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EFFICIENCY OF SVM AND PCA TO ENHANCE INTRUSION DETECTION SYSTEM

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ABSTRACT

Intrusion detection system (IDS) is a system that gathers and analyzes information from various areas within a computer or a network to identify attacks made against these components. This research proposed an Intrusion Detection Model (IDM) for detection intrusion attempts, the proposal is a hybrid IDM because it considers both features of network packets and host features that are sensitive to most intrusions. The dataset used to build the hybrid IDM is the proposed HybD (Hybrid Dataset) dataset which composed of the 10% KDD '99 dataset features (41) and suggested host-based features (3). Two Data Mining DM classifiers (Support Vector Machine (SVM)) classifier and Naïve Bayesian (NB) Classifier) are used to build and verify the validity of the proposed model in term of accuracy rate. The proposal trying to ensure the detection speed of the hybrid IDM, that by reducing the HybD dataset features used by considering the most critical features in the detection but with saving of high accuracy rate without degradation that may be caused by that reduction. Two different measures are used for selecting and ranking HybD dataset features; they are Principle Component Analysis (PCA) and Gain Ratio (GR). The sets of features that have been resulted from these two measures and the all features set will be the feeding of both SVM and NB. The results obtained from executing the proposed model showing that SVM classifier accuracy rate is generally higher than that of NB classifier with the three sets of features. With SVM classifier the best accuracy rate resulted with set of features selected by PCA. The most critical features obtained by PCA are ranging to (17) features from 44 features: three of the suggested host features and (14) of the 10% KDD'99 features.

Keywords: SVM, NB, PCA, IDS, GR.

INTRODUCTION

An intrusion is a very common threat to computer systems. It is defined to be any unauthorized access attempt to manipulate, modify, or destroy information, or to render a system unreliable or unusable. With the increasing creativity of intrusions, the development of effective IDS is becoming a greater challenge. ID is a set of techniques and methods that are used to detect suspicious activity in computer systems, both at network and host level. Therefore, the main goal of IDS is to identify unauthorized use, misuse, and external penetrations (Mohammed, 2006).

DM-based ID techniques generally fall into two main categories: misuse detection and anomaly detection. In misuse detection systems, use patterns of well-known attacks to match and identify known intrusion. These techniques are able to automatically retrain ID models on different input data that include new types of attacks, as long as they have been labeled appropriately. Unlike signature-based IDSs, models of misuse are created automatically, and can be more sophisticated and precise than manually created signatures. A base stone of misuse detection techniques strength is their high degree of Precision in detecting known attacks and their variations. Misuse detection techniques in general are not effective contra new attacks that have no matched rules or models yet. Anomaly detection, on the other hand, builds models of normal behavior, and flags observed activities that deviate significantly from the established normal usage profiles as anomalies, that is, possible intrusions. Anomaly detection techniques thus identify new types of intrusions as diversions from usual usage. Anomaly detection techniques can be effective contra unknown or new attacks since no a priori knowledge about fixed intrusions are required. However, anomaly-based IDSs tend to generate more false alarms than misuse-based IDSs because an anomaly can just be a new normal behavior. Some IDSs use both anomaly and misuse detection techniques (Moses *et al.*, 2008).

