

Artificial Neural Network and Genetic Clustering based Robust Intrusion Detection System

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ABSTRACT

To improve network security different steps has been taken as size and importance of the network has increases day by day. In order to find intrusion in the network IDS systems were developed. In this paper main focus was done on finding the type of session i.e. normal or intrusion where if intrusion found than class of intrusion was detected. Here whole work was so designed that automatic clustering of various sessions are done by using genetic algorithm steps while clustered data is taken as the input in the neural network for training. So, the need of special identification was required in this work for session class. Error back propagation neural network was used by this work training and testing. Experiment was done on real dataset where various set of testing data was pass for comparison on different evaluation parameters.

Keywords

Anomaly, ANN, Clustering, Genetic Algorithm, Intrusion Detection.

1. INTRODUCTION

Giving network security to various web services on the web, distinctive network foundations, communications arrange numerous means that has been taken like encryption, firewall, and virtual private network and so forth organize Intrusion detection framework is a noteworthy advance among those. Intrusion detection field rises up out of most recent couple of years and built up a great deal which uses the gathered data from various sort of interruption attack, based on those distinctive business and open source programming items appear to solidify your network to enhance security of the diverse correspondence, service giving networks. As the quantity of network clients and machine are expanding step by step to give diverse sort of administrations and effortlessness for the smoothness of the world. Be that as it may, some unapproved clients or exercises from various sorts of aggressors which may inward attack or outer attack keeping in mind the end goal to hurt the running framework, which are known as programmers. The fundamental thought process of such sort of programmer and gatecrashers is to cut down cumbersome networks and web administrations. Because of increment in enthusiasm of network security of various kinds of attack, numerous scientists has included their enthusiasm for their field and wide assortment of conventions and in addition calculation has been produced by them, with a specific end goal to give secure administrations to the end clients. Among various kind of assault interruptions is a sort of assault that build up a business intrigue. Interruption discovery framework is presented for the insurance from interruption attack.

From the above exchange this work can close the primary point of the network Intrusion discovery framework is to identify all conceivable interruption which perform malevolent movement, PC assault, spread of infections, PC abuse, and so forth so a network interruption recognition framework investigations distinctive information bundles as well as screen that move over the web for such sort of vindictive action. So the smooth running of general network distinctive server needs to settle overall network which go about as network Intrusion detection framework that screen every one of the parcels developments and recognize their conduct with the noxious exercises.

2. RELATED WORK

Yogitha et. al. [1] Offered interruption discovery framework with Support Vector Machine (SVM). Affirmation is finished by coordinating explores on NSL-KDD Cup'99 data collection which is reformer type of KDD Cup'99 data index. By utilizing this NSLKDD Cup'99 data collection they have condensed wide time obligatory to shape SVM exemplary by achievement proper pre-training on data collection. In this association SVM made clustering of data. By obligation appropriate part accumulation assault location rate is opened up and false positive rate (FPT) is lessened. In this proposed work author has utilized Gaussian Circular Basis.

A.R. Jakhale, et. al [2] In this work the author portrays a anomaly discovery framework and its two stages particularly training and testing. The slipping window and bunching is accustomed to nursing the network movement by mining the repetitive examples utilizing calculations. The calculations are so genuine and utilized as a part of constant observing. The normal multi-design catching calculation has high location rate. At long last, increase the identification rate and reduced the false alert rate.

Research by Jiefei, Lobo and Russo [3] explores the event of Multi-way steered attack where an assault is divided and sent over different courses to endeavor to trick an IDS framework. This is influenced conceivable due to multi way TCP (MPTCP) which enables transmissions to course finished numerous ways between a source and target

Barolli et al [4] researches the utilization of IDS utilizing neural network for giving IDS arrangement in a Tor (The Onion Router) organize. Tests did utilized a Tor server and customer with back engendering NN to reproduce exchanges over the Tor organize while catching for examination. The framework proposed is a prepared ANN with information caught from Wireshark, at that point the server and customer information are analyzed, contrasts will recognize an interruption or misuse. The outcomes from testing were fruitful in giving viable exactness when assessed in the test condition.

