International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Statistical Based Feature Selection and Ensemble Model for Network Intrusion Detection using Data Mining Technique

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Abstract: ***In today's world, Information society, computer networks and their interconnected applications are the emerging technologies. Intrusion Detection System (IDS) is used to distinguish the attitude of the network. Now a days, due to frequent and heavy attacks an Network devices, the Intrusion Detection System has become growing and censorious component to secure Network devices. A huge amount of data is needed to build the perfect Intrusion Detection System. This proposed system focuses on feature selection and ensemble of tree based classification methods to build Intrusion Detection System. The implementation of feature selection is fulfilled by using the NSL-KDD dataset. Statistical based feature selection methods such as Pearson's Correlation, Chi-square, Gain ratio and Symmetrical uncertainty are used to generate four modified datasets. By using that modified datasets the tree based Intrusion Detection models are built using J48, REP Tree and simple CART algorithms. To acquire better prediction of accuracy the algorithms J48, REP tree and simple CART are combined using ensemble method and built perfect tree based Intrusion Detection System.***

Index Terms: ***CART, Ensemble model, Feature selection, Intrusion Detection System, J48, REP Tree.***

I. INTRODUCTION

Intrusion Detection Systems is a necessary task held for security management system to protect the computer network. The intruders attempt to break or misuse our network systems to steal confidential details, to make backdoors for succeeding attacks and to hack others network account. IDS are mostly split into two categories such as Misuse or Signature based Intrusion Detection System and Anomaly based Intrusion Detection System. In Misuse IDS intrusions are noted based on parameter of system weakness and well known attack signature. Mostly misuse based IDS are simple and pattern matching. It is not aware on new or unfamiliar attacks. On the other hand in Anomaly based Intrusion Detection Systems depend on normal behaviors parameter and detect the intrusion which are slightly distinct from standard behavior.[1] Precious details is all time captivating to attackers so it is vulnerable to intensive network attacks. The word Intrusion is mentioned as a process when an attacker obtains access to the server or host system by sending illegal malicious packets over network so that they can easily steal or recast any deceitful important information. The Intrusion is occurring in the host system or server as the result of already existing system vulnerabilities, like misconfiguration of system, user misuse and defects on program. One can easily build a clever intrusion by placing multiple vulnerabilities at the same time [2]. In IDS, network attacks are grouped into 4 types. They are described as (1) Denial Of Service (DOS), (2) Probe, (3) User To Root (U2R) and (4) Remote To Local (R2L).

- DOS : This attacker does not permit legitimate users' approach to network resource or overloads them so that the request cannot be performed in real time. The outcome of this attack is inaccessibility of network resource to its intended user. The resource becomes as too busy or unavailable.
- Probe: This attack gathers information about the network resource to identify the known vulnerabilities by scrutinizing the system or network device to discover the deficiency or vulnerabilities that may occur in order to compromise the system.
- U2R: The unauthorized user can avoid the security control system to acquire root user privileges.
- R2L: This attacker doesn't have the user account but as an authorized user of that victim's resource and tries to get the privileges without having an account.

In the proposed system, we find appropriate features by using statistical based functions and builds the optimal model using data mining tree based machine learning techniques to reorganize the normal and anomaly classes using NSL-KDD dataset [3,4]. The proposed work is ordered in following manner: Section 2 describes the review of literature. Section 3 describes dataset description and Section 4 explains the statistical based feature selection methods. Section 5 describes tree based ensemble model, Section 6 focus on the results and its deliberation. In section 7 the results are summarized then concluded.

