Protocol_type	Nominal	23	Count	numeric
3	Service	Nominal	24	Srv_count	numeric
4	Flag	Nominal	25	Serror_rate	numeric
5	Src_bytes	Numeric	26	Srv_serror_rate	numeric
6	Dst_bytes	Numeric	27	Rerror_rate	numeric
7	Land	Nominal	28	Srv_reerror_rate	numeric

8	Wrong_fragment	Numeric	29	Same_srv_rate	numeric
9	Urgent	Numeric	30	Diff_srv_rate	numeric
10	Hot	Numeric	31	Srv_diff_host_rate	numeric
11	Num_failed_logins	Numeric	32	Dst_host _count	numeric
12	Logged_in	Nominal	33	Dst_host_srv_count	numeric
13	Num_compromised	Numeric	34	Dst_host_same_srv_rate	numeric
14	Root_shell	Numeric	35	Dst_host_diff_srv_rate	numeric
15	Su_attempted	Numeric	36	Dst_host_same_src_port_rate	numeric
16	Num_root	Numeric	37	Dst_host_srv_diff_host_rate	numeric
17	Num_file_creations	Numeric	38	Dst_host_serror_rate	numeric
18	Num_shells	Numeric	39	Dst_host_srv_serror_rate	numeric
19	Num_access_files	Numeric	40	Dst_host_rerror_rate	numeric
20	Num_outbound_cmds	Numeric	41	Dst_host_srv_rerror_rate	numeric
21	Is_host_login	Nominal			

1.2 Network Traffic Attacks

Table 2 Network Traffic Attacks

Attack group	Attacks
Probe	ipsweep, mscan, nmap, portsweep, saint, satan
DoS	apache2, back, land, mailbomb, Neptune, processtable, pod, udpstorm, smurf, teardrop
U2R	buffer_overflow, httptuneel, loadmodule, perl, rootkit, xterm, ps, sqlattack
R2L	ftp_write, imap, guess_passwd, named, multihop, phf, sendmail, snmpgetattack, snmpguess, spy, warezclient, worm, warezmaster, zsnoop, xlock

The network traffic attacks are basically of these four types of attack. We are considering these attacks and considering a binary value for the attack and normal data packets.

