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MIDDLE EAST UNIVERSITY

Intrusion Detection System Based on Carpenter/Grossberg Artificial Neural Network

نظام كشف التطفل استنادا على شبكة كاربنتر/كروسبيرك العصبونية الاصطناعية

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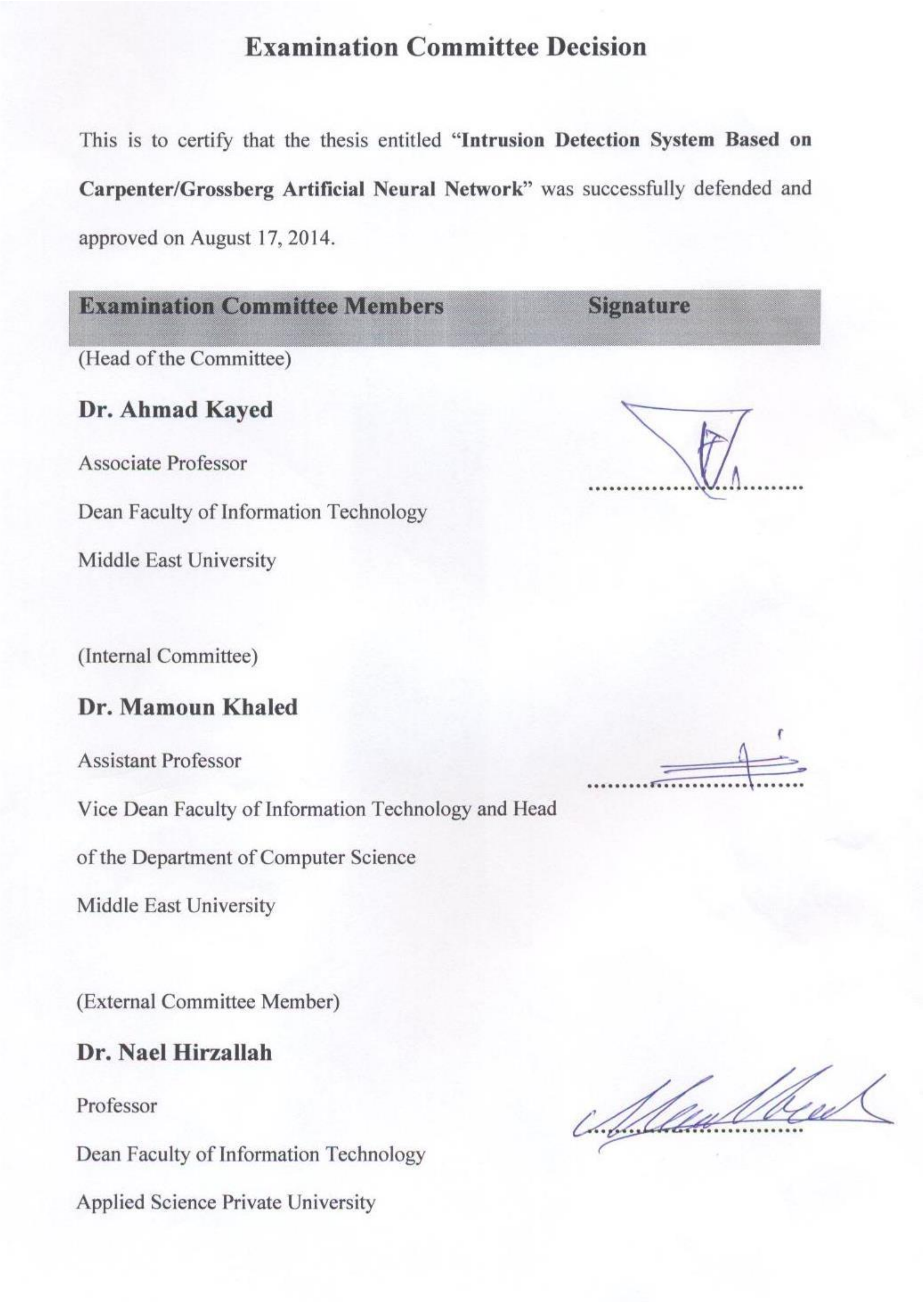

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Dedication

I dedicate this work to my wonderful father and mother, and my wife Aseel, and my lovely kids; Suhaib and Humam, and my brother and sisters, for their praying, love and encouragement. Finally, this worked is dedicated to my brother "Jamal"…..

May God bless his soul

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List of Abbreviations

ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
DARPA	Defense Advanced Research Projects Agency
DoS	Denial of Service
DMA	Data Mining Algorithms
DR	Detection Rate
FL	Fuzzy Logic
FNR	False Negative Rate
FPR	False Positive Rate
GAs	Genetic Algorithms
HIDS	Host-Based Intrusion Detection Systems
ID	Intrusion Detection
IDS	Intrusion Detection System
KDD	Knowledge Discovery and Data Mining
NIDS	Network Based Intrusion Detection systems
PCA	Principal Component Analysis
PE	Process Element
RL	Reinforcement learning,
RR	Recall Rate
SA	Statistical Analysis
SL	Supervised Learning,
USL	Unsupervised learning
PR	Precision Rate
R2L	Remote to Local Attack
RS	Rough Set
SOM	Self-Organizing Map
U2R	User to Root Attack
AccR	Accuracy Rate

Abstract

Over the last few decades, computer applications have evolved and became very important part of our life. This led to widespread concerns of network service disruption due to large-scale malicious attacks on computer networks. The development of a secure infrastructure to defend these applications from all challenges coming from intruders, hackers, and unauthorized access is a major challenge.

Intrusion detection system (IDS) is regarded as the second line of defense against network anomalies and threats. IDSs play an important role in detecting malicious and suspicious activities, and providing warning for unauthorized access over the network.

This research simulates a model of intrusion detection system. Artificial neural network (ANN) and machine learning (ML) combined with clustering algorithm as a pre-classifier are used to enhance the detection of network intrusion.

This IDS use both Adaptive Resonance Theory (ART1) and k-mean clustering algorithm, where ART1 is a version of Carpenter/Grossberg's ANN and the key core in this system.

The simulation system includes three main phases:

1. Preprocessing, in which converts the data and cluster the categories.
2. Training phase, in which trains ART1 neural network.
3. Testing phase, which tests ART1 network and check the performance and the stability of the IDS system.

At training phase, the sample space was randomly selected, where all known attack patterns are selected from KDD 99 dataset. Furthermore, many parameters were adjusted such as; norm, vigilance test, and weight factors. For testing purposes, the sample space is also randomly selected, that contains a number of duplicated patterns in order to test the stability.

The results of this research has a detection rate about 96.8% with an accuracy rate 96% , false positive rate 1.19% and False Negative Rate about 0.54% The results are compared with other previous studies. The results from this research showed better performance than the compared approaches.

الملخص

على مدى العقود القليلة الماضية، تطورت تطبيقات الحاسوب، وأصبحت جزء مهم جدا من حياتنا. وأدى ذلك إلى مخاوف واسعة النطاق من انقطاع خدمة الشبكة بسبب الفعاليات الخبيثة على اطار واسع في مجال شبكات الحاسوب.حيث يعد تطوير بنية تحتية آمنة للدفاع عن هذه التطبيقات تحديا كبيرا من جميع التحديات القادمة من المتسللين وقراصنة الكمبيوتر، والوصول غير المصرح به.

ويعتبر نظام كشف التطفل هو خط الدفاع الثاني ضد السلوك الغير الطبيعي وتهديدات الشبكة. ويلعب (IDS) دورا هاما في الكشف عن الأنشطة الخبيثة والمشبوهة، ويقديم تحذير للوصول غير المصرح به عبر الشبكة .

يحاكي هذا البحث نموذجا للنظام كشف التطفل. وتستخدم الشبكة العصبونية الاصطناعية (ANN) وتعلم الآلة (LM) جنبا إلى جنب مع خوارزمية التجميع بمثابة تصنيف اولي والذي يعزز كشف التطفل للشبكة. هذا و ان نظام كشف التطفل يستخدم كلتا النظريتين; التكيف الرنين (ART1) وk-mean نظرية – خوارزمية التجميع, حيث ART1 هو نسخة من Carpenter/Grossberg's ANN وهو جوهر أساسي في هذا النظام .

يتضمن نظام المحاكاة من ثلاث مراحل رئيسية :

١. مرحلة التجهيز: والذي يحول البيانات وتجميع فئات .

٢. مرحلة التدريب: التي تدرب شبكة ART1 العصبية .

٣. مرحلة الاختبار: التي تختبر شبكة ART1 العصبية والتحقق من أداء واستقرار نظام ال IDS

في مرحلة التدريب تم اختيار فضاء العينة بشكل عشوائي، حيث يتم تحديد كافة أنماط الهجوم المعروف ب KDD 99 مجموعة البيانات (اي انه عينه عشوائية مشروطه). وعلاوة على ذلك، يتم تعديل العديد من المعايير مثل؛ نورم، اختبار اليقظة، وعامل الوزن. ولغرض الاختبار، يتم أيضا اختيار فضاء العينة بشكل عشوائي، الذي يحتوي على عدد من أنماط تكرار لاختبار الاستقرار .

قد كشفت نتائج هذا البحث عن نسبة ٩٦,٨٪ مع معدل دقة ٩٦% ومعدل الإيجابية الخاطئه ب ١,١٩٪ ومعدل السلبيه الخاطئه٠,٥٤% وتمت مقارنة النتائج هذه الدراسه مع الدراسات السابقة الأخرى. حيث أظهرت نتائج هذا البحث أداء أفضل من المناهج المقارنة الاخرى لها نفس الية التعلم, وايظا تعتبر جيده جدا نسبة الى التعلم (supervised learning) لانه لا يمكن التحكم بالخوارزميه والنتائج المطلوبه.

Chapter One

Introduction

Chapter One

Introduction

1.1 Introduction

Nowadays, no one can deny that security has become a serious problem and necessary in our life according to the growing of development that the world witnesses. Last few decades, there is an urgent need to secure the operations in computer systems and networks for both private and governmental institutions which are relying heavily on networking and internet. The perspective of security has got involved in the process of insurance and evaluation of the computer system and its resources in which is connected on networks such as; stability, flexibility, reliability, confidentiality, availability, and integrity for most aspects of critical information data.

It is obvious that, researchers recently time have got a promised interest at the intrusion detection's area through designing many approaches and methods to get good results in this field. The main goal of Intrusion detection system (IDS) is to provide protection against malicious activity and unauthorized access of the network or computer system by monitoring the traffic data, analyzing audit, log file data.

(IDSs) is to detect attacks against information systems in general, and against computer systems and networks in particular.

1.2 Research Motivation

Many requirements of security in information system need to satisfy secure working environment, it is necessary to invent a system which is responsible for providing such requirements. This has inspired the researchers to model IDS, because of lack of the sufficiency like; anti-virus, and firewalls programs which do not prevent networks from all attack types.

Moreover, IDS which is based on ANN considered a distinguished technique in this field, but it does not meet the purpose, since it does not guarantee the learning process to be stable. For instance, even if the same set of input vectors is continuously presented to the Neural Network (NN), the winning unit (Node) may continue to change. One way to prevent such case, is gradually reducing of the learning rate to zero, thus this will freeze the learned categories. However when this case is carried out stability gained at the expense of losing plasticity or ability of the network to react to new data (that means, the network will not be able to learn new categories).

The host-based attacks are generally attacks either built-in machine as hardware or software intentionally (by design), or attacks from remote distance that target a machine on a network. These attacks are used to gain access to some features of the machine, such as user accounts or files on the machine (Smith 2002).

1.3 The Problem Statement

IDS based on ANN can be used to detect the intrusion, but there is slight complication that is the ANN lacks stability in the learning process of detection and classification. This problem is called stability /plasticity dilemma.

The Adaptive Resonance Theory 1 (ART1) is a solution to such dilemma. So the researcher proposes an approach based on Carpenter/Grossberg ANN-ART1 and K-mean clustering to overcome the current problem.

1.4 Contributions

The researcher follows certain steps which are indicated below:

1. Design IDS model to classify normal and attacks with their different types (Normal, DoS, R2L, U2R, and Prob) .

2. Achieve IDS which is stable in learning stage and final classification’s operation.

3. Apply hybrid system consists of two different classifiers which are:

    - K-mean cluster algorithm as preliminary classifier.

    - Carpenter /Grossberg-ART 1 ANN as a key classifier.

4. Achieve IDS which is can minimize FNR and has a small value to FPR.

1.5 Objectives of the Research

The main objectives of this research are as follow:

1. Applying the Carpenter/Grossberg Algorithm to detect the intrusion.
2. Using Carpenter/Grossberg Algorithm to improve the convergence speed
3. Making clustering stable in Intrusion Detection.
4. Comparing results of the Carpenter / Grossberg ANN-ART1 with previous algorithm’s results.

1.6 Questions of the Research

The main questions in this research are identified as following:

- By using the above algorithm ART1, can it cluster the data patterns according to their types (Normal, DoS, R2L, U2R, & Prob)?
- Can ART1 algorithm produce high performance for Intrusion Detection (ID)?
- Can ART1 algorithm get clustering stable when applying learning and testing phases for Intrusion Detection (ID)?
- Can we use the algorithm to maximize Detection Rate (DR) and minimize the False Negative Rate (FNR)?

1.7 Methodology

There are many research works and applications about the IDS, where it was built through many techniques such as; statistical and computational methods, data mining, artificial neural network approaches, and the genetic algorithms. These techniques may be hybrid (that takes more than one technique).

In this study, the researcher builds a model to simulate intrusion detection system, which it based on artificial intelligence and machine learning throughout artificial neural network that performance has been improved by the former use of one of clustering algorithm as a pre-classifier.

The simulation system uses both; ART1 (which is one of Carpenter/Grossberg's ANNs) that it is the key core in this system, and k-mean clustering algorithm.

The simulation system includes three main phases:

1. Preprocessing phase, which contains receive, convert, and cluster the KDD 99 dataset into the categories.
2. Training phase, which trains ART1 neural network.
3. Testing phase, which tests ART1 network by getting best results and ensuring its stability.

At training phase, the sample space is randomly selected, where all known attack patterns are selected from KDD 99 dataset.

And also adjust many parameters such as; norm, vigilance test, and weight factor. At level of the testing, the sample space is also randomly selected, that contains a number of duplicated patterns in order to test the stability.

Chapter Two

Literature Review and Related Works

Chapter Two

Literature Review and Related Works

2.1 Introduction

In this chapter, the researcher sheds a light on the previous related works about the field of intrusion detected system. It tackles related literature on the clustering techniques including several ways such as; K-mean clustering algorithm, IDS via the use of both; supervised and unsupervised ANN.

2.2 Literature Review and Related Works

2.2.1 IDS Based on Clustering and Classification

Dipali (2013) applied K-means clustering algorithm for an intrusion detection system to train KDD dataset that contain normal and attack traffic. She assumed that normal and malicious traffic form different clusters. The corresponding cluster centroids are used for efficient distance based on detection of anomalies.

She also provided a specific description of the data mining and anomaly detection process. Moreover, she implemented k-Means clusters via applied SVMs (Support Vector Machines), which considered a useful technique for data classification. A classification task usually involves separating data into training and testing sets. She used the DARPA 98 Lincoln Laboratory evaluation dataset as training and testing data set. The data consists of unlabeled flow records are divided into clusters of normal and anomalous traffic.

Sumit , et al (2014) proposed to implement Intrusion Detection System on each node of the MANET(Mobile Ad-Hoc Networks , consist of peer-to-peer infrastructure less communicating nodes that are highly dynamic) which is using Zone Routing Protocol (ZRP) that adds the qualities of the proactive and reactive protocols for packet flow. To solve the problem of the MANET security is possible that a node can turn malicious and hamper the normal flow of packets in the MANET. They would apply effective k-means to disjoint the malicious nodes from the network. Consequently, it would be no malicious activity in the MANET, and also the normal flow of packets would be possible (Sumit , et al 2014).

2.2.2 IDS Based on ANN

Amini and Jalili (2004), introduced an Unsupervised Neural Net based Intrusion Detector (UNNID) system for classifying network traffic using different types of unsupervised neural nets. The system is used to tune, train and test two types of Adaptive Resonance Theory (ART) nets, (ART-1 and ART-2). The results show that ART-1 in 93.5 percent of times and ART-2 in 90.7 percent were able to recognize attack traffic from normal one.

Xiao and Song (2009) used novel intrusion detection approach based on Adaptive Resonance Theory (ART) and Principal Component Analysis (PCA) is raised according to analyzing now intrusion detection methods. (PCA-MART2) model defines as network behaviors relied upon the datagram. PCA is applied to feature selection about input samples and the multi-layered ART2 is designed to subdivide the decrease clustering. They stated that the modified algorithm improved the speed and accuracy of detection. The results indicated that the intrusion detection system based on PCA-MART2 can detect intrusion behavior in network efficiently.

Srivastav and Challa (2013) indicated that, Intrusion Detection System which includes two models (Model A and Model B) are designed by integrating layered framework with neural network. It is observed that Model A considered all features of training dataset attains high accuracy, the classification has been achieved through the use of backpropagation neural network (BPN), and 'trainscg' as training algorithm is used to classify the records as normal or attack. On other hand, Model B considered feature extraction reduces training time but with a slight decrease in success rate of attack detection, while Principal Component Analysis (PCA) is applied for individual layer of the features extracting operation. They stated the results as DoS = 99.54, Prob= 95.46, R2L= 99.58, U2R= 90.

2.2.3 IDS Based on Clustering and ANN Hybrid Methods

Wang et al (2010) proposed a new technique, named FC-ANN, based on ANN and fuzzy clustering. They indicated the general procedure of FC-ANN as: firstly fuzzy clustering method is for generating different training subsets, via the heterogeneous training set is divided to several homogenous subsets. Subsequently, based on different training subsets, different ANN models are trained to formulate different base models. Thus complexity of each sub training set is reduced and the detection performance is increased, also gets a less false positive rate and stronger stability for detection process could help IDS achieve higher detection rate. They concluded that the result as the average accuracy detection rate of FC-ANN is 96.71.

Al-Rashdan (2011) has proposed an intelligent model using Hybrid Artificial Neural Networks, supervised and unsupervised learning capabilities to classify and / or detecting network intrusions from the KDDCup'99 dataset. She designed three cooperative phases by using an enhanced k-means clustering algorithm in Phase-1 "clustering phase", a Hybrid Artificial Neural Network (Hopfield and Kohonen-SOM with Conscience Function) in Phase-2 "training phase" and a Multi-Class Support Vector Machines in Phase-3 "testing phase". The Hybrid Neural Network Machine Learning Model achieved a detection rate of 88%.