Related Works

In (Risto, 2009), Risto Vaarandi, proposed a novel unsupervised DM based approach for IDS alert classification. With this strategy, knowledge is mined from IDS logs and processed in an automated way, in order to build an caution classifier. The classifier is then used in real-time for discerning important IDS warns from frequently occurring false positives and events of low significance. In (Risto and Karlis, 2010), Risto Vaarandi, and Karlis Podinš. extended their previous work on IDS alert classification, and present a novel unsupervised real time alert classification method which is based on frequent itemset mining and data clustering techniques. Their method first applies a frequent itemset mining algorithm to past IDS alert logs, in order to discover patterns that describe redundant alerts. After that, data clustering methods are used for finding detailed subpatterns for each detected pattern. Finally, the detected knowledge is explained and used for real time classification of IDS alerts, in order to characterize critical alerts from irrelevant ones. In (Muamer *et al.*, 2011), Muamer N. Mohammad et al introduced an improved approach for IDS based on combining DM and expert system that is presented and implemented in WEKA (Waikato Environment for Knowledge Analysis). They aimed to design and develop intelligent DM IDS and its core part a composite detection engine with anomaly detection and misuse detection features and the two detection engines work serially to detect the user's activity in turn. The system collects the data of DB audit system in real time, analyzes the audit data, judges that it is a normal behavior, abnormal behavior or aggressive behavior and responds to the result obtained by the operation behavior and finally reports the result to the manager in a comprehensible form. In (Zhang *et al.*, 2011), the next generation Internet protocol IPv6 brings a new challenge to the information security. Zhang Guojun et al presented a cooperative IDS based on IPv6 to address this challenge. Such a system consists of four parts: data flow tracking and analysis, capturing packets and rules matching, disaster recovery, and blocking. The technique of cooperative ID is introduced into the system for realizing the coordination control among parts. The system has a perfect detection rating. In (Sufyan and Hadeel, 2011), Sufyan T. Al-Janabi and Hadeel A. Saeed proposed an anomaly based IDS that can promptly detect and classify various attacks. Anomaly-based IDSs need to be able to learn the unstable behavior of users or systems. The proposed IDS experimenting with packet behavior as parameters in anomaly ID. There are several methods to assist IDSs to learn system's behavior, the proposed IDS uses a back propagation artificial neural network (ANN) to learn system's behavior and uses the KDD CUP'99 dataset in its experiments and the obtained results satisfy the work objective. In (Hassina Bensefia, 2011), Hassina Bensefia and Nacira Ghoualmi proposed a new approach for IDS adaptability by oriented toward Evolving COnnectionist Systems (ECOS) and Learning Classifier Systems (LCS). These two learning machine approaches are actually suggested very suitable to build adaptive learning intelligent systems in a dynamic changing environment. This integration puts in relief an adaptive hybrid ID core that plants the adaptability as an intrinsic and native functionality in the IDS. In (Nur *et al.*, 2012), Haldar N. et al presented an IDS which employs usage of classification methods to model the usage patterns of authenticated users and uses it to detect intrusions in wireless networks. The key idea behind the proposed IDS is the identification of discriminative features from user's activity data and using them to identify intrusions in wireless networks. The detection module uses statistical methods to accumulate interested statistical variables and compares them with the thresholds derived from users activities data. When the variables exceed the predestined thresholds, an alarm is put forward to alert about a sensible intrusion in the network.

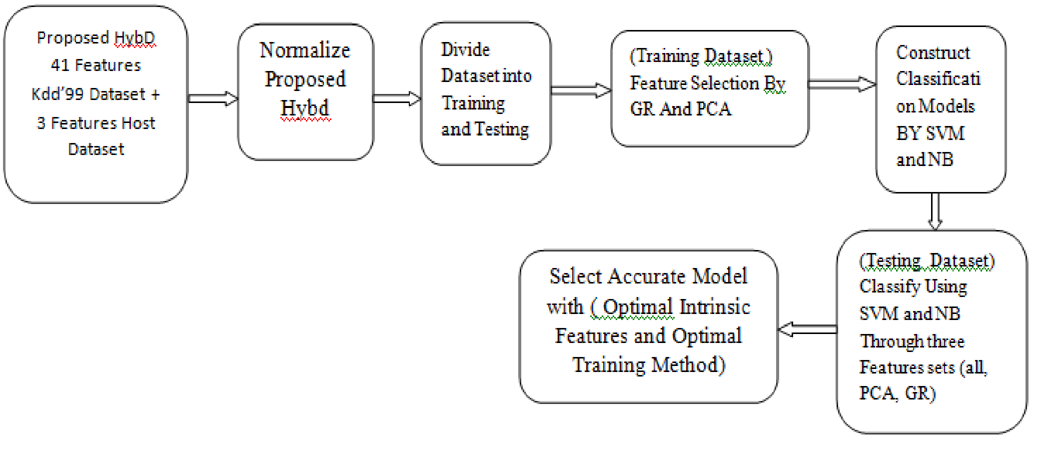
The Proposed Model of Intrusion Detection System

The proposed IDS is a "hybrid IDS" (NIDS and HIDS) that because it consider all features of data network packets and consider critical features of host that are directly affected by all attacks. The proposal is a DM-based IDS in which both the misuse and anomaly detection techniques depended in the detection of intrusion, where each instance in a dataset is labeled as "normal" or "intrusion" and a learning algorithm is trained over the labeled data. Misuse technique is able to automatically retrain ID models on different input data that include new types of attacks, as long as they have been labeled appropriately. While anomaly technique should first learn the characteristics of normal activities and abnormal activities of the system, and then the IDS detect traffic that deviate from normal activities.