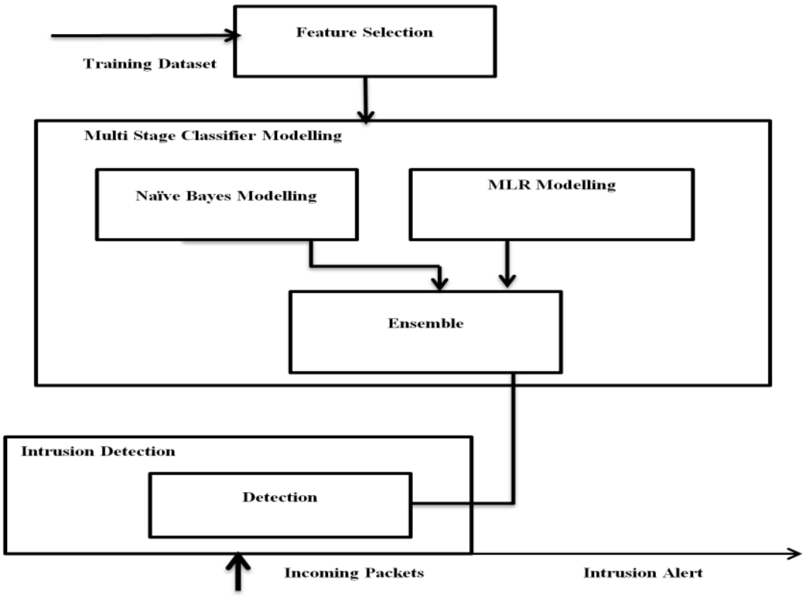
2. Literature Review

The study done by Srinivas Mukkamala, Guadalupe Janoski, Andrew Sung (2002) was on Support Vector machine (SVM) and Neural Network. They gave high priorities to fast training and scalability but then, restricted it to the binary classifications for few of the features in the dataset used. There was a comparative results of technique with other existing Intrusion detection system are evaluated using binary class NSL KDD dataset and multi class NSL KDD dataset in the study done by Raman Singh, Harish Kumar, R.K.Singla (2015), where the network traffic dataset was huge and imbalanced. It could give the highest accuracy rate of 97.6%precision. In the opinion given by the research done by K. A. Taher, B. Mohammed Yasin Jisan, and M.M. Rahman (2019), they presented different machine learning models using feature selection methods, but the analysis of the result was network traffic detection rate was 94.02% with the known attacks. Anomaly based intrusion detection system using Ad Hoc network was proposed by A. A. Korba, M. Nafaa and Y. Ghamri-Doudane (2016), it explained the clustered network topology. The idea was to enable the cluster head node to detect the malicious node. U. S. Musa, M. Chhabra, A. Ali and M. Kaur (2020) tried to give the review of emergence of machine learning new techniques for intrusion detection. By giving a comparison table, they are highly giving the dataset comparison and algorithms comparison. In the opinion of L. Koc and A. D. Carswell, (2010) the use Hidden Naïve Bayes algorithms for the intrusion detection system, for the attacks where they have challenges for a huge feature of datasets, is better than the Naive Bayes algorithm. Using the KDD’99 dataset, they need to apply data mining methods and concluded that future work can be done to balance the imbalanced data in the dataset. Using Naïve Bayes along with Ada Boost to enhance network anomaly intrusion detection was proposed by W. Li and Q. Li (2010) where they could improve the detection rate of positive rate keeping the false positive rate low. By introducing class information to Feature extraction methods by Chen, Long-Shen & Syu, J.-S (2015) by keeping the classification performance and tried to reduce the computations time, but it could not be generalized for multiclass classification. By improving the performance, using ensemble methods proposed by Ngoc Tu Pham, Ernest Foo, Suriadi Suriadi (2018) using feature selection method. The techniques reduce the number of irrelevant features and classification accuracy. The drawback is that, only one dataset was used to evaluate the built classifier. To reduce the false alarm rate and true positive rate by using the Real Valued Negative Selection algorithm proposed by F.Selahshoor, H. Jazayeriy and H.Omranpour (2019). There were overlapping samples where the expressions were not accurate. In the paper proposed by J. Olamantanmi Mebawondu, Olufunso D. Alowolodu, Jacob O. Mebawondu, Adebayo O. Adetunmbi (2020) using, supervised learning paradigm method was adopted for real time intrusion detection, but it failed to test the performance of the model using different attributes. Compared to Support Vector Machine and Discriminative Restricted Boltzmann Machine the detection rate is much higher in the case of Dos, Probe, U2R and normal traffic detection this was the proposed paper given by M. Raihan-Al-Masud and H. A. Mustafa (2019). It needs to improve the detection rate of R2L. A study done by M. Azizjon, A. Jumabek and W. Kim (2020) 1D CNN based Network intrusion detection, in which they have used normalization on imbalanced data. Where, convolution neural network is used with a 3-layer model, which outperformed by achieving the highest accuracy. But, the imbalanced data problem led to poor performance of the neural network model.

3. System Architecture

The proposed system consists of the Feature Selection method and ensemble based machine learning methods. As shown in figure 1, Feature selection is responsible to extract most feature attributes to identify the instances. The ensemble based machine learning algorithms used are Naïve Bayes and the Multivariate Linear Regression Model. The real time data has been captured and trained using the Feature selection.

Figure 1 System Model for Network Intrusion Detection



3.1 Feature Selection

Feature Selection is an important process where we can automatically or manually select those features which will contribute to our prediction variable, even the output in which we are interested, as there might be irrelevant features that can decrease the accuracy of the model. The major benefit of Feature selection before modelling the data is, it reduces overfitting, improves accuracy, and reduces training time.