In the study of Na'mh (2012), she used Unsupervised Learning (USL) technique by presenting hybrid intrusion detection system models, by using K-Nearest Neighbor machine learning algorithm and an enhanced resilient backpropagation artificial neural network. She listed the system into five main phases: environment phase, dataset features and pre-processing phase, feature classification K-Nearest Neighbor (KNN) phase, training the enhanced resilient backpropagation neural network phase and testing the hybrid system phase. The first use of K-Nearest Neighbor as a machine learning algorithm was at the first stage of classification, whereas the multilayer perceptron was used for classification of trained by using an enhanced resilient backpropagation training algorithm was used in the second stage. She indicated that the hybrid system (KNN_ERBP) was able to classify normal class, while by using the enhanced resilient back-propagation was also able to classify intrusions classes with high detection rate (and with less time) than the normal resilient back propagation.

Chapter Three

Intrusion Detection System (IDS)

Chapter Three

Intrusion Detection System (IDS)

3.1. Overview

This chapter provides a brief description about the types of IDS, using IDS as complement to firewall, and provides a general overview about different types of attacks on different protocols. Also displays valuation criteria to IDS performance and takes a glimpse of the approach of ANN based on IDS.

3.2. Intrusion Detection and IDS

Singh and Saxena, (2014) said that the Information Technology (IT) was represented as a primary component for any business organization. Hence, IT provides a strong platform for a lot of critical services in our society (Singh and Saxena, 2014).

Shaveta et al, (2014) tackled the core idea behind designing the internet is to make communications between different hosts in order to exchange data between them. For this purpose, the common protocol used to suit data communication between hosts called Transmission Control Protocol / Internet Protocol (TCP/IP) protocol. In this context, internet design supposed that hosts that are working over the network have no malicious intention. Hence, such assumptions open up this design on many opportunities for intrusion (Shaveta et al, 2014).

The significant increase in using computer networks such as internet makes it vulnerable to attacks (Sharma et al., 2014). Furthermore, various tools and techniques were proposed to secure Electronic assets from attacks at both levels individual level and organizational level (Majeed and Kumar, 2014). According to the National Institute of Standards and Technology (NIST) intrusion was defined as "*The process of monitoring the events occurring in computer system or network and analyzing them for signs of possible incidents, which are violation or imminent threats of violation of computer policies, acceptable use policies, or standard security practices*" (Sacrfone and Mell, 2007). Figure (3-1) shows a general framework of IDS.

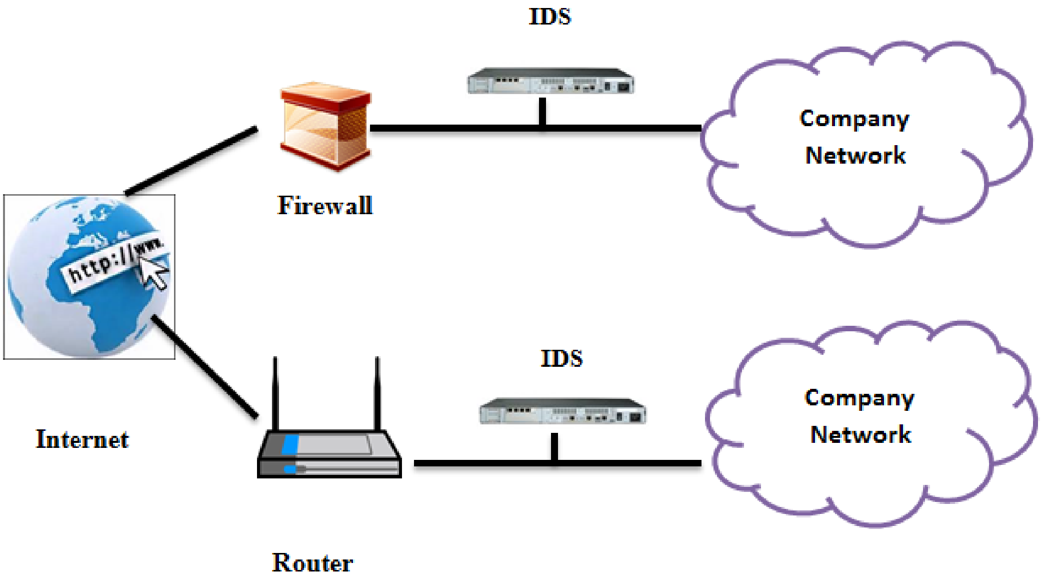


Figure 3-1 the General Framework of IDS (Anand A., and Patel, B., 2012)

Several methods were proposed to detect intrusions in network environment such as: Genetic Algorithm (GA), Artificial Neural Network (ANN) classifier, Modified Mutual Network (MMN) classifier, Modified Mutual Information Feature Selection (MMIFS), Linear Correlation Feature Selection (LCFS), and Forward Feature Selection (FFS) (Dastanpour et al., 2014).

Defending computer networks from malicious or unexpected activities lead to propose several techniques such as IDS (Anand and Patel, 2012). Scarefone and Mell, (2007) defined the IDS as the software that is responsible for automating intrusion detection process. Recently, many scientific research works focused on the use of IDS based on several approaches (Scarefone and Mell, 2007).

Naoum, et al.(2014) made a Steady State Genetic Algorithm (SSGA) is applied to support IDS by providing the rule pool with additional data, these data can be used in testing phase to detect the attacks. Thus, they conducted the enhancement of replacement steady state genetic algorithm to detect intrusions. As well as, they compared it with the existed studies (Naoum et al. 2014).

Singh et al. (2014) made a comparative study on IDS based on Artificial Intelligence (AI) techniques. Thus, they used decision trees, and Self Organization Maps (SOM). Hence, they worked on finding the impact of using these techniques in detecting intrusions through network environments (Singh et al. 2014).

3.3. Firewall

Lubna and Cyriac, (2013) defined a firewall is a network secure from unauthorized access by controlling the traffic to/from a network. It can be either software-based or hardware-based as shown in Figure (3-2). The key purpose of a firewall is monitors the suspicious and unauthorized traffic to Internet-based enterprises. A firewall involving of a set of rules which it are defined by the system administrators to filter the incoming and outgoing packets by allowing or denying them (Lubna and Cyriac 2013)

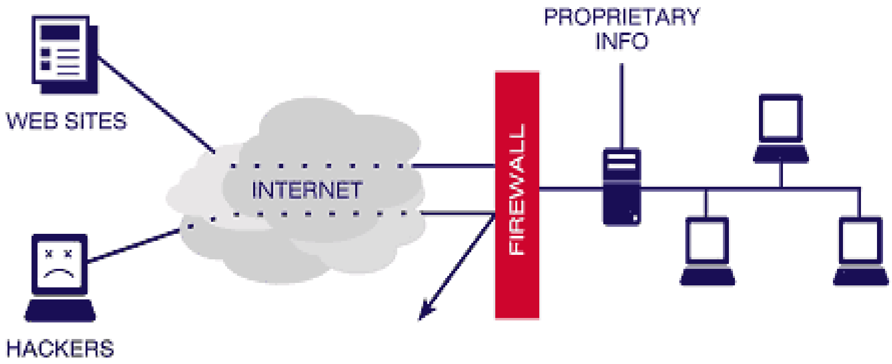


Figure 3-2 diagram of firewall protecting network

The main different between IDS and firewall existed in the functionally. Hence, firewall is capable to detect the attacks that are simple rules, and didn’t have a dynamic in nature. On the other hand, IDS techniques are capable to detect more complex attacks and have a dynamic in nature (Singh and Singh, 2014).

Basically, firewall focused on the network traffic that is coming from outside and react according to the predefined rules. Thus, firewall system is responsible on accepting or blocking the communication. Furthermore a firewall is represented as a hedge that protects the information flow and prevents intrusions; in this case, firewall is capable to prevent some protection not full one, whereas IDS based on detecting weather the network is under attack or the security imposed by the firewall which has been penetrated. Intrusion detection process initiated from inside the network, and come into the action after the suspected intrusion has taken place on the network (Sunke, 2008).

Krishna and Victoire, (2013) found that firewalls have their limitations in some situations where an Intrusion Detection System does not, this include the following:

- The firewall cannot protect against risk associated with connections that bypass the firewall or it never sees, because not all access to the Internet occurs through the firewall.
- Since not all threats originate outside so the firewall does not protect against internal threats.
- Firewalls itself exposed to attack and tricks such as a common strategy is to use tunneling to bypass firewall protections.
- The variety of operating systems type, and the applications that are supported by inside the perimeter, this lead to impractical or maybe impossible for the firewall to scan emails, massages from viruses. Consequently, firewall cannot protect against the transfer of the infection of programs or files.

It is because of these limitations that intrusion detection systems are needed even though a firewall may already be in place (Krishna and Victoire, 2013)

3.4. Types of Network Attacks

Security is a continue process of protecting an object from unauthorized access. Thus, that object may be a person, an organization such as businesses, or property such as a computer system of file (Kizza, 2013). Network environments are exposed from different types of attacks. Thus, four basic types of attacks are found in computer network environment: Denial of service, remote to user attack, user to root attacks, and probe attacks (Ireland, 2013).

1. **Denial of Service (DoS) :** In this type, the attacker is capable to deny users access to machine by making computing, or memory resources too busy, or too full to serve authorized networking requests (Mostaque and Hassan, 2013).

2. **Remote to Local (R2L) attack:** User send packet to machine over the internet. Thus, this user does not have an access in order to expose the machine vulnerabilities and exploit privileges which local user would have on the computer (Paliwal and Gupta, 2012).

3. **User to Root (U2R) attack:** In this type, the attacker starts using the system as a normal user. Hence, the attacker attempts to abuse system vulnerabilities in order to work on system as a super user and exploit super user privileges (Paliwal and Gupta, 2012).

4. **Probing:** In this type, the attacker scans network environment to find a vulnerabilities or weaknesses on machine or other network devices in order to exploit them such technique is sued in data mining (Ireland, 2013).

Any type of attack found in the network environment could be classified under these categories (Kayacik, et al 2005). Table (3-1) shows some examples on these categories.

Categories	Attack Examples
DoS	*Land, Smurf, Neptune, Ping of Death, Back.*
R2L	*Guess_Passwd, Ftp_Write, Imap, Phf, Multihop, Spy, Warezclient, Warezmaster,*
U2R	*Perl, Buffer_Overflow, Loadmodule, Rootkit.*
Probing	*Satan, Portsweep, Ipsweep, Nmap.*

Table 3-1 some examples on different types of network attacks.

3.5. IDS Techniques

Basically, Gaidhane, et al (2014) showed that there are two primary techniques are used to detect intruders which are misuse detection, and anomaly detection. In this context, also Ghandi, (2014) displayed that four main techniques are available in network environments, which take the responsibility to detect the unauthorized access or unauthorized users. Thus, these techniques are: Anomaly detection, misuse/signature detection, target monitoring, and stealth probes (Gandhi 2014). Table (3-2) shows these techniques in details.

IDS Techniques	Basic Idea	Detection Criteria
Anomaly Detection	The system establishes line of usual pattern behavior.	Any behavior differ from stored behavior is notified as a possible intrusion.
Misuse / Signature Detection	The system is capable to store unusual patterns of unauthorized activities which called Signature.	Any specific number of failed activities is determined as possible intrusion.
Target Monitoring	The system is capable to look for alteration of specific files than storing usual or unusual behaviors.	System uncovers an unauthorized action after it occurs. By reversing that action for specific time interval using integrity checksum hashes.
Stealth Probes	System is capable to detect any attacks tries to carry out a mission over prolonged period of time.	Any attempts from attacker to collect much information to find the weaknesses take long period of time, it determined as possible intrusion.

Table 3-2 IDS techniques and its basic idea for detection (Gandhi, 2014).

3.6. IDS Classification

Any IDS can be classified based on several categories: Host based IDS (HIDS), Network based IDS (NIDS) and Stack Based Intrusion Detection System (SIDS) (Boncheva, 2007) and (Vinchurkar and Reshamwala, 2012) as stated in Figure (3-3).

A HIDS examine data on individual computer that is working as a host. Thus, this category is efficient to detect unauthorized modifications on files by analyzing data that originate on a computer. Hence, the idea of this category based on aggregating data for that host and analyzes it locally or by sent it separately to an analysis machine (Gandhi, 2014). HIDS category concentrates on particular host activities (Aziz, et al., 2014). The network architecture in this category is agent-based. Hence, this agent represents a software agent, and it is located at each host node which is governed by a system (Boncheva, 2007).

A NIDS category examines the exchange of data between computers in network environment. Thus, NIDS analyzed data packets that are traveled over the network. Hence, the NIDS is responsible to examine and compare these data packets with empirical data (Gandhi, 2014). NIDS monitor the network communications activities (Gaidhane, et al., 2014). NIDS provide flexible mean of security administration. Furthermore, NIDS monitoring and collecting system audit trails in real time by providing the utilization of Central Processing Unit (CPU) and network (Boncheva, 2007). NIDS category systems are capable to provide network traffic monitoring (Aziz, et al., 2014).

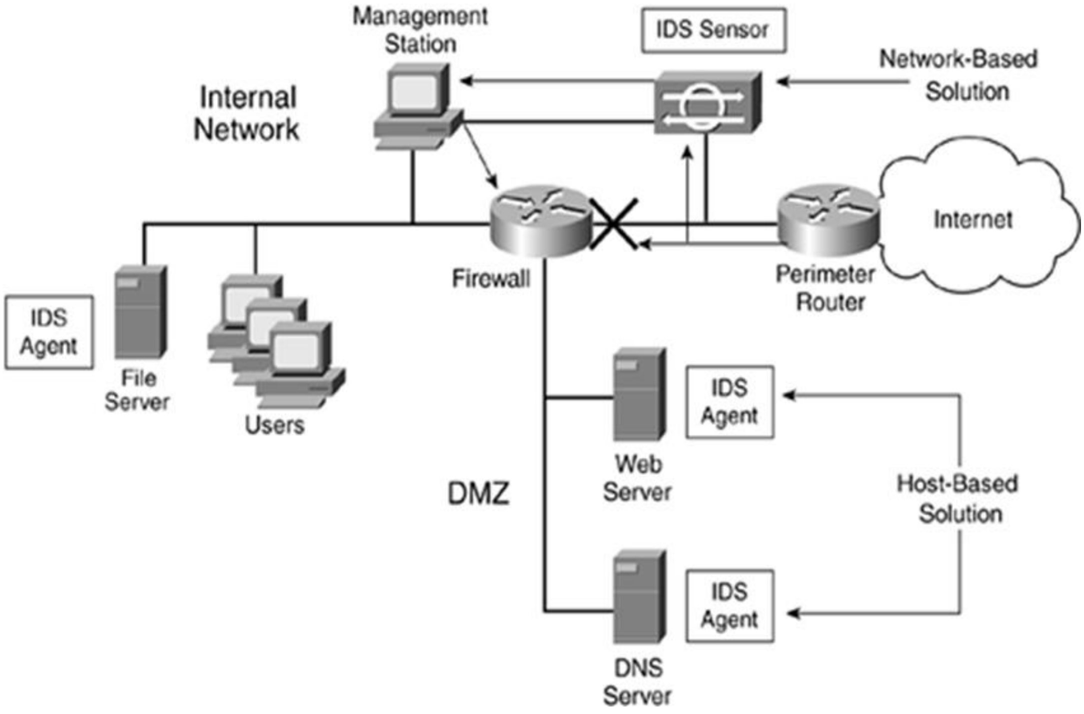


Figure 3-3 Types of intrusion detection systems

A SIDS is latest technology, which works by integrating meticulously with the TCP/IP stack, allowing packets to be watched as they traverse their way up the OSI layers. Watching the packet in this way allows the IDS to pull the packet from the stack before the OS or application has a chance to process the packets (Vinchurkar and Reshamwala, 2012).

Various classification and techniques of the Intrusion Detection System are possible as per the different criteria. Initially the categorization can be done as follows as shown in Figure (3-4)

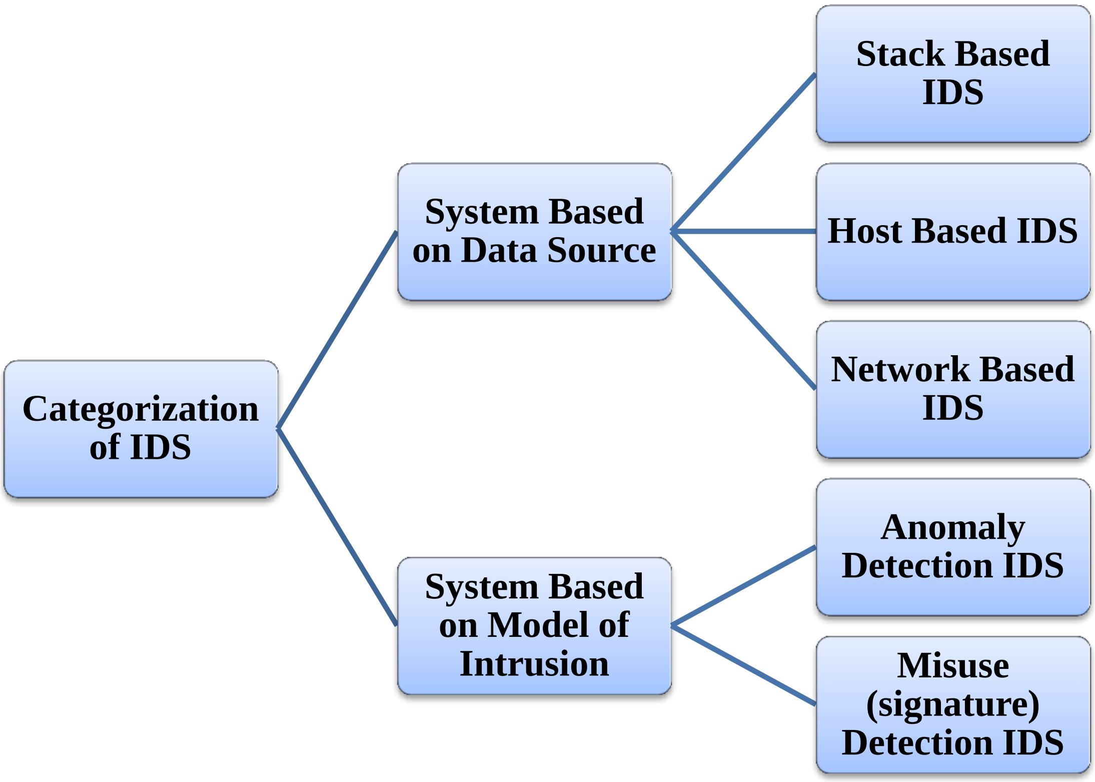

Categorization of IDS
System Based on Data Source
System Based on Model of Intrusion
Stack Based IDS
Host Based IDS
Network Based IDS
Anomaly Detection IDS
Misuse (signature) Detection IDS

Figure 3-4 diagram of the Categorization of Intrusion Detection System

3.7. Requirements for Idealism of IDS

There are some requirements to the system needed to meet the purpose of this work, such as:

- **Effectiveness:** a system is effective when has the ability to adapt easily and detect intrusions in any case, like as it must be able to detect new unknown attack, as well as already known attacks.

- **Efficiency:** describes what run-time efficiency of an intrusion detection system, such as, computing resources, amount of storage used and if it can make detection in real-time.

- **Continually running**: The system must run continually without human supervision. It must be reliable enough to allow it to run in the background of the system being observed.

- **Fault tolerance:** the system should be fault tolerant means that there must be survive a system crash.