For training and testing of the proposed IDS a proposed dataset, named "HybD", will be used. HybD dataset composed of: 1) "KDD'99 dataset" which represents the most wildly used dataset for the evaluation of ID methods since 1999. This dataset is intended by Stolfo et al. and is built based on the data captured in DARPA’98 IDS evaluation program (KDD, 1999) Host-based features combined with the KDD'99 dataset. This HybD dataset could be used in researches for designing

NIDSs, HIDSs, and hybrid IDSs. This new features are related to host and are used in conjunction with the 41 features in order to be able to detect intrusion in host level as well as in network level. The design and the implementation of the proposed hybrid IDS explained in Fig.1.

Fig-1. Detailed Proposed hybrid IDS



DESCRIPTION OF PROPSED DATASET

The 10percent KDD'99 Dataset

DARPA'98 is about 4 gigabytes of compressed raw (binary) training data of 7 weeks of network traffic. The 2 weeks of test data have around 2 million connection records. KDD'99 training dataset consists of approximately 5 million connection records (a connection is a sequence of TCP packets starting and ending at some well-defined times, between which data flows to and from a source IP address to a destination IP address under some well-defined protocol) each of which contains 41 features and is labeled as either normal or an attack, with exactly one specific attack type. The simulated attacks fall in one of the following four categories: Denial of Service Attack (DoS), User to Root Attack (U2R), Remote to Local Attack (R2L), and Probing Attack. KDD'99 features can be classified into three groups: Basic features, Content features, and Traffic features (KDD, 1999).

The New Host-based Features

The proposed HybD dataset includes the aforementioned 41 features and the new added host-based features. Each category of attacks has different effects on a host, thus a different host-based features have to be added to ensure the precision of detection of the different attack types. In this proposed dataset only some of host-based features that related to attack category will be considered and added, they are cpu usage ratio, memory space ratio, and kernel space ratio. They are the most features affected by the attacks. All the connection records of "attacks" and "normal" will be used in both training and testing of the classifiers to be designed.

Preprocessing on the Proposed HybD Dataset

The following processes have been applied to the "proposed HybD dataset" before it being used in design of the proposed system:

1. Converting the original KDD'99 10percent dataset from a text file to SQL server.
2. Adding of new host-based features to construct the proposed HybD dataset and adding their values.
3. Since type of some of HybD dataset's features is continuous, thus a process for normalization these features have been done in order to become of categorical type so it becomes more convenient with the used DM classification algorithms.
4. The resulted dataset from process three will be split into two distinct datasets by using, one for classifiers' training which equal of resulted dataset from process three and the other for classifiers testing which equal of resulted dataset from process three.

Process of Feature Reduction

This is an essential process to reduce, if possible, number of features and select the most intrinsic of these features in the classification decision, and hence to minimize the computation time of implementing the classification algorithms and so of the proposed system. It has been accomplished with two techniques from different fields: Principle Component Analysis (PCA) is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. The complete subject of PCA statistics is based on the idea that you have this huge set of data, and you want to analyze that set expressions of the relationships between the single points in that set. PCA is applied to the training dataset to find the intrinsic features, see algorithm (1), and GR from information theory that selects features with the highest GR value, see algorithm (2). Thus two sets of features in addition to set of all features in the training dataset will be used in design (learning) of the proposed classifiers.

Algorithm (1): *Customized_PCA*

The goal of PCA is to minimize the dimensionality of the data while keeping as much as possible of the difference present in the original dataset. It is a way of characterize intrinsic features and theorize all of these features' values.