3.2 Naïve Bayes Modelling

Naïve Bayes classifier is one of the simplest and effective classification algorithms of Bayesian network classifiers, which helps in building fast machine learning models, which can make quicker predictions. It is a probabilistic classifier that is; it predicts based on the probability of an instance or object.

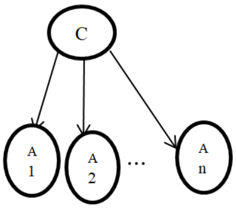
A Bayesian classifier maps the A features which consist of {a1, a2,.., an} into C classes that consist of {c1,c2,.., cn} on a dataset D which consists of {E1, E2,.., Et} instances and can be defined as the equation(1)

$$c(E) = \ arg \max_{c \in C} P(c)P(a_1, a_2, \ldots, a_n|c). \tag{1}$$

Then, with the consideration of Naïve assumptions of the independence of the attributes given in the class as in equation (2), Naïve Bayes classifier is illustrated in figure 2

$$P(E|c) = \ P(a_1, a_2, \ldots, a_n|c) = \prod_{i=1}^{n} P(a_i|c). \tag{2}$$

Figure 2 Naïve Bayes Structure



3.3 Multivariate Linear Regression Modelling

When we have multiple features and we need to train a model that can predict the value given for those features, multivariate linear regression can be used here. This is a similar method as a simple linear regression model with multiple independent variables contributing to determine and complex computation due to the added variables.

$$Y_i = \alpha + \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \ldots + \beta_n x_i^{(n)}$$

Yi is the estimate of i^{th} component of dependent feature *y*, where we have *n* independent feature and x_i^j denotes the i^{th} component of j^{th} independent feature. Also, the cost function is as follows

$$E(\alpha, \beta_1, \beta_2, \ldots, \beta_n) = \frac{1}{2m} \sum_{i=1}^{m} (y_i - Y_i)$$

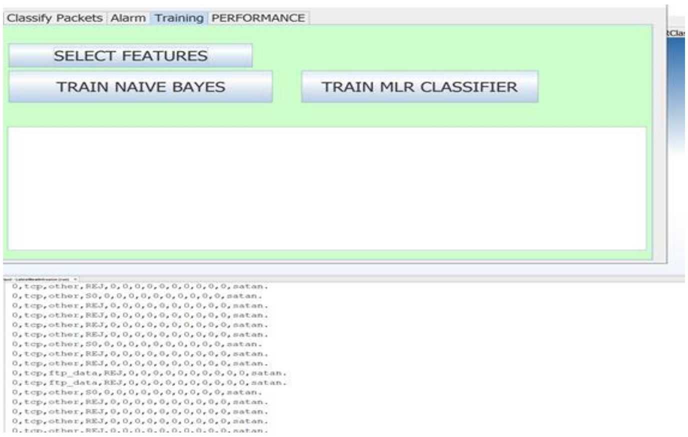
3.4 Ensemble Method

Ensemble learning helps improve machine learning results by combining several methods, in our model we ensemble the Naïve Bayes and Multivariate Linear Regression. This method approaches the production of better predictive performance compared to a single model. The main advantage to use the ensemble method is, it gives an improvement in predictive accuracy.