- **Ease of use:** the system must be user friendly (i.e. a system must be easy to use even for the non-expert user).

- **Security:** The system must be difficult to fool and able to resist to all attacks that are directed to it by monitoring itself to ensure that it has not been subverted.

- **Interoperability and Collaboration:** describes the need of cooperation between various vendors of the network devices, where the system must send and receive information from intrusion detection systems.

- **Transparency:** The product evaluation process to system is important characteristic, because it must deal with changing system behavior over time as new applications are being added, such as: costs and management.

Consequently all the above listed are the features that an ideal Intrusion Detection System must have. So that the system becomes perfect to defend the attacks and the intrusions (Vinchurkar and Reshamwala, 2012) and (Prasad et al 2013).

3.8. Passive and Reactive IDS

Na'mh (2012*)* said that according to the kind of the response to the intrusion notes Figure (3-5), can be classified the Intrusion Detection System as Passive IDS and Reactive IDS as following:

- **Passive IDS:** the system detects a suspicious activity, by gathering this interesting information to be comparing this information with storage Database and when it realizes it is an attack, it will send this information to the alarm server to alerts the user. Subsequently the each form of response to the intrusion is not specifying the nature of detection.

- **Reactive IDS:** performs the same as the Passive IDS when the system detects an attack, in addition that when the alarm server warns the user, the IDS collector will send information to the router or the firewall and notify these devices to block that activity to getting to the network, such as logging off a user or by reprogramming a firewall to block network traffic from the suspected malicious source (Na'mh, 2012*).*

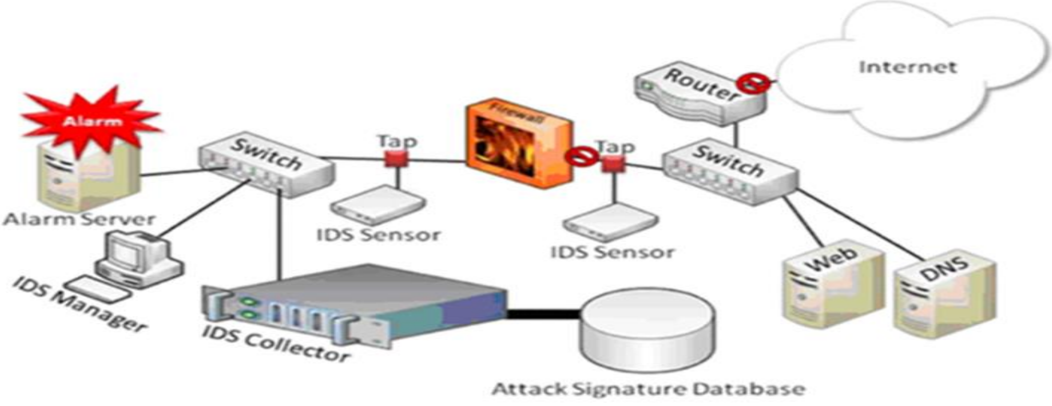


Figure 3-5 Passive & Reactive Intrusion Detection System

3.9. Evaluation Criteria of IDS

Al-Rashdan, (2011) enquired about "how we can test these proposed systems", so the testing proposed method can provide a good indicator on whether the proposed method can give high performance compared with others or not in solving problems or trying to find optimal solution for them.

These measures have been widely used for comparisons between ID methods. But in case of learning very imbalanced data is lead to the classification accuracy in general is not often an appropriate measure of performance (Na'mh, 2012).

The effectiveness of an IDS is assessed on how capable the detection method is to make correct attack detection (Detection Precision). According to the real nature of a given event compared to an IDS prediction, (Shamshirband, et al 2013). four possible outcomes which are calculated based on the Confusion Matrix (CM). The CM is a square matrix where columns correspond to the predicted class, while rows correspond to the actual classes as shown in Table (3-3) (Elngar, et al 2013) and (Madbouly, et al 2014).

	Classified Class	
Actual Class	Normal	Attack
Normal	True Negative (TN)	False Positive(FP)
Attack	False Negative (FN)	True Positive(TP)

Table 3-3 Confusion Matrix

Where:

- **True negatives (TN)**: indicates the number of normal events is successfully labeled as normal.

- **False Positives (FP**): Refer to the number of normal events being predicted as attacks.

- **False Negatives (FN)**: The number of attack events incorrectly predicted as normal.

- **True Positives (TP)**: The number of attack events correctly predicted as attack.

Shamshirband, et al (2013) showed that a high FP rate that seriously affects the system's performance can be detected, and an elevated FN rate leaves the system vulnerable to intrusions. Both FP and FN rate sought to be minimized, together with maximizing TP and TN rates simultaneously (Shamshirband, et al (2013).

To summarize evaluation criteria of IDS, based on the following definitions and equations (Al-Rashdan, 2011), (Madbouly, et al 2014), (Na'mh, 2012) and (Shamshirband, et al (2013) were given:

- **True Negative Rate (TNR) (Specificity)**: is the ratio of correctly classified normal records to the total number of true negative and false positive.

$$\boldsymbol{True\ Negative\ Rate(TNR) = \frac{TN}{TN +\ FP} = \frac{No. of\ True\ Alerts}{No. of\ Alerts}}$$

- **True Positive Rate (TPR):** is the ratio of correctly classified attacks records to the total number of true positive and false negative.

$$\boldsymbol{True\ Positive\ Rate(TPR)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}$$

- **False Positive Rate (FPR):** the ratio of incorrectly classified normal examples (false alarms) to the total number of normal examples it is the same as False Alarm Rate.

$$\boldsymbol{False\ Positive\ Rate\ (FPR)} = \frac{\boldsymbol{FP}}{\boldsymbol{TN+FP}} = \mathbf{1} - \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}}$$

- **False Negative Rate (FNR):** is the ratio of incorrectly classified attacks (when system classify attacks as normal) records to the total number of true positive and false negative.

$$\boldsymbol{False\ Negative\ Rate(FNR)} = \frac{\boldsymbol{FN}}{\boldsymbol{TP+FN}}$$

- **Detection Rate (DR):** or classification rate for all classes (5 classes) where the system is evaluated by calculating the corrected classified records for each sub class (5 classes) of the total number of records.

  (i.e. the ratio of correctly classified intrusive examples of the total number of intrusive examples)

$$\boldsymbol{Detection\ Rate\ (DR)} = \frac{\sum \textbf{No. of detected attacks}}{\sum \boldsymbol{No.of\ attacks}} * \mathbf{100}\%$$

- **Accuracy Rate (AR):** the performance of the system is evaluated by calculating the ratio of correctly classified records as attacks (either normal or attack) to the total number of records.

$$\boldsymbol{Accuracy\ Rate\ (AR) = \frac{(TP\ +\ TN\ )}{(TP +\ FP +\ FN\ +\ TN\ )}}$$

- **Precision Rate:** is the ratio of true positives to combined true and false positives.

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

- **Recall Rate (sensitivity):** recall stands for an attack is happened and IDS detects attacks from really attacks. This formula use TP divide TP adds FN to find recall value.

$$\boldsymbol{Recall\ Rate = \frac{TP}{TP + FN}}$$

- **F-Measure:** is the harmonic mean of recall and precision tends to be closer to the smaller of the two. Hence a high f-measure value ensures that both recall and precision are reasonably high.

$$\boldsymbol{F - Measure = \frac{2 * TP}{(2 * TP) + FP + FN}}$$

3.10. Artificial Neural Network Approach for IDS

The Artificial Neural Networks (ANNs) are the most commonly used soft computing approach in Intrusion Detection Systems (IDS), since the ANN has an ability of soft computing techniques for dealing with uncertain and partially true data makes them attractive to be applied in intrusion detection (Moradi, and Zulkernine, 2004), and (Reddy, 2013). The use of neural networks for intrusion detection was chosen because intrusion detection is a complex problem, and neural network are used to solve complex problems. Also, the power of neural networks to make sound decisions about the problem it is knowledgeable about made them a great candidate for detecting anomalous patterns in a network (Smith, 2002).

Also Wang, et al (2010) explained that the Artificial Neural Networks (ANNs) can improve the performance of intrusion detection systems (IDS) when compared with traditional methods. However for ANN-based IDS, detection precision, especially for low-frequent attacks, and detection stability, are still needed to be enhancing (Wang, et al. 2010).

When the Neural Network(NN) apply to the Intrusion Detection(ID), must be display a normal and attacks data(i.e. normal and abnormal behavior) to train the Neural Network by automatically adjust coefficients of the Neural Network during the training phase. After training is accomplished, the performance tests are then conducted with real network traffic and attacks. Thus apply this approach to Intrusion Detection (Vinchurkar, and Reshamwala, 2012).

A pattern recognition technique is one of the characteristics of ANN, thus it can be implemented in IDS by using any method of neural networks that has been trained accordingly. During training, the neural network associates outputs with corresponding input patterns through optimizing its coefficients. The neural network is determines the input pattern and attempt to output the consistent class (Reddy, 2013).

Chapter Four

Artificial Neural Network (ANN)

Chapter Four
Artificial Neural Network (ANN)

4.1 Overview

This chapter describes several topics starting from discussing the emergence of neural networks and its historical aspects. The architecture of ANN and its features are defined. As well as, explain the Adaptive Resonance Theory (ART) as a solution for stability/plasticity dilemma, network structure, and the analytical study of ART1 algorithm.

4.2 Using Neural Network for IDSs

Traditional IDSs are based on the profile of attacks or expert rules. Hence, it may be not able to discover the new version of this malicious activity, which has been modified by an attacker in order to pass through the firewall system when did not update it. The neural networks could be a good solution for detection of a well-known attack because of their generalization feature; it is able to operate with imprecise and incomplete data. It means that they can recognize also patterns not presented during a learning phase (Kukielka, 2008). In the following we addressed the main features for this purpose:

- Neural network algorithms, supervised, unsupervised or reinforcement can produce high performance with unique properties for IDS (Oks¨uz, 2007)
- Neural Network has Flexibility.
- The ability to process and analyzing data from a number of sources in a non-linear relation even if the data is incomplete or distorted.

- Because it has predictions capability to the detection this lead to the inherent speed for outputs.
- It can predict where these events, intrusion, are likely to occur in the attack.
- Neural Network observed and tracking the subsequent occurrence of these events(abnormal activities), for improving the analysis and learning of the events and possibly conducting defensive measures before the attack is successful (Pervez, 2006)**.**

4.3 The Implementations of ANN

ANN refers to a group of neurons that perform or work together to solve a special function and process information (Beqiri et al., 2010). The learning criteria in this type could be supervised or unsupervised. ANN is a system simulating a work of the neurons in the human brain (e.g. processing models in the brain is inspired by the nervous system). Hence, the processing system in ANN is implemented as neuron which called capabilities (Beqiri et al., 2010).

Basically, three layers are presented in a typical ANN. Thus, each layer has it own responsibilities such as emulating dendrites of the biological neuron, activating computer system functions, and emulating an axon of the biological neuron. In this context, these layers called input, hidden, and output respectively. Furthermore, each layer is composed of one or more nodes which could be classified into a process element, neurons, or the communication paths between them. Figure (4-1) shows an illustration of these layers and the relationship between them.

Some ANN architectures provide a feedback flow between the input and the output nodes. Consequently, the hidden nodes are produced by the input layer nodes after carrying out the hidden relationships. Thus, the hidden layer contains the interaction weight between input nodes. The importance of a particular input can be intensified by the weights that simulate biological neuron’s synapses. The input layer represents the stimulus or information forwarded to the network by the input signals are multiplied by the values of weights, and next the results are added in the summation block. Hence, the summation is sent to the activation block in order to be processed by the activation function. Consequently, the output layer is the final product of the neural processing.

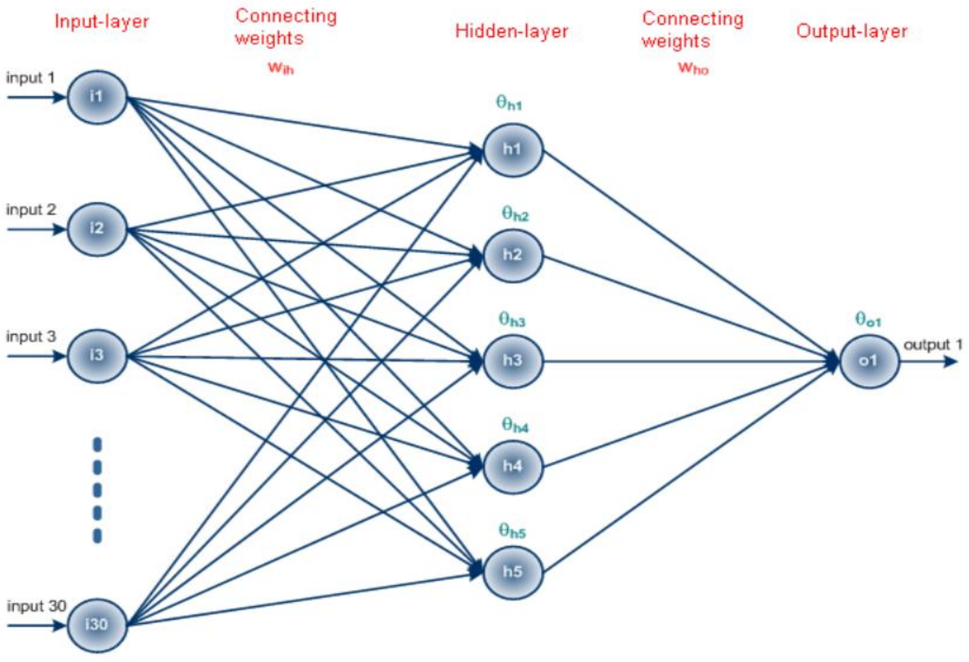


Figure 4-1 Structure of a simple fully-connected neural network with three layers

4.4 Artificial Neuron Model

The artificial neuron is basic building block of every ANN, and it is represented as a Process Elements (PEs) (Zurada, 1992). Every neuron model consists of a processing element with synaptic input connections and a single output (Zurada, 1992). The artificial neuron model was represented as simple mathematical models which contain three primary set rules. These rules are reception and multiplication rule, summation rule, and the activation rule.

In the reception and multiplication rule, the assumptions from the previous studies showed that the artificial neuron should have a local memory in order to implement localized data processing operations. In this context, the artificial neuron act as the receptor of a set of ’n’ inputs xi arrives either from environment or from the output of other neurons in the neural network, when (i = 1, 2,……, n). Thus, each input is weighted before it reaches the main body of processing element by connection strength, or the weight factor corresponding to the synaptic strength (i.e. every input value is multiplied with the individual weight) (Sivanandam, 2009).

Consequently, the amount of information about the input that is required to solve the problem is stored in the form of weights. The weighting factor in the reception and multiplication rule is limiting or amplified the input signals, in order to constitute the special connectivity between the signal source and the neuron. Hence, the learning process would adapt these weights to the specific problem (Lara, F., 1998).

In the summation rule, the summation is executed for all weighted inputs and bias by the respective synapses of the neuron (Hajek, 2005). In this context, the core idea of the activation rule is centered on entering the summation rule results to a function called transfer function to produce the output of the neuron (Singh and Verma, 2011). Figure (4-2) indicates the rules implementation for a nonlinear transfer function. The equation that is used to compute the rules is:

$$y_j = f_i \left(\sum_{i=0}^{n} wij\ xi - Ti\ \right)$$

Where:

- **y_j** : *The output at node j.*
- **x_i** : *The input from node i.*
- **w_{ij}** : *The weight between nodes i and j.*
- **T_i** : *The threshold of the node.*
- **f_i** : *A non-linear transfer function such as, Sigmoid or Hyperbolic.*

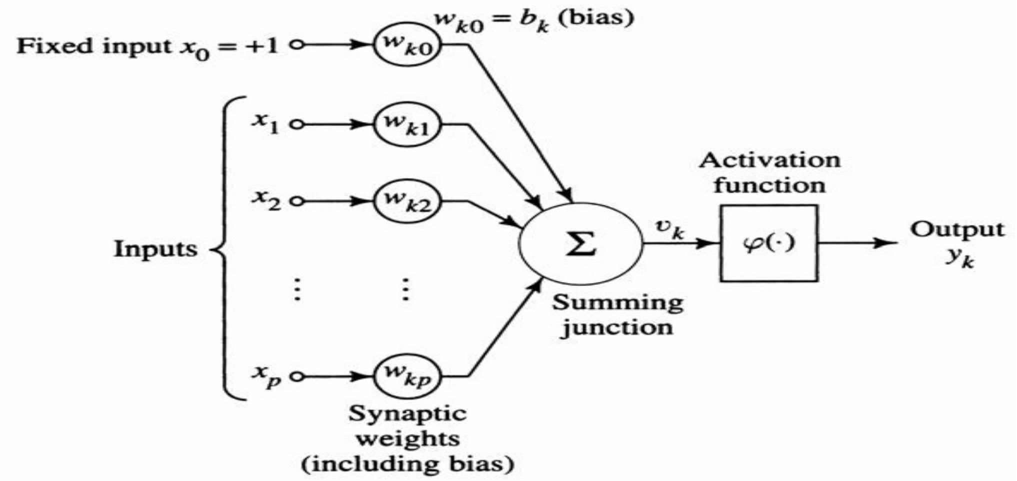


Figure 4-2 Neuron model

4.5 Classification of ANN

Basically, the ANN can be classified according to pattern of connection between neurons (i.e. topology of the neural network), the raw materials or the type of inputs (e.g. binary, images…etc.), the mechanism and the behavior of propagation of activation function applied among neurons and weights, or the type of algorithms of learning that is responsible to show the method of determining weights on the connection (Sivanandam, (2009). Figure (4-3) illustrates the hierarchical classifier used in ANN.

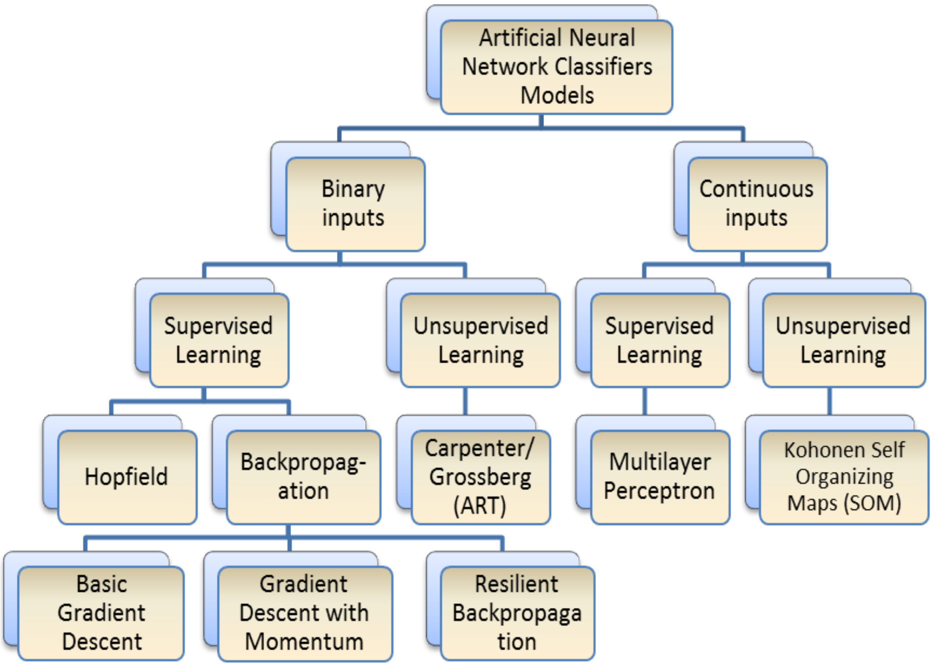


Figure 4-3 the hierarchical ANN Classifiers

In this context, ANN achieved better features from pattern recognition tasks point of view compared with modern Artificial Intelligent (AI) techniques (Hajek, 2005). Table (4-1) shows the primary features existed in the ANN.