Input: *Proposed TrainD training dataset.*

Output: *PCAS set of most frequent and related features.*

Steps:

1. Obtain training KDD'99 transactions.
2. Represent every transaction Ii as a vector xi.
3. Compute the average transaction $\Psi = \frac{1}{M}\sum_{i=1}^{M} xi$ …………………………..(1)
4. Subtract the mean transaction $\varphi i = xi - \Psi i$……………………………..…. (2)
5. Compute the covariance matrix $C = \frac{1}{M}\varphi_n \varphi_n^T = AA^T$…………………..……(3)

6. From C Compute eigenvectors ui of AAT:
   a. Consider matrix AAT as a $M \times M$ matrix.
   b. Compute the eigenvectors vi of AA^T such that:
      $A^TAv_i \rightarrow \mu_i V_i \rightarrow AA^TAV_i = \mu_i Av_i \rightarrow Cu_i = \mu_i u_i$ where $\mu_i = Av_i$..........(4)
   c. Compute the μ best eigenvectors of AA^T: $\mu_i = Av_i$ ....(5)
7. Keep only K eigenvectors, (K features with their values).

Algorithm (2): ***Gain_Ratio***

Input: *Proposed TrainD training dataset*

Output: *GRS set of GR values for each feature in (D)*

Steps:

1. For each feature in (D)
2. Find feature's InfoGain
3. Find its Split Information
4. If value of Split Information = 0
   then set it to very small value(<0)
5. Find its GR and add it to GRS
6. End

Customized SVM and NB Classifiers

After the intrinsic features had been selected, the two popular DM classification algorithms: Support Vector Machine SVM from statistical field and Naïve Bayesian from Bayesian theorem field, used in the design of the proposed IDS.

A "*Support Vector Machine Classifier*" SVM is a useful technique for data classification. Even though it's looked that Neural Networks are simpler to use than SVM, however, sometimes wrong results are gained. A classification task usually includes with training and testing data which consist of some data examples. Each example in the training set contains one base values and several attributes. The goal of SVM is to introduce a model which predicts base value of data example in the testing set which are given only the attributes. Classification in SVM is Supervised Learning. Known typecast help indicate whether the system is performing in a right way or not. This information points to a coveted response, validating the precise of the system, or be used to help the system learn to do correctly.

On the other hand, various empirical studies of "*Bayesian classifier*". In theory, Bayesian classifiers have the lower error rate in comparison to all other classifiers. Bayesian classifiers are also useful in that they supply a theoretical warrant for other classifiers that do not explicitly use Bayes' theorem. For example, under certain assumptions, it can be shown that many ANN algorithms output the *maximum posteriori* hypothesis, as does the NB classifier. NB classifiers assume that the effect of a feature value on a given class is independent of the values of the other features. This hypothesis is called *class conditional independence*. Both of SVM and NB classifiers will be used 3 times with each of these 3 sets of features to design the proposed classifiers:

1. All 44 features of *training dataset*.
2. Subset of features in (1) according to the result of implementation of the *PCA* method.
3. Subset of features in (1) according to the result of implementation of the *GR* measure.

Thus, six classifiers will be obtained: three SVM classifiers and three NB classifiers. Then the classification of the *testing dataset*'s records will be done with each one of these classifiers, and a comparison among their classification results will be done in to specify the most efficient feature selection method with the most accurate classifier.

SVM Classifiers in proposed IDM

SVM is a good technique for data classification. Now a set of training data $\{(\mathbf{x}_1,y_1)\dots(\mathbf{x}_l,y_l)\}$ in $R^n \times R$ sampled according to unknown probability distribution $P(\mathbf{x},y)$, There are many linear classifiers (hyper planes) that separate the data. Only one of these achieves maximum separation. The reason we need it is because if use a hyper plane to classify, it might end up closer to one set of datasets compared to others and we do not want this to happen and thus we see that the concept of maximum margin classifier or hyper plane as an apparent solution. For calculating the SVM we see that the goal is to correctly classify all the data. For mathematical calculations have,

If Y_i= +1; $wx_i + b \geq 1$ ....(6)

If Y_i= -1; $wx_i + b \leq 1$ ....(7)

For all i; $y_i\,(w_i + b) \geq 1$ ....(8)

In this equation x is a vector point and w is a vector weight. So to separate the data (6) should always be maximal than zero. Among all potential hyper planes, SVM selects the one where the distance of hyper plane is as max as possible. If the training data is reasonable and every test vector is located in radius r from training vector. Now if the chosen hyper plane is located at the outmost possible from the data . This coveted hyper plane which maximizes the margin also halves the lines between closest points on convex hull of the two datasets. Distance of closest point on hyper plane to origin can be discovered by maximizing the x as x is on the hyper plane. Similarly for the other side points we have a similar strategy. Thus fixing and subtracting the two distances we get the summed distance from the separating hyper plane to nearest points.