4. Experiment and Result

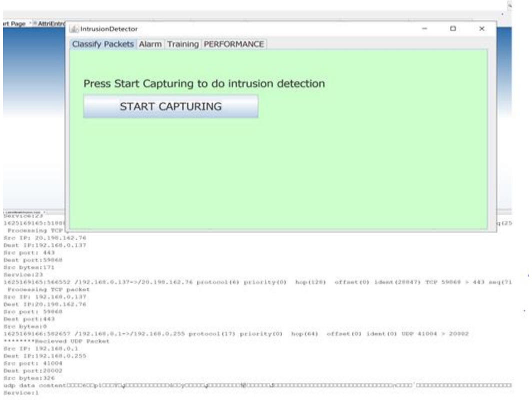
The data is captured from the real time data from the internet as shown in figure 3. The data is trained by the algorithms, the Feature selection method is used to train for the features in particular for the attacks, then train the model using the Naïve Bayes algorithm and Multivariate algorithm. We use the Support Vector Machine where the data is partitioned into two classes: normal and attack, the objective of our experiment is to separate normal and attack patterns. In our experiment, all attacks are classified as +1, and normal data classified as -1 in our experiment we have considered 11 features of the NSL KDD data set and trained the real time packets captured and classify them and detection will be alerted as the data are captured.

Figure 3 Feature Selection



```
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,S0,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,S0,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,ftp_data,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,ftp_data,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,S0,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
0,tcp,other,REJ,0,0,0,0,0,0,0,0,0,0,satan.
```

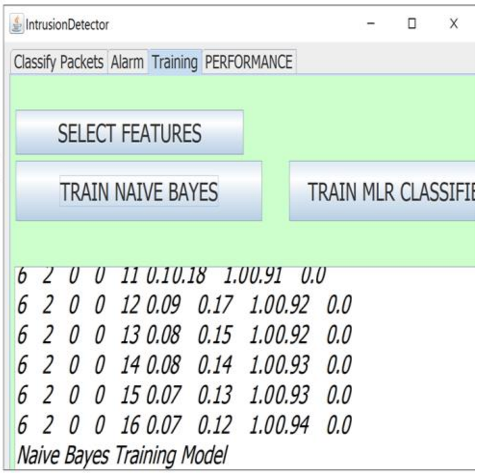
Figure 4 Capturing the Real Time Data



Press Start Capturing to do intrusion detection

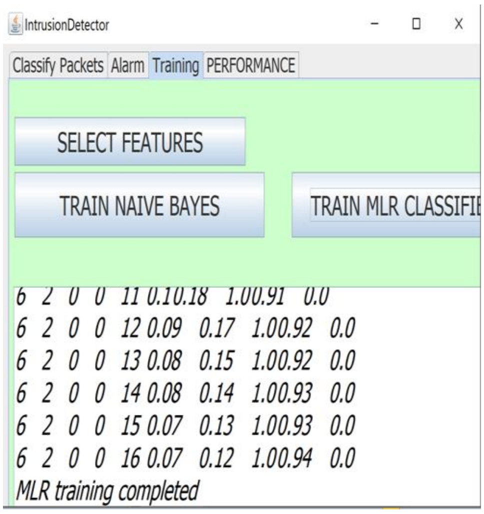
```
Service:23
1625169165:51888
 Processing TCP
Src IP: 20.190.162.76
Dest IP:192.168.0.137
Src port: 443
Dest port:59868
Src bytes:171
Service:23
1625169165:566552 /192.168.0.137->/20.190.162.76 protocol(6) priority(0)  hop(128)  offset(0) ident(28847) TCP 59868 > 443 seq(71
 Processing TCP packet
Src IP: 192.168.0.137
Dest IP:20.190.162.76
Src port: 59868
Dest port:443
Src bytes:0
1625169166:582657 /192.168.0.1->/192.168.0.255 protocol(17) priority(0)  hop(64)  offset(0) ident(0) UDP 41004 > 20002
********Recieved UDP Packet
Src IP: 192.168.0.1
Dest IP:192.168.0.255
Src port: 41004
Dest port:20002
Src bytes:326
udp data content□□□□€□□pi□□□Ÿ□□□□□□□□□□□□□□□□□y□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
Service:1
```