Manuscript published on November 30, 2019.
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II. REVIEW OF LITERATURE

D. Arunkumar et al. analyzed and criticizes the way of using, functioning the intrusion detection system in data mining. And also describe the various methods and types involved in the IDS and in which way they operate when an attack occurred [1]. Shadi Aljawarneh et al. proposed the new hybrid model that can be used to estimate the intrusion scope threshold degree based on network transaction data's optimal features that were made available for training [2]. Shubhangi Dongre et al. used the filtering techniques for feature selection by using the KDD cup 99 dataset and identify the DOS attack [3]. Danijela D.Protic analyzed the review article on network intrusion detection datasets likes KDD Cup 99, NSL-KDD etc., and also described the details about the features in that datasets.[4]. L. Dhanabal et al. proposed the various classification algorithms in detecting the anomalies in the network traffic patterns and also analyzed the relationship of the protocols available in the commonly used network protocol stack with the attacks used by intruders to generate anomalous network traffic [5]. Opeyemi Osanaiye1 et al. proposed an ensemble-based multi-filter feature selection method that combines the output of four filter methods to achieve an optimum selection. We then perform an extensive experimental evaluation of our proposed method using intrusion detection benchmark dataset, NSL-KDD and decision tree classifier [6]. Sushilkumar Kalmegh described the model for performance evaluation of REPTree, Simple Cart and Random Tree classification algorithm and make comparative evaluation of classifiers REP Tree, Simple Cart and Random Tree in the context of dataset [7].

III. DATASET DESCRIPTION

The inherent downside in KDD cup 99 dataset has been disclosed by different statistical methods. It has the detection accuracy of numerous IDS represented by the researchers. The NSL-KDD dataset processed and collected as the refined version of KDD cup 99 dataset and contains only the essential instances from complete KDD dataset and allows the classifier to build a fair model for IDS. Sufficient numbers of instances are obtainable in training and testing dataset, which are reasonable and enable to experiment on full set. The number of specific instances from each difficult level group is conversely proportional to the instances in the actual KDD dataset. There are 42 features in every record. The last feature identifies, either as normal or attack. The Table 1 shows the details of the features that are available in NSL-KDD dataset [5].

Basic features are obtained from the packet header, without analyzing the packet content. Content features are regulated by examining the content of TCP packet. The duration of the connection is determined in time features and the interval of given number of connections are described in traffic features. The required information about host is determined in host based features [4].

In the proposed system the statistical based heuristic technique is used for feature selection to identify normal and anomaly in NSL-KDD dataset. The techniques are Pearson's Correlation, Chi-square, Gain ratio and Symmetrical uncertainty. The tree based classification techniques J48 and REP Tree and simple CART are used for identifying the normal and anomaly by using the feature selected datasets. Ensemble technique is used to combine the above three classifiers and creating the new model to improve the classification result.

Table 1 Features number and name

Attr. No.	Attribute Name	Attr. No.	Attribute Name
Basic features of every network connection		22	Is_guest_login
1	Duration	Time related traffic features of every network connection	
2	Protocol_type	23	Count
3	Service	24	Srv_count
4	Flag	25	Serror_rate
5	Src_bytes	26	Srv_serror_rate
6	Dst_bytes	27	Rerror_rate
7	Land	28	Srv_rerror_rate
8	Wrong_fragment	29	Same_srv_rate
9	Urgent	30	Diff_srv_rate
Content related features of every network connection		31	Srv_diff_host_rate
10	Hot	Host based traffic features in a network connection	
11	Num_failed_logins	32	Dst_host_count
12	Logged_in	33	Dst_host_srv_count
13	Num_compromised	34	Dst_host_same_ srv_rate
14	Root_shell	35	Dst_host_diff_ srv_rate
15	Su_attempted	36	Dst_host_same_ src_port_rate
16	Num_root	37	Dst_host_srv_diff_ host_rate
17	Num_file_creations	38	Dst_host_serror_ rate
18	Num_shells	39	Dst_host_srv_ serror_rate
19	Num_access_files	40	Dst_host_rerror_ rate
20	Num_outbound_cmds	41	Dst_host_srv_ rerror_rate
21	Is_host_login	42	Class name

IV. FEATURE SELECTION TECHNIQUES

Feature selection is used to enables the machine learning technique to train faster and improve the accuracy of the model. The proposed system uses attribute evaluator for ranking all features in NSL-KDD dataset according to the metrics.