Getting Maximum Margin = MM = 2 / ||w||. ………………… (9)

Really maximizing the margin is same as minimum.

$$\Phi(w) = \frac{1}{2} w^t w \qquad \text{................................ (10)}$$

and for all points $\{(x_i, y_i)\}$: $y_i\,(w^T x_i + b) \geq 1$, must optimize a *quadratic* function subject to *linear* constraints. The solution involves constructing a *dual problem* where a *Lagrange multiplier* α_i is associated with every constraint in the primary problem: Find $\alpha_1 \dots \alpha_N$ such that

$Q(\alpha) = \Sigma\alpha_i - \frac{1}{2}\Sigma\Sigma\alpha_i\alpha_j y_i y_j x_i^T x_j$ …………………(11)

is maximized and we calculate $\Sigma\alpha_i y_i = 0$ and $\alpha_i \geq 0$ for all α_i

The solution will has the form:

$w = \Sigma \alpha_i y_i x_i$ and $b = y_k - w^T x_k$ for any x_k such that $\alpha_k \neq 0$

Each non-zero α_i references that corresponding x_i is a support vector. Then the classifying function will have the following form:

$f(x) = \Sigma \alpha_i y_i x_i^T x + b$ …………………… (12)

It relies on an *inner product* between the test point x and the support vectors x_i. Solving the optimization problem involved caculating the inner products $x_i^T x_j$ between all pairs of training points. The old formulation: Find w and b such that $\Phi(w) = ½\, w^T w$ is minimized and for all $\{(x_i, y_i)\}$, $y_i (w^T x_i + b) \geq 1$.

Algorithm (3) explain SVM algorithm with Intrusion detection depending on proposed TrainD and TestD.

Algorithm (3): *The SVM*

Input: *TrainD training dataset, TestD testing dataset that has not been classified*

Output: *TestD testing dataset that has been classified*

Steps:

1. Initialize all points in training dataset as (Xi, Yj) where X is a vector of data x1, ……, xn and Y is vector of classes.
2. Initialize vector of weight W.
3. Distribute all points (x, y) and extract the hyper plane separator.
4. If the hyper plane give optimal separation then depend hyper plane as classifier model to classify TestD testing dataset and go End else must do the following steps
5. Maximize the hyper plan using equation (9) and for minimum using equation (10)
6. Initialize *Lagrange multiplier* α_i *vector* $\alpha_1 \ldots \alpha_n$ using equation (11)
7. Apply classification function using equation (12)
8. Determine the support vectors xi with non-zero α_i (support vectors are the points determine the area of hyper plan)
9. Depend the hyper plan resulted after determining support vectors as the classifier model to classify TestD testing dataset

End

Naïve Bayesian Classifier in Proposed IDM

In NB classifier a set of probabilities (*a priori, conditional, and posteriori*) has been found instead of constructing a set of classification rules. Firstly, compute the "*a priori probability*" of each class (i.e. the frequency of each class in the *training dataset*). The a priori probability computed just once time for the whole *training dataset*. Then the following computations will be performed for classifying each record in the *testing dataset*. The conditional probability $P(a_j|C)$ for every feature's value in the record of the *testing dataset* is estimated as the relative frequency of records having value a_j as the *j*th feature in class C. Assuming *conditional independence* of features, the "*conditional probabilities*" $P(X|C_i)$ of the testing record at each class is computed using equation (13). Finally, the "*postpriori probability*" $P(h|X)$ of the testing record at each class computed using equation (14), the class with the maximum postpriori probability h_{MAP}will be the label for the testing record according to equation (15).

