Analysis of Different Machine Learning Classifiers on KDD CUP'99 Dataset

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***Abstract*— Nowadays information security is very crucial aspect all around the world. All the organizations are trying to secure their confidential information and data from unauthorized access over the network. So, there is a need for analysis of different behaviors over the network for detecting all types of intrusion attacks. This paper presents the Machine Learning methodologies of Intrusion Detection System (IDS) on the network. Based on the source of data, IDS is classified into Host-Based IDS and Network-Based IDS. This paper deals with Network-Based IDS, each packet flowing through the network is analyzed. Principle Component Analysis (PCA) algorithm used to reduce the dimensionality of KDD CUP dataset for classifying in less time. In addition, four classifications used namely Naïve Bayes, K-Means Clustering, Support Vector Machine and Fully Connected Neural Network have been used for effective classification of the dataset. The proposed algorithms enhance the performance of IDS in detecting the attacks with 98.9% accuracy.**

Keywords—Network Intrusion Detection System, KDD CUP'99

I. INTRODUCTION

Billions of Computers have been networked together with very large users over the internet and so security plays a vital role in many organizations such as Industries, Business, Government, Educational Networks. Since, there is a rapid growth of internet communication systems and applications with the availability of tools to intrude the networks, security for network has become indispensable. Most of the users are using computer systems has no knowledge on unauthorized access to their system. IDS systems are used to detect this illegal access to a target application or a computer system over a network.

Network-based IDS's are kept in main areas of network structures in an organization that passively scan and inspect network traffic packets traversing the router or host systems, auditing the packet information and checks its own database of known attack signatures and assign a severity level for each packet. Based on the level assigned, a warning alarm goes-on.

In the past decade, Researchers used statistical approaches and rule-based techniques in IDS development. Due to enormous network traffic leads to oversized large datasets, their methods are now time consuming and not very useful for fast intrusion detection.

Recently, Machine Learning algorithms are providing very promising performance in detecting abnormal behavioral and malicious attacks in the networks.

Machine learning is a subset of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. **Machine learning focuses on the development of computer programs** that can access data and use it to learn for themselves. In year 1959, Machine Learning (ML) concept first introduced by Arthur Samuel, defined ML as" field of study that gives computers the ability to learn without being explicitly programmed". It consists in the development of algorithms in order to obtain a predictive analysis from data. There are three kinds of learning based on the nature of the tasks to be performed,

i. Supervised Learning: the machine learns output predictions based on a set of known output for given inputs. In most applications, supervised learning consists in learning the optimal manner to map the inputs to the outputs, by minimizing the value of a loss function representing the difference between prediction and original target.

ii. Unsupervised Learning: the machine learns from input data for which there is no target values. This type of learning method identifies the patterns and features from the inputs, with the aim of extracting new knowledge from the available data.

iii. Reinforcement Learning: at the beginning of the learning, instead of target values feedback about the correctness of the execution is provided after the execution of the task has been completed, thus acting like a reward or punishment, learning reinforcement are often used in dynamic environments.

In this paper, we analyzed KDD CUP dataset using four different Machine Learning techniques namely SVM, Naïve Bayes, K-Means Clustering and Fully connected Neural Network.

A. Support Vector Machine(SVM) :

SVM is a supervised machine learning algorithm that analyzes data for classification and regression analysis. SVM attempts to separate data into multiple classes. It is designed to find the optimal solution to a classification problem. SVM classifiers produces a better binary classification compared to Decision Tree and Neural Network. Based on the hyper tuning of kernel function and

its parameters SVM performance differs. Different types of separating hyperplanes can be achieved by applying a kernel, such as linear, polynomial, Gaussian Radial Basis Function (‘ rbf ’). In datasets, many features are duplicated or less effect in separating datapoints into correct classes. Thus, feature selection should be considered while SVM training. From a set of 41 features of dataset, a subset of features was selected by using feature selection method.