The ranker search technique ranks each feature by their individual analysis and combines with attribute evaluator.

A. Pearson's correlation

The Pearson's correlation is used as the measure of correlation between the features and the prediction class. Nominal features are examinded on value by value and treating each value as indicator. It chooses the most apposite features and enumerates the correlation between each feature and the output variable. Then choose those features that have an average value of either high positive or negative correlation which is close to -1 or 1 and drop those features with low correlation value which is close to 0. Overall correlation is evaluated through weighted average.

B. Chi-square

The Chi-square statistical test is applied to group of categorical features to assess the association between them using their frequency distribution. This test is performed by reckoning the chi-squared statistic value of feature with respect to the output class. The following formula is used to evaluate the chi-square test.

$$\text{Chi-square} = \sum \frac{(Ob_i - Ex_i)^2}{Ex_i}$$

Where Ob_i – Observed value,
Ex_i – Expected value

C. Gain ratio

The Gain ratio was used to raise the bias of information gain towards features huge variety of values. Gain ratio reveals a high value while it gives small value when entire data belongs to one branch of attribute. It uses both size and number of branches to decide an attribute and improves Information Gain by considering the inherent information. Gain ratio of given feature gf and a feature value fv can be calculated using the following formula

$$\text{Gain ratio(fv,gf)} = \frac{\text{Information Gain (fv,gf)}}{\text{Intrinsic value(gf)}}$$

Where

$$\text{Intrinsic value(gf)} = -\sum \frac{|G_i|}{|G|} * \log_2 \frac{|G_i|}{G}$$

Where |G| is the number of feasible values in feature gf and $|G_i|$ is the number of real values in feature gf [6]

D. Symmetrical Uncertainty

The Symmetrical uncertainty is used to measure the fitness for feature selection by computing between the features and the output class. It is important for the feature with SYU to have high value. It is given by the following equation

$$\text{SYU} = 2\,\frac{\text{Gain(FA)}}{\text{Info(D)+SplitInfo(FA)}}$$

Where SYU value = 0, indicates that the two features have no association and SYU value = 1 indicates that knowledge of one feature completely predicts the other feature.

V. TREE BASED ENSEMBLE MODEL

In data mining, the classification tools that allocate items in a group as target groups or classes. The objective of classification is to predict the target class in the given dataset. Classification is used to create a model to classify the dataset to appropriate class. The modified feature selection datasets are used to classify the normal and anomaly in network using tree based classifiers. This section describes the proposed tree based classifiers such as J48, REP Tree (Reduced Error Pruning Tree) and Simple CART (Classification And Regression Tree). Finally the classifiers are combined by using ensemble technique to build the perfect intrusion detection model.

A. J48

J48 tree induction technique starts with root node that constitutes decision tree with the given dataset and repeatedly splits the data into tiny subsets by testing the given attribute at each and every node. The sub tree indicates the separation of given original dataset that satisfies the defined attribute value test. This process is repeatedly done again and again until all instances are branched into the appropriate class, and the process is terminated. Decision tree is constructed by using the series of questions that are efficiently arranged, each question queries an attribute and branches them to appropriate sub tree based on the value. At leaf node the prediction of the class variable is placed. The following steps show the algorithm of J48.

Algorithm:

1. Tree = {}, Input: Dataset DS
2. if DS is "pure" or other stopping condition arrives then
3. stop the process
4. end if
5. for all attribute Atr in DS do
6. compute information-theoretic measure if we split on Atr
7. end for
8. AB = Best attribute according to above measure
9. Tree = Built a decision node that tests AB in the root
10. SDS = Induced sub-datasets from DS based on AB
11. for all SDS do
12. Treesds = C4.5(SDS)
13. Fix Treesds to the corresponding branch of Tree
14. end for
15. return Tree

B. REP Tree (Reduced Error Pruning Tree)

Reduced Error Pruning (REP) Tree is the easiest and understandable technique in decision tree pruning. It is a fast decision tree learner, which is used to generate a decision tree or a regression tree. Here the splitting measure is based on information gain and prunes it by using reduced error pruning method. Using this algorithm, the tree traversal has performed from bottom to top. Then examines every internal node and replaces by the most recurrent class and concern about accuracy of the tree. This procedure will perform again and again until any other further pruning will decrease accuracy of the tree.