$$P(X|C_i)= \prod_{j=1}^{n} P(a_j|C_i) \qquad \text{.........} \qquad (13)$$

$$P(h|X) = \frac{P(X|h)P(h)}{P(X)} \qquad \text{...............} \qquad (14)$$

$$h_{MAP} \equiv arg\ max_{h\in H} = \ arg\ max_{h\in H}\ P(X|h)P(h) \qquad (15)$$

Algorithm(4) ***Naive Bayesian***
Input: *TrainD training dataset, TestD testing dataset that has not been classified*
Output: *TestD testing dataset that has been classified*
Steps:

1. Initialize MaxValue to a small value
2. For each class C_i in TrainD find its a priori probability AP_i
3. For each record R in TestD do step 4 and 8
4. For each class C_i in TrainD repeat steps 5-7
5. Find the conditional probability CP_i of R at C_i using equation(13)
6. Find the postpriori probability $PP_i$of R using equation (14)
7. If PP_i value greater than MaxValue value
   then MaxValue = PP_i and class_label = C_i equation (15)
8. Assign class_label to the class of R
9. End

DISCUSSION AND EXPERIMENTS

The proposal had been implemented on the following platform: Windows 7 Ultimate Service Pack1 and 32-bit OS, 4GB RAM, and Intel® Core (TM) 2 Duo CPU with 2.00GHz; and by using Visual Basic 6.0 and SQL server.

Training of the two used classifiers (NB and SVM) on *TrainingHD* has been done with three sets of features (*All_F*, *PCA_F*, and *GR_F*), so the proposed model has been experimented (i.e., trained and tested) for many times to assess the accuracy of the classifiers. Results of three conducted experiments (Exp1, Exp2, Exp3), which producing the most accurate results, have been presented in this section. Six classification models have been constructed in each of these three experiments. Next these models have been applied on the same *TestingHD*, which has been constructed during Exp1, to assess the validation and accuracy of these constructed models on the same testing dataset. The classification results of testing are either **TP** (intrusion), **TN** (normal), false positive (**FP**) (misclassified as intrusion), false negative (**FN**) (misclassified as normal), **Unknown** (new user behavior or new attack). Table 1 presenting the sets of selected features according to PCA and GR for Exp1, Exp2, and Exp3.

Table-1. Selected Features according to PCA and GR (Exp1 (a), Exp2 (b), Exp3 (c))

PCA	GR_F
protocol_type	land
Service	urgent
Flag	num_failed_logins
src_byte	root_shell
wrong_fragment	su_attempted
logged_in	num_root
count_	num_file_creations
srv_count	num_outbound_cmds
same_srv_rate	is_hot_login
dst_host_count	wrong_fragment
dst_host_srv_count	hot
dst_host_same_srv_rate	num_compromised
dst_host_diff_srv_rate	logged_in
dst_host_same_src_port_rate	service
cpu_usage_rate	srv_serror_rate
memory_space_rate	flag
kernel_space_rate	src_byte
	same_srv_rate
	srv_count
	count_
	protocol_type
	dst_host_srv_serror_rate

A

PCA_F	GR_F
protocol_type	land
service	urgent
flag	num_failed_logins
src_byte	root_shell
wrong_fragment	num_root
logged_in	num_file_creations
count_	num_access_files
srv_count	num_outbound_cmds
same_srv_rate	is_hot_login
dst_host_count	is_guest_login
dst_host_srv_count	wrong_fragment
dst_host_same_srv_rate	hot
dst_host_diff_srv_rate	num_compromised
st_host_same_src_port_rate	logged_in
cpu_usage_rate	srv_serror_rate
memory_space_rate	src_byte
kernel_space_rate	same_srv_rate
	srv_count

	protocol_type
	count_
	diff_srv_rate
	dst_host_srv_rerror_rate

B

PCA_F	GR_F
protocol_type	land
service	urgent
flag	num_failed_logins
src_byte	root_shell
wrong_fragment	num_root
logged_in	num_file_creations
count_	num_shells
srv_count	num_access_files
same_srv_rate	num_outbound_cmds
dst_host_count	is_hot_login
dst_host_srv_count	is_guest_login
dst_host_same_srv_rate	wrong_fragment
dst_host_diff_srv_rate	hot
dst_host_same_src_port_rate	num_compromised
cpu_usage_rate	logged_in
memory_space_rate	src_byte
kernel_space_rate	srv_serror_rate
	srv_count
	same_srv_rate
	protocol_type
	count_
	Service