Features	Evidence
Robustness and fault tolerance	The decay of cells never does seem to affect the performance significantly.
Nonlinearity	A neuron is basically a nonlinear device.
Contextual information	Knowledge is represented by structure and activation state of a neural network.
Flexibility and adaptively	The network automatically adjusts its synaptic weights to a new environment without using any preprogrammed instructions.
Ability to deal with a variety of data situation	The network can deal with information that is fuzzy, probabilistic, noisy and inconsistent.
Collective computation	The network performs routinely many operations in parallel and also a given task in distributed manner.
Uniformity of analysis and design	Neural networks working as information processors.

Table 4-1 Features of neural networks (Yegnanarayana, 2009).

4.6. Architecture of ANN

Indeed, the neurons or the processing elements have the same behavior and fully ordered elements. Moreover, in each layer these neurons are either fully interconnected or not connected at all. Thus, these neurons have the same activation functions. Hence, the arrangement of neurons in layers and the style of connection between elements called the ANN architecture (Sivanandam, 2009).

The external specification of the problem represented as a set which determine the number of inputs to the target network. Thus, if the neuron has received one input then it is called single-input neuron. Otherwise, it is called Multiple-Input Neuron when the neuron has more than one input (Hagan et al., 1996). Neural networks are often classified as single layer or multilayer (Fausett, 2008).

Therefore, in case of single-layer network it contains one layer of connection weights. Thus, the basic units are the input units that are responsible for receiving signals from the environment. Furthermore, the output units are represented as the response of the network that can be read (e.g. results). Figure (4-4) shows the general framework of single layer of neural network.

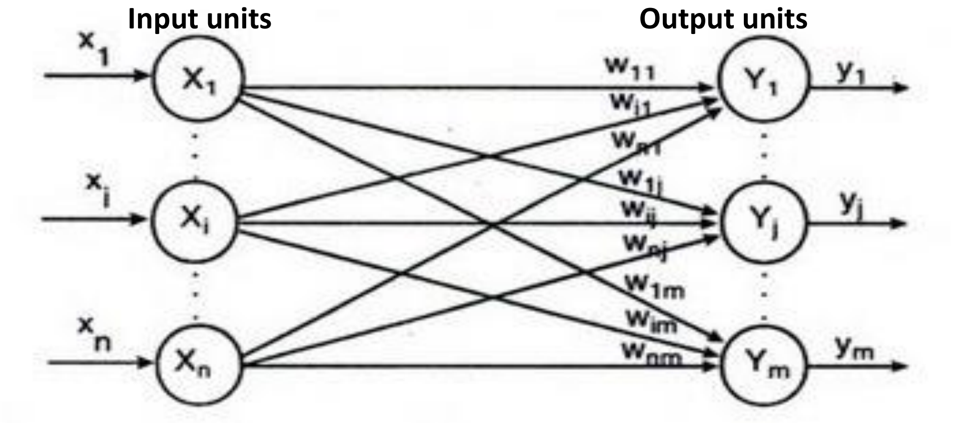


Figure 4-4 Single-layer neural net

On the other hand, the multilayer network is consisted into one or more layers (i.e. levels) of neurons. Furthermore, these neurons (i.e. nodes) are known as hidden units which are located between the input and output units. Figure (4-5) shows the relationship between the input and output units in the multilayer networks. The need to use multilayer networks arise when the complicated mapping problems existed and represented as a challenge for using single layer network. In this context, using multilayer networks leads to have a successful and difficult training way ().

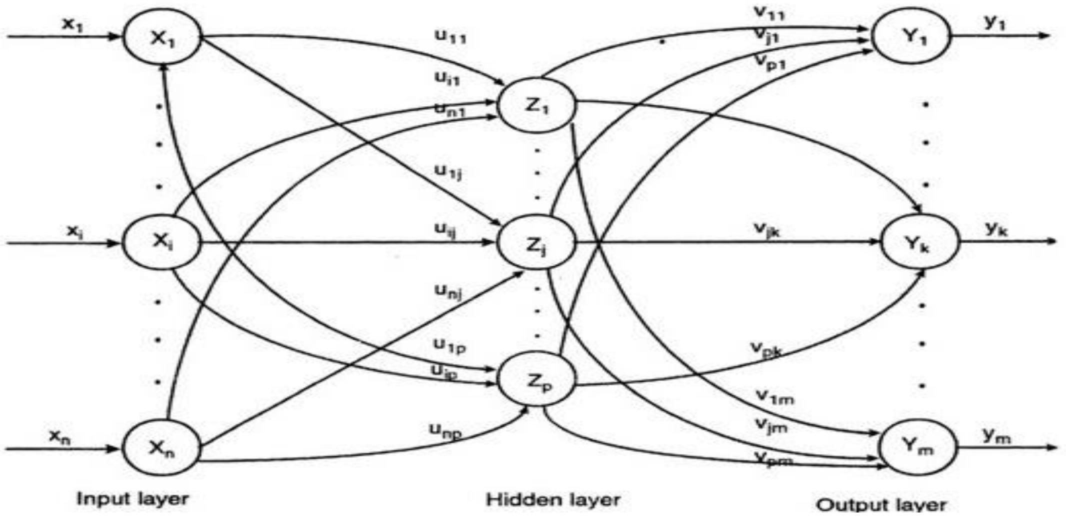


Figure 4-5 A multilayer neural networks

In order to determine the complexity of a specific function, it is necessary to specify the functions that are almost have arbitrary complexity with the number of layers (i.e. the number of hidden layers). Therefore, both the number of units in each layer and the number of hidden layers have a relationship with function's complexity (Eluyode. and Akomolafe, 2013).

4.7. Models of ANN

Two primary models are found in the field of ANN. Feed-Forward Networks (FFN) model is capable to allow signals to be transferred in the forward directions (i.e. from the input toward the output units). This model is represented depending on the association between inputs and outputs. Hence, in this model no feedback or cycles which leads to make isolation between input and output units (i.e. the output of any layer does not affect the same layer input units (King and Pribram, 2013).

The second model is called Feedback networks. The basic idea behind this model is to allow signals to be propagated in form of bidirectional by introducing cycles in the network. In this model the outputs are depend on the inputs and on the previous input as well. In this scenario, the feedback network model is dynamic and extremely complicated model. Hence, there are continuous changes until reach the equilibrium point (Eluyode and Akomolafe, 2013). Figure (4-6) shows an illustration of feedback network architecture.

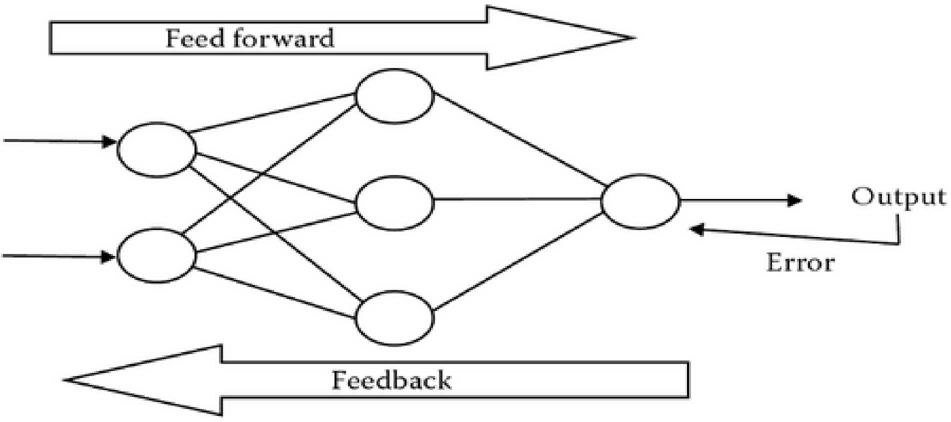


Figure 4-6 A diagram of feed-forward & feedback networks

4.8. ANN Learning

Basically, many studies showed the importance of learning processes in ANN. Thus, these studies focused on showing the main rules based on adjusting the weights of network (Haykin 2004). The learning rules which are found in the field of ANN are summarized in Table (4-2) that shows each learning rule and its goal.

Learning Rules	The main target
Error-correction learning rule	The goal is to minimize the cost function to correct the errors (e.g. Delta Rule or Widrow-Hoff).
Hebbian learning rule	These are the oldest and most famous of all learning rule. It is used to change weights on connections from the output to the input layer. As a result, an input pattern calls a pattern on the output layer, which in turn of projects the prototype of the winning group back onto the input layer.
Competitive learning rule	A process in which the output layer neurons compete among themselves to acquire the ability to fire in response to a given input patterns. A winner-take-all CLN (Competitive Learning Network) consists of an input layer and a competition, or output layer.
Memory–Based learning rule	All algorithms in this category involve two essential ingredients: - Criterion used for defining the local neighborhood of the test vector X, - Learning rule applied to the training examples in the local neighborhood of X.
Boltzmann learning rule	Can classified it within a stochastic learning algorithm derived from ideas rooted in statistical machines. The neurons constitute a recurrent structure and they operate in a binary manner. The machine is characterized by an energy function E.

Table 4-2 ANN learning rules (Haykin, 2004).

4.9. Learning Models

ANN learns by training and the type of learning determined by the manner in which the parameter changes. Learning process in ANN can be classified into:

Supervised learning Model

Supervised learning is needed to external teacher to assist in learning the neural network by routing the neural network what the desired output to a given motivation should be. The desired output is then used to create an error signal that adapts the weights of the network by comparing each current output with a desired output to an input signal as shown in figure (4-7) (Priddy and Keller 2005). An important concerning is the problem of error convergence, which is the minimization of error between the desired output and computed unit values; the aim is to determine a proper set of weights which minimize the error E by:

$$E=\| Z - Y \|$$

Using Mean Square Error (MSE) as following:

$$1/\mathrm{n}\sum_{i}^{n}(\mathrm{zi}-\mathrm{yi})2$$

Where z is the desired output and y is the ANN computed value (current output).

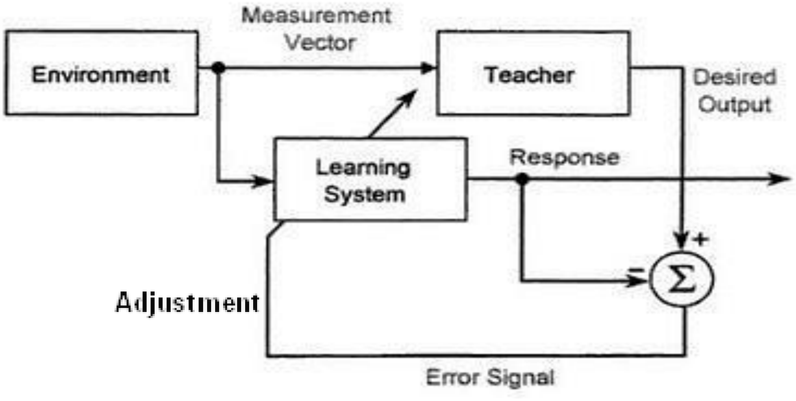


Figure 4-7 Block diagram of supervised-learning model

Unsupervised learning Model

The unsupervised learning or self-organized learning *"is a machine learning technique that sets parameters of an artificial neural network based on given data, when the network is not given any external indication (i.e. without of using desired output). What the correct responses should be nor whether the generated responses are right or wrong"* (Krenker, et.al, 2011).

In unsupervised learning aims to determine how the data is organized by learning the network only on the local input pattern and find regularization in the data presented by the exemplars as shown in Figure (4-8) (Al-Rashdan, 2011).

Unsupervised learning is much more important than supervised learning since it likely to be much more common in the brain than supervised learning. The kind of learning is determined by the way in which the changes to network parameters have done. (Kumar and Thakur, 2012).

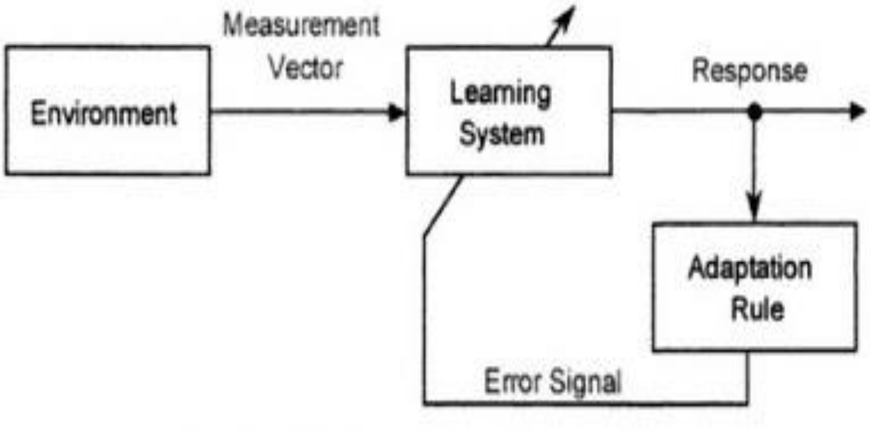


Figure 4-8 block diagram of unsupervised-learning model

Reinforcement Learning Model

The reinforcement learning is a type of learning may be considered as an intermediate form of the supervised learning, which the system is provided with the desired output, and the unsupervised learning, in which the system gets no feedback at all (Dongare, et. al, 2012).

In this technique the learning machine does some action on the environment and receives a feedback response from the environment. Hence, to tell whether the output response is right or wrong. In contrast, there are no information is provided on what the right output should be. The weights adjustments are continued until equilibrium state occurs. Figure (4-9) show the block diagram of reinforcement learning model.

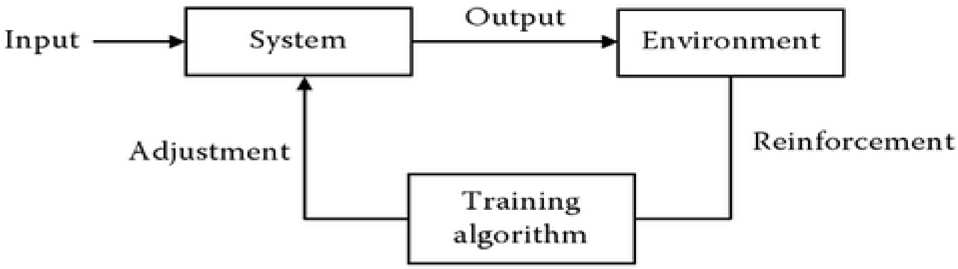


Figure 4-9 block diagram of reinforcement learning model.

Semi-Supervised learning Model

Al-Rashdan, (2011) defined the Semi-supervised learning is a relatively new area of research which combines unsupervised and supervised learning approaches (Al-Rashdan, 2011). Generally, these approaches use unsupervised learning techniques to learn the structure of data, making it easier to identify the ‘most interesting’ examples in a training set. This enables a supervised learning technique to gain better performance with fewer labeled examples.

Hybrid learning

Hybrid Learning is the newer learning technique. Thus, it is a combination between supervised learning and unsupervised learning.

4.10. The stability-plasticity dilemma

One of the drawbacks which is facing artificial and biological neural systems is the stability-plasticity dilemma. The basic idea is that learning in a parallel and distributed system requires plasticity for the integration of new knowledge, but also stability in order to prevent the forgetting of previous knowledge. The old learning being constantly forgotten when increasing the plasticity, also, increasing stability will impede the efficient learning at the level of the synapses (Mermillod et al 2013).

Freeman and Skapura, (1991) have been describing what Stephen Grossberg calls the stability/ plasticity dilemma by following questions:

- How can a learning system remain adaptive (plastic) in response to significant input, yet remain stable in response to irrelevant input patterns?
- How does the system known to switch between its plastic and its stable modes?
- How can the system retain previously learned information while continuing to learn new things? (Freeman and Skapura, 1991)

Grossberg and Carpenter have developed adaptive resonance theory (ART) to answers such questions and solving the stability/plasticity dilemma by adding a feedback mechanism between the competitive layer and the input layer of a network. This feedback mechanism facilitates the learning of new information without destroying old information, automatic switching between stable and plastic modes, and stabilization of the encoding of the classes done by the nodes. The results from this approach are (ART family) neural network architectures that are particularly suited for pattern classification problems in realistic environments.

4.11. Adaptive Resonance Theory (ART)

The ART was proposed to deal with the forgetting problem of ANNs. Furthermore, this forgetting poses a problem for traditional ANNs, because the previous learning is fading with time and prone to forget when is not revised a long time, even as the ANNs continues to learn newer rules (Shukla et al, 2012).

Many types of ART were found in the field of ART. Each ART type have its own core idea such as ART1, ART2, ART3, Fuzzy ART, ARTMAP, and Fuzzy ARTMAP (Grossberg, 2013). Table (4-3) shows the basic idea for ART types. In this research, we focused in only ART1 algorithm, which will be explained in detail and applied in the intrusion detection system simulation.

ART Type	**Supervised / Unsupervised Learning**	**The basic idea**
ART 1	Unsupervised	Is the simplest variety of ART networks, accepting only binary inputs.
ART 2	Unsupervised	Extends network capabilities to support continuous inputs.
ART 3	Unsupervised	Is network performs parallel searches of distributed recognition codes in multilevel network hierarchy.
Fuzzy ART	Unsupervised	The network is almost exactly the same as ART1, except that it can also handle continuous input pattern implements fuzzy logic into ART's pattern recognition.
ARTMAP	Supervised	Also known as predictive ART combines two slightly modified ART-1 or ART-2 units into a supervised learning structure.
Fuzzy ARTMAP	Supervised	Is merely ARTMAP using fuzzy ART units, resulting in a corresponding increase in efficacy**.**

Table 4-3 the types of ART techniques and its analysis (Priddy and Keller 2005).

4.12. ART1 Learning

The ART1 network has two separate learning laws (Hagan,1996):

- X connections from F1 layer to F2 layer, it uses a type instar learning to learn to recognize a set of prototype patterns.
- Y connections weight from F2 layer to F1 layer and also called it expectations pattern, uses outstar learning in order to reproduce (or recall) a set of prototype patterns.

Freriks, et.al (1992) confirm when implementing ART1training algorithm, the F2 layer nodes produces output Y (expectations pattern) is associated with input vector S, this output node represents a cluster. The combining input vector into the cluster to stress this relation between them. The way this is done in ART1 is a winner-take-all method, which means, that only weights to and from the winning node j are allowed to change. Thus Adaptive Resonance name come from weights will be adapted if input pattern and LTM-prototype resonate, i.e. weights only change if an association is made.