Steps for error pruning:

1. Consider each node for pruning
2. Pruning = removing the subtree on that node
3. Make it as a leaf node and assign the most common class on that node.
4. A node is removed if the resulting tree performs no worse than the original.
5. In each iterations, pruning of node increases the accuracy of the outcome.

6. Pruning process extends until further pruning is harmful.

C. CART (Classification And Regression Tree)

CART which means Classification And Regression Tree which is used for machine learning process that generates the binary tree. So the outcome is two children only. The best splitting attribute is selected by using the entropy. This technique avoids the instances which hold the missing data. This algorithm is mostly suitable for the training data. Simple CART is a learning method, which gives the output as either classification or regression trees, depending on categorical or numeric data.

Algorithm:

1. Takes labeled input data with target variable and a list of independent variables.
2. Find the best split for each of independent variables.
3. Select the best variable for the split.
4. Split the input data as leaf and nodes
5. Continues steps 2 to 4 until built the perfect tree.

E. Ensemble Technique

To improve the performance and accuracy of detection and categorization, we use the ensemble technique. In this method, we take the average voting of output of the multiple classifiers which is described above. In voting and averaging ensemble method, the proposed system creates multiple classification/regression models using modified dataset. Each base model created by using different splits of the same training dataset with same algorithms, or by using the same dataset with different algorithms, or any other method. The pseudo code shows the ensemble of same dataset with different algorithm.

Prediction with individual classifiers the combine using ensemble

Steps for ensemble

```
1. Predict the outcome with classifiers.
2. Final_prediction = [ ]
3.        for row_number in length(predicition)
4.                final_prediction.append (mean
                          (prediction(row_number, ]) )
5. End for
```

The Figure 1 shows, structure of the proposed tree based ensemble model composed of three phases which are feature selection phase by using statistical based function, classifier phase by using tree based machine learning classifier and finally the classifiers are combined and built the ensemble model for Intrusion Detection.