3.1.5 Cross-Over

Top possible solution after sorting will act as the best for other possible solutions. Now selected solution will modify other possible solution by replacing fix number of centroid as present in best solution. By this all possible solution will learn from best solution.

This difference modifies the existing solution according to the following expression

$$X_{new,i} = \text{Crossover}(X_{best,i}, X_i)$$

Accept Xnew if it gives a better function value. Once this cycle is over then check for the maximum iteration for the genetic if iteration not reach to the maximum value then GOTO step of finding fitness function and rest of steps in regular fashion of genetic algorithm stop learning and the best solution from the available population is consider as the final centroid of the work. Now sessions are cluster as per centroid.

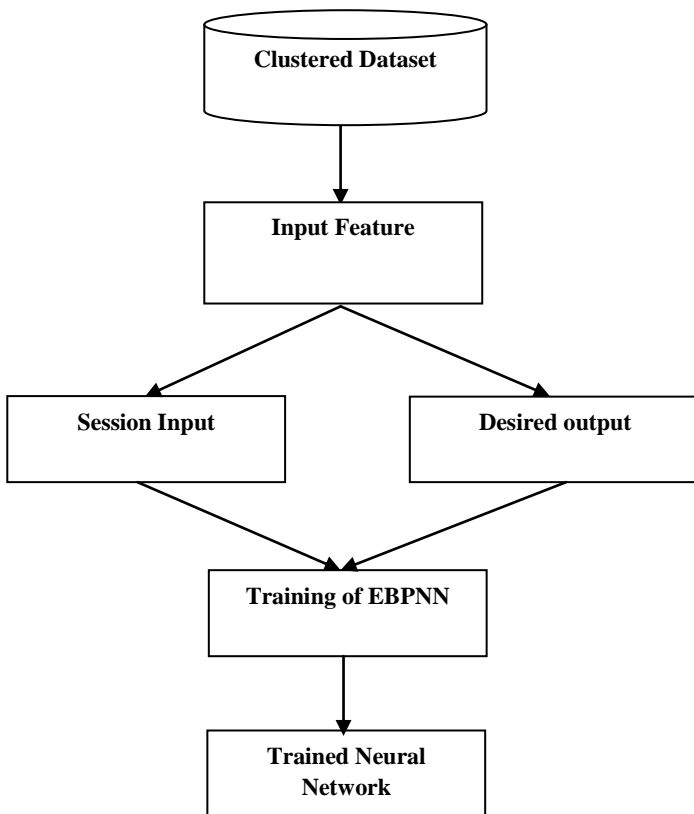


Fig 2: Proposed work testing module.

3.2 Error Back Propagation Neural Network

In this module cluster dataset of sessions are utilize to train the EBPNN. Then trained dataset is utilized for the testing of unknown attack session.

3.2.1 Input Feature

As cluster dataset provide the sessions in group as per the genetic algorithm so it has to divide into two group first act as neural network input while other act as desired output. Considering first input feature vector which consist of numeric values where clustered numeric values are arrange in the input matrix. While second desired output vector consist of the class of session which was obtained from the genetic algorithm. This can be understand by below example where

Training of Error Back Propagation Neural Network (EBPNN): Here feature vector obtained are used as the input in the neural network while desired output make proper weight adjustment in the network. So with fix number of iteration or epochs work will get trained neural network

3.2.2 Proposed Algorithm: Neural Network Algorithm

Input: D // Dataset

Output: EBPNN // Trained Neural Network

1. PD ← Pre_Process(D) // Preprocessed Dataset
2. P ← Generate_population(c, s) //c: number of classes, s: population size, P: population
3. Loop 1: iter // iter: number of iterations
4. F ← Fitness_function(P, PD) // F: fitness value of each probable solution
5. Best ← Min(F)
6. Loop 1:s
7. P ← Crossover(Best, P[s])
8. EndLoop
9. EndLoop
10. CD ← Cluster(PD, Best) // CD: Clustered Dataset
11. Loop 1:n // n : number of session in the dataset
12. S ← CD[n]
13. [X D] ← Input_Feature(S) // X input session feature and D desired output
14. EndLoop
15. EBPNN ← Initialize(In, Hn, On,) // In: neurons in inputs layer, Hn Number of Hidden layer, On: number of output layer
16. Loop 1:n
17. Loop 1: iter // iter: number of iterations
18. EBPNN ← Train(EBPNN, X[n], D[n])
19. EndLoop
20. EndLoop

3.2.3 Testing of EBPNN

In this step input query is preprocess as done in the training module, similarly feature vector is create for input in the neural network. Finally feature vector is input in the EBPNN which give output. Now analysis of that output is done that whether specified class is desired one or not.