B. *Naïve Bayes(NB) :*

This approach is based on the theorem called Bayes’ principle with robust independence assumptions among the features. Naïve Bayes produce the result of the probability of a particular kind of attack is occurring, given the observed system activities. Naïve Bayes relies on features with different probability of what happens to attacks and normal behavior. Naïve Bayes is the most powerful classification model in IDS due to its ease of use and calculation efficiency, both of which are taken from its conditional independence assumption property. But, in KDD’99 dataset, the IDS do not operate well if this independence assumption is not valid, as the dataset has the complex attribute dependencies.

C. *K-Means Clustering :*

The K-means method is one of the best common integration techniques of clustering analysis that aims to separate ‘n’ data objects into ‘k’ clusters in which each data object is chosen with nearest mean in the cluster. K means is a centroid-based iterative clustering algorithm that provides the highest value for every iteration. The main idea is to reduce the sum of the distances between the datapoints and their respective centroids, it does not need to calculate the distance between all combinations of data as it is a distance-based clustering technique. It uses a Euclidean metrics as a similarity measure, the number of clusters is mentioned by the user in advance if not by default it is 8. Thus, K means clustering is a better approach to classify the data using unsupervised methods for intrusion detection.

D. *Fully-Connected Neural Network :*

Fully Connected Neural Networks is a feedforward standard neural network architecture applied in mainly basic neural network applications. Fully connected refers to an individual neuron in the earlier layer is linked to every neuron in the sub sequent layer. In neural network parameter selection and optimization has great impact on the model. activation function. Optimizer selection. There are many different optimizers for neural networks, and we mainly focus on the Adam algorithm Adam is an adaptive optimizer, where the learning rate is automatically adjusted based on the current situation during training, so that all weights are always updated with the appropriate learning rate. The dropout layer is to reduce the number of intermediate features and thus redundancy, it can prevent overfitting by randomly selecting some of the neurons according to probability. The activation function introduces a non-linear factor to the neurons, allowing the neural network to approximate any non-linear function, so that it can be applied to a multitude of non-linear models.

II. METHODOLOGY

In this research, we developed a network-based IDS since we are differentiating the intrusions packets from normal flow traffic based on the underlying network behavior.

A. *Dataset Used*

There are so many popular datasets such as KDD Cup’99, NSL-KDD’99, UNSWL-NB-15. In this paper, we used most widely adopted for NIDS analysis is KDD CUP’99 dataset for analysis.

KDD CUP’99 is a dataset used for detection of abnormal behaviour of network from normal connections. The dataset is extracted from DARPA dataset in 1999, which contains records of military network environment with injected attacks. KDD’99 is an extremely large dataset that used with intrusion detection experiments, the whole dataset consists of 4,898,430 records that is larger than other data sets. There are 22 kinds of attacks in this dataset, falls into four major categories, they are

i. Denial of Service (DoS): occurs when an attacker prevents legitimate users from accessing the file system, by making the program software (computer or memory) very busy with official handling applications. E.g., synz-flood

ii. Remote to User (unauthorized access from a remote machine): occurs when the attacker sends packets from a remote machine over a network without having authorized access. E.g., Guessing a password

iii. User to Remote (unauthorized access to Root): occurs when the attacker has local access to a normal user on the system and through some vulnerability attempts to obtain root access to the system to gain the capabilities of the supervisor. E.g., buffer overflow

iv. Probing: occurs when the attacker tries to gain the information about the network to find some vulnerability. Here the attacker maps the topology of the network and discovers the type of services operating over the network. E.g., port scanning