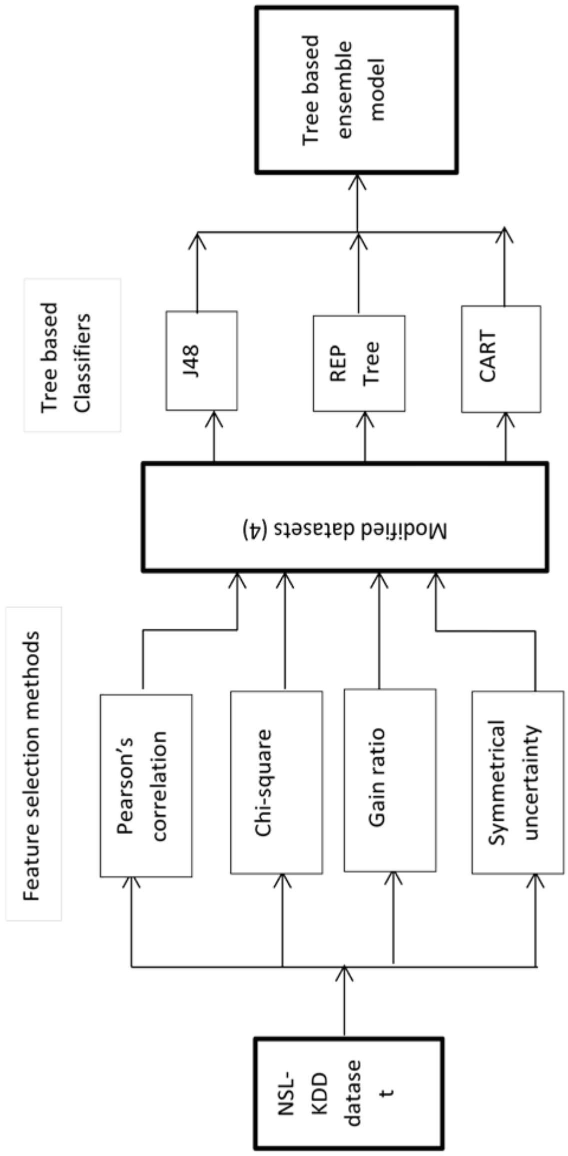

Figure 1 Structure of proposed system

VI. RESULT AND DISCUSSION

Proposed system discovers the best feature selection method and classification algorithm that attains the best performance on NSL-KDD dataset to detect the normal and anomaly. It focused on feature selection and tree based classification methods. The statistical functions Pearson's Correlation, Chi-square, Gain Ratio and Symmetrical Uncertainty are used to perform feature selection in NSL-KDD dataset. Based on these functions Table2 shows the ranking order of each method. The classification techniques J48 and REP Tree, and simple CART are used for identifying the normal and anomaly by using the feature selected modified datasets. Ensemble vote technique is used for combining the above three classifiers and creating the new model to improve the classification result.

Table 2 Ranking of the original dataset

Feature selection method	Features in Ranking order
Pearson's correlation	26,30,31,9,36,41,35,22,23,20,29,40,38,24,37,25,32,27,28,5,33,39,34,1,19,16,12,13,10,11,14,15,7,3,6,2,21,4,8,17,18
Chi-square	2,40,3,41,26,27,30,31,32,9,20,35,22,36,23,34,33,29,28,21,38,39,24,37,25,1,7,5,10,13,16,19,14,12,11,15,4,6,17,18,8
Gain Ratio	9,23,41,22,36,3,27,35,2,26,34,40,31,30,5,32,20,28,38,29,25,24,33,13,12,39,7,10,16,1,37,15,14,21,11,19,4,8,17,18,6
Symmetrical Uncertainty	3,41,9,2,23,27,22,36,26,35,40,30,31,34,32,20,29,28,33,38,39,24,25,37,21,1,7,5,10,13,16,19,14,12,11,15,4,6,18,17,8

Based on the ranking Table 3 shows the percentage of top ranking in NSL-KDD dataset feature. From this ranking to detect normal and anomaly we have to use more host based traffic features than the other features.

Table 3 Feature Selection with ranking order

Feature selection method	Top Ranking percentage			
	Basic Features	Content Features	Time Related Feature	Host based traffic Feature
Pearson's correlation	7.3170	7.3170	21.9512	24.3902
Chi-square	7.3170	7.3170	21.9512	24.3902
Gain Ratio	9.7560	9.7560	21.9512	19.5121
Symmetrical Uncertainty	7.3170	4.8780	24.3902	24.3902

Based on the top ranking percentage, Figure 2 shows that most of the host based features are used to detect normal data and anomaly data in the dataset.

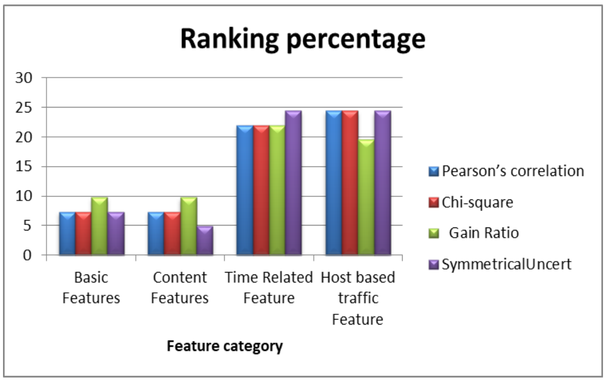

Figure 2 Features in ranking percentage order

After feature selection the resultant datasets are fed into the tree based classification algorithms like J48 and REP Tree, and simple CART and the accuracy is measured. The tree based classifiers are ensemble to improve the accuracy of prediction Table 4 and Figure 3 shows the percentage of correctly classified instances in the model. The algorithm simple CART with Gain Ratio feature selection method gives the more accuracy than the other methods. While ensemble the classifiers the Chi-square based feature selection method gives the more accuracy than the other methods.