During learning, bij weights and tji weights have to be distinguished. The bij vector in LTM to the winning node becomes:

$$\mathrm{b}_{ij} = \frac{L * X}{L + ||\mathrm{X}||^2 - 1}$$

In which L can be seen as a normalization parameter, where L > 1

Adjustment of the top-down vector from the winning node is easier:

$$t_{ji} = X$$

The type of learning used here is so called fast learning, which means that an input is stored into LTM in only a few learning cycles. Learning in this ART network is even very fast. After adjustment of the weights, the input is totally incorporated into LTM. It’s clear from these equations becomes the prototypes in LTM are smaller during learning. The process of blend of fast learning and prototypes which are decreasing, this will lead to changing prototypes very often.

When the LTM is not totally adapted to the present input pattern during one learning cycle but only partially, that operation is called slow learning is the opposite of fast learning. Only if the same input pattern is applied to the network and assigned to the same cluster repeatedly it can be totally stored into LTM. In this way prototypes can be a mixture of the patterns which are stored into the same cluster, but it can take a long time before LTM stabilizes.

4.13. Resonance of ART1

It’s not necessary to update the bij connections weight and t_{ji} connections weights in the same time. Whenever the input pattern X and the F2 output Y (i.e. expectation) have an adequate match (e.g. similarity factor), as determined by orienting subsystem (i.e. vigilance test), both b_{ij} and t_{ji} are adapted. This process of matching, and subsequent adaptation, is referred to as resonance, which is the name of adaptive resonance theory (Hagan, 1996).

Chapter Five

Proposed Model and Methodology of the IDS Based on (Carpenter/Grossberg-ART1ANN)

Chapter Five
Proposed Model and Methodology of the IDS based on (Carpenter/Grossberg-ART1ANN)

5.1 Introduction

In different approaches, there are many researchers that have attempted and successfully used neural networks for intrusion detection. This chapter shows the IDS model which used KDD 99 dataset as an intrusion environment in order to train this model, intended to classify the normal and attack patterns and the type of the attack. Besides, the researcher clarifies all phases that include its units in details.

5.2 Proposed Model

In this study, the researcher builds a model IDS, which it depended on artificial intelligence and machine learning via artificial neural network that its performance has been enhanced by the former application of one of clustering algorithm as initial classifier.

The IDS model uses both; unsupervised learning of ART1 (which is one of Carpenter/Grossberg's ANN) that it is the main part in this system and k-mean clustering algorithm (which is considered machine learning) as shown in Figure (5-1).

The simulation system includes three main phases:

1. Preprocessing, which contains receive, convert, and cluster the categories.
2. Training phase, which trains ART1 neural network.
3. Testing phase, which tests ART1 network by getting best results and ensuring its stability.

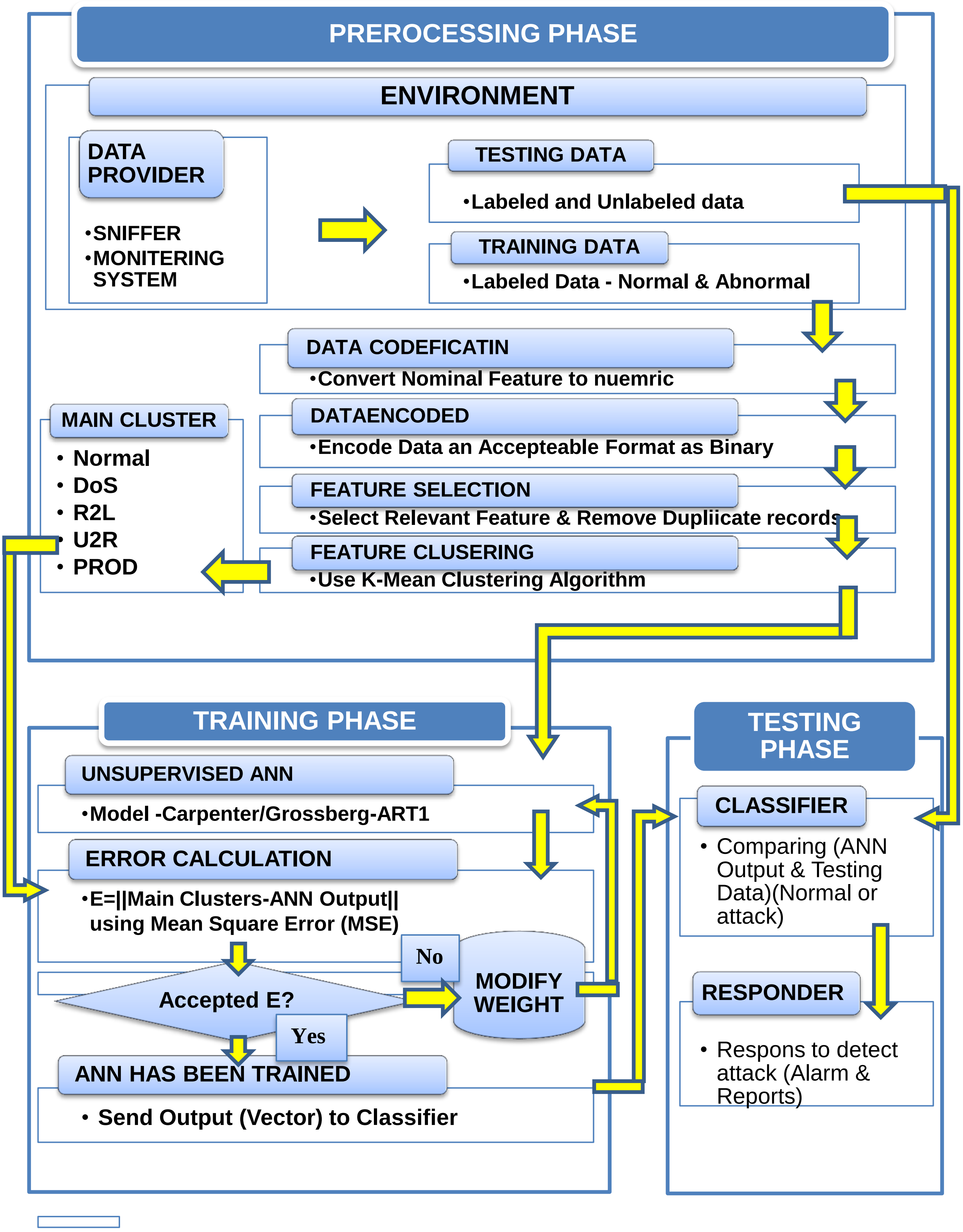

PREROCESSING PHASE
ENVIRONMENT
DATA PROVIDER
•SNIFFER
•MONITERING SYSTEM
TESTING DATA
•Labeled and Unlabeled data
TRAINING DATA
•Labeled Data - Normal & Abnormal
DATA CODEFICATIN
•Convert Nominal Feature to nuemric
DATAENCODED
•Encode Data an Accepteable Format as Binary
FEATURE SELECTION
•Select Relevant Feature & Remove Dupliicate records
FEATURE CLUSERING
•Use K-Mean Clustering Algorithm
MAIN CLUSTER
• Normal
• DoS
• R2L
• U2R
• PROD
TRAINING PHASE
UNSUPERVISED ANN
•Model -Carpenter/Grossberg-ART1
ERROR CALCULATION
•E=||Main Clusters-ANN Output||
using Mean Square Error (MSE)
Accepted E?
No
MODIFY WEIGHT
Yes
ANN HAS BEEN TRAINED
• Send Output (Vector) to Classifier
TESTING PHASE
CLASSIFIER
• Comparing (ANN Output & Testing Data)(Normal or attack)
RESPONDER
• Respons to detect attack (Alarm & Reports)

Figure 5 - 1 diagram of Intrusion Detection using Carpenter/Grossberg Model

5.3 The Proposed Model Phases

Our proposed model structure is composed of three main phases; preprocessing phase, training phase, and testing phase. Each phase represents and feeds the next phase with the needed data in an efficient format, as an attempt to get more workflow and efficient intrusion detection system.

5.3.1. Preprocessing Phase

The preprocessing phase consists of several units. It receives and collects traffic data from external world (environment), selects appropriate features, converts features into numerical form and then encodes into acceptable format as a binary based on ANN Algorithm, and then sends this coded data to the clustering unit. The description of units works as follow:

(A) The Environment Unit

This work deals with KDD Cup 99 intrusion detection dataset in which provides designers for intrusion detection systems (IDSs) with a benchmark on which to evaluate different methodologies. The KDD Cup 99 dataset, originally developed by the DARPA1998 IDS evaluation program, DARPA’98 is about 4 gigabytes of compressed record (binary) tcpdump data of 7 weeks of network traffic, which can be processed into about 5 million connection records; each one contains about 100 bytes. The two weeks of test data have about 2 million connection records (Tavallaee, 2009), (Song et al., 2014).

Basically KDD Cup 99 dataset consists of approximately 4,900,000 connection records plus can be involves as 10% KDD, Corrected KDD or Whole KDD (Kayacik, et al. 2005). Since “10% KDD” is employed as the training set in the original competition. It performed analysis on the “10% KDD” dataset approximately 500,000 records in which can be divided either binary class case as 97,278 are considered normal and 396,744 are labelled as attacked or a multiple class case as normal pattern and 22 different attack patterns that can be classified into 4 main categories (Olusola et al., 2010), (Kumar et al., 2013), (Song, et al., 2014). In this research, it considered the 10% KDD of KDD Cup 99 dataset as a multiple category case (5 categories: Normal, DoS, U2R, R2L, and Prob).

The KDD Cup 99 data set has 41 features for each connection record plus one class label as shown in Table (5-1). Some features are derived features, which are useful in distinguishing normal connection from attacks. These features are either nominal or numeric (Olusola, et al 2010), (Chebrolu et al. 2004); Features are grouped into four categories:

(1) Basic Features: its can be derived from packet headers without inspecting the payload.

(2) Content Features: These features that look for suspicious behavior in the payload of the data packets because the previous attacks are embedded in the data packets such as the number of failed login attempts.

(3) Time-based Traffic Features: These features are designed to capture only the connections in the past two seconds that have the same destination host as the current connection.

(4) **Host-based Traffic Features**: Host based features are therefore designed to assess attacks, which span intervals longer than two seconds, by Utilize a historical window estimated over the number of connections to the same destination host. (Chebrolu and et al. 2004), (Kayacik et al. 2005), (Tavallaee, 2009).

No	Feature Name	Feature Type		No	Feature Name	Feature Type	
1	Duration	Cont.	Basic features of individual TCP connections.	22	is_guest_login	Disc	
2	protocol_type	symbolic		23	count	Cont.	Traffic features using a two-second time.
3	Service	symbolic		24	serror_rate	Cont.	
4	Flag	symbolic		25	rerror_rate	Cont.	
5	src_bytes	Cont.		26	same_srv_rate	Cont.	
6	dst_bytes	Cont.		27	diff_srv_rate	Cont.	
7	Land	Disc.		28	srv_count	Cont.	
8	wrong_fragment	Cont.		29	srv_serror_rate	Cont.	
9	urgent	Cont.		30	srv_rerror_rate	Cont.	
10	Hot	Cont.	Content features in a connection suggested by domain knowledge.	31	srv_diff_host_rate	Cont.	
11	num_failed_logins	Cont.		32	dst_host_count	Cont.	
12	logged_in	Disc		33	dst_host_srv_count	Cont.	
13	num_compromised	Cont.		34	dst_host_same_srv_rate	Cont.	
14	root_shell	Cont.		35	dst_host_diff_srv_rate	Cont.	
15	su_attempted	Cont.		36	dst_host_same_src_port_rate	Cont.	
16	num_root	Cont.		37	dst_host_srv_diff_host_rate	Cont.	
17	num_file_creations	Cont.		38	dst_host_serror_rate	Cont.	
18	num_shells	Cont.		39	dst_host_srv_serror_rate	Cont.	
19	num_access_files	Cont.		40	dst_host_rerror_rate	Cont.	
20	num_outbound_cmds	Cont.		41	dst_host_srv_rerror_rate	Cont.	
21	is_hot_login	Disc		42	Lable	Symbolic	

Table 5-1 KDD Cup 99 Feature Columns Name and Type

The function of environment unit provides the dataset to the system, and then the system selects sample space randomly for training dataset (10,000 records are Labeled Data - Normal and Abnormal), Since the records number for each attack is not equal in dataset, thus the selected sample space in training phase is not equal in term of attack type. Consequently the chosen mechanism progressively begins from the smallest representation to normal and attack type are more appearing in dataset. Whereas the system randomly selects sample space in testing dataset as (10,000 records are Labeled and 3000 records Unlabeled data - Normal and Abnormal).

(B) Data Codification Unit

The raw data from the above unit will be converted from its current unacceptable format such as symbolic (nominal) into an accepted numeric ANN format. To meet this we will apply converting data depending on the column content analyzing as follow:

- **Nominal 2 Numeric:** when a feature contains a symbolic (nominal) value such as protocol, service, flag and label are transformed to numeric values using customize transformation table. Each column has its own customization table. This step should be applied for the testing data set as done in the training data set. As shown in Tables (5-2) and (5-3).

- **Implemented scaling:** when a feature contains a big number values or a floating-point numbers (between 0 and 1), such as (650,220,000), (0.1, 0.004) respectively, then it would be coded to serial numbers as demonstrated in Table (5-5) Carpenter/ Grossberg (ART1) Net is used with discrete binary input. Therefore, it is difficult to encod this feature to binary, since numbers above often take huge values.

Protocol type	**No.**
TCP	**1**
ICMP	**2**
UDP	**3**

Table 5-2 Transformation for Protocol Feature No.2

Flag	**No.**	**Flag**	**No.**
OTH	**1**	**S1**	**7**
REJ	**2**	**S2**	**8**
RSTO	**3**	**S3**	**9**
RSTOS0	**4**	**SF**	**10**
RSTR	**5**	**SH**	**11**
S0	**6**		

Table 5-3 Transformation for Flag Column Feature no.3

No.	Attack Name	Attack Cluster	No.	Attack Name	Attack Cluster
1	Normal	Normal	3	Back	DoS
7	Ipsweep	Prob	15	Land	
11	Nmap		2	Neptune	
9	Portsweep		10	Pod	
5	Satan		8	Smurf	
19	ftp_write	R2L	13	buffer_overflow	U2R
12	guess_passwd		18	Loadmodule	
16	Imap		17	Rootkit	
20	Multihop		22	Perl	
21	Phf				
23	Spy				
6	Warezclient				
14	Warezmaster				

Table 5-4 Sub Attack cluster into Main Attack type

No.	Feature has big values	No.	Feature has a floating-point number (between 0 and 1).
1	1	1	0
2	15500	2	0.001
3	808888	3	0.02
4	77700077	4	0.9
5	112220000	5	1

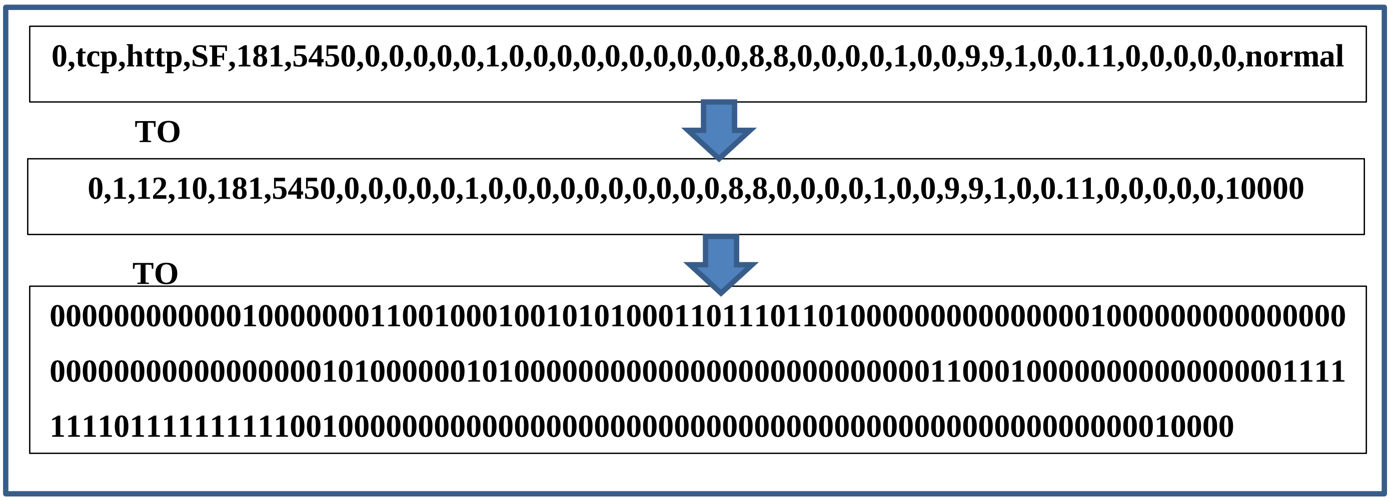
Table 5-5 Feature has big values and Feature has a Floating-Point Number.

(C) Data Encoding Unit

The Adaptive Resonance Theory (ART1) classifier is one of kinds of the Carpenter\Grossberg ANNs. ART1 accepts the inputs and targets only in the form of binary data (i.e. 0 or 1). So processing of the data according to the demand of neural network architecture plays an important role in their successful implementation (i.e. generate an acceptable data format for ART1, by encoding incoming data to binary format) (Kavuri and Kundu, 2011).

In the work of Liu, et al (2002), they use binary encoding in order to generate homogeneous code and a homogeneous environment. Binary encoding method is the most common encoding method (Liu, et al 2002). Gong, et al (2013) indicated that the compact binary strings can enable large efficiency gains in storage and computation speed for similarity (Gong, et al 2013).

In this model, the researcher uses binary encoding with adaptive representation according to a long of feature for each character of those network data vectors as input for our ART1 classifier. So, as they can see the binary representation for a 41-features data vector will be very long as shown in Figure (5.2), for this the database size is very huge taken in mind that all data vectors in the environment unit is encoded binary.



0,tcp,http,SF,181,5450,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0,0,0,0,1,0,0,9,9,1,0,0.11,0,0,0,0,0,normal

TO

0,1,12,10,181,5450,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0,0,0,0,1,0,0,9,9,1,0,0.11,0,0,0,0,0,10000

TO

```
000000000000100000001100100010010101000110111011010000000000000001000000000000000
000000000000000001010000001010000000000000000000000000110001000000000000000001111
11110111111111100100000000000000000000000000000000000000000000000000010000
```

Figure 5-2 Transformation and encoding data process

(D) Feature Selecting Unit

Feature selection is the operation of choosing a subset of relevant features which it used in model structure. When using a feature selection technique in KDD99 dataset, that the data contains many irrelevant features or redundant records that provide no more useful information than the currently selected features in any context, because these extra features can increase the process of computation time to make classifications, as well as it has an effect on the accuracy of the clustering and classifier built. These techniques are concentrated on obtaining a subset of features that sufficiently describe the problem (Song, et al. 2014).