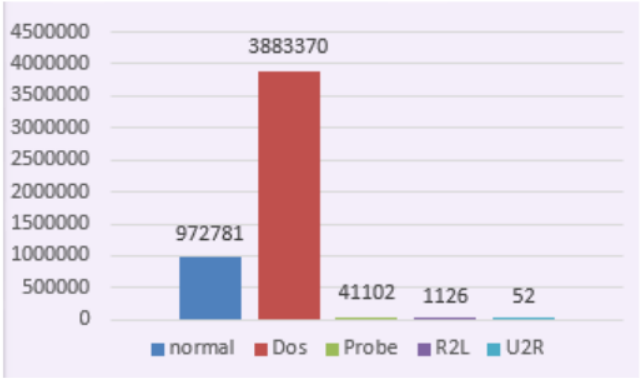


Figure: Classification of Class of KDD CUP’99 dataset

ID	feature name	description
		TCP connections features
1	duration	length (number of seconds) of the connection
2	protocol_type	type of the protocol, e.g. tcp, udp, etc.
3	service	network service on the destination, e.g., http, telnet, etc.
4	src_bytes	number of data bytes from source to destination
5	dst_bytes	number of data bytes from destination to source
6	flag	normal or error status of the connection
7	land	1 if connection is from/to the same host/port; 0 otherwise
8	wrong_fragment	number of ``wrong'' fragments
9	urgent	number of urgent packets
		Content features
10	hot	number of ``hot'' indicators
11	num_failed_logins	number of failed login attempts
12	logged in	1 if successfully logged in; 0 otherwise
13	num_compromised	number of ``compromised'' conditions
14	root shell	1 if root shell is obtained; 0 otherwise
15	su_attempted	1 if ``su root'' command attempted; 0 otherwise
16	num_root	number of ``root'' accesses
17	num_file_creations	number of file creation operations
18	num_shells	number of shell prompts
19	num_access_files	number of operations on access control files
20	num_outbound_cmds	number of outbound commands in an ftp session
21	is_hot_login	1 if the login belongs to the ``hot'' list; 0 otherwise
22	is_guest_login	1 if the login is a ``guest'' login; 0 otherwise
		Traffic features
23	count	number of connections to the same host as the current connection in the past two seconds
24	dst_host_count	count of the connections having same dst host
25	serror_rate	% of connections that have ``SYN'' errors
26	rerror_rate	% of connections that have ``REJ'' errors
27	same_srv_rate	% of connections to the same service
28	diff_srv_rate	% of connections to different services
29	srv_count	number of connections to the same service as the current connection in the past two seconds
30	srv_serror_rate	% of connections that have ``SYN'' errors
31	srv_rerror_rate	% of connections that have ``REJ'' errors
32	srv_diff_host_rate	% of connections to different hosts
33	dst_host_srv_count	count of connections have same dst host and using same service
34	dst_host_same_srv_rate	% of connections have same dst port and using same servic
35	dst_host_diff_srv_rate	% of different services and current host
36	dst_host_same_src_port_rate	% of connection to current host having same src port
37	dst_host_srv_diff_host_rate	% of connections to same service coming from diff. hosts
38	dst_host_serror_rate	%of connection to current host that have an S0 error
39	dst_host_srv_serror_rate	%of connection to current host and specified service that have an S0 error
40	dst_host_rerror_rate	% of connection to current host that have an RST error
41	dst_host_srv_ rerror_rate	%of connection to the current host and specified service tha have an RST error

Figure: Features of KDD CUP'99 dataset

KDD CUP'99 dataset containing of 41 features along with class label. The features are classified into four types, they are

i. Basic features of individual TCP connections (#1 to #9),

ii. Content features within a connection suggested by domain knowledge (#10 to #22),

iii. Traffic features computes using a two-second time window (#23 to #31),

iv. Host based traffic features (#32 to #41)

B. *Pre-processing*

In order to perform our experiments, we need to preprocess the raw data files. In KDD CUP'99 dataset has no noise or null values; thus, it is a clear dataset. It has both categorical and numerical features and numerical data dominates text attributes, it will slow down the training and complicate the process. And the text values cannot be processed in the operations of machine learning. Hence, the dataset needs to be pre-processed. The pre-processing in this model is classified into three main steps:

i. Normalization: some numerical features are having large number of unique values and scaling ranges differs from each attribute which may reduce the prediction accuracy. So, in this model we used Standard Scaler technique to normalize numerical features to lessen its values and reduce the training processes.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