Figure 5 Training the Naïve Bayes Model



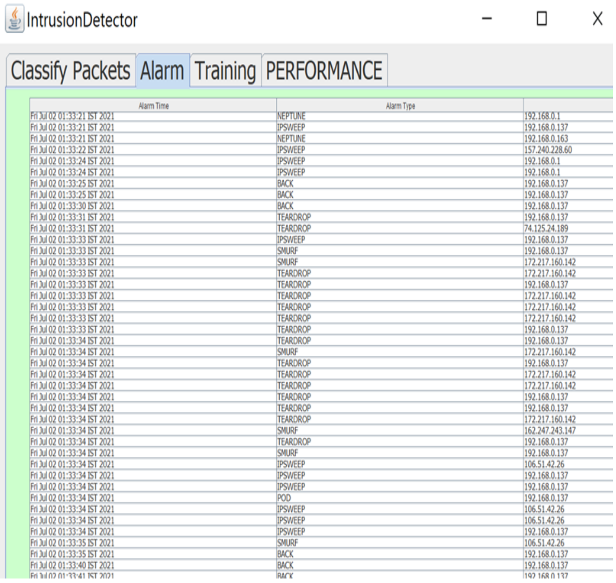
```
6  2  0  0  11 0.10.18  1.00.91  0.0
6  2  0  0  12 0.09  0.17  1.00.92  0.0
6  2  0  0  13 0.08  0.15  1.00.92  0.0
6  2  0  0  14 0.08  0.14  1.00.93  0.0
6  2  0  0  15 0.07  0.13  1.00.93  0.0
6  2  0  0  16 0.07  0.12  1.00.94  0.0
Naive Bayes Training Model
```

Figure 6 Training the Multivariate Linear Regression Model



```
6  2  0  0  11 0.10.18  1.00.91  0.0
6  2  0  0  12 0.09  0.17  1.00.92  0.0
6  2  0  0  13 0.08  0.15  1.00.92  0.0
6  2  0  0  14 0.08  0.14  1.00.93  0.0
6  2  0  0  15 0.07  0.13  1.00.93  0.0
6  2  0  0  16 0.07  0.12  1.00.94  0.0
MLR training completed
```

Figure 7 Alarms for the Intrusion



Alarm Time	Alarm Type	
Fri Jul 02 01:33:21 IST 2021	NEPTUNE	192.168.0.1
Fri Jul 02 01:33:21 IST 2021	IPSWEEP	192.168.0.137
Fri Jul 02 01:33:21 IST 2021	NEPTUNE	192.168.0.163
Fri Jul 02 01:33:22 IST 2021	IPSWEEP	157.240.228.60
Fri Jul 02 01:33:24 IST 2021	IPSWEEP	192.168.0.1
Fri Jul 02 01:33:24 IST 2021	IPSWEEP	192.168.0.1
Fri Jul 02 01:33:25 IST 2021	BACK	192.168.0.137
Fri Jul 02 01:33:25 IST 2021	BACK	192.168.0.137
Fri Jul 02 01:33:30 IST 2021	BACK	192.168.0.137
Fri Jul 02 01:33:31 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:31 IST 2021	TEARDROP	74.125.24.189
Fri Jul 02 01:33:33 IST 2021	IPSWEEP	192.168.0.137
Fri Jul 02 01:33:33 IST 2021	SMURF	192.168.0.137
Fri Jul 02 01:33:33 IST 2021	SMURF	172.217.160.142
Fri Jul 02 01:33:33 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:33 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:33 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:33 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:33 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:33 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	SMURF	172.217.160.142
Fri Jul 02 01:33:34 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:34 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:34 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	TEARDROP	172.217.160.142
Fri Jul 02 01:33:34 IST 2021	SMURF	162.247.243.147
Fri Jul 02 01:33:34 IST 2021	TEARDROP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	SMURF	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	106.51.42.26
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	POD	192.168.0.137
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	106.51.42.26
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	106.51.42.26
Fri Jul 02 01:33:34 IST 2021	IPSWEEP	192.168.0.137
Fri Jul 02 01:33:35 IST 2021	SMURF	106.51.42.26
Fri Jul 02 01:33:35 IST 2021	BACK	192.168.0.137
Fri Jul 02 01:33:40 IST 2021	BACK	192.168.0.137
Fri Jul 02 01:33:41 IST 2021	BACK	192.168.0.137

The result of the experiment is shown graphically. We can achieve 98% of accuracy rate. We can achieve a better accuracy than compared to other algorithms by using the ensemble method. Figure 8,9,10 shows the accuracy rate, true positive value, and False Positive value. Our experiment results in giving a high True Positive value and low False Positive value.