The researcher intends to reduce the dataset dimensional in both; vertically and horizontally like as numbers of records by removing the redundant records and number of features by breaking up the irrelevant features. Dataset change number records from (494,021) to (145,587) records as shown in Table (5-6) and its features become less, from (41) to (25) features. It is considered the basis for high-performance intrusion detection using machine learning methods.

Attack Types	Number of Records before remove duplicate	Number of Records after remove duplicate
Normal	97277	87832
Denial of Service	391458	54572
Remote to User	1126	999
User to Root	52	52
Probing	4107	2139
Total	494020	145586

Table 5-6 Compression between numbers of records before\after remove duplicate

(E) Feature Clustering Unit

Clustering technique can be considered as the important part of our model. Sahu and Jena (2014) stated that the clustering is categorizes the groups data objects based only on the information found in the data that display the objects and their relationships with finding a structure in a group of the data. The aim of the clustering is a combination of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters (Sahu and Jena 2014). The cause of its simplicity and efficiency K-means clustering algorithms would be used as a clustering method.

K-means Clustering Algorithms

The K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem (Faraoun and Boukelif, 2006).

Liu, et al (2014) defined k-mean as a sort of indirect clustering method based on statistical properties and distance measures between patterns to classify the data objects. The objective function of this technique is to define a distinct k centroid or mean for each cluster, where k is the number of cluster, which divides n data objects based on features into k clusters with minimum standard deviation, by determined it automatically in the process of clustering (Liu, et al. 2014).

A distance function is required in order to compute the distance (i.e. similarity) between two objects. The Euclidean is the most commonly used distance function, which is define as: Formula

$$d(x, y) = \sqrt{\sum_{i=1}^{m} (xi - yi)^2} \dots\dots\dots\dots.(5-1)$$

In previous equation (5-1) two input vectors are with m quantitative features where x = (x1,… , xm) and y = (y1,….,ym) .In the Euclidean distance function, all features contribute equally to the function value. (Münz, et al, 2007).

Riad, et al (2013) is described the general steps for the K-means algorithm as follows:

1. Number of clusters (K) is choosed

2. Centroids Initialization

3. Each pattern Assigned to the cluster with closest centroid

4. Means of each cluster is calculate to be its new centroid

5. Repeat step 3 until stopping criteria is met

6. The best clustering solution was chosen after repeating this procedure 10 times (Riad, et al. 2013)

The following Figure 5-3 demonstrates the pseudo code of k-mean algorithm:

```
MSE=large-number;
Select initial cluster centroids$\{mj\}_j^k = 1$;
Select clusters number k
Do
    Old-MSE=MSE;
    MSE1=0;
    For j=1 to k
        mj=0; nj=0;
    end for
    For i=1 to n
        For j=1 to k
            Compute squared Euclidean distance d2(xi, mj);
        end for
        Find the closest centroid mj to xi;
        mj=mj+xi; nj=nj+1;
        MSE1=MSE1+d2(xi, mj);
    end for
    For j=1 to k
        nj=max(nj, 1); mj=mj/nj;
    end for
    MSE=MSE1;
while (MSE<Old-MSE)
```

Figure 5-3 k-mean algorithm pseudo code

The first function is the basic function of the k-means algorithm, it is used in to find the nearest center (k) for each data point, it is based on computing the distances between each data point and the centers, then the minimum distance kept in a especial table in our system database. The first function is shown in Figure (5-4), to keep the distance between each point and its nearest cluster. This function is called distance () (Al-Rashdan, 2011).

```
`Function distance()
//assign each point to its nearest cluster
For i=1 to n
    For j=1 to k
        Compute squared Euclidean distance d2(xi, mj);
    end for
    Find the closest centroid mj to xi;
    mj=mj+xi; nj=nj+1;
    MSE=MSE+d2(xi, mj);
    Clusterid [i]=number of the closest centroid;
    Pointdis[i]=Euclidean distance to the closest centroid;
end for
For j=1 to k
    mj=mj/nj;
end for
```

Figure 5-4 Pseudo Code of the K-Mean Function Distance ( ) -

The other function is shown in Figure (5-5), is called distance-new ( ). Line 1 finds the distance between the current point i and the new cluster center assigned to it in the previous iteration, if the computed distance is smaller than or equal to the distance to the old center, the point stays in its cluster that was assigned to in previous iteration, and there is no need to compute the distances to the other k−1 centers. Lines 3~5 will be executed if the computed distance is larger than the distance to the old center, this is because the point may change its cluster, Lines 9 and 10 keep the cluster id, for the current point assigned to it, and its distance to it to be used in next iteration of that function. This information allows this function to reduce the distance calculation required to assign each point to the closest cluster, and this makes the function faster than the function distance in Algorithm as shown in Figure (5-4). In the second implementation, in our system implementation the function distance () is executed two times, while function distance_new () is executed the reminder of iteration. This implementation referred to as "enhanced k-means" algorithm.

```
Function distance_new ()

//assign each point to its nearest cluster

    12) 1 For i=1 to n
          Compute squared Euclidean distance d2(xi, Clusterid[i]);
          If (d2(xi, Clusterid[i])<=Pointdis[i])
          Point stay in its cluster;
    13)  Else
    14)   For j=1 to k
    15)   Compute squared Euclidean distance d2(xi, mj);
    16)   End for
    17)  Find the closest centroid mj to xi;
    18)   mj=mj+xi; nj=nj+1;
    19)   MSE=MSE+d2(xi, mj);
    20)   Clustered[i]=number of the closest centroid;
    21)   Pointdis[i]=Euclidean distance to the closest centroid;
    22)  endfor
```

Figure 5-5 Pseudo Code of The K-Mean Function Distance- new ( )

The results of K-mean will be saved in a particular table then we will pass it to the training unit (Carpenter /Grossberg ANN ART1) in order to re-cluster to get more representative clusters.

5.3.2. Training phase

The key component of this phase is the Unsupervised Learning (USL) neural network (Carpenter /Grossberg ANN- ART1 Algorithm) is implemented when a collection of input patterns needs to be appropriately clustered into categories (clustering algorithm as it mentioned in (Hartigan, 1975) which are similar to the so called Simple Sequential Leader Clustering Algorithm. This Algorithm selects the first input as the exemplar of the first cluster; the next input is compared to the first cluster exemplar. It follows the leader and is clustered with the first if the distance between the it and a leader is less than a given threshold, i.e. is classified as the leader, otherwise it is the exemplar of a new cluster, this process is repeated for all following inputs which mean number of clusters will grows with time and also depend on the threshold and distance metric used to compare inputs to cluster exemplars (Tyugu, 2007). In this proposed ANN model we will use three layers (input, hidden, output) as Figure (5-6) clarify.

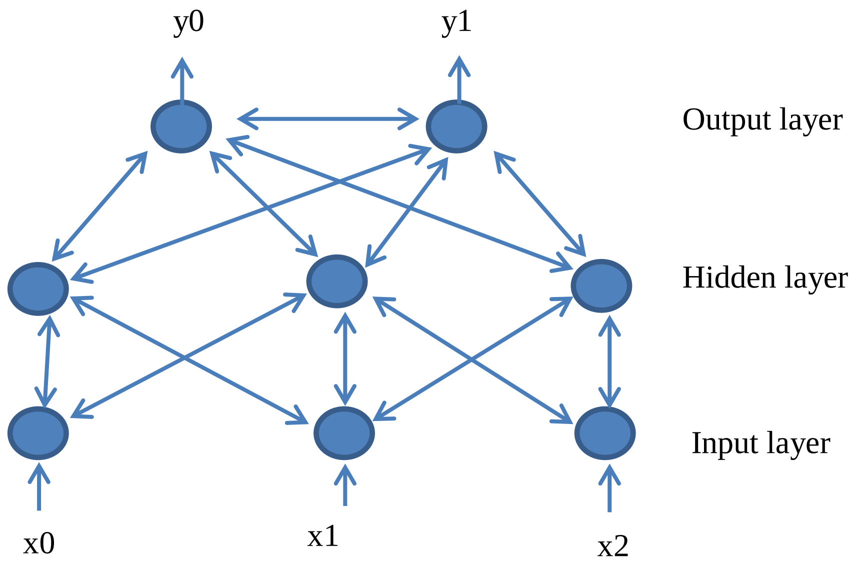


Figure 5-6 Carpenter/Grossberg net for three binary and two classes

The mean function of this phase can be described as a training the system for intrusion detecting.it will act as classifier unit, by classify KDD 99 records inputs data based on their similarity, ART1 nets are used in our model for clustering and classifying network traffic into normal and intrusive, where learning process should be stable.

ART1 is designed to allow the user to control the degree of similarity of patterns placed on the same cluster. This can be done by tuning the vigilance parameter in such net. In ART1, the number of clusters is not required to be determined previously, so the vigilance parameter can be used to determine the proper number of clusters in order to decrease the probability of merging different types of clusters into the same cluster.

(A) ART1 Architecture

Historically the first (and simplest) member of the ART family is ART1. The basic architecture of an adaptive resonance neural net involves three parts: attentional subsystem, the orienting subsystem and gain control.

- **Orienting Subsystem** (Reset Mechanism)

  Depending on the similarity between the top down weight (tji) and the input vector X, the cluster unit is allowed to learn a pattern or not. This is done at the reset unit, based on the signals it receives from the input and interface portion of the F1 later. If the cluster unit is not allowed to learn, it becomes inhibited and a new cluster unit is selected for learning. It dictates the three possible states for F2 layer neurons; they are namely active, inactive and inhibited. The difference between the inactive and inhibited is that for both the cases activation state of F2 unit is zero. In its inactive state, the F2 neurons are available in next competition during the presentation of current input vector which is not possible when the F2 layer is inhibited (Kavuri and Kundu, 2011).

- **Gain control**

  The gain controller (G) is nothing but a data controller. It controls the attentional subsystem by sending data or not.

- **Attentional Subsystem**

  Attentional Subsystem is a central part of the ART1 network, it divided to:

  - **Input**: Represents and stores the given input vector (I) from external environment to F1 layer (no dynamics).
  - **Bottom F1 layer**: Is consists of N binary valued nodes. The output(X) of these nodes is controlled by a so called 2/3 rule . F1 layer exchanges the input portion signal with the F2 layer. The main purpose of F1 layer is to compare the binary input pattern X with the binary expectation pattern (Y) from F2 layer. In a F1 layer occur at the excitatory and inhibitory inputs to shunting model. The excitatory input to F1 layer of ART1 consists of a combination of the input pattern and the Y expectation. The inhibitory input consists of the gain control signal from F2 layer (Hagan, 1996).

F1 Layer Equation:

$$\varepsilon \frac{d\mathbf{n}^1(t)}{dt} = -\mathbf{n}^1(t) + \left({}^{+}\mathbf{b}^1 - \mathbf{n}^1(t)\right)\left\{\mathbf{p} + \mathbf{W}^{2:1}\mathbf{a}^2(t)\right\} - \left({}^{-}\mathbf{b}^1 + \mathbf{n}^1(t)\right)[{}^{-}\mathbf{W}^1]\mathbf{a}^2(t) \ldots\ldots\ldots\ldots\ldots\ldots (5-2)$$

- **Top F2 layer(cluster):**

The F2 layer has M binary valued nodes. It is the output layer Y (expectation) of the ART 1 network. Every node in F2 layer can represent a cluster (exemplar), i.e. each node Performs template selection.

In ART1the main purpose of F2 layer is to contrast enhance its output pattern Y, the contrast enhancement will be a winner-take-all competition, then only the neuron (node) is the winner when that get the maximum value of input X and will have a nonzero output. F2 layer of the ART1 network uses an integrator that can be reset, this means any positive output Y expectation (F2 layer output winner) is reset to zero whenever test the F2 layer Y expectation and input I (matching test between cluster with input from external environment) depending the vigilance factor.

Equation of operation of F2 layer:

$$\varepsilon\frac{d\mathbf{n}^2(t)}{dt} = -\mathbf{n}^2(t) + \left({}^{+}\mathbf{b}^2 - \mathbf{n}^2(t)\right)\overbrace{\left\{[B^2]\mathbf{f}^2\left(\mathbf{n}^2(t)\right) + BX\right\}}^{\boxed{\text{Excitatory}}}$$

$$-\underbrace{\left({}^{-}\mathbf{b}^2 + \mathbf{n}^2(t)\right)[{}^{-}T^2]\mathbf{f}^2\left(\mathbf{n}^2(t)\right)}_{\boxed{\text{inhibitory}}}\ldots\ldots\ldots\ldots\ldots\ldots(5-3)$$

The rows of adaptive weights (bij), after training, will represent the prototype patterns Y.

$$Yj = \begin{cases} 1, & \text{if } (jbij)^T xi = \max_j[({}_j bij)^T xi] \\ 0, & \text{otherwise} \end{cases} \ldots\ldots\ldots\ldots(5-4)$$

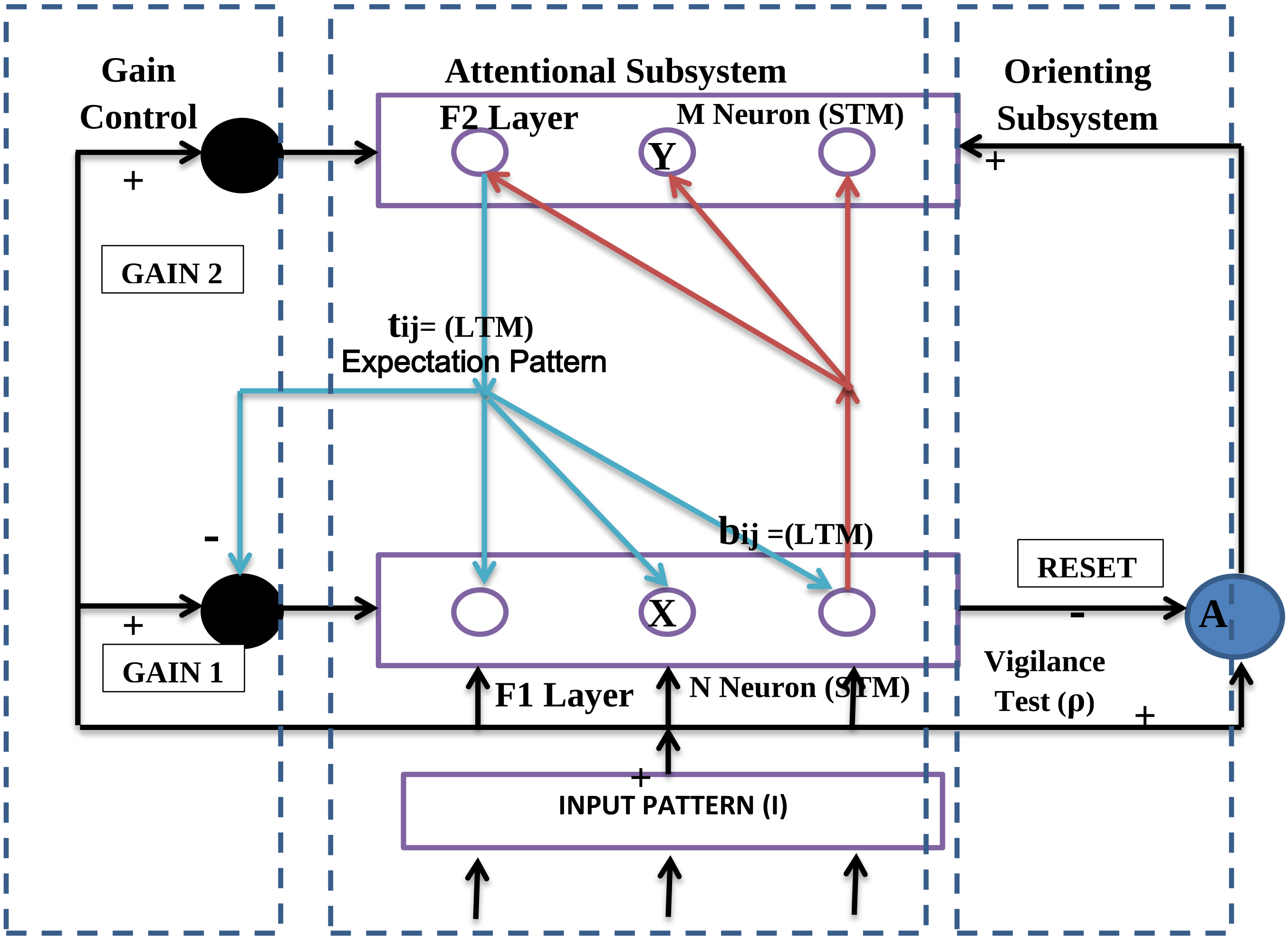


Figure 5-7 diagram of Basic structure of ART1.

As shown in Figure (**5-7**) every node in the input layer is connected to the corresponding node in the F1 layer (interface). Each node in the input layer and F1 layer is connected to the reset unit, which in turn is connected to every F2 layer. All nodes Xi in the F1 layer are fully connected to all nodes Yi in the F2 layer by two weighted connections, denoted as (bij) bottom-up weights and (tji) top-down weights is a representative weight for the connections between nodes in the F2 and F1, layer Fausett, (2008).

These connections weights, (bij) (tji) are also indicated as the Long Term Memory (LTM) and the same time the F1 and F2 are also denoted as the Short Term

Memory (STM) of the ART 1 network. X and Y are therefore called the F1 STM pattern and the F2 STM pattern) (Freriks, et.al 1992).

(B) ART1 Algorithm

From two perspectives of Lippmann (1987) and Laurene Fausett (2008)the researcher formed the following steps:

Step 1: Initialization

Put $t_{ji}(0)=1$ ……………….. (5-5)

$$b_{ij}(0) = \frac{L}{L+N-1} \text{ ……………… (5-6)}$$

Where

L > 1 ; 0 ≤ i ≤ N-1 , 0 ≤ j ≤ M-1

Set **ρ** to some number 0 ≤ **ρ** ≤ 1

In these equation $b_{ij}(t)$ is the bottom up connection weight and $t_{ji}(t)$ is the top down connection weight between input node (i) and output node (j) at time (t) of a Carpenter/Grossberg net with N inputs x0…..xn-1 and M output y0…..ym-1. After learning, these weights define the exemplar specified by output node (j).

The function **ρ** is the vigilance threshold which indicates how close an input must be to a stored exemplar to match. The value of the **ρ** close to 1 means that an input must be close to the learnt pattern in order to be classified respectively.

Step2: apply new input

Step3: compute matching scores

$\boldsymbol{\mu j} = \sum_{i=0}^{n} \boldsymbol{bij(t)\ xi},$ **…….….….** (5-7) $0 \le j \le M\text{-}1$

μj is output of node (j) and xi is the element (i) of the input which can be (0) or (1).