$$z = \frac{x - \mu}{\sigma}$$

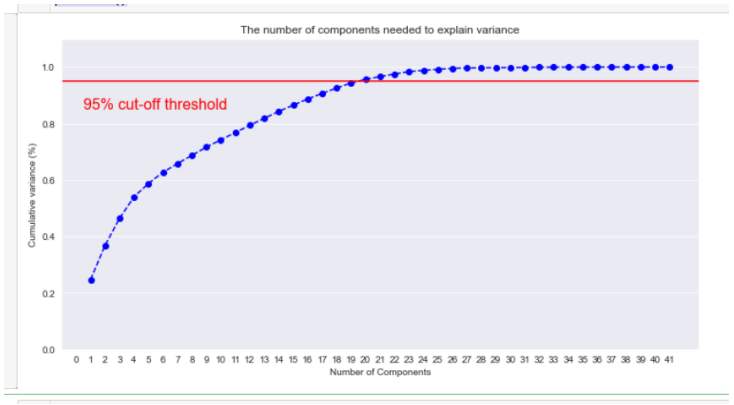
Where A refers to the Z-score normalization, X refers to the feature values, μ indicates to the mean of that feature column and $\boldsymbol{\sigma}$ indicates the standard deviation of the attribute.

ii. One-Hot Encoding: Since categorical values cannot handle the operations, we convert the text attributes to numerical values using One-Hot encoding technique. After executing one-hot encoder on the dataset, the number of features has been increased to 125 features rather than 41 features.

Protocol type
tcp
tcp
udp
icmp
tcp
icmp

Protocol type tcp	Protocol type udp	Protocol type icmp
1	0	0
1	0	0
0	1	0
0	0	1
1	0	0
0	0	1

iii. Principle Component Analysis: PCA is a very useful mathematical technique to obtain the patterns in higher dimensional dataset. The goal of the PCA is to reduce the dimensionality of the data while retaining as much as possible of the variation present in the original dataset. It is a way of identifying patterns in data and expressing data in such a way that highlights their similarities and difference. As the number of features increased to 125 using PCA method reduced the dimension to 21 features with 95% as cut off accuracy.



III. Experimental Results & discussion

The analysis on proposed NIDS model has been implemented using Jupyter Notebook on Anaconda navigator, which is an open-source platform based on python. KDD CUP'99 dataset is divided into training and testing sets in a ratio of 67% and 33%, respectively. Further training set is divided with 10-fold for cross validating the trained model.

A. Experiment Setup

This experiment is executed in Jupyter Notebook (python interface) on Dell G3 3590 laptop with configuration Intel(R) Core (TM) i7-9750H CPU @ 2.60GHz 2.59 GHz, 16GB memory without GPU usage, windows 10 64-bit operating system.

B. Evaluation Metrics

Evaluating a model is a major part of building an effective machine learning model to rank the different results. This paper uses sci-kit learn metrices such as Accuracy, Precision, Recall, F1 score to measure the Binary and multi class classification.

- True Positive (TP): Observation is positive and is predicted to be positive.
- False Negative (FN): Observation is positive but is predicted negative.
- True Negative (TN): Observation is negative and is predicted to be negative.
- False Positive (FP): Observation is negative but is predicted positive.

1. **Accuracy:** It is a common evaluation metric for classification problem. It's the number of correct predictions made as a ratio of all predictions made.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

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

2. **Precision:** also called as positive predictive value is the fraction of relevant instances among the retrieved instances.

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

3. **Recall:** also called as sensitivity is the function of relevant instances that were retrieved. Both precision and recall are therefore based on relevance.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. **F1-score:** The F measure is a measure of a test's accuracy and is defined as the weighted harmonic means of the precision and recall of the test.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

5. **False positive rate:** The false positive rate is calculated as the ratio between the number of negative events wrongly categorized as positive (false positive) and the total number of actual negative events (regardless of classification).

$$\frac{FP}{N} = \frac{FP}{FP + TN}$$

FP = number of false positives
TN = number of true negatives
N = total number of negatives

C. Analysis of Experimental Results

i. Binary Classification:

In binary classification, we applied SVM, Naïve Bayes, K-means and Fully Connected Neural Network on optimal hyper-parameters. Accuracy results achieved are shown below. Here, we can see that the best result in terms of accuracy score is 99.8% obtained by applying fully connected neural network. In SVM, the best accuracy score is 97.9% achieved with mean imputation. In K-means and Naïve Bayes, the best accuracy score is 96.78% achieved. Confusion matrices is shown below. Overall, we can see that accuracy achieved using various techniques is not significant difference. The misclassification is more significant in the case of weak classifier finds it difficult to classify those samples correctly.