C

Table 2 and table 3 summarized values of classification results for the three experiments. Generally in the three experiments, **TP** and **TN** results of SVM classifiers with *PCA_F* and *GR_F* are always higher than that of SVM with *ALL_F* and NB classifiers with *PCA_F*, *GR_F* also always higher than that of NB with *ALL_F*, **FP** and **FN** results of SVM classifiers with *PCA_F* and *GR_F* are always smaller than that of SVM with *PCA_F* and *GR_F NB* classifiers. In particular with SVM classifiers in the three experiments, **TP** and **TN** results with *PCA_F* and *GR_F* are almost higher (1) than with *ALL_F*, **FP** and **FN** results with *PCA_F* and *GR_F* are almost smaller (*zero*) than with *ALL_F*. ***Unknown*** results were always "*zero*" for both SVM and NB with the three sets of features.

Table-2. Classification Results of SVM Classifiers

Classifier	Feature selection measure	Experiment No.	TP	TN	FP	FN	Unknown
SVM	PCA	1	1	1	0	0	0
		2	1	1	0	0	0
		3	1	1	0	0	0
	GR	1	1	0.99	0.01	0	0
		2	1	1	0	0	0
		3	1	1	0	0	0
	ALL	1	0.995	0.97	0.03	0.005	0
		2	0.998	0.99	0.01	0.002	0
		3	0.995	0.93	0.07	0.005	0

Table-3. Classification Results of NB Classifiers

Classifier	Feature selection measure	Experiment No.	TP	TN	FP	FN	Unknown
NB	PCA	1	0.995	0.97	0.03	0.007	0
		2	0.99	0.98	0.02	0.012	0
		3	0.995	0.97	0.03	0.007	0
	GR	1	0.993	0.96	0.04	0.005	0
		2	0.995	0.97	0.03	0.01	0
		3	0.993	0.96	0.04	0.005	0
	ALL	1	0.993	0.93	0.03	0.007	0
		2	0.988	0.93	0.03	0.007	0
		3	0.993	0.93	0.03	0.007	0

The detection rate (DR) of an IDM is the ratio between the number of TP and the total number of intrusion patterns presented in the testing dataset. It has been calculated using

$$DR = \frac{TP}{TP+FN+Unknown2} *100\% \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(16)$$

, and the false alarm rate (FAR) of an IDM is the ratio between number of "normal" patterns classified as attacks (FP) and the total number of "normal" patterns presented in the testing dataset. It has been computed using

$$FAR = \frac{FP}{TN+FP+Unknown1} *100\% \qquad \ldots\ldots\ldots\ldots\ldots(17)$$

Values for both of DR and FAR for each classifier in the three experiments have been illustrated in table 4.

Table-4. DRs and FARs of both of them SVM and NB Classifiers

SVM Classifier				**NB Classifier**			
Feature Selection Measure	**Experiment No.**	**DR**	**FAR**	**Feature Selection Measure**	**Experiment No.**	**DR**	**FAR**
PCA	**1**	1	0	**PCA**	**1**	0.995	0.03
	2	1	0		**2**	0.993	0.02
	3	1	0		**3**	0.995	0.03
GR	**1**	1	0.01	**GR**	**1**	0.993	0.04
	2	1	0		**2**	0.993	0.03
	3	1	0		**3**	0.993	0.04
ALL	**1**	0.995	0.03	**ALL**	**1**	0.993	0.03
	2	0.998	0.01		**2**	0.988	0.03
	3	0.995	0.07		**3**	0.993	0.03

DR are higher with SVM classifiers (often greater than "0.995") than with NB classifiers that often did not exceed "0.995". And FAR often ranging between (0 - 0.07) with SVM classifiers while it is often ranging between the range of (0.02 - 0.04) with NB classifiers. It is very clear from these comparisons that SVM classifiers are better than NB. In particular, with SVM classifiers in the three experiments, DR with *PCA_F* and *GR_F* is always higher (1) than with ALL*_F*. And FAR is *"zero"* with *PCA_F* and *GR_F*, while it is ranging between the range of (0.01-0.07) with *ALL_F* .