Step 4: Select best matching exemplar

$\boldsymbol{\mu_j^{*} = Max\{\mu_j\}}$…………… (5-8) Using (quick sort)

Step 5: Vigilance Test

The vigilance test is performed by dividing the dot product || TX|| of input and best matching exemplar (i.e. the number of bits in common) by the number of bits ||X||equal to 1in the input, and comparing this ratio with the vigilance **ρ.**

Where

$||\boldsymbol{X}||_2 = \sum_{i=0}^{n} \boldsymbol{xi}$ **(we can use $||\boldsymbol{X}||_1$ & $||\boldsymbol{X}||_\infty$)**

$||\boldsymbol{TX}||_2 = \sum_{i=0}^{n} \mathbf{tij} * \mathbf{xi}$

Is $||\boldsymbol{TX}||_2 / ||\boldsymbol{X}||_2 \ge \rho$

If yes go to step 7 i.e. (the input (i) is similar to the best matching exemplar and exemplar is updated by using logical and operation between its bits and those in the input)

If no go to step 6 i.e. (the input different form all exemplars and added as new exemplars)

Step 6: Disable best matching exemplar

The output of the best matching node selected in step 4 is temporarily set to zero and no longer takes parts in the maximization of step 4 then go to step 3.

Step 7: Adapt best matching exemplar

The given input is used for learning by computing new connection weights $t_{ji}(t+1)$ and $b_{ij}(t+1)$ as follows:

$\boldsymbol{t_{ji}(t+1)}$ = $\boldsymbol{t_{ji}(t)x_i}$ **……….**(5-9)

$\boldsymbol{b_{ij}(t+1)}$ **= tji(t)xi/0.5 +** $\sum_{\mathbf{i=0}}^{\mathbf{n}} \boldsymbol{t_{ji}}(\mathbf{t}) * \boldsymbol{x_i}$ **=** $\boldsymbol{t_{ji}}$**(t+1)/0.5 +** $\sum_{\mathbf{i=0}}^{\mathbf{n}} \boldsymbol{t_{ji}}\,(\mathbf{t}) * \boldsymbol{x_i}$ **xi**

……(5-10)

Step 8: Repeat by go to step 2

compute error rate by

If **|| bij(t+1) - bij(t)|| < Є** ………..(5-11)

where Є very small value

IF **Yes** go to End

else go to step 2

(C) ART1 Training

First the LTM will be initialized by assigning small random values to the bij weights and setting the tji weights equal to 1. At this stage the vigilance is set as $0<\boldsymbol{\rho}<1$. The input pattern I is hatched across both the gain controller, the orienting subsystem and the feature detectors at F1 layer as a short term memory (STM) activity pattern X. The gain controller immediately feeds this input I to F1. The nodes in F1 now receive 2 inputs both equal to I. Because of the 2/3 rule this pattern will be copied into X, the F1output signal. This signal will be applied to the orienting subsystem A very quickly. Now a RESET at A will be suppressed, because these signals which received are the same.

The F1STM output signal is not only used to suppress a RESET. It will also be passed through the bij. Before this happens, it can be transformed to a pattern S, the F1 activation pattern. This possibility enables the network to do some pattern processing. Very often, X is just copied into S. After that, a bij calculation takes place in which S will be multiplied with the bij by a weighted summation. This results in an initial F2 pattern T at F2:

$$\mathbf{Tj} = \sum_{\mathbf{i=0}}^{\mathbf{n}} \boldsymbol{b_{ij}S_i} \qquad \ldots\ldots\ldots\ldots.(\mathbf{5-12})$$

For all j where $0 \leq j \leq M\text{-}1$

As stated before, every F2 node Tj represents a c1ass or cluster. In the vectors to and from these nodes the prototypes of the input patterns of these clusters are stored. This means that eq. (1) is nothing but a series of vector multiplications of a pattern S with the prototypes of each clusters. To find the cluster to which the input belongs, the output node which represents this cluster has to be selected. This is reached by letting the values Tj undergo a competitive process. During such a process a criterion is defined; the output node which satisfies this criterion most is selected. This node is called the winning node. A criterion which is often used in neural networks is selection of the output node with the maximum response to the bij calculation. This winning node Tj will be stored in Y by making Yj = 1 and all other Yj nodes = 0. The cluster assigned or represented by this node is assumed to be the best match to the applied input as illustrated in Figure (5-8).

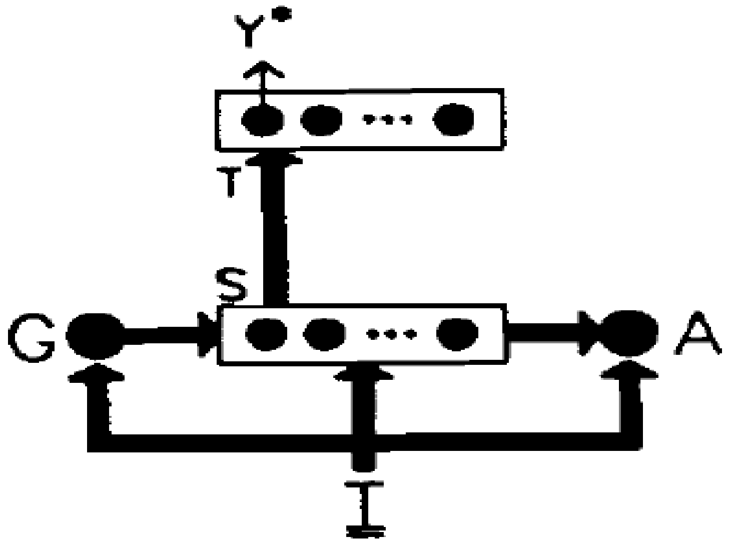


Figure 5-8 first stage of an ART1 training cycle

To test whether this match is valid, the prototype of this cluster has to be compared with the applied input. This is done by a tji calculation from the F2 layer to the F1 layer. The F2 STM pattern Y eventually can, similar to X, be transformed into a F2 activation pattern U. Often U = Y. This pattern is sent to the tji LTM. Simultaneously a signal is sent to the gain controller (G). This signal shuts off the feed through of pattern I at G. Now a new pattern enters F1 as a result of the weighted summation of pattern S and the tji LTM. This pattern B can be calculated as follows:

$$\mathbf{Bi} = \sum_{\mathbf{j=0}}^{\mathbf{m}} \boldsymbol{t_{ji}}\,\boldsymbol{U_j} \qquad \dots\dots\dots\dots.(\mathbf{5-13})$$

For all i where 0 ≤ i ≤ N-1

B is called a (tji) template or (tji) learned expectation. It represents the prototype of the input of the cluster assigned by the winning node. F1 now receives two signals I and B. Those nodes Xi in F1, which receive two input values, elicit an output signal equal to 1. Output vector X will be sent to the orienting subsystem A. There, two things can happen now.

- If I and B look alike X will resemble I very much. Therefore X is able to suppress a RESET in the orienting system. the input is said to match the assigned cluster as Figure (5-9).
- If I and B differ much, X does not resemble I. Now X is not able to prevent A from generating a RESET, so this RESET will be generated.

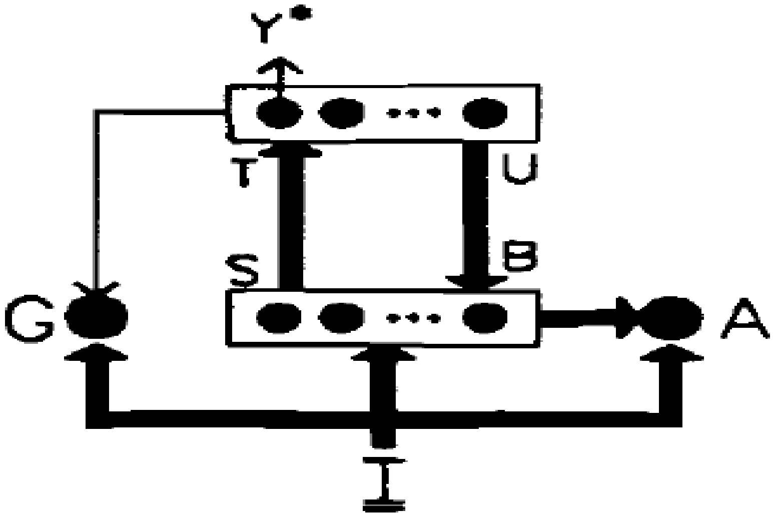


Figure 5-9 second stage of an ART1 training cycle

In the first case the match cycle ends. It is known to which cluster the input belongs. The learning phase can start now to incorporate I in that cluster. In the second case the search process or training algorithm has to continue because the input is not accepted as a member of the assigned class. The RESET signal disables the winning node in Y. As a consequence of this, the tji control signal and the F2 activation pattern are removed as shown in Figure (5-10).

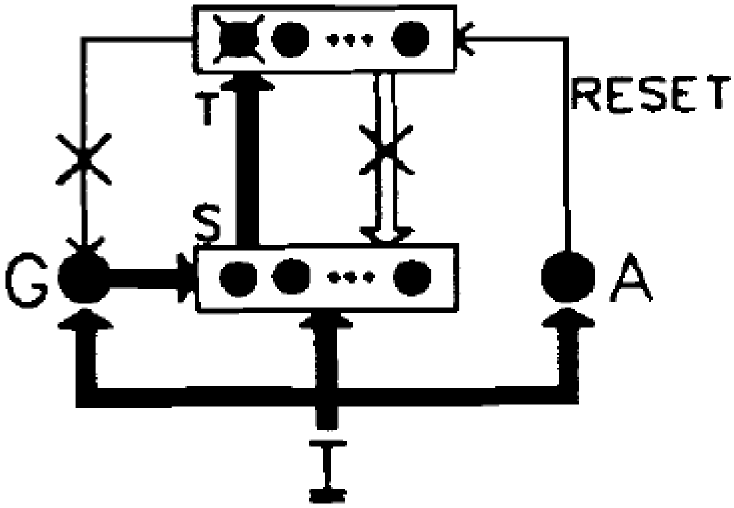


Figure 5-10 three stage of an ART1 training cycle

This results in a new feed through of I at G, suppression of the RESET signal and a new bij calculation. The outcome of this calculation is the same as after the first bij calculation. When the competitive process starts the preceding winning node is excluded from competition. This results in a new winning node. Now again this winning node is stored into Y, transformed into U and calculated back to B. At F1 will be tested then, whether the prototype of the cluster assigned by this winning node matches I. If so, the training algorithm has come to an end. If not, the above described process of bij calculation and tji matching has to be repeated until a match is found. This will always happen if there still remains at least one so called uncommitted node.

This is an output node which is not assigned to any cluster yet. If an uncommitted node wins the competition, due to the initialization of the tji LTM this node will always be assigned to input pattern I. Only if there are no uncommitted nodes left it can happen that an input pattern I doesn't fit to any cluster. In that case this has to be made clear although it is always possible within the ART network to add new nodes without influencing the behavior of the net.

(D) The vigilance test

Zurada (1992) says in orienting subsystem running the vigilance test. the vigilance threshold is a parameter take values between (0,1) specified by a user which is has control on The criterion of similarity or "match," required between a cluster or pattern or exemplar already stored in the ART1 network and the current input in order for this new pattern to resonate with the encoded one. If the match between the input vector and $\boldsymbol{j^{th}}$ cluster is found, the network is said to be in resonance (Zurada 1992).

Grossberg (2013) considered that by lowering of the vigilance threshold permits the learning of general categories with abstract pattern in other word allows the system to be more noise tolerant and broad generalization. High vigilance leads to narrow generalization and forces a memory search to occur for a new category when even small mismatches exist between an exemplar and the category that it activates (Grossberg 2013)

During training this test will be executed at least 2 times. The first time is when an input I is applied to the ART1 network, then input layer I is on, and since this value is positive an excitatory signal is sent to orienting subsystem A. The strength of that signal depends on how many input layer I are on. However, A also receives inhibitory signals from the F1 layer that are on. If enough F1 layer interface are on, orienting subsystem A is prevented from firing (That is a RESET signal is suppressed).

If the ratio of $||I||_2$ and $||Y||_2$ is greater than or equal to the vigilance parameter, the weights (bij and tji) for the winning cluster unit are adjusted.

The vigilance test now becomes:

$$\frac{||\boldsymbol{Y}||_2}{||\boldsymbol{I}||_2} \leq \boldsymbol{\rho} = \boldsymbol{vigilance}\ldots\ldots\ldots\text{..(5-14)}$$

Where:

I: is (input layer) output

Y: is output of (F2) layer

$||\boldsymbol{x}||_{\boldsymbol{n}} = \sum_1^n \sqrt[n]{x^n}$. ……………. (5-15)

However, if the ratio is less than the vigilance parameter, the candidate unit is rejected, and another candidate unit must be chosen. The current winning cluster unit becomes inhibited, so that it cannot be chosen again as a candidate on this learning trial, and the activations of the F1 units are reset to zero Freriks, et.al (1992).

5.3.3. Testing Phase

In this phase, testing dataset will be implemented by the ART1 neural network which was trained during the training phase using the best number of parameters such as norm, weight factor and vigilance test (threshold). furthermore the selected records should be involve on some the duplicated records when testing system, to ensure the learning is a stable .The designed system will be evaluated by calculating the Detection Rate (DR), accuracy Rate (AR), False Positive Rate (FPR) etc. for our model. The results and experiments details are described in chapter six.

5.4 Intrusion detection simulation

When test data traffic network by passing it through the database that contains a saved trained patterns in order to detect intrusion if found by:

- **Classifier:** compare between ANN output and data testing set for classifying network traffic into normal or intrusive, sends its results to the responder.

- **Responder:** response to the detected intrusions by generating alarms (such as sending e-mail to system administrators) and generating reports on the collected data in IDS log files.

Chapter Six

Experiments Results and Conclusion

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Experiments Results and Conclusion

6.1 Introduction

In this chapter, the researcher tackles the main experiment results and its evaluation criteria which are produced by implement the proposed simulation by applying k-mean clustering algorithm and Carpenter / Grossberg-ART1 ANN system, and compare it with previous studies. The chapter ends with conclusion and future work.

6.2 Implementing Technique

Heaton (2008) displays that the neural networks are constructed of neurons that form layers. Java can be used to construct such network. Java can used to calculate the output of ART1 neural network from inputs, connection weights, and threshold values to determine the final result by the mathematical equations (Heaton 2008).

The researcher uses java version 1.7 to program the proposed simulation. Firstly, from KDD 99 dataset the system convert row data to another forms through tow process; codification and encoding as acceptable format to ART1 ANN.

Secondly, the system passing these modified data to K-mean clustering algorithm to get initial classification, this process increases the similarities between normal patterns and in other hand, it increases the differences between normal patterns and attack types. In order to get high performance and accuracy of ART1 ANN.

Finally, ART1 receives these classified data work as training pattern data, after the system has been trained; it works as classifier in testing phase. In order to have normal and types of attacks (Normal, Dos, Probe., R2L,U2R) such as stable IDS, which achieves high detection rate and minimize false negative rate.

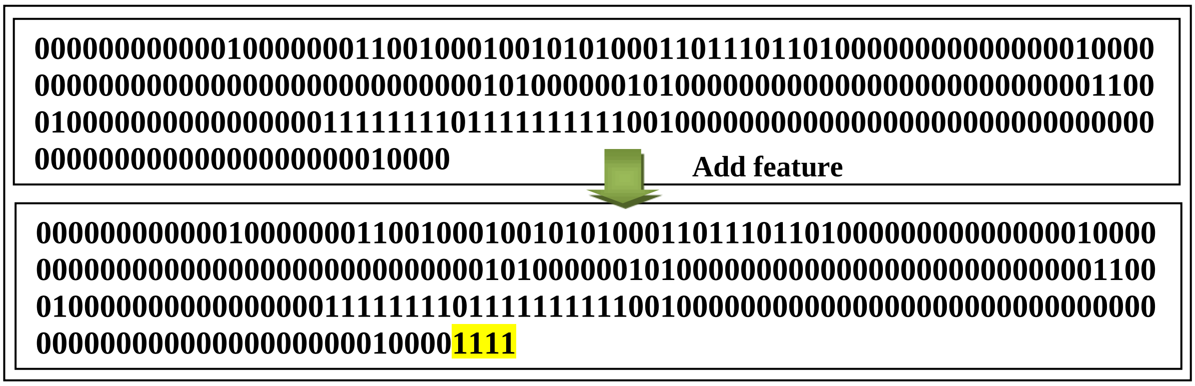
6.3 K-mean algorithm results

The system at first stage uses K-mean clustering algorithm for grouping KDD 99 dataset into five categories involved (Normal, DoS, Prob,R2L and U2R). The main function of this stage that it has initial classification and it increases the similarity between the same category and the same time supports the difference between others by adding new feature to dataset notes the Figure (6-1).

Table (6-17) shows the category size, detected size, and detection rate for K-means results in labeled dataset as follows:

Testing Datasets (Labeled)	Category Size	Detected Size	Detection Rate
Normal	2556	2506	98.04%
DoS	4785	4025	84.12%
PROB	1863	1791	96.14%
R2L	744	683	91.80%
U2R	52	36	69.23%
TOTAL	10000	9046	90.46%

Table 6-1 K-mean clustering results



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0000000000000000000000000000101000000101000000000000000000000000001100
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00000000000000000000010000

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0100000000000000001111111101111111111001000000000000000000000000000000
000000000000000000000100001111

Figure 6-1 add feature to dataset after know it as normal

6.4 Carpenter / Grossberg-ART1 ANN Results

At the second stage in classification implements by the Carpenter / Grossberg-ART1 ANN. It uses also to classify the testing dataset into 5 categorizes. The neural network is trained by using the best adjusted values of parameters such as norm, weight factor, and vigilance test (threshold). Furthermore, the selected records should be containing some the duplicated records when testing system, to test and ensure the stability of the learning process.

During training network ART1, we noticed when the norm parameter is used in vigilance test as shown in equation (5-15) and (5-14) respectively. Using the second norm demonstrates better results than using the first norm and infinity norm, because first norm has low detection rate and infinity norm has high misclassification in the categories.

The parameter of weights factor (L) as displayed in equation (5-6). It has been adjusted and changed to many values which are bigger from 1. We get the best results when using L=2.