1. Naïve Bayes:

- Metrics:

Accuracy	98.7014%
Precision	99.6698%
Recall	98.7104
F1 Score	99.1878
False Positive Rate	1.34

- Confusion Matrix:

	Predicted: NO	Predicted: YES
Actual: NO	38353	519
Actual: Yes	2047	156689

2. K-Means Clustering:

- Metrics:

Accuracy	99.9574
Precision	99.9729
Recall	99.9741
F1 Score	99.9735
False Positive Rate	1.1

- Confusion Matrix:

	Predicted: NO	Predicted: YES
Actual: NO	38829	43
Actual: Yes	41	158695

3. SVM (Support Vector Machine):

- Metrics:

Accuracy	99.7069
Precision	99.8682
Recall	99.7669
F1 Score	99.8175
False Positive Rate	5.4

- Confusion Matrix:

	Predicted: NO	Predicted: YES
Actual: NO	38663	209
Actual: Yes	370	158366

4.Fully Connected Neural Network:

- Metrics:

Accuracy	99.90
Precision	99.86
Recall	99.78
F1 Score	99.82
False Positive Rate	0.22

- Confusion Matrix:

	Predicted: NO	Predicted: YES
Actual: NO	4510647	9780
Actual: Yes	6484	99446639

ii. Multi-class Classification:

In the multi-class classification, we performed experiments on reduced dataset with full features and used all imputations techniques used in binary classification. Multi-class classification model is evaluated with all the four ML algorithms. We achieved highest accuracy of 97.9% by applying Fully connected accuracy. In SVM, the best accuracy score is 97.9% achieved with mean imputation. In K-means and Naïve Bayes, the best accuracy score is 96.78% achieved. Confusion matrices is shown below.

1.Naïve Bayes:

- Metrics:

Accuracy	89.9270%
Precision	47.7873%
Recall	62.7815
F1 Score	44.8814

2.K-Means Clustering:

- Metrics:

Accuracy	99.9509
Precision	72.9829
Recall	74.7004
F1 Score	73.3674

3.SVM (Support Vector Machine):

- Metrics:

Accuracy	99.4833
Precision	53.8200
Recall	54.9822
F1 Score	53.3663

4.Fully Connected Neural Network:

- Metrics:

Accuracy	99.80
Precision	99.67
Recall	98.88
F1 Score	99.27
False Positive Rate	0.33

- Confusion Matrix:

	Predicted: NO	Predicted: YES
Actual: NO	9492279	31578
Actual: Yes	107539	211172624

IV. CONCLUSION

In this paper, we proposed two models (Binary and Multi-Class Classification) using multiple machine learning techniques for detecting network attacks. The Accuracy, Precision, Recall, False Positive Rate scores are compared with different ML algorithms. We can achieve highest accuracy by using fully connected neural network as compared to other ML methods. But this approach is a time consuming for training the model instead we can use other techniques for faster intrusion detection.

Our experimental results showed that the fully connected neural network shows better accuracy with 99.8% accuracy score. SVM model able to detect and classify with 97.9% accuracy while K means, and NB predicts with 96.6% accuracy score.

Our future work is to detect intrusions instantly by increasing the time efficiency and to reduce the training process rate for fully connected neural network. And we compare modern datasets with more new features and intrusion attacks with the existing analysis.

ACKNOWLEDGMENT

The source code and dataset used in this paper is available in the following links.
GitHub Link:
https://github.com/bhukyavamshirathod/Network-Intrusion-Detection-System
Google Drive Link:
https://drive.google.com/drive/folders/1cJWMalzB94lDsXQdQIb23aukCMzOtdzP?usp=sharing

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