Selection of the best classification model would be done significantly according to its classification accuracy, which is introduced as the ratio between the number of the correctly classified patterns (TP, TN) and the total number of patterns of the testing dataset. The ***accuracy (Accu)*** of each classifier has been calculated using

$$Accu = \frac{TP+TN}{TP+FP+TN+FN+unknown} * 100\% \qquad \ldots\ldots\ldots \quad (18)$$

Table 5 summarizes *Accu* of both SVM and NB classifiers with *PCA_F*, *GR_F*, ALL*_F* in the three experiments. According to these results, the most accurate classifiers were SVM classifiers with *PCA_F Accu* equal 1 in Exp1, Exp2 and Exp3 followed by SVM classifier with *GR_F* with *Accu* equal 1 in Exp2 and Exp3, were SVM classifier with *ALL_F* with *Accu* equal to 0.996 in Exp2.

A comparison between *Accu* of NB and SVM, it is obvious that *Accu* of SVM classifier with all sets of features and in the three experiments was almost higher than *Accu* of NB classifier. And for SVM classifiers, the best classification accuracy was with *PCA_F* and *GR_F*. Therefore PCA method is the feature selection measure that will be used in design of the proposed hybrid IDM.

Table-5. Accuracy of SVM and NB Classifiers

Classifier	Experiment No.	PCA_F	GR_F	ALL_F
SVM	**1**	1	0.998	0.990
	2	1	1	0.996
	3	1	1	0.982
NB	**1**	0.988	0.988	0.988
	2	0.986	0.986	0.988
	3	0.988	0.988	0.988

CONCLUSIONS

This paper design and implement a hybrid IDM for detecting intrusions. The design of model relies on using of DM classification algorithms with a proposed dataset, named **HybD**, composed of the 10% KDD'99 dataset's features and suggested host-based features. Where these features related to host itself not to network traffic give a support for proposed hybrid IDS to detect attacks, since these features have clear affect on host resources performance.

The aim of considering two measures for feature selection is to get diversiform of subsets of features, to make comprehensive comparisons. PCA find the most strong attributes in dataset and GR selecting features that having greatest GR values. The "PCA" has given better results rather than results of GR measure when they used with SVM and NB classifier, see tables (2, 3). Accuracy of SVM classifier higher than NB in all cases of features (PCA, GR, ALL), see table (4, 5).

REFERENCES

Hassina Bensefia, a.N.G., 2011. A new approach for adaptive intrusion detection, 2011 seventh international conference on computational intelligence and security. pp: 983-987.

KDD, 1999. Kdd cup 1999 data, the uci kdd archive, information and computer science, university of california, irvine, 1999. Available from http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html.

Mohammed, A.N., 2006. A honey pot resources approach to divert system intruders, m.Sc. Thesis, iraqi commission for computers and informatics, informatics institute for postgraduate studies.

Moses, G., L. Chunmei and F. Duane, 2008. Intrusion techniques: Comparative study of network intrusion detection systems. pp: 592-598.

Muamer, N.M., S. Norrozila and A.M. Osama, 2011. A novel intrusion detection system by using intelligent data mining in weka environment, published by elsevier ltd. Procedia computer science 3: 1237-1242.

Nur, A.H., A. Muhammad and A.P. Syed, 2012. An activity pattern based wireless intrusion detection system. pp: 846-847.

Risto, V., 2009. Real-time classification of ids alerts with data mining techniques, milcom'09 proceedings of the 28th ieee conference on military communications. 1786-1792.

Risto, V. and P. Karlis, 2010. Network ids alert classification with frequent itemset mining and data clustering, the 2010 international ieee conference on network and service management. 451-456.

Sufyan, T.A.-J. and A.S. Hadeel, 2011. A neural network based anomaly intrusion detection system, ieee computer society, 2011 Developments in E-systems Engineering: 221-226.

Zhang, G., L. Chen and W. Ha, 2011. The design of cooperative intrusion detection system. 764-766.