The vigilance threshold is an important parameter which determined through researcher in order to get best results. this parameter take values between (0,1) is has control on the measurement of the matching desired between a cluster or pattern already stored in the Carpenter / Grossberg-ART1 ANN and the current input in order for this new pattern to resonate with the encoded one. The comparison between different threshold (when vigilance value take: 0.7, 0.8, 0.9 and 0.95) in Carpenter / Grossberg-ART1 ANN, we choose vigilance = 0.9 because it gives the best results for DR, AccR, FPR, and FNR as showed in Figure (6-2)

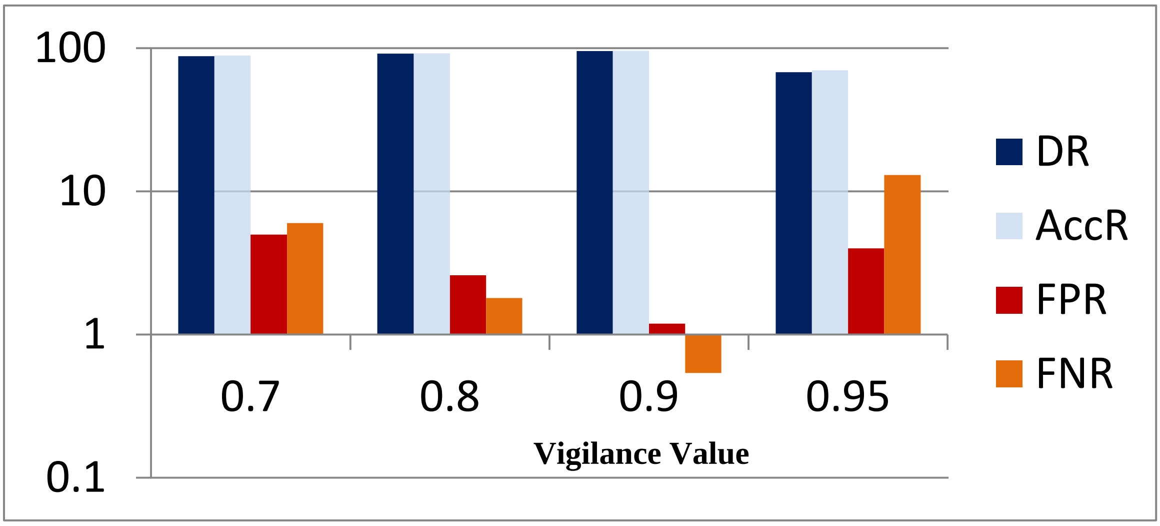

Figure 6-2 comparison between vigilance tests

Depending on the adjusted values of parameters as **(weight factor = 2, second norms = 2, vigilance = 0.9)** of the previous experiment Carpenter / Grossberg-ART1 ANN is able to classify the labeled testing dataset which has results demonstrated in Table (6-2) that represent the confusion matrix of the 5 categorizes (labeled):

Confusion Matrix (Labeled)							
		Detection					
		Normal	DoS	PROB	R2L	U2R	TOTAL
Actual	Normal	2526	11	4	13	2	30
	DoS	11	4694	23	42	15	91
	PROB	13	52	1731	58	9	132
	R2L	15	31	2	683	13	61
	U2R	1	6	1	13	29	23
	TOTAL	2566	4794	1761	809	68	10000

Table 6-2 Confusion Matrix of testing data (Labeled)

From Confusion Matrix of testing data (Labeled) above, it indicates the detected size for each category. Table (6-3) below displays Category Size, Detected Size, and Detection Rate as follows:

weight factor = 2 , second norms = 2 , vigilance = 0.9			
Testing Datasets (Labeled)	**Category Size**	**Detected Size**	**Detection Rate**
Normal	2556	2526	98.83%
DoS	4785	4694	98.10%
PROB	1863	1731	92.91%
R2L	744	683	91.80%
U2R	52	29	55.77%
TOTAL	10000	9608	96.08%

Table 6-3 Carpenter / Grossberg-ART1 ANN detection

Figure (6-3) displayed the Category Size and Detected Size for each Category (normal and attack types).

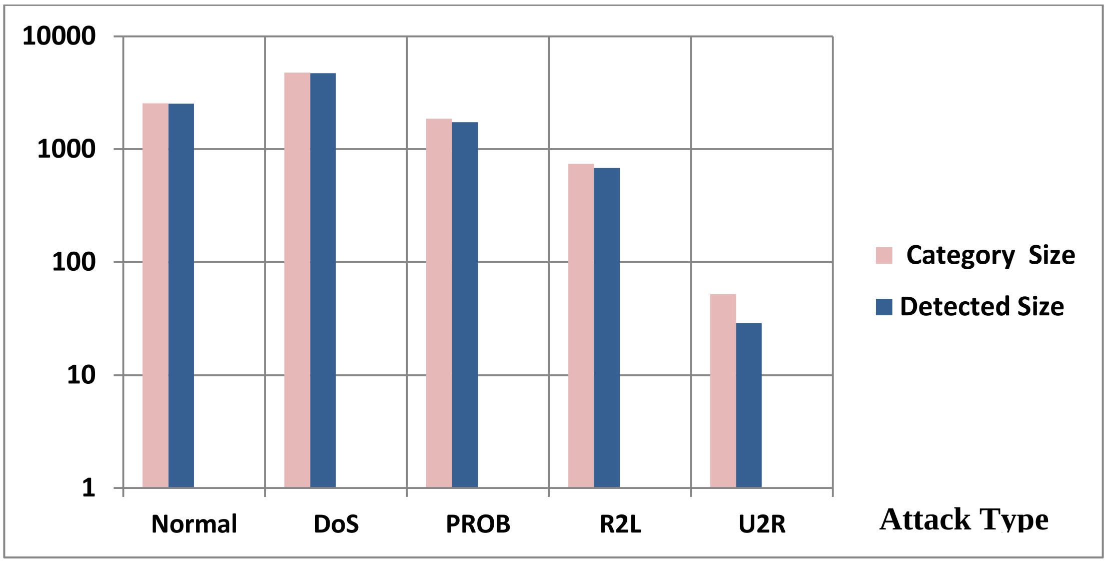

Figure 6-3 Category Size and Detected Size

From Figure (6-3) we note the ART1 has a very good results that belong to normal and DoS about 98.83% and 98.10% respectively. Since the system used k-mean cluster as a pre-classifier which increasing similarity between the same category and dissimilarity between others. But the drawback of the ATR1 was the U2R detects 29 patterns (records) from 52 patterns as total in testing phase.

In Table (6-4), we apply 3000 testing unknown (unlabeled) dataset of KDD 99 in ART1. It is obvious that there is a good percentage in simulation of ID that detects the new unknown attack with **Detection Rate** of approximately 87.10%, **Non-detection Rate** 12.90% as listed below:

Testing (Unlabeled)Datasets 3000Unknown Attacks			
Attack	**Detected**	**Not Detected**	
Normal	961		
DoS	722		
PROB	581		
R2L	336		
U2R	13		
Unknown		387	
TOTAL	2613	387	3000
Detection Rate	87.10%		
Not Detection Rate		12.90%	

Table 6-4 Testing Unlabeled Dataset

6.5 Evaluation Criteria

The results in Table (6-5) show the true classified and misclassified for each category such as; **True Positive, False Positive, and False Negative** by applying the ART1 classifier in testing phase as shown below:

Attack	TP	FP	FN
DoS	4694	11	11
PROB	1731	4	13
R2L	683	13	15
U2R	29	2	1

Table 6-5 the true classified and misclassified

The Evolution Criteria ID attacks that consist of **the Accuracy Rate, Precision, Recall, FPR and FNR** can be displayed in Table (6-6) as follows:

Attack	Accuracy Detection Rate	Recall	Precision	F-Measure	FPR	FNR
DoS	99.70%	99.8%	99.77%	99.77%	0.43%	0.234%
Prob	99.03%	99.3%	99.77%	99.51%	0.16%	0.745%
R2L	96.13%	97.9%	98.13%	97.99%	0.51%	2.149%
U2R	93.62%	96.7%	93.55%	95.08%	0.08%	3.33%

Table 6-6 The Evolution Criteria ID attacks

It is concluded from Table (6-6) above which detailed the testing of labeled data the use of ART1 ANN that Accuracy Detection Rate for each DoS detect about 99.70% , Prob has value of 99.03%, R2L detect about 96.13%, and U2R get value as 89.80%. Recall rate with DoS. PROB, R2L, U2R has value of 99.8%, 99.3%, 97.9%, 90.6% respectively. Also FPR with DoS. PROB, R2L, U2R has value of 0.43%, 0.16%, 0.51%, 0.08% respectively. Whereas FNR includes DoS ; has a False Negative Rate 0.234%, PROB attack has about 0.745%, R2L attack has False Negative Rate of about 2.149%,, U2R attack has about 3.38% False Negative Rate. Below Figures (6-4) and (6-5) demonstrates the evaluation criteria Accuracy, Detection Rate, Recall Precision, F-Measure, FPR, and FNR

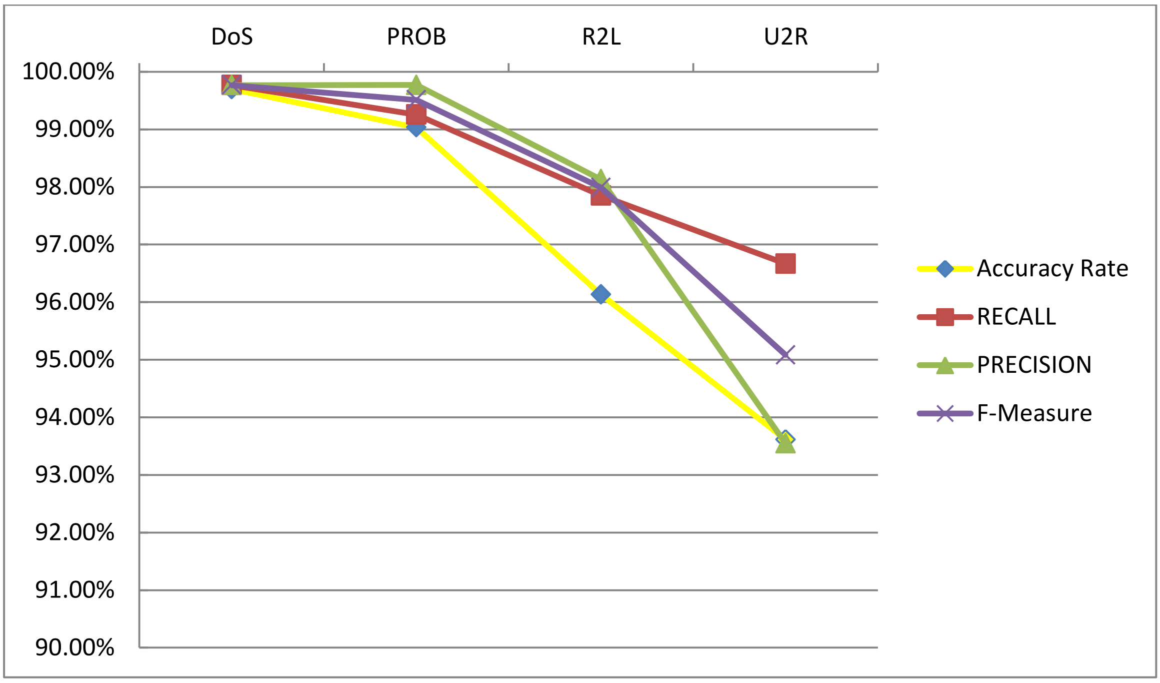

Figure 6-4 evaluation criteria

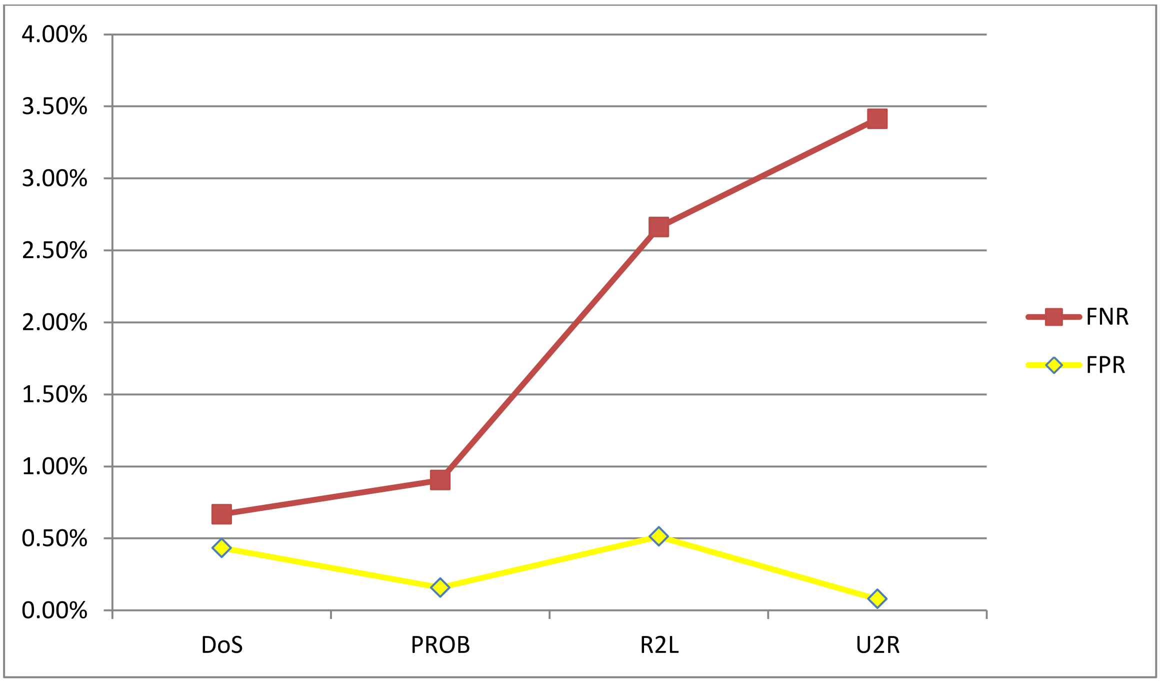

Figure 6-5 evaluation criteria (FPR) and (FNR)

The effectiveness of an ID is evaluated on how capable the detection method is to make correct attack detection Al-Rashdan (2011) and Shamshirband, et al (2013), according to the following criteria:

$$\boldsymbol{DR} = \frac{\sum \boldsymbol{No.of\ Detected\ Attack}}{\boldsymbol{No.of Attacks}} \boldsymbol{X100}\ \% \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ \textbf{(6-1)}$$

$$\boldsymbol{FPR} = \frac{\sum \boldsymbol{No.of\ misclassified\ processes}}{\boldsymbol{No.of\ normal\ processes}} \boldsymbol{X100}\ \% \ \ldots\ldots\ldots\ldots\ \textbf{(6-2)}$$

$$\boldsymbol{FNR} = \frac{\sum \boldsymbol{No.of\ misclassified\ processes\ AS\ Normal}}{\boldsymbol{No.of\ Attacks}} \boldsymbol{X100}\ \% \ \ldots\ldots\ \textbf{(6-3)}$$

$$\boldsymbol{AccR} = \frac{\sum \boldsymbol{No.ofcorrect\ classified\ processes}}{\boldsymbol{No.of\ processes}} \boldsymbol{X100}\ \% \ \ldots\ldots\ldots\ldots\ldots\textbf{(6-4)}$$

Evaluation Criteria	**Value**
False Positive Rate (FPR)	1.19%
False Negative Rate (FNR)	0.54%
Detection Rate (DR)	96%
Accuracy Rate (AccR)	96.08%

Table 6-7 important results of ART1 for IDS

From Table (6-7) it can be concluded that Carpenter / Grossberg-ART1 ANN classifier was able to detect records with a detection rate of approximately 96% with accuracy rate 96.08% which is considered very good were the system trustworthy is guaranteed to detect intrusions. The ART1 very good performance results and rates especially false positive rate about 1.19% and false negative rate equal 0.54% when the false negative patterns (records) were only 40 records from 10,000 records (intrusions detected as normal).

6.6 Comparison Between Our Method and Others Methods

This proposed system work compared with other previous intrusion detection systems researches that use either neural network (supervised, unsupervised), clustering algorithm (machine learning).

Methods	DR	AccR	FNR	FPR	F- Measure
ART1	**96.08%**	**96%**	**0.54%**	**1.19%**	**98.80%**
Al-Rashdan, 2011/ SOM+ Conscience	**92.5%**	**-**	**5.2%**	**3.5%**	**95.5%**
Na'mh,(2012) Hybrid (kNN_ERBP)	**97.2%**	**99%**	**1%**	**7%**	**99%**
Al-Nuimat, (2013) HNKMIDS	**99.38%**	**-**	**0.14%**	**1.32%**	**-**

Table 6-8 comparison between proposed system and previous researches

The proposed model (IDS based on ART1) performance is compared with Al-Rashdan (2011) which it is unsupervised learning by using IDS evaluation criteria such as in Table (6-8). We can see that our proposed IDS produces the most accurate result in **DR , AccR, FNR, FPR and F- Measure** which indicates that it has better results rather than her results.

Also it is compared with **Na'mh, (2012) Hybrid (KNN_ERBP)** which is supervised learning with KNN clustering algorithm by using same criteria. The results have better performance according to false positive rate and false negative rate. On other hand, it is satisfied that the results of this research have minimized **FPR** and **FNR** which is considered the most critical evaluation.

Finally, the proposed system is compared to **HNKMIDS** proposed **by Al-Nuimat, (2013)** which is used supervised learning with K-means clustering algorithm. Table (6-8) illustrates that the DR and FNR of HNKMIDS system has better results from our proposed system (ART1). In contrast, we gain FPR batter results. Although, our system is unsupervised learning, so is considered a good results in term of comparison in supervised learning.

6.7 Conclusion

This research introduces an Intrusion Detector based on the Carpenter / Grossberg-ART1 ANN system. It used KDD 99 dataset that converted row data to another forms through two processes; codification and encoding as acceptable format to ART1 ANN for training and testing phase. In addition, K-mean clustering algorithm has been used to improve performance of the proposed system, where ART1 categorizes network data flow into normal and four attacks (DoS, Probe, R2L and U2R). Also ART1 sub system recognize and memories the old learning attack patterns.

The main function of this process (which mentioned above) that it has initial clustering and it increases the similarity between the same category, and at the same time supports the difference between others by adding new feature to dataset notes the Figure (6-1).

In training phase, there is an important parameter so called the vigilance threshold. We noticed that the comparison between different threshold (when vigilance value take: 0.7, 0.8, 0.9 and 0.95) in Carpenter / Grossberg-ART1 ANN, preferred to select vigilance = 0.9 because give the best results for DR, AccR, FPR, and FNR as showed in Figure (6-2)

Depending on the adjusted values of parameters as (weight factor = 2, second norms = 2, vigilance = 0.9) we have got results demonstrated in Table (6-3) that ART1 has a very good results that belong to normal and DoS about 98.83% and 98.10% respectively. But the drawback of the ATR1 was the U2R detects 29 patterns (records) from 52 patterns as total in testing phase. From the results of the research we conclude that our system has many advantages over than supervised NN system such as resilient back-propagation. Beside, our system doesn’t suffer from stability / plasticity while previous IDSs suffer from (i.e. forgetting old learning). This proposed simulation system compute the FPR and FNR which is better than previous results of Al-Rashdan, 2011 Na'mh, Z. (2012) as shown in Table (6-8)

6.8 Future Work

The researcher recommends the following suggestions:

- Enhance the capability of ART1 algorithm in proposed IDS by choosing best candidate rather than minimum index max value for winning node in layer 2 such that has more than one candidate
- Enhancing FPR and FNR by saving several patterns for well-known types(normal or attack)
- Reduce number of features by considering the importance features for each class and discarding the weak ones.
- Enhance the optimal features for each class.
- Design IDS to detect attacker before they get access, or during the process of getting access
- Design an IDS to prevent the intrusion
- Design optimal an algorithm to improve the vigilance in proposed IDS.
- Enhance our proposed system, so except continuous data

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