Table 4 Percentage of correctly classified instances

Feature selection methods	Accuracy for classification algorithms			
	J48	REP Tree	Simple CART	Tree based ensemble model
Pearson's correlation	99.56	99.55	99.60	99.69
Chi-square	99.55	99.55	99.63	99.72
Gain Ratio	99.54	99.54	99.64	99.71
Symmetrical Uncertainty	99.54	99.54	99.64	99.71

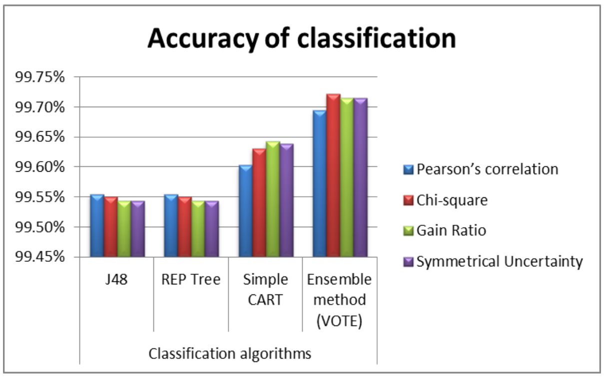

Figure 3 Percentage of correctly classified instances

A. Evaluation of parameters

The NSL-KDD dataset contains forty two attributes; the last attribute describes the category label that is the affiliation is either normal or anomaly. The performance measures are used to assess the classifier. Analysis is generally performed by using the parameters namely True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). To resolve the classification problems, various performance metrics are available in terms of confusion matrix. In this proposed work we have chosen Accuracy, Precision, Detection rate and False alarm.

Accuracy $$= \frac{TP + TN}{TP + TN + FP + FN}$$

Precision $$= \frac{TP}{TP + FP}$$

Detection Rate (DR) $$= \frac{TP}{TP + FN}$$

False Alarm (FA) $$= \frac{FP}{FP + TN}$$

The performance measures are extracted from the confusion matrix. True and false classification outcome is represented in confusion matrix. Table 5 shows the confusion matrix for feature selected datasets.

We have to calculate the evaluation metrics like accuracy, precision, detection rate and false alarm by using the confusion matrix. Table 6 and Table 7 show the Evaluation metrics.

Table 5 Confusion matrix for feature selected datasets

Feature selection methods	Classification algorithms							
	J48				REP Tree			
	Accuracy	Precision	Detection Rate	False Alarm	Accuracy	Precision	Detection Rate	False Alarm
Pearson's correlation	99.56%	0.9956	0.9961	0.005	99.56%	0.9967	0.995	0.0038
Chi-square	99.55%	0.9955	0.9961	0.0051	99.58%	0.9968	0.9952	0.0037
Gain Ratio	99.54%	0.9954	0.996	0.0052	99.57%	0.9968	0.9951	0.0037
Symmetrical Uncertainty	99.54%	0.9954	0.996	0.0052	99.57%	0.9968	0.9951	0.0036

Table 6 Evaluation metrics

Feature selection methods	Confusion matrix for Classification algorithms						Tree based ensemble model	
	J48		REP Tree		Simple CART			
Pearson's correlation	13390	59	13404	45	13406	43	13420	29
	53	11690	67	11676	57	11686	48	11695
Chi-square	13389	60	13406	43	13410	39	13425	24
	53	11690	64	11679	54	11689	46	11697
Gain Ratio	13388	61	13406	43	13410	39	13424	25
	54	11689	65	11678	51	11692	47	11696
Symmetrical Uncertainty	13388	61	13406	43	13410	39	13424	25
	54	11689	65	11678	52	11691	47	11696