Figure 8 Accuracy Rate

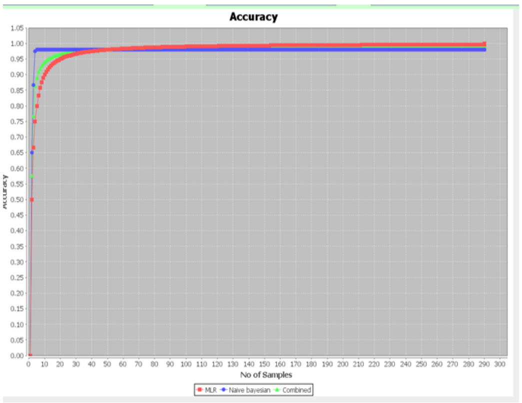


Figure 9 True Positive Values

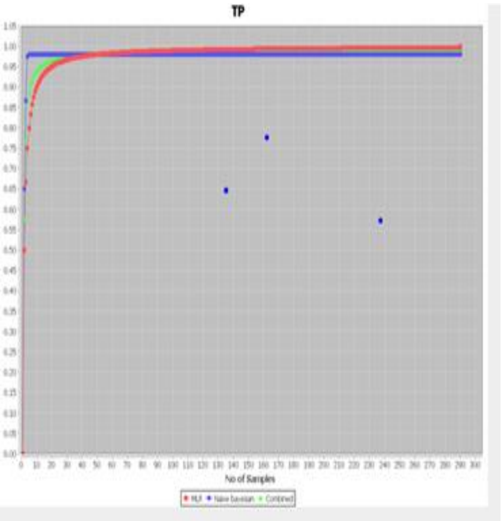
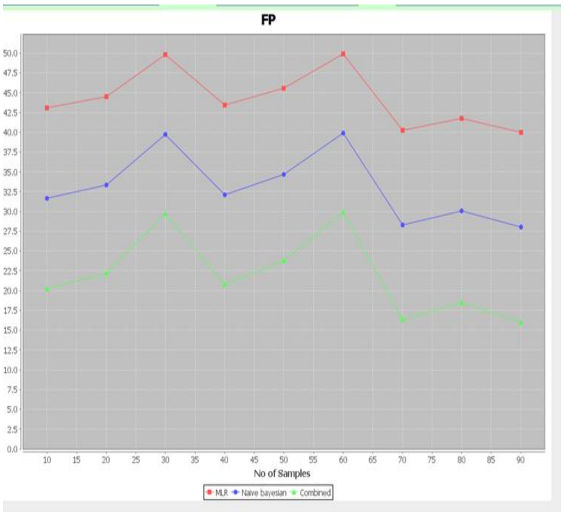


Figure 10 False Positive Values



5. Conclusion

We have performed an adaptive ensemble method of machine learning to measure the intrusion detection, using the NSL KDD dataset feature for the real time packets for intrusion evaluation. The classifications were performed on a binary attack/normal basis.

The ensemble method delivers highly accurate performance, with the Naïve Bayes and Multivariate linear regression algorithms showing positive rates and accurate results. The performance is for the few features of the NSL KDD data set that have been trained, the data were trained to deliver accurate results. Comparative to [1] the result is high. The True positive value rate is high and the False positive rate is low. The accuracy rate is around 98% for the set of features trained in the model. Future work can be done for more number of features which can be checked for accuracy with a faster rate of detection for the real time data.

Future work can be taken forth for training more features from the dataset considered for training.

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