4. EXPERIMENT AND RESULTS

Data Set: For the evaluation of the whole work the dataset used is NSL KDD [12] about which previous chapter has already explained and the collection of the all evaluating vectors look like. Where numeric terms are used for feature learning and at the end of each vector it has the corresponding class. The pre-processing step and its requirement have already been explained.

Evaluation Parameter

To test our result this work use following measures the accuracy of the, that is to say Precision, Recall and F-score. These parameters are depend on the TP, TN, FP and FN.

$$\text{Precision} = \frac{\text{True_Positive}}{\text{True_Positive} + \text{False_Positive}}$$

$$\text{Recall} = \frac{\text{True_Positive}}{\text{True_Positive} + \text{False_Negative}}$$

$$F_Score = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

In order to make the better evaluation for this work one more parameter has introduced that is accuracy of the class of the intrusion. Accuracy of the work is calculate by:

$$\text{Accuracy} = (\text{true positives} + \text{false negatives}) / (\text{Total_Normal} + \text{Total_Intrusion})$$

4.1 Results

Table 1. Precision value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	Precision Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	0.879694	0.981552
6000	0.877468	0.981516
9000	0.876332	0.983288

From above Table1, it is obtained that with the increase in dataset size precision value rate increases. As the number of patterns are more in the dataset so the results are more accurate. Here it was shown that use of genetic algorithm increase the precision value.

Table 2. Recall value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	Recall Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	0.978754	0.987204
6000	0.977995	0.987705
9000	0.976717	0.987621

From above table 2 it is obtained that with the increase in dataset size recall value rate increase. As number of patterns are more in the dataset so results are more accurate. Here it was shown that use of genetic algorithm increase the recall value.

Table 3. F-Measure value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	F-Measure Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	0.926584	0.98437
6000	0.925008	0.984601
9000	0.923805	0.98545

From above table 3 it is obtained that use of EBPNN in proposed work has high F-measure value as compared to previous work. Here it was shown that use of new approach of neural network training reduce the execution time as compared to RNN used in previous method.

Table 4. Execution time value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	Training Execution time (second) Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	19.1139	6.5586
6000	43.0747	10.3615
9000	76.064	16.8743

From above table 4 it is obtained that with the increase in dataset size execution time value increase. Here it was shown that use of new approach of neural network training reduce the execution time as compared to RNN used in previous method.

Table 5 Execution time value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	Testing Execution time (second) Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	51.5539	18.2219
6000	68.0965	37.6935
9000	92.9525	69.0244

From above table 5.5 it is obtained that with the increase in dataset size execution time value increase. Here it was shown that use of new approach of neural network training reduce the execution time as compared to RNN used in previous method.

Table 6. Execution time value comparison of RNN and EBPNN at different Dataset Size

Data-Set Size	Accuracy Value Comparison	
	RNN (Existing)	EBPNN (Proposed)
3000	0.927	0.983672
6000	0.924333	0.983669
9000	0.923111	0.984557

From above table 6 it is obtained that with the increase in dataset size execution time value increase. Here it was shown that use of new approach of neural network training reduce the execution time as compared to RNN used in previous method.

5. CONCLUSION

Network security is one of the most important nonfunctional requirements in a system. Over the years, many software solutions have been developed to enhance network security and this paper provides an efficient system which has been a promising one for detecting intrusion of different kind where, one can get the detail of the class of attack as well. Results show that all type of attacks are identified accurately by the system as the accuracy value is above 96%. In future it needs to be improved by putting data on the unsupervised network, so it automatically updates the new behavior of the intruder. One more issue that remains in this work is to use dynamic adaptable technique for learning new type of attack.

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