Table 7 Evaluation metrics

Feature selection methods	Classification algorithm							
	CART				Tree based ensemble model			
	Accuracy	Precision	Detection Rate	False Alarm	Accuracy	Precision	Detection Rate	False Alarm
Pearson's correlation	99.60%	0.9968	0.9958	0.0036	99.69%	0.9978	0.9964	0.0025
Chi-square	99.63%	0.9971	0.996	0.0033	99.72%	0.9982	0.9966	0.002
Gain Ratio	99.64%	0.9971	0.9962	0.0033	99.71%	0.9981	0.9965	0.0021
Symmetrical Uncertainty	99.64%	0.9971	0.9961	0.0033	99.71%	0.9981	0.9965	0.0021

The method with low false alarm and high detection rate is considered as the perfect Intrusion Detection model in recently developed systems. So in this proposed system we compare the detection rate and false alarm. The proposed system describes the tree based ensemble method with Chi-square feature selection method give higher detection rate and lower false alarm than the other feature selection methods. Figure 4 shows the detection rate of various statistical based feature selection techniques in the tree based ensemble method.

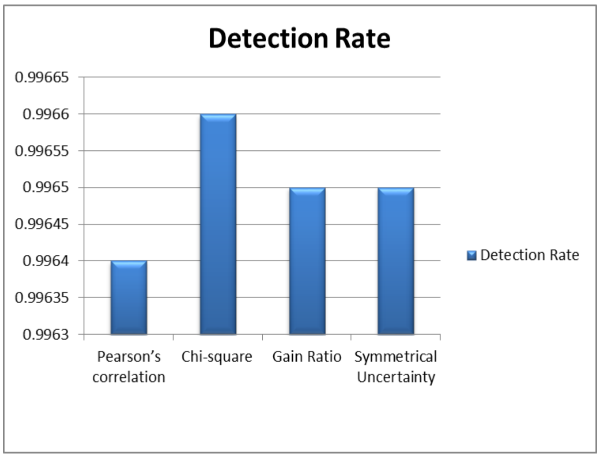

Figure 4 Detection rate of tree based ensemble model

False alarm is defined as the amount of normal data that has been wrongly classified as an attack. Figure 5 shows the false alarm of various statistical based feature selection techniques in the tree based ensemble method.

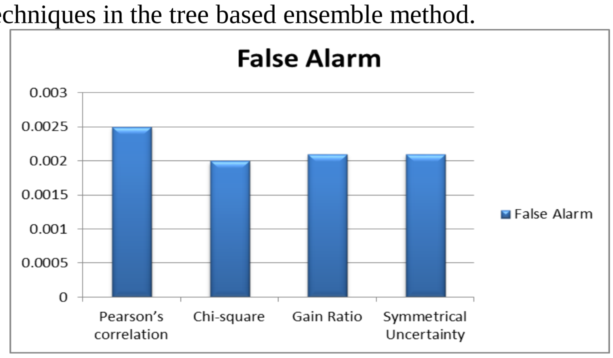

Figure 5 False alarm of tree based ensemble model

CONCLUSION

In the proposed system, in order to improve the exactness and effectiveness of the model, the statistical based feature selection techniques like Pearson's Correlation, Chi-square, Gain ratio and Symmetrical uncertainty are performed. Based on the top ranking percentage of four feature selection methods, most of the host based features are selected from the NSL-KDD dataset to detect the normal and anomaly. After feature selection the resultant modified datasets are fed into the tree based classification algorithms like J48 and REP Tree, and simple CART to build the Intrusion Detection System. Then to improve the prediction accuracy the three trees based algorithms are ensemble and perfect Intrusion Detection System is built. From this analysis, we obtain that the algorithm simple CART with Gain ratio feature selection method gives the more accuracy than the other methods. While ensemble the classifiers the Chi-square based feature selection method gives the more accuracy, higher detection rate and also the lower false alarm rate than the other